Land use change, agricultural markets and the environment

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Doctorat ParisTech

THÈSE

pour obtenir le grade de docteur délivré par

L'Institut des Sciences et Industries
du Vivant et de l'Environnement
(AgroParisTech)

Domaine : Sciences de l'Homme et de la Société
Spécialité : Sciences Économiques

présentée et soutenue publiquement par

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le 17 mars 2014

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Changement d'usage des sols, marchés agricoles et environnement

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REMERCIEMENTS / ACKNOWLEDGEMENTS

REMERCIEMENTS

La réalisation d'une thèse renvoie souvent l'image d'une longue traversée en solitaire. Bien sûr, les jours et les nuits passées à faire progresser seul ce travail ne se comptent plus. Pour autant, ces dernières années resteront associées, dans mon souvenir, à une aventure où le collectif a aussi eu toute sa place. À l'heure de clôturer ce manuscrit, les noms de nombreuses personnes me viennent à l'esprit, sans lesquelles ce travail n'aurait pas vu le jour.

Mes premiers remerciements vont à mon directeur de thèse Sébastien Jean, avec qui cette aventure a démarré, en 2009, autour du projet de compléter mon expertise de modélisation par la réalisation d'une thèse "probablement courte", et qui depuis cinq ans fait preuve de patience depuis Paris face à mes retards et absences, dus à mes engagements professionnels en Autriche. Je lui suis reconnaissant d'avoir accepté de me superviser sur ce sujet nouveau pour lui et de m'avoir encouragé à mener ce travail à son terme, malgré des contraintes de temps grandissantes pour l'un comme pour l'autre. Son exigence et son pragmatisme ont été une aide précieuse pour ce travail dont j'espère il sera au final satisfait. Mes remerciements vont aussi à cet égard à mon comité de thèse, qui m'a aussi aidé à structurer le matériau glané au cours de mes recherches : Jean Château, Stéphane De Cara et Petr Havlík.

L'équipe d'IIASA a joué un rôle central et déterminant dans mon travail ces dernières années et je suis extrêmement reconnaissant à Michael Obersteiner et Petr Havlík de m'avoir offert l'opportunité de rejoindre leur équipe de recherche il y a trois ans. Ces dernières années n'ont pas été faciles puisqu'il a fallu mener de front les responsabilités qu'ils m'ont confiées et les exigences de la thèse. Mais les sujets sur lesquels ils m'ont permis de travailler, les personnes qu'ils m'ont fait rencontrer et l'environnement de travail qu'ils m'ont offert ont été un atout fondamental pour ma motivation et tous ces éléments m'ont permis de prendre grand plaisir à cette recherche, tout en en tirant au final de multiples co-bénéfices. Florian Kraxner a également été un soutien précieux cette dernière année pour m'aider à aménager mon temps en bonne intelligence, en fonction de mes besoins et de ceux du programme. Et c'est en grande partie grâce à lui que ce travail a matériellement pu aboutir. Enfin, mes très nombreux collègues et complices de modélisation à Laxenburg m'ont bien sûr été un soutien quotidien, Stefan, Amanda, David, Géraldine, Nicklas, Gaspard, Sabine, Hannes, Sylvain, Oskar, Steffen, Cynthia... Une mention spéciale revient à Aline Mosnier, ma fidèle coéquipière de bureau, qui a permis que les journées se passent toujours dans le sourire et la bonne humeur. La liste des collègues et amis de l'institut qui ont su faire de ces années des moments heureux et du coup productifs est bien sûr bien plus longue. J'espère qu'ils accepteront mes remerciements ici sans que je n'aie besoin de tous les citer ; une pensée toutefois particulière va à José, Anna, Alessandra et Nuno.

Les origines de ce travail sont toutefois à chercher ailleurs qu'en Autriche. À l'AgroParisTech tout d'abord, où les professeurs du Mastère d'Économie du Développement Durable de l'Environnement et de l'Énergie m'ont permis d'affirmer mon goût pour les sciences économiques. Je leur suis reconnaissant de m'avoir fait découvrir les facettes passionnantes de cette matière appliquée aux défis environnementaux de ce début de siècle, alors que j'en cherchais encore la finalité au fil des équations. Jean-Christophe Bureau a su donner le goût des problématiques de politique agricoles à l'étudiant parisien que j'étais et je lui dois aussi de m'avoir ouvert la porte du CEPII et de l'INRA, par l'intermédiaire du CGE. J'ai passé de nombreux mois sur de multiples bureaux de l'UMR d'Economie Publique à Paris et en garde aussi d'excellents souvenirs. Que tous les collègues avec lesquels j'ai pu partager des moments de réflexion ou de détente autour de la machine à café

ou à la cantine de l'X soient ici chaleureusement remerciés pour leur accueil toujours chaleureux, notamment Christophe, Jean-Marc, Cécilia, Rajah, Estelle, Stéphane, Bajak, Anne-Célia, David, Hélène, Elodie, Shoun, Adam et bien d'autres.

Ma première expérience professionnelle au Centre d'études prospectives et d'informations internationales (CEPII) m'a donné la chance de pouvoir approfondir une bonne partie de mes connaissances en économie qu'un cursus initial d'ingénieur ne m'avait permis que de partiellement développer. Mes premiers remerciements vont ici à Lionel Fontagné qui m'a fait confiance en me proposant un poste de modélisateur en 2006 et à Agnès Benassy-Quéré qui m'a renouvelé cette confiance. Ils m'ont notamment permis de me concentrer dès 2007 sur des questions touchant à l'environnement, un domaine alors peu développé au CEPII, et de démarrer l'aventure du travail présenté ici. Yvan Decreux m'a fait faire mes premiers pas avec MIRAGE et David Laborde m'a fait découvrir les subtilités des mesures tarifaires. Cristina, Priscila, Houssein et Christophe me font garder de cette époque le souvenir d'une équipe de modélisation joyeuse et soudée et m'ont donné envie de poursuivre dans cette voie. Mes visites plus récentes au CEPII m'ont permis de constater que cet état d'esprit s'était perpétué ; merci à Houssein, Charlotte, Jean, Julien pour leur accueil l'été dernier. Christophe Gouel mérite des remerciements particuliers, puisqu'au delà des nombreuses discussions qui m'ont fait profiter de ses connaissances, il m'a encouragé – pour ne pas dire forcé ! – à renoncer à tous mes logiciels standards pour adopter les outils les plus rudimentaires mais performants du monde libre, sur lesquels je continue de travailler avec plaisir et efficacité, avec toujours bien sûr un temps de retard sur lui (non, je n'ai pas encore installé le package `markdown.el` sur *Emacs*, même si ça change la vie...). Merci aussi à Benjamin Carton pour m'avoir davantage sensibilisé à la macroéconomie mais aussi, à ses heures perdues, à la musique et à la philosophie !

J'ai enfin une pensée pour d'autres collaborateurs plus lointains, à commencer par ceux de l'IFPRI à Washington, avec lesquels j'ai beaucoup collaboré sur MIRAGE-BioF. Un grand merci à Antoine Bouët pour m'avoir confié une grande partie du travail sur les biocarburants en 2008 et m'avoir beaucoup encouragé sur ce sujet. Une pensée amicale également pour David Laborde qui a poursuivi cette aventure avec moi à partir de 2009 et a permis à ce travail de gagner une notoriété et un impact impressionnants. Merci enfin à mes camarade de K Street de l'époque, Elisa et Laetitia, pour leur inaltérable bonne humeur. Parmi mes coauteurs plus récents, je ne saurais m'empêcher d'avoir aussi une pensée pour Mario Herrero et Jerry Nelson, qui m'ont fait prendre le pari de participer à des travaux à fort impact académique, en plus de cette thèse, et qui me permettent aujourd'hui de la clôturer avec quelques autres publications parallèles appréciables.

Mes derniers remerciements vont bien sûr à tous ceux qui n'ont malheureusement pu voir que l'autre face de ce travail, parmi mes amis à Paris et à Vienne, ma famille et mes plus proches. Longtemps ils se sont demandés à quoi tous ces nouveaux efforts pouvaient bien servir et ont dû subir le contrecoup de cet investissement de temps. Peut-être se poseront-ils toujours la question après avoir parcouru ce document, mais je tiens à leur dire ici à nouveau combien leur soutien, et les moments de détente qu'ils m'ont offerts, ont été précieux pour mon moral, mon équilibre et mon optimisme pour mener ce travail à son terme. Merci à Sébastien, Aurélie, Aymeric, Johann, Pierre, JB, Lucile, Franz, Alex, Mathieu, Isabelle. Merci à Marie, Pauline, Rebecca, Claire, Jeff. Merci à beaucoup d'autres. Merci à Amandine. Merci à mes parents, à mes frères et à ma chère famille.

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Acknowledgements

even if it is supposed to change your life...). I also express special thanks to Benjamin Carton, for sharing his passion for macroeconomics, but also in his spare time, for music and philosophy!

One thought also goes to my colleagues from other parts of the world, starting with those from IFPRI in Washington with whom I have worked a lot on MIRAGE-BioF. I would like to express my gratitude to Antoine Bouët for putting me in charge of a large part of the work on biofuels in 2008 and encouraging me a lot about this topic. A thought also goes to David Laborde who continued this adventure with me after 2009 and has allowed this work to earn an outstanding outreach and impact. I would also like to thank my young colleagues during my stay at K Street, Elisa and Laetitia, for their always welcome freshness. Among my more recent coauthors, my appreciation also goes to Mario Herrero and Jerry Nelson, who invited me to contribute to some challenging projects in parallel to this thesis, and allow me today to wrap it up today with some nice other publications beside.

My final thanks will go of course to all of those who only saw the other side of this work, among my friends, in Paris and Vienna, my family and the dearest of them. For long, they have wondered where all these new efforts were leading to and they have been affected by this investment of my time. Even if they might still have the same question after having been through this document, I want to make clear here how much the unwavering support and diverting time they gave me were invaluable for my mood, my balance and the confidence necessary to finalise this work. I would like to thank Sébastien, Aurélie, Aymeric, Johann, Pierre, JB, Lucile, Franz, Alex, Mathieu, Isabelle. I also thank Marie, Pauline, Rebecca, Claire, Jeff, and many others that I can't cite here. Some special thanks to Amandine. Last, my deep gratitude goes to my parents, my brothers and my family for their continuous support and encouragements.

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List of Abbreviations

AEZ agro-ecological zone.

AFOLU agriculture, forestry and other land use.

AgMIP Agricultural Models Intercomparison and Improvement Project.

ASEAN Association of Southeast Asian Nations.

AVE ad-valorem equivalent.

BACI Base pour l'Analyse du Commerce International.

CARB California Air Resource Board.

CARD Center for Agricultural Research and Development.

CDM Clean Development Mechanism.

CEPII Centre d'Études Prospectives et d'Informations Internationales.

CES constant elasticity of substitution.

CET constant elasticity of transformation.

CGE computable general equilibrium.

CITES Convention on International Trade in Endangered Species of Wild Fauna and Flora.

COSIMO COmmodity SImulation MOdel.

CV coefficient of variation.

DDGS dried distillers' grains with solubles.

EF emission factor.

EISA Energy Independence and Security Act.

EPA Environmental Protection Agency.

EPIC Environmental Policy Integrated Climate Model.

EU European Union.

FAO Food and Agriculture Organization of the United Nations.

FAPRI Food and Agriculture Policy Research Institute.

FASOM Forest and Agriculture Sector Optimization Model.

FBS food balance sheet.

G4M Global Forestry Model.

GAEZ Global Agro-Ecological Zones.

GDP gross domestic product.

GHG greenhouse gas.

GLOBIOM Global Biosphere Management Model.

GSP Generalised Scheme of Preferences.

GSP+ Generalised Scheme of Preferences "plus".

GTAP Global Trade Analysis Project.

HS6 Harmonized System 6 digits.

IEA International Energy Agency.

IFA International Fertilizer Industry Association.

IFPRI International Food Policy Research Institute.

IIASA International Institute for Applied Systems Analysis.

ILRI International Livestock Research Institute.

ILUC indirect land use change.

IMPACT International Model for Policy Analysis of Agricultural Commodities and Trade.

IPCC Intergovernmental Panel on Climate Change.

JRC Joint Research Center.

LCA life-cycle analysis.

LCFS Low Carbon Fuel Standard.

LES-CES linear expenditure system with constant elasticity of substitution.

LP linear programming.

LULUCF land use, land use change and forestry.

MAcMap-HS6 Market Access Map HS6.

MERCOSUR Mercado Común del Sur.

MIRAGE Modelling International Relationships in Applied General Equilibrium.

NDF net displacement factor.

NGO non-governmental organisation.

NPP net primary productivity.

NREAP National Renewable Energy Action Plan.

OECD Organisation for Economic Co-operation and Development.

PE partial equilibrium.

POLES Policy Outlook on Long-term Energy Systems.

PU production unit.

RED Renewable Energy Directive.

REDD Reduction of Emissions from Deforestation and Degradation.

REDD+ Reduction of Emissions from Deforestation and Degradation "plus".

RIA Regulatory Impact Assessment.

RSE relative standard error.

SIA Sustainable Impact Assessment.

SimU simulation unit.

SRP short rotation plantation.

SSP Shared Socioeconomic Pathway.

TFP total factor productivity.

TMS technical marginal substitution.

TRQ tariff rate quota.

UK United Kingdom.

UNFCCC United Nations Framework Convention on Climate Change.

US United States.

USDA United States Department of Agriculture.

WTO World Trade Organization.

RÉSUMÉ / SUMMARY

Résumé court

La contribution des changements d'usage des sols aux émissions de gaz à effet de serre d'origine anthropique est estimée à 17% pour la décennie 2000, en grande partie liée à la déforestation. L'un des facteurs principaux de ces changements est l'expansion des terres agricoles pour les besoins locaux de développement, mais également sous l'effet des exportations stimulées par la mondialisation. Pour cette raison, des préoccupations nouvelles surgissent quant aux effets des politiques sur l'usage des sols par le biais des marchés internationaux. Ce travail présente trois illustrations concrètes où ces effets peuvent être d'ampleur conséquente : i) l'intensification de l'agriculture dans les pays en voie de développement, ii) les accords commerciaux, et iii) les politiques d'agrocarburants. Les résultats montrent que pour chacune de ces politiques, les réponses des marchés sont susceptibles de jouer un rôle déterminant dans le bilan des gaz à effet de serre. L'atténuation du changement climatique par l'intensification des cultures conduit à des réductions d'émissions, mais l'effet rebond de la demande pourrait annuler une part substantielle des bénéfices attendus sur les surfaces de terres cultivées. L'exemple d'un possible accord entre l'Union européenne et le Mercosur montre les effets négatifs que peut induire la libéralisation de certains produits agricoles si des mesures d'accompagnement adéquates ne sont pas mises en place. Enfin, l'effet des changements indirects d'affectation des sols est susceptible d'effacer une part substantielle des réductions d'émissions alléguées aux agrocarburants. Les réponses de l'affectation des sols aux différentes politiques dépendent néanmoins de nombreux paramètres comportementaux, et il est difficile d'en fournir une estimation chiffrée précise. Plusieurs approches de modélisation sont utilisées ici pour quantifier ces effets et explorer les intervalles de confiance découlant des estimations actuelles de la littérature économétrique. La prise en compte de cette externalité dans l'évaluation des politiques publiques nécessite des approches nouvelles intégrant mieux les différents niveaux d'incertitude sur ces effets.

Mots-clefs: politiques agricoles; gaz à effet de serre; intensification durable; accord commerciaux; UE-Mercosur; agrocarburants; changement indirect d'affectation des sols; CASI; modèle d'équilibre général calculable; programmation linéaire.

Résumé long

Les changements d'usage des sols ont contribué pour environ 17% aux émissions de gaz à effet de serre d'origine anthropique sur la décennie 2000. Une grande partie de ces émissions est liée à la déforestation, dont l'un des principaux facteurs est l'expansion des terres agricoles, tirée par les besoins du développement local, mais également par les exportations agricoles dans un contexte de mondialisation croissante. Par conséquent, de nouvelles préoccupations surgissent quant aux effets sur l'usage des sols des politiques agricoles et commerciales, par le biais des marchés internationaux. Quelles pourraient être leurs répercussions environnementales ? Faut-il revoir les modes d'analyse de ces politiques pour mieux prendre en comptes ces impacts indirects ? Mon travail tente d'apporter des éléments de réponse à travers trois illustrations concrètes qui présentent de tels effets : en premier lieu, l'intensification de l'agriculture dans les pays en voie de développement ; deuxièmement, les accords de libéralisation commerciale ; et enfin, les politiques de développement des agrocarburants.

Le premier cas d'étude porte sur les effets des politiques d'intensification agricole dans les pays en voie de développement. Plusieurs scénarios d'intensification de la production sont examinés, considérant alternativement un rattrapage des rendements des cultures dans les pays du Sud, une augmentation des rendements de l'élevage, ou bien les deux simultanément. A l'inverse, les conséquences d'un ralentissement des rendements sont aussi examinées. Les résultats font apparaître une tendance à la réduction des gaz à effet de serre en cas d'intensification, mais l'amplitude de cette réduction dépend du mode d'intensification. Les bénéfices environnementaux les plus nets sont obtenus pour une intensification des cultures sans fertilisants chimiques additionnels, tandis que l'intensification conventionnelle par augmentation des intrants ne permet de réduction d'émissions qu'au travers d'une diminution des besoins en terre. Lorsque les gains de rendements sont obtenus par une augmentation de la productivité totale des facteurs, les émissions sont dopées par un effet rebond de la demande, lié à la baisse des coûts de production et des prix de marché. Cet effet rebond est bénéfique en termes de sécurité alimentaire mais dégrade le bilan environnemental. Les effets de l'intensification de l'élevage, à l'inverse, sont toujours plus bénéfiques d'un point de vue environnemental, mais d'effet mitigé sur la sécurité alimentaire en raison de la faible part des aliments d'origine animale dans le régime alimentaire des populations des pays les moins avancés. La combinaison simultanée des gains de rendements sur les deux secteurs apparaît finalement comme la meilleure option pour obtenir les deux bénéfices, la magnitude de l'effet rebond déterminant le niveau final du bénéfice environnemental.

La seconde illustration concerne les politiques de libéralisation commerciale, avec une application à un potentiel accord entre l'Union européenne et le Mercosur. J'examine ici les conséquences d'une ouverture accrue des frontières à la circulation de certains biens agricoles et industriels de la part des deux blocs. Une attention particulière est portée à l'accès des biens agricoles du Mercosur aux marchés européens, notamment les céréales, la viande de bœuf, la volaille, les produits laitiers ou encore le bioéthanol. L'étude est ici conduite en modélisant cet accord au moyen de deux modèles distincts. MIRAGE, un modèle d'équilibre général calculable, représente la demande et le commerce

des différents biens, ainsi que l'offre pour les secteurs industriels ; les résultats de ce modèle sont ensuite utilisés dans GLOBIOM, modèle d'équilibre partiel spécialisé sur l'agriculture et la forêt, qui calcule les impacts sur le secteur agricole, l'usage des terres et les changements d'émissions de gaz à effet de serre associés. L'intérêt de cette approche est de permettre une comparaison directe des gains de bien-être économique, mesurés en variation équivalente de surplus du consommateur, par rapport à l'impact environnemental, que j'évalue ici en considérant plusieurs valeurs tutélaires du carbone. Les résultats varient significativement d'un produit à une autre, ainsi qu'en fonction de la période de référence considérée pour l'évaluation de l'accord. Pour certains produits cependant, comme la viande exportée par le Mercosur, les bénéfices économiques de l'accord sont mis à mal par les émissions de gaz à effet de serre engendrées, qui nécessitent de nombreuses années de libéralisation commerciale pour être compensées. Un paramètre d'incertitude important est la réponse du système de production en termes de rendements. Si la libéralisation conduit à une amélioration de la productivité agricole, les effets néfastes pour l'environnement sont nettement atténués, ce qui montre l'importance des mesures d'accompagnement pour les négociations commerciales avec les pays à l'environnement vulnérable.

Mon troisième cas d'étude porte sur les politiques de développement des biocarburants pour l'Union européenne. La substitution des carburants fossiles par des produits issus de la biomasse a en effet été perçue comme une opportunité d'atténuer les changements climatiques, les émissions de gaz à effet de serre étant dans ce cas séquestrées dans les plantes au cours du cycle de production. Cette analyse ne prend cependant pas en compte l'effet de réallocation des terres agricoles lorsque les biocarburants sont déployés à grande échelle. A l'aide d'un modèle d'équilibre général, j'analyse ici comment les émissions liées au changement d'usage des sols peuvent affecter le bilan de l'analyse de cycle de vie. Plusieurs scénarios sont explorés : une augmentation du niveau d'incorporation des biocarburants jusqu'à l'objectif réglementaire pour 2020 à partir d'une augmentation de l'usage du biodiesel seul, du bioéthanol seul, ou des deux produits simultanément. Les émissions associées aux changements d'usage des sols peuvent atteindre des niveaux élevés, qui compromettent les réductions attendues sur la base des seules analyses de cycle de vie. Un soin particulier est apporté à l'analyse de sensibilité dans les simulations, afin de mieux représenter les intervalles d'incertitude associés aux paramètres comportementaux. La magnitude des impacts est variable en fonction des paramètres choisis, mais dans tous les cas de figure, des émissions additionnelles associées à la terre apparaissent. La hiérarchie des scénarios reste inchangée selon les paramètres choisis, le biodiesel affichant des performances inférieures au bioéthanol. Ces résultats questionnent la pertinence du programme européen de biocarburants au regard des objectifs affichés de diminution des émissions de gaz à effet de serre.

La dernière partie de ce travail aborde de nouveau la question des politiques de biocarburant, mais sous la perspective plus générale de l'analyse de l'incertitude des réponses d'affectation des sols aux chocs sur les marchés agricoles. A l'aide d'une décomposition analytique des effets à l'œuvre, j'identifie les différentes sources d'incertitude dans les paramètres comportementaux pour mieux

expliquer leurs contributions respectives. Il s'agit en particulier de l'élasticité d'offre de terre, de l'élasticité de la réponse en rendement et de l'élasticité de la demande, qui affectent au premier ordre les résultats. Leurs interactions sont notamment étudiées pour le cas d'un choc de bioéthanol à base de céréales et de biodiesel à base de colza. En reliant les paramètres sources d'incertitude à la littérature économétrique, il est possible de mieux caractériser l'étendue des intervalles de confiance autour de l'évaluation des changements d'usage des terres. Ce travail permet du même coup d'identifier les paramètres les mieux connus, mais aussi ceux aux bases empiriques plus fragiles et qui nécessitent un nombre plus élevé d'études économétriques. L'utilisation du cadre formel que je présente, ainsi que la base d'élasticités associée, peut servir de support pour une diminution des intervalles de confiance à l'avenir si la base de paramètres est progressivement étendue.

En conclusion, les résultats de l'ensemble de ce travail soulignent à quel point les réponses des marchés aux politiques agricoles sont susceptibles de jouer un rôle déterminant dans le bilan des gaz à effet de serre liés à l'usage des terres. Plusieurs approches de modélisation peuvent être utilisées pour quantifier ces effets. La magnitude des réponses d'affectation des sols aux différentes politiques ne peut cependant être déterminée avec précisions car de nombreux paramètres comportementaux l'influencent. L'évaluation des politiques publiques nécessite donc des approches nouvelles prenant en compte les différents niveaux d'incertitude associés à ces effets, et donnant tout son rôle à l'exploration des intervalles de confiance en liant plus directement les estimations à leur fondations économétriques. Les impacts des effets indirects de ces politiques permettront dès lors d'être plus largement compris, donnant la possibilité de définir les mesures d'accompagnement ou de compensation les plus appropriées.

ABSTRACT

Land use change is estimated to have generated 17% of anthropogenic greenhouse gas emissions in the 2000s, a large part coming from deforestation. The main driver of these emissions is expansion of agricultural activities, for the need of local development in tropical regions. However, they have also been caused by the dynamics of globalisation which has stimulated agricultural trade flows. Thus, today, there are new concerns with respect to how agricultural policies are influencing land use changes in other parts of the world through international market responses. In this work I consider three concrete illustrations of where these effects can be of significant magnitude: i) agriculture intensification in developing countries, ii) trade agreements, and iii) biofuel policies. I find that for each of these policies, market responses are likely to play a significant role in the final greenhouse gas emission balance. Mitigation of emissions through agricultural intensification could have quite beneficial outcomes, but the rebound effect on the demand side would offset a large part of greenhouse gas emission savings attributable to the land sparing effect. With the example of a possible EU-MERCOSUR trade agreement, I also show the adverse effect of liberalising certain specific agricultural products closely connected to land use change dynamics without adequate accompanying measures. Last, the indirect land use change effect of biofuels is likely to offset a large part of their alleged GHG emission savings. Land use change responses depend on many behavioural parameters, however, and providing precise estimates constitutes a challenge. I use different modelling approaches to quantify their magnitude and extensively explore the level of confidence on the basis of current state of econometric findings. New approaches should be elaborated to take account of this externality in public policy assessments, together with an appropriate consideration of the uncertainty ranges associated with these effects.

Keywords: agricultural policies; greenhouse gas emissions; sustainable intensification; trade agreement; EU-MERCOSUR; biofuels; indirect land use change; ILUC; computable general equilibrium; linear programming.

Summary

Land use change is estimated to have generated 17% of anthropogenic greenhouse gas emissions in the 2000s, a large part coming from deforestation. The main driver of these emissions is expansion of agricultural activities, for the need of local development in tropical regions. However, they have also been caused by the dynamics of globalisation which has stimulated agricultural trade flows. Thus, today, there are new concerns with respect to how agricultural policies are influencing land use changes in other parts of the world through international market responses. What could be the environmental impacts of these policies? Should their evaluation criteria be reconsidered to take these indirect effects into account? My work aims at clarifying these issues with three concrete illustrations of where these effects can be of significant magnitude: i) agriculture intensification in developing countries, ii) trade agreements, and iii) biofuel policies.

The first case study focuses on the effects of agricultural intensification policies in developing countries. Several intensification scenarios are examined considering alternately closing part of the crop yields in the South, or increasing yield of livestock, or targeting both simultaneously. Conversely, the impact of a slowdown in yield is also discussed. The results show a reduction in greenhouse gas emissions in most case of intensification, but the magnitude of this reduction depends on the intensification pathway. The clearest environmental benefits for crops are obtained for an intensification without additional chemical fertilisers, while conventional intensification through input increase requires considering land sparing effects to obtain emission reductions. When yield gains are obtained by total factor productivity increase, emissions are boosted by a rebound in demand, due to lower production costs and market prices. This rebound effect is beneficial in terms of food security, but decreases the environmental benefits. The effects of livestock intensification, by contrast, better perform from an environmental point of view, but show mixed outcomes on food security due to the low share of animal calories in people's diet in least developed countries. The simultaneous combination of yield gains in both sectors finally appears the best way to maximise benefits, with the magnitude of the rebound effect determining the final level of environmental benefits.

The second illustration looks at trade liberalisation policies, with the case of a possible agreement between the EU and MERCOSUR. I examine here the consequences of a more open trade regime for some agricultural and industrial products. A specific attention is paid to access of agricultural goods from MERCOSUR to European markets, in particular cereals, beef, poultry, dairy products and bioethanol. The study is conducted here by modelling this agreement through two distinct models. MIRAGE, a computable general equilibrium model represents the demand and trade of the different goods and supply functions of the industry and services sectors; MIRAGE results are then used in GLOBIOM, a partial equilibrium model specialised in agriculture and forestry, that calculates the impacts for the agricultural sector, land use change and associated greenhouse gas emissions. The advantage of this approach is to allow for a direct comparison of economic welfare gains, measured in equivalent variation of consumer surplus, with the environmental impact, that

I evaluated here using several values of carbon. The results vary significantly from one product to another, and depend on the reference period of the assessment. However, for some products such as meat from MERCOSUR, the economic benefits of the agreement are jeopardised by the magnitude of greenhouse gas emissions that require many years of payback due to the initial carbon debt from activity reallocation after liberalisation. An important source of uncertainty, however, is the response of system intensification. If liberalisation leads to an improvement in agricultural productivity, adverse effects on the environment can be significantly buffered, which shows how important accompanying measures can be for trade negotiations with environmentally-sensitive countries.

My third case study focuses on the development of biofuels policies in the European Union. The substitution of fossil fuels with biomass products has indeed been perceived for long as an opportunity to mitigate climate change, greenhouse gas emissions being then sequestered in the plants during the production cycle. However, such analysis does not take into account the effect of reallocation of farmland when biofuels are widely deployed. Using a general equilibrium model, I analyse here how emissions from land use change can affect the conclusions of the life cycle analysis. Several scenarios are explored: an increase in the regulatory incorporation level of biofuels in 2020, through an increase in biodiesel use alone, or in bioethanol use, or both simultaneously. Emissions associated with land use change can reach high levels that jeopardise the expected reductions from life-cycle analysis. A particular attention is given in the simulations to sensitivity analysis to better represent uncertainty range associated with behavioural parameters. The magnitude of impacts is variable and depends on selected parameters, but overall, additional land use emissions are systematically found. The hierarchy of scenarios remains unchanged across parameter changes, biodiesel showing lower performance than bioethanol. These results question the efficiency of the European biofuels program with respect to their greenhouse gas emissions reduction objectives.

The last part of this work develops further the question of biofuel policies, but in the broader perspective of the uncertainty analysis of land use change responses to agricultural markets shocks. Using an analytical decomposition of effects at work, I identify the different sources of uncertainty in behavioural parameters to clarify their role. I look in particular at the contribution of land supply elasticity, yield response elasticity and demand elasticity, that all affect results at first order. Their interactions are studied in the case of a bioethanol shock on cereals market and a biodiesel shock on rapeseed market. By connecting the sources of parameter uncertainty to the econometric literature, it is possible to better characterise the confidence intervals of land use change responses. This work can help identifying what the best known responses are, but also what the more fragile ones are from an empirical perspective and where more econometric studies are required. The use of this formal framework, as well as the associated elasticities database, can be used as a support to narrow confidence intervals in the future if the econometric input is extended.

In conclusion, the results from all this work highlight how market responses in agricultural policies are likely to play a key role in the assessment of land use change greenhouse gas emissions.

Several modelling approaches can used to quantify these effects. The magnitude of land use responses to policies can however hardly be measured with precision because many behavioural parameters influence them. Therefore, the evaluation of public policies requires new approaches taking into account the different levels of uncertainty associated to these effects, favouring the exploration of confidence intervals and more directly linking responses to empirical estimates from the econometric literature. The impacts of these indirect effects of policies will then be more widely understood, opening possibility to better tailored accompanying measures or appropriate compensation schemes.

CHAPTER 1

INTRODUCTION

LAND – from the first organised human settlements to the modern age – has always been a major strategic asset. Its use for farming has allowed strong empires to prevail from the Tigris to the Nile, and the rules for its management have significantly shaped the way civilisations have been organised (Diamond, 1997, Mazoyer and Roudart, 2006). History is full of episodes where the search for new productive land has symbolised emancipation, greater freedom, and chance of a better future: from the biblical account of the Israelite exodus from Egypt, to the migration of American pioneers to the Far West, to the more contemporary expansion of Brazilian farming in Matto Grosso.

A great deal of economic thinking has been devoted to the link between human activities and the fundamental resource of land. In the 18$^{\text{th}}$ century, the French Physiocrats, drawing up the first analytical description of the functioning of the economy of their time (*Economic Table* in Quesnay, 1766), argued that land was the most elementary source of economic wealth creation. Most of the well-known classical economists helped to define the role of this resource in the production process. Adam Smith conceptualised it, together with labour and capital, as an important production factor, subject to market rules (Smith, 1776). Thomas Malthus emphasized how the linear productivity growth of this factor would lead to food availability problems under exponential population growth (Malthus, 1798). David Riccardo explained how land rents depend on land quality, which determines the level of agricultural investments and productivity increase (Riccardo, 1817). And Johann Heinrich von Thünen developed the premises of economic geography by studying the spatial consequences of the marginal productivity of land (von Thünen, 1826).

Although there has continued to be interest in land in the economic literature, attention to the topic declined over the second half of the 20$^{\text{th}}$ century, accompanying "The Declining Economic Importance of Agricultural Land" in Western economies (Schultz, 1951). In a society oriented towards industry and services, the focus moved to questions of farm behaviour under uncertainty, market and trade organisation, environmental services, innovation, etc. (see for instance the topics developed in the last edition of the Handbook of Agricultural Economics, Pingali and Evenson, 2010).[1] In parallel, development economics and environmental economics got increased interest into

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[1]   In the last edition only three chapters in a total of 74 focus on land: Chapter 6 on Land Institutions and Land

new localised issues related to land management and planning (e.g. Kline and Alig, 1999, Shiferaw and Holden, 2000), land valuation (e.g. Bastian et al., 2002, Geoghegan, 2002), or land ecosystems services (e.g. Bockstael et al., 1995, Björklund et al., 1999).

Global land use change, a new concern

In this early 21st century, economic analysis of land issues has seemed to take on a new importance, with a broader perspective. For a few decades, land use and more particularly land use change have been revived as a dynamic field of research, with a more global scope, that reflects how different local, regional and global drivers interact and can be influenced by policies. Several factors explain this renewed interest.

The first factor is related to the emergence of new global environmental challenges, resulting from our deeper understanding of how the Earth system works and how human activities affect it. Climate change, ozone depletion and biodiversity losses were all concerns that first began to be seriously voiced in the 1970s to 1980s; and they had two new characteristics. First, the challenges were global, and second, they needed to be tackled via coordinated action. These concerns found their clearest expression in the United Nations Conference on Environment and Development in 1992 in Rio. Land was related to many of the topics raised at that time: i) climate change, to which land use change in the 2000s was contributing 17% of total greenhouse gas emissions through deforestation, drained wetlands, savannah burnings, according to the Intergovernmental Panel on Climate Change (Parry et al., 2007); ii) biodiversity losses, triggered in particular by deforestation and forest degradation in tropical areas, but also by intensification of agriculture across the world; iii) desertification and other forms of land degradation due to unsustainable farming practices and poor land management.

The second factor that renewed attention to land use change at a global dimension was the return of the Malthusian concern that emphasized the depletion of our natural resources due to the growing pressure from population and economic development, first in the 1970s with the *Limits to Growth* report (Meadows et al., 1972), and more recently with the food price spike of 2007–2008 which revived fears that the world food system was approaching a tipping point. The observed tensions in the agricultural markets in particular provoked a debate about the real state of land availability and the capacity of our societies to feed the future population. The wave of land acquisitions by land-scarce countries occurring in Africa, Latin America and Southeast Asia was denounced by non-governmental organisations in a highly symbolic reaction as "land grabbing". As some of the areas "grabbed" already appeared to be under cultivation by farmers without formal land rights, the concerns about the effect of intense land competition only increased. This debate was intensified with the parallel emergence of first-generation biofuels which placed further pressure on agricultural

Markets, Chapter 51 on Efficiency and Equity Effects of Land Markets, and Chapter 59 on Land Use: Forest, Agriculture, and Biodiversity Competition.

markets. Moreover, the search for "marginal" land available to grow energy crops without competing with food production is still prominent in current debates on bioenergy.

The third factor that pushed land use further up the global agenda crosscuts the two previously mentioned. This is the closer interdependency of agricultural markets in a now highly globalised world. Policy makers realised that in the "global village", land use decisions no longer had implications just for their own particular local constituencies. As market leakages could indeed seriously undermine the environmental efficiency of a measure, the perspective on land-related policies began to evolve. This problem was first emphasized in the case of forest protection and carbon sequestration projects encouraged by the Clean Development Mechanism (CDM) of the Kyoto Protocol (Schwarze et al., 2002, Murray et al., 2004). It was suspected that afforestation in some regions could lead to forest destruction in others, cancelling out the expected benefits. In the food debate, the idea also emerged that expansion of biofuel cultivation in developed regions could put people at risk of hunger in other places on the planet. This new way of thinking paved the way for a global perspective on land resources, with greater attention being given to the pressure placed by consumption patterns in developed regions on land use requirements across the globe (von Witzke and Noleppa, 2010).

MOTIVATION FOR THIS WORK AND RESEARCH QUESTION

The research presented in this thesis, by its scope but also by its historical perspective, is at the intersection of the three different factors mentioned in the preceding section. It is structured around the following overarching question: "how do agricultural policies generate land-use change impacts through market responses?" – and subsequently, "how do the resulting environmental impacts affect the assessment of these policies?" This double-sided question is addressed with reference to three different types of policies: i) agriculture intensification in developing countries (Chapter 2), ii) agricultural trade agreements (Chapter 3), and iii) biofuel policies (Chapters 4 and 5). In the context of increasingly integrated world markets, I consider environmental impacts at the global scale, from the standpoint of greenhouse gas (GHG) emissions. This is motivated by the fact that climate change mitigation has a high priority on the environmental policy agenda, having already been subject to some internalisation efforts, with different taxation schemes and cap-and-trade programs at the international level. Limiting the analysis to GHG emissions could be seen as restrictive, as these impacts are relatively more spread out over time than other environmental damage or pollution; moreover, the real extent of climate damage will strongly depend on our future actions. However, these impacts are important because local environment can be affected by greenhouse gas sources in other parts of the world. Additionally, other resources such as biodiversity are often concentrated in carbon-rich areas (Strassburg et al., 2010), which makes the scope of potential environmental impacts covered in this work even wider. With appropriate data, the methodology used here can also easily be adapted to other land use-related damages generated by agriculture or other activities.

The question of emissions generated by agriculture through "market-mediated" land use change responses (Hertel et al., 2010a) appears to be of particular interest with respect to the policy

agenda. Just as for those of agriculture, GHG emissions from land use, land use change and forestry (LULUCF), have, to date, been kept out of most of the constraining mechanisms of climate change mitigation. A better understanding of how these LULUCF sources react to various policies is therefore crucial. Emissions from these sources are officially accounted for as part of the national inventories of the United Nations Framework Convention on Climate Change (UNFCCC). And they are also included in the commitments from Annex I Parties to the Kyoto Protocol.[2] However, Annex I countries only account for a minor part of these emissions, with 80% of them coming from developing regions that made no mitigation commitments.[3] In the case of deforestation emissions, many initiatives are ongoing under the Reduction of Emissions from Deforestation and Degradation (REDD) program, but methodological issues for evaluating mitigation efforts and institutional problems are affecting the efficiency of their implementation. As no consistent agriculture or LULUCF mitigation scheme is in place, other policies are more likely to influence these GHG emissions. And reciprocally, in absence of a first best mitigation policy directly targeting emissions at their source, the side-effects of various other policies (agriculture, trade, energy) in terms of LULUCF emissions deserve closer attention to assess their current efficiency.

Global land use change impacts and the case of biofuels

The question of indirect land use change (ILUC) from first-generation biofuels is probably the most sophisticated example of attempts to consider global land use change emissions in policy assessment. The context is worth emphasizing here, as these effects will also be discussed in two of the chapters that follow (Chapter 4 and Chapter 5).

Biofuels have been extremely controversial in the United States (US) and the European Union (EU) since 2007. First, the potential role of biofuels as a source of pressure on the markets through land competition has been emphasized (Elobeid et al., 2006, Rosegrant, 2008, Hertel et al., 2010b, Roberts and Schlenker, 2010, Zilberman et al., 2012) as have their impacts on price volatility (Wright, 2011a,b, Hertel and Beckman, 2011, Diffenbaugh et al., 2012). This has triggered a particularly heated debate during the two episodes of price surge in 2007–2008 and 2010–2012, where the US and the EU were accused of diverting food from poor people's mouths in order to fuel vehicles. However, a second complementary issue raised in the same period related to the environmental

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[2]   The countries of Annex I of the Kyoto Protocol have signed commitments to reduce their GHG emissions by 2008–2012 for their first commitment period and by 2020 for the second commitment period. These signatories are the European Union, Switzerland, Norway, Ukraine, Australia and for the first commitment period only, Canada, Japan, Russia, and New Zealand. These last four countries declared in 2012 that they would not commit to any new reduction targets on their emissions within the Kyoto Protocol. Belarus and Turkey are also part of Annex I countries but without any target.

[3]   International market mechanisms under the Kyoto Protocol recognise the possibility of these countries gaining carbon credits from afforestation or agricultural mitigation projects but very few projects have been certified so far due to methodological difficulties in accounting and certification.

sustainability of biofuels.[4] GHG emission savings from biofuel production were questioned both in terms of life-cycle analysis (LCA) (Pimentel and Patzek, 2005, Farrell et al., 2006, Scharlemann and Laurance, 2008, Bureau et al., 2010) and land use change emissions (Fargione et al., 2008). ILUC, that is, the displacement of crops to other locations than those where biofuel feedstocks are grown, could drive significant additional emissions (Searchinger et al., 2008).

In the US, the Environmental Protection Agency (EPA) was obliged by law to take into account the full scope of greenhouse gas emissions in the LCA of biofuels, "including direct emissions and significant indirect emissions such as significant emissions from land use changes" (US Congress, 2007, Sec. 201 (H)). The release of the Draft Regulatory Impact Assessment (EPA, 2009) generated a huge controversy, as the modelling work performed for this report found emissions savings from corn ethanol to be below the minimum level required to participate in the biofuel mandate. In parallel, the California Air Resource Board (CARB) was charged of defining the emission levels of different fuel types in the context of the Low Carbon Fuel Standard (LCFS). In its ruling of 2009, CARB also introduced ILUC factors into the LCA of the different biofuels (CARB, 2009), which was widely commented upon.[5]

In Europe, the Renewable Energy Directive (RED) (EP, 2009) also set up an ambitious program of biofuel development, although this was centred more on biodiesel. Inclusion of ILUC in the calculation of biofuel LCA has not been requested to date, but a thorough examination of the question has been put on the agenda, and ILUC calculation was performed for the Impact Assessment (EC, 2010). The European Commission, after a major consultation with stakeholders in 2010,[6] acknowledged the importance of considering the phenomenon (EC, 2010). A proposal for EU member states to report the ILUC factors of their biofuels was released by the European Commission in 2012 but without these results being integrated in the LCA calculation (EC, 2012). Because of ILUC, the Commission proposed to increase biofuel saving requirements for new bio-refineries and to cap the overall level of first-generation bioenergy use in the renewable energy target. The European Parliament proposed in 2013 to go further (EP, 2013) and to take into account ILUC factors in the GHG saving calculation after 2020, but this proposal was not adopted by the European Council.

These policy initiatives gave rise to a burgeoning literature investigating the potential impact of these policies and discussing the scientific ground of these market-mediated land use change impacts in the US (inter alia Searchinger et al., 2008, Keeney and Hertel, 2009, O'Hare et al., 2009, EPA, 2010, Hertel et al., 2010a, Taheripour et al., 2010, Hertel et al., 2010b, Plevin et al., 2010), and in the EU (inter alia Banse et al., 2008, Valin et al., 2010a, Al-Riffai et al., 2010b, Fonseca et al., 2010, Overmars et al., 2011, Laborde, 2011). Several reviews and comparisons of these works have been produced to date (Edwards et al., 2010, von Witzke and Noleppa, 2010, De Cara et al., 2012, Broch

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[4]   Note that these two effects are structurally opposed, as will be analyzed in Chapter 5. More impact on the food demand implies less impact on the land use side, and reciprocally. This will also be apparent in Chapter 3 for the trade-offs between food supply and land sparing.

[5]   Available at www.arb.ca.gov/lispub/comm/bccommlog.php?listname=lcfs09

[6]   http://ec.europa.eu/energy/renewables/consultations/2010_10_31_iluc_and_biofuels_en.htm

et al., 2013, among others) showing the significant variations in the potential effects depending on the model used. Some studies emphasized the potentially very large land use change emissions from biofuels (Plevin et al., 2010). Estimating the extent of these effects and the perspective of associating the potential GHG emissions from ILUC with the usual LCAs have been the subject of intense controversy, considering the potentially disastrous implications for the sector (de Gorter and Just, 2010, Babcock, 2009a, Zilberman et al., 2010); other authors have openly questioned the validity of these estimations, which has led to scientific controversy (Kim and Dale, 2011, O'Hare et al., 2011, Dale and Kim, 2011). Chapters 4 and 5 of the present work relate directly to these efforts of ILUC quantification and try to bring more clarity to the extent of the uncertainty associated wih ILUC emissions from biofuels.

Beyond this thematic focus on market-driven global land use emissions, two defining methodological choices for this work should also be emphasized here. The first is interdisciplinarity, the second quantitative modelling.

AT THE INTERFACE OF ECONOMIC AND ENVIRONMENTAL SCIENCES

The topics developed in this dissertation directly relate to global environmental challenges. There is now increasing recognition that these questions cannot be fully addressed within the scope of traditional academic disciplines alone (Carpenter et al., 2009). A new "sustainability science" (Kates et al., 2001, Bettencourt and Kaur, 2011) has developed to foster cross-disciplinary approaches at the interface of environmental and social sciences. On the one hand, the complex global environmental changes require a detailed description of the geo- and biophysical mechanisms at play, and their consequences for natural and human systems. On the other hand, being able to influence these mechanisms requires a good understanding of how human activities and societies shape their environment and how they can react to policies. As land use change is among the topics at the intersection of these questions (Rindfuss et al., 2004, Turner et al., 2007), this thesis fits into this interdisciplinary context. For instance, studying the large-scale effects of agricultural intensification as set out in Chapter 2 requires simultaneous exploration of the potential yield increases of different crops and livestock under various management options (agronomy and animal science), of demand and supply responses following price changes on the market triggered by this policy (neoclassical economics), of the magnitude of carbon stocks emissions and sequestration in biomass (geo- and biophysical sciences), and of food consumption patterns (nutrition science), etc. Other chapters follow in the same vein, land use being at the interface between human and environmental domains (Chapter 3 dealing with trade economics; Chapters 4 and 5 connecting land use issues with energy policy).

Navigating these different domains, although an exciting intellectual challenge, faces two inherent difficulties. The first is a difficulty of substance: stepping into a scientific domain that is outside one's initial area of expertise entails risks of approximation. As this can be a source of errors, I have tried to mobilise the most relevant literature in different disciplinary field to support my research on

each topic. This work also benefited from the support of contributors and reviewers with different backgrounds, who provided advice in their own discipline.

The second difficulty is more one of form and is the direct consequence of the remark above: this manuscript can hardly be anchored in a single academic discipline. The thesis does not focus on a strictly delineated topic in agricultural, trade, or environmental economics using the methods specific to these fields. Rather than a canonical work based on a well-established theoretical stream, it takes a more hybrid perspective, due to the horizontal nature of the issues at stake and the applied dimension of the questions raised. This is particularly well illustrated by the journals in which two of the chapters have been published to date;[7] both are relatively young titles and not part of the traditional titles of the economic literature (*Environmental Research Letters*[8] for Chapter 2, and *Climate Change Economics*[9] for Chapter 4).

SIMULATION METHODS FOR GLOBAL LAND USE CHANGE ANALYSIS

The second defining methodological choice is of the use of simulation methods, based on large-scale applied economic models and more specifically equilibrium models. This choice was motivated by several factors. First of all, the applied nature of the questions at stake required computational methods, based on extended datasets of the real economy and environmental accounts, rather than analytical models. Indeed, while understanding the mechanisms at stake is fundamental for the analysis, this is not sufficient as long as the effects interact with each other within a complex framework. In such a context, applied tools are useful, particularly when the questions at stake are related to a policy debate. The two applied models I used for this work are quite detailed: a partial equilibrium (PE) model, GLOBIOM, based on the FAOSTAT dataset and incorporating geospatial information on the supply side, and a computable general equilibrium (CGE) model, MIRAGE, relying on the comprehensive Global Trade Analysis Project (GTAP) economic database and its environmental satellite accounts: I will detail the motivations behind the choice of these specific models further below. Second, thanks to improvements in dataset richness and quality and the fast development of computing capacities, modelling approaches have now spread over a large community. Numerical methods have become increasingly recognised for the assessment of a large number of policies, and I was naturally encouraged to explore these methods.

Historically, the number of modelling approaches applied to land use change issues is quite large: from spatial (Mertens and Lambin, 1997) and non-spatial (Barbier and Burgess, 1996) regression models to multi-agent models (Parker et al., 2003), large-scale empirical-statistical models (Verburg

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[7] Although these two articles have been authored with colleagues, note that I have conducted the major part of these works, from the design and modelling to the paper writing.

[8] *Environmental Research Letters* is an open-source high-impact factor journal created in 2006, emphasizing the importance of binging together contributions from different disciplines to address environmental issues. See http://iopscience.iop.org/1748-9326

[9] *Climate Change Economics* is an economic journal created in 2010 by influential climate change economists among whom are Robert Mendelsohn, William Nordhaus, Thomas Schelling, Robert Stavins, Richard Tol, Martin Weitzman. See www.worldscientific.com/page/cce/editorial-board

et al., 1999), rule-based models (Stéphenne and Lambin, 2001), optimisation models (Schaldach et al., 2011), integrated assessment models[10] (Alcamo et al., 1994, Rounsevell et al., 2003), and partial equilibrium (Rosegrant et al., 2008, Sands and Leimbach, 2003, Adams et al., 2005) and general equilibrium approaches (Darwin et al., 1996, Hertel, 1997). Many comparisons of these modelling techniques are available in the literature of the different disciplines looking at land use change (see for instance Kaimowitz and Angelsen, 1998 for tropical deforestation; Lambin et al., 2000, Heistermann et al., 2006, Hertel et al., 2009c for agriculture; Kretschmer and Peterson, 2010 or Wicke et al., 2014 for bioenergy). These tools have been used in particular to produce projections of land use at regional and global scale, and this has given birth to a dense literature of model results comparisons (Carpenter et al., 2005, Rounsevell et al., 2006, Smith et al., 2010, Vuuren et al., 2011, Schmitz et al., 2014). Without going into too many of the details of the different model representations, it may be worth stressing some of their main criteria that supported the choice of my modelling approaches for this work.

First of all, different land use modelling frameworks apply to different geographical and temporal scales (Veldkamp and Lambin, 2001). All the questions raised in this work adopt a global and fairly long term perspective, which required the use of frameworks that could operate at these scales. Second, I did not need here to capture fine-scale allocation details of land use changes as attempted in empirical statistic approaches. More important was the consistency across model drivers and their interactions; these called for structural approaches, which are more robust for long-term analyses and complex scenarios. For that reason, I did not consider regression or econometric approaches. The latter force some variables to be independent from others, a difficult assumption to work with in the case of long-term land use change response: agricultural land conversion, for instance, increases when prices are higher, but it also contributes to a greater production level that, in turn, stabilises market prices. Another key criterion to take into account was the role of economic drivers, which play the central role in the different questions studied here. Many models used in geographical science tend to neglect the consistency of economic representation (Irwin and Geoghegan, 2001). Equilibrium models endogenously represent the price response and reaction of agents to these price signals and appeared to be a particularly suitable framework from this respect. Considering the high level of sectoral details required for the questions addressed here (crop and livestock yield, traded products, biofuel feedstocks), the applied partial and computable general equilibrium approaches, with their fine multi-market representation, were adopted for several of the analyses below.

THREE SENSITIVE POLICY ISSUES DEVELOPED OVER FOUR CHAPTERS

Three different issues related to the question of market-mediated land use change emissions from agriculture are covered in the four chapters of the thesis. These topics, related to specific current scientific or societal debates, look successively at each component of the market; first supply, then

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[10]   Note that this denomination usually does not refer to a specific modelling technique but rather to a mix of modelling techniques integrated in a single framework, linking economic and environmental systems.

trade, and lastly demand. They also explore different methodological approaches to represent the land use change impacts: a PE model based on a linear programming (LP) approach (Chapter 2), a soft linkage between a CGE model and a PE model (Chapter 3), a pure CGE approach refined on the representation of land (Chapter 4), and a complementary simplified framework to characterise the most important drivers of land use change response and explore uncertainty range in the results (Chapter 5). The detailed contents of these four chapters are as follows:

Chapter 2 – Supply side policy responses – Intensification of agriculture

> The objective of this chapter is to analyse the impact of agricultural intensification on GHG emissions and on the possible level of achievable food production benefits. My work here tries to address several related questions raised in the literature, using an applied PE model. First, bridging yield gaps is often put forward as a solution for future food availability (Lobell et al., 2009, Licker et al., 2010, Mueller et al., 2012), as too is the importance of achieving this objective through a sustainable intensification of production (Foley et al., 2011, Garnett et al., 2013). But intensification is also often cited as the best way of mitigating future GHG emissions through land sparing (Tilman et al., 2011, Burney et al., 2010), which contradicts the previous objective because intensification is then thought of as a way to produce the same on less land. Chapter 2 investigates the trade-offs between these two options. The implications are not only important for the debate on how to best mitigate GHG emissions from land use, in particular when comparing supply-side and consumption-side measures (Stehfest et al., 2009, Popp et al., 2010, Smith et al., 2013, Havlík et al., 2014). They also raise a very concrete challenge to policy makers and development programs supporting agricultural intensification. Indeed, some options may not be delivering the expected environmental benefits, because increased farms' profitability can drive production expansion – an illustration of Jevons' paradox in agriculture (Ewers et al., 2009, Hertel, 2012, Villoria et al., 2013).

Chapter 3 – Trade policy responses – Trade agreement between EU and MERCOSUR

> This chapter investigates the environmental impact of a would-be EU-MERCOSUR trade agreement. This work echoes more general concerns raised for many years about the trade-offs between globalisation and environmental challenges (WTO, 2004, 2009). The ambiguous effect of trade on the environment is not a new topic for economics (e.g. Grossman and Krueger, 1991, Copeland and Taylor, 2005). However, most attention has been drawn to transboundary pollutions (Copeland and Taylor, 1995) and carbon flows in industrial goods (Davis and Caldeira, 2010, Davis et al., 2011a). The focus on agricultural and LULUCF GHG emissions is more recent (Verburg et al., 2009, DeFries et al., 2010, West et al., 2010, Karstensen et al., 2013, EC, 2013) and has not so far compared the expected economic benefits of trade with the extent of potential carbon emissions damage. As I show in this chapter, these emissions may not only be substantial, but may also offset a large share of expected gains from the trade agreement, if some specific products are liberalised without suitable accompanying measures.

In the case of the EU-MERCOSUR, these emissions could be particularly substantial, due partly to the comparative advantages of Latin America in agricultural products, and partly to the strong land use change dynamics in that continent. At a time when the EU is considering granting greater access to products from MERCOSUR, the point, when assessing alternative options, is not to call into question the potential economic benefits of such an agreement, but rather to take account of the ensuing environmental impacts. From a methodological point of view, this chapter is also an opportunity to explore some variation around the two equilibrium modelling approaches used in this thesis, which are combined here in a single framework. A CGE is used to represent welfare change and trade policies, while a LP model allocates the associated changes on the supply side.

Chapter 4 – Demand side policy responses – EU biofuels mandate

This chapter analyses the land use change impacts of the EU biofuel policy which entered into force in 2009. As demonstrated earlier in this chapter, the effect of ILUC from biofuels has been a subject of controversy and European policy is no exception. The EU Renewable Energy Directive (RED) introduces some objective of incorporation of biofuels into the transportation fuel used in Europe, with a mix of feedstocks reflecting the diversity of the vehicle fleet. In particular, in contrast with the US, the role of biodiesel is preponderant, which calls for a comparison with ethanol feedstocks. Here, I present the analysis of indirect land use change performed with the most comprehensive version of the MIRAGE-BioF CGE model which I began to develop in 2008 at the *Centre d'Études Prospectives et d'Informations Internationales (CEPII)*. This model has been used for several assessments of the EU biofuel policies over the past five years (Bouët et al., 2008, Valin et al., 2009, 2010a, Bouët et al., 2010, Al-Riffai et al., 2010b). Some simulations performed with this model (Laborde, 2011) have been used as an input for the Impact Assessment of the RED by the European Commission in 2012 (EC, 2012). The results presented in Chapter 4 compare the impact of different biofuel portfolios for the EU mandate and explore the sensitivity of results to variations in the behavioural parameters and the model specifications.

Chapter 5 – Land use response uncertainties – An exploration around ILUC from biofuel policies

This last chapter develops the exploration on the analysis of biofuel ILUC impacts from chapter 4 through a simpler decomposition approach aimed at shifting the discussion from model specifications to parameter uncertainties. The objective is to better understand how accurate ILUC estimations can be, and to show more clearly the mechanisms at play and the magnitude of plausible results. It extends the work from Plevin et al. (2010) with a deeper exploration of economic responses, as illustrated in Hertel (2011). In this respect, the investigation in this chapter emphasizes intervals of uncertainties that apply not only to the ILUC topic but are also valid for the explorations from Chapters 2 and 3. All final land use change impacts are indeed subject to the same market adjustments where demand, yield and land response will

distribute the effect of a biophysical shock (Nelson et al., 2013). The analytical decompositions performed in this chapter can be easily reproduced through an Excel-based tool that allows exploration of the effects on the final results of various elasticity changes.

CHAPTER 2

AGRICULTURAL PRODUCTIVITY AND GREENHOUSE GAS EMISSIONS: TRADE-OFFS OR SYNERGIES BETWEEN MITIGATION AND FOOD SECURITY?

AGRICULTURE is a major contributor to greenhouse gas (GHG) emissions through crop cultivation, livestock, and land use change. These sources altogether account for about one-third of total anthropogenic GHG emissions, and four-fifth of them are located in developing countries (Metz et al., 2007, Tubiello et al., 2013). Various mitigation strategies exist at different costs (Smith et al., 2008) but would require either change in consumption patterns, or some constraints on agricultural activities, with some implications for food supply (Smith et al., 2013). Investing in productivity improvement is usually presented as an efficient way to achieve simultaneously GHG emission reduction and ensure food availability, one of key pillars of food security (Tilman et al., 2011, Havlík et al., 2013, FAO, 2009).

Major productivity gaps remain that could be exploited to supply more food on existing agricultural land, at lower costs (Foley et al., 2011). Increasing land productivity would in particular relax the pressure from land conversion on current deforestation frontiers and help avoid large emissions and biodiversity losses (DeFries and Rosenzweig, 2010). Indeed, past crop yield increases are estimated to have spared 85% of cropland over 50 years and avoided some 590 $GtCO_2$ of land use-related GHG emissions (Burney et al., 2010). On the livestock side, feed productivity increase is generally perceived as the most effective mitigation option (Wirsenius et al., 2010), as add-on technologies (anti-methanogens, digesters) can only achieve limited levels of abatement (Beach et al., 2008).

However, the effect of agricultural productivity increase on climate change mitigation can be ambiguous. First, investments focusing on input intensification only increase productivity of some factors, and can worsen pressure on the environment. Fertiliser application, for instance, can lead to additional nitrous oxide emissions with a high radiative forcing power (Reay et al., 2012) and machinery used for tillage, harvest, or irrigation burn extra fuel (Lal, 2004). In addition, even when production increase is reached through resource-saving total factor productivity (TFP) gains, decrease in prices stimulates further demand and consequently production and input use, a phenomenon commonly referred to as the rebound effect (Lambin and Meyfroidt, 2011, Hertel, 2012). Indeed, empirical studies find mixed results when looking at local land sparing effects in regions where yields were substantially increased (Ewers et al., 2009). Overall, the level of environmental and food supply benefits that can arise from land productivity increases reveals to be highly dependent on which technology and which investment scheme are chosen from among the large array possible (FAO, 2012).

This chapter proposes an overview of the implications from different productivity development in agriculture with respect to climate change mitigation and food supply in developing countries. The analysis relies on a comprehensive agriculture and land use partial equilibrium model covering the major GHG emission sources and agricultural product markets. Contrasting scenarios of crop yields and livestock feed conversion efficiencies development are studied, with stagnation or catching up of these countries at levels of more advanced ones. Three different productivity pathways are looked to achieve these yield levels; two are relying mainly on partial productivity gains with input intensification with or without fertiliser increase, one on total factor productivity gains, with higher effect on production prices. The scenarios are presented in detail in the next section, followed by a presentation of the model and GHG accounting methods. Scenarios results for future food availability and GHG emissions and the various trade-offs and synergies are analyzed in section 2.3, and the implications are discussed in the last part of the chapter.

2.1   Exploring different agricultural developments

2.1.1   Baseline assumptions

We draw our analysis from a reference situation describing a plausible future up to 2050 for the different regions of the world. Population and gross domestic product (GDP) changes follow the assumptions from scenario SSP2 ("Middle of the Road") of the Shared Socioeconomic Pathways (SSPs) developed by the climate change community (O'Neill et al., 2012). Under this scenario, the world population reaches 9.2 billion people by 2050, whereas the average world GDP per capita increases from US\$ 6,700 in 2005 to US\$ 16,000 in 2050. The food demand projections in GLOBIOM are based on income elasticities calibrated on trends from the Food and Agriculture Organization of the United Nations (FAO) (Alexandratos and Bruisma, 2012) and the world food consumption grow in our model by 68% in kcal terms between 2000 and 2050 and reaches 3,045 kcal/cap/day at that

horizon (see complementary Table 2.6 at the end of this Chapter for details). The share of animal products in diet only slightly increases, from 16% in 2000 to 17.3% in 2050 because the increase in developing countries are partly compensated by some decrease in developed regions. Other competitive uses of agricultural products are increasing with bioenergy demand. First generation biofuels are assumed to continue in line with current commitments levels until 2030 and are later stabilised. Bioenergy and biomass use for heating and cooking are fixed exogenously following scenarios from the POLES model (Russ et al., 2007).

2.1.2 FUTURE YIELD DEVELOPMENT

Yield growth for crops and livestock are assumed to follow in the baseline recent historical trends, which are extended linearly to 2050. In the case of crops, such trends are derived from the analysis of past FAOSTAT yields between 1980 and 2010. Fertiliser use is assumed to increase with crop yield with an elasticity of 0.75, following the world average trend observed over the last 30 years. For livestock, we rely on the feed conversion efficiency information from Bouwman et al. (2005) and apply them to the different grass-based and mixed systems in the model. For both crops and livestock, we consider in the baseline that other input and factors than land and feed are increased and production costs per unit of output are only marginally affected.

Four different yield scenarios and three productivity pathways are considered around the baseline (scenario "TREND" with pathway "High-Input"). Yield scenarios only modify crop yields projections (Figure 2.1) and ruminant feed efficiencies projections (Figure 2.2) in developing countries and economies in transition, according to assumptions in Table 2.1. The productivity pathways distinguish how these yield changes are attained (Table 2.2).

Table 2.1. Crop yield and ruminant feed efficiency assumptions in the different scenarios.

Scenario name	Crops yield	Ruminant feed conversion efficiency
TREND	FAO historic trend 1980-2010	Bouwman et al. (2005) trend
SLOW	50% TREND growth rate	50% TREND growth rate
CONV	TREND + 50% yield gap closure	TREND + 25% efficiency gap closure
CONV-C	TREND + 50% yield gap closure	TREND
CONV-L	TREND	TREND + 25% efficiency gap closure

YIELD SCENARIOS

The first alternative scenario to the baseline considers that yield improvements cannot keep on the present trends and stall over the next decades at half the currently observed growth rate ("SLOW"). This scenario is a stylised representation for the interplay of many factors that could affect yield differently, such as failure in technology adoption, increase in rural poverty due to resource scarcity, land degradation, pressure from climate change, or lack of investments or access to credit.
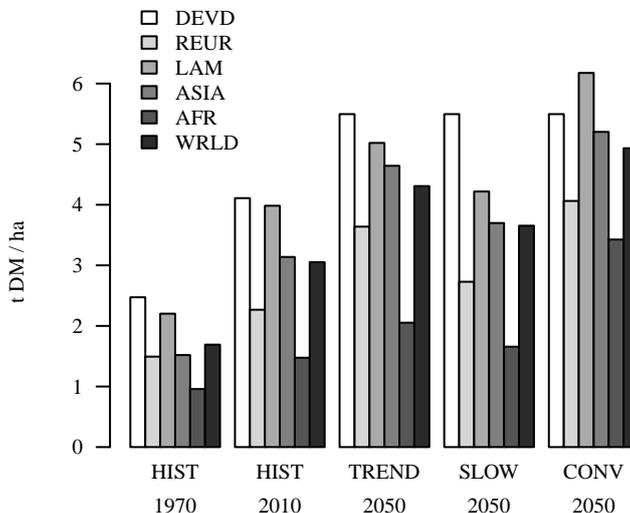
Figure 2.1. Average crop yield in historical record and in 2010–2050 GLOBIOM baseline.
Calculation relies on a selection of 17 crops represented in GLOBIOM. Years 1970, 1990, and 2010 are
sourced from FAO PRODSTAT database (5-year average for 1970 and 1990 and 3-year average for 2010).
Aggregation for all years is based on the 2000 harvested area. Region definition: DEVD = North America,
Oceania and Western Europe; REUR = Eastern Europe and Former USSR; ASIA = South-East and East
Asia; LAM= Latin America; WRLD = World average.

Table 2.2. Management assumptions for the different productivity pathways.

Pathway name	Crops		Livestock
	Fertilizer adjustment	Other input adjustment	Non-feed cost adjustment
High-Input	Yes	Yes	Yes
Sust-Intens	No	Yes	Yes
Free-Tech	No	No	No

We contrast this perspective with a convergence scenario ("CONV"), where efficient rural
development policies improve cropping and herd management practices. As a result, we assume that
50% of the estimated yield gaps in the baseline are bridged for crops. These yield gaps are calculated
comparing current observed crop yields from FAO with potential yield for rain-fed and irrigated
systems estimated with the EPIC model. In the case of livestock, developed regions are used as the
benchmark for feed conversion efficiency for ruminants and 25% only of the distance to this frontier
is bridged, to avoid too strong structural breaks for this sector. For non-ruminant animals, we do
not consider any change from the baseline trend because productivity gaps for industrial systems,
where most of the future production will take place, appear much more limited across regions (see
Appendix A).

To better understand the contribution of the different sectors on the results, the convergence
scenario is further decomposed into two additional variants: "CONV-C" which corresponds to a
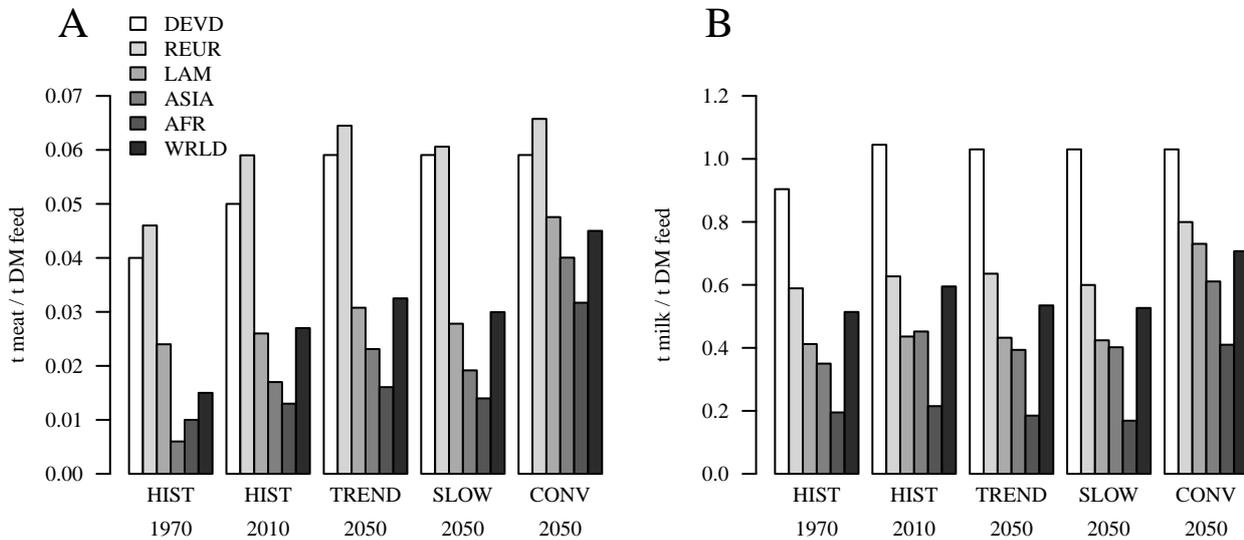
Figure 2.2. Average feed efficiency for ruminant meat (A) and milk (B) in the past and in 2010–2050 GLOBIOM baseline. Past trend is sourced from Bouwman et al. (2005) who propose historic estimations between 1970 and 1995 and projections follow their assumptions up to 2030, extrapolated here until 2050. Aggregation for all years is based on the 2000 animal production in FAOSTAT. Milk productivity calculation takes into account feed for replacement animals. Region definition: DEVD = North America, Oceania and Western Europe; REUR = Eastern Europe and Former USSR; ASIA = South-East and East Asia; LAM= Latin America; WRLD = World average.

convergence in crop yield only, while livestock feed efficiency remains unchanged; and "CONV-L" which considers the opposite situation where only ruminant efficiency is increased.

PRODUCTIVITY PATHWAYS

Pathways describe how yield scenarios are reached. The reference pathway considered for the baseline and all scenarios is a conventional intensification of practices ("High-Input" pathway). We increase for this pathway all inputs requirements and factor costs associated with yield improvement. For crops, such scenario implies additional fertilisers, pesticides, and irrigation, as well as investment in machineries and equipment, which are still limiting in many developing regions (Neumann et al., 2010, Mueller et al., 2012). Given the possibilities of increasing yield through more sustainable practices, we also consider a pathway where these crop yield improvements are obtained without additional synthetic fertilisers, mainly through more efforts on optimised rotation, crop-livestock systems integration, and precision farming ("Sust-Intens" pathway). On the livestock side, these two previous pathways are considered similar: they rely on investment in adequate capital and labor and a better management of herd, to decrease mortality, improve feeding practices and hence increase meat and milk output per head (McDermott et al., 2010). Last, a third pathway is explored, relying much more on innovation and total factor productivity gains. For this pathway, all input and factor requirements are kept constant, and the extra production is reached through new technologies

adoption and public expenditures towards R&D and infrastructure investments, bringing substantial yield boost overall without extra cost for farmers ("Free-Tech").

2.2 MODELLING FRAMEWORK

We analyse the effects of the previous scenarios using a linear programming (LP) model of agriculture, forestry, and land use change: the GLOBIOM, developed atIIASA by a collective team (Havlík et al., 2011, 2013).

GLOBIOM is a global partial equilibrium model allocating land-based activities under constraints to maximise the sum of producer and consumer surpluses. It is grounded in a well-established tradition of LP models (Takayama and Judge, 1971, McCarl and Spreen, 1980), and similar in structure to the US-FASOM model (Schneider et al., 2007, Beach et al., 2012). The model operates at two levels: on the supply side, a detailed resolution grid based on a 0.5×0.5 degree cells structure; on the demand and trade side, a representation of the world into 30 markets, separated by trade costs and tariffs. The model is used under a recursive dynamic approach, and for the current work is run 10-year time steps over the 2000-2050 period. The main characteristics of this model are presented below[1] and the modifications to implement the scenarios are described in Subsection 2.2.3.

2.2.1 SUPPLY SIDE REPRESENTATION

On the supply side, crop, livestock and forestry activities in the model are described at the grid-cell level. Data are supplied at the most detailed resolution, called Simulation Units (SimUs, Skalský et al., 2008), that are latter aggregated at the model resolution, the production unit (PU). Each production unit can be used to supply a combination of up to 18 crops, seven livestock products sourced from eight animal types and five primary wood products.

SIMULATION AND PRODUCTION UNITS

SimUs are the most detailed units, delineated at the 5 minute of arc resolution as the intersection of zones of same altitude, slope, and soil class, 0.5×0.5 degrees grid, and the country boundaries. These units are used as the base architecture to input all geographically explicit data to the model (land use, crops and animal location, etc.). It is also the level at which productivities for crops can be calculated using the EPIC model, as well as the biomass net primary productivity (NPP) to estimate grazing potential for livestock, and forest productivity.

The total number of SimUs being greater than 200,000, raw data can be aggregated in the model to reduce the computation time. For this study, we use a 2×2 degree resolution to run the model, only keeping a layer of differentiation across three agro-ecological zones to distinguish

---

[1]   Only the main structural equations are presented here. We do not go into the details of equations of crop and livestock management, supply chain processing, and recursivity constraints, as they do not play a major role for the problem studied here.

livestock systems (Seré and Steinfeld, 1996). This leads to a total of 10,894 different production units distributed across the 30 regions.

CROP PRODUCTION

Each activity at the PU level u can produce various products i according to different Leontief technologies or management m. Input and output characteristics of these technologies are calculated with a specific biophysical model – the crop productivity model EPIC, the digestibility model RUMINANT for livestock, and the forest model Global Forestry Model (G4M).

GLOBIOM represents up to 18 crops.[2] Production $S_{i,u}$ of each crop i in unit u can then be written as:

$$S_{u,i} = \sum_m \mathrm{Y}_i(A_{u,i,m}, K_{u,q_1,i,m}, ..., K_{u,q_n,i,m}), \tag{2.1}$$

where Y_i is the production function of product i, $A_{u,i,m}$ is the land area demand for this production and $K_{u,q,i,m}$ a list of required inputs $q \in (q_1, ..., q_n)$. Because we assume fixed technologies (i.e. fixed shares of K and A) for each management system m, we can use the crop activity model to calculate land productivity for crops in all PUs as $y_{u,i,m} = \mathrm{Y}_i(A_{u,i,m}, K_{u,q_1,i,m}, ..., K_{u,q_n,i,m})/A_{u,i,m}$.

Four different management systems m are considered for each crop: subsistence, low input, high input, and irrigated, when water resource is available (see below). Crop yields $y_{u,i,m}$ are generated with EPIC for all locations u on the basis of soil, slope, altitude and climate information from the SimU, as well as climate information. Each management is associated with a fixed cost per unit of area $c_{u,i,m}^A$, calculated as a function of yield $y_{u,i,m}$, initial market price $p_{i,r}$ in the region r, and the cost of the different inputs.

At the market level in region r, supply can simply be defined as

$$S_{i,r} = \sum_u \sum_s y_{u,i,m} A_{u,i,m}. \tag{2.2}$$

LIVESTOCK PRODUCTION

Livestock production depends, among other inputs, on feed crops and, for ruminants, on consumption of grass g, whose production function is the same as for crops. We represent production here with a function depending on number of animals $N_{u,a,m}$, where a is animal species. Productivities of animals $y_{r,i,a}$ are defined at the regional level by animal species and management system. The production of product i for unit u in region r can be expressed as:

$$S_{u,i} = \sum_a \sum_m y_{r,a,i,m} N_{u,a,m} = \sum_a \sum_m \mathrm{Y}_{r,a,i,m}(D_{u,a,m}^G, D_{u,a,i_1,m}^F, ..., D_{u,a,i_n,m}^F), \tag{2.3}$$

---

[2]   Crops represented in the model are: barley, cassava, chick pea, cottonseed, dry bean, groundnut, maize, millet, palm fruit, potato, rapeseed, rice, sorghum, soybean, sugar cane, sunflower, sweet potato and wheat. These represent around 70% of the total world harvested area and 85% of the vegetal calorie supply.

where $D^G_{u,a,m}$ and $D^F_{u,a,i,m}$ are the demand for grass and for feed product $i \in (i_1,...i_n)$, respectively, from animal a in location u and system m. The corresponding production functions $Y_{r,i,a,m}$ therefore directly depends on feed consumption.

The model incorporates seven animal types – dairy and other bovines, dairy and other sheep and goats, laying hens and broilers, and pigs – that produce four meat types, milk, and eggs. These animals are distributed across different management systems (Seré and Steinfeld, 1996) using spatial distribution data from Robinson et al. (2011).[3] Feed is distinguished between: grass, stover, and feed crops.[4] Feed and stover are provided by the regional market, whereas the constraint on grazing demand for ruminants can simply be written for each unit u in function of production of grass g:

$$\sum_a D^G_{u,a,m} \leq S_{u,g,m} \tag{2.4}$$

Feed composition and efficiency $y_{r,a,i,m}$ are calculated according to Herrero et al. (2013) who process regional data on animal diet with the RUMINANT model. Efficiency could be differentiated across all management systems m and animal types i, and for 28 different regions.

Production cost depends on feed market prices, but also of a fixed cost of animal maintenance $c^N_{r,a,m}$ specific to the animal and management type of each region.

Forestry and bioenergy

Although not the focus of this study, the forestry sector also participates to land use dynamics in GLOBIOM. Five forest primary products – pulp logs, saw log, biomass for energy, traditional fuel wood, and other industrial logs – are consumed by industrial energy, local population for traditional use, or processed as final wood products (pulp and sawn wood). These products are supplied by two different land use types (managed forests and short rotation plantations) that follow the same production specifications as for crops. Yields $y_{u,i,m}$ and harvesting costs $c^A_{u,i,m}$ are sourced from the G4M model (Kindermann et al., 2006) on the basis of information on species selection, variation of thinning and choice of rotation length.

Forestry products, as well as some biofuel crops can be processed in the model through sawmill and bioenergy supply chains. These transformation chains z can process a quantity $D^T_{r,z,i}$ of product i into $T_{r,z,i'}$ of product i' with a linear processing cost $c^T_{r,z}$ per unit produced.

---

[3] For ruminants, we distinguish eight production systems – grass-based (arid, humid, temperate/highlands), mixed crop-livestock (arid, humid, temperate/highlands), urban and other; for monogastrics, we split animals between two systems: smallholders and industrial.

[4] Within grass, the model contains some locally consumed grass ("grazing") and some regionally supplied grass ("occasional") that can be transported within a region. We will for simplification here only describe the "grazing" part. Similarly, the description of stover, a crop co-product in the model, will not be detailed here. See Havlík et al. (2014) for more details.

LAND USE COMPETITION

Each PU has an initial allocation of land cover $\bar{L}_{u,l}$ within its total land area $\bar{L}_u$, where l defines six possible land use types: cropland, grassland, managed forest, short rotation plantations (SRPs), primary forest, and other natural land. Land dynamics $L_{u,l}$ is subject to several constraints related to supply and demand for land:

$$
\begin{cases}
\displaystyle\sum_{i\in\text{Crops}}\sum_m A_{u,i,m} & \leq L_{u,\text{cropland}} \\[2ex]
\displaystyle\sum_m A_{u,g,m} & \leq L_{u,\text{grassland}} \\[2ex]
\displaystyle\sum_{i\in\text{WoodM}}\sum_m A_{u,i,m} & \leq L_{r,\text{managed forest}} \\[2ex]
\displaystyle\sum_{i\in\text{WoodP}}\sum_m A_{u,i,m} & \leq L_{r,\text{SRP}} \\[2ex]
\displaystyle\sum_c L_{u,l} & \leq \bar{L}_r,
\end{cases}
\tag{2.5}
$$

where we call *WoodM* the group of products specifically produced in managed forest and *WoodP* the group of products specifically produced in SRPs.

Managed land use is associated an initial land rent $\bar{w}_{r,l}$, that increases with land supply with an elasticity $\varepsilon^L_{r,l}$. Additionally, land conversion $LUC_{r,l,l'}$ from land use type l to another l' is associated a specific conversion cost with a constant term $\alpha_{r,l,l'}$ and a linearly increasing one $\beta_{r,l,l'}$.

RESOURCE CONSTRAINTS

The supply side is also subject to several input constraints. The most notable is water for irrigation, but a constraint on fertilisers can also be considered. For a resource q supplied in quantity $Q_{r,q}$ in region r, the model integrates the constraint on demand $K_{u,q,i,m}$ for input of resource q simply as:

$$
\sum_{u\in r}\sum_i\sum_m K_{u,q,i,m} \leq Q_{r,q}.
\tag{2.6}
$$

The constraint on resource q for this study is defined for water at the regional level. The resource price varies around its initial level $\bar{p}_{r,q}$ and is linked to supply level $Q_{r,q}$ through an elasticity of supply $\varepsilon^Q_{r,q}$.

TOTAL PRODUCTION COSTS AND PRODUCER SURPLUS

All the relations above allow us to express the production cost PC_r for each region of the model. If we define $\bar{S}$ and $\bar{L}$ the production and land use levels at calibration, we then obtain:

$$PC_r = \sum_{u \in r} \sum_{i,m} c^A_{u,i,m} \, A_{u,i,m} \qquad\qquad\qquad \text{(activity costs)}$$

$$+ \sum_{u \in r} \sum_{a,m} c^N_{r,a,m} \, N_{u,a,m} \qquad\qquad\qquad \text{(livestock capital costs)}$$

$$+ \sum_{u \in r} \sum_{a,i,m} p_{r,i} \, D^F_{u,a,i,m} \qquad\qquad\qquad \text{(livestock feed costs)}$$

$$+ \sum_{z,i} p_{r,i} \, D^T_{r,z,i} \qquad\qquad\qquad\qquad \text{(process input costs)}$$

$$+ \sum_{z,i} c^T_{r,z} \, T_{r,z,i} \qquad\qquad\qquad\qquad \text{(processing costs)}$$

$$+ \sum_{q} \frac{\bar{p}_{r,q} \, \bar{Q}_{r,q}}{1 + \varepsilon^Q_{r,q}} \left(\frac{Q_{r,q}}{\bar{Q}_{r,q}} \right)^{(1+\varepsilon^Q_{r,q})} \qquad\quad \text{(resource expansion costs)}$$

$$+ \sum_{c} \frac{\bar{w}_{r,l} \, \bar{L}_{r,l}}{1 + \varepsilon^L_{r,l}} \left(\frac{L_{r,l}}{\bar{L}_{r,l}} \right)^{(1+\varepsilon^L_{r,l})} \qquad\quad \text{(land management costs)}$$

$$+ \sum_{l,l'} \alpha_{r,l,l'} LUC_{r,l,l'} + \sum_{l,l'} \frac{\beta_{r,l,l'}}{2} (LUC_{r,l,l'})^2 \qquad \text{(land conversion costs).} \qquad (2.7)$$

The producer surplus can then be simply written:

$$PS_r = \sum_i p_{r,i}(S_{r,i} + \sum_z T_{r,z,i}) - PC_r. \qquad\qquad (2.8)$$

2.2.2 DEMAND AND TRADE

Product processing, trade and consumption occur at the level of the region r. The world is split into 30 economic regions for which all products i are homogeneous.

DEMAND

Users of agricultural and wood products in the model are households, livestock for intermediate consumption of feed, industrial demand for sawn wood and wood pulp, and bioenergy demand. Livestock demand directly enters the production function of livestock products as input requirements. Bioenergy demand is treated as an exogenous constraint, according to the scenario assumptions (see Section 2.1.1).

Food demand $D_{r,i}$ is in the model endogenous for any period t and depends on product prices. To clarify how exogenous trends are taken into account over time, let's add a price index and note for this subsection demand and price of period t as $D_{r,i,t}$ and $p_{i,r,t}$, respectively. Population and GDP from the socio-economic scenario (Section 2.1.1) are taken into account to redefine along the

baseline the initial level of demand $\bar{D}_{r,i,t}$. The change in final demand can then be expressed as a function of base year price $\bar{p}_{r,i,2000}$ and elasticities, as:

$$\frac{D_{r,i,t}}{\bar{D}_{r,i,t}} = \left(\frac{p_{r,i,t}}{\bar{p}_{r,i,2000}}\right)^{\varepsilon_{r,i,t}^{Pr}} \text{ where } \bar{D}_{r,i,t} = \frac{Pop_{r,t}}{Pop_{r,2000}} \left(\frac{GDP_{r,t}^{Cap}}{GDP_{r,2000}^{Cap}}\right)^{\varepsilon_{r,i,t}^{Inc}} \bar{D}_{r,i,2000} \quad (2.9)$$

For each product i in region r and period t, the prior demand quantity is calculated as a function of population $Pop_{r,t}$, GDP per capita $GDP_{r,2000}^{Cap}$ adjusted by the income elasticity $\varepsilon_{r,i,t}^{Inc}$, and the base year 2000 consumption level as reported in the food balance sheet (FBS) of FAOSTAT.[5] The final demand quantity is however also affected by the change in price $p_{r,i,t}$ when compared to the base year price $\bar{p}_{r,i,2000}$, through a price elasticity $\varepsilon_{r,i,t}^{Pr}$ sourced from Muhammad et al. (2011). Because food demand in developed countries is more inelastic than in developing ones, the value of this elasticity is assumed to depend on time and decrease with the level of GDP per capita. We consider that the elasticity values of developing countries converge to US elasticity values in 2000 at the same pace as GDP per capita are catching up US GDP per capita. This representation allows us to capture the effect of change in relative prices on food consumption taking into account heterogeneity of responses across regions, products and over time. It however also brings some limitations as cross-price effects are not represented, which means that no substitution can occur at the final demand level between food products. This could induce some overestimation in the final demand response, which highlights the importance of including a sensitivity analysis on the demand response in our analysis.[6]

Using the previous formula, we can express the final consumer surplus of region r with respect to the initial price $\bar{p}_{r,i,2000}$ and demand $\bar{D}_{r,i,t}$:

$$CS_r = \sum_i \int_{p_{r,i,t}}^{\bar{p}_{r,i,2000}} D_{r,i,t} \, \mathrm{d}p = \frac{\bar{D}_{r,i,t} \, \bar{p}_{r,i,2000}}{1 + \varepsilon_{r,i,t}^{Pr}} \left[1 - \left(\frac{p_{r,i,t}}{\bar{p}_{r,i,2000}}\right)^{1+\varepsilon_{r,i,t}^{Pr}}\right]. \quad (2.10)$$

Bilateral trade and market clearing

Bilateral trade is represented in the model assuming some linear but also non-linear transportation costs. Because all products are considered homogeneous, no cross flows are present but only a net trade flow. Each region pair r and r' can trade a quantity $X_{i,r,r'} = -X_{i,r',r}$. When such trade occurs, market equilibrium imposes:

$$p_{i,r'} = p_{i,r} + \tau_{i,r,r'} \left(\frac{X_{i,r,r'}}{\bar{X}_{i,r,r'}}\right)^{\rho_{i,r,r'}}, \quad (2.11)$$

---

[5] Because we rely on FAOSTAT, it is important to note that our representation of "food" use corresponds to final demand of households (Food supply to households or Food availability), i.e. it includes effective food consumption by households but also domestic waste. Therefore, an increase or decrease in food demand does not only inform on change in food ingestion by individuals, but also on change in consumer habit with respect to food handling.

[6] We propose a method to circumvent this issue with this modelling approach in Valin et al. (2010b).

where $\tau_{i,r,r'}$ is the linear cost, representing fixed trade costs and tariffs, and $\gamma_{i,r,r'}$ is a non-linear cost parameter paired with an elasticity $\rho_{i,r,r'}$.

Total trade costs can be written:

$$TC = \sum_{r,r',i} \frac{\tau_{i,r,r'} \bar{X}_{i,r,r'}}{1 + \rho_{i,r,r'}} \left(\frac{X_{i,r,r'}}{\bar{X}_{i,r,r'}} \right)^{1+\rho_{i,r,r'}}. \tag{2.12}$$

Market clearing conditions impose the constraint that, for all products i and for all regions r, market supply should exceed final demand and input demand:

$$D_{r,i} + \sum_z D_{r,z,i}^T + \sum_{u \in r} \sum_{a,m} D_{u,a,i,m}^F \leq S_{r,i} + \sum_z T_{r,z,i} - \sum_{r'} X_{i,r,r'} + \sum_{r'} X_{i,r',r} \tag{2.13}$$

OBJECTIVE FUNCTION

The partial equilibrium of the model is determined by maximising the sum of the producer and consumer surplus, once trade costs are taken into account under all the production and consumption constraints above, i.e.

$$\operatorname*{Max}_{(S,T,Q,X)} \left(\sum_r (CS_r + PS_r) - TC \right), \tag{2.14}$$

subject to constraints on: land use (2.5),
                             grazing (2.4),
                             resource (2.6),
                             and market balance (2.13).

2.2.3   IMPLEMENTATION OF THE PRODUCTIVITY SCENARIOS

Yield in GLOBIOM are usually endogenously determined at the PU level by the composition in management systems. Additionally, spatial reallocation introduces an additional composition effect that can affect the final yield observed at the regional level (see equation (2.2)). These mechanisms are useful to assess the response of the supply side to various types of shocks. However, for the purpose of the current study, we want to test the response of production to a predetermined yield trajectory that can be easily characterised and compared to other assessments. We therefore implement two additional constraints to the model to neutralise the composition effects identified above:

$$A_{u,i,m} \leq \theta_{u,i,m} \sum_m A_{u,i,m} \qquad\qquad \text{with } \theta_{u,i,m} = \frac{\bar{A}_{u,i,m}}{\sum_m \bar{A}_{u,i,m}} \qquad\qquad (2.15)$$

$$\sum_u A_{u,i,m} \leq \lambda_{i,m} \sum_{u,m} A_{u,i,m} \qquad\qquad \text{with } \lambda_{i,m} = \frac{\sum_u \bar{A}_{u,i,m}}{\sum_{u,m} \bar{A}_{u,i,m}}, \qquad\qquad (2.16)$$

where $\bar{A}_{u,i,m}$ is the initial value of $A_{u,i,m}$. The first constraint (2.15) allows to neutralise the management effect, whereas the second constraint (2.16) manages the reallocation effect.

The long term projections on yield associated to the different scenarios are then managed through an exogenous shifter applied to the yield $y_{u,i,m}$ in each unit. This simplified representation means that the yield gap closing is not implemented for the scenarios in a geographically explicit manner but applied homogeneously in the region r.[7] Input requirements and production costs are also varied exogenously according to assumptions from section 2.1.2. For the "High-Input" pathway, the crop requirements in $K_{u,q,i,m}$ are increased for all inputs q, as well as the fixed production cost $c^A_{u,i,m}$. For "Sust-Intens", the assumption is similar, except for fertiliser requirements that are kept constant. For the "Free-Tech" scenario, only $y_{u,i,m}$ is increased, but $K_{u,q,i,m}$ and $c^A_{u,i,m}$ are unchanged.

Switches between livestock production systems in each PU and at regional level are neutralised the same way as for crops to implement the productivity scenarios.[8] Because yield increase is not per unit of area but per unit of feed, we do not change the input requirements of livestock $D^F_{u,a,i,m}$ and $D^G_{u,a,i,m}$ but only increase the fixed cost per animal $c^N_{r,a,m}$.

2.2.4   GHG emission accounts

Each PU in GLOBIOM is associated a location specific emission factor per sector. The different activity models used for input data allow for a precise estimation of these GHG emission factors, based on Tier 1 to Tier 3 methodologies from the IPCC agriculture, forestry and other land use (AFOLU) guidelines (IPCC, 2006). For crops, the emission factor $e^A_{u,i,m}$ depends first on rates of synthetic fertiliser use, calculated using the output from the EPIC model, after harmonisation with the consumption statistics from the International Fertilizer Industry Association (IFA). Methane emissions from rice cultivation are based on area harvested and emission factors from FAO (Tubiello et al., 2013). Livestock emissions factors $e^N_{u,a,m}$ are sourced from the RUMINANT model which has been applied in each country to the different livestock systems from the Seré and Steinfeld (1996)

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[7]   This assumption can in principle affect where land use change takes place. However, because no internal transportation costs are implemented in the global version of the model, the relevance of the intra-regional allocation remains limited also without this assumption. Moreover, because the land conversion costs are implemented at the regional level, distribution of agricultural land expansion across land use types is likely to be only marginally impacted. On the contrary, this assumption does not impact the land use requirements, because average yield remains the same and the demand for products is at the regional level.

[8]   It is noteworthy that livestock system transition can be a significant source of land sparing (see Havlík et al., 2014, for the specific study of livestock systems transition with GLOBIOM). This effect is here exogenously controlled through the feed conversion efficiency assumption over time, specified in our scenarios.

Table 2.3. GHG emission accounts in the GLOBIOM model for agriculture and land use change.

Sector	Source	GHG	Reference	Tier	Emissions 2000 (MtCO$_2$-eq)
Crops	Rice methane	CH$_4$	Emission factors from FAO	1	487
Crops	Synthetic fertilizers	N$_2$O	EPIC output/IFA + IPCC EF	1	523
Crops	Organic fertilizers	N$_2$O	RUMINANT + Livestock systems	2	83
Livestock	Enteric fermentation	CH$_4$	RUMINANT + Livestock	3	1,501
Livestock	Manure management	CH$_4$	RUMINANT + Literature	2	251
Livestock	Manure management	N$_2$O	RUMINANT + Literature	2	207
Livestock	Manure grassland	N$_2$O	RUMINANT + Literature	2	404
			Total agriculture		**3,455**
Forest	Land use conversion	CO$_2$	G4M model carbon stocks	2	1,300[a]
Other vegetation	Land use conversion	CO$_2$	Ruesch and Gibbs (2008)	1	600[a]

[a] No value of land use change in the model for the initial year. Value reported is average for the period 2000–2030. For forest, these values are lower than the historical record (see SI).

classification. Three GHG sources are considered: enteric fermentation (CH$_4$), manure management (CH$_4$ and N$_2$O), and manure left on pasture or applied to cropland (N$_2$O). The values of these emission factors are highly influenced by the management system m.

Land use change emissions are calculated as changes in carbon stocks, based on data from the G4M model, consistent with FAO inventories (FAO, 2010b). Forest conversion to agricultural land or plantation is considered to release all the carbon per hectare $f_{u,l}$ contained in above- and below-ground living biomass into the atmosphere. Carbon stocks for land use types other than forests are sourced from the Ruesch and Gibbs (2008) database. Soil organic carbon stocks are not considered in our standard accounting.

Overall, for a time-step of 10 years, the level of annual emissions E is calculated as:

$$E = \sum_u \sum_i \sum_m e^A_{u,i,m} A_{u,i,m} + \sum_u \sum_a \sum_m e^N_{u,a,m} N_{u,a,m} + \frac{1}{10} \sum_u \sum_{l,l'} LUC_{u,l,l'}(f_{u,l'} - f_{u,l}). \quad (2.17)$$

The list of GHG emissions sources represented in the model and their magnitude are summarised in Table 2.3. For agriculture, flows cover around 80% of official inventories sources (crop residues, savannah and waste burning are missing; see Appendix B for a comparison with FAO accounts and other sources). Land use change emissions are only partially representative because we do not account for peatland and soil organic carbon emissions, whose dynamics and interaction with land use activities are more complex to model and hindered by lack of reliable global datasets.

2.3   Results

2.3.1   Patterns of GHG emissions in developing countries across scenarios

The predominant contribution from emerging and less advanced regions is clearly visible in present and future emissions from agriculture and land use change in our baseline calculations (see Figure 2.3). World agriculture emissions increase from 3,455 $MtCO_2$-eq in 2000 to 4,238 $MtCO_2$-eq in 2030, and 4,508 $MtCO_2$-eq in 2050, following expansion of agricultural production ($+72\%$ for cereals, $+97\%$ for meat). Developing regions account for a stable share of 80% of these emissions all over the period. This expansion additionally stimulates land use conversion and the model estimates 216 Mha of forest decrease and 283 Mha of other natural land losses by 2050, representing an average of 1,895 $MtCO_2$-eq per year.[9] Detailed land use changes are available at the end of this chapter (Table 2.9).

By 2050, emissions from livestock CH_4 and N_2O emissions account for a large share of the emissions, with 50% of agricultural and land use flows, while crops contribute 23% through rice methane and fertiliser use emissions. Asia appears to be the most significant emitter for cropping activities through the rice sector and the high use of fertilisers, whereas Latin America leads for livestock emissions. Additional emissions from land use change mainly occur in Latin America and sub-Saharan Africa where a stronger link between agricultural expansion and deforestation is found than in Asia (FAO, 2010b).

Following a different scenario of agricultural productivity can, however, significantly change the balance of future GHG emissions. In Figure 2.4, the left panel shows how different regions react to the yield scenarios around the baseline under the "High-Input" pathway. The right panel illustrates how the world total is modified when the pathway is changed. Under the "High-Input" pathway, increasing yield allows emissions to be substantially decreased (-456 $MtCO_2$-eq for "CONV"), whereas a yield slow-down would lead to additional GHGs ($+340$ $MtCO_2$-eq). The magnitude of change around the initial baseline, however, appears relatively limited (-7% for "CONV"/$+5\%$ for "SLOW") when compared with the magnitude of yield deviation. The effect of livestock feed efficiency alone appears to be slightly less efficient when compared to "CONV" (-371 $MtCO_2$-eq in "CONV-L"), whereas crop yield change contribution appears very limited (-67 $MtCO_2$-eq in "CONV-C").

Different effects are indeed at the interplay of emission changes and can explain the observed patterns. First, yield growth obviously affects the emission factors of some sectors directly. For crops, immersed areas used for rice cultivation decrease as yield increases. However, in the case of the "High-Input" pathway, this effect does not occur for fertiliser emissions, because the use of this

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[9]   The land use change estimate in the baseline is lower than the historical deforestation emission rate in certain regions because: (i) the model does not account for some drivers of deforestation such as illegal logging, infrastructure expansion, mining activities; (ii) some policy shifts are reflected such as better protection of forest recently observed in Brazil; (iii) the baseline follows a productivity trend for crop and livestock that relieves a part of the pressure on land (see Appendix B for more details on land use change emissions).
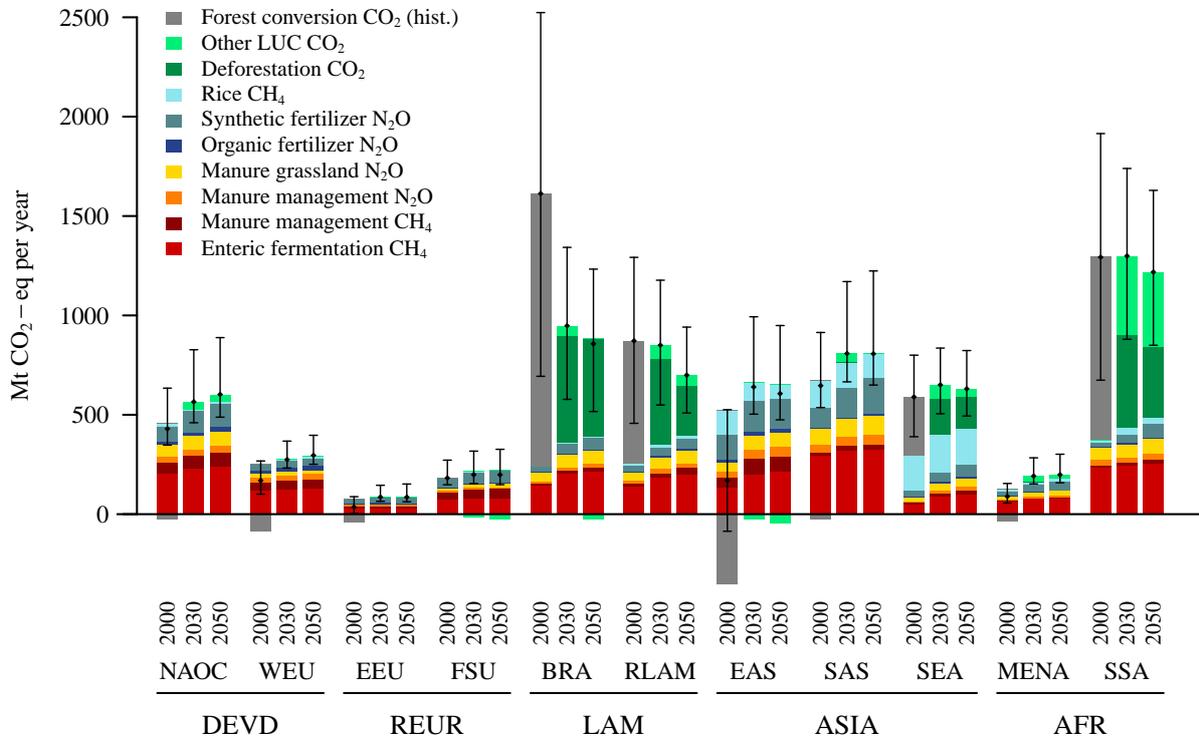
Figure 2.3. GHG emissions along the baseline for different regions and sources. All calculations from the model, except for historical emissions from forest conversion in grey, sourced from FAOSTAT (2000-2005 average). Error bars indicate 95% confidence intervals for total of our emissions sources (see Appendix B). Regional groups are the same as in 2.1. Sub-regional breakdown: NAOC = North America and Oceania; WEU = Western Europe; EEU = Eastern Europe; FSU = Former Soviet Union; BRA: Brazil; RLAM = Rest of South and Central America; EAS = Eastern Asia; SAS = South Asia; SEA: South-East Asia; MENA= North Africa and Middle East; SSA = sub-Saharan Africa.

input is increased to obtain greater yield. In case of livestock, we also observe that, in most regions, livestock CH_4 and N_2O emissions decrease in "CONV", because less animal are necessary per unit of output, and symmetrically, increase in "SLOW".

A second channel of emissions comes from the interaction of crop and livestock sectors with land use. Higher crop yield and improved feed conversion is expected to drive cropland and grassland sparing and decrease other land conversion, in particular deforestation. This is notably illustrated in the "CONV" and "CONV-L" scenarios in Latin America, as livestock pressure in this region is recognised as being a significant driver of deforestation. However, this effect is not observed in all cases. In the "CONV-C" scenario, potential land savings for crops seem unexploited for the same region. This is explained by a third driver of emission changes: the rebound effect.

Indeed, the third factor of emissions comes from the demand response to prices when larger quantities are available on the market. As a result, a clear rebound effect is observed in several regions, canceling out part of the benefits from previous effects. In the "CONV-C" scenario, livestock numbers increase by 2% as a result of more abundant feed and additional demand for cheaper
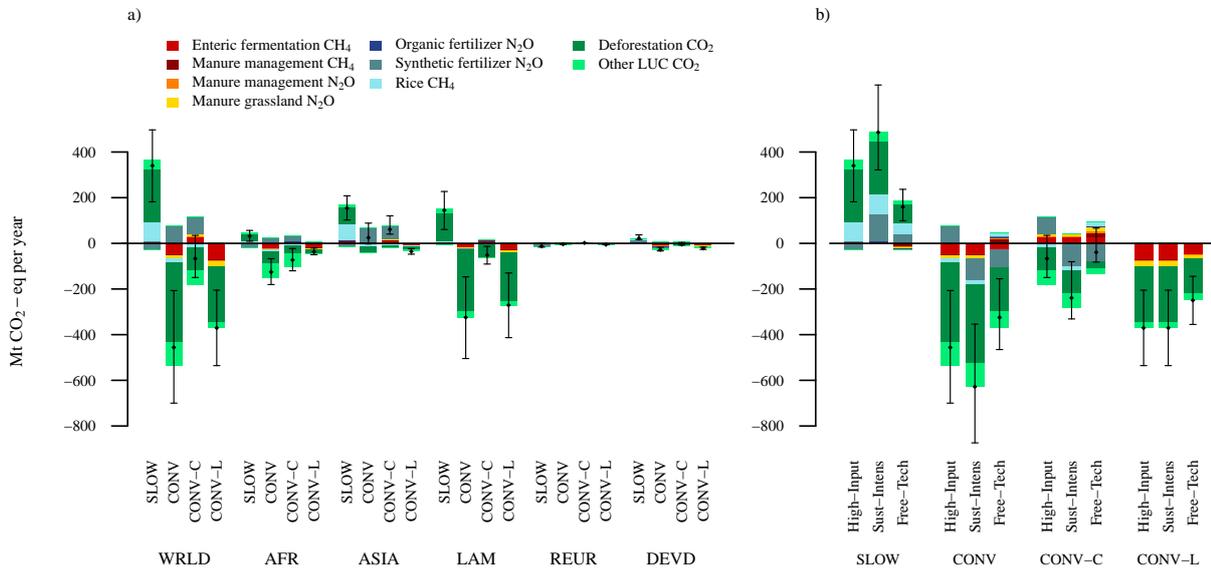
Figure 2.4. Differences in GHG emissions levels by 2050 across yield scenarios and regions (panel a) and productivity pathways by scenario at world level (panel b) with respect to the baseline ("TREND"). Error bars indicate 95% confidence intervals for total of our emissions sources (see Appendix B). Region definition: DEVD = North America, Oceania and Western Europe; REUR = Eastern Europe and Former USSR; ASIA = South-East, East Asia; LAM= Latin America; WRLD = World. Land use change annual emissions are calculated as an average over the simulation period.

ruminant and non-ruminant meat, driving one third of extra agricultural emissions. Fertiliser emissions represent the rest of this increase, although their intensity per unit of output is assumed to decrease (elasticity of 0.75 for the "High-Input" pathway). For regions such as Asia, this even contributes to a net increase in emissions under both "CONV" and "CONV-C" scenarios. The overall magnitude of such rebound effects is in fact considerable, as we will see in section 2.3.3. This emphasizes the need for more careful attention on the ambiguous impact of yield increase through this channel (Hertel, 2012).

As we have seen, the combination of these three effects plays differently across regions and scenarios. The way technology can be implemented is, however, another determining factor in these results. For example, total emission savings under the "CONV-C" scenario are more than tripled when switching from high input management to sustainable intensification (from -67 to -239 MtCO$_2$-eq). In contrast, under the "Free-Tech" pathway, the rebound effect appears even more important and agricultural emission savings are almost canceled out in "CONV-C" (-39 MtCO$_2$-eq) and decreased by 29% in "CONV". Overall, total savings vary from a ratio of 1 to 2 in the "CONV" scenario depending on the way technology is implemented. However, total abatement always remains below the 10% magnitude.
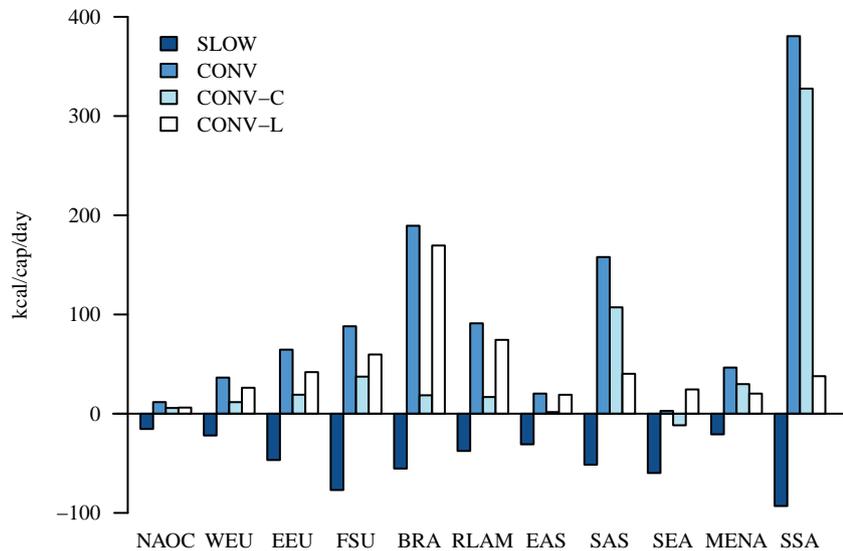
Figure 2.5. Change in domestic food demand (kcal/cap/day) in 2050 for the different yield scenarios and the "High-Input" pathway.

2.3.2   TRADE-OFFS AND SYNERGIES BETWEEN GHG MITIGATION AND FOOD AVAILABILITY

We now balance the environmental performance of yield scenarios and productivity pathways with their implications for food provision. The most direct effect of yield improvement is the increase in available calories, which reduces the price of crops and livestock for final consumers. We can therefore observe in Figure 2.5 that the response of food demand is in the same direction as productivity change, here in the case of the "High-Input" pathway. On average, the world consumption increase is higher by 144, 102, and 37 kcal per capita per day in the "CONV", "CONV-C" and "CONV-L" scenarios, respectively, and lower by 52 kcal/cap/day for the "SLOW" scenario. Patterns appear to differ across scenarios and regions. Demand is more elastic in less advanced regions and developing countries therefore tend to react much more than developed ones. Sub-Saharan Africa and South Asia benefit the most from closing the crop yield gap, as they are far from their potentials and have a larger share of vegetal calories in diet. On livestock side, Brazil and Rest of Latin America increase demand for ruminant meat and milk when feed efficiency is improved. This therefore leads to different diet composition across scenarios, livestock products representing 16.9% of world consumption in "CONV-C" versus 18.2% in "CONV-L" by 2050. We find similar results for the "Sust-Intens" pathway as we assume the same production costs in this scenario as for "High-Input". When comparing with "Free-Tech", the rebound effect is however much larger with increase in consumption by 287, 252, and 35 kcal/cap/day for the "CONV", "CONV-C" and "CONV-L" scenarios, respectively, and −145 kcal/cap/day for the "SLOW" scenario, compared with "TREND".

How do these changes compare with the environmental gains for developing regions? Interestingly,

the situations appear to contrast across scenarios and depend on the nature of productivity changes. Figure 2.6 presents an overview of the GHG emissions (x-axis) and consumption changes (y-axis) at the world level for the different scenarios and pathways. Most points are located in the quadrant B and C of the graph, illustrating the strong synergies between food supply and GHG savings. The "SLOW" scenario clearly appears negative for the two environmental and food dimensions, especially when land use emissions are accounted for (panel C). In contrast, the "CONV" scenario is beneficial for both dimensions, with greater effects for the environment under the "Sust-Intens" pathway, and better food supply performance under "Free-Tech". However, as illustrated previously, GHG emissions in agriculture tend to increase if crop yields alone are boosted through the "High-Input" pathways and total savings are in that case limited. When fertiliser effects are removed under "Sust-Intens", "CONV-C" gains are much larger (blue triangles). Under the "Free-Tech" scenario, however, the rebound effect cancels out 84% of the savings (blue squares), which illustrates well the trade-offs between mitigation and food provision through the price channel. These results contrast with the outcome from yield change in the livestock sector that allow large savings of GHG emissions with, however, limited benefit in terms of food availability. Overall, only the combination of the two productivity increases appears to be an efficient mix to obtain both food security and environmental benefits.

2.3.3 Sensitivity analysis

So far in our analysis, uncertainty has only been approached through confidence intervals on GHG emission factor values. However, some model settings or scenario assumptions also significantly influence the simulation outcomes. We summarise in Table 2.4 the results of sensitivity analyses on four parameters: yield trend for developed regions (1); fertiliser to yield elasticity (2-3); price elasticity of demand (4-6); carbon accounted for forest (7). The sensitivity analysis confirms that the most critical parameters are demand elasticities. In particular, removing all rebound effect leads to about a doubling of GHG emission savings. Fertiliser to yield elasticity is important for the outcome of intensification when considering agricultural emissions alone, but nitrous oxide emissions are always compensated by land use change CO_2 savings. Yield growth assumptions on developed countries play only secondary role for our findings.

2.4 Discussion and conclusions

The role of agricultural productivity as a potential source of mitigation has already been underlined by several studies (Tilman et al., 2011, Burney et al., 2010, Choi et al., 2011, Havlík et al., 2013). However, none of these used an integrated framework to concurrently analyze different sectors contributions and contrast the total mitigation effect related to crop, livestock, and land use change emissions together with the food provision impacts.

Table 2.4. Sensitivity analysis on difference between CONV and TREND scenarios for GHG emissions and consumption at world level by 2050. HI = "High-Input"; SI = "Sust-Intens"; FT = "Free-Tech"; LUC = Land use change.

No	Name	TREND		CONV − TREND							
		Agri 2050	LUC Avg/yr	Agri			Agri + LUC			Conso	
		HI	HI	HI	SI	FT	HI	SI	FT	HI SI	HI FT
0	Central scenario	4,508	1,895	−7	−182	−62	−456	−628	−325	144	287
1	Yield slow–down in developed countries 50% linear trend)	4,526	1,950	8	−169	−40	−411	−587	−310	137	285
2	Less fertilizer needs (elasticity fertilizer to yield: 0.5)	4,408	1,895	−53	−170	−52	−502	−616	−315	144	287
3	More fertilizer needs (elasticity fertilizer to yield: 1)	4,608	1,895	38	−195	−72	−410	−641	−334	144	287
4	More rebound effect (demand elasticities x 1.5)	4,443	1,743	40	−143	14	−307	−491	−86	183	407
5	Less rebound effect (demand elasticities x 0.5)	4,626	2,231	−75	−238	−157	−704	−869	−688	92	156
6	No rebound effect[a] (fully inelastic demand)	4,508	1,895	−441	−590	−541	−1,470	−1,617	−1,587	0	0
7	More land use emissions (dead biomass and soil organic carbon accounted)	4,508	3,402	−7	−182	−62	−854	−1,023	−543	144	287

[a] To ensure better comparability, this scenario is run on the same baseline as TREND.
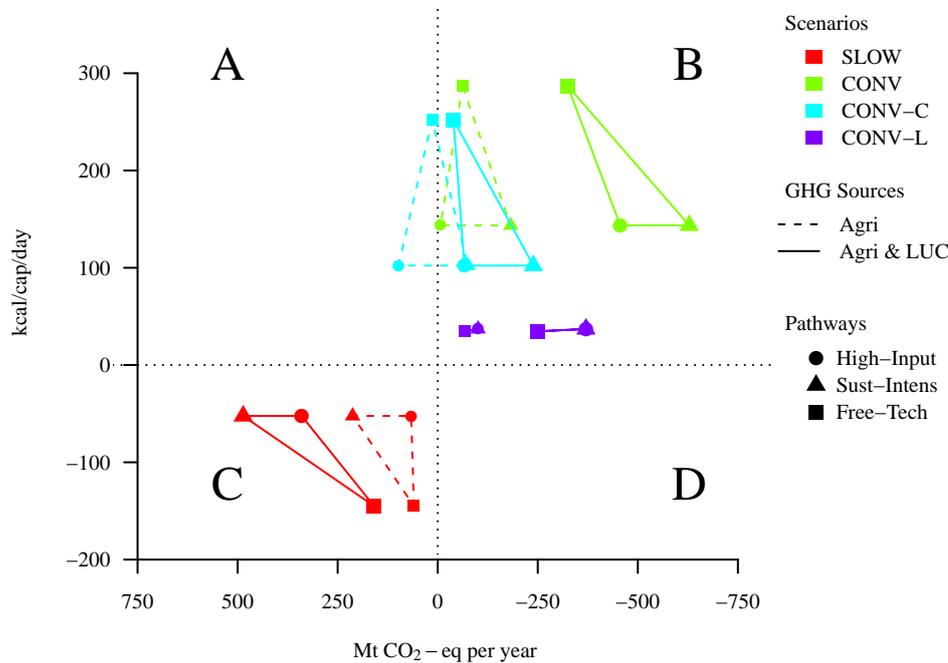
Figure 2.6. Difference in GHG emissions (x-axis) and food availability (y-axis) in 2050 for the different scenarios with respect to "TREND". Panels A, B, C and D delineate domains where food provision increases (A, B) or decreases (C, D) and GHG emission savings increase (B, D) or decrease (A, C). Colours correspond to the four scenarios, and the symbols at the corner of the triangle to the three productivity pathways. For the "CONV-L" scenario, the "Sust-Intens" and "High-Input" pathways are similar by construction. Plain lines indicate full agriculture and land use emission accounting, and dashed lines agricultural emissions only. Land use change annual emissions are calculated as an average over the simulation period.

Our results in particular allow three important aspects to be stressed. First, mitigation potentials from yield increase are very different for crops and for livestock. Many authors focus on crop cultivation impact alone (Tilman et al., 2011, Burney et al., 2010); however, livestock is recognised as the main emitter of GHGs and the sector with the largest impact on land use (Steinfeld et al., 2006, Bustamante et al., 2012). Omitting livestock from yield trends analysis can lead to a significant part of agricultural mitigation potential being overlooked. This mitigation would be even greater if the potential effect of lower crop prices on livestock system intensification and associated pasture sparing are taken into account (Havlík et al., 2013). However, the overall magnitude of the land use change savings still needs to be refined: some of our emissions are the result of complex dynamics, the extent of which could be influenced by proactive land policies, some of them already initiated in some regions (Nepstad et al., 2009). Nevertheless, our conclusions still stand if non-CO_2 gases alone are considered, as illustrated in Figure 2.6.

Second, we have illustrated the importance of the rebound effect using an economic equilibrium model. Although this effect is not well captured by pure biophysical analyses, it does have a critical importance. The results to this extent are dependent on the values of our price elasticities. Our

sensitivity analysis shows that with elasticities twice lower, the rebound effect would be smaller and the mitigation increased by 54% (Table 2.4, row 5). And without any rebound at all, mitigation of up to 1.5 $GtCO_2$ would have been reached (Table 2.4, row 6). Environmental implications of these rebound effects should be more systematically considered when associating food security virtues with productivity policies, as they are intrinsically linked to the increase of production for more food provision.

Last, we have shown that different productivity pathways would have different implications. In particular, the combined effect of rebound and fertiliser increase would not allow for GHG emission savings when crop yields alone are increased ("CONV-C" under "High-Input"). More importantly, the implications of productivity gains for producer prices are fundamental to anticipate the magnitude of the rebound and the environmental benefits. Pathways relying on TFP gains like "Free-Tech", by reducing producer costs, maximise production but limit environmental benefits. Literature indicates that TFP played a greater role in recent production development (Fuglie, 2010) and that this trend should continue (Ludena et al., 2007). Therefore, complementary measures may be needed on the consumer side to counter-balance this effect. For example, the efficiency of a diet shift to less meat has been demonstrated (Stehfest et al., 2009, Popp et al., 2010). More general combination of supply and demand side measures appear desirable but also faces some reality constraints, as change of consumer demand is subject to more inertia (Smith et al., 2013). The gains from investment towards agricultural productivity gains would allow more immediate GHG savings, but a combination of efforts in the crop and livestock sectors appears as the most efficient way to create synergies on both food supply and mitigation sides.

2.A COMPLEMENTARY TABLES AND FIGURES

Table 2.5. Demand elasticities applied for a selection of most important food products

	Wheat	Corn	Rice	Soya	Cassava	Bovine meat	Pig meat	Poultry meat	Diary
NAOC	-0.05	-0.05	-0.05	-0.05	-0.22	-0.26	-0.27	-0.26	-0.28
WEU	-0.05	-0.05	-0.05	-0.06	-0.23	-0.36	-0.36	-0.36	-0.37
EEU	-0.17	-0.17	-0.16	-0.21	-0.34	-0.47	-0.46	-0.46	-0.48
FSU	-0.22	-0.22	-0.22	-0.25	-0.36	-0.5	-0.5	-0.5	-0.52
BRA	-0.27	-0.27	-0.27	-0.29	-0.38	-0.51	-0.51	-0.51	-0.53
RLAM	-0.23	-0.19	-0.27	-0.25	-0.39	-0.5	-0.5	-0.5	-0.53
EAS	-0.36	-0.35	-0.36	-0.35	-0.43	-0.51	-0.55	-0.53	-0.49
SAS	-0.38	-0.38	-0.38	-0.4	-0.46	-0.57	-0.57	-0.57	-0.59
SEA	-0.32	-0.33	-0.33	-0.34	-0.41	-0.55	-0.55	-0.54	-0.56
MENA	-0.28	-0.28	-0.29	-0.3	-0.39	-0.52	-0.52	-0.52	-0.53
SSA	-0.39	-0.4	-0.41	-0.4	-0.49	-0.57	-0.58	-0.55	-0.59
WRLD	-0.27	-0.28	-0.35	-0.24	-0.45	-0.44	-0.47	-0.44	-0.46

Table 2.6. Food demand per capita for each region and for the world under the "High-Input" and "Sust-Int" pathways (kcal/cap/day).

	2000	2030	2050	2050			
		TREND		SLOW	CONV	CONV-C	CONV-L
NAOC	3,650	3,644	3,665	3,650	3,677	3,671	3,671
WEU	3,488	3,459	3,472	3,450	3,509	3,484	3,498
EEU	3,136	3,324	3,401	3,355	3,466	3,421	3,443
FSU	2,796	3,068	3,208	3,131	3,296	3,245	3,268
BRA	2,881	3,019	3,165	3,110	3,355	3,184	3,335
RLAM	2,752	3,011	3,179	3,141	3,270	3,195	3,253
EAS	2,898	3,230	3,361	3,330	3,381	3,363	3,380
SAS	2,324	2,617	2,800	2,748	2,958	2,907	2,840
SEA	2,402	2,690	2,898	2,838	2,902	2,886	2,922
MENA	3,134	3,201	3,270	3,249	3,317	3,300	3,291
SSA	2,177	2,501	2,742	2,649	3,123	3,070	2,780
WRLD	**2,731**	**2,921**	**3,045**	**2,993**	**3,189**	**3,147**	**3,082**

Table 2.7. Production, demand and trade for main product aggregates for scenarios "TREND", "SLOW" and "CONV" and for each pathway, in 2000 and 2050 (million tons).

| | 2000 | 2050 | | | | |
| | TREND | TREND | SLOW | | CONV | |
	HI	HI	HI/SI	FT	HI/SI	FT
Cereals						
Supply	1,998	3,436	3,385	3,268	3,536	3,703
Trade	148	362	437	711	340	325
Feed Demand	712	1,383	1,368	1,305	1,390	1,478
Final Demand	1,270	1,875	1,838	1,784	1,967	2,046
Oilseeds						
Supply	394	897	887	854	932	966
Trade	153	326	401	429	310	337
Feed Demand	155	304	299	281	308	332
Final Demand	237	549	543	528	579	589
Other crops						
Supply	1,918	4,979	4,909	4,642	5,016	5,360
Trade	148	246	247	409	215	328
Feed Demand	281	1,104	1,050	908	1,152	1,333
Final Demand	1,484	2,727	2,712	2,587	2,717	2,880
Ruminant meat						
Supply	70	107	98	98	130	132
Trade	3	10	11	11	7	7
Final Demand	70	107	98	98	130	132
Pig and poultry meat						
Supply	215	454	450	430	459	484
Trade	7	10	11	14	10	9
Final Demand	215	454	450	430	459	484
Milk						
Supply	585	943	910	907	1,055	1,049
Trade	24	184	177	176	168	174
Final Demand	585	943	910	907	1,055	1,049

Table 2.8. Price index for crops and livestock products by regions and scenario in 2050. Index 2000 = 1.

	TREND	SLOW		CONV		CONV-C		CONV-L	
	HI	HI/SI	FT	HI/SI	FT	HI/SI	FT	HI/SI	FT
Crops									
BRA	0.98	1.02	1.18	0.97	0.85	0.97	0.85	0.98	0.98
EAS	0.98	1.00	1.19	0.98	0.93	0.98	0.93	0.98	0.98
EEU	0.96	1.00	1.18	0.94	0.89	0.94	0.89	0.96	0.96
FSU	0.97	1.02	1.17	0.93	0.72	0.94	0.72	0.97	0.97
MENA	1.00	1.02	1.15	0.97	0.87	0.97	0.88	1.00	1.00
NAOC	0.99	1.03	1.19	0.98	0.94	0.98	0.94	0.99	0.99
RLAM	1.01	1.03	1.18	1.00	0.79	1.00	0.79	1.01	1.01
SAS	1.08	1.13	1.29	1.03	0.89	1.04	0.89	1.07	1.08
SEA	1.03	1.07	1.28	1.03	0.90	1.03	0.9	1.03	1.03
SSA	1.08	1.15	1.25	0.95	0.74	0.96	0.74	1.07	1.08
WEU	0.96	1.02	1.18	0.93	0.87	0.93	0.87	0.96	0.96
WRLD	**1.02**	**1.06**	**1.21**	**0.98**	**0.85**	**0.98**	**0.85**	**1.01**	**1.02**
Livestock									
BRA	1.44	1.64	1.74	0.84	0.79	1.4	1.31	0.87	0.88
EAS	1.04	1.14	1.22	0.97	0.94	1.03	1.00	0.98	0.98
EEU	1.05	1.14	1.2	0.93	0.91	1.02	0.99	0.95	0.97
FSU	1.12	1.22	1.26	1.00	0.93	1.10	1.00	1.03	1.03
MENA	1.71	1.82	1.84	1.53	1.51	1.71	1.69	1.56	1.53
NAOC	1.08	1.14	1.23	1.02	1.00	1.06	1.04	1.04	1.03
RLAM	1.15	1.25	1.3	0.93	0.88	1.11	1.05	0.96	0.96
SAS	1.81	1.93	1.99	1.43	1.34	1.77	1.7	1.46	1.45
SEA	1.11	1.27	1.4	0.93	0.8	1.09	0.94	0.95	0.94
SSA	1.61	1.77	1.85	1.16	0.99	1.53	1.36	1.20	1.19
WEU	1.39	1.48	1.54	1.22	1.18	1.36	1.32	1.25	1.24
WRLD	**1.27**	**1.37**	**1.44**	**1.09**	**1.04**	**1.24**	**1.18**	**1.12**	**1.11**

Table 2.9. Land use change at world level on the periods **2000-2030** and **2000-2050** for the different scenarios and pathways (Mha). "Diff" is the calculation of the difference to the reference scenario (TREND HI). HI = High-Input; SI = Sust-Intens; FT = Free-Tech.

		2000-2030					2000-2050				
		CrpLnd	GrsLnd	Forest	NatLnd	PltFor	CrpLnd	GrsLnd	Forest	NatLnd	PltFor
TREND	HI	126	61	-131	-116	61	204	150	-216	-283	145
CONV	HI/SI	59	-36	-91	8	61	118	16	-164	-114	145
	diff	*-66*	*-97*	*40*	*124*	*0*	*-87*	*-133*	*51*	*169*	*0*
	FT	83	44	-116	-72	62	133	110	-193	-196	146
	diff	*-43*	*-17*	*14*	*44*	*1*	*-72*	*-39*	*23*	*87*	*1*
CONV-C	HI/SI	56	77	-116	-77	61	108	172	-200	-225	145
	diff	*-69*	*16*	*14*	*39*	*0*	*-96*	*22*	*16*	*58*	*0*
	FT	83	88	-128	-105	62	130	185	-214	-247	146
	diff	*-43*	*27*	*3*	*11*	*1*	*-74*	*35*	*2*	*36*	*1*
CONV-L	HI/SI	130	-47	-109	-34	61	212	3	-179	-181	145
	diff	*4*	*-108*	*22*	*82*	*0*	*8*	*-146*	*36*	*102*	*0*
	FT	127	24	-121	-91	61	208	83	-197	-238	145
	diff	*2*	*-36*	*9*	*25*	*0*	*4*	*-67*	*18*	*45*	*0*
SLOW	HI/SI	175	93	-151	-176	60	267	172	-243	-341	144
	diff	*49*	*32*	*-20*	*-60*	*-1*	*63*	*23*	*-27*	*-58*	*0*
	FT	153	61	-139	-134	60	231	148	-228	-296	145
	diff	*27*	*0*	*-8*	*-18*	*0*	*27*	*-2*	*-12*	*-13*	*1*
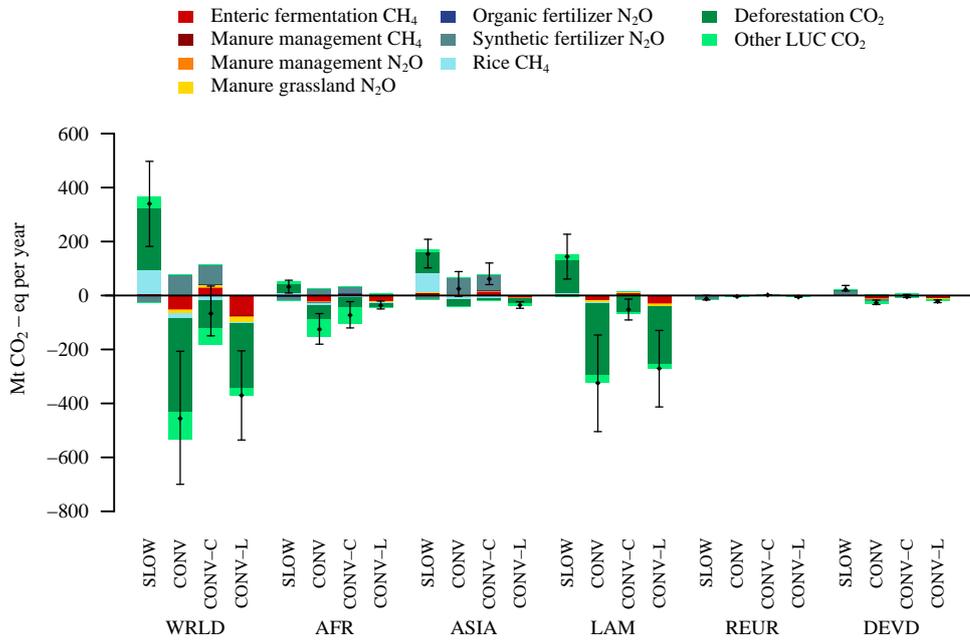
Figure 2.7. Difference in emissions per region for scenario "CONV" and High-Input pathway.
Same conventions as in Figure 2.4.
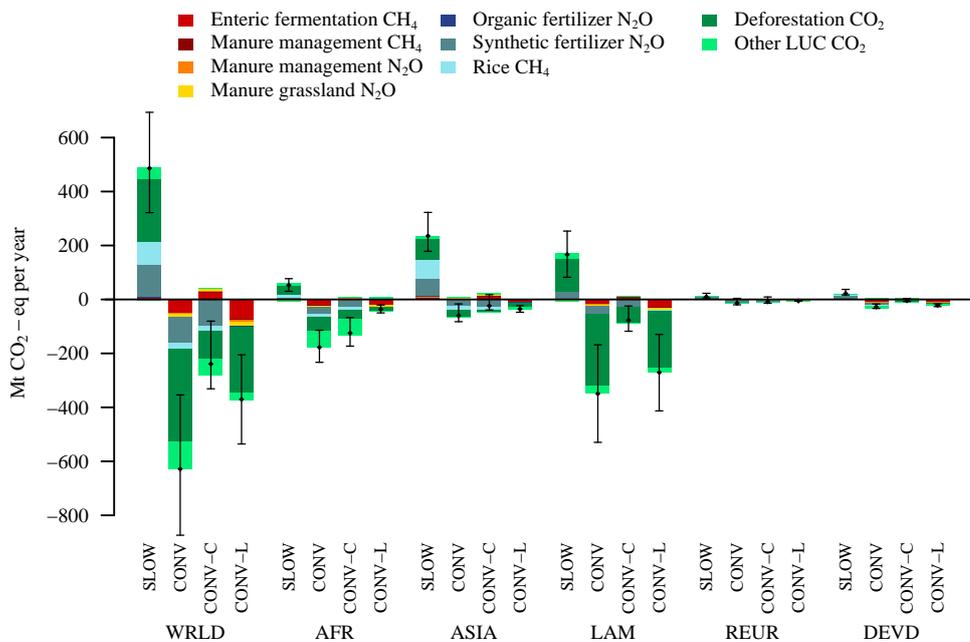
Figure 2.8. Difference in emissions per region for scenario "CONV" and Sust-Int pathway.
Same conventions as in Figure 2.4.
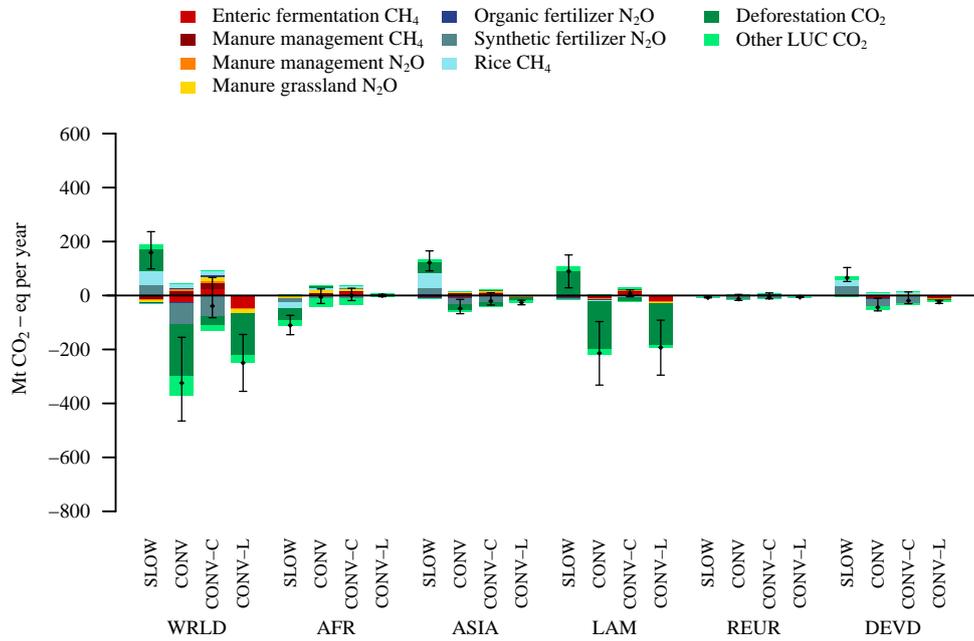
Figure 2.9. Difference in emissions per region for scenario "CONV" and Free-Tech pathway. Same conventions as in Figure 2.4.
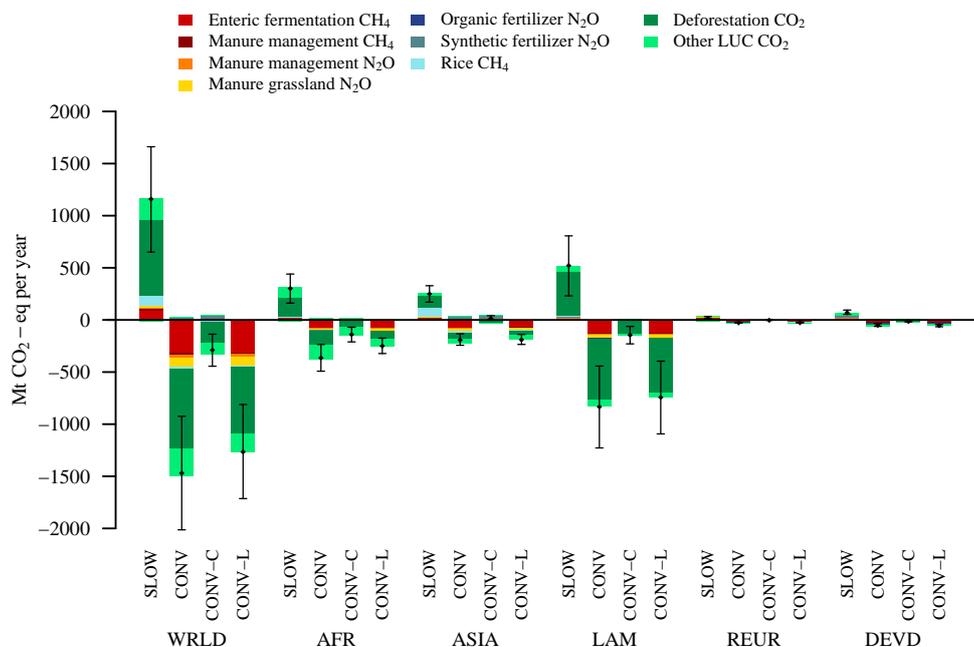
Figure 2.10. Difference in emissions per region for scenario of fixed demand (no rebound effect) with the Conventional pathway. Same conventions as in Figure 2.4.

CHAPTER 3

POTENTIAL ENVIRONMENTAL IMPACTS OF A TRADE AGREEMENT: THE CASE OF EU-MERCOSUR

TRADE policies have been extensively scrutinised with respect to their welfare implications as well as their effect on employment and their potential to reduce poverty in developing countries facing tariff barriers (Bouët et al., 2005). However, sustainable development cannot be achieved if economic and social developments are not accompanied by environmental stewardship (Rockstrom et al., 2009). The trade and environment debate has long been a sensitive issue in the regulation agenda discussed at the World Trade Organization (WTO). On the one hand, environment has risen on the agenda of international negotiations and expansion of certain export sectors has attracted attention from some trade partners because of their environmental consequences on natural resources or other negative externalities associated with their production processes.[1] On the other hand, there has been much concern to ensure environmental domestic measures are not used as protection against international trade (WTO, 2004).

As one of the most pressing issues on the current environmental agenda is climate change, this problem becomes more acute. Indeed, there is much evidence that the current patterns of trade are not optimal from a greenhouse gas (GHG) emission perspective. Some exporters of industrial goods use GHG intensive production processes that undermine the efforts of their trade partners to limit their domestic emissions (Davis and Caldeira, 2010, Davis et al., 2011b). Trade in agriculture is also a significant source of additional GHG emissions. Verburg et al. (2009) show that a full liberalisation of agriculture (end of agricultural support and trade barriers) would induce significant GHG emissions in the first years following its implementation. Similar concerns are found in the literature on biofuel policies and their impact on land use change. Increase in trade of agricultural

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[1] Many cases have been brought to the Dispute Settlement Body of the WTO, most often with the purpose of protecting endangered species (salmon in 1988, dolphins in 1991, sea turtles in 1998). When countries could demonstrate that their complaint was falling under the General Exceptions of article XX of the GATT (necessary for protection of human, animal or plant life or health, XX(b); or related to conservation of natural exhaustible resources, XX(g)) and was not constituting "a mean of arbitrary or unjustifiable discrimination between countries" or "disguised restriction on international trade" (chapeau of article XX, GATT, 1947), the WTO ruling was favorable to environmental measures.

products to supply biofuel feedstocks are found to drive additional GHG emissions and jeopardise the environmental benefits from biofuels (see Chapter 4 and 5). Proposed remedies consist of deploying border tax adjustments that would complement domestic taxations on GHG emissions and avoid leakages. Such measures are in debate in the literature (McKibbin and Wilcoxen, 2009, Lockwood and Whalley, 2010, Burniaux et al., 2013) but could be considered as compatible with WTO rules (WTO, 2009).[2] At the same time, such ex-post "correction" measures should not divert from more preventive action. Surprisingly, ex-ante assessments of trade policies impact on greenhouse gas emissions are rarely conducted, for example when new trade agreements are under negotiation. The European Union usually investigates adverse effects of its trade agreements with specific Sustainable Impact Assessments (SIAs) but these rely on a qualitative analysis than on a comprehensive quantification of greenhouse gases emissions associated with the policy, especially for land use change emissions (Kirkpatrick and George, 2009).

In this chapter, we provide an illustration of the interaction of trade and the environment by focusing on a possible trade agreement between Mercado Común del Sur (MERCOSUR) and the European Union (EU). We take a climate change perspective and investigate in particular the potential consequences of such an agreement on GHG emissions from the agricultural and industrial sectors but also from land use changes. Such an agreement would indeed give further boost to agricultural development in Latin America with a high risk of increasing non-CO_2 emissions and expanding agricultural land into forest or other carbon-rich natural land. Countries such as Brazil have already experienced dramatic losses of the Amazon forest due to cropland and pasture expansion. Our work aims to confront the potential economic benefits from this trade agreement with the associated changes in greenhouse gas emissions. To our knowledge, this is the first assessment of a bilateral trade agreement to investigate GHG emissions impact while also considering land use change effects.

For our analysis, we use a combination of two economic models. First, the MIRAGE computable general equilibrium (CGE) model, developed at CEPII, is used to represent the implications from the potential agreement on trade flows and economic welfare. Second, we look at the land reallocation patterns using a detailed bottom-up partial equilibrium model, GLOBIOM. The detailed description of the supply side at grid-cell level in this second model allows for a precise representation of non-CO_2 emissions from agriculture and a fine accounting of land use changes and associated carbon flows. We distinguish different intensification assumptions associated with the trade agreement and compare costs of emissions with expected economic benefits for the two blocks of countries.

The chapter is organised as follows: in Section 3.1, we provide a conceptual overview of the economic and environmental trade-off of a trade agreement. We then describe in Section 3.2 the

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[2]   In the introduction of the UNEP and WTO report of 2009 on this topic, the two directors of these institution declare that "there is considerable scope and flexibility under WTO rules for addressing climate change at the national level, and that mitigation measures should be designed and implemented in a manner that ensures that trade and climate policies are mutually supportive" (WTO, 2009, p. v). But environmental measures taken to mitigate GHGs have never been so far screened by an official WTO panel.

main aspects of the EU-MERCOSUR negotiation and its expected economic and environmental impacts. We introduce in Section 3.3 the modeling framework, the data and the two models used for the analysis. The scenarios and their results are discussed in Section 3.4 as well as their implications for trade policies. Section 3.5 concludes.

3.1 Environmental impact of a trade agreement

3.1.1 Welfare gains from a trade agreement with environmental externality

We focus our environmental analysis of a trade agreement on greenhouse gas emissions, as one of the most easily quantifiable sources of environmental damage and a major axis of environmental and energy policy in the European Union.

Let's take two regions A and B, trading together in state S_0 but maintaining trade protections (tariff barriers or non-tariff measures). A and B commit to liberalise their bilateral trade, in initial state S_1. We note $W_{A,0}$ and $W_{B,0}$ their respective economic welfare before trade liberalisation and $W_{A,1}$ and $W_{B,1}$ once the new equilibrium is reached. Standard trade models show that, under a certain set of conditions (perfect competition, perfect mobility of factors, homogenous good and sectors, etc.), trade liberalisation leads to a global increase in welfare:

$$W_{A,0} + W_{B,0} \leq W_{A,1} + W_{B,1} \tag{3.1}$$

However, this does not take into account the environmental externality from GHG damage. Climate change impact is not expected to be observed at its full magnitude within the time when state S_1 is reached. How to value the anticipated damage from climate change under uncertainty is debated in the literature (Stern, 2007, Nordhaus, 2007, Weitzman, 2007). However, because emitted carbon dioxide remains in the atmosphere, the social cost of carbon emitted today is usually found significant. For instance, Anthoff et al. (2009) estimate the most plausible range for current emissions costs spreads from US\$ 60 to 200 per ton carbon. Nordhaus (2011) proposes a value closer to US\$ 40. In its report on the value of carbon from 2009, the French Center for Strategic Analysis proposes as a central value a much higher assumption of € 100 per tonne CO_2 by 2030, i.e. 367 € per tonne carbon to reflect the objectives of the EU carbon policy (Centre d'Analyse Stratégique, 2009).[3] We will then for this paper work with an assumption of a range of US\$ 40–400 per tonne carbon, keeping in mind that these estimates are disputed, with among the most controversial parameters the value of the actualisation rate.

Let's note c the cost of carbon, E the level of annual emissions from economic activities. The social welfare U (economic and environmental) associated with regions A and B needs to be adjusted

---

[3]   Conversion from tonne CO_2 to tonne C is obtained by multiplying by a ratio 44/12.

by an overall term $c\,(E_A + E_B)$ (damage is global). The final change in utility arising from the trade agreement is therefore:

$$\Delta U = U_1 - U_0 = \Delta W_A + \Delta W_B - c\,(\Delta E_A + \Delta E_B). \tag{3.2}$$

However, the previous formula only describes carbon flows tied to economic activity levels, mainly associated with combustion of fossil fuels. Due to the presence of carbon stocks in biomass and soil, this static approach needs to be complemented by a dynamic term, because levels in carbon stock F can vary as a consequence of activity level changes. Let's consider that the trade policy is implemented at time $t = 0$ and the new equilibrium in carbon stock is reached after a time T. We now obtain the more complete description below:

$$\int_0^T U(t)\,\mathrm{d}t = \int_0^T \left(W_A(t) + W_B(t)\right)\,\mathrm{d}t - c\int_0^T \left(E_A(t) + E_B(t)\right)\,\mathrm{d}t - c\int_0^T \frac{\mathrm{d}F}{\mathrm{d}t}\,\mathrm{d}t. \tag{3.3}$$

For sake of simplification, we consider that economic adjustments are quick, i.e. $W_A(t)$ and $W_B(t)$, as well as $E_A(t)$ and $E_B(t)$, reach their equilibrium value of state S_1 for $t > 0$. The relation then simplifies as:

$$T\Delta U = T\,(\Delta W_A + \Delta W_B) - c\,T\,(\Delta E_A + \Delta E_B) - c\,\Delta F, \tag{3.4}$$

$$\text{i.e. } \Delta U = \Delta W_A + \Delta W_B - c\,(\Delta E_A + \Delta E_B) - \frac{c\,\Delta F}{T}. \tag{3.5}$$

As the latter formula shows, the presence of negative terms from carbon cost externality can potentially alter the social utility of the trade agreements if GHG emissions increase. Two important parameters independent from the level of emissions strongly influence the final outcome: the cost of carbon c and the length of the timeframe T considered for the evaluation of welfare gains.[4]

3.1.2 Emission changes from economic activities

The contribution of economic activities to greenhouse gases emissions can first be related to changes in activity levels and their associated emission flows. Following Grossman and Krueger (1991), we can decompose the change in GHG emission levels by different effects: i) scale effect uniquely related to total level of activity, ii) composition effect depending on what activity is favoured by the trade agreement in each region, each activity having different level of GHG emission intensity; iii) technological effect that can affect the emission level of each activity, in response to investment in production efficiency.

For the different activities $i \in I$ in region A, the total level of emissions is written as:

---

[4]   The critical role of the amortisation period will also be commented on in Chapter 5 in the case of biofuels.

$$E_A = \sum_{i \in I} e_{A,i} Y_{A,i} = \sum_{i \in I} e_{A,i} Y_A \, s_{A,i}, \tag{3.6}$$

where $s_{A,i}$ is the production share of activity i within region A ($\sum_{i \in I} s_{A,i} = 1$).

This leads to:

$$
\begin{aligned}
\Delta E_A &= E_{A,1} - E_{A,0} \\
&= \sum_{i \in I} \left[(e_{A,i,1} - e_{A,i,0}) \left(\frac{Y_{A,i,1} + Y_{A,i,0}}{2} \right) + (Y_{A,i,1} - Y_{A,i,0}) \left(\frac{e_{A,i,1} + e_{A,i,0}}{2} \right) \right] \\
&= \sum_{i \in I} \left[\Delta e_{A,i} \, \overline{Y_{A,i}} + \overline{e_{A,i}} \, \Delta Y_{A,i} \right] \\
&= \sum_{i \in I} \left[\Delta e_{A,i} \, \overline{Y_{A,i}} + \overline{e_{A,i}} \, \overline{s_{A,i}} \, \Delta Y_A + \overline{e_{A,i}} \, \Delta s_{A,i} \, \overline{Y_A} \right],
\end{aligned} \tag{3.7}
$$

where $\overline{Y_{A,i}}$ and $\overline{e_{A,i}}$ are average of the variables $Y_{A,i}$ and $e_{A,i}$, respectively, between S_0 and S_1.

By introducing $e_A = \left(\sum_{i \in I} e_{A,i} \, \overline{Y_{A,i}} \right) / \overline{Y_A} = \sum_{i \in I} e_{A,i} \, \overline{s_{A,i}}$, one obtains:

$$\Delta E_A = \Delta e_A \, \overline{Y_A} + \Delta Y_A \underbrace{\left(\sum_{i \in I} \overline{e_{A,i}} \, \overline{s_{A,i}} \right)}_{\overline{e_A}} + \overline{Y_A} \left(\sum_{i \in I} \overline{e_{A,i}} \, \Delta s_{A,i} \right). \tag{3.8}$$

The first term $\Delta e_A \, \overline{Y_A}$ represents the technological effect on emissions, the second term $\overline{e_A} \Delta Y_A$ is the scale factor and the third term $\overline{Y_A} \left(\sum_{i \in I} \overline{e_{A,i}} \, \Delta s_{A,i} \right)$ is the composition effect of emission intensities across sectors.

This formula can be expanded to region B and others in the rest of the world. For a full set of regions $r \in R$, one finally finds:

$$\Delta E = \sum_{r \in R} \left[\Delta e_r \, \overline{Y_r} + \Delta Y_r \left(\sum_{i \in I} \overline{e_{r,i}} \, \overline{s_{r,i}} \right) + \overline{Y_r} \left(\sum_{i \in I} \overline{e_{r,i}} \, \Delta s_{r,i} \right) \right]. \tag{3.9}$$

We now pose $e = \left(\sum_{r \in R} e_r \, \overline{Y_r} \right) / \overline{Y} = \left(\sum_{r \in R} \sum_{i \in I} e_{r,i} \, \overline{Y_{r,i}} \right) / \overline{Y}$, and $s_r = Y_r / Y$.

The previous formula can be rewritten:

$$\Delta E = \Delta e \, \overline{Y} + \sum_{r \in R} \left[\Delta(Y \, s_r) \sum_{i \in I} \overline{e_{r,i}} \, \overline{s_{r,i}} + \overline{Y_r} \sum_{i \in I} \overline{e_{r,i}} \, \Delta s_{r,i} \right]. \tag{3.10}$$

And finally,

$$
\begin{aligned}
\Delta E = \Delta e\, \overline{Y} & & \text{(technological change effect)} \\
+ \Delta Y \sum_{r \in R} \sum_{i \in I} \overline{e_{r,i}}\, \overline{s_r}\, \overline{s_{r,i}} & & \text{(scale effect)} \\
+ \sum_{r \in R} \Delta s_r \left[\overline{Y} \sum_{i \in I} \overline{e_{r,i}}\, \overline{s_{r,i}} \right] & & \text{(regional composition effect)} \\
+ \sum_{r \in R} \sum_{i \in I} \overline{Y_r}\, \overline{e_{r,i}}\, \Delta s_{r,i} & & \text{(sector composition effect).} \quad (3.11)
\end{aligned}
$$

One can recognise the first term of technological change and the second term of expansion. The composition term is now decomposed into two components: the first one for composition across regions, and the second one for composition across sectors within each region.

3.1.3 EMISSIONS FROM CHANGE IN CARBON STOCK

Changes in the level of agricultural production can also drive changes in carbon stock, generating additional GHG flows, as is the case of land use change associated with agricultural expansion. Let's note $f(u,t)$ the stock of carbon in an elementary geographical unit u in the world space W, at a time t, such that the stock F of region r can be written:

$$
F(t) = \int_u f(u,t)\, \mathrm{d}u = \sum_{r \in R} \int_{u \in r} f(u,t)\, \mathrm{d}l. \tag{3.12}
$$

We can then express the total carbon stock difference between S_0 at time $t = 0$ and S_1 at time $t = T$:

$$
\Delta F = \sum_{r \in R} \int_{u \in r} \underbrace{[f(u,T) - f(u,0)]}_{\Delta f(u)}\, \mathrm{d}u. \tag{3.13}
$$

$\Delta f(u) = f(u,T) - f(u,0)$ corresponds to the difference in carbon stock difference in location l due to the shock. It can be negative if agricultural land expands in l and forest or natural vegetation are converted to cropland; or positive if abandoned agricultural land returns to natural vegetation (natural land reversion).

Let's consider $L(u)$ the area of agricultural land in location l. We note $f_a(u)$ the carbon stock of agricultural land, $f_n(u)$ the average carbon stock of natural vegetation and $f_r(u,T)$ the carbon stock of agricultural land after reversion after a period T ($f_r(u,T) \leq f_n(u), \forall l \in W$). We can write:

$$
\Delta F = \int_{u, \Delta L(u) > 0} \underbrace{(f_a(u) - f_n(u))}_{<0}\, \Delta L(u)\, \mathrm{d}u + \int_{u, \Delta L(u) < 0} \underbrace{(f_r(u) - f_a(u,T))}_{>0} (-\Delta L(u))\, \mathrm{d}u. \tag{3.14}
$$

To simplify this expression, we can define:

$$f_c(u) = \begin{cases} f_a(u) - f_n(u) & \text{if } \Delta L(u) > 0, \\ f_r(u) - f_a(u, T) & \text{if } \Delta L(u) < 0. \end{cases} \tag{3.15}$$

Let's now express regional emission factors. We pose $L_r = \int_{u \in r} L(u) \, du$ and we can write for the average land use emission factor from state S_0 to state S_1:

$$F_{r,0 \to 1} = \frac{1}{\Delta L_r} \int_{u \in r} f_c(u) \Delta L(u) \, du, \tag{3.16}$$

The value of $F_{r,0 \to 1}$ is dependent on the nature of the shock between S_0 and S_1 because it can be strongly influenced by the distribution of $\Delta L(u)$ across locations (composition effect). To simplify our approach, we will then assume expansion patterns to be independent from the shock and linear, i.e. there exists a fixed $\theta_r(u)$ distribution such that $\Delta L(u) = \theta_r(u)\Delta L_r$, $\forall S_1$ and with $\int_{u \in r} \theta_r(u) \, du = 1$. With this assumption, we can define an average land use expansion emission factor from formula 3.16:

$$\widetilde{F_r} = \int_{u \in r} f_c(u)\theta_r(u) \, du, \tag{3.17}$$

Using these notations, we can now decompose the land use change emissions. These emissions can be related to activity levels $Y_{r,i}$. We can decompose for each region r: $L_r = \sum_{i \in I} Y_{r,i} a_{r,i} = \lambda_r L$, with $a_{r,i}$ the land requirement of activity i and L the world total agricultural land. The general expression of carbon stock change can be rewritten:

$$\begin{aligned} \Delta F &= \int_{u \in W} f_c(u)\Delta L(u) \, du \\ &= \sum_{r \in R} \widetilde{F_r} \Delta(\lambda_r L) \\ &= \sum_{r \in R} \widetilde{F_r} \left(\overline{\lambda_r} \, \Delta L + \Delta \lambda_r \, \overline{L} \right) \\ &= \underbrace{\left[\sum_{r \in R} \tilde{F}_r \, \overline{\lambda_r} \right]}_{\tilde{F}} \sum_{r \in R} \sum_{i \in I} \Delta \left(a_{r,i} Y_{r,I} \right) + \overline{L} \sum_{r \in R} \widetilde{F_r} \, \Delta \lambda_r. \end{aligned} \tag{3.18}$$

The last term of this formula can be restructured using the property of λ_r.[5]

$$\Delta F = \widetilde{F} \sum_{r \in R} \sum_{i \in I} \Delta Y_{r,i}\, \overline{a_{r,i}} \qquad\qquad \text{(scale effect)}$$

$$+ \widetilde{F} \sum_{r \in R} \sum_{i \in I} \overline{Y_{r,i}}\, \Delta a_{r,i} \qquad\qquad \text{(technological change effect)}$$

$$+ \overline{L} \sum_{(r,r') \in R^2} (\widetilde{F_r} - \widetilde{F_{r'}}) \frac{\Delta \lambda_r}{\dim(R)} \qquad\qquad \text{(reallocation effect)}, \qquad (3.19)$$

with $\dim(R)$ for the number of regions r.

This expression of ΔF shows that the carbon stock depends of how much land is used (production and technological scale effects) but also where the production takes place. If a region A has high carbon stocks (tropical forests) whereas another region B cannot sequester much carbon (temperate afforestation), then $(\widetilde{F_A} - \widetilde{F_B})$ is negative and relocating production from B to region A decreases carbon stocks globally and increases GHG emissions.

The environmental externalities associated with a trade agreement therefore can potentially affect the final outcome, when compared with a welfare change estimation based on market internalities only. We are now going to evaluate the magnitude of these effects on a specific bilateral trade relation, between the European Union and the MERCOSUR region.

3.2   The EU-MERCOSUR trade agreement as an application framework

The EU-MERCOSUR negotiation provides an interesting example of two regions where the previous framework can be applied. These two regions have a high potential for reallocation of activities, due well characterised comparative advantages, and MERCOSUR faces environmental challenges, in particular from a land use change perspective due to emissions from deforestation.

3.2.1   Trade patterns between MERCOSUR and the European Union

Negotiations for an EU-MERCOSUR bilateral trade agreement started in the 2000s but have still not led to an agreement. Trade flows between the EU and the five member states of MERCOSUR – Argentina, Brazil, Paraguay, Uruguay and Venezuela – remain relatively limited today.[6] In 2011, the bilateral trade flow accounted for € 52 billion from MERCOSUR to Europe and € 46 billion

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[5]   Here we use the fact that $\sum_{i=1}^{N} x_i = 0 \Rightarrow \sum_{i=1}^{N} \sum_{j=1}^{N} (a_i - a_j) \frac{x_i}{N} = \sum_{i=1}^{N} a_i x_i$.

[6]   This does not mean that no market preferences are currently granted to MERCOSUR countries. Its Member States had been eligible for the European Generalised Scheme of Preferences (GSP) for several decades until its reform in 2012. This improved market access also existed before MERCOSUR creation in 1991. However, some sectors were excluded from preferential access under the mechanism of graduation (see Estevadeordal and Krivonos, 2000, for some examples).

from Europe to MERCOSUR, which represents 3% of the EU trade and 20% of all MERCOSUR exports and imports.

The composition of trade between the two regions is significantly contrasted, reflecting current comparative advantages and natural endowments. Exports from MERCOSUR to Europe are based mainly on primary products – agricultural and raw materials (48.3% in 2011) and minerals (25.2%). In 2011, these represented only 3% of all merchandise imported by the EU. However, for food products, MERCOSUR represented around 20% of EU imports. Reversely, the EU exports to MERCOSUR mainly chemical (19.3%) and manufactured products such as machinery (33%) and vehicles (16.1%), part of products in which the EU has a comparative advantage, with some export surplus.

MERCOSUR exports to the EU have boomed in the agri-food sector over the last decade, in value terms, but flows of material have remained quite stable in quantity (Figure 3.1). Indeed, exports have benefited from the increase in commodity prices but also from a composition effect with higher value products. Although soybean meal accounts for half of these exports, expansion of trade in coffee, bovine and poultry meat, orange juice, tobacco or vegetable oil and sugar has increased the value of trade. Even within a single sector like beef, the quality content of trade flows has increased (Ramos et al., 2010). This is an effect of high tariffs and tariff rate quotas (TRQs) that limit imports of low value product.

Therefore, trade negotiations between the EU and MERCOSUR have focused a lot, on the MERCOSUR side, on requesting improved market access for agricultural goods, in particular from Brazil and Argentina, and the European Union thus asked in return for a decrease in protection on manufactured goods. Studies assessing such symmetric liberalisation scenarios usually find an increase in welfare for the two regions (for instance, around +0.25% in Bchir et al., 2003). However, the role of agriculture and land use makes this bilateral relationship interesting from a GHG emissions point of view.

3.2.2 Protection structure

The level of protection of the European Union can be measured using ad-valorem equivalent (AVE) tariffs and TRQs applied to different categories of products. Table 3.1 displays AVE tariffs faced by the five MERCOSUR countries for their exports to the EU, using reference group trade-weighted method.[7] Protection faced in the agriculture and food sector accounts for around 30% of the export unit value. This is much higher than the average level of tariffs for other primary sectors or industry (around 4–7%).

The most protected products are livestock products and sugar, all controlled through TRQs. Precise information at the Harmonized System 6 digits (HS6) line level is represented in appendix

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[7] The reference group trade weighting approach consists in aggregating tariffs with trade flows to all regions of the same development level as the importer. This method allows for correcting some endogeneity bias in the import-weighted approach. Indeed, in this latter approach, a higher tariff generates a low trade flow and therefore a lower weight. See Bouët et al. (2008) for more details.

Agricultural exports (Bn US$)

Agricultural exports (Mln tons)
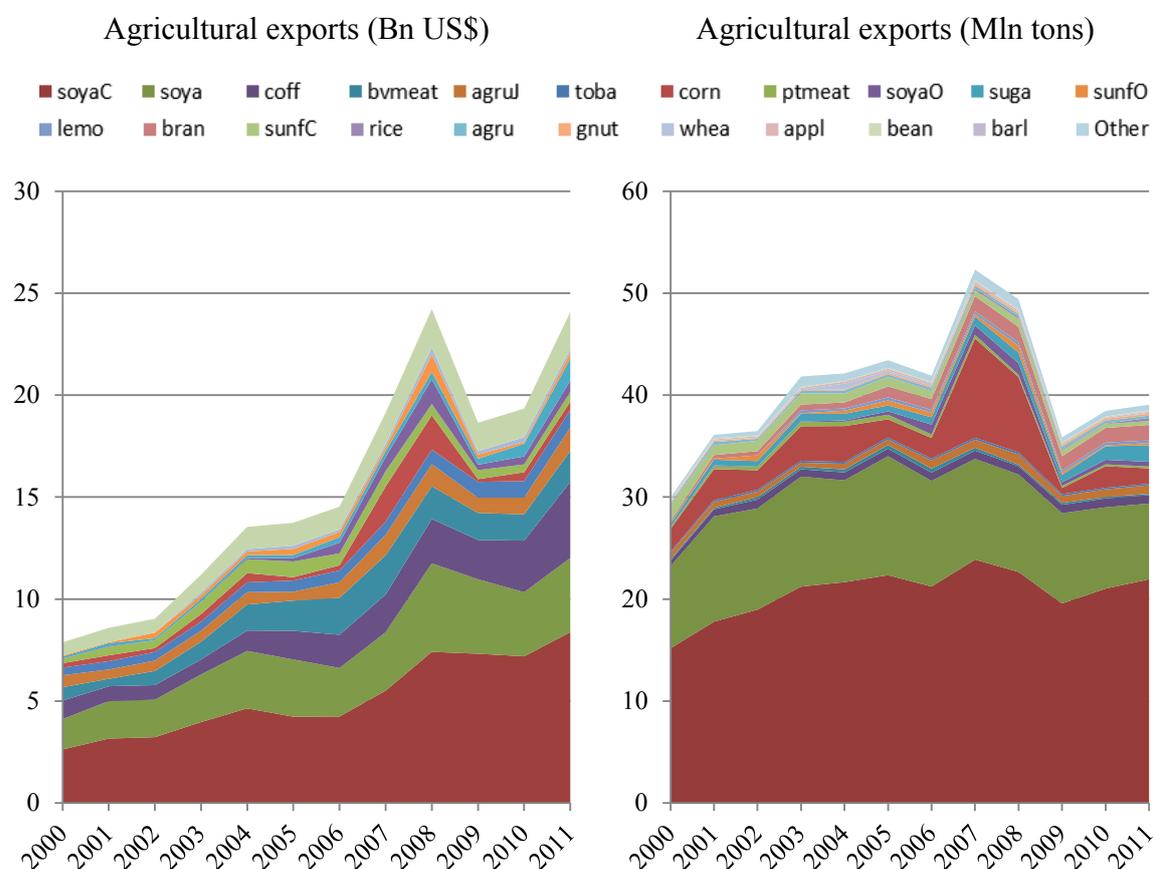
Figure 3.1. Export of primary and processed agricultural products from MERCOSUR to the European Union from 2000 to 2011. Product acronyms are: soyaC = soya cake; soya = soyabeans; coff = coffee; bvmeat = bovine meat; agruJ = agrume juice; toba = tobacco; corn = maize; ptmeat = poultry meat; soyaO = soya oil; suga = sugar; sunfO = sunflower oil; lemo = lemon; bran = bran; sunfC = sunflower cake; rice = rice; agru = agrumes; gnut = groudnuts; whea = wheat; appl = apple; bean = beans; barl = barley; other = all other agricultural commodities. Source: BACI.

Table 3.12 at the end of this chapter. Trade restrictive measures are absent on soybean cake and soybean seeds. However, beef meat, orange juice, poultry meat, or sugar are all targeted by differentiated levels of quotas. A certain quantity of products is allowed to access the EU market at a preferential tariff (in-quota tariff). Once the quota is filled, subsequent imports are taxed at a higher tariff rate (out-of-quota), limiting the competitiveness of these additional imports. Negotiations therefore aim to obtain lower tariff rates (in-quota and out-of-quota) but also larger quota allocations.

Overall, MERCOSUR countries face a protection of 17.5% on EU agricultural markets but only 1.1% on industrial markets. In contrast, the EU faces the situation with a lower 13.6% on agricultural exports to MERCOSUR but also 12.2% on industrial exports. Products the most protected in MERCOSUR countries are in transport equipements, metal and textile; but tariff rates remain moderate relatively to the EU agricultural AVEs, with most lines below 25% (Bchir et al., 2003).

Table 3.1. Ad valorem equivalent tariff applied to agricultural and other imports from MERCOSUR countries to the European Union in 2007.

	Argentina	Brazil	Paraguay	Uruguay	Venezuela
Wheat	10.2%	10.3%	7.9%	10.2%	na
Coarse grains	4.8%	2.7%	2.9%	4.9%	2.2%
Rice	26.0%	20.0%	25.1%	21.6%	17.6%
Oilseeds	0.0%	0.0%	0.0%	0.0%	0.0%
Veg. and fruits	15.3%	6.2%	5.9%	18.2%	0.8%
Plant fibers	0.0%	0.0%	0.0%	0.0%	0.0%
Other crops	3.1%	3.5%	2.7%	1.0%	0.0%
Veg. oil and meals	0.7%	0.6%	1.0%	2.4%	2.7%
Sugar	73.2%	126.3%	132.8%	74.0%	3.3%
Ruminant meat	60.8%	113.1%	84.8%	96.6%	18.9%
Mong. meat	29.2%	28.5%	30.8%	34.0%	28.6%
Dairy	46.2%	50.0%	75.1%	67.2%	22.1%
Animal fibers	0.0%	0.3%	0.3%	0.2%	0.0%
Fishing	3.4%	2.2%	0.3%	2.9%	0.0%
Other food	9.3%	18.3%	11.2%	7.7%	3.1%
Beverage and tobacco	8.7%	28.0%	21.8%	11.5%	4.7%
Agriculture and food	**9.7%**	**19.9%**	**10.3%**	**55.4%**	**2.9%**
Other primary	**0.0%**	**0.0%**	**0.5%**	**0.2%**	**0.0%**
Other industry	**1.2%**	**1.2%**	**0.8%**	**0.9%**	**0.4%**

Source: MAcMap-HS6 v3.

3.2.3 Environmental challenges of production reallocation in a EU-MERCOSUR agreement

Considering the tariff structure displayed above, a trade agreement should lead to the reallocation of agricultural activities from the EU to MERCOSUR, whereas MERCOSUR industries would give greater market share to manufactured exports from the EU. Other regions of the world should also lose market shares in the two regions. Agricultural exports from MERCOSUR should significantly increase, in particular for bovine meat, pig and poultry products, sugar from cane, and to a lower extent cereals and soybean oil. However, the production pathways of these products are quite different, which raises questions about their impact on greenhouse gases.

Livestock

As we have presented in Section 3.1, differences in GHG emissions intensities can be a source of environmental costs. For livestock production, these are primarily non-CO_2 gases, due to CH_4 emissions from enteric fermentation and N_2O and CH_4 emissions from manure management and deposition. The contrast between emission efficiencies in the EU and other regions of the world is shown in Table 3.2. For ruminant meat and milk, MERCOSUR emissions per unit of products are, on average, much higher than in Europe, 2.5 times for milk, three times for beef and four times

for small ruminant meat, due to the large differences in herd productivities. This is the result of the lower quality of the feed given on average to the animals as well as the higher mortality rate and suboptimal herd management (see Herrero et al., 2013). Emissions from monogastric meat are lower in intensity but pig meat impacts remain twice as high in MERCOSUR. Only poultry products are close in magnitude with EU emissions, and even lower in MERCOSUR for chicken meat. This suggests that environment would not benefit from a reallocation of livestock production to MERCOSUR if productivities are not improved in that region.

Table 3.2. Non-CO_2 emissions from livestock production in MERCOSUR and EU28 (kgCO_2-eq per tonne carcass weight).

	Bovine meat	Sheep and goat meat	Pig meat	Poultry meat	Eggs	Milk
EU28	10,493	11,936	1,969	890	384	857
Other Europe and FSU	11,074	12,183	5,660	1,354	674	1,254
North & Central America	14,266	32,117	4,749	766	502	737
MERCOSUR	29,161	42,837	3,705	582	441	2,008
Other South America	20,135	50,537	4,476	1,142	541	1,593
Asia	40,436	23,867	1,902	752	582	1,424
Africa	53,937	26,123	3,583	871	735	4,302
World	25,515	22,723	2,530	796	555	1,350

Source: GLOBIOM database, based on Herrero et al. (2013).

CROP CULTIVATION

GHG emissions from crop cultivation can be similarly compared. We focus here the discussion on N_2O emissions from fertilisers.[8] Globally, these emissions represent around 523 MtCO2-eq (see Chapter 2) and the EU and MERCOSUR represent 17% of them. An overview of emissions per ton of product is shown in Table 3.3. Emissions intensity depends on the quantity of fertiliser applied and the suitability of land, that allows reaching different levels of yield for the same quantity of input. Oilseed cultivation appears more efficient in MERCOSUR than in Europe, whereas cereals production is more efficient in Europe, with less fertiliser emissions per unit produced.[9] Therefore, crop reallocation should be less problematic than for livestock.

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[8]   Rice cultivation is also a significant source of emission (CH_4) in some regions but, according to FAOSTAT, Europe and MERCOSUR only account for 2% for this source because most rice is cultivated in Asia.
[9]   The results on cereals differ from the statistics provided by the International Fertilizer Industry Association (IFA) that finds a lower level of fertiliser use in Brazil and Argentina per unit of product, owing to the fact that IFA only accounts for synthetic fertilisers, whereas our approach also takes into account organic fertilisers.

Table 3.3. Emissions from N$_2$O associated with crop production in MERCOSUR and EU28 (kgCO$_2$-eq per tonne dry matter).

	All crops	Corn	Rape	Soya	SugB[a]	SugC[a]	Sunf[a]	Wheat
EU28	142	188	340	—	72	—	578	183
Other Europe and FSU	317	560	1055	13	—	—	1059	411
North & Central America	170	235	339	66	na[a]	108	413	208
MERCOSUR	135	407	61	163	—	59	258	342
Other South America	124	472	271	105	—	72	531	307
Asia	240	414	465	257	—	88	—	391
Africa	205	380	—	78	—	73	728	350
World	203	293	300	128	na[b]	80	455	277

[a] Abbreviations used: SugC = sugar cane; SugB = sugar beet; Sunf = sunflower.
[b] Only data for the European Union were available for sugar beet in GLOBIOM.
Source: EPIC/GLOBIOM database. Nitrogen requirements are calculated for different management systems and matched with crop production levels from FAOSTAT. IFA statistics are used as a floor value for nitrogen use.

LAND USE CHANGE

The third significant source of emissions from agriculture is land use change from agricultural expansion. We have seen in Subsection 3.1.3 that change in cultivated areas could drive emissions from change in carbon stocks depending on the carbon stocks densities. MERCOSUR countries have many carbon rich areas, such as the Amazon forest. Land use change emissions in tropical forests is estimated to be a major source of global emissions, 4 GtCO$_2$-eq per year, including 2.5 GtCO$_2$-eq in Latin America (Pan et al., 2011). Land use change in Latin America therefore accounts for 8% of total anthropogenic CO$_2$ emissions in 2010 (Friedlingstein et al., 2010). According to Hosonuma et al. (2012), agriculture is responsible for around 90% of deforestation in MERCOSUR countries. Karstensen et al. (2013) allocate historical deforestation to some agricultural products exported by Brazil. He finds that Brazil beef production is responsible for around 500 MtCO$_2$-eq of land use change emissions for the year 2010, and soybean production for 120 MtCO$_2$-eq. Gerber et al. (2013) also finds a significant impact of pasture expansion on GHG emissions from beef products, with an increase by 50% of emissions per unit of product in Latin America. Reallocating meat production in these regions appears risky from an environmental perspective. Indeed, according to FAO (2010a), average carbon density for living biomass in Brazil or Argentina forest is 121 and 104 tC/ha, respectively, whereas it is usually lower in Europe (76 tC/ha for France, 31 tC/ha for Ireland). Therefore, if agricultural production is relocated to Latin America and results in additional deforestation, reversion of forest in Europe cannot compensate for the induced carbon emissions.

Energy intensive activities

Last but not least, GHG emission intensities from industrial sectors are significantly different in the European Union and the MERCOSUR. Two factors influence this indicator: first, the energy efficiency of the different sectors can vary depending on the technology used; second, the emissions associated with energy use can be different depending on the source of primary energy used, in particular for producing electricity. GHG emission intensity from fossil fuel is the lowest in the European Union, with 289 tCO_2 per million US\$ in 2007 versus 398 tCO_2 for MERCOSUR. But the level of MERCOSUR is 15% lower than in North America and twice lower than in other developing regions (see Table 3.A in this chapter appendix). Some regions, like Brazil, even show a level lower than the EU average, at 268 tCO_2 per million US\$. But the comparative advantages of MERCOSUR appear the most clearly when comparing GHG emission per unit of electricity produced. Due to the high capacity in hydropower energy, electricity emissions in MERCOSUR appear to be 2.5 times lower than in Europe and even close to zero in the case of Paraguay that sources its electricity from hydropower.

3.3   Modeling framework for assessing the trade agreement

In order to evaluate the different economic and environmental impacts of a possible EU-MERCOSUR trade agreement, we use an applied modeling framework based on two different models: a global CGE model for the assessment of the economic and trade effects of the agreement; and a partial equilibrium (PE) gridcell-based model of agricultural and forestry to more precisely determine the land use change effects and GHG emissions from crop and livestock production changes. The two models are run in combination, by using the CGE output on income, market price and trade as an input for the PE model. The characteristics of the two models are summarised below.

3.3.1   A CGE model for trade policy analysis

We use for the evaluation of the economic impact of EU MERCOSUR trade liberalisation scenarios the MIRAGE CGE, developed at CEPII. This model has been used in multiple assessment exercises for trade liberalisation (Bchir et al., 2003, Bouët et al., 2005, Decreux and Fontagné, 2006, Gouel et al., 2011) and analysis of agricultural policies, in particular in the context of biofuels (see Chapter 4). It follows standard CGE specifications, with a representation of all productive sectors of the economy through a nested constant elasticity of substitution (CES) production supply function. Agricultural sectors for this analysis are fully decomposed at the most refined level in the nomenclature of the Global Trade Analysis Project (GTAP).

The model is calibrated on the GTAP8 database (Narayanan et al., 2012), with a base year in 2007. The tariff information for the same year is provided by the last version of the MAcMap-HS6 database (Guimbard et al., 2012). Because trade flows in the GTAP database are only provided in value terms, we also combine the model with a trade matrix based on the BACI database (Gaulier

and Zignago, 2008), which allows a representation of prices and quantities associated with the CGE trade flows.

3.3.2 A PARTIAL EQUILIBRIUM MODEL FOR IMPACTS ON AGRICULTURE AND LAND USE CHANGE

GLOBIOM is a linear programming model with a spatial equilibrium approach a la Takayama and Judge (1971). The model follows a bottom-up structure starting from a detailed dataset on land use at the grid-cell level and its main activities: crops cultivation, livestock farming and forestry (Havlík et al., 2011). The model is based on FAOSTAT and has a more detailed representation of agricultural and wood products than in GTAP. It also incorporates detailed GHG emission accounts from agriculture and land use change in a geographically explicit setting (see Chapter 2).

For the purpose of this study, the model uses a version with additional geographic disaggregation on the supply side. For Brazil, the largest emitter of land use change emissions in MERCOSUR, the geographical resolution has been refined from 200×200 km to 50×50 km. On the EU side, all Member States are described with their NUTS2 subunits, calibrated by EUROSTAT data.

3.3.3 MODEL LINKAGE FOR AN INTEGRATED ASSESSMENT

The two models are used in combination as follows. First, trade liberalisation scenarios are run in the CGE which provides results on change in prices, trade flows and level of income associated with the shock. This information is supplied to the PE on the demand side (income and prices) and on trade, after calculation of change in trade in quantities using the trade matrix based on BACI (see Figure 3.2). Therefore, only supply is assumed endogenous in GLOBIOM with this setting. Price responses to the shock on the supply side in GLOBIOM allows recalibrating the CGE supply side for agricultural sectors, through the elasticity of substitution between the constrained factor (land) and variable factors (labour, capital). A second iteration between the CGE and the PE allows for production of a more harmonised set of responses, once the supply side elasticities are of similar magnitude. The final set of output indicators are sourced from the different models according to Table 3.4.

Because both models are dynamic recursive, but with different time-frames, the simulation periods of both models need to be made consistent. GLOBIOM is usually run in a ten year time step approach, with a base year in 2000. MIRAGE starts in 2007 but runs with one year time steps. Therefore, 2010 and 2020 are used reference years to compare model baseline trajectories, whereas the year 2020 is used for implementation of the scenario shocks.

Table 3.4. Input and output parameters for the CGE and PE assessment framework.

|	**CGE**	**PE**
Economic input	- Tariff change (scenario) - Supply elasticities for agricultural and forestry sectors (PE)	- Trade (CGE) - Market prices (CGE) - Income (CGE)
Economic indicator output	- Welfare - GDP, income - Trade - Market prices - Production and demand in industry and services	- Production and demand in agricultural and forestry products - Land use change
Environmental indicator output	- Fossil fuel CO_2 emissions for industry and services	- Fossil fuel CO_2 emissions from agriculture (using emission factor from CGE) - Non-CO_2 emissions from agriculture - CO_2 emissions from land use change
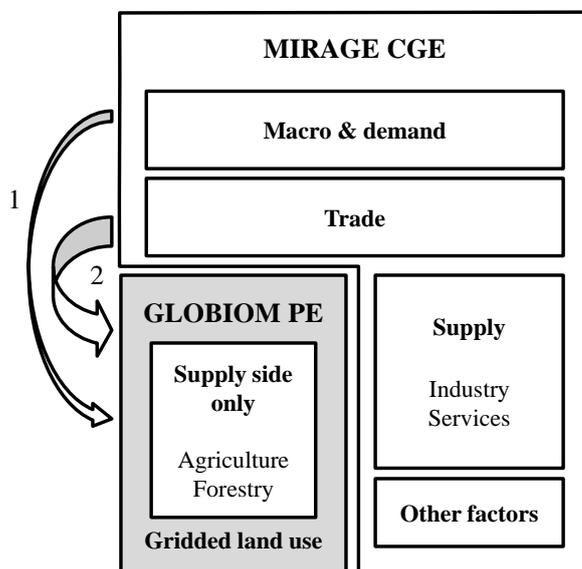
Figure 3.2. Stylised representation of the linkage between the CGE and PE models. The CGE model provides changes in income and market prices to determine in the PE the change in demand level (1); trade flows are also extracted from the CGE and directly applied as shocks in the PE (2).

3.4   Analysis of different trade liberalisation scenarios

3.4.1   Trade scenarios

We apply the modeling setting above to the assessment of different trade scenario shocks between MERCOSUR and EU28 to compare economic and environmental impacts. Considering the trade protection structure presented in Section 3.2.2, the most sensitive products for opening on the EU side are bovine and monogastric meat, dairy, sugar, and to a lower extent cereals. These products are also expected to drive important changes on land use, therefore we consider some specific scenarios to understand the contribution of each of these. Five different scenarios represent an increase in imports for each of these products, either with tariffs set to zero (cereals), or in the case of TRQs, with an increase in the level of quota allocated to MERCOSUR countries (Table 3.5). The reference values for the volumetric increase are adapted from the proposal of MERCOSUR as reported by Decreux and Ramos (2007) for ruminant meat, monogastrics and dairy products.[10] Quotas are allocated to EU-MERCOSUR countries on a historical trade basis. For sugar, we assume that the EU implements a policy increasing its use of ethanol based on sugar cane and for this purpose put in place a quota allowing an additional 2 billion tonnes of imports of ethanol of sugar cane from MERCOSUR (30% of EU ethanol production).

We then test the implications of wider set of trade liberalisation policies on the EU and/or the MERCOSUR side, with four scenarios that compare opening in of agriculture as a whole or opening of industry. For MERCOSUR, due to the high level of initial protection of industry, we consider only a partial liberalisation, reflected by a cut in tariffs by 50%. A last trade agreement scenario ("EU-MCS") combines all the measures considered above at the same time.

Shock on tariff levels are directly implemented in the model as a reduction in the tax applied to imported products. For TRQs, the change in quota allocation is simply modelled by an endogenous adjustment of the AVE tariff associated with the quota. The tax level is changed proportionally for all bilateral relations between MERCOSUR and EU28 countries until the overall trade flow has reached the new allocation. Modelling of TRQ regime change is therefore not considered in our approach. According to Decreux and Ramos (2007), explicit representation of quotas at HS6 level allows a more precise characterisation of trade policy assessment but depends highly on how quota rents are introduced and their administration methods. Junker and Heckelei (2012) additionally show that in the case of meat quota rent transfers, quota rent needs a very detailed representation to be accurately represented as they can play differently depending on the country and tariff line. Therefore, we keep in our approach a simplified representation, where quota rents are assumed to accrue to the importer, which is equivalent to a tariff mechanism (see Figure 3.6 in this chapter appendix).

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[10]   These authors report a request from MERCOSUR to get increased access for 315,000 tons for bovine meat, 40,000 tons for pig meat, 250,000 tons for chicken meat, 34,000 tons for milk, 60,000 tons for cheese and 10,000 tons for butter. EU proposition are much lower, usually 1/3 of these numbers, and in the case of chicken one tenth.

Table 3.5. Scenarios tested for EU-MERCOSUR liberalisation.

Scenario name	EU28 trade measure	MERCOSUR trade measure
EU cere	0% duty on wheat and coarse grains	
EU rum	+300,000 tonnes quota for beef meat from MERCOSUR	
EU mong	+300,000 tonnes quota for monogastric product from MERCOSUR	
EU dairy	+800 million liters milk equivalent for butter, cheese and milk[a]	
EU etha	+2 billion liters sugar cane based ethanol from MERCOSUR	
EU agri5	Combination of five EU agricultural markets opening above	
EU agri	EU agri5 + 0% tariff on all other EU agricultural, fishing and forestry products	
EU indus	0% for all industrial products	
MCS agri		0% for all agriculture, fishing and forestry
MCS indus		50% decrease for all industrial products
MCS-EU	All measures above	All measure above

[a] For butter, we assume that 1 kg of cheese requires approximately 10 kg of milk and 1 kg of butter 20 kg of milk. See for instance conversion coefficient used by the International Livestock Research Institute (ILRI) www.ilri.org/InfoServ/Webpub/fulldocs/ilca _manual4/MilkProcessing.htm.

3.4.2 ECONOMIC IMPACT OF TRADE SCENARIOS WITHOUT ENVIRONMENTAL EXTERNALITIES

Results from the CGE model provide indications on the change of welfare associated with the different trade liberalisation scenarios (Table 3.6). Opening of the EU on the cereals side appears of relatively small efficiency to trigger welfare gains (around US$ 32 million at world level), when compared with sugar crops for ethanol (US$ 780 million) and for livestock products (US$ 1,380 million and US$ 205 million for ruminant and monogastric meat, respectively). These gains accrue to MERCOSUR, but also to the EU in benefits from cheaper agricultural products in its markets. However, some countries in Europe experience losses if the liberalised sector is also of significant importance for the local economy. Beef liberalisation for instance more significantly expose Ireland, Central European countries and France, that benefit relatively little when compared with other EU countries of comparable size (Germany, UK, Spain, Italy). The contrast is even more striking if EU liberalises its full agricultural sector, with Ireland and Poland losing even more, whereas UK, Italy and Spain show the largest gains. In total, the world would be better off by US$ 2.8 billion with an opening of the EU to MERCOSUR agricultural products, and MERCOSUR would gain US$ 1.7 billion whereas EU would preserve US$ 1.6 billion welfare gains. However, the price to pay would be high for MERCOSUR if the industrial sectors were opened. EU would gain market shares on

all its competitors and benefits would mainly accrue from a reallocation of trade, with significant welfare losses for MERCOSUR (US\$ 1.2 billion) but large gains for the EU (US\$ 2.9 billion). As a consequence, a full EU-MERCOSUR trade agreement under these terms would be only slightly beneficial to MERCOSUR, with a gain of US\$ 0.9 billion. The EU would be the largest benefiter with a US\$ 4.5 billion gain, with the most favoured Member States being Germany, Italy and the United Kingdom (UK), well positioned on the relevant industry sectors.

Impacts in terms of agricultural gross domestic product (GDP) also illustrate the heterogeneity of impact across regions, and the dynamics at play (Table 3.7).

3.4.3   GHG emissions from the trade agreement

We can now compare the welfare achievements above with the environmental impacts in terms of GHG emissions. The different GHG emission sources are provided by the different models according to the distribution from Table 3.4, with changes for agriculture and land use change sources from PE and fossil fuel carbon emissions from the CGE.[11]

We first consider the case where intensification in the PE model is limited to reallocation of production across sectors and locations. No change in management systems is allowed for crops (increase of fertilisers) or for livestock (change from grass-fed to mixed systems). Sensitivity analysis will be performed on this point later in Section 3.4.4. Results for emissions are displayed in Table 3.8, on an annual emissions basis for all sources, except land use change emissions that are emitted once over the period considered. As can be observed, annual emissions at world level increase for most scenarios. When MERCOSUR opens its industrial sectors, emissions decrease for industry (reallocation to more efficient Europe) but increase for agriculture due to a reallocation of the labour force (2.01 $MtCO_2$-eq for "MCS indus"). A strong increase in annual emissions is also observed when EU quotas are increased for beef meat, mostly due to enteric methane emissions in MERCOSUR countries. In a few scenarios however, annual emissions are reduced with the liberalisation. It is the case when the EU opens its industry (-0.17 $MtCO_2$-eq/yr) or increases its imports of cereals, sugar or milk from Brazil (-0.21, -0.17 and -0.11 $MtCO_2$-eq/yr, respectively). Overall, the total liberalisation scenario increases direct emissions from activities by 2 $MtCO_2$-eq/yr, in particular due to the increase in non-CO2 agricultural emissions in MERCOSUR. Emissions in the EU also increase for industry (0.9 $MtCO_2$-eq/year) but these are offset by the decrease of industry emissions in MERCOSUR (-1.52 $MtCO_2$-eq/year). Emissions from transport are significant (1 $MtCO_2$-eq/year) but they appear mostly related to industrial goods shipped from Europe to MERCOSUR (limited transportation emissions for agricultural liberalisation scenarios).

Emissions from land use change are much larger in magnitude but only emitted once over the adjustment period of the trade agreement. In total, we find that the trade agreement would generate 287 $MtCO_2$-eq of carbon emissions from land use change, i.e. 28.7 $MtCO_2$-eq per year over the decade considered for the shock. This is primarily the result of emissions from ruminant herd

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[11]   For fossil fuel emission from agriculture, emission factors from the CGE are applied to activity levels of the PE.

Table 3.6. Change in welfare (million US$ equivalent variation) associated with the different liberalisation scenarios.

	EU cere	EU etha	EU rum	EU mong	EU milk	EU agri5	EU agri	EU indus	MCS agri	MCS indus	EU-MCS
World	32	798	1380	205	34	2473	2881	20	162	942	3935
EU28	−11	532	1037	108	1	1679	1630	−229	196	2923	4524
MERCOSUR	48	365	432	145	36	1039	1752	448	−7	−1177	965
OthSouthAm	−2	−7	−10	−6	0	−25	−68	−4	−11	−43	−127
NorthCentAm	−3	−43	−20	−9	−2	−77	−135	3	14	−175	−301
OthEurFSU	2	−6	−2	−1	1	−4	−2	−21	−15	−126	−167
Asia	−4	−18	−55	−33	−4	−116	−222	−163	16	−213	−588
Africa	0	−25	−3	0	3	−24	−73	−14	−31	−248	−371
Argentina	21	30	215	16	19	304	582	42	−11	−241	360
Brazil	24	324	170	128	15	672	1050	375	−24	−890	475
Paraguay	3	13	2	0	0	18	21	2	0	−2	21
Uruguay	0	0	51	2	1	55	114	13	−3	−10	113
Venezuela	0	−3	−6	−1	0	−10	−15	16	30	−35	−3
EU_DeuAut	−4	53	183	26	1	262	222	−73	35	1141	1333
EU_Benelux	−5	−20	123	18	−4	114	58	−33	39	282	345
EU_GrekMed	1	64	13	5	1	85	97	2	0	−5	94
EU_Central	−1	103	7	1	−1	108	107	−8	3	92	198
EU_North	−1	7	85	−2	−1	89	89	−13	13	220	309
EU_Baltic	0	5	2	0	0	8	15	1	0	−1	14
EU_France	−3	−14	53	3	1	41	49	−15	22	337	397
EU_Ireland	−1	−6	−9	1	−1	−16	−25	−6	6	70	45
EU_Italy	0	38	239	3	0	282	275	−47	19	324	569
EU_Poland	0	9	−7	−1	0	0	−4	−4	8	58	59
EU_Iberic	0	129	151	9	3	294	297	−18	16	207	500
EU_UK	2	59	195	39	1	299	328	−15	35	200	543
EU_BulgRou	0	105	3	6	0	114	122	−1	0	−1	118

Table 3.7. Percentage change in value added of agricultural sectors for the EU agriculture liberalisation scenario ("EU agri5").

	Rice	Wheat	Coars Grn	Veg & Fruits	Oilseeds	SugCB	Other Crops	Cattle	Other Anim	Dairy
World	0.0	0.0	0.0	0.0	0.0	0.5	0.0	0.1	0.0	0.0
EU28	0.0	−0.1	−0.5	0.0	0.2	−4.9	0.0	−2.0	−0.2	−0.1
MERCOSUR	0.0	−0.3	1.0	−0.1	−0.5	5.1	−0.3	3.2	1.0	0.4
OthSouthAm	0.0	0.1	0.1	0.0	0.1	−0.2	0.0	0.1	−0.1	0.0
NorthCentAm	0.0	0.0	0.0	0.0	0.1	−0.1	0.0	0.0	0.0	0.0
OthEurFSU	0.0	0.0	0.0	0.0	0.1	−0.1	0.0	0.0	0.0	0.0
Asia	0.0	0.0	0.0	0.0	0.1	0.0	0.0	−0.1	0.0	0.0
Africa	0.0	0.0	0.0	0.0	0.0	−0.6	0.0	0.0	0.0	0.0
Argentina	−0.1	−0.5	0.9	−0.3	−0.7	10.9	−0.5	7.4	0.7	1.4
Brazil	0.0	0.0	1.1	−0.1	−0.4	4.9	−0.3	1.9	1.2	0.3
Paraguay	0.0	−0.1	1.2	0.1	−0.6	19.1	−0.4	0.1	0.0	0.1
Uruguay	−0.8	−0.1	0.2	−0.3	−0.9	1.6	0.0	5.2	0.3	−0.5
Venezuela	0.0	0.0	0.0	0.0	0.1	0.3	0.0	0.2	0.1	0.3
EU_DeuAut	0.1	−0.1	−0.3	0.0	0.2	−4.9	0.0	−3.8	−0.6	−0.1
EU_Benelux	0.0	−0.1	−0.9	0.0	0.2	−2.2	0.0	−3.5	−0.5	−0.1
EU_GrekMed	0.0	0.0	−0.3	0.0	0.1	−7.9	0.0	−0.4	−0.1	0.0
EU_Central	0.1	0.2	−0.1	0.1	0.3	−19.0	0.2	−0.7	0.2	0.1
EU_North	0.0	−0.1	−0.2	0.0	0.2	−2.3	0.0	−3.8	−0.3	−0.1
EU_Baltic	0.1	0.0	−0.1	0.0	0.1	−1.2	0.0	−1.6	−0.1	0.0
EU_France	0.0	0.0	−0.6	0.0	0.2	−3.8	−0.1	−1.4	−0.2	−0.1
EU_Ireland	0.0	−0.6	−0.7	0.1	0.2	−0.5	−0.4	−1.6	−0.2	−0.1
EU_Italy	0.0	0.0	−0.5	0.0	0.2	−1.0	0.0	−2.6	−0.1	−0.1
EU_Poland	0.0	−0.1	−0.3	0.0	0.1	−1.2	0.0	−2.8	−0.2	−0.1
EU_Iberic	0.1	−0.1	−1.2	0.0	0.2	−11.0	0.0	−1.9	0.0	0.0
EU_UK	0.0	−0.5	−0.7	0.0	0.2	−6.4	−0.1	−1.9	−0.4	−0.1
EU_BulgRou	0.1	0.1	−0.2	0.1	0.2	−15.2	0.1	−0.4	0.0	0.1

Table 3.8. **Change in annual GHG emissions associated with trade liberalisation scenarios (MtCO$_2$-eq/yr).** Land use change emission are divided by a reference period of 10 years.

		EU cere	EU etha	EU rum	EU mong	EU milk	EU agri5	EU agri	EU indus	MCS agri	MCS indus	EU-MCS
EU28	Agri CO$_2$	−0.02	0.02	−0.03	−0.01	0	−0.03	−0.22	0.01	0.05	0	−0.21
EU28	Agri non-CO$_2$	−0.25	−0.03	−1.08	0.07	0	−1.32	−1.52	−0.01	0.05	0.28	−1.34
EU28	Indus	0	0.12	0.08	0.04	0.01	0.25	0.37	−0.03	−0.06	0.65	0.94
EU28	Serv	0	0.02	−0.04	0	−0.01	−0.03	−0.09	0.15	0.02	−0.21	−0.13
EU28	Trsp	0	0.05	0.02	0.01	0	0.09	0.17	0	0.03	0.15	0.36
EU28	**Tot annual GHG**	**−0.26**	**0.26**	**−0.98**	**0.1**	**0.01**	**−0.9**	**−1.15**	**−0.08**	**0.12**	**1.51**	**0.2**
EU28	**LUC (10 years)**	**−0.16**	**0**	**0.05**	**0.01**	**0**	**−0.04**	**0.07**	**0.01**	**0**	**−0.18**	**−0.2**
MERCOSUR	Agri CO$_2$	0.02	−0.01	0.01	0.03	0	0.06	0.43	−0.03	0.14	0.23	0.61
MERCOSUR	Agri non-CO$_2$	0.03	−0.43	2.36	0	−0.05	2.35	2.17	−0.49	0.16	1.17	2.29
MERCOSUR	Indus	−0.03	−0.2	−0.4	−0.09	−0.04	−0.78	−1.31	0.28	0.2	−0.71	−1.52
MERCOSUR	Serv	0	0.02	−0.04	0	−0.01	−0.03	−0.09	0.15	0.02	−0.21	−0.13
MERCOSUR	Trsp	−0.01	0.03	−0.03	0	0.01	0	−0.06	0	−0.03	−0.1	−0.2
MERCOSUR	**Tot annual GHG**	**0.02**	**−0.54**	**1.99**	**−0.04**	**−0.08**	**1.8**	**1.47**	**−0.02**	**0.46**	**0.12**	**1.16**
MERCOSUR	**LUC (10 years)**	**2.14**	**−8.05**	**36.23**	**1.1**	**−0.53**	**35.32**	**29.15**	**−8.1**	**2.9**	**23.87**	**36.09**
World	Agri CO$_2$	0	0.05	0.01	0.02	0	0.06	0.16	0	0.17	0.12	0.29
World	Agri non-CO$_2$	−0.17	−0.37	1.62	0.16	−0.05	1.3	1.04	−0.34	0.25	1.42	1.28
World	Indus	−0.03	−0.05	−0.34	−0.05	−0.04	−0.52	−0.77	0.13	0.2	−0.36	−0.8
World	Serv	−0.01	0.13	−0.02	0	−0.01	0.08	0.1	0.08	0.06	−0.03	0.21
World	Trsp	0	0.08	−0.04	−0.01	0	0.02	0.07	−0.02	0.11	0.85	1.02
World	**Tot annual GHG**	**−0.21**	**−0.17**	**1.3**	**0.12**	**−0.11**	**1.02**	**0.67**	**−0.17**	**0.8**	**2.01**	**2.06**
World	**LUC (10 years)**	**2.5**	**−6.72**	**28.75**	**1.97**	**−0.31**	**28.64**	**22.87**	**−6.35**	**2.22**	**21.53**	**28.69**

Table 3.9. Welfare gains and cost of carbon emissions from the trade agreement for different values of carbon (US$).

	Economic welfare gains	Annual GHG emissions dividend				Land C stock value change			
	Mln US$	$40	$100	$200	$400	$40	$100	$200	$400
EU cere	32	2	6	11	23	−272	−681	−1,362	−2,723
EU etha	798	2	5	9	19	733	1,832	3,663	7,326
EU rum	1,380	−14	−35	−71	−142	−3,136	−7,840	−15,680	−31,360
EU mong	205	−1	−3	−7	−13	−215	−537	−1,074	−2,148
EU milk	34	1	3	6	12	34	85	170	341
EU agri5	2,473	−11	−28	−56	−111	−3,125	−7,812	−15,624	−31,247
EU agri	2,881	−7	−18	−37	−73	−2,495	−6,238	−12,476	−24,952
EU indus	20	2	5	9	19	693	1,732	3,465	6,929
MCS agri	162	−9	−22	−44	−87	−242	−605	−1,211	−2,422
MCS indus	942	−22	−55	−110	−219	−2,349	−5,872	−11,744	−23,487
EU-MCS	3,935	−22	−56	−112	−225	−3,130	−7,824	−15,648	−31,296

expansion in MERCOSUR countries, particularly in Brazil. When decomposing the agricultural liberalisation scenarios across sectors, we can observe that effects are quite different for other sectors. Monogastric meat has a much lower impact on land use, because feed only relies on cereals, without grazing needs, but also because feed conversion efficiency is higher for these systems. Milk is an interesting case where land pressure decreases. This occurs because co-production of meat associated with dairy herd leads to a reduction in the number of suckler cows specialised in beef production, which are highly demanding in grazing areas.

Emissions associated with the trade agreement represent overall a significant negative externality that can cancel the benefits of the liberalisation. Table 3.9 compares the welfare gains from the trade agreement at the world level (calculated in Table 3.6) to the value of GHG emissions, using different carbon prices, US$ 40, 100, 200 and 400 per tC-eq, i.e. a range from US$ 10 to 100 per tCO_2-eq. Generally, annual emission changes are of lower magnitude than pure economic welfare gains from trade liberalisation, even at a price of US$ 400 per ton of C. In some cases ("EU etha", "EU milk" and "EU indus"), they even reinforce the benefits from the trade agreement due to the reduction in annual GHG emissions. However, in a few cases, these annual emissions are significant. At a carbon price of US$ 400, one quarter of gains from MERCOSUR industrial market opening would be offset, and this effect would represent half of the gains if agriculture were liberalised. However, the most influential factor for assessment of the final agreement remains the change in carbon stock associated with the trade policy. The "debt" created by GHG emissions often amount to several billion dollars magnitude, especially when high carbon prices are considered. The value of emitted carbon for the full MERCOSUR agreement range from US$ 3 billion to US$ 31 billion for the total period, directly driven by the impact of ruminant meat quota on production allocation.

In order to understand implications for the final assessment of the different trade policy options,

Table 3.10. Payback time in years for different carbon prices (US$) and time to reach 50% and 75% of initial expected gains. Negative payback time are reported as zero. When no payback is possible, a dash is used.

	Time for positive welfare gain				Time for 50% welfare gain				Time for 75% welfare gain			
	$40	$100	$200	$400	$40	$100	$200	$400	$40	$100	$200	$400
EU cere	8	18	32	50	15	32	50	70	27	50	70	88
EU etha	0	0	0	0	0	0	0	0	0	0	0	0
EU rum	2	6	12	25	5	12	25	57	9	25	57	154
EU mong	1	3	5	11	2	5	11	24	4	11	24	56
EU milk	0	0	0	0	0	0	0	0	0	0	0	0
EU agri5	1	3	6	13	3	6	13	28	5	13	28	62
EU agri	1	2	4	9	2	4	9	18	4	9	18	39
EU indus	0	0	0	0	0	0	0	0	0	0	0	0
MCS agri	2	4	10	33	3	10	33	–	8	33	–	–
MCS indus	3	7	14	33	5	14	33	93	11	33	93	1456
EU-MCS	1	2	4	8	2	4	8	18	3	8	18	41

we can calculate, at different prices, the number of years that would pass before the trade agreement would yield a positive outcome (Table 3.10). For a low carbon price (US$ 40), most trade policy options have positive outcome after a couple of years, with the exception of cereal opening that requires 8 years. At a price of US$ 400, however, the period of amortisation is much longer and four options require more than 20 years to yield a positive outcome. The effect of GHG emissions also alter the final gains that can be reached and the timing of these. Indeed, when considering the time needed to recover 50% of initially expected gains, amortisation periods increase, while reaching 75% of initial gains, seven policy options require more than 30 years at US$ 400.

The outcome of the final agreement itself seems significantly challenged by the effect of GHG emissions. The benefits would be reached only after 1 year at US$ 40 and 8 years at US$ 400. And to obtain half of the initial gains, the number of years would be approximately doubled.

3.4.4 DECOMPOSITION OF EFFECTS AND ROLE OF TECHNOLOGICAL CHANGE

In order to understand the different effects of scale, reallocation and efficiency have in shaping these results, we can decompose the different components of annual activity emissions using the formula from Section 3.1.2. To do so, we use the emission factors from the model, as reported in Section 3.2.3. Results of the decomposition are displayed in Figure 3.3, with a decomposition across three regions (EU, MERCOSUR and the rest of the world) and across two sector categories (agriculture and industry/services).

The decomposition illustrates how the different mechanisms of adjustment contribute to the final change in emissions. In the case of the EU opening to agricultural products, GHG emissions increase mainly due to sectoral effects within each country, rather than through a geographical

EU agri5
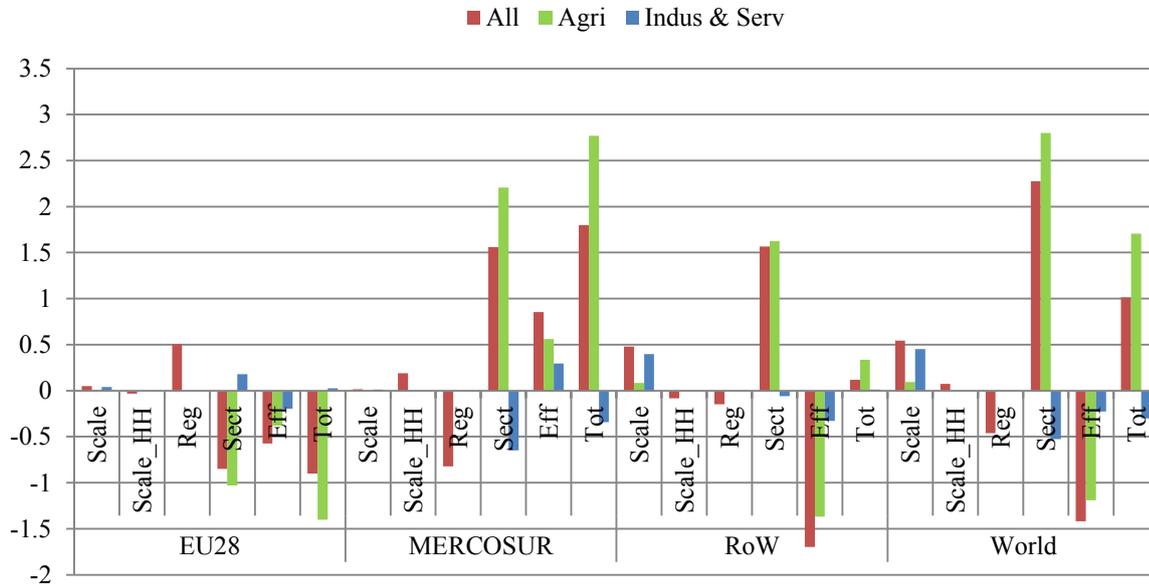
EU-MCS
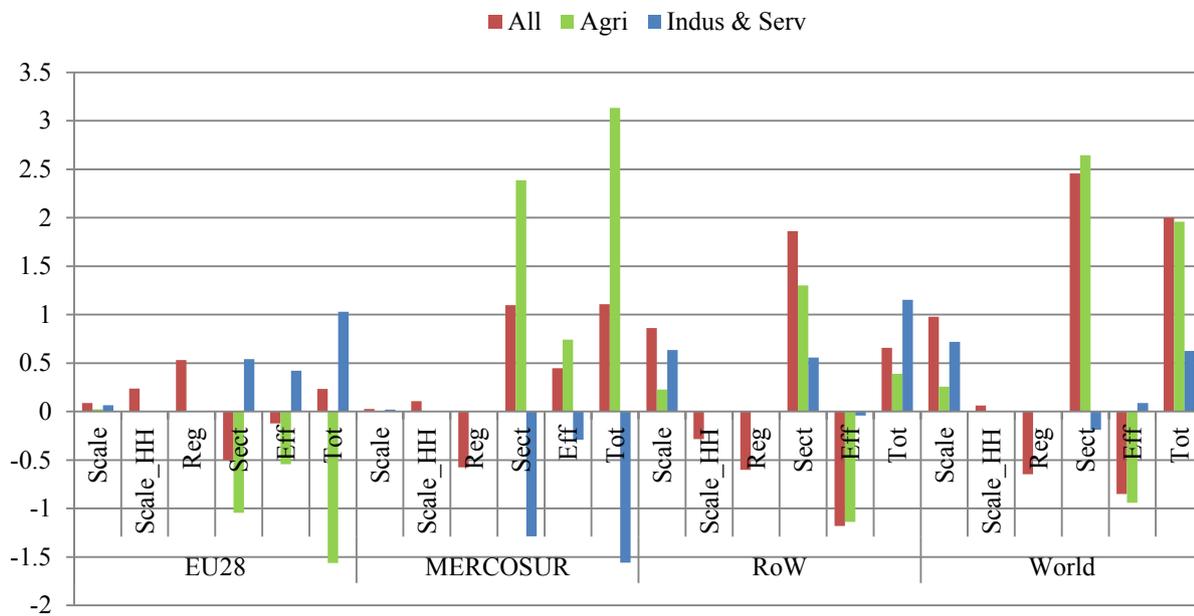
Figure 3.3. Decomposition of annual GHG emissions change (MtCO$_2$-eq) by scale, reallocation and efficiency effect, for EU agricultural opening of the five targeted products, and for the full agreement.

reallocation effect. Emissions decrease in the EU because agriculture production is replaced by industrial emissions which are, on average, less GHG intensive per unit of value added ("Sect" bar group). Efficiency increases due to reallocation of the production within the EU to regions with lower levels of emission. The international reallocation effect slightly increases emissions in Europe due to the transfer of industrial and services production to the EU. However, the net result of the scale effect, sectoral and regional reallocation, and efficiency change also decreases GHG emissions in Europe. On the contrary, MERCOSUR emissions increase, driven by a strong reallocation effect of production towards agricultural activities, which are more GHG emission intensive. The regional reallocation of industrial production to Europe decreases emissions in MERCOSUR but this is largely offset by emissions from sectoral reallocation and a loss of efficiency from marginal expansion in more GHG intensive sectors and locations. A last interesting effect can be observed in the rest of the world, also a source of GHG emissions. Because emission factors can be very high in Africa or Asia (see Section 3.2.3), trade diversion can have significant consequences in those regions. It is necessary to increase agricultural production in those parts of the world to replace a part of MERCOSUR export to other regions than EU. The same trends are observed when decomposing the full trade agreement. Greater emissions occur, in that case, partly triggered by the response of the industry and services sectors. Regional reallocation tends to decrease emissions, but the scale effect and sectoral shift in MERCOSUR and rest of the world cancel this effect.

The same type of decomposition can be applied for land use change emissions using formula from Section 3.1.3. This is illustrated in Figure 3.4 which displays the distribution of land use change emissions across reallocation effects, scale effect and technological change effect. At the world level, reallocation of land use is the main driver for the additional emissions, whereas scale effect only accounts for 15% of the positive contribution to land use change. Efficiency generates savings of 30% on these emissions, primarily through changes in emission factors in EU and in Asia.

The contribution of efficiency to the reduction of land use change emissions shows the importance of this parameter. As illustrated by the decomposition of Figure 3.4, the productivity response we observed remains limited in MERCOSUR when compared to some other regions. In the previous scenario, we have considered that crop and livestock sector productivity in the PE would react to price through reallocation within regions, with limited intensification response within a single grid-cell unit. To illustrate the potential role of the intensification response, we run an alternative scenario where management system can also vary at local level for crop and for livestock (see Havlík et al., 2014, for herd dynamic feature in GLOBIOM). The effect of this scenario on the main variables is provided in Table 3.11. Emissions from land use change at the world level are divided by a factor of 2 to 3 for most trade policy options, and emissions associated with "EU agri5" and "EU-MCS" decrease to 91 MtCO$_2$-eq and 178 MtCO$_2$-eq, respectively.

The response of intensification is therefore key to ensure that environmental damage remains limited. We can compare the effect of this intensification on the pay-back time associated with "EU agri5" and to the full agreement "EU-MCS" (Figure 3.5). In case of limited intensification, the policy
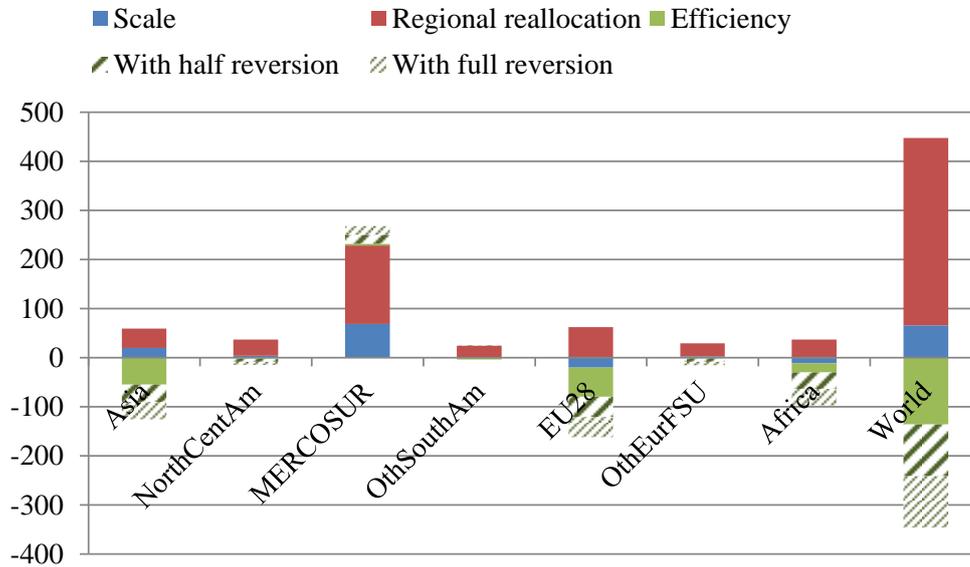
Figure 3.4. Decomposition of land use change emissions (MtCO₂-eq) associated with the scenario "EU agri5". Two levels of reversion are added to the initial calculation without reversion. MERCOSUR positive reversion does not mean that forest regrowth occurs with negative sequestration but that the scale and allocation factors are stronger due to higher average carbon emission factor.

Table 3.11. Land use change emissions (tCO₂-eq) in central scenario and alternative intensification scenario.

	EU cere	EU etha	EU rum	EU mong	EU milk	EU agri5	EU agri	EU indus	MCS agri	MCS indus	EU-MCS
Central scenario											
EU28	−1.6	0.0	0.5	0.1	0.0	−0.4	0.7	0.1	0.0	−1.8	−2.0
MERCOSUR	21.4	−80.5	362.3	11.0	−5.3	353.2	291.5	−81	29	238.7	360.9
World	25.0	−67.2	287.5	19.7	−3.1	286.4	228.7	−63.5	22.2	215.3	286.9
Intensification scenario											
EU28	−0.1	−0.1	1.4	0.3	0.2	1.5	1.8	1.1	0.3	2.3	2.2
MERCOSUR	9.0	−36.3	265.2	3.3	−15.5	193.9	116.5	−16.3	1.9	101.2	291.7
World	7.3	−21.6	153.1	13.4	−14.1	91.5	25.7	−1.5	−1.2	71.1	178.4

agreement takes almost 8 years to repay at a carbon price of US$ 400. This contrasts with the case of greater intensification where this payback time is reduced to 5 years. The benefits of such scenarios are therefore directly dependent on the yield response associated with the agreement.

3.5   Conclusion

Trade agreements can drive economic benefits when barriers to trade prevent comparative advantages to mutually benefit two regions. Because market allocations only take into account market internalities, some adverse effects can occur if a collateral damage is associated with increased trade. The analysis of consequences of a possible trade agreement between the EU and MERCOSUR illustrates well this risk. We have shown that if the European Union opens its trade to agricultural products from MERCOSUR, its welfare could grow significantly, by US$ 1.7 billion for the scenario studied here, and MERCOSUR would also benefit. However, some products would trigger significant GHG emissions, in particular beef, cereals and monogastric meat. The associated cost could outweigh the benefits of the trade agreement. If carbon is valued at US$ 40, we find that the carbon debt is reimbursed after 1 year; however, if the price is US$ 400, 9 years are required before obtaining some benefits, and reaching half of the initially expected value requires waiting 18 years. Even when signing a full deal including industry, the benefits would not be large enough to compensate for these effects. For a median value of US$ 100, four years would be required to reach half of the deal value and eight years to reach three-quarters of it.

These results invite us to consider with greater care the emissions dynamics associated with agricultural trade. The most sensitive product in our example is beef meat that is less efficient in Latin America than in Europe and is participating to Amazon deforestation dynamics in Brazil. We observe that if intensification occurs under the trade agreement, most of the negative effects listed below are offset. More interestingly, milk liberalisation encourages the production of dairy herd with meat co-production and reduces the need for grass-fed livestock systems and pressure on land use, leading to GHG emissions savings.

In the future, sustainable impact analysis should examine more closely the GHG intensity of sectors considering liberalisation, paying a particular attention to land use emissions dynamics. Provision in these agreements should be enforced to make sure that exporting sectors lead to sustainable intensification of production rather than a pure scaling effect that would potentially put more pressure on the environment.

a) limited intensification
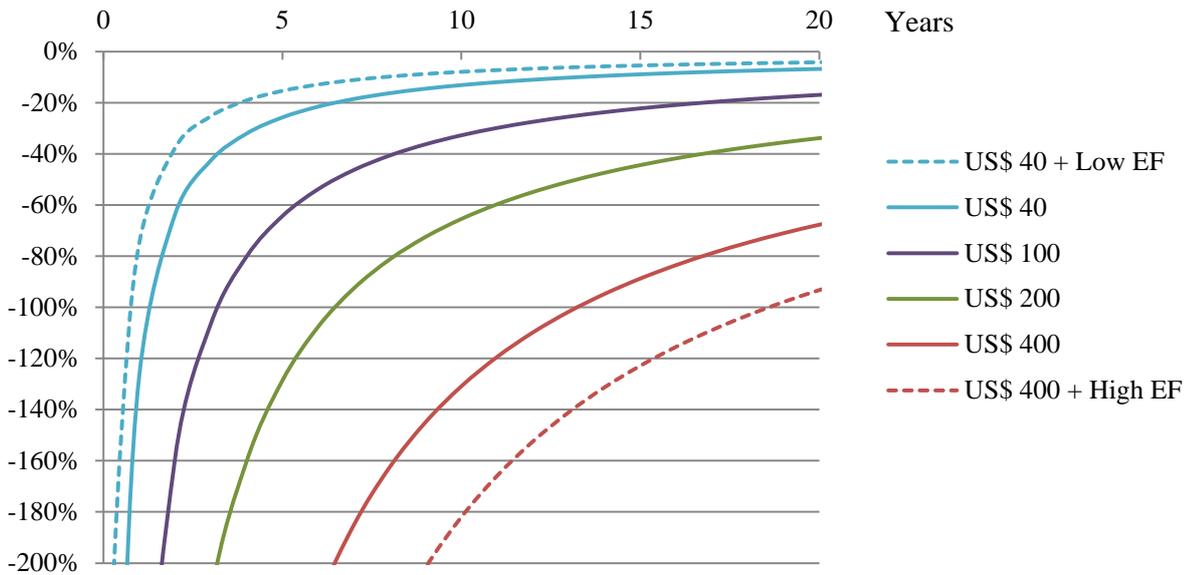

b) improved intensification
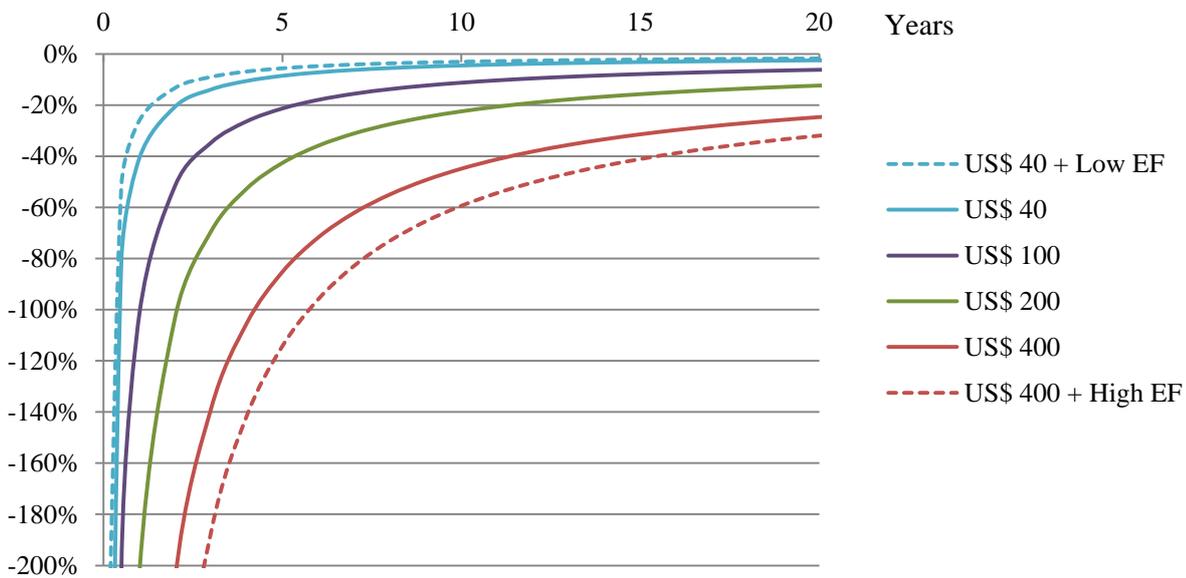
Figure 3.5. Reduction in welfare gains in the "EU agri5" scenario, with two intensification assumptions: limited (panel a) and improved (panel b). Four different carbon prices are tested, as well as a sensitivity analysis with lower and higher emission factor (EF) to determine bound of results interval.

3.A   COMPLEMENTARY TABLES AND FIGURES

Table 3.12. Intensity of CO_2 fossil fuel emissions per unit of GDP for full country and by sector (tCO_2-eq/million US\$), and emission from electricity (gCO_2 per kWh) in 2007. Abbreviations: Agri. & For. = agriculture and forestry; Mach. Equi. = machinery and equipement industry; Serv. = services; Elec. = electricity sector. Source: GTAP8 database with energy data.

	GHG em. per unit GDP	Agri For.	Industry			Serv.	Elec.
			All	Metal	Mach. Equ.		
EU28	289	154	254	640	39	243	1288
MERCOSUR	398	198	699	2539	93	237	499
Other South America	406	92	375	332	147	359	861
North and Central America	468	255	519	809	66	362	1554
Other Europe and Russia	990	316	989	2522	206	883	1028
Asia	882	268	964	2175	126	835	3634
Africa	989	187	710	946	348	1064	1894
Argentina	850	433	1536	4055	526	541	1251
Brazil	268	171	504	1822	16	155	238
Paraguay	312	2	82	169	86	332	0
Uruguay	252	183	248	748	221	190	240
Venezuela	734	91	896	7053	357	486	757
Germany/Austria	265	86	184	625	24	228	1604
Benelux	330	280	578	492	38	216	1463
Greece/Cyprus/Malta	799	153	342	968	39	853	2403
Central-Eastern Europe	575	179	404	1128	52	590	1733
Sweden/Finland/Denmark	217	153	160	384	14	200	405
Baltic countries	583	107	444	663	31	646	906
France	184	153	217	496	31	133	280
Ireland	220	117	65	1326	18	228	1659
Italy	249	144	219	727	60	205	1901
Poland	813	471	380	674	46	848	2095
Spain/Portugal	275	122	281	451	37	237	1537
United Kingdom	238	123	228	735	65	180	1525
EFTA	174	150	273	245	17	108	24
RoEur	855	262	1097	4927	199	721	1376
Bulgaria/Romania	783	101	715	1725	103	843	1510

Table 3.13. Largest agricultural trade flows at the HS6 level from MERCOSUR countries to EU28 and EU tariff measure. Only trade flows greater than US$ 1 million on average in 2000-2011 are displayed, in decreasing order.

Code HS6 (HS 2002)	Description	Export value (US$ 1000)			EU tariff in 2011	GSP status
		2000	2007	2011		
230400	Oilcake and other solid residues, resulting from the extraction of soybean oil	2,624,778	5,507,737	8,378,678	0	excluded
120100	Soybeans, whether or not broken	1,487,499	2,862,970	3,633,937	0	sensitive
90111	Coffee, not roasted, not decaffeinated	901,434	1,840,795	3,719,242	0	non sensible
20130	High-qual. beef cuts, boneless, processed, fresh or chld., descr. in gen. note 15 of the HTS	364,639	1,321,293	1,009,355	20% in quota, 12.8% + 303.4 €/100kg out quota	excluded
100590	Yellow dent corn	216,037	1,720,032	407,360	0	excluded
240120	Leaf tobacco, the product of two or more countries or dependencies, when mixed or packed together, partly or wholly stemmed, not threshed	331,477	602,621	808,212	18.4% min 22 €/100kg max 24 €/100kg, (or 11.2% min 22 €/100kg max 56 €/100kg for specific cases)	sensitive
200919	Orange juice, not frozen, of a Brix value exceeding 20, unfermented	75,459	746,787	822,653	20% in quota, 33.6% (+ 20.6 €/100 kg for some lines) out quota	sensitive
21099	Meat and edible offal of poultry of heading 0105, in brine, dried or smoked; edible flours and meals thereof	40,560	385,485	622,892	Differentiated quotas	excluded or sensitive
20230	Bovine meat cuts (except high-qual. beef cuts), boneless, processed, frozen, descr in gen. note 15 of the HTS	288,187	596,771	513,045	20% in quota, 12.8% + 221.1 €/100kg, (or 303.4 €/100kg) out quota	excluded

(continued)

Table 3.13. (continued) **Largest agricultural trade flows at the HS6 level from MERCOSUR countries to EU28 and EU tariff** .
Only trade flows greater than US$ 1 million on average in 2000-2011 are displayed, in decreasing order.

Code HS6 (HS 2002)	Description	Export value (US$ 1000) 2000	2007	2011	EU tariff in 2011	GSP status
170111	Cane sugar, raw, in solid form, w/o added flavoring or coloring, subject to gen. note 15 of the HTS	87,267	190,541	979,371	98 €/1000kg + 1.372 €/10 000kg/polar in quota, 33.9 €/100kg out quota	excluded
20714	Cuts and offal of chickens, frozen	172,450	632,620	390,371	Differentiated quotas	excluded or sensitive
30613	Shrimps and prawns, cooked in shell or uncooked, dried, salted or in brine, frozen	275,583	400,005	465,701	12% to 20% depending on species, GSP+ applied to Paraguay	sensitive
160232	Prepared or preserved meat or meat offal of chickens, nes	23,921	353,940	492,537	Differentiated quotas	excluded
150710	Crude soybean oil, whether or not degummed	2,099	325,918	514,947	6.4% (food) or 3.2% (non food)	sensitive
200911	Orange juice, frozen, unfermented and not containing added spirit	515,541	170,758	125,778	20% or 15.2% in quota, 33.6% (+ 20.6 €/100 kg for some lines) out quota	sensitive
230800	Acorns and horse-chestnuts, of a kind used in animal feeding, not elsewhere specified or included	77,477	216,929	221,735	0% (agrum pulp), 1.6% other except grape (0% to 1.62 €/kg alcool)	sensitive

(continued)

Table 3.13. (continued) Largest agricultural trade flows at the HS6 level from MERCOSUR countries to EU28 and EU tariff . Only trade flows greater than US$ 1 million on average in 2000-2011 are displayed, in decreasing order.

Code HS6 (HS 2002)	Description	Export value (US$ 1000)			EU tariff in 2011	GSP status
		2000	2007	2011		
160231	Prepared or preserved meat or meat offal of turkeys, nes	48,516	253,014	271,959	Differentiated quotas	excluded
80550	Lemons, fresh or dried	NA	167,952	202,401	lemon 6.4% (if price greater than 55.8 €/100 kg), lime 12.8%	sensitive
220710	Undenatured ethyl alcohol of 80 percent vol. alcohol or higher, for beverage purposes	7,364	410,862	123,815	19.2 €/hl (undenatured; NB 10.2 €/hl if denatured 220720)	excluded
120220	Peanuts (ground-nuts), not roasted or cooked, shelled, subject to gen note 15 of the HTS	83,384	151,072	248,701	0	sensitive
151211	Sunflower-seed or safflower oil, crude, and their fractions, whether or not refined, not chemically modified	50,947	171,975	250,451	6.4% (food) or 3.2% (non food)	sensitive
200811	Peanut butter and paste, subject to gen. note 15 of the HTS	13,583	157,786	271,940	11.2% to 12.8%	sensitive
200912	Orange juice, not frozen, Brix value not exceed 20, not concentrate & not made from juice degree concentration of 1.5 or >, unfermented	NA	89,392	193,720	0.122	sensitive
30420	Frozen fish fillets, skinned, in blocks weighing over 4.5 kg, to be minced, ground or cut into pieces of uniform weight and dimension	61,775	186,311	175,276	Differentiated tariff per fish species	sensitive
230250	Bran, sharps (middlings) and other residues, derived from the sifting, milling or other working of leguminous plants	11,081	169,006	231,784	0.051	sensitive

(continued)

Table 3.13. (continued) Largest agricultural trade flows at the HS6 level from MERCOSUR countries to EU28 and EU tariff[a]. Only trade flows greater than US$ 1 million on average in 2000-2011 are displayed, in decreasing order.

Code HS6 (HS 2002)	Description	Export value (US$ 1000)			EU tariff in 2011	GSP status
		2000	2007	2011		
150790	Pharmaceutical grade soybean oil meeting FDA requirements for use in intravenous fat emulsions, valued over $5 per kg	1,352	369,225	33,601	9.6% (food) or 5.1% (non food)	sensitive
80610	Grapes, fresh, if entered during the period February 15 through March 31, inclusive	27,935	178,934	148,957	14.1% or 17.6% or 0%	sensitive
220421	Effervescent grape wine, in containers holding 2 liters or less	53,889	129,921	155,477	Differentiated by type of wine	sensitive

a
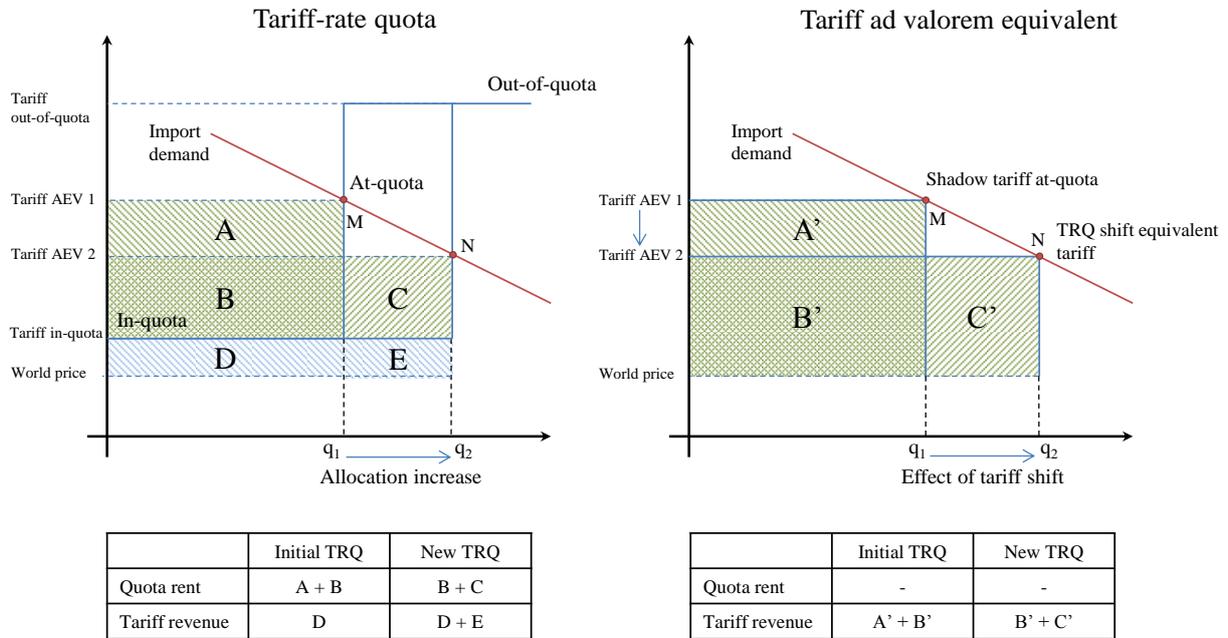
Figure 3.6. Price-quantity (P-Q) graph accounting for tariff revenue and quota rents in case of imports under quota ((at-quota, left-hand side) and import under ad valorem equivalent tariff (right-hand side). The graphs show how tariff revenue and quota rent are modified when implementing two equivalent shocks to move from imported quantity q_1 to q_2, through a change in quota allocation (left) or a change in equivalent tariff (right). If the quota rent is allocated to the importing region, and the TRQ regime is at-quota, the variation is the same for the two representations.

CHAPTER 4

MODELLING LAND USE CHANGES IN A GLOBAL CGE: ASSESSING THE EU BIOFUEL MANDATES WITH THE MIRAGE-BIOF MODEL

The potential positive environmental impacts of first-generation biofuels is currently under intense scrutiny. Indeed, the debate on indirect land use change (ILUC), which was exacerbated by Searchinger et al. (2008) and Fargione et al. (2008), has seriously questioned the principle that biofuel policies would lead to greenhouse gas (GHG) savings as long as land use diversion effects are taken into account. The cultivation of biofuel crops would lead to displacement of production historically dedicated to food and feed needs in other regions and would drive massive natural land conversion to cropland. This relocation of production under intense agricultural management could release significant new volumes of carbon into the atmosphere as well as negate the carbon benefits associated with biofuel programs. This issue has become a more significant concern following policymakers' decision to consider calculations of these effects in the United States (US) or the European Union (EU) legislation as a complement to the reduction of the usual life-cycle analysis (LCA) of different biofuels pathways.

As a consequence, a large number of studies were commissioned to investigate the possible range of ILUC "coefficients". The first integrated assessments were realised by US research teams for the California Air Resource Board (CARB, 2009) and the US Environmental Protection Agency (EPA, 2010) using a computable general equilibrium (CGE) approach (GTAP model, Purdue University) and an integrated framework centred on two partial equilibrium (PE) models (FASOM and CARD-FAPRI), respectively. On the EU side, different methodologies were also applied, the results of most having been released in the first semester of 2010 (PE with AGLINK-COSIMO, Organisation for Economic Co-operation and Development, OECD) and CGE with MIRAGE-BioF (International Food Policy Research Institute, IFPRI) and additional work focusing on feedstock-specific results

and uncertainties issues have been conducted in 2011 (Laborde, 2011) using the MIRAGE-BioF model.

This chapter describes how land use is represented in the MIRAGE-BioF CGE model. Providing details about the data and methodology used, we describe why such models are relevant for understanding the implications of biofuel policies and, among other aspects, land use competition and environmental impacts related to land use change.[1] We illustrate our setting with simulations of EU biofuel policy. As the future composition of the EU biofuels mandate in terms of fuel type and feedstock use may still evolve, comparing different scenarios is of particular interest. Until recently, biodiesel has been used as the main fossil fuel substitute (80% in 2009), seeing as the ethanol market is still underdeveloped. We show that in the case of the EU, this orientation could be more costly in terms of land use change and associated carbon emissions.[2]

Using a CGE model to study such issues, however, presents significant challenges since it requires dealing with some inherent limitations of the approach. First, CGE models are, in general, highly aggregated in sectors and regions, whereas tracking land use change requires a good geographical resolution and disaggregation of crops and technological pathways to correctly represent the substitution effects. Second, as change in these models is driven by relative prices and calibration based on value shares, physical units are not represented traditionally and results, which are expressed in percentage change on volume index, can be inconsistent when evaluating detailed sectors with homogenous goods. In this analysis, physical linkages (crushing ratio, yield per hectare, energy content of one liter of biodiesel versus ethanol) and appropriate rates of substitution through price levels are precisely reproduced. Third, the key production factor, land, is traditionally treated as any other factor without paying particular attention to the specific nature of this input or to its supply and substitution elasticities. However, supply and demand elasticities used in CGE models for agricultural sectors are often significantly larger compared with their PE equivalent, even when focused on the long term.[3] Therefore, price fluctuations are more limited, whereas in the case of biofuels and their land use effects, the distribution of effects between increased acreage, reduced demand, and yield intensification is strongly determined by the calibration assumptions on price elasticities.

The structure of the chapter falls as follows. In Section 4.1, we present the modified global input-output database used for our CGE, which significantly corrects usual flaws and lack of details found in commonly used databases in agricultural CGEs. Section 4.2 presents the modelling structure

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[1]   It is worth noting that using a global model where all markets are cleared simultaneously does not allow computing the "indirect land use" effect of a policy versus a "direct" effect. If this discrimination can make sense in a causal analysis or in a policy debate, it is purely artificial in a general equilibrium perspective: the modelling approach used in this chapter determines the net land use changes of the policy studied.

[2]   However, it is important to keep in mind that this chapter is not aimed to provide an exhaustive emission analysis of the biofuel mandate. We focus on land use emissions and its uncertainties and do not look at the emissions related to the production of crops (energy, fertilisers) or to the processing of biofuels.

[3]   Difference in short-term elasticities can also be attributable to the fact that significant drivers of price fluctuations are not explicitly represented (see Wright, 2011b for an overview or Hochman et al., 2011 for the role of inventories).

and the underlying behavioural assumptions. In Section B.1.3, we stress some interesting qualitative learning from a central scenario and discuss the role of uncertainty on some parameters. In Section 4.4, we describe some important specifications that play a critical role in the results. We conclude with Section 4.5 concerning the potential consequences of different EU policy options.

4.1   AN INNOVATIVE DATABASE FOR A CONSISTENT REPRESENTATION OF AGRICULTURAL SECTORS IN CGE

The CGE models are highly dependent on a high quantity of inputs, and very few available datasets currently address this issue. As far as we know, most applied CGE approaches at the global level rely on the database provided by the Global Trade Analysis Project Center (Narayanan and Walmsley, 2008). Assessments of biofuel policies are no exception (Hertel et al., 2010a, Banse et al., 2008, Kretschmer et al., 2008), even though modellers have developed various techniques to cope with the absence of the biofuel sectors in the commercial version of the database (see Kretschmer and Peterson, 2010, , for an overview of the different approaches used). In this section, we explain why the usual work on data, consisting of creating new sectors by splitting aggregates through value shares, can lead to flawed analysis. We present our approach to reconstruct more reliable data for consistent modelling behaviours.

Our initial source of data has been the latest available GTAP database, version 7, which describes global economic activity for the 2004 reference year in an aggregation of 113 regions and 57 sectors (Narayanan and Walmsley, 2008). Due to the multiplicity of feedstocks involved in the biofuel production for the EU markets and their different technological pathways, we decided to significantly disaggregate some Global Trade Analysis Project (GTAP) sectors, starting with the oilseed production and processing sectors. A total of 23 new sectors were carved out of the GTAP sector aggregates – the liquid biofuel sectors (an ethanol sector with four feedstock specific sectors and a biodiesel sector), major feedstock sectors (maize, rapeseed, soybeans, sunflower, palm fruit, and the related oils), coproducts and by-products of distilling and crushing activities, the fertiliser sector, and the transport fuels sector. This process did not consist of a simple disaggregation of parent sectors but instead required a full rescaling of agricultural production data according to statistics from the Food and Agriculture Organization of the United Nations (FAO) on quantity and prices, harmonisation of prices for substitutable homogenous goods such as biofuels or vegetable oils, and bottom-up reconstruction of production costs for biofuel sectors and crushing sectors for oilseeds. More details on the methodology and the full list of sectors are provided in appendices at the end of this chapter.

Finally, we paid much attention to building a consistent dataset in value and in volume – thanks to a reliable price matrix. Indeed, the role of initial prices and price distortions is of crucial importance in a modelling framework using constant elasticity of substitution (CES) and constant elasticity of transformation (CET) functions. CGE models usually work on small magnitude shocks

and traditional calibration adopts a normalisation of all prices in the model. Physical quantities are therefore not explicitly considered in the analysis. This approach generally makes sense when the goods represented are imperfect substitutes and/or the level of product aggregation is large. In particular, the impact of trade policies and fiscal policies can accommodate such approximations. However, agricultural and energy policies are different because the goods considered are more homogenous. Even when some products can be differentiated (soft versus durum wheat or gasoline versus diesel), applying CES functions to such goods assumes that the substitution occurs with a technical marginal substitution (TMS) rate between two goods A and B equal to:

$$TMS_{AB} = \frac{dq_B}{dq_A} = -\frac{\partial Q/\partial q_A}{\partial Q/\partial q_B} = -\frac{p_A}{p_B} \qquad (4.1)$$

where q stands for quantities, p stands for prices relative to two substitutable goods A and B, and Q is the CES aggregated good of q_A and q_B. In a case of high substitution elasticity, prices vary little around their initial level in the CES; therefore the TMS rate remains almost the same and its value equals the initial price ratio. In the case of a CGE calibrated with normalised prices, the substitution for a substitutable good is consequently operated on the basis of US$1 of good A for US$1 of good B. When comparing the change in consumption with data in physical units, the implicit conversion ratio is therefore determined by the relative prices. In the case of a homogenous good, the implicit price ratio differing from one can lead to serious misinterpretation of results (e.g., one ton of palm oil can replace only half a ton of sunflower oil, one ton of imported ethanol can replace 1.5 tons of domestic ethanol, etc.). This is the reason why, considering the critical role of physical linkages and substitutions in this analysis (from the crop side to the energy content of different fuels and meals), we develop a world price matrix for homogenous commodities in order to be consistent with physical quantities and international price distortions (transportation costs, tariffs, and export taxes or subsidies).

We look at three different examples to illustrate the importance of our treatment: changes in commodity prices and relative prices between the GTAP7 and our dataset, changes in cost structure of vegetal oils, and the cost structure of new sectors such as ethanol in the European Union. Table 4.1 shows the prices in our dataset for two types of commodities: Wheat and vegetable oils. In the first case, we can see that although production data are consistently adjusted in the original GTAP database for OECD countries, significant distortions appear for some others (e.g., China and US). In the second case, much wider discrepancies are present, probably resulting from inaccurate information in the sources provided to GTAP and various aggregation problems when building the database. In addition, Table 4.2 displays the evolution of the cost structure for producing vegetable oils from oilseeds for key countries. As it appears, our adjustment significantly increases the link between oilseed prices and vegetable oil prices, a key mechanism for the investigation at stake. Figure 4.1 provides an example of the ethanol supply chain implemented in the data based on a unique ethanol price per liter in the European market.

Several other databases have been utilised with our core input-output tables to specifically

Table 4.1. Summary table with different alternative scenarios on mandate and on model specifications.

	Argentina	Brazil	China	EU27	USA
Initial GTAP7 database					
(production value/FAO production 2004)					
Wheat	118	266	103	144	139
Vegetable oil	1231	1818	517	2826	1589
MIRAGE-BioF dataset[a]					
Wheat	80	137	118	144	110
Palm Oil	643	643	571	673	719
Rapeseed Oil	808	678	773	676	569
Soybean Oil	512	589	675	616	519
Sunflower Oil	582	669	594	700	590

[a] Price differences reflect transportation costs, export restrictions, tariffs, etc.
Source: MIRAGE-BioF database, GTAP7.

Table 4.2. Cost share in the processing of oilseeds in the vegetable oil sector.

	Argentina	Brazil	China	EU27	USA
Initial GTAP7 database					
Oilseeds	61.7%	51.3%	10.7%	13.0%	36.7%
MIRAGE-BioF dataset					
Rapeseed	46.3%	63.5%	77.3%	78.9%	73.0%
Soybeans	75.3%	75.2%	92.1%	81.5%	78.4%
Sunflower	65.5%	70.4%	93.9%	87.5%	79.7%

Source: MIRAGE-BioF database, GTAP7.

convert changes in endowment allocation and input use into physical units. For land use, we relied on FAO for national occupation and on the M3 database (Monfreda et al., 2008, Lee et al., 2009, see) for land distribution between different agroclimatic regions. We relied on data from IIASA (Fischer et al., 2002) for land available for crops in rainfed conditions and on IPCC agriculture, forestry and other land use (AFOLU) guidelines (Tier 1) for computations of GHG emissions contained in biomass and in soil. Carbon stock coefficients used for the analysis by agro-ecological zone (AEZ) and regions (i.e., Brazil, China, and the EU among others) is provided in Appendix 4.C. More details on the incorporation of these databases into the model are provided in (Valin et al., 2010a).
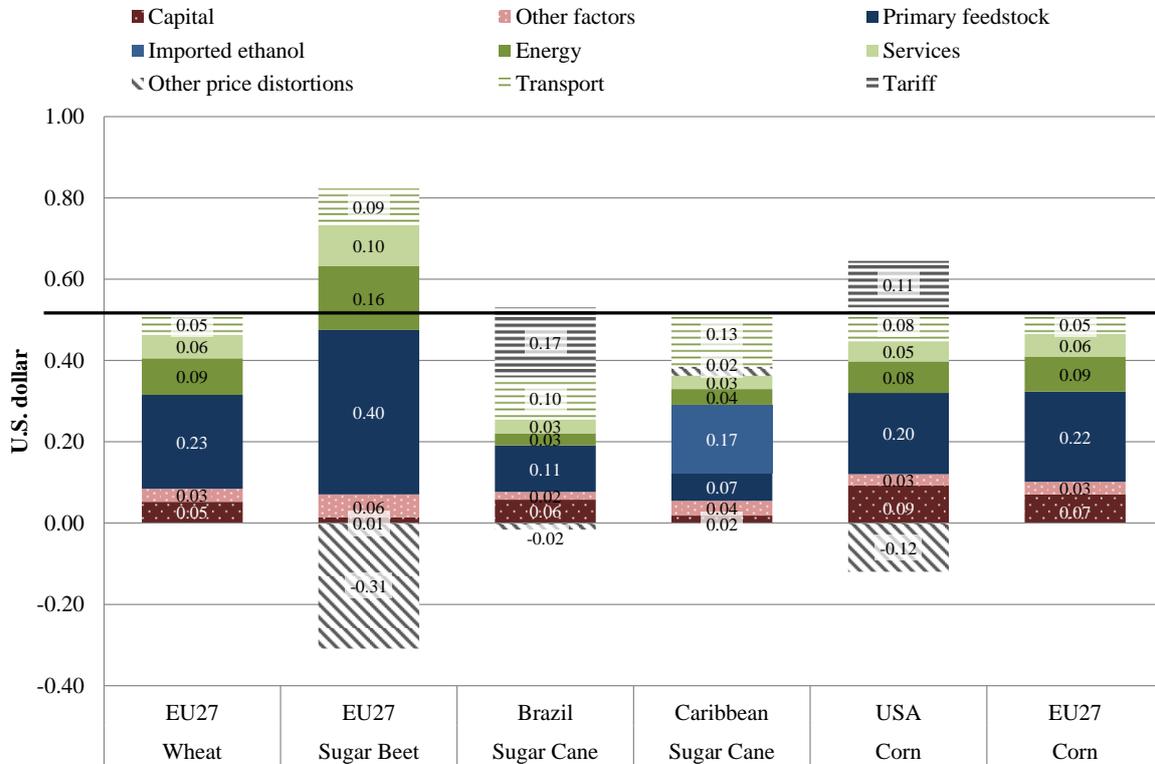
Figure 4.1. Price decomposition of one liter of ethanol sold in the European market per country of origin and process in the model reference year (2008), US$. To avoid the distortions caused in the cost structure by high agricultural prices in 2008, the database is calibrated on a 2006–2007 price average for input and output prices. The ethanol market price is set to 0.514 US cents per liter at EU market price, before application of fuel and value added taxes (horizontal black line). Plain colours represent pure processing costs (key feedstocks indicated with the darkest colours), whereas horizontal stripes area indicate market access costs. As required in a CGE framework, capital payments incorporate both interests paid, capital depreciation cost but also net profits of firms. Additional price distortions include explicit public subsidy: Blender tax credit in the US or in the case of sugar beet ethanol, a shadow subsidy that has been calibrated to ensure the profitability of the technology based on existing regulated sugar beet price in the EU.

4.2   MIRAGE-BioF: A MODEL DEDICATED TO LAND USE AND BIOENERGY POLICY ANALYSIS

In order to evaluate the impact of public policies regarding first-generation biofuels, we developed an extended version of the global CGE MIRAGE, nicknamed MIRAGE-BioF, by improving the standard version in several directions. This section gives a quick overview of the different features, emphasizing the land market description.[4]

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[4]   More details on this model is also provided in (Bouët et al., 2010) and in other studies (Al-Riffai et al., 2010b,a).

4.2.1 General features

The core structure of the MIRAGE model follows the one of standard multi-country, multi-sector, recursive dynamic CGEs. Each country produces a certain quantity of goods through a nesting of production functions: In MIRAGE, intermediate inputs and value added are aggregated through Leontieff technology, each being a CES composite of different aggregates of inputs and factors, respectively. Goods are consumed by final consumers (public and private agent) and firms or are exported to foreign markets. The final consumption demand system is represented through a linear expenditure system with constant elasticity of substitution (LES-CES) that is recalibrated each year along the baseline to reproduce consistent income and price elasticities. Imported goods are differentiated from domestic goods following the Armington assumption, which allows us to distinguish different levels of market integration. Real exchange rates between regions are endogenously adjusted to maintain current account as a share of the world gross domestic product (GDP). The model is recursively dynamic, and total factor productivity is adjusted along the baseline to follow GDP projections. Total factor productivity in each agricultural sector is adjusted to match the crop yield projection of the AGLINK-COSIMO model for each region (OECD, 2010).

In order to properly address land use change considerations, special attention has been paid to the representation of land with substitution and expansion possibilities for land uses detailed in Section 4.2.3. Moreover, the model relies on many features specifically introduced to adequately represent the effects of biofuel policies. In particular, it includes a detailed description of the insertion of biofuel in the consumption chain, a modelling of binding incorporation mandates, and a representation of coproducts for the bioethanol sector by type of pathway (wheat, maize, sugar beet) and for the four oilseed processing sectors that have been explicitly introduced (rapeseed, soybean, sunflower, and palm fruit). Particular care has been paid in the final and intermediary consumption nesting to the substitution possibilities of similar products on the one side (vegetable oils, oilseed meals, ethanol feedstocks) and to the rigidity relative to certain inputs in the production chain (vegetable oil to produce biodiesel, sugar raw products to produce refined sugar, etc.). Although quite obvious in the reasoning from a bottom- up approach, this focus on the input structure, which requires multi-level CES nesting structures for input and is specific to many sectors, did not seem to be used in many works based on generic CGE applications, relying more instead on standardised sector descriptions.

4.2.2 Agricultural production function

A first major improvement of the model was the refinement of agricultural production functions. We implemented a more precise disaggregation of factors, isolating a bundle of land and chemical fertiliser in the tree structure of factors to better control for yield response to shock in fertiliser prices and to increase in demand. This allows for precise tracking of the effect of fertiliser input, other factor inputs, and land expansion. Elasticities of fertiliser use with respect to price change are derived from the IFPRI IMPACT model (Rosegrant et al., 2008). Elasticity of other inputs constitutes the complement that matches a final endogenous yield elasticity target. There is significant controversy surrounding

the question of whether or not such endogenous yield should be represented. Some authors argue that such endogenous response is not established, whereas others find significant value in econometric testing for an endogenous yield response (CARB, 2011). Following the recommendation of the CARB expert group on elasticities, we assumed an average magnitude of 0.2 for such elasticities. EU27 is closer to 0.15, US to 0.2, and developing countries to 0.3 to take into account these regions' larger intensification margins as well as double-cropping possibilities.

4.2.3   LAND USE SUBSTITUTION AND EXPANSION

Among other factors, land was subject to a specific decomposition. In most CGE models, land markets are represented through CET functions. This can imply high substitution of land use between certain categories of crops depending on the value of elasticity chosen. We used a nested design to replicate substitution between cereals and oilseeds, as well as (to a lesser extent) other agricultural uses. Therefore, in our nested structure, substitutable crops are considered in a separate bundle from other categories of crops that are less easily substitutable (rice, vegetable and fruits, plantations). The land rent values are represented in the model through a volume of productive land equivalents based on several databases, including the GTAP-AEZ land database and the FAO ProdSTAT. Indeed, we did not follow the complete land rent allocation proposed in the GTAP framework because substituting land rent on a value basis corresponding to areas with completely different land rent yield created many conceptual problems. Therefore, our CET functions operate on land rent values that have similar yields (in dollar per hectare) within an AEZ, which ensures that our substitution occurs at a 1:1 technical substitution ratio and that overall land area is preserved when total land rent is fixed.[5] The CET nesting approach, already used in some previous works (OECD, 2001, Banse et al., 2008) appeared as an important prerequisite to represent flexible-enough production functions and obtain a good fit in the calibration procedure on price elasticities. Several authors pointed out the limitations of a single CET for land substitutions (Babcock and Carriquiry, 2010, CARB, 2011). The nesting used in MIRAGE-BioF relies on several levels, as illustrated in Figure 4.2. Crops considered as highly substitutable are wheat, maize, rapeseed, soybeans and sunflower. Other crops are located at the lower level with less possible substitution. In order to represent pressure from uses other than cropland, the nesting structure can be optionally extended to include pasture land and managed forest land with additional levels ("pasture and forest competition" closure; see below the discussion on cropland expansion setting).

In addition to the choice of this nesting structure, two specificities on the substitution characterise the model. First, each nesting structure is independent at the agro-ecological level in the different regions, which allows for more consistent description of substitution patterns between crops that follow the same agro-climatic cultivation conditions. By default, perfect substitution is assumed

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[5]   In order to obtain similar yield within AEZs, we rebuilt land rent values on the basis of GTAP production data for land rent at the aggregated level, and production distribution across AEZs according to the source M3 database used by GTAP, and finally mapping the aggregated harvested area with FAO data.
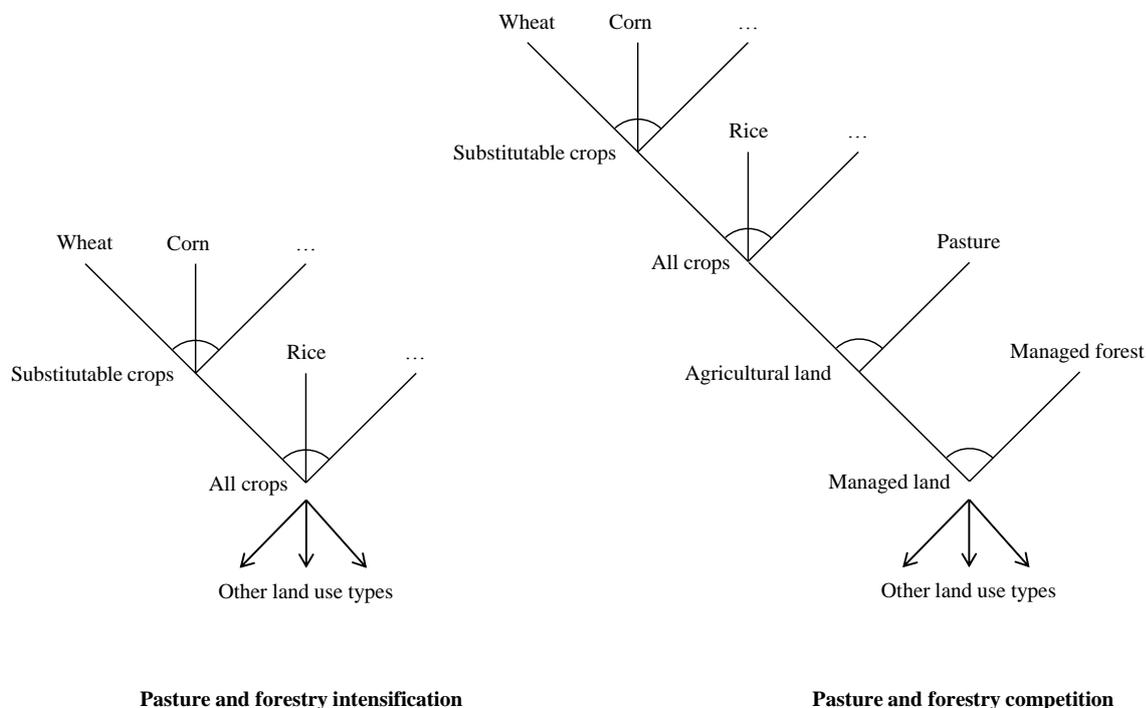
Figure 4.2. Nesting of CET functions and expansion patterns in the two representations of land use substitution and expansion. "Pasture and forestry intensification", composed of two nested CET functions, is the default representation and assumes fixed share of expansion into pasture, managed forest, and other land-use types. "Pasture and forestry competition" is composed of four nested CET and expansion into pasture and managed forest is endogenously determined depending on demand for cattle and wood.

within each region for location of production across AEZs. Second, transformation elasticities are endogenously calibrated to fit at the regional level land supply elasticities from the FAPRI elasticity database, which ensures consistency with aggregated regional observation on agricultural system responses. In order to illustrate the advantages of this approach, we compared the different fits to the FAPRI elasticity dataset with three different designs (Table 4.3). The first design (1×1) corresponds to the assumptions followed by models such as GTAP-BIO, where a single nest is used and the same elasticity is applied to all regions. Calibrating the system with region-specific elasticities ($n \times 1$) decreases the relative standard errors (RSEs) from 1.12 to 0.75. Adding a second nest ($n \times 2$) improves the fit even more, mainly within crops, giving a final RSE of 0.53. Although a two-tier structure is not flexible enough for a perfect fit of all the heterogeneity of the FAPRI dataset, our final calibration allowed us to obtain a land supply elasticity response close to FAPRI figures, as displayed in Figure 4.3.

A second innovation introduced in the model for land use change is a mechanism that allows for land use expansion into different land covers at the level of AEZ. In most standard agricultural CGE

Table 4.3. Calibration results for different designs of CET nesting across crops and regions.

Name (Region × nest level)	Description	Overall RSE on sample	Average RSE per region across crops	Average RSE per crop across regions
1 × 1	One value for all region, one level nest	1.12	1.02	0.72
n × 1	Different values for regions, one level nest	0.75	0.67	0.57
n × 2	Different values for regions, two levels nest	0.53	0.55	0.56

Note: Relative standard error (RSE) are obtained by dividing standard error, measured as the difference between FAPRI elasticities and the CGE calibrated values, by the average FAPRI elasticity. For the computation of the average and the standard deviation over crops and regions, all values are weighted acreage. Crops with FAPRI values available included in the estimation are: Wheat, Maize, Soybeans, Rapeseed, Sunflower, OtherOilseeds and OtherCrops.
Source: MIRAGE-BioF simulations.

approaches, cropland, pasture, and forest are substituted through a CET function on a value basis, which introduces many problems relative to the mapping between physical land units and land rent information. Additionally, the role of non-managed land is usually underestimated in the pure CET approach (EPA, 2010) and generally leads to an overestimation of deforestation when compared with past observations (Babcock and Carriquiry, 2010). By default, we will represent cropland expansion into new land such as pasture, forests, savannah, or other natural cultivable land through a specific elasticity calibrated based on the literature (OECD, 2001, Barr et al., 2011, Roberts and Schlenker, 2010). The value of this elasticity decreases linearly depending on the distance to the limit of cultivable land based on the IIASA Global Agro-Ecological Zones (GAEZ) database.[6] It is important to recognise that such parameters are quite uncertain and that values from the literature vary and are not available for many regions. That is why we conduct a sensitivity analysis on this parameter in the next subsection. The role of the substitution and expansion design is significant for the allocation behaviour and the associated results. We compare the differences in behaviours for different settings of land-use expansion in Table 4.4. The setting A corresponds to the most standard specification found in the literature (Hertel et al., 2010a). We illustrate how expansion varies in distribution along a series of specification improvements: Adding a second level in the nesting to take into account the fact that cropland substitutes more easily with pasture than with forest (B); a correction on land value to take into account the fact that all grassland areas are not under effective use as grazed land (C); an expansion elasticity to incorporate possibility of expansion (D, corresponding to the "competition pasture and forest" closure mentioned above); a setting with cropland expansion fully allocated through historical expansion coefficients per region (E, "pasture and forest intensification" closure). By default, all the results presented in this chapter will be

[6]   Elasticity reaches 0 when total cultivable within an AEZ is used.
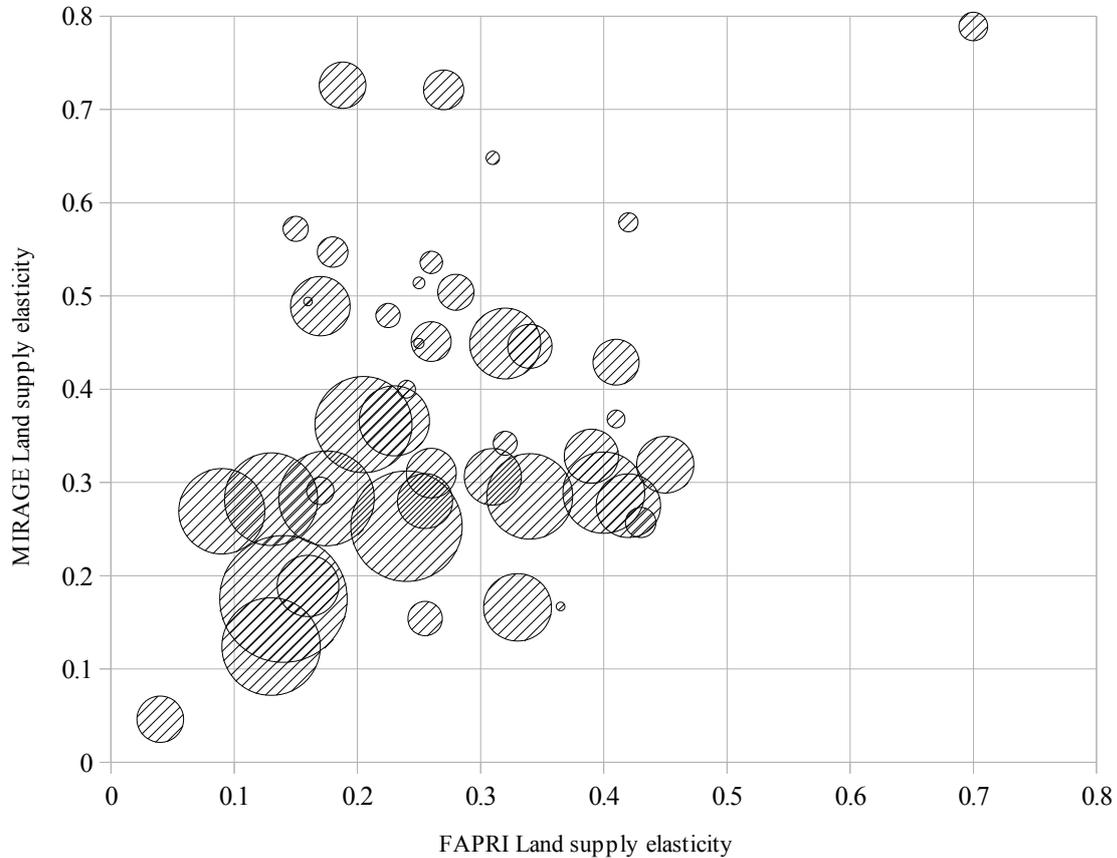
Figure 4.3. Calibrated land supply elasticities for crops and regions in the model compared with FAPRI supply elasticities. Crops represented are wheat, maize, soybeans, rapeseed, sunflower, and other oilseeds for regions where FAPRI elasticities were available. Circle areas are proportional to the harvested area for the corresponding crop × region couple.

following the E specification. With this design, expansion of cropland is not restricted by an increase in forestry or animal products; production of forest and pasture is possible without retroaction on cropland. Level of expansion into pasture, forest, or other land cover is therefore determined by historical share and has the advantage of full transparency and consistency with past observations (see distribution on Figure 4.4). This assumption is convenient, allowing one to precisely track the expansion of cropland independently from what occurs in a non-crop system and to accurately measure effects of coproducts. A coefficient of marginal productivity is also applied to this new land in order to reflect the fact that expansion can occur to land of different quality from the land already being used. In Subsection 4.4.3, we will change this assumption and see what happens if pressure from cattle and forest activities is added in the competition for land (setting D).

In addition to the two previous specificities, a last important particularity of MIRAGE-BioF is its consistent description of land use change along its recursive dynamic framework. Our setting allows

Table 4.4. Distribution of world cropland expansion along the 2008–2020 baseline according to different modelling specifications.

	A	B	C	D	E
Total grassland	**−66%**	**−79%**	**−68%**	**−61%**	**−60%**
Managed pasture	−66%	−79%	−68%	−56%	−13%
Unused grassland and savannah	0%	0%	0%	−6%	−47%
Total forests	**−34%**	**−21%**	**−32%**	**−27%**	**−19%**
Managed forest	−34%	−21%	−32%	−25%	−5%
Unused primary or unaccessed forest	0%	0%	0%	−2%	−14%
Other natural land	**0%**	**0%**	**0%**	**−12%**	**−21%**

Source: MIRAGE-BioF simulations.
Note: Modeling specifications:
(A) Single CET Cropland-Pasture-Forest, without pasture rent correction;
(B) Two CET Cropland-Pasture and Agricultural Land/Forest, without pasture rent correction;
(C) Two CET Cropland-Pasture and Agricultural Land/Forest and pasture rent correction;
(D) Two CET Cropland-Pasture and Agricultural Land/Forest, pasture rent correction and expansion for other land with historical coefficient;
(E) No CET for Cropland-Pasture-Forest, expansion of cropland with historical coefficients for all land covers.

us to track non-market-driven land use change – from urbanisation, infrastructure development, land management measures and demographic pressure on forest – along the baseline affecting cropland area (or agricultural land area in the case of "pasture and forest competition" closure). In addition to the endogenous price-driven evolution, the model includes an exogenous trajectory based on the 1995–2005 average trends computed from FAO ResourceSTAT database. However, allocation within agricultural land remains driven by endogenous relative price variation. As a result, our baseline can reproduce historical trends, but non-market drivers do not play any role in the shock assessment; they simply change the initial land allocation before the shock along the baseline.

4.3 Land-use change from three potential scenarios for EU biofuel policies

4.3.1 Description of baseline and scenarios

We illustrate the effect of the previous setting and calibration with an evaluation of the impact of different biofuel policy scenarios in the EU. These three scenarios are implemented on a baseline starting in 2004 and extend through 2020, which is the final year for the EU directive target of incorporation of renewable energy in European road transportation fuel. The levels of sectoral and geographical disaggregation used in the simulations are displayed in Appendix 4.A.
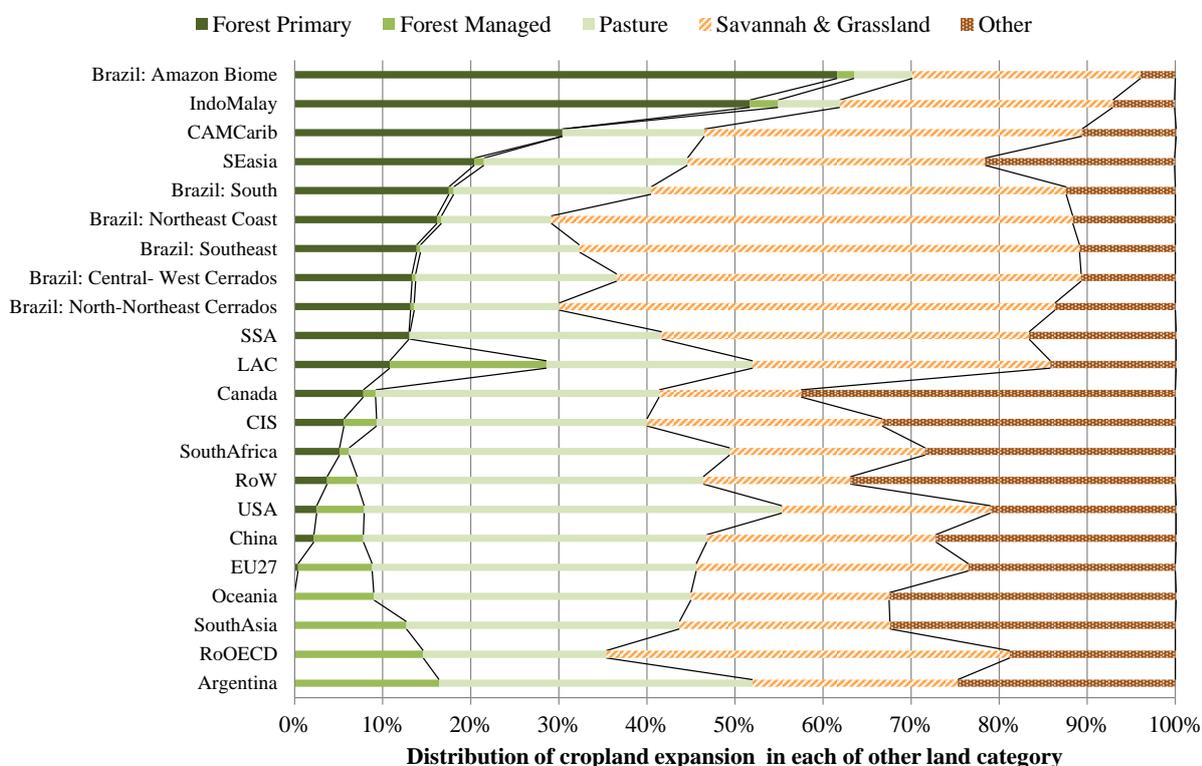
Figure 4.4. Distribution of cropland expansion across land-use type categories for regions in the model. Brazil has been decomposed among six regions corresponding to different AEZ explicitly represented in the model in order to better track expansion effect of sugarcane. To map land use categories, some changes are made to raw Winrock data from US EPA: Forest category is split within primary and managed forest, grassland category is split between pasture and natural grassland, wetland and barren are merged with other land and mixed land is distributed between all land-use categories. Note that when cropland substitution is measured endogenously with forest managed and pasture, expansion shares are only used in the model for primary forests, savannah, and grassland and other land, after a rescaling to 100%.

In our baseline, we consider a global adoption of biofuel targets across major world economies, according to existing programs and announced future commitments from major countries. The US program is continued under the Renewable Fuel Standard, requiring incorporation of 36 billion gallons in 2022, with no more than 15 billion gallons from maize ethanol, at least 1 billion gallons of biodiesel, and some imports of sugar cane, which is considered as an advanced biofuel, to compensate for the slow emergence of second-generation fuels. However, we consider that trade policies with respect to ethanol remain at status quo, and consequently, the share of sugar cane ethanol in US consumption remains minor. Japan and Korea develop biofuel programs that range up to 5% of their consumption of transportation fuel. Brazil follows its ethanol program with a share of 35% of incorporation.[7] ASEAN countries and Argentina are also supposed to reach a 5% mandate by

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[7] The Brazilian policy on ethanol does not involve a so high mandatory incorporation. Thanks to a large and growing fleet of flex fuel cars, the Brazilian consumption is not driven any by policies longer but by the relative prices

2020, which seems in line with recent observations of the rapidly growing biofuel industries in these regions. We finally consider a similar target for China, although recent developments in Chinese policy suggest some deviation from the initial objectives if high food prices are maintained.[8] Some countries implement these biofuel programs through incorporation mandates, while other countries adapt their energy consumption according to oil price evolution. We suppose a linear increase in oil prices along the baseline from the base year 2004 (US$40) to the projected long-term price forecasts from the International Energy Agency (IEA) with US$110 by 2020 for a business-as-usual scenario (IEA, 2010).

In the EU, the reference case is supposed to be a moderate biofuel policy with a stabilisation of incorporation at 2008 levels, which represents 3.3% of total fuel consumption. Generally, trade policies are supposed unchanged. The only notable intervention is the end of biodiesel imports from the US, for which we consider that EU countervailing and antidumping measures, represented as a prohibitive tariff, are maintained after their implementation in 2009.

Three scenarios are modeled with respect to the baseline:

(1) Our main central scenario on EU biofuel policies is based on the current 27 National Renewable Energy Action Plans (NREAPs, called therein "NAP") implemented as a transposition of the EU directive in the different Member States (see Laborde, 2011). At the aggregated EU level, it represents an amount of 27.5 Mtoe of biofuel incorporated in 2020, with a share of 72% of biodiesel and 28% of bioethanol. The additional amount of biofuel consumed in the EU, compared to the scenario shock baseline, reaches 15.2 Mtoe.

This central scenario is complemented by two other scenarios aimed at disentangling the composition effect between ethanol and biodiesel impact:

(2) A scenario of 15.2 Mtoe addition consumption of biodiesel only ("BIOD").

(3) A scenario where the same target is reached through an increase in ethanol consumption ("ETHA").

If in all scenarios the ethanol/biodiesel split is modeled as an explicit constraint, the choice of feedstocks for each biofuel is determined endogenously by the model.

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between ethanol and conventional gasoline. However, due to the role of the national oil company PETROBRAS in the fuel market, we consider that the EU policy will not displace Brazilian own consumption and that the blending rate will be stabilised by Brazilian national actors. The average blending rate of 35% used here is lower bound of UNICA recent projections about domestic consumptions (see Al-Riffai et al., 2010a, for a discussion of Brazilian policies and alternative consumption level).

[8]   We do not incorporate the Indian biofuels target of 20% blending rate by 2020 due to the uncertainty commitments and the official objective of using marginal land and new crops (Jatropha, Sweet Sorghum) not included in our model.
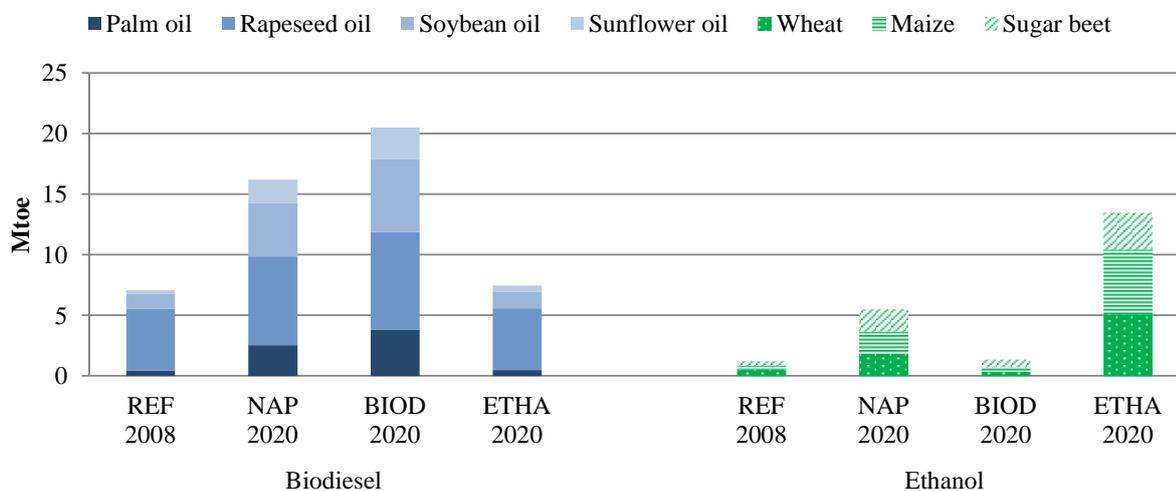
Figure 4.5. Composition of EU biofuel production according to the different feedstocks for each scenario of the mandate.

4.3.2 RESULTS

European consumption mandates the participation and increase in the development of the biofuel industry along the baseline. Ethanol and biodiesel sectors expand from an initial value of around 40 Mtoe in 2008 up to 111 Mtoe globally in 2020, which includes the EU program. In our results displayed in Table 4.5, the central scenario leads to a higher consumption of biodiesel (according to the National Renewable Energy Action Plans (NREAPs)), with 85% of biodiesel being produced domestically (even if some feedstock products are imported) and the rest being provided by Malaysia and Indonesia (1.7 Mtoe) and Argentina (1.7 Mtoe). In addition, Malaysia and Indonesia become leading exporters in the pure biodiesel scenario, with 2.5 Mtoe of exports, i.e., around 3.2 billion liters of palm oil-based biodiesel (in addition to palm oil imports). In the EU, this type of biodiesel is balanced with other feedstock use, as illustrated by Figure 4.5, which shows the production mix between crops. On the ethanol side, in spite of the EU protection level, the incorporation target relies much more on imports, representing more than half of all consumption and attributed to the low production costs of Brazilian sugar cane ethanol. Indeed, Brazil provides most of the 5 Mtoe of ethanol imported to the EU in addition to exports in the direction of other regions in the baseline. At the same time, expansion of EU domestic production is considerable to satisfy the large ethanol demand, as the sector is to grow by a factor of 10. However, in the situation of the central scenario "NAP", the contribution of Brazilian exports is reduced to 1.9 Mtoe, which then represents 3.7 billion liters (around 20% more than the record total exports of the country observed in statistics for the year 2006).

This rapid and large contribution of South American and East Asian exports to the EU program does not mean that all land use effects are to take place in these regions. Indeed, significant trade

Table 4.5. Production, consumption, and trade of biofuels in different regions (Mtoe).

	Production				Consumption				Net trade			
	2008	2020			2008	2020			2008	2020		
	REF	NAP	BIOD	ETHA	REF	NAP	BIOD	ETHA	REF	NAP	BIOD	ETHA
Biodiesel												
Argentina	0.2	1.8	2.1	0.8	0.1	0.1	0.1	0.1	0.1	1.7	2	0.7
Brazil	0.3	1.5	1.1	2.5	0.3	1.5	1.1	2.5	0	0	0	0
EU27	7.1	16.2	20.5	7.5	8.7	19.6	25.1	8.6	−1.6	−3.4	−4.6	−1.2
IndoMalay	0.3	4.8	5.6	3.5	0.2	3.1	3.1	3	0.1	1.7	2.5	0.4
USA	1.7	0.8	0.7	1.2	0.3	0.8	0.6	1.2	1.4	0	0	0
RoWorld	0.1	0.4	0.3	0.5	0.1	0.4	0.3	0.5	0	0	0	0
World	**9.6**	**25.5**	**30.3**	**16**	**9.6**	**25.5**	**30.3**	**16**	**0**	**0**	**0**	**0**
Ethanol												
Brazil	12.1	29.1	28.5	30.3	10.9	20	20.7	18.7	1.2	9.2	7.9	11.6
China	1.8	13.8	13.8	13.8	1.8	13.8	13.8	13.8	0	0	0	0
EU27	1.2	5.5	1.3	13.5	1.8	7.4	1.7	18.4	−0.6	−1.9	−0.4	−5
JPNKOR	0	0	0	0	0	6.7	6.7	6.7	0	−6.7	−6.7	−6.7
USA	14.1	33.3	33.3	33.2	14.6	34	34.2	33.6	−0.5	−0.8	−0.9	−0.4
RoWorld	1.3	4.2	4.2	4.3	1.4	4	4.1	3.9	0	0.2	0.1	0.4
World	**30.4**	**85.9**	**81.2**	**95.1**	**30.4**	**85.9**	**81.2**	**95.1**	**0**	**0**	**0**	**0**

Source: MIRAGE-BioF simulations.

Note: Changes between 2008 REF and scenarios in 2020 incorporate elements of the dynamic baseline. For instance, the large growth in production of ethanol at the world level is related to growing production and demand in non-EU regions during the baseline.
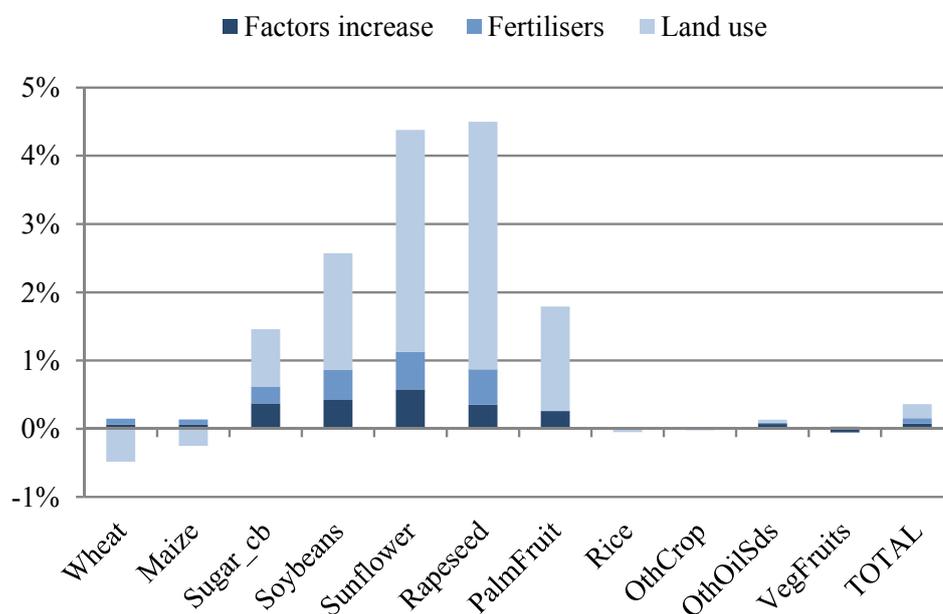
Figure 4.6. Increase in the world production in the "NAP" scenario, decomposed by source of growth: Land expansion, fertilisers increase, and other factors increase.

repercussions also occur on the feedstock side, as illustrated by Table 4.6. Producing biodiesel for the central scenario requires a significant increase in imports of all types of vegetable oils. The EU transforms all of its production of rapeseed oil and relies more on large quantities of imports of palm oil and soybean oil, which are provided by trade partners. A more ethanol-oriented policy appears less critical on the cereal trade balance in absolute; under an assumption of sufficient yield increase, exports are significantly reduced under an ethanol scenario. Interestingly enough, the exports of cereals also increase with the level of incorporation of biodiesel, as oil meals produced during the crushing can be used as feed input into the livestock sector.

Increase in worldwide production to provide for the new biofuel demand in the shocks triggers extensive and intensive margin response in the agrosystem. Yields tend to increase with a contribution from investment and other factors mobilisation, as well as from the addition of more inputs such as fertilisers and pesticides. These sources are, however, less significant in the reaction of agricultural production than land use expansion, as illustrated in Figure 4.6.

This consequently leads to a significant change in land use across regions due to requirements of crops to be either processed as biofuels or directly exported in order to be transformed elsewhere or to replace other diverted crops. We find that the fulfillment of the National Action Plans would require 2.7 million ha of converted land for growing new crops, whereas very small expansion would occur in the EU, most of the domestic effect being driven by crop substitutions on existing cropland (Table 4.7). The first source of land cover converted to cropland would be savannah and grasslands (accounting for almost half of converted land), whereas primary forest, pasture, and other mixed

Table 4.6. Production, biofuel use, and EU trade of different feedstocks (1000 tonnes).

	EU27 production				Use for biofuel				Net trade			
	2020	Diff 2020			2020	Diff 2020			2020	Diff 2020		
	REF	NAP	BIOD	ETHA	REF	NAP	BIOD	ETHA	REF	NAP	BIOD	ETHA
Wheat	150,345	−519	−1,206	1,021	2,023	6,506	−290	21,602	6,633	−2,176	2,791	−12,816
Maize	72,103	−171	−444	543	1,994	6,261	−366	22,959	−12,284	−4,146	2,589	−20,265
Sugar beet	157,013	2,818	87	4,598	14,005	23,365	−1,205	45,959	−344	−601	77	−1,507
OilPalm	25	15	26	0	633	2,191	3,711	−111	−2,998	−2,485	−4,053	107
OilRape	7,270	1,711	2,470	−330	6,062	2,336	3,279	−419	−52	−278	−380	33
OilSoyb	3,050	1,191	2,114	−333	2,155	3,407	5,532	−491	−543	−2,086	−3,267	203
OilSunf	3,072	783	1,207	−115	670	1,427	2,246	−132	−843	−628	−977	57

Source: MIRAGE-BioF simulations.

Note: "Diff" indicates the difference between the scenario value and the reference value in 2020.

Table 4.7. Area expansion under the scenarios and associated emissions.

| | *2008* | **2020** | | | | | |
| | *Area* | **Area change (1000 ha)** | | | **CO$_2$ emissions (Mt)[a]** | | |
	(Mha)	**NAP**	**BIOD**	**ETHA**	**NAP**	**BIOD**	**ETHA**
EU27							
Cropland	*93*	72	80	67	6	7	6
Pasture	*68*	−35	−39	−33			
SavnGrasslnd	*20*	−30	−33	−28			
Other	*50*	1	0	1			
Forest managed	*151*	−8	−9	−8	2	2	2
Forest primary	*7*	0	0	0	0	0	0
World							
Cropland	*1,239*	2,708	3,694	1,547	240	331	131
Pasture	*990*	−357	−490	−199			
SavnGrasslnd	*3,364*	−1,278	−1,763	−696			
Other	*3,111*	−569	−806	−279			
Forest managed	*1,150*	−127	−187	−45	34	51	11
Forest primary	*2,772*	−378	−448	−329	179	199	176
Peatland[b]		−33	−51	2	37	59	−2
TOTAL					**491**	**639**	**316**

[a] Cropland emissions correspond to soil organic carbon release for newly cultivated land. Forest emissions correspond to living above and below ground biomass removals.
[b] Peatland area is already accounted for in primary forest area. However, peatland emissions (from organic soil) come in addition to emissions from primary forest biomass losses.
Source: MIRAGE-BioF simulations.

land covers would come from secondary sources. Because of the carbon contained in the biomass and soil, this expansion leads to a large amount of carbon emissions. In addition, expansion of palm oil plantations in Southeast Asia is also particularly significant in the case of scenarios with biodiesel, which releases additional quantities of carbon from peatlands. In total, the "NAP" scenario is found to have emitted around 491 MtCO$_2$ in the atmosphere by 2020, and biodiesel contributes significantly to this number. Indeed, the "BIOD" scenario is associated with 639 MtCO$_2$, whereas the "ETHA" scenario emits two times less, with 316 MtCO$_2$.

These levels of emissions can be compared with the quantity of energy produced with the biofuel feedstocks. A good way to conduct the comparison is to decompose the overall ILUC effect, expressed as gCO$_2$/MJ of biofuel (also known as ILUC factor) in several intermediate factors, as proposed in Plevin et al. (2010). These authors introduce the notion of net displacement factor (NDF), defined as the quantity of cropland expansion divided by the area of grown feedstocks used to produce the fuel. The relation behind the decomposition follows:

Table 4.8. Decomposition of ILUC effect for the three main scenarios.

	NAP	BIOD	ETHA
Crop energy yield (GJ/ha)	47	38	80
NDF	0.2	0.22	0.19
ILUC yield (ha/TJ)	4.3	5.9	2.4
Average emission factor (tCO2/ha)	181.2	173.1	204.2
ILUC emissions 20 years (gCO2/MJ)	**38.6**	**51**	**24.8**

Source: MIRAGE-BioF simulations.

$$\text{ILUC factor (gCO}_2/\text{MJ)} = \frac{\text{NDF (ha/ha)} * \text{EF (tCO}_2/\text{ha)}}{\text{Crop yield (GJ/ha/yr)} * \text{Project period (years)}} * 1000 \quad (4.2)$$

We use a project period of 20 years, as suggested in preparatory works by the European Commission of calculation of ILUC. The ILUC factor and its decomposition are detailed in Table 4.8. The "NAP" scenario leads to an average emission of 39 gCO$_2$/MJ, which represents around 40% of the fossil fuel emissions (84 gCO$_2$/MJ). The role of biodiesel is illustrated by the results of the decomposition in the two scenarios. Using only biodiesel would raise the coefficient to 51 gCO$_2$/MJ, whereas the ethanol scenario is closer to 25 gCO$_2$/MJ.

Interestingly enough, it appears that the difference of results between ethanol and biodiesel is not significantly driven by the NDF, which is in fact of similar magnitude for the three cases (0.19 for ethanol on average, 0.20 for "NAP", and 0.22 for biodiesel). The average value of emission factors (EFs) is not more explicative, as these factors do not appear to diverge by more than a few percent. The real meaningful value is indeed the average energy yield of crops used in each of the scenarios. In the case of the ethanol scenario, the use of high-yield crops like sugar cane significantly pushes up the total yield to 80 GJ per ha. In comparison, the "BIOD" scenario cannot produce more than 38 GJ per ha with its mix of rapeseed, soybean, and palm oils. The place of biofuel crop yield in the previous formula (Equation (1)) also illustrates why the question of yield improvement for main crops used in current biofuel policy has taken an important place in the debate. This expression, however, shows that the role of a 10% or even 20% improvement in yield for rapeseed or soybean oil would not radically affect the conclusions in terms of ILUC, as the final effect would only be decreased by 9% and 17%, respectively as a first order of approximation (inverse of the increase).

The value of NDF can appear counter-intuitively low. However, as explained by Plevin et al. (2010), this indicator mixes several effects: Intensification response, coproducts effect, change in demand, and declining marginal production yield; the first three clearly mitigate land use expansion. A fifth factor could be added in the geographical and cross-sectoral composition effect on yield due to reallocation of production in different regions of the world. Last, demand displacement allowed by elastic demand (final and intermediate) helps supply the biofuels sectors without additional

Table 4.9. Market balance in the "NAP" scenario for most agricultural goods (1000 tonnes) and price changes.

	Biofuel shock demand	Extra supply	Final demand diversion	Livestock demand diversion	Other demand diversion	World producer price changes
Wheat	6,842	−2,490	917	8,086	328	2.2%
Maize	9,722	−2,368	934	10,734	423	2.0%
Sugar_cb	54,668	28,902	428	29	25,308	10.3%
Rice	—	−553	86	185	282	0.1%
OthCrop	—	−218	178	33	6	−0.1%
VegFruits	—	−1,424	854	266	304	0.0%
Soybeans	—	7,392	53	1,430	−8,875	14.9%
Sunflower	—	1,652	6	1,051	−2,710	32.3%
Rapeseed	—	2,572	16	884	−3,473	34.8%
PalmFruit	—	3,519	345	921	−4,785	37.0%
OthOilSds	—	208	−85	−46	−76	0.6%
OilPalm	3,586	1,174	817	0	1,594	29.7%
OilRape	2,263	930	496	0	838	36.9%
OilSoyb	3,633	1,929	544	0	1,160	33.0%
OilSunf	1,377	1,141	175	0	62	32.9%
DDGSWheat	—	2,630	0	−2,630	0	na
DDGSMaize	—	4,995	0	−4,995	0	na
DDGSBeet	—	1,385	0	−1,385	0	na
MealPalm	—	13	0	−13	0	na
MealRape	—	1,364	0	−1,364	0	na
MealSoyb	—	8,367	0	−8,367	0	na
MealSunf	—	684	0	−684	0	na

Source: MIRAGE-BioF simulations.

production. Indeed, demand for biofuels puts pressure on the markets, raises prices, and diverts some products usually used as food, feed, or processed and then used by various industries. Table 4.9 displays the distribution of the change on each market between supply and demand and illustrates how some diversion helps to limit the extra production required. For example, the increase in sugar price following the demand for ethanol processing leads to a decrease in refined sugar use and reduces by one-third of the total sugar supply for biofuel production. In addition, this table clearly demonstrates the significant cross-sectoral effect of coproducts. Production of cereals finally diminishes in the "NAP" scenario because they are replaced by rape meals, and more indirectly by soy meals, which frees up some land to grow other crops in the EU and in America. This contribution of coproducts will be more precisely investigated in Section 4.4.

4.3.3 SENSITIVITY ANALYSIS

The previous section clearly illustrated the variability between results associated with different shocks through deterministic scenarios. However, this should not mask the significant uncertainty

surrounding the provision of such estimates. Indeed, many behavioural parameters are important in the representation of land use EFs. This was already emphasized in Hertel et al. (2010a) and very clearly illustrated by the article on uncertainty from Plevin et al. (2010). In this section, we therefore investigate intervals of confidence around our initial estimates by running many alternative simulations, combining in a systematic approach all possible bounds for our parameters.

We especially focus on the uncertainty in the NDF, because, while the other sources identified in Plevin et al. (2010) have been extensively discussed there, the NDF remains a shadowy area determined by the agroeconomic models.

We identified six biophysical and behavioural parameters that are generally considered important for the determination of this NDF variance. They directly affect the source of supply of crops and biofuels. Of course, demand parameters also play a critical role in how the additional demand of crops for biofuels is split between demand displacement and increased supply. The parameters considered for the sensitivity analysis are:

(1) Elasticity of endogenous yield response.

(2) Elasticity of land substitution between highly substitutable crops.

(3) Elasticity of land substitution between other crops.

(4) Elasticity of land expansion into other land covers.

(5) Elasticity of Armington (between domestic production and imports and between imports).

(6) Marginal yield return on cultivated land.

The elasticities chosen for this systematic sensitivity analysis are considered to be correlated across regions and sectors. They therefore correspond to an overall measurement of uncertainty rather than to variability across regions or sectors. For most parameters, we change their value from 50% to 200% of their initial magnitude. Trying to derive a corridor of boundary values, we only looked at combination of value bounds, which represented $2^6 = 64$ simulations to test. The different parameters that we tested, as well as the range of values used, are summarised in Table 4.10.

The results on the sensitivity analysis clearly illustrate the large interval of uncertainty concerning estimates of ILUC factors (Figure 4.7). Values range from 10 gCO_2/MJ up to 116 gCO_2/MJ for the central scenario, with a median at 37.7 gCO_2/MJ and a higher mean at 46.8 gCO_2/MJ. Interestingly enough, NDF ranges are wide (from 0.06 to 0.46) but are quite homogenous across the three scenarios. The difference is driven on the one side by crop energy yields, where ethanol shows great performance with a mix containing a share of high-yield sugar beet ethanol production and sugar cane ethanol imports. On the other side, the EF associated with land use change is slightly higher, on average, in the case of ethanol policy because of the stimulation of Brazil land use change for sugar cane and possible repercussions in terms of deforestation. However, it is the biodiesel policies that show the most extreme values for emissions. This scenario corresponds to cases where imports of biodiesel or

Table 4.10. Effect tested in the sensitivity analysis and relative parameters varied.

Effect to test	Target parameter	Initial range	Source	Lower bound	Upper bound
Endogenous yield response	Elasticity of substitution between land and other inputs	Yield elasticity in the 0.1-0.3 range for most crops	CARB (2011), Huang and Khanna (2010)	/ 2	× 2
Land substitution between highly substitutable crops	Elasticity of substitution at higher level of CET nesting	Land supply elasticity in the 0.2-0.5 range for most crops	FAPRI elasticity database	/ 2	× 2
Land substitution between other crops	Elasticity of substitution at intermediate level of CET nesting	Land supply elasticity around 0.1	OECD (2001)	/ 2	× 2
Land expansion into other land covers	Elasticity of land expansion	From 0.01 to 0.05	Barr et al. (2011), Roberts and Schlenker (2010), OECD (2001)	/ 2	× 2
Armington effect	Armington elasticity	From 0.9 to 17.4	Hertel et al. (2007)	/ 2	× 2
Marginal yield return on new cultivated land	Marginal yield return coefficient	0.75 for all	CARB (2011)	0.5	1

vegetable oil from Malaysia and Indonesia lead to conversion of peatlands that represent very dense carbon stocks.

This test of parameter ranges clearly illustrates the potentially high effects of land use change emissions related to biofuel policies on the one side and the imprecision of measurements for such an effect on the other. In fact, this type of analysis allows for testing uncertainty depending only on parameter values. Another source of uncertainty we are now going to examine is the role from model specifications on different market responses affecting land use change.

4.4 Fuel versus feed versus food: Domino effects on the demand side

Indirect land use change is based on the idea that displaced production should be grown elsewhere. This approach gives the intuition that the Net Displacement Factor relative to this production should be close to 1, and even greater if marginal lands are less productive.

However, as Plevin et al. (2010) clearly emphasize, three other factors in addition to the marginal yield come into play to limit this displacement: change in demand, coproducts, and intensification. The authors therefore assume that a plausible range for NDF would be between 0.25 and 0.85, based on the few studies they reviewed. Our own range of NDF values pushes for a range merely around the lower bound of the range offered by Plevin et al. (2010), and possibly even lower. Indeed, price
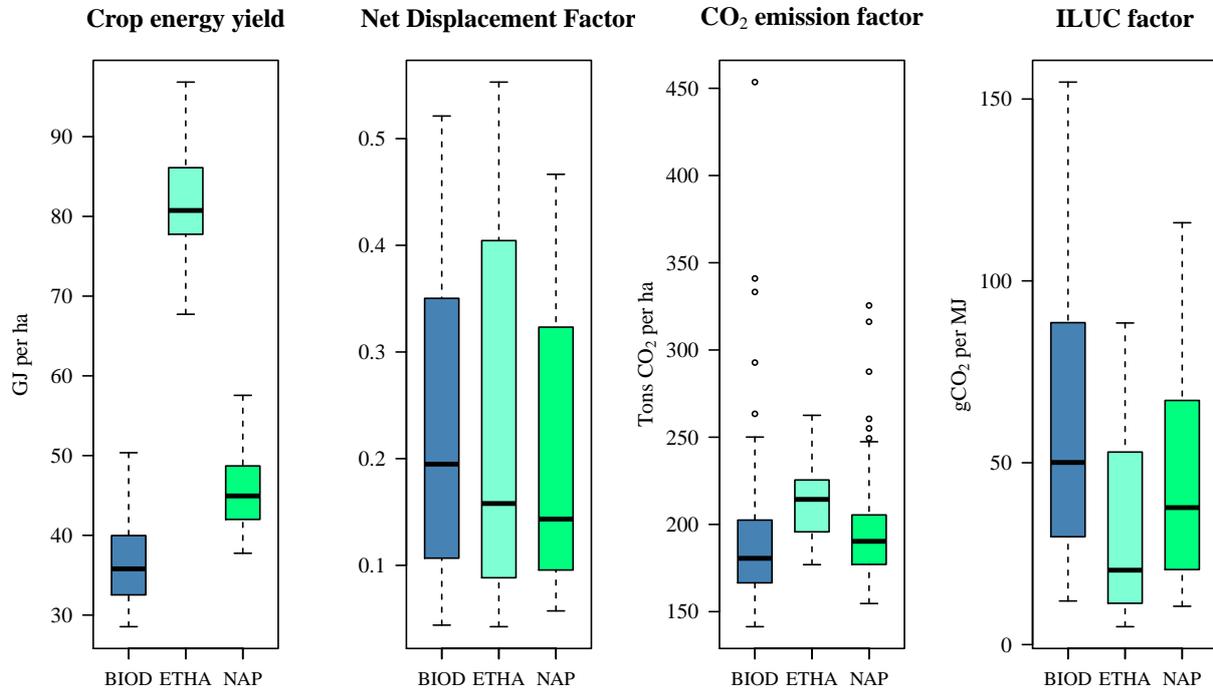
Figure 4.7. Decomposition of the different components of ILUC factor effect in our sensitivity analysis. ILUC factor can be computed in function of the three other parameters according to the formula 4.2

increases provide significant incentives on both the production and the demand side. In this section, we focus on the latter by looking at how displacement of the demand for land directly (pasture) or indirectly (crops) is affected by the response of final consumers and intermediate sectors, particularly the livestock industry, to the price changes. We discuss the role of food disappearance and the substitution pattern in the feed, looking at both the issue of coproducts and the intensification consequences of the demand for pasture land.

4.4.1 Disappearing food: the role of final demand

As illustrated in Table 4.9, a significant portion of food is diverted following food price increases in order to replace a portion of the production allocated to biofuels. Although the competition for land leads to an overall decrease in wheat production due to a positive increase of relative land rent for oilseed compared to cereals, prices for cereals increase in our central "NAP" scenario; this carries impact in some parts of the world. In total, 917,000 tons of wheat and 934,000 tons of maize are diverted from the food and feed market in our scenario. Most of this is provided from three regions: Asia (565,000 tons), the Middle East and North Africa (464,000 tons), and Sub-Saharan Africa (309,000 tons) because these regions are the most dependent on imports from world markets, and

from the EU exports in particular, and their demand is more sensitive to a change in price.[9] Despite the fall in demand, we still have significant increases in the prices of oilseeds (except for soybeans) and vegetable oils (above 30%), meaning that at the same time, consumers (households and firms) will reduce their normal consumption in volume of these goods and sacrifice the consumption of other goods to reallocate a share of their income to this increasing expenditure.

This effect occurs in the cereals market but is also visible in the meat market, which is influenced by the change in the price of feed. As a consequence of increases in the price of cereal feed and decreases in income due to oil price contraction,[10] demand for cattle, pig, and chicken meat decreases by 0.7% in Middle East and North Africa. In Sub-Saharan Africa, the demand for pigs and poultry decreases by 1.4%. Indeed, the share of cereals is low in the feed ratio of cattle bred in these regions, and the excess of soybean meals leads to an even more limited effect on production costs. The contribution of food effects on the carbon balance is illustrated in Table 4.11. Overall, the effects of maintaining the consumption of food constant increase the ILUC factor by 58% (scenario "CST FOOD").[11] The lack of new supply from demand change indeed requires an expansion of land use, although some more intensification may partly compensate for the extra pressure. The food demand effects can be decomposed into two components: assuming that crop consumption for food is not affected ("CST CROP") or assuming that meat consumption for food is constant ("CST MEAT"). It appears that although meat production consumes a significant portion of crop production, the first scenario changes the results much more than the second (+18.8 gCO_2/MJ for crops versus +0.6 gCO_2/MJ for meat). This mainly comes from the fact that the price of meat reacts less than the price of crops (value chain effect), and therefore the quantity of change in demand to compensate remains low in the second case. Second, significant crop substitution can occur in order to more efficiently distribute crops within feed and allow compensation for the additional pressure on feed input.

4.4.2 Role of coproducts: the first feed retroaction

Coproducts have also been shown to be a significant source of attenuation of ILUC effects (Searchinger et al., 2008). Some papers have used applied models to test how supplying additional dried distillers' grains with solubles (DDGS) could save some land by substituting other types of feed, such as oilseed meals made from low-yield soybean (Taheripour et al., 2010, Hertel et al., 2010a). However, the case

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[9] In MIRAGE, price and income elasticities for household demands are calibrated to US$A data (Seale et al., 2003). As a matter of fact, price elasticity for wheat in Sub-Saharan Africa, MENA and Asia are three to ten times higher than those of developed countries.

[10] We do not explore in this chapter the different role of the oil market, depending on behaviour of oil producers, on the indirect effect of biofuel policies. Using MIRAGE-BioF model, Laborde (2011) estimates that change in oil prices would lead to a leakage of 30% of the amount of fossil fuel saved by the EU consumed by other countries. For more insight on this question, see for example Rajagopal et al. (2011).

[11] This is implemented in the model through a state subsidy that compensates for the price change for final consumers and also for food industries relying structurally on food intermediates (Sugar, MeatDairy and OthFood sectors). Substitution of vegetable oil by consumers and industries remains however unconstrained.

Table 4.11. Summary table with different alternative scenarios on mandate and on model specifications.

	NAP	BIOD	ETHA	NO MEAL	NO DDGS	NO CPT	CST CROP	CST MEAT	CST FOOD	CTL & FOR COMP	HIGH NDF
Crop energy yield (GJ/ha)	46.6	37.7	80	45.9	48.9	47.1	45.2	46.6	45.2	48.9	60.9
NDF	0.199	0.222	0.194	0.232	0.221	0.25	0.296	0.203	0.307	0.213	0.828
ILUC yield (ha/TJ)	4.3	5.9	2.4	5	4.5	5.3	6.5	4.4	6.8	4.4	13.6
Avg. emission factor (tCO$_2$/ha)	181.2	173.1	204.2	178.9	183.8	180.6	181.4	180	179.6	192.9	170.8
ILUC factor 20 yrs (gCO$_2$/MJ)	**38.6**	**51**	**24.8**	**45.2**	**41.6**	**48**	**59.4**	**39.2**	**61**	**42**	**116.1**

Source: MIRAGE-BioF simulations.

of maize is easier to apprehend, as grain distiller side products have a low price and are *by*-products in the pure sense: The demand for DDGS alone can hardly drive new transformation of maize.

The case of biodiesel coproducts is significantly different and of critical importance for the consideration of the biofuel policy in the EU. Oilseeds are crushed to produce vegetable oil and protein meals, and the latter usually have more commercial value. Therefore, accounting for meals as by-products is not appropriate, as meals could be produced even without the extra demand for vegetable oil transformed into biodiesel.

In our model, the modelling of these aspects is reproduced by an explicit representation of the coproducts, which are produced in fixed proportions in volume, with flexible prices summing to give the crushing production price. The markets for the product and its coproduct are therefore simultaneously balanced, and the model determines endogenously if the demand for the product or its coproduct drives an extra demand for new production. Coproducts are inserted in the feed composition by substituting with other protein meals, and they substitute on a protein content ratio, as prices have been equalised per quantity of protein content in the data. The protein feed group is then considered as a substitute for other feed.

In order to test the role of coproducts in our model, we ran alternative scenarios where we removed the effect of biofuel coproducts as a substitute in feed.[12] We consider a scenario where grains are transformed into ethanol without producing DDGS ("NO DDGS"), another where oilseed crushing leads to sales of vegetable oil only ("NO MEAL"), and a last one where both joint productions are removed ("NO CPT"). The results are displayed in Table 11.

We find that coproducts have significant effects on the displacement of land. When compared with our central "NAP" scenario, removing oil cakes increases the NDF by 16.6%, while removing DDGS increases it by 11.1%. This larger contribution of oil cakes is partly due to the significantly higher share of biodiesel coproducts used in our scenario. The combined effect of removing all coproducts increases the NDF by 25.6%, which means that according to our calculation, the savings resulting from coproducts for the central EU scenario would be around 20.4%. These results are close to the estimate of Taheripour et al. (2010), who found a decrease of 21.2% of cropland expansion due to by-product incorporation in their model when modelling the impact of US and EU biofuel mandates.

4.4.3 ROLE OF PASTURE LAND: THE SECOND FEED RETROACTION

In all the previous simulations, we have been considering that cropland expansion could be done with some constraints, but independently from evolution of other land- use activities. However, if some grassland is available for expansion in regions such as Sub-Saharan Africa or Latin America (Bouwman et al., 2005), cropland expansion in some other regions could compete with livestock

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[12] This was achieved technically by diverting the meals and DDGS output from livestock to the manufacturing sector, where it was substitutable with ordinary other processed input. Therefore, the price dynamics on ethanol and vegetable oil remains a joint-production one.

production and forestry output if the land resources are scarce. We therefore distinguish between two different approaches to pasture and forested activities representation:

(a) "Pasture and forest intensification": This has been the assumption used so far. Cropland can expand into other land types following historic observations and if necessary, intensification is assumed to follow the previous trends to free the available land required for this new cropland.

(b) "Pasture and forest competition": In this design, pasture and forest land are considered as direct factors necessary for livestock and wood production. Therefore, increasing production puts a higher pressure on available land and can compete with cropland expansion. Projections of land used for cropland expansion can consequently depart from preceding observations, either because pastureland and forest landforestland would be less accessible if the demand for their products increased, due to higher meat or wood prices, or because a decrease in the associated demand would free more land from pasture and managed forests.

In this latter design, substitution between cropland, pasture, and managed forests is implemented using nested low-elasticity CETs and calibrated to obtain the same value of elasticity of cropland expansion at the base year.

The results of switching from assumption "Intensification" to "Competition" can be seen in Table 4.11 with the "NAP" and "CTL FRS COMP" scenarios, respectively. As cropland expansion is calibrated on similar elasticities, results differ little with the new competition introducing a slight increase in NDF ($+7\%$); however, one can note the increase in the average land EF that denotes a shift in the place of expansion of cropland in most regions.

The way closure affects cropland expansion is interestingly illustrated by the situation in Brazil (Figure 4.8). When pressure from pasture is introduced, regions that are characterised by higher use of pasture for cattle (AEZ5 and AEZ6, corresponding respectively to Brazil Cerrado Central and Central-West zone and the Amazon Basin area) experience less expansion than with the historical expansion settings that allow much more cropland to expand into pasture.

4.4.4   Testing the possibility of higher NDF: a worst case scenario

In all the variation of modelling specifications that we tested, we obtained a NDF reaching a maximum of 0.3. We have, however, previously illustrated in Section 4.3.3 how different parameters could lead to much higher coefficients. Theoretically, a NDF could be as high as 1 or even higher if marginal yields are low, corresponding to a situation where one hectare of new energy crops would require one additional hectare of cropland. In order to provide a counterfactual argument to our previous scenarios, where coproducts, demand diversion, and yield response play a significant role, we run an additional set of specifications where we disable most of these sources of market supply through diversion and substitutions. In this additional scenario, we combine the removal of coproduct from scenario "NO CPT" with the fixation of food consumption from scenario "CST
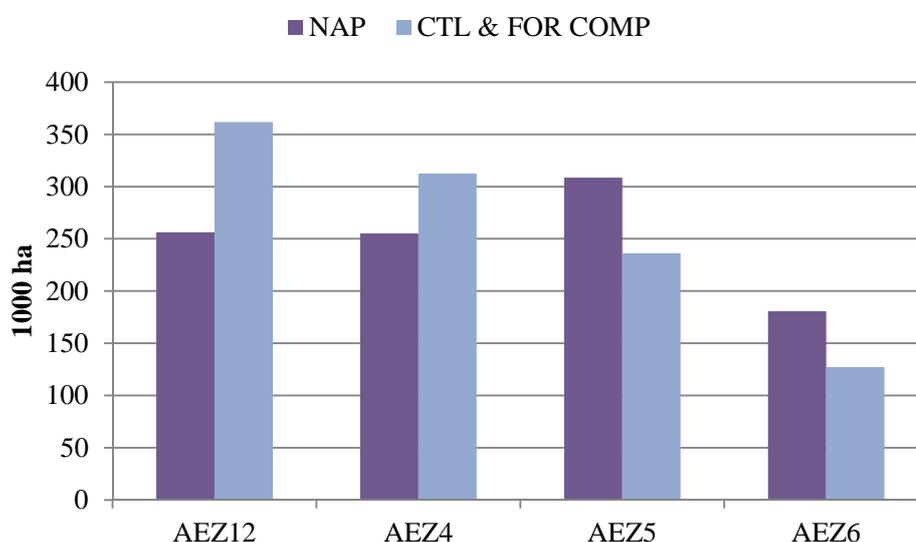
Figure 4.8. Cropland expansion in Brazil in different agro-ecological zones, according to two land-use closures. The two closures tested are "pasture and forests intensification" (default assumption in all scenarios, included the central scenario "NAP") and "pasture and forests competition" ("CTL & FOR COMP" scenario based on other land conversion assumptions).

FOOD". We additionally neutralise the endogenous yield effect and prevent all forms of substitution within feed in livestock.

The cumulated effects of these restrictions significantly boost the results obtained so far and illustrate the significant contribution of all these aspects, as suggested by Plevin et al. (2010). Indeed, the results of this scenario "HIGH NDF", presented in Table 4.11, are three times higher than the previous ones. Interestingly enough, the crop energy yield has increased by 31% at 60.9 GJ/ha, indicating a composition effect with more contribution from efficient crops, in particular sugar cane. However, the NDF is increasing drastically up to 0.83, which leads to an ILUC factor of 116 gCO_2/MJ. This value corresponds to a situation where indirect land use emissions would be greater than emission from use of usual fossil fuel in road transportations over a 20-year period.

4.5   CONCLUSION

This chapter describes the different channels driving land use changes in a global multi- sectoral CGE and provides an illustration of land use change driven by EU biofuel policies, in particular the implementation of current National Renewable Energy Action Plans. The model presented, MIRAGE-BioF, benefits from specific development on the data side, as well as on the modelling, that makes it particularly suitable to study such policies. Applied to the assessment of the EU biofuel policy, if current targets are followed, we confirm that emissions driven by land use changes would most likely be significant (38 gCO_2/MJ for our median case) and require some attention. Indeed, through direct and indirect effects on the commodity markets, the increased demand for

energy crops in the EU will lead, ceteris paribus, to land use changes all over the world; considering the present restriction on pasture conversion and the already large use of set-aside land for bioenergy crops, we find that most future needs would be met by global cropland expansion outside of Europe and primarily in Latin America, Eastern Europe and Russia, and Sub-Saharan Africa.

The EU policy differs significantly from other biofuel mandates around the world due to the diversity of feedstocks involved and the large share of biodiesel (78%). It affects both the cereals and the vegetable oil markets, linking the EU biofuel demand to potentially high carbon stock regions (e.g., peatlands in Southeast Asia). By looking at alternative composition mixes for the future of EU biofuels consumption (current targets, only biodiesel, only ethanol), we confirm previous results (Al-Riffai et al., 2010b, Britz and Hertel, 2011) that ethanol and biodiesel demands have quite different effects: biodiesel releasing twice as much CO_2 from land use changes as ethanol. However, significant uncertainty exists for measuring such effects, driven by behavioural parameters, confidence intervals and some modelling specifications. Parameter values and modelling assumptions affect the distribution of effects between land, allocation decisions for crops, marginal yields and intensification or expansion possibilities on the supply side, and on the demand side the final consumption and the inputs demand of downstream sectors, in particular, the feed and land demand of the livestock sectors. Performing sensitivity analysis on these key parameters, we show that the emissions can vary from 10 to more than 116 gCO_2/MJ, and that additional land requirements would represent 1 to possibly more than 12 ha per TJ with a median value of 3.4 ha per TJ.

Overall, our results are located in the low range of literature estimates of possible effects of biofuel policies on land use (Searchinger et al., 2008, Plevin et al., 2010), although the ILUC factors are sufficiently high to seriously question the sustainability of current policy orientations. These low values, in comparison with some other evaluations may come partly from lower default coefficients on carbon stock, whose uncertainty has not been explored here. Plevin et al. (2010) show that we could have used average EFs at least twice as high. Another much more structure-related reason is the low value of the net displacement factor, resulting notably in a decrease in demand accompanying food price increases. As prices of various crops used for biofuels have surged to historic heights several times in recent years, a limited land use change effect could imply a dangerous trade-off with food security in the short run as long as yield response is not yet effective. Considered from this perspective, it is not assured that assumption of low indirect land use change emissions would guarantee more satisfying policy implications. From a policy perspective, our results illustrate the difficulty of integrating ILUC factor directly as input into LCA analyses as once envisaged by the EU and the US legislators. As some other authors have already argued (Zilberman et al., 2011, de Gorter and Just, 2010), the level of uncertainty makes such an attempt subject to arbitrary choices. However, at the same time, the magnitude of results in spite of uncertainty calls for some other more flexible policy provisions, targeted at mitigating ILUC leakage in a more comprehensive land policy framework and taking precautionary measures for biofuel programs orientations. In this respect, as supported by this analysis, it appears that the current EU biofuel policy, largely based on

rapeseed and soybean-based biodiesel, would most likely miss any chance of environmental benefits. Lower input and higher yield crops should be preferred to meet the objectives of the EU Renewable Energy Directive.

4.A   LIST OF SECTORS AND REGIONS IN THE MODEL

Table 4.12. List of the 55 sectors in the model. Sectors in bold represent sectors whose representation is particularly important for representation of the impact of biofuel policies. Coproducts are also represented through complementary output of vegetable oil and ethanol processing sectors, going respectively to Ethanol and Biodiesel for biofuel, and Cattle and OthAnim for coproducts. Source: MIRAGE-BioF.

#	Sector	Description	#	Sector	Description
1	Rice	Rice	**29**	**Forestry**	**Forestry**
2	**Wheat**	**Wheat**	30	Fishing	Fishing
3	**Maize**	**Maize**	31	Coal	Coal
4	**PalmFruit**	**Palm Fruit**	**32**	**Oil**	**Oil**
5	**Rapeseed**	**Rapeseed**	33	Gas	Gas
6	**Soybeans**	**Soybeans**	34	OthMin	Other minerals
7	**Sunflower**	**Sunflower**	**35**	**Ethanol**	**Ethanol - Main sector**
8	OthOilSds	Other oilseeds	**36**	**EthanolCane**	**Sugar Cane Fermentation**
9	VegFruits	Vegetable & Fruits	**37**	**EthanolBeet**	**Sugar Beet Fermentation**
10	OthCrop	Other crops	**38**	**EthanolMaize**	**Maize Fermentation**
11	**Sugar_cb**	**Sugar beet and cane**	**39**	**EthanolWheat**	**Wheat Fermentation**
12	**Cattle**	**Cattle**	40	DDGSCane	**Sugar Cane Bagasse**
13	**OthAnim**	**Other animals (inc. hogs and poultry)**	41	DDGSBeet	Sugar Beet Pulp
14	**CrushPalm**	**Palm Fruit processing**	42	DDGSMaize	Maize DDGS
15	**CrushRape**	**Rapeseed crushing**	**43**	**DDGSWheat**	**Wheat DDGS**
16	**CrushSoyb**	**Soybean crushing**	**44**	**Biodiesel**	**Biodiesel transformation**
17	**CrushSunf**	**Sunflower crushing**	45	Manuf	Other Manufacturing activities
18	**OilPalm**	**Palm Oil**	46	WoodPaper	Wood and Paper
19	**OilRape**	**Rapeseed Oil**	**47**	**Fuel**	**Fuel**
20	**OilSoyb**	**Soy Oil**	48	PetrNoFuel	Petroleum products, except fuel
21	**OilSunf**	**Sunflower Oil**	**49**	**Fertiliz**	**Fertilizers**
22	**MealPalm**	**Palm Fruit Fiber**	50	ElecGas	Electricity and Gas
23	**MealRape**	**Rape Meal**	51	Construction	Construction
24	**MealSoyb**	**Soybean Meal**	52	PrivServ	Private services
25	**MealSunf**	**Sunflower Meal**	**53**	**RoadTrans**	**Road Transportation**
26	OthFood	Other Food sectors	54	AirSeaTran	Air & Sea transportation
27	**MeatDairy**	**Meat and Dairy products**	55	PubServ	Public services
28	**Sugar**	**Sugar**			

Table 4.13. List of the 14 regions represented in the model. Note: Regions in bold are regions whose representation is of particular importance for representation of the impact of EU biofuel policies. Source: MIRAGE-BioF Nomenclature.

#	Region	Description	#	Region	Description
1	**Argentina**	**Argentina**	**8**	**EU27**	**European Union (27 members)**
2	**Asia**	Rest of South and South-East Asia	**9**	**IndoMalay**	**Indonesia and Malaysia**
3	**Brazil**	**Brazil**	10	JPNKOR	Japan and Republic of Korea
4	**CAMCarib**	**Central America and Caribbean**	11	LAC	Other Latin America countries
5	Canada	Canada	12	Oceania	Australia, New-Zealand and Pacific Islands
6	China	China	**13**	**SSA**	**Sub Saharan Africa**
7	**CISRoEur**	**CIS countries and Rest of Europe**	**14**	**USA**	**United States of America**

4.B Main characteristics of the MIRAGE-BioF database from GTAP7 and FAOSTAT

The MIRAGE-BioF model required for a more precise study of agricultural and energy dynamics the development of a new database, based on the GTAP data but overcoming some of its main limitations to address the topic.

The GTAP datasets combine domestic input-output matrices, which provide details on the intersectoral linkages within each region, and international datasets on macroeconomic aggregates, bilateral trade, protection and energy. We started from the latest available database, GTAP 7, which describes global economic activity for the 2004 reference year in an aggregation of 113 regions and 57 sectors (Narayanan and Walmsley, 2008).

However, after some first tests, we found that an approach based on pure splitting in a top-down settings – as proposed by built-in tools in the GTAP community, such as SplitCom – lead to severe issues, in particular for critical sectors such as several feedstock crops, vegetable oils and biofuel sectors. We therefore developed an original and specific procedure to generate a database that is consistent in both values and quantities. The general procedure is as follows:

1. Agricultural production value and volume are targeted to match Food and Agriculture Organisation of the United Nations (FAO) statistics. A world price matrix for homogenous commodities was constructed in order to be consistent with international price distortions (transportation costs, tariffs, and export taxes or subsidies).

2. Production technology for new crops is inherited from the parent GTAP sector and the new sectors are deducted from the parent sectors.

3. New vegetable oil sectors are built using a bottom-up approach based on crushing equations. Value and volume of both oils and meals are consistent with the prices matrix, physical yields and input quantities.

4. Biofuel sectors are built using a bottom-up approach to respect the production costs, input requirements, production volume, and for the different type of ethanols, the different by-products. Finally, rates of profits are computed based on the difference between production costs, subsidies and output prices.

5. For Steps 2, 3, and 4, the value of inputs is deducted from the relevant sectors (other food products, vegetable oils, chemical and rubber products, fuel) in the original social accounting matrix (SAM), allowing resources and uses to be extracted from different sectors if needed (n-to-n).

At each stage, consumption data are adjusted to be consistent with production and trade flows. Targeting only in value often generates inconsistencies in the physical linkage that thereby leads to erroneous assessments (e.g. wrong yields for extracting vegetable oil).

It is important to emphasize that this procedure, even if time consuming and delicate to operate with so many new sectors, was crucial for an adequate representation of the sectors. In particular, we were surprised and concerned to see that little attention was usually given in the literature to this aspects. Indeed, each step allows us to address several issues. For instance, Step 1 allows us to correct for the level of production compared to the GTAP database wherein production targeting is done only for Organisation for Economic Co-operation and Development (OECD) countries, with some flaws, and therefore outdated agricultural production structure for many countries. Finally, a flexible procedure is needed (Step 5) since some of our new sectors can be constructed from among several sectors in GTAP. SplitCom allows only a 1-to-n disaggregation, which is rather restrictive for the more complex configuration that we face with the data. For instance, Brazilian ethanol trade data falls under the beverages and tobacco sector while its production is classified under the chemical products sector. For the vegetable oils, we face similar issues since the value of the oil is in the vegetable oil sector but the value of the oil meals are generally under the food products sector.

New sectors introduced in the database are:

- five crops (maize, soybeans, rapeseeds, palm fruits, sunflower). Production technology for new crops sectors was inherited from the parent GTAP sector.

- four vegetable oil and four of their co products following information on the crushing cost structure (rapeseed oil and meal, soybean oil and meal, sunflower oil and meal, palm fruit). Value and volume of both oils and meals were made consistent with the matrix of prices, the physical yields, and the inputs quantity.

- four ethanol processing sectors and three of their by-products (ethanol from wheat and their DDGS, ethanol from corn and their DDGS, ethanol from sugar cane, ethanol from sugar

beet and their beet pulp). The four ethanol products are then considered almost perfectible substitutable inputs in a single ethanol final product.

- three fuel sectors (fossil fuel, biodiesel, aggregated ethanol). Biodiesel was also built with a bottom-up approach to respect the production costs, input requirements, and production volume.

The specific data sources, procedures and assumptions made in the construction of each new sector are described with more details in (Al-Riffai et al., 2010b, Annex I).

4.C EMISSION FACTORS RELATED TO LAND USE CONVERSION IN THE MIRAGE-BIOF MODEL.

Table 4.14. Carbon stock in managed forests (tCO$_2$ per ha)

	Brazil	CAM Carib	China	CIS	EU27	Indo Malay	LAC	Ro OECD	RoW	SSA	USA
AEZ1							72		72		
AEZ2							72		72	72	
AEZ3	134						134		134	134	
AEZ4	134		134			134	134	134	134	134	
AEZ5	252		252			252	252	252	252	252	
AEZ6	354		354			354	354	354	354	354	
AEZ7			68	68			68		68		68
AEZ8			68	68			68	68	68	68	68
AEZ9			224	224	224		224	224	224	224	224
AEZ10	224		224	224	224		224	224	224	224	224
AEZ11			246	246	246		246	246	246	246	246
AEZ12	294		294	294	294		294	294	294	294	294
AEZ14			34	34	34		34	34	34		34
AEZ15			90	90	90		90	90	90		90
AEZ16			90	90	90		90	90	90		90
AEZ17							90	90			
AEZ18							90				

Peatland emissions are also accounted for in the case of Indonesia and Malaysia. We assume that 33% of palm oil plantation in that region expands on peatlands, accordingly to Edwards et al. (2010). Emission factors used is 55 tCO$_2$-eq ha-1 yr-1 of drained peatland.

Table 4.15. Carbon stock in primary forests (tCO$_2$ per ha)

	Brazil	CAM Carib	China	CIS	EU27	Indo Malay	LAC	Ro OECD	RoW	SSA	USA
AEZ1									169		
AEZ2										169	
AEZ3	291						291			291	
AEZ4	291	291	291			291	291			291	
AEZ5	378	378	378			378	378			378	
AEZ6	708	708	708			708	708			708	
AEZ7			159	159			159				159
AEZ8			159	159				159		159	159
AEZ9			269	269			269	269		269	269
AEZ10	269		269	269	269		269	269	269	269	269
AEZ11			347	347			347			347	347
AEZ12	463	463	463	463			463		463	463	463
AEZ14			34	34				34			34
AEZ15			112	112				112			112
AEZ16			112	112				112	112		112
AEZ18							112				

Table 4.16. Carbon stock in mineral soil (tCO$_2$ per ha)

	Brazil	CAM Carib	China	CIS	EU27	Indo Malay	LAC	Ro OECD	RoW	SSA	USA
AEZ1	56						56	9	54	58	
AEZ2	58						56	24	57	58	
AEZ3	58						55	23	49	57	
AEZ4	57	57	49		58	46	56	18	37	56	
AEZ5	88	86	79			57	82	41	58	89	
AEZ6	113	112	95			93	101	41	99	113	
AEZ7			27	27			28	28	26	28	34
AEZ8			36	36	37		36	37	35	37	37
AEZ9			103	108	107		107	108	104	108	108
AEZ10	108		102	108	108		107	105	104	108	107
AEZ11	73		63	76	75		75	73	62	76	74
AEZ12	98	100	72	98	100		98	96	73	91	99
AEZ14			50	50	50		41	26	48		50
AEZ15			73	77	77		71	77	72		77
AEZ16			74	77	77		72	24	69		76
AEZ17			74				73	39			
AEZ18							77				

EXPLORING UNCERTAINTY IN INDIRECT LAND USE CHANGE ESTIMATES

THE DEBATE on indirect land use change (ILUC) has seriously questioned the assumption that producing ethanol and biodiesel to replace fossil fuel could lead to greenhouse gas (GHG) savings, as illustrated in the previous chapter. This issue took a critical importance after regulatory agencies decided in the United States (US) and in the European Union (EU)European to take these effects into account for the life-cycle analysis (LCA) of the different biofuels pathways. Many studies were conducted to assess the possible range of extra land use emissions associated to biofuels, the so-called "ILUC factors", and complement the more standard life-cycle analysis at the process level. However, the extent of uncertainty in the results led to many difficulties for the incorporation of these parameters in the legislation.

A large literature is now available proposing estimates for the ILUC effect of biofuels as a whole or of certain specific feedstocks. Most of these studies rely on complex applied economic models or group of models, or on consequential analyses derived from the LCA approaches. They propose deterministic values for the ILUC factor, sometimes complemented by more or less sophisticated sensitivity analyses. However, the complexity of models used was often raised as a real obstacle to a sound policy, with suspicion from some stakeholders that models would either largely underestimate the real extent of the phenomenon, or on the contrary generate some ILUC factor as a pure modelling artifact. Indeed, whether ILUC estimates are robust enough to support some policy decision on first generation biofuels is still a hot debate in the policy arena of the US and the EU.

A first attempt to unveil the real extent of uncertainty range behind ILUC estimates can be found in Plevin et al. (2010). Using a reduced form model for ILUC, the authors explore how results would be changed if some of the main components shaping the results were varied. They show that uncertainty can be much larger than previously anticipated, but emphasize the possibility of some very high levels of emissions. Their analysis, based on the decomposition of the ILUC factor into four components, identifies in particular the important role of the "net displacement factor" (NDF), defined as the extent of total cropland expansion for one ha of cropland allocated to bioenergy crops. The NDF is typically generated by economic models and cannot be estimated based on a data survey

or allocation rules as for the other components of the decomposition. Therefore, Plevin et al. (2010) were constrained to take representative values from a review of some past model results, but without any direct link to drivers and data. From this perspective, they did not succeed to provide a deeper understanding of how modelling assumptions drive the results.

This chapter invites to push this analysis further by directly linking ILUC calculation to main economic behaviour parameters. Mechanisms that lead to different land use change values are broadly the same in economic models and we propose here a stylised representation of them. In particular, our approach provides an expression of the NDF as a function of main behavioural parameters and clarify their respective importance for discussion of ILUC. Expressing ILUC calculation with such simplified framework has several important advantages: it brings more transparency on what determines ILUC values, opening the "black box" of applied models, while preserving the full consistency of the economic concepts. It also provides a framework that can be used to analyze and compare model results in the literature. The simplicity of the model representation makes all calculations possible on an easily-accessible spreadsheet.[1] And last but not least, it allows for first order exploration of uncertainty ranges in direct connection with the econometric literature. This is of significant importance as some parameters are less known than some others. This framework can then be used to illustrate where more research is needed to derive precise estimates and what level of precision can be reasonably expected.

The paper structure falls as follows: in the next section, we review the treatment of uncertainty around ILUC in the major contributions to the literature. In Section 5.2, we develop our stylised model for expressing ILUC as a function of main behavioural parameters and give some numerical applications. Section 5.3 uses the stylised model to explore how the different behavioural parameters influence the final results. Section 5.4 examines the values of elasticities provided by the literature and infer from them some uncertainty ranges for ILUC final values.

5.1 Overview of ILUC uncertainty treatment in the economic literature

A large number of studies have been realised over the last five years to compute possible ranges of ILUC factors. In the US, the Regulatory Impact Assessment (RIA) of the Energy Independence and Security Act (EISA) produced some estimates for a certain number of feedstocks using a combination of approaches centered around two partial equilibrium models: FASOM for the US, and FAPRI-CARD for the international agricultural markets EPA (2010). Some other studies based on a computable general equilibrium (CGE) approach (Hertel et al., 2010a, Taheripour et al., 2010, etc.) were also used, in particular to support the ruling of the California Air Resource Board (CARB) on Low Carbon Fuel Standard (LCFS). On the EU side, different methodologies were also applied

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[1]   An Excel version of the model can be downloaded at following address http://user.iiasa.ac.at/ valin/thesis/ILUC_mini_model_demo.xlsx.

as soon as 2010 with partial equilibrium analysis (Fonseca et al., 2010) and CGE with MIRAGE (Al-Riffai et al., 2010b). All these works produced deterministic values of ILUC factors with limited emphasis on sensitivity analysis. The various reviews of that period illustrate the difficulties to derive policy prescriptions considering the large range of estimates in each reference (see reviews from Edwards et al., 2010, Fonseca et al., 2010, Prins et al., 2010, Witzke et al., 2010, Broch et al., 2013).

Indeed, although uncertainty in modelling assessment of ILUC was recognised as an important issue in that time, it was kept as a secondary issues in the methodology adopted by the first studies. This is mainly due to the LCA perspective adopted by the legislation. For example, CARB has to provide for LCFS one single value of ILUC factor that can be later revised and uncertainty cannot be taken into account. In 2010, following several critics on the validity of the methodology and significant revision of the estimates, CARB decided to create an expert working group on ILUC estimations to tackle uncertainty issues. At the federal level, US Environmental Protection Agency (EPA) underlined in its RIA for EISA its concern about uncertainty in estimates following peer-review comments on the draft version EPA (2010). However, the analysis of uncertainty remained limited, especially with regards to economics modelling. First academic papers used to put forward point estimates of ILUC effect and often limited the exploration of uncertainty to some additional scenarios around their central values (Searchinger et al., 2008, Fonseca et al., 2010, Timilsina et al., 2010, Taheripour et al., 2010, Dumortier et al., 2011).

More systematic testing of the modelling has since been conducted: first, Hertel and associates (Hertel et al., 2010a,b) used Gaussian Quadrature approach (DeVuyst and Preckel, 1997, Pearson and Arndt, 2000) to test the most critical behavioural parameters and derive coefficient of variation around their average results. The models parameters were varied following triangular or Gaussian distribution and implications on model output coefficient of variations (CVs) are discussed (CV of 0.37 for land use change and 0.46 for emissions in Hertel et al., 2010a). Laborde (2011) performed some Monte-Carlo analysis to explore sensitivity to seven different parameters, assuming normal distributions. These two methods have the advantage of proposing confidence intervals around the results of central scenarios. However, they introduce a bias towards the mean in the distribution of parameters assumed, due to the use of triangular or normal distributions. Laborde and Valin (2012) depart from this assumption and propose with their modelling framework a larger range of plausible values, based on an approach where six behavioural parameters are assumed to follow uniform distribution, a much more neutral assumption. This widens the range of their results which vary from a factor one to ten (10 to 115 gCO_2/MJ), still centered around an average value close to previous studies findings.

Other recent approaches tried to remove model-specific bias. De Cara et al. (2012) explore all the dispersion of the estimate produced across studies available in 2012. After presenting an extensive review of approaches used and modelling assumptions, they ran a meta-analysis where effects from modelling assumptions and model-specific effects could be identified through an econometric

approach. Based on their results, they were able to propose a representative meta-model based on all other models' behaviours and calculate uncertainty range by varying their model results around a certain number of significant dummies (type of fuel, presence of co-products, place of feedstock production, etc.) Their approach allows for a very useful model-bias free estimate of ILUC, but their results remain dependent on the method applied to the reviewed sample and on autocorrelation across studies and modelling tools.

Indeed, even such meta-analysis remains dependent on results from applied models, which make the review and acceptation of results difficult. Approaches trying to move from large-scale economic tools to more transparent analysis, while keeping the consistency of various economic responses, have been more scarce. On consequential analysis side, Overmars et al. (2011) convincingly tested a large number of assumptions on feedstock type, level of production response and role of trade and land use converted to provide range of ILUC factors. Their method implies however prolongation of historical trends for many parameters, and does not consider some adjustments such as demand response, losing some of the consistency of economic approaches.

Plevin et al. actually proposed the most simplified framework to put better in evidence uncertainty issues. Their analysis based on a reduced form model for ILUC, illustrates how uncertainty in different drivers for ILUC measurement undermines any effort to obtain a precise estimate in the current state of available data. Their model corresponds simply to a multiplication of four factors:

$$ILUC = \frac{NDF \times EF}{T \times y_{Fuel}},\tag{5.1}$$

where NDF designates the Net Displacement Factor (area of cropland expansion per area of cropland allocated to biofuel), EF the average emission factor (EF) associated to the converted land bundle, T the production time of biofuel considered and y_{Fuel} the field yield of the biofuel crop. Using various range of estimates based on a literature review, they compute confidence intervals for some values of ILUC emissions. With a uniform distribution, they find values distributed between 21 and 142 gCO_2e/MJ with a 95% confidence interval. However, although most other parameters could be precisely documented in their approach, the range of the NDF value remained highly speculative. Plevin et al. (2010) explains that "the NDF is perhaps the most challenging parameters to estimate since it is a result of a system of globally linked economic markets and thus depends on many uncertain parameters and subjective choices in the economic models used". Indeed, the authors list at least four factors determining NDF: (i) price-induced yield increase, (ii) relative productivity of land converted to cropping, (iii) price-induced reductions in food consumption, (iv) substitution of crop products by biofuel coproducts. Because the studies they review display NDF values from 28% (Hertel et al., 2010a) to 72% (Searchinger et al., 2008), they choose a value range of 25–80%. If the production period is fixed, the NDF accounts for 70% of the variability in their estimate.

So far, our understanding of the literature is that the NDF variability has not been explored upfront in the ILUC debate. Although importance of elasticity values has been acknowledged (CARB, 2011), discussion remained much focused on the choice of the adequate or even "top model"

(Nassar et al., 2011). Keeney and Hertel (2009) may have been the authors discussing the most in details the importance of some elasticity values and implications of their uncertainty. However, they still relied on the complex GTAP model framework to evaluate the land use implications of this uncertainty in the US for corn ethanol and they relied on normal distribution of their parameters. Hertel (2011) proposed a simpler framework to explain how decomposition of extra supply can be related to main values of elasticities. In particular, he expresses the long run demand for land as follows:

$$q_L^* = \frac{\Delta_A^D + \Delta_L^S + \Delta_L^D}{1 + \eta_A^{S,I}/\eta_A^{S,E} + \eta_A^D/\eta_A^{S,E}} - \Delta_L^S, \qquad (5.2)$$

where Δ_A^D, Δ_L^S and Δ_L^D are exogenous shocks (in relative terms) respectively on demand, land available and yield, and η_A^D, $\eta_A^{S,E}$ and $\eta_A^{S,I}$ are elasticities on demand, land expansion (extensive margin) and yield (intensive margin). This formula highlights the importance of the different contributions of extensive and intensive margins on the final land use impact, but also of the role of demand. However, the implications of this type of decomposition for analysis of ILUC have not been fully explored so far. We propose in the next section to combine the framework from Plevin et al. and the stylised approach of Hertel to relate ILUC and NDF to the main elasticities of relevance for indirect land use change. This framework, summarised in Appendix C can be used to decompose and transparently discuss the direct influence of most important parameters and their uncertainties without the need for a large applied models.

5.2 A SIMPLIFIED ECONOMIC FORMULATION OF ILUC

We will use hereafter as a definition of ILUC the total cropland expansion at the world scale resulting from a biofuel policy.[2] ILUC factor designates the emission from ILUC for a given quantity of biofuel produced, as a result of conversion of various land into cropland.

Let's therefore consider a rigorous decomposition of ILUC based on equilibrium theory. This formulation will be based on first order decomposition of effects from a biofuel policy shock and allow us to understand the source of uncertainty coming from modelling approaches.

5.2.1 DECOMPOSITION OF A BIOFUEL SHOCK

We start from an initial situation where agricultural markets are at the equilibrium in an open economy, composed of a home region r_0 with several trade partners r. For each agricultural commodity

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[2] Another definition could be to distinguish the land use change resulting from direct allocation of an area to the biofuel feedstock (direct LUC), and land use change occuring in a different place (indirect LUC). This definition has been widely used because of the life cycle assessment (LCA) approach initially applied to biofuel pathways evaluation, and used as a regulatory framework (EP, 2009, EPA, 2010). Indirect land use change in that case refers to land use change occurring outside of the boundaries of the biofuel pathway LCA analysis. However, from an agricultural economics perspective, markets are fungible, therefore only the marginal land use change on the demand side is relevant, which is captured with the total land use change.

i, we observe the relation between demand $d_{i,r}$, supply $s_{i,r}$ and trade $x_{i,r} - m_{i,r}$, difference between exports and imports:

$$s_{i,r} + m_{i,r} = d_{i,r} + x_{i,r}. \tag{5.3}$$

On this initial equilibrium, a new exogenous additional demand is added following a biofuel incorporation policy in the region r_0, using the feedstock i_0. We note f_{i_0,r_0} the mandated feedstock quantity in that region and the new market equilibrium for (i_0, r_0) becomes:

$$\begin{cases} s_{i,r}^* + m_{i,r}^* = d_{i,r}^* + x_{i,r}^*, & \forall (i,j) \neq (i_0, r_0), \\ s_{i_0,r_0}^* + m_{i_0,r_0}^* = d_{i_0,r_0}^* + x_{i_0,r_0}^* + f_{i_0,r_0}^*. \end{cases} \tag{5.4}$$

To represent the multi-market equilibrium on all products i, let's now use a vector notations index along products. We introduce $S = (s_i)$ and $D = (d_i)$ for supply and demand respectively.[3] We can now express the difference between the two equilibrium. Summing equations $\sum_r (5.3) - (5.4)$ makes trade disappear and we obtain in vector notation:

$$F = \sum_r (\Delta S_r - \Delta D_r) \tag{5.5}$$

where $F = (0, ..., 0, f_{i_0,r_0}, 0, ..., 0)$ the biofuel feedstock demand in region r_0. This relation immediately shows the globalised nature of ILUC effect: domestic supply in the region r_0 will not be the only response to the additional feedstock demand. An inelastic local supply can displace more cultivated areas to other parts of the world through trade mediated effects. A part of the shock can also be absorbed by decrease in demand, as a result of price increase. This trade-off illustrates the second ambivalent effect of biofuel, at the core of the food *vs* fuel debate exacerbated during the 2007–2008 food price crisis (Roberts and Schlenker, 2010, Wright, 2011b,a). Note that demand in our framework represents both demand for final consumer and for the livestock sector, because the sectors i on which we focus are crops.

To characterise more precisely the biofuel shock, it can be useful at this stage to introduce a representation of biofuel coproducts, as these products (dried distiller grains with solubles for cereals and protein meals for oilseeds) allow a reduction of land use impacts by providing additional feed for animals. We introduce the production of these coproducts P in formula (5.5) and the relation can be rewritten:

$$F - P = B = \sum_r (\Delta S_r - \Delta D_r) \tag{5.6}$$

with B representing the overall market shock from the biofuel policy.

We can now decompose supply in each regions between the response in yield on the initially cultivated area (intensive margin) and the response in land expansion to cultivate new crops

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[3] We use for the rest of the article the following notations: bold upper case for matrixes, slanted upper case for vectors and lower cases for scalars. The dimensions of vectors and matrices are always the number of products considered.

(extensive margin). We can write this as follows:[4]

$$\Delta S = \Delta_y S + \mathbf{Y}_m(\Delta_s L + \Delta_e L) \tag{5.7}$$

with $\mathbf{Y}_m = \mathrm{diag}(y_i^m)$ the diagonal matrix of marginal expansion yields, Δ_y the production variation from the intensive margin and for extensive margin, a decomposition in two terms: Δ_s due to (positive or negative) net expansion of each crop within total cultivated area, at the expense of other crops, and Δ_e due to expansion of crop cultivated area into uncultivated land. Because all elements of the vector $\Delta_s L$ sum to zero by substitution of land, it is the last term $\Delta_e L$ that represents the ILUC effect.

Note that here, we assume that substitution and expansion occur with a specific marginal yield, different from the average yield of the crop.[5] Marginal expansion yield is an important variable in the biofuel debate. We will see later the role played by $\mathbf{Y}_m$ the diagonal matrix of marginal yield, as opposed to $\mathbf{Y} = (y_i)$ the diagonal matrix of average yield.

Market response to the biofuel shock from relation (5.7) can then be decomposed between substitution, expansion, yield and demand response as follows:

$$B = \sum_r \left(\mathbf{Y}_m(\Delta_s L + \Delta_e L) + \Delta_y S - \Delta D \right)_r , \tag{5.8}$$

5.2.2   ECONOMIC RESPONSES AND PRICE ELASTICITIES

Let's now develop the decomposition above as a function of prices to explicit agents' behaviours. This can be done by differentiating the different terms of expression (5.7) at the first order in prices. Because most of the biofuel debate on supply and demand responses has focused on values of elasticities (Keeney and Hertel, 2009, CARB, 2011), i.e. relative responses, we choose here a similar analytical framework. Elasticities are the most commonly used inputs to calibrate agricultural models (Rosegrant et al., 2008, Baldos and Hertel, 2013), due to the econometric literature providing such estimates on supply and demand (see later in Section 5.4.1).[6] Furthermore, we only look here at a decomposition at the first order associated to shocks of small magnitudes relatively to the rest of the production. That does not mean that use of feedstock for biofuel is always small.[7] But we are only interested here in the first order effect of ILUC and not in the non-linear effect related to

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[4]   For sake of simplification, index r is now dropped or factorised when no confusion is possible.

[5]   Indeed, land suitability being crop specific, crop allocation is usually optimised to offer most suitable land for each crop. We then assume that yield y_i^m of an area previously cultivated with a different crop j will be notably different from the average yield y_i of crop i.

[6]   Overall, the choice of this analytical framework through elasticities does not have here strong implications because we only look at shocks of small magnitude. Therefore, elasticities can be directly related to partial derivatives because the solution remains in the close neighborhood of the initial point.

[7]   In the US, 40% of the maize production was processed into ethanol in the year 2011. And in the EU, 74% of rapeseed oil was used as fuel the same year. Cereals used in the EU are relatively more limited, with 4% of corn and 3% of wheat in 2011.

an up-scaling of the production.[8] Indeed, the debate has focused on a single value of ILUC that could be applied to each feedstock pathways, independently from the overall size of the mandate. For this reason, we limit the decomposition to the first order effect, which is sufficient to exhibit all the important parameters discussed in the debate.

To do so, we first express Δd_i and $\Delta_s l_i$ as a function of price changes p_i, with own and cross-price effects. We note $\mathbf{E}^d$ and $\mathbf{E}^s$ the matrices of own and cross-price elasticities. To simplify the writing, we change some vectors into diagonal matrices and introduce cultivated area $\mathbf{L} = \mathrm{diag}(l_i)$, supply $\mathbf{S} = \mathrm{diag}(s_i) = \mathbf{YL}$ and demand $\mathbf{D} = \mathrm{diag}(d_i)$. We can then write:[9]

$$\varepsilon_{i,j}^d = \frac{\partial d_i}{\partial p_j} \cdot \frac{p_j}{d_i} \qquad \implies \Delta D = \mathbf{D}\mathbf{E}^d \left(\frac{\Delta p_j}{p_j} \right), \tag{5.9}$$

$$\varepsilon_{i,j}^s = \left(\frac{\partial l_i}{\partial p_j} \right)_{(s)} \cdot \frac{p_j}{l_i} \implies \Delta_s L = \mathbf{L}\mathbf{E}^s \left(\frac{\Delta p_j}{p_j} \right). \tag{5.10}$$

To preserve the properties of substitution, we impose some constraints on the matrix $\mathbf{E^s}$, and assume that the two following relations hold: $\sum_i l_i \varepsilon_{i,j}^s = 0, \forall j$ (land market clearing) and $\sum_j \varepsilon_{i,j}^s = 0, \forall i$ (price homogeneity).

With respect to Δy_i and Δ_{ei}, in order to keep the framework consistent with parameters supplied by the econometric literature, we follow the same approach but assume these quantities to depend only on own-price effects, and set cross-price effects to zero.[10] These effects are then represented by $\mathbf{E}^y = \mathrm{diag}(\varepsilon_i^y)$ the diagonal matrix of own price yield elasticities and $\mathbf{E}^e = \mathrm{diag}(\varepsilon_i^e)$ for own price expansion elasticities, as follows:

$$\varepsilon_i^y = \frac{\partial y_i}{\partial p_i} \cdot \frac{p_i}{y_i} \qquad \implies \Delta_y S = \mathbf{S}\mathbf{E}^y \left(\frac{\Delta p_i}{p_i} \right), \tag{5.11}$$

$$\varepsilon_i^e = \left(\frac{\partial l_i}{\partial p_i} \right)_{(e)} \cdot \frac{p_i}{l_i} \implies \Delta_e L = \mathbf{L}\mathbf{E}^e \left(\frac{\Delta p_i}{p_i} \right). \tag{5.12}$$

According to our previous definition, we have $\mathbf{E}^d$ and $\mathbf{E}^s$ as general $n \times n$ matrices, with n the number of products, whereas $\mathbf{E}^y$ and $\mathbf{E}^e$ are only diagonals matrices.

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[8]   Al-Riffai et al. (2010b) found some non-linear effect associated with the expansion of the EU mandate, but mainly driven by a change in the biofuel mandate composition. The non-linear effect of ILUC at the level of a single crop has been little investigated by applied models.

[9]   Our notation here to distinguish the substitution and the expansion effects is: $\left(\frac{\partial l_i}{\partial p_j} \right) = \left(\frac{\partial l_i}{\partial p_j} \right)_{(s)} + \left(\frac{\partial l_i}{\partial p_j} \right)_{(e)}$.

[10] For yield endogenous responses, it is indeed not standard to test cross-price yield responses and we did not find any estimates for these (see Appendix C for a literature overview). For expansion response, elasticities are usually estimated for cropland as a whole, as a function of crop prices (or of land rent). We therefore only represent this effect at crop level by an own-price effect. In practice, because cross-prices effects across crops are captured in our framework through substitution on supply and demand side (with $\mathbf{E}^d$ and $\mathbf{E}^s$), there will be some clear cross-price effects on yield and expansion in the results of our decomposition.

Introducing elasticities in the decomposition from formula (5.8), we can now write:

$$B = \sum_r \left[\mathbf{L}(\mathbf{YE}^y + \mathbf{Y}_m(\mathbf{E}^s + \mathbf{E}^e)) - \mathbf{DE}^d \right]_r \left(\frac{\Delta p_{i,r}}{p_{i,r}} \right) \tag{5.13}$$

$$= \sum_r \mathbf{\Gamma}_r \left(\frac{\Delta p_{i,r}}{p_{i,r}} \right), \tag{5.14}$$

$$\text{with } \mathbf{\Gamma}_r = \underbrace{\mathbf{YLE}^y}_{\substack{\text{Endogenous} \\ \text{yield} \\ \text{response}}} + \underbrace{\mathbf{Y}_m\mathbf{LE}^s}_{\substack{\text{Land} \\ \text{recomposition} \\ \text{response}}} + \underbrace{\mathbf{Y}_m\mathbf{LE}^e}_{\substack{\text{Land} \\ \text{expansion} \\ \text{response}}} - \underbrace{\mathbf{DE}^d}_{\substack{\text{Demand} \\ \text{response}}} \text{ specific to each region } r. \tag{5.15}$$

The matrix $\mathbf{\Gamma}_r$ represents the market responsiveness to price in the region r. Expression (5.15) makes clear the roles of price elasticities to determine the relative contributions of responses to supply the market, between land expansion, yield increase, recomposition of the production, or decrease in demand of other goods. The magnitude of land expansion response will be directly affected by elasticity values in other terms.

The relation (5.15) above can easily be generalised at the world level. For this, we need an assumption on the transmission of prices across regions. If markets are fully integrated, we can just assume $p_{i,r} = p_{i,r_0}$ for all regions and prices can be immediately factorised in equation (5.13). A more realistic assumption however requires a description of market restrictions. We can make a stylised representation of this case by assuming a relation of the form $\left(\frac{\Delta p_{i,r}}{p_{i,r}} \right) = \alpha_{i,r_0,r} \left(\frac{\Delta p_{i,r_0}}{p_{i,r_0}} \right)$ where the parameter $\alpha_{i,r_0,r}$ is the price transmission index of the region r_0 to the region r.[11] Let's note $\mathbf{A}_{r,r_0} = \text{diag}(\alpha_{i,r,r_0})_i$ the price transmission matrix of region r_0. If markets are insulated markets, this simply implies: $\mathbf{A}_{r_0,r} = 0, \forall r \neq r_0$. On the contrary, if markets are fully integrated, prices are all equal across regions and we can write, $\mathbf{A}_{r_0,r} = \mathbf{Id}$. Many intermediary cases are however plausible, as agricultural markets are still significantly protected (Bouët et al., 2008).[12] This price transmission matrix $\mathbf{A}_{r_0,r}$ allows us to express all prices in reference to region r_0 in expression (5.14) and to express price relative deviation as a function of the biofuel shock B:

$$\left(\frac{\Delta p_{i,r_0}}{p_{i,r_0}} \right) = \left[\sum_r \mathbf{A}_{r_0,r} \mathbf{\Gamma}_r \right]^{-1} \cdot B. \tag{5.16}$$

The matrix $\tilde{\mathbf{\Gamma}}_{r_0} = \sum_r \mathbf{A}_{r_0,r} \mathbf{\Gamma}_r$ represents the *global market response* to price shocks in region r_0. In case of free trade and no transportation costs, $\tilde{\mathbf{\Gamma}}_{r_0} = \sum_r \mathbf{\Gamma}_r$ is the same for all regions, but in a world with asymmetric trade barriers, it remains region specific. This has implications for ILUC

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[11]   This relation can be connected to a more complete representation of trade restrictions as follows. Let's assume $p_{i,r} = (1 + t_{i,r})(p_{i,r_0} + c_{i,r}) + \tau_{i,r}$ in case of net trade from region r_0 to r with $\tau_{i,r}$ standing for an *ad valorem* tariff and $c_{i,r}$ the bilateral cost related to transport and other trade costs. We obtain in this case $\alpha_{i,r_0,r} = 1/(1 + c_{i,r}/p_{i,r_0} + \tau_{i,r}/(p_{i,r_0} * (1 + t_{i,r}))$.

[12]   On the basis of the formula used in footnote 11, for an export from region r_0 to region r, $\alpha_{i,r_0,r}$ would be inferior to 1, except in case of export subsidies, equivalent to a case with $\tau_{i,r} < 0$.

calculation because it means that effect from growing biofuel crop will be *feedstock dependent*, but also *region dependent*.

Now that we have obtained a formulation of prices as a function of the shock, we can express cropland expansion as a function of elasticities only:

$$\sum_r \Delta_e L_r = \sum_r \left[\mathbf{L}_r \mathbf{E}_r^e \left(\frac{\Delta p_{i,r}}{p_{i,r}} \right) \right] \tag{5.17}$$

$$= \sum_r \left(\mathbf{A}_{r_0,r} \mathbf{L}_r \mathbf{E}_r^e \right) \left(\frac{\Delta p_{i,r_0}}{p_{i,r_0}} \right) \tag{5.18}$$

$$= \left[\sum_r \mathbf{A}_{r_0,r} \mathbf{L}_r \mathbf{E}_r^e \right] \tilde{\mathbf{\Gamma}}_{r_0}^{-1} \cdot B. \tag{5.19}$$

This formulation has some similarity with the long run equilibrium expression (5.2) from Hertel (2011), when applied to a shock on the demand side.[13] But it also differs on several points: i) it provides a representation with different regions and products, emphasizing the role of price transmission; ii) it adds a terms of reallocation in the supply decomposition; iii) it explicits the role of marginal yield, an important aspect of the ILUC discussion.

5.2.3 ALGEBRAIC EXPRESSION OF ILUC AND NDF

The previous section led us to an expression of land use expansion as a function of price elasticities only. It is now easy to express ILUC in a form suitable comparable with the literature. We can first rescale the shock and characterise the biofuel policy by a normalised vector $U_B = (F - P)/\|F\|$. We also note ρ_{i_0} the energy yield of the biofuel feedstock i_0 (MJ per ton). The "indirect" land use change vector (ha expansion per MJ) associated to the biofuel policy is directly given by formula (5.16):

$$\text{ILUC} = \underbrace{\left[\sum_r \mathbf{A}_{r_0,r} \mathbf{L}_r \mathbf{E}_r^e \right]}_{\substack{\text{Global} \\ \text{expansion} \\ \text{response}}} \cdot \underbrace{\tilde{\mathbf{\Gamma}}_{r_0}^{-1}}_{\substack{\text{Domestic} \\ \text{price} \\ \text{response}}} \cdot \underbrace{\frac{U_B}{\rho_{i_0}}}_{\substack{\text{feedstock and} \\ \text{coproducts} \\ \text{efficiency}}}. \tag{5.20}$$

It can be however convenient to reorganise this expression to better explicit homogeneity across terms. For this, we introduce the diagonal matrix of *average* marginal yield, relative to region r_0, which expresses what is the average yield of crops in regions where expansion takes place, when a shock is applied to region r_0. Because price transmission patterns are region specific, as discussed

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[13] If only a shock on the demand side is considered, the formula from Hertel (2011) simplifies into $q_L^* = (\eta_A^{S,E} \Delta_A^D)/(\eta_A^{S,E} + \eta_A^{S,I} + \eta_A^D)$. We can recognise the land elasticity on the numerator and the sum of land, demand and yield elasticities on the denominator.

above, the average marginal yield is also specific to the region where the shock is applied.[14] We can define it as below:

$$\tilde{\mathbf{Y}}_{r_0} = \sum_r \mathbf{W}_{r_0,r} \mathbf{Y}_m \tag{5.21}$$

$$\text{with } \mathbf{W}_{r_0,r} = \mathbf{A}_{r_0,r} \mathbf{L_r} \mathbf{E}_r^e \cdot \left[\sum_{r'} \mathbf{A}_{r_0,r'} \mathbf{L}_{r'} \mathbf{E}_{r'}^e \right]^{-1}. \tag{5.22}$$

$\mathbf{W}_{r_0,r}$ is a diagonal matrix indicating the share of cropland expansion taking place in each region r. We therefore have $\sum_r \mathbf{W}_{r_0,r} = \mathbf{Id}$. As for other quantities before, this geographical distribution of land expansion is dependant on the region r_0 where the biofuel demand takes place.

A second useful expression is the matrix of contribution of land expansion to all supply and demand adjustments. We define it as:

$$\mathbf{\Phi}_{r_0} = \left[\sum_r \mathbf{Y}_m \cdot \mathbf{A}_{r_0,r} \mathbf{L}_r \mathbf{E}_r^e \right] \tilde{\mathbf{\Gamma}}_{r_0}^{-1}, \tag{5.23}$$

$\mathbf{\Phi}_{r_0}$ can be interpreted as a matrix of extensive margin contribution to market response, that we call *extensive margin factor*. The term on row i and column j indicates the relative contribution of expansion of crop i to responses on its market, following a shock on market j. Diagonal elements are then a good proxy of the relative magnitude of land expansion response.

Using the new notations (5.21) and (5.23) above, we can now reformulate our first expression of ILUC (5.20) and also derive a simple expression of the NDF from Plevin et al. (2010), defined as $\text{NDF} = y_{Fuel} \text{ILUC}$, with $y_{Fuel} = \rho_{i_0} y_{i_0,r_0}$ the energy yield per ha. We obtain the final formulas below:

$$\text{ILUC} = \underbrace{\tilde{\mathbf{Y}}_{r_0}^{-1}}_{\substack{\text{Land} \\ \text{marginal} \\ \text{requirement}}} \underbrace{\mathbf{\Phi}_{r_0}}_{\substack{\text{Extensive} \\ \text{margin} \\ \text{factor}}} \underbrace{U_B / \rho_{i_0}}_{\substack{\text{Biofuel feedstocks} \\ \text{and coproducts} \\ \text{requirement}}}, \tag{5.24}$$

$$\text{NDF} = \underbrace{\frac{y_{i_0,r_0}}{\tilde{\mathbf{Y}}_{r_0}}}_{\substack{\text{Domestic to} \\ \text{marginal} \\ \text{yield gap}}} \cdot \underbrace{\mathbf{\Phi}_{r_0}}_{\substack{\text{Extensive} \\ \text{margin} \\ \text{factor}}} \cdot \underbrace{U_B}_{\substack{\text{Biofuel feedstock} \\ \text{and coproduct} \\ \text{choice}}}. \tag{5.25}$$

[14]   For instance, in a world with no trade, average marginal yield equals for each region to the domestic marginal yield, because all expansion occurs at home. On the contrary, in a fully integrated market, average marginal yield is the same for all regions, because expansion patterns are independent from the region where the shock occurs.

These two expressions (5.24) and (5.25) will be at the core of the analysis of the next sections, and used for all our future calculations.

The formula of the NDF (5.25) deserves some more particular attention as it was not formalised in Plevin et al. (2010).

First of all, this formula expresses the NDF as function of main market responses through $\mathbf{\Phi}_{r_0}$. This matrix depends on values of elasticities of yield $\mathbf{E}^y$, substitution $\mathbf{E}^s$ and demand response $\mathbf{E}^d$ and, as expected, on expansion elasticities $\mathbf{E}^e$. Expansion elasticity is the only term that has a direct multiplicative effect on the results. $\mathbf{\Phi}_{r_0}$ is homogeneous of degree zero in elasticity values, which emphasizes that it is not the elasticity values *per se* that are important but rather their relative magnitude when compared to each others. The values of these elasticities are therefore a main challenge for estimation of ILUC and we will explore them in section 5.4.

Second, the NDF factor also directly depends on the crop type used for biofuel and the associated co-products, U_B. Because some co-product elements of P are negative, the sign of the overall displacement is not *a priori* obvious. Note that even in case where co-products are absent, the sign of the NDF is not necessarily positive because of the ambiguous role that can play reallocation within cropland and cross-effects on the demand side (terms $\mathbf{Y}_m\mathbf{LE}^s$ and $\mathbf{DE}^d$, respectively, in $\mathbf{\Gamma}_r$; see equation (5.15)). Section 5.4 will however show that such negative ILUC values occur with very small probabilities.

Last, marginal yield appears as a first order parameter for the final results. However, marginal yield is also present at the numerator and the denominator of the matrix $\mathbf{\Phi}_{r_0}$. Therefore, this term will only play a significant role if expansion and reallocation effects are preponderant on other effects in the denominator of $\mathbf{\Phi}_{r_0}$ (the two terms in numerator and denominator of the matrix therefore cancel each other). If expansion is small compared to other effects, the numerator of $\mathbf{\Phi}_{r_0}$ tend to neutralise the role of the marginal yield value.[15]

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[15]   Note that it is very likely that $\mathbf{Y}_m$ and $\mathbf{E}^e$ influence each other, although the direction is not clear. A region with a low marginal yield should not give big incentives to expand crop acreage, which could make expansion elasticity lower. However, if expansion still reveals profitable, it is likely then that large areas would be cropped to generate sufficient production, implying higher value of expansion elasticity. We then keep here the discussions on the two parameters separate.

5.2.4 Emissions and ILUC factor

The formulas above have been focusing on land use change. To look at the final efficiency of biofuel policies, we can complement them by expressing the ILUC factor measuring annual GHG emissions. We note Em(.) the function providing total emissions as a function of cropland expansion. Emissions from ILUC are specific to the type of land cover c converted to cropland. One can consider for each region that one unit of cropland expansion leads to the conversion of $\theta_{c,r}$ unit of land cover type c with $\sum_c \theta_{c,r} = 1$ in each region. Land cover type c in region r contains $e_{c,r}$ quantity of carbon released from conversion of land to cultivation. Noting $N = (1, 1, ..., 1)$, this leads to the relation:

$$\text{Em(ILUC)} = \text{Em}(\sum_r \Delta_e L_r) \tag{5.26}$$

$$= \sum_r \left[\sum_c \theta_{c,r} \; e_{c,r} \Delta_e L_r \right] \cdot N \tag{5.27}$$

$$= \text{ILUC} \cdot \text{EF}_{r_0}, \tag{5.28}$$

$$\text{with EF}_{r_0} = \sum_{c,r} \theta_{c,r} \; e_{c,r} \, \mathbf{W}_{r_0,r} \, N. \tag{5.29}$$

Our expression of emission factor EF_{r_0} (5.29) is similar to the one from Plevin et al. (2010) with the notable difference that the composition effect from location of land expansion is here clearly identified with the $\mathbf{W}_{r_0,r}$ allocation parameter.

The final ILUC factor is derived from ILUC emissions by dividing by a period of reference t_{ref} (set in practice to 20 years in the EU and 30 years in the US) and we can write:

$$\text{ILUC factor} = \frac{\text{ILUC} \cdot \text{EF}_{r_0}}{t_{ref}} \tag{5.30}$$

This last expression shows that ILUC factor depends on ILUC as calculated in Section 5.2.1 but also on the world average emission factor EF_{r_0}, that is related to localisation of expansion associated to region policies r_0.

The three outlined formulas above express the important indicators we will focus on in the next sections. We will first apply these formulas to a stylised case in the last part of this section, , in order to better explicit how this framework can be used in practice.

5.2.5 ILLUSTRATION WITH A TWO REGIONS THREE CROPS SIMPLIFIED CASE

To illustrate our decomposition, we consider a case with two regions, Home and Foreign and we note the variables without bar for Home and with bar for Foreign. [16] The three crops considered are cereals (Cer), oilseeds (Osd) and other crops (Oth). Values for production, trade and consumption patterns for Home are rounded figures inspired from the European Union (EU) and Rest of the world characteristics in 2007 (FAOSTAT database).

We therefore define areas, yield, production and demand as follows:

$$\mathbf{L} = \begin{pmatrix} 60 & 0 & 0 \\ 0 & 10 & 0 \\ 0 & 0 & 10 \end{pmatrix}, \qquad \mathbf{Y} = \begin{pmatrix} 5 & 0 & 0 \\ 0 & 6 & 0 \\ 0 & 0 & 3 \end{pmatrix}, \qquad \mathbf{S} \begin{pmatrix} 300 & 0 & 0 \\ 0 & 60 & 0 \\ 0 & 0 & 30 \end{pmatrix}, \qquad \mathbf{D} = \begin{pmatrix} 310 & 0 & 0 \\ 0 & 140 & 0 \\ 0 & 0 & 55 \end{pmatrix},$$

$$\bar{\mathbf{L}} = \begin{pmatrix} 500 & 0 & 0 \\ 0 & 200 & 0 \\ 0 & 0 & 400 \end{pmatrix}, \quad \bar{\mathbf{Y}} = \begin{pmatrix} 2.5 & 0 & 0 \\ 0 & 3 & 0 \\ 0 & 0 & 2 \end{pmatrix}, \quad \bar{\mathbf{S}} \begin{pmatrix} 1250 & 0 & 0 \\ 0 & 600 & 0 \\ 0 & 0 & 800 \end{pmatrix} \text{ and } \bar{\mathbf{D}} = \begin{pmatrix} 1240 & 0 & 0 \\ 0 & 520 & 0 \\ 0 & 0 & 775 \end{pmatrix}.$$

Areas correspond to million hectares, yields are in ton of cereal equivalent per hectares, production and demand are million tons of cereal equivalent. Other crops than cereals are converted to cereal equivalent on the basis of their relative calorie content per ton. This conversion allows for a consistent metric of substitution on the demand side.[17]

For this first example, values of elasticities are chosen to be close to literature estimates on ILUC modelling. More discussion on plausible ranges will take place in Section 5.4. For land substitution, we use the following values:

$$\mathbf{E}^s = \begin{pmatrix} 0.15 & -0.15 & 0 \\ -0.85 & 0.9 & -0.05 \\ -0.05 & 0 & 0.05 \end{pmatrix} \text{ and } \bar{\mathbf{E}}^s = \begin{pmatrix} 0.2 & -0.2 & 0 \\ -0.4 & 0.6 & -0.2 \\ -0.05 & -0.05 & 0.1 \end{pmatrix}.$$

We assume similar range of own price land supply elasticities for both regions. Cereals and oilseeds are main substitutes on cropland, whereas other crops substitute little in this design with them. Own price elasticity of cereals is lower than oilseeds because areas is three to four times larger, and other crops have a more significant role in Foreign because their area is relatively larger in this region. The relations assumed for substitution matrixes are verified with lines and area-weighted columns summing to zero.

Other calibration characteristics of the supply side are calibrated according to Chapter 4: endogenous yield elasticities are assumed to be 0.25 for both regions and land expansion elasticity 0.05 in Home (land constraint) and 0.1 in Foreign (land available).[18] We suppose as default setting

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[16]   This example is already implemented in the Excel template provided online. See footnote 1.

[17]   Average coefficients of correction for an equivalent content of calories per ton are for Home: 1 for cereals (reference), 2 for oilseeds and 0.2 for other crops; for Foreign: 1.15 for cereals, 2 for oilseeds, 0.3 for other crops.

[18]   Land expansion elasticities in MIRAGE-BioF are elasticities of land expansion with respect to land rent. To obtain the elasticity of land expansion with respect to commodity price, we correct the elasticity value by the share of land rent in total cost (assumed around 20%), as suggested by Salhofer (2000) for long term equilibrium.

that marginal yield equals 0.75 average yield.

For demand, we also consider simple matrices, assuming this time more inelastic demand in Home region, supposed to have a higher level of development.

$$\mathbf{E}^d = \begin{pmatrix} -0.1 & 0.01 & 0.01 \\ 0.05 & -0.1 & 0.01 \\ 0.05 & 0.05 & -0.1 \end{pmatrix} \text{ and } \bar{\mathbf{E}}^d = \begin{pmatrix} -0.25 & 0.01 & 0.01 \\ 0.05 & -0.25 & 0.01 \\ 0.05 & 0.05 & -0.25 \end{pmatrix}.$$

The aggregated demand elasticity associated for these matrixes can be computed as a demand-weighted average of the different elasticities and equal -0.06 for Home and -0.20 for Foreign. They are consequently suppposed of lower magnitude than supply elasticity in the range 0.25–1 (if yield and land response are considered together).

Using formula (5.23), we can therefore compute the land expansion response matrix:

$$\mathbf{\Phi} = \begin{pmatrix} 0.110 & 0.040 & 0.011 \\ 0.020 & 0.080 & 0.015 \\ 0.012 & 0.017 & 0.120 \end{pmatrix}.$$

Figures in this matrix can be interpreted as the share of market response that comes from land expansion in each crop type (Cer, Osd, Oth, in line) for a shock on a feedstock (Cer, Osd, Oth, in column).

For our calculation, co-products returns are based on coefficients from the JRC (Edwards et al., 2004). Co-products from use of one tonne equivalent of wheat replace 0.32 tonne cereals and 0.06 tonne equivalent of oilseeds. Co-products from use of one tonne of rapeseed replace 0.13 tonne of cereals and 0.17 tonnes equivalent of oilseed.[19]

We illustrate the functioning of this analytical framework with a focus on the effect of price transmission by varying the value of $\bar{\mathbf{A}}$, the diagonal matrix of price correlation of region "Foreign" with region "Home". Let's look first at the impact per quantity of feedstock transformed (i.e. we do not divide by the energy yield ρ_{i_0} in formula (5.24)).

- We take first a case where Home does not trade ("Autarky"). This corresponds to the case $\bar{\mathbf{A}} = 0$ and brings $\tilde{\mathbf{\Gamma}} = \mathbf{\Gamma}$ and $\tilde{\mathbf{Y}} = \mathbf{Y}$. Formula (5.20) provides ILUC $= \mathbf{L}\mathbf{E}^e\mathbf{\Gamma}^{-1}U_B$. By summing elements of this vector, we find for cereals an ILUC effect of 18 ha per 1000 tonnes

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The formula applied is $\varepsilon_C = \frac{\theta \, \varepsilon_L}{\alpha}$ with ε_C and ε_L elasticities of land supply with respect to commodity price and land rent, respectively, α the cost share of land and θ the share of benefits transmitted to land. According to Salhofer, θ value is typically in the range 1/3 to 2/3 in medium run and converges to 1 in the long run.

[19] These coefficients are obtained by converting to cereal equivalent tons the initial substitution ratio. JRC assumes one tonne of wheat dried distiller grains with soluble replaces 0.95 tonne of corn and 0.12 tonne of soybean meal. One tonne of rapeseed meal replace 0.48 tonne of corn and 0.40 tonne of soybean meal. All our equivalents are here based on calorie content with the following values: 5,900 kcal per tonne of EU oilseeds, 2,700 kcal per tonne EU cereals and 4,200 kcal per tonne of soybean meal displaced. Because we assume a different value to soybean meal than to EU oilseeds, this is equivalent to consider that not all the soybean area is substituted (but only 72%) due to the value of soybean oil. We will vary this assumption later.

transformed and 34 ha per 1000 tonnes oilseeds transformed (here converted back to oilseed primary equivalent).[20] Considering the respective crop yields of these crops and relation (5.25), this provides a net displacement factor of 0.09 for these two feedstocks.

- We now consider a small price transmission on all markets with $\bar{\mathbf{A}} = 0.1\,\mathbf{Id}$. Such scenarios will be noted "Reduced trade". Results now display an effect induced in the Foreign region that represents 67% of expansion for wheat ethanol and 77% of expansion for rapeseed biodiesel. As a consequence, expansion effect is now of 31 ha per 1000 tons of cereals transformed and 70 ha per 1000 tons of oilseeds, which corresponds to a NDF value of 0.15 and 0.19 respectively, a significant increase.

- Last, in the case of an "Integrated market", $\bar{\mathbf{A}} = \mathbf{Id}$ and the effect in Foreign is preponderant. Expansion effect jumps to 45 ha per 1000 tons for cereals and 99 ha per 1000 tons for oilseeds. The NDF goes up at a level of 0.23 for cereals and 0.27 for oilseeds.

The contribution of the different effects from equation (5.14) and from co-products return to the NDF of ethanol and biodiesel are shown in Figure 5.1 across crops and Figure 5.2 across regions, for the different price transmission scenarios. We also express in these figures the ILUC effect per energy produced.[21]

As can be seen in Figure 5.1, the two largest sources of reduction of land use expansion with the current settings are yield response and co-products return, especially in the case of ethanol (over 40%). Contribution of demand is below 20% when trade is restricted but progressively increase when moving to free trade, whereas contribution from yield is decreased. Reallocation of crops does not play a big role in the case of ethanol but can also buffer a small fraction of the shock in the case of biodiesel (contribution of 7% for free trade). Land expansion and ILUC significantly increase when markets get connected and reaches 5.2 ha/TJ for ethanol and 6.9 ha/TJ for biodiesel. If we assume an emission factor of 100 tCO$_2$-eq in Home and 200 tCO$_2$-eq for Foreign and an amortisation period of 20 years, this corresponds to ILUC factors of respectively 51 and 68 gCO$_2$-eq/MJ, which is higher than the median values from Chapter 4, where the ILUC factors corresponded to some feedstock mixes, but remains in the middle of the range of estimates from 10 to 115 gCO$_2$-eq/MJ.

The magnitude of the price transmission effect is however not the only one important parameter and the various other sources of uncertainty will be studied in the next section.

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[20]   Conversion from tonnes cereal equivalent to oilseeds equivalent is done by multiplying by 5,900/2,700, ratio of kcal per tonne.

[21]   We use for energy conversion coefficients from Edwards et al. (2004). Cereal ethanol is assumed to be based on wheat with a transformation coefficient of 8.72 GJ per tonne. Oilseed is based on the rapeseed pathway with a coefficient of 14.37 GJ per tonne, which is equivalent to 6.58 GJ per tonne of cereal equivalent.
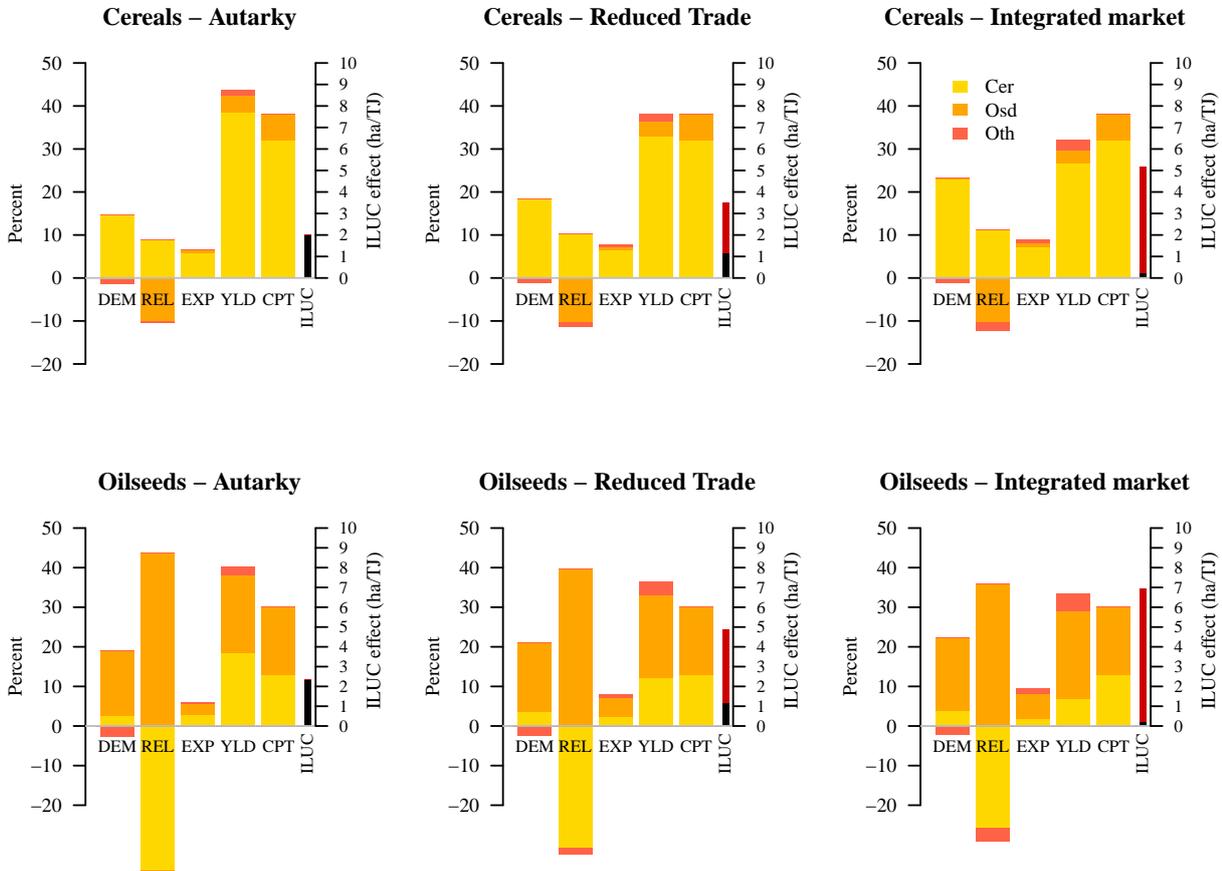
Figure 5.1. Decomposition between crops of ILUC effect of two feedstocks with three trade settings. Effects for decomposition are: DEM= demand drop, REL=relocation, EXP=expansion, YLD=yield increase, CPT=coproducts. Each large bar indicates the percentage of contribution of the effect to the supply of extra quantity of crop required for biofuel production (left axis). Thin bars indicate the magnitude of ILUC per unit of energy (right axis) and are decomposed between the domestic expansion (black) and the foreign expansion (red). Sectors are Cer for cereals, Osd for oilseeds and Oth for other crops.
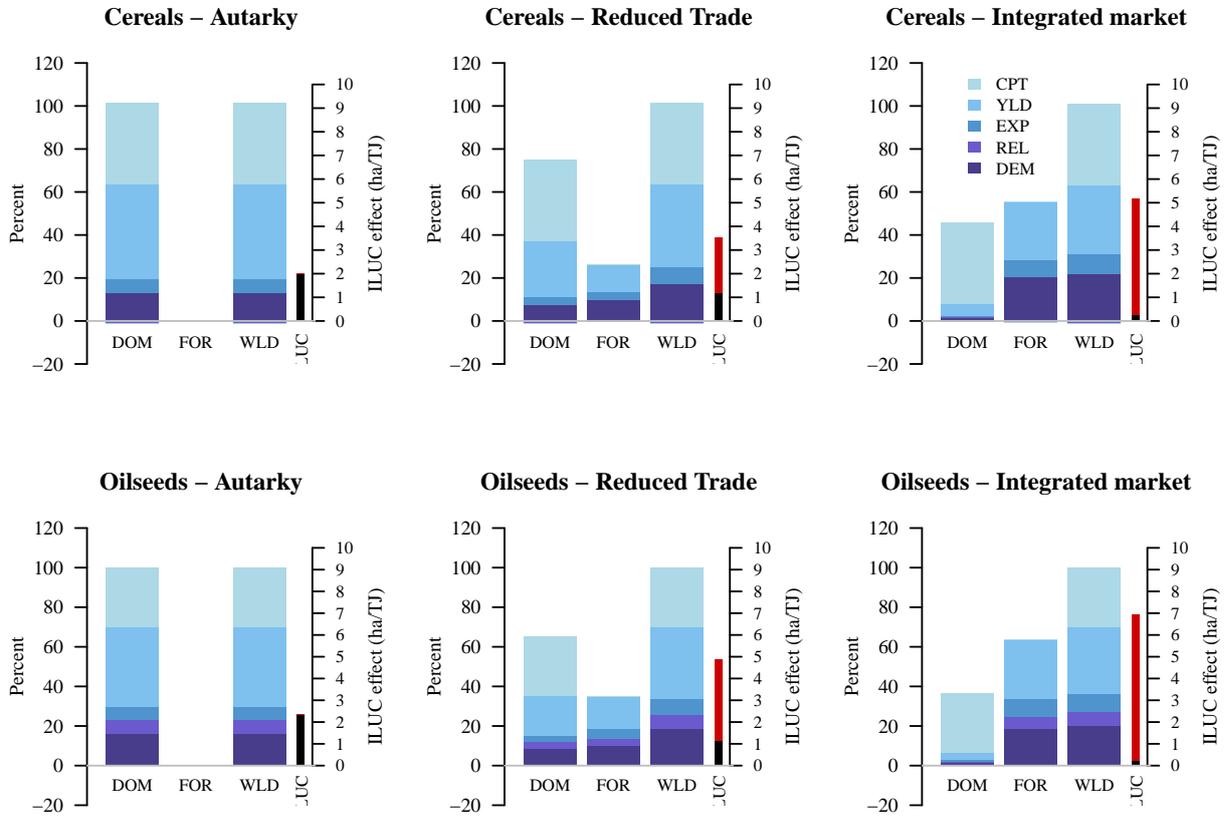
Figure 5.2. Decomposition between region of ILUC effect of two feedstocks with three trade settings. Effects for decomposition are: DEM= demand drop, REL=relocation, EXP=expansion, YLD=yield increase, CPT=coproducts. Each large bar indicates the percentage of contribution of the effect to the supply of extra quantity of crop required for biofuel production (left axis). Thin bars indicate the magnitude of ILUC per unit of energy (right axis) and are decomposed between the domestic expansion (black) and the foreign expansion (red). Regions are DOM for Home, FOR for Foreign and WLD for the entire world.

Table 5.1. Range of parameter explored for the sensitivity analysis around the central estimate.

Name	Description	Central estimate		Sensitivity analysis
$\mathbf{E}^d$	Elasticity of demand	Aggregate elasticity: Home: -0.06, Foreign: -0.2		$\pm 50\%$[a]
$\mathbf{E}^s$	Elasticities of substitution between crops	Own-price value from 0.05 to 0.9		$\pm 50\%$[a]
$\mathbf{E}^e$	Elasticities of land expansion	Home: 0.05, Foreign: 0.1		$\pm 50\%$
$\mathbf{E}^y$	Elasticity of yield response	0.25 for all regions		$\pm 50\%$
P	Co-product feedback	Ethanol wheat:	0.32 tonne of cereals 0.06 t eq. oilseeds[b]	$\pm 50\%$
		Biodiesel rape:	0.13 t cereals 0.17 t eq. oilseeds[b]	
$\mathbf{Y}_m/\mathbf{Y}$	Marginal yield relative value	0.75		$\pm 50\%$
$\bar{\mathbf{A}}$	Coefficients of price transmission	1		-50%

[a] Cross-price elasticities are varied accordingly.
[b] Tonne equivalent corresponds to tonnes of cereals equivalent on a kcal basis.

5.3   Sensitivity analysis around usual models results

The simplified representation of ILUC developed above – equations (5.24), (5.25) and (5.26) – provides a convenient framework to freely explore in a transparent framework how parameterisation choices influence the results of applied models on ILUC.

As we have seen above, applying our framework to two regions and three products allows for mimicking some of the results in the literature. Using parameterisation based on MIRAGE-BioF (Chapter 4), we find results close to the central estimates of this model. The results here are not identical to those of the CGEs for many understandable reasons: i) dataset used for the analysis is much simplified, ii) co-products are substituting on the market without any constraint, iii) feedstocks considered here are single crops versus portfolio of crops in the MIRAGE-BioF analysis, iv) land expansion elasticity is the same for all the Foreign regions, v) the livestock sector dynamic is not represented.

5.3.1   Sensitivity analysis around mean value

As a first step, we can perform a sensitivity analysis similar to what is usually performed for large scale models. For each parameter, we first test the effect of increasing or decreasing the value of that parameter only and look at the impact on final output. We here focus on the economic parameters and examine the impact of changing seven parameters already identified above: elasticities of demand, substitution, land expansion and yield response, as well as co-product feedback value, marginal yield value and coefficient of price transmission. Our assumptions on the range explored are summarised in Table 5.1.

For a first analysis, we vary each of these parameters by $\pm 50\%$, except for $\mathbf{A}$ that we do not increase over 1 (only -50% is tested). Parameters are changed homogeneously for the two regions and the three crops. Implications for the NDF and ILUC values are reported in Figure 5.3 for two feedstocks. Results show very similar patterns for both wheat ethanol and rapeseed biodiesel. The most sensitive parameters appears to be elasticity of expansion, without any strong surprise, as it is a multiplicative factor of the matrix $\mathbf{\Phi}$, according to (see eq. (5.23)). But other parameters also reveal important: elasticity of yield response, elasticity of demand and last, value of co-products feedback. On the opposite, some parameters appear relatively less influent, in particular, linkage to international price, value of marginal yield, and substitution elasticities. We have seen in Section 5.2.5 that trade plays a strong role for indirect land use change, but this effect already appears for small values – reduced trade is equivalent to a 10% linkage in Figures 5.1 and 5.2, whereas we look in Figure 5.3 at the 50–100% interval. The small response to change in marginal yield comes from the fact that this quantity is at the numerator in matrix $\mathbf{\Phi}$ but is also at the denominator of the first term $y_{i_0,r_0}/\tilde{\mathbf{Y}}$ in the NDF formula (eq. (5.25)). As will be seen later, marginal yield value plays a stronger role when other elasticities at the denominator of $\mathbf{\Phi}$ are small. Last, the limited sensitivity to elasticity of land substitution for crops finds its source in the similarity of yields across sectors (when expressed in kcal per ha), as well as the homogeneity of most other parameters for the three different crops (yield response, expansion elasticity). As we had observed in Section 5.2.5 however, more substitution occurs with our parameterisation in the case of oilseeds. We find this effect again in the sensitivity analysis where substitution effect is slightly more influent on the final result of rapeseed biodiesel than for wheat ethanol.

To examine how these different intervals of confidence interact, we run all possible combination of the sensitivity analyses above, first for the four parameters on the supply side ('SUP', targeting elasticities of substitution, expansion, yield and marginal yield value) and second, for all parameters ('ALL'). The two darker bars on the upper side of charts in Figure 5.3 show the corresponding results. Cumulated effects appear large and asymmetrical, to the difference of most individual effects that were symmetrical (except to a smaller extent for yield response and trade). For wheat, the total effect range from 1 to 15 ha/TJ and for biodiesel from 2 to 19 TJ/ha. The results obtained are in line with what was observed in Chapter 4 (range from 1 to 12 TJ/ha) but the asymmetry is here more pronounced. We obtain slightly higher values of possible NDF than with our CGE model sensitivity analysis, which also echos the flat right-tail already identified by Plevin et al. (2010), but here directly for the NDF contribution.

5.3.2 Uncertainties interactions

To better understand how the different individual effects observed above interact, we now widen the design of our uncertainty analysis. The intervals we test are extended to $\pm 100\%$ and, more importantly, we perform explore sensitivity results by parameter pairs. Results are reported in Figure 5.4 and 5.5 for ethanol and biodiesel, respectively. Each chart indicates the range of ILUC
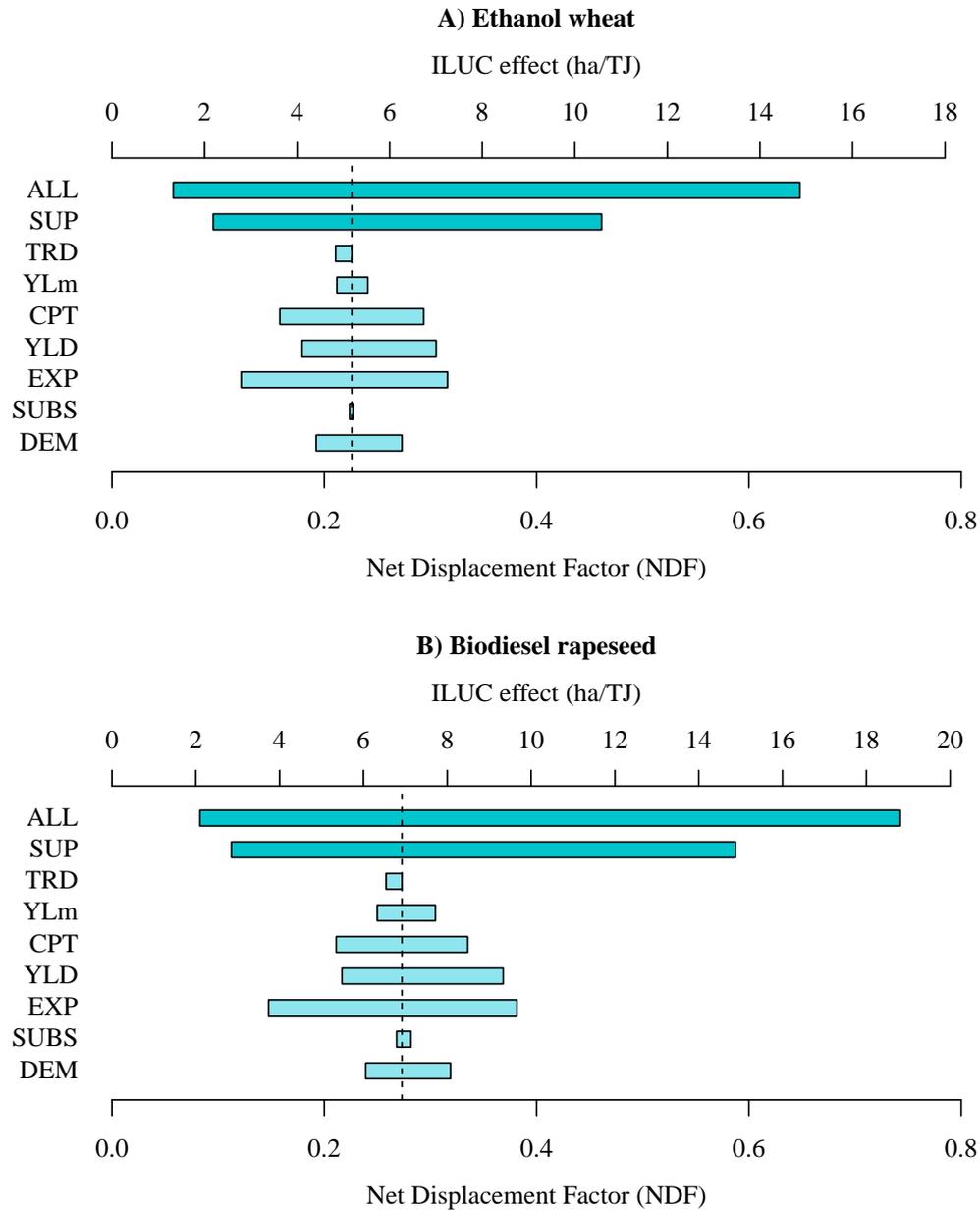
Figure 5.3. Sensitivity analysis on results for ethanol (A) and biodiesel (B) net displacement factor (bottom axis) and indirect land use change (top axis). Parameters are varied by $\pm 50\%$ around the central values selected in section 5.2.5. Parameters targeted are: DEM=demand elasticities, SUBS=substitution elasticities, EXP=expansion elasticities, YLD=yield elasticities, YL_m marginal yield value, CPT=co-products and TRD=international market price transmission. Dark bars at top take into account cumulated effects: SUP when all supply side parameters are varied (SUBS, EXP, YLD, YL_m) and ALL for all parameters. For cumulated effects, ranges are obtained by running Monte-Carlo analysis with uniform distribution on parameter ranges (10,000 runs). NDF scales are similar for the two crops but not ILUC effect scales. Conversion from NDF to ILUC is obtained by applying the conversion efficiency of the feedstock (MJ/ha), a parameter that is feedstock specific.

results along the dimension of the two parameters indicated in row and column, all others being kept constant at the initial value.

Some interesting behaviours can be observed. First, a very large range of values can be spanned. A certain number of parameter changes allows to reach very high values of ILUC (black areas, greater than 16 ha/TJ), but also some very small values of ILUC (white areas, lower than 1 ha/TJ). Generally, no single parameter variation leads to extreme values, except in the case of land expansion elasticity (ILUC null when this elasticity gets close to zero), and price transmission index (small ILUC when price transmission goes close to zero). Most other extreme values are obtained in corners of the panels, which indicates interaction effects of two parameters. Strongest interactions observed are:

- elasticities of demand $\mathbf{E^d}$ and expansion $\mathbf{E^e}$: when demand effects decrease, the results become very reactive to increase in expansion elasticities;

- elasticities of demand $\mathbf{E^d}$ and yield $\mathbf{E^y}$: when these elasticities are decreased together, the values of ILUC clearly explode, because the matrix $\mathbf{\Phi}$ goes close to identity matrix, meaning that the NDF is only a function of yield gap and coproduct feedback, according to equation (5.25);

- co-product return with elasticities $\mathbf{E^e}$, $\mathbf{E^d}$ and $\mathbf{E^y}$: lower co-product return tend to increase ILUC value but the sensitivity of results to this feedback is particularly strong when $\mathbf{E^d}$ and $\mathbf{E^y}$ are small, or $\mathbf{E^e}$ is high;

- co-product return with market price transmission and elasticity of expansion: if the co-product return is improved and price transmission or land expansion remains low, it becomes possible to reach ILUC values close to zero.

- in the case of biodiesel, we also observe some interaction between marginal yield value and land expansion $\mathbf{E^e}$ and yield elasticities $\mathbf{E^y}$. Marginal value of yield, in that case, lead to high values of ILUC when getting small. This is due to the stronger substitution possibilities associated to oilseeds in our assumptions, and to which the marginal yield is also applied.[22]

5.3.3 Role of parameter heterogeneity

The sensitivity analysis from Section 5.3.1 has been performed by applying to each parameters a same deviation across regions and products. For crops, initial elasticities were set at the same value except for land substitution and demand elasticities. Moreover values were set at the same level for Home and Foreign for yield response elasticity and marginal yield. It is unlikely that

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[22] Remind that in our approach, expansion/substitution and marginal yield are completely decoupled. This means that even if a land is very little fertile, farmer will expand in response to a market signal if land expansion elasticity is high.
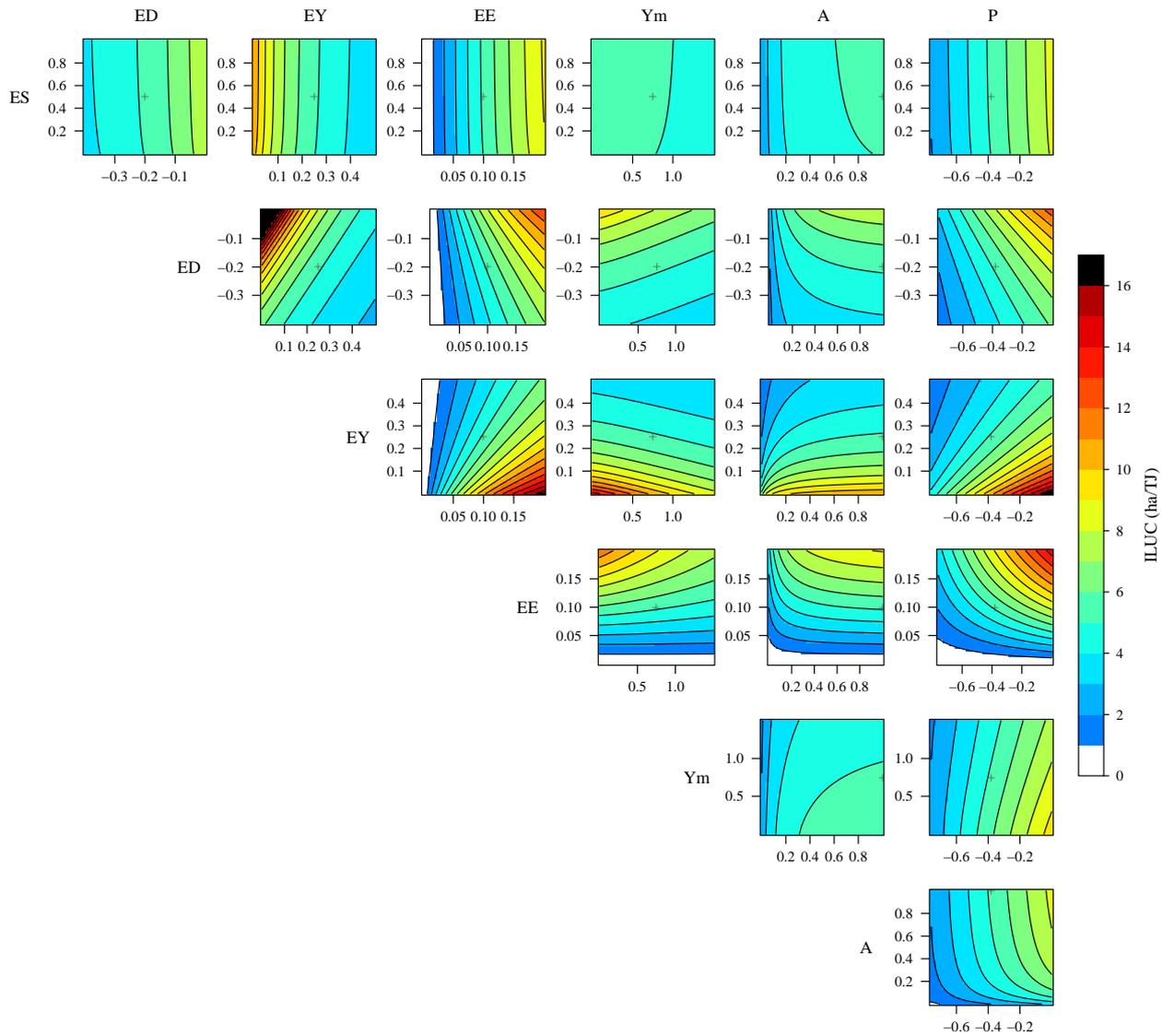
Figure 5.4. Sensitivity analysis on indirect land use change of ethanol for pairs of parameters.
ES=substitution elasticities, ED=demand elasticities, EY=yield elasticities, EE=expansion elasticities, Y_m marginal yield value, A=international market price transmission and P=co-products. Parameters are varied by ±100% around the central values selected in Section 5.2.5, other parameters being kept unchanged at their initial central value, indicated by the grey cross. Only A, capped to 1, is varied from -100% to 0% (grey cross on the border of the box). Values reported on the x- and y-axes of the charts correspond to exact parameter values, except for demand and substitution parameters for which they represent an average value. Black colour corresponds to ILUC values greater than 16 ha/TJ, whereas white colour indicates ILUC values lower than 1 ha/TJ.

Figure 5.5. Sensitivity analysis on indirect land use change of biodiesel for pairs of parameters.
ES=substitution elasticities, ED=demand elasticities, EY=yield elasticities, EE=expansion elasticities, Y_m marginal yield value, A=international market price transmission and P=co-products. Parameters are varied by ±100% around the central values selected in Section 5.2.5, other parameters being kept unchanged at their initial central value, indicated by the grey cross. Only A, capped to 1, is varied from -100% to 0% (grey cross on the border of the box). Values reported on the x- and y-axes of the charts correspond to exact parameter values, except for demand and substitution parameters for which they represent an average value. Black colour corresponds to ILUC values greater than 16 ha/TJ, whereas white colour indicates ILUC values lower than 1 ha/TJ.

behavioural parameters be the same in reality for different crops and regions. To measure the impact of behavioural parameter heterogeneity, we perform a new Monte-Carlo analysis but this time, ±50% parameters deviation is calculated independently for each region and crop.[23]

Results of the different correlation settings are presented in table 5.2. Each type of parameter is tested separately as in Section 5.3.1. The general trend is that heterogeneity limits the interaction of extreme coefficients and decrease the standard deviation of results around the mean. This trend is observed for most parameters, and has some visible consequences on the final results with all parameters varied together. From homogeneous shocks to full heterogeneity analysis, the standard deviation decreases by 23% for rapeseed biodiesel and by 30% for wheat ethanol. The contribution of regional parameter heterogeneity is generally smaller than crop parameter heterogeneity, which can be explained by the larger number of interaction for crops in the model, through the demand and supply matrices. However, heterogeneity influences the results differently for some parameters. For instance, heterogeneity of marginal yield distribution tends to increase significantly the deviation of results (multiplied by five), and the maximum ILUC effect obtained. This is understandable as the marginal yield plays a role in the land substitution patterns, and heterogeneity of this parameter across crops significantly amplifies the responses obtained through this effect.

This analysis illustrates how the distribution of parameters matters not only for the magnitude of values chosen but also for the level of heterogeneity introduced in the model. Modellers are often performing their sensitivity analyses by varying all parameters homogeneously around the initial value. What we found here is that varying several parameters at the same time is crucial to take into account interaction effects. At the same time, heterogeneous distribution across regions and products is likely to decrease the distribution of the final results. Still, all the results from these types of sensitivity analyses are strongly influenced by the central value initially chosen for the different parameters. In the next section, we will try to depart from such an approach to base our analysis directly on the raw input of the econometric literature.

5.4 EXPLORING THE FULL RANGE OF PARAMETERS UNCERTAINTY

We have been looking so far at what we could call the "relative" uncertainty of ILUC estimates. We have varied the different behavioural parameters of our model around an initial assumed value, following the usual sensitivity analysis approach performed in modelling. But we did not question the quality of this primary input. Modellers usually choose these parameters on the basis of literature practices but rarely come back to the econometric or biophysical studies underlying their

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[23]   This applies to diagonal elements of the matrices. However, for non-diagonal elements of $\mathbf{E}^D$ and $\mathbf{E}^s$, additional assumptions are necessary. For $\mathbf{E}^d$, cross-price elasticity of each product is shifted by the same value as the own-price elasticity of the product. For $\mathbf{E}^s$, because we want to conserve the homogeneity and land conservation properties across rows and columns, we do not calculate three own-price elasticities but instead two substitution elasticities ε_1^S and ε_2^S, corresponding to a two-level nest of Constant Elasticity of Transformation (CET) functions. Formula to derive own-price elasticities from these nested production functions are detailed in Sato (1967).

Table 5.2. Descriptive statistics for Monte-Carlo analysis of ILUC values (ha/TJ) with different correlation settings across parameters. Number of Monte-Carlo runs for each row is 10,000 per feedstock.

Scenario	Type	Ethanol wheat			Biodiesel rapeseed		
		Min	Max	SD	Min	Max	SD
DEM	Homogeneous regions & crops	2.29	3.53	0.35	3.16	4.53	0.39
	Heterogenous regions	2.29	3.52	0.33	3.17	4.52	0.36
	Heterogenous crops	2.31	3.50	0.28	3.22	4.52	0.23
	Heterogeneous regions & crops	2.31	3.49	0.26	3.22	4.47	0.22
SUBS	Homogeneous regions & crops	2.75	2.80	0.02	3.64	3.86	0.06
	Heterogenous regions	2.75	2.80	0.01	3.64	3.86	0.06
	Heterogenous crops	2.74	2.82	0.01	3.66	3.89	0.05
	Heterogeneous regions & crops	2.74	2.82	0.01	3.67	3.88	0.04
EXP	Homogeneous regions & crops	1.45	4.00	0.74	1.94	5.35	0.97
	Heterogenous regions	1.46	4.00	0.72	1.95	5.34	0.97
	Heterogenous crops	1.49	3.98	0.58	2.06	5.30	0.65
	Heterogeneous regions & crops	1.50	3.98	0.57	2.08	5.30	0.65
YLD	Homogeneous regions & crops	2.21	3.73	0.43	2.97	4.96	0.56
	Heterogenous regions	2.22	3.72	0.36	2.98	4.95	0.51
	Heterogenous crops	2.23	3.70	0.34	3.01	4.91	0.38
	Heterogeneous regions & crops	2.26	3.59	0.28	3.05	4.86	0.34
CPT	Homogeneous regions & crops	1.72	3.85	0.62	2.58	4.87	0.66
	Heterogenous regions	1.73	3.84	0.52	2.59	4.86	0.48
	Heterogenous crops	1.72	3.86	0.62	2.59	4.89	0.67
	Heterogeneous regions & crops	1.73	3.85	0.53	2.60	4.88	0.49
YLm	Homogeneous regions & crops	2.69	2.86	0.05	3.49	4.04	0.16
	Heterogenous regions	2.69	2.87	0.05	3.49	4.04	0.15
	Heterogenous crops	2.02	3.50	0.30	2.05	6.02	0.82
	Heterogeneous regions & crops	2.07	3.46	0.26	2.15	5.91	0.71
TRD	Homogeneous regions & crops	2.54	2.78	0.07	3.47	3.72	0.07
	Heterogenous regions	2.54	2.78	0.07	3.47	3.72	0.07
	Heterogenous crops	2.56	2.79	0.06	3.49	3.74	0.05
	Heterogeneous regions & crops	2.56	2.79	0.06	3.49	3.74	0.05
SUP	Homogeneous regions & crops	1.15	5.55	0.86	1.52	7.82	1.18
	Heterogenous regions	1.20	5.45	0.82	1.54	7.62	1.13
	Heterogenous crops	1.10	5.69	0.76	1.22	9.43	1.15
	Heterogeneous regions & crops	1.20	5.48	0.70	1.33	8.46	1.05
ALL	Homogeneous regions & crops	0.68	9.11	1.16	1.07	11.24	1.44
	Heterogenous regions	0.77	7.97	1.02	1.11	10.24	1.30
	Heterogenous crops	0.42	8.04	1.04	0.69	11.63	1.38
	Heterogeneous regions & crops	0.69	7.51	0.90	0.94	9.74	1.16

data.[24] For instance, the value of yield elasticity is often assumed to be in a range 0.1–0.35 with a reasonable default value at 0.25, (CARB, 2011), but as reported in Keeney and Hertel (2008) for the specific case of corn in the US, the range provided by the econometric literature is larger, from negative value (for one State) to 0.76. To reflect the full range of uncertainty, we therefore need to come back directly to the diversity of econometric and empirical estimates of our parameters.

5.4.1   OVERVIEW OF PARAMETER UNCERTAINTY FROM LITERATURE

Although all inputs to our framework have an uncertainty range, some parameter are better known than others: collection of statistics allows retrieving good information on the value of current supply S, land use L or demand D. Average yield are also known although they can vary significantly from year to year and marginal yields are less accurately documented, even if they remain within agronomic plausible values. The parameters which are subject to much more uncertainty are first elasticities, and second emission factors. We will focus in this subsection on elasticites, and will look at emission factors in Subsection 5.4.3.

Price elasticities have been strongly debated in the context of biofuel modelling, in particular the value of endogenous yield response $\mathbf{E}^y$ (Keeney and Hertel, 2008, Berry, 2011, CARB, 2011) or the land expansion elasticities $\mathbf{E}^e$ (Babcock and Carriquiry, 2010, Barr et al., 2011, Golub et al., 2012). Substitution elasticities $\mathbf{E}^s$ and demand elasticities $\mathbf{E}^d$ have been more studied, however, they are also subject to some uncertainty. As illustrated by equation (5.24) and emphasized by Hertel (2011), it is not the absolute magnitudes of elasticities that matter but rather their relative values with respect to each other, which determines distribution of effects – absolute values only influence prices and ILUC therefore remains unchanged if all elasticities are multiplied by a same factor.

Values of elasticities presented in the econometric literature vary significantly across papers. We provide in appendix C an overview of the current findings. Elasticities referenced are:

Demand elasticities: United States Department of Agriculture (USDA) database (Muhammad et al., 2011) and FAPRI (2008) database provide different estimations for a large number of country and product couple. We only reported a subset of them in appendix, in order to keep a even distribution of our sample across the different sources. We also took input data from Gardner (1988), from a recent econometric estimation at the global level by Roberts and Schlenker (2010) and from the GTAP database (Hertel et al., 2009a). Our final range is from -0.01 to -0.7 for the US. The variability is in particular due to the different level of product

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[24]   Babcock (2009a) is very clear on the approach followed by modellers: "Most of the parameters used to capture supply and demand responses to price changes that populate the models economists use to estimate the impact of biofuels on land [...] are based on previous work (the applicability and quality of which is typically not addressed), insight of the analyst, and overall 'reasonableness' with respect to the problem at hand. Economists need not apologize for constructing models in this manner: it simply is the only way to proceed because of a lack of data and specialized knowledge about agricultural and food systems around the world." (p.5).

aggregation (all crops vs single crop), to the period considered, and to the level of processing of the product (raw cereal versus processed product).

Land supply elasticities: We build a part of our database on the review from OECD (2001). These elastities were complemented by information from Gardner (1988) and FAPRI (2008) already used above. We added for Europe information from the CAPRI model (Britz and Hertel, 2011) and for the US recent estimates by Lin and Dismukes (2007) and Huang and Khanna (2010). For regions outside the US and the EU, data from the Food and Agriculture Policy Research Institute (FAPRI) database were complemented for Brazil by data from Elobeid et al. (2012). Ranges for own-price land supply elasticities are 0.05 to 0.95 for cereals, and 0.2 to 0.95 for oilseeds.

Yield elasticities: We built for this parameter on the recent review from Keeney and Hertel (2008) or Berry (2011). Our sample in particular contains yield values from econometric literature but also from two models directly based on literature estimates: the PEM model (OECD, 2001) and the ERS/PSU model (Stout and Abler, 2004). Our final range of values goes from zero to 0.76 for cereals, and from zero to 0.72 for oilseeds.

Land expansion elasticities: This sample is probably the weakest from our analysis because very few studies were available. We mainly used Barr et al. (2011) and Baldos and Hertel (2013) as source of data. Two caveats however appear: first, the authors report cropland elasticity, or cropland and grassland elasticity. Although we do not represent grassland in our analysis, we decided to take both estimates here to capture a larger number of points. The second caveat is that Baldos and Hertel (2013) report elasticities with respect to land rent and not with respect to commodity prices. Following the conversion proposed by Salhofer (2000), we decided not to alter the values of these elastities for short term effect, and to multiply by three these values when considering long term effect (a proxy for inverse of land share in factor costs).[25]

Marginal expansion yield: We based here our sample on the review from CARB (2011). We obtain a rather narrow range of value, from 0.71 to 1.23.

Co-product substitution: We used two different assumptions for coproducts: i) co-products substitute with soybean meal only; ii) co-products substitute with soybean meal and soybean oil. These two assumptions are necessary because the precise co-product effect related to soybean meal cultivation is not represented here. We calculated our substitution ratio using data from three different studies (Edwards et al., 2004, Croezen and Brouwer, 2008, Hoffman

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[25]   See footnote 18 for more details. We can note that this factor three is very close to the difference between 5 years and 40 years elasticities in Baldos and Hertel (2013).

and Baker, 2011). The return for cereals is found to go from 35% to 55% for cereals and from 30% to 41% for oilseeds, in kcal basis.[26]

The data collected above can then be used to test the sensitivity of the NDF to uncertainty in the literature.

5.4.2   Sensitivity of ILUC to literature values

We now investigate how the model from section 5.2 behaves when we use randomised selection of behavioural parameters based on the distribution above. For this, we will follow three different approaches:

1. randomised selection on literature values only ("Random"), where we select for each parameter one random value in our dataset (parameter distribution is in that case related to the number of occurrences in the literature),

2. Monte-Carlo with uniform distributions ("Uniform") of parameters on the range of values collected in our dataset,

3. Monte-Carlo with normal distributions ("Normal") of parameters on the range of values collected above. The distribution is in that case centered on the middle of the range of values and we set the standard deviation of the Gaussian at 1/6 the range, which ensures that 99% of the distribution remains within the selected boundaries – the range is therefore covered by three standard deviations.

To explore the role of some assumptions on elasticities, we also distinguish three subsets of values according to three scenario settings:

- "Short term" effect: in this subset, we follow the recommendations of CARB (2011) and do not consider the yield elasticities of values greater than 0.2.

- "Long term" effect: in this subset, again following CARB (2011), we do not consider yield elasticities with values lower to 0.1. Additionally, we do not take land expansion elasticities sourced from short term assessment (Barr et al., 2011) and as explained above, we convert Baldos and Hertel (2013) elasticities to their long term values by multiplying these elasticities by three.

- "Restricted land" scenario: in this last subset, we keep the "long term" assumptions above but we also apply for all regions the sample of land expansion elasticities of the US and the EU. This reflects a situation where more active land policies lead to better control of agricultural land expansion.

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[26]   Substitution ratios on a ton or a protein basis would be different. Full details on calculation assumptions are provided in appendix C.

By using the full range of possible elasticities in the literature, we obtain notably higher results than in section 5.3 for the "short-run" and the "long-run" scenarios (see Figure 5.6 for ethanol and 5.7 for biodiesel). The distribution of results spans from 0 to 1 for the NDF of ethanol and from 0.1 to 1.2 for biodiesel. These high results are in particular driven by the high values of land expansion elasticities present in our data sample for developing regions. When we use the elasticities from the US and the EU in the "restricted land" scenario, the overall magnitude of the NDF decreases strongly into the range 0–0.4. The "short-run" setting lead to the highest results, although we used short term estimates of land expansion elasticities from Baldos and Hertel (2013). This is due to the more limited role of yield response and to some high point estimates in the short-run expansion elasticities of Barr et al. (2011).

The role of parameter distribution is also interesting. Without surprise, the normal distribution reduces the standard deviation and skewness of results when compared with the uniform one, whereas the results are centered around the same mean value. But when using a fully randomised selection of variables, the mean value is altered, notably for short run shocks, whereas the spread remains generally comparable to the uniform distribution. For ethanol with short-term settings, the "Random" mean results are at 10 ha/TJ, versus 13 ha/TJ for "Uniform" and "Normal". For biodiesel, the "Random" mean is at 15 ha/TJ instead of 19 and 20 ha/TJ for "Uniform" and "Normal", respectively. In the case of long-term setting, a different trend is observed, as the mean of "Random" is unchanged for biodiesel, when compared to other distributions, but increases by 20% for ethanol.

In order to assess the underlying behaviours associated to these distributions, we can decompose the shock as we did in section 5.2.5 across the different contributions of market responses. Results are presented in Table 5.3. As we can see, the mean effect of the different contributions are relatively stable across the scenario and specifications. Co-product return is on average in our framework 50% of the calories for cereals and 35% for rapeseed biodiesel, a direct result of the input data used (see Appendix C).[27] The most significantly contributing responses are then demand, expansion and yield, whose mean values can reach 25% of the contribution, with coefficients of variation (standard deviation over mean) reaching 40% for demand in some scenarios, or even 50% for expansion and yield. Demand contribute the most in the "short-term" and the "restricted land" settings because prices react more. We did not assume here any difference in demand elasticities depending on the time horizon. By assumption, yields contribute less in the "short-term" scenario. They are also the most important market response in the "restricted land" scenario, ahead of demand. Reallocation plays a more minor role in the case of ethanol, but can be contributing as much as expansion in the case of biodiesel with "restricted land". With respect to the influence of parameter distribution, standard deviation comes to be the highest with the random selection approach, and the lowest with the normal distribution, which was expected. The random selection also tend to increase demand response, decrease role of co-products. On the contrary, the mean values for expansion and yield

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[27]   These coefficients of return shown here are higher than in Chapter 4, because the substitution is imperfect in the CGE modelling framework, and the overall feed demand of the livestock sector responded to prices (see also Taheripour et al., 2010).
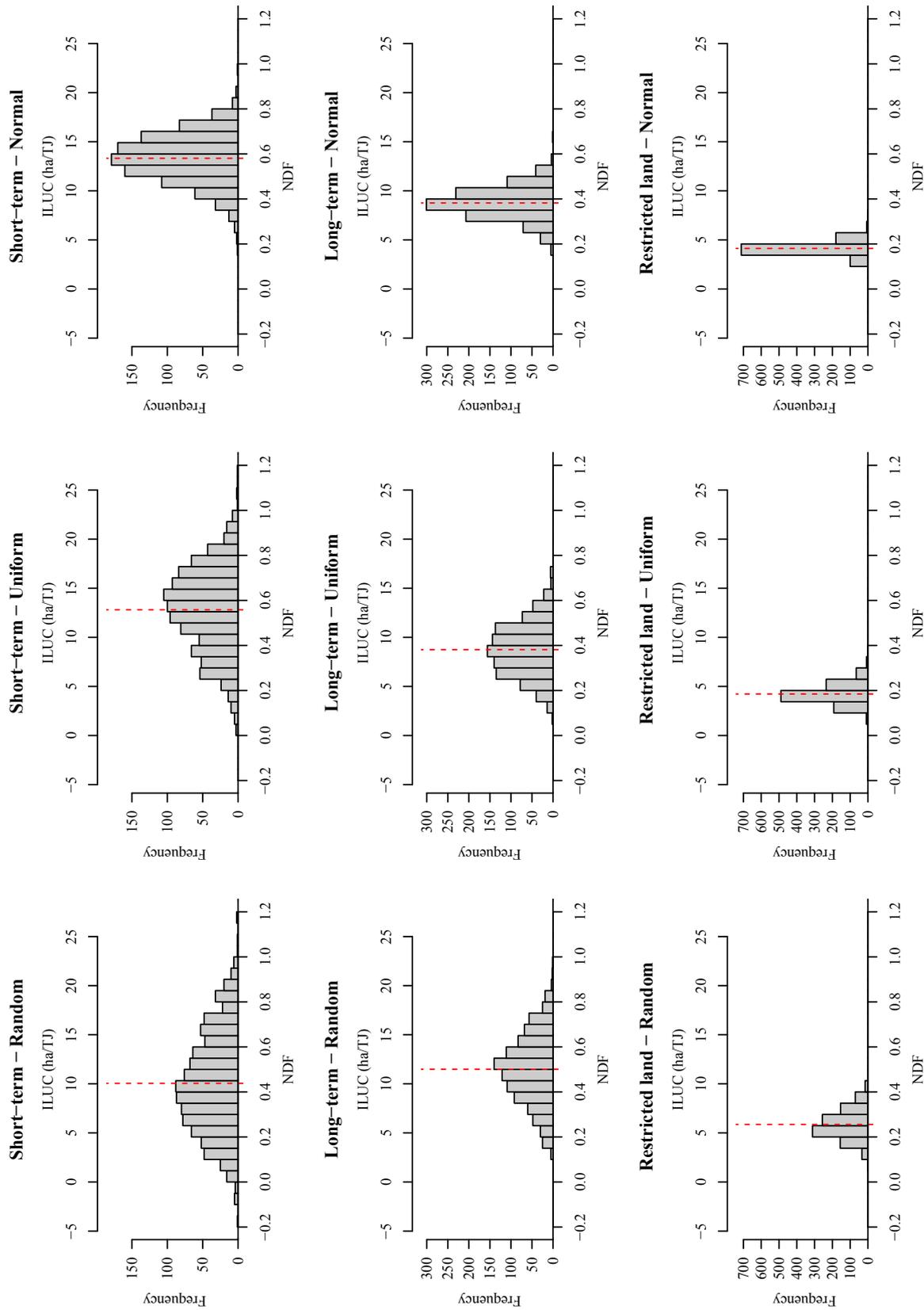
Figure 5.6. NDF (bottom-axis) and ILUC (top-axis) of wheat-based ethanol associated to the full range of parameters in the literature. Results are obtained by running Monte-Carlo simulations with 1,000 iterations. Three type of parameter distributions are distinguished (random selection, uniform distribution, normal distribution). Three subset of the parameters are also differentiated to describe short-term and long-term effects, as well as a restricted land assumption.
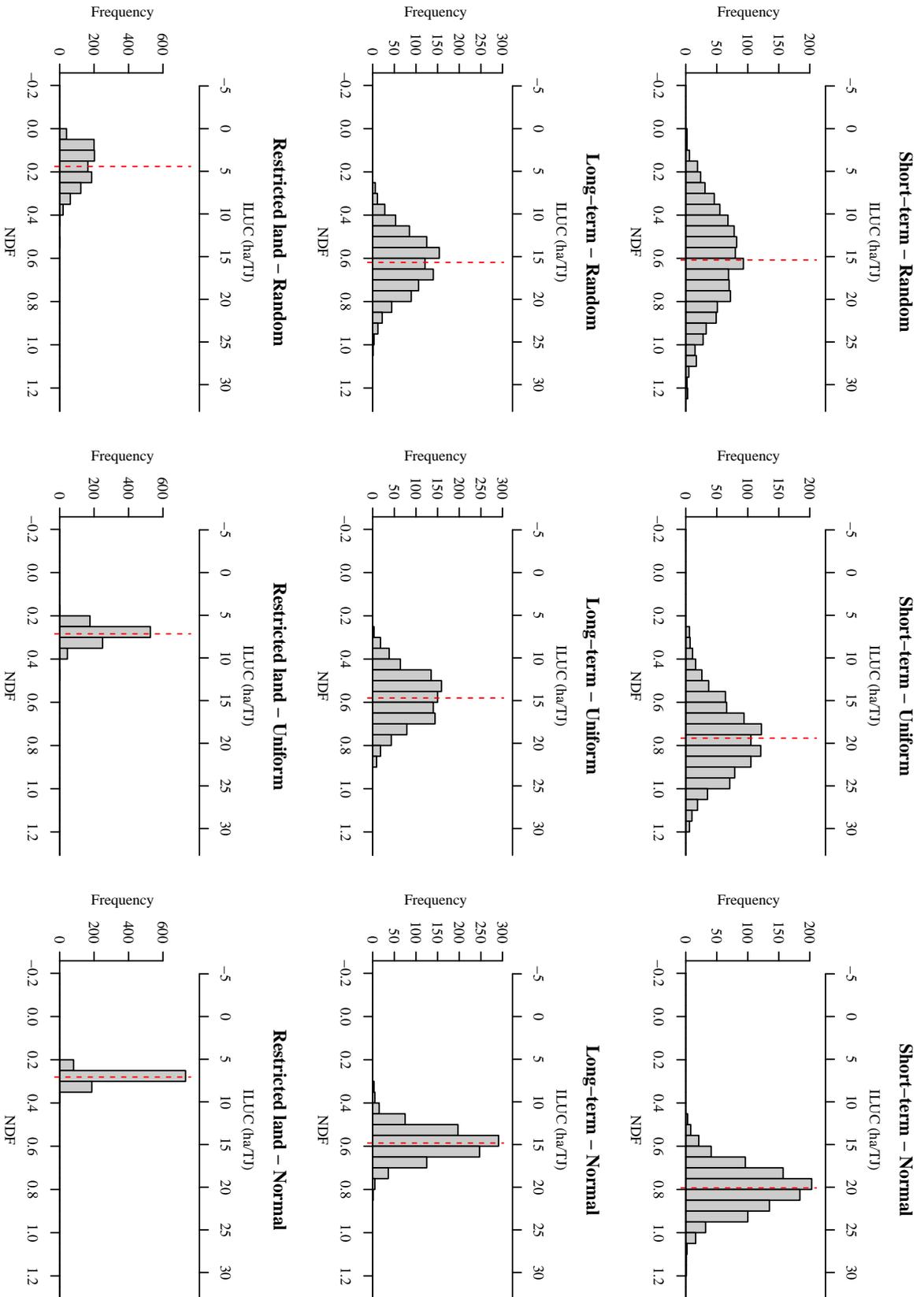
Figure 5.7. NDF (bottom–axis) and ILUC (top–axis) of rapeseed–based biodiesel associated to the full range of parameters in the literature. Results are obtained by running Monte–Carlo simulations with 1,000 iterations. Three type of parameter distributions are distinguished (random selection, uniform distribution, normal distribution). Three subset of the parameters are also differentiated to describe short-term and long-term effects, as well as a restricted land assumption.

are notably shifted, but in various directions depending on the scenarios, when random selection is compared to normal and uniform distribution that have the same mean values. This stresses the importance of incorporating the full range of the literature to better represent the parameter distribution.

The last column of Table 5.3 displays the ratio of expansion contribution over the total of all supply side contributions, i.e. expansion, yield and reallocation. This parameter is crucial as it helps checking if the model response reproduces the usually observed trends in terms of production change. The role of yield versus land expansion increase are much discussed in the literature. There is strong evidence on the fact that in the long-run, land productivity increase played a much larger role globally than land expansion to increase production. Fuglie (2010) analyze that when crop and livestock are considered together, the role of land is below 10% since a few decades. This level, in particular related to technical change, depends on the level of development. Developing countries are close to 20% of land expansion contribution and Sub-Saharan Africa is around 70%. This trend is also confirmed at the level of single crops in the case of cereals, although oilseeds have benefitted more from expansion than from yield increase (Foley et al., 2011, Figure S2a). In the short term, however, (Berry, 2011) argue that very little yield increase can be obtained, which suggests that the marginal effect would not necessarily follow the long term trend. We obtained here for the "short-term" setting that land expansion provides 60 to 80% of the marginal production increase. This share falls down to 50% in our "long-term" settings, and in the range 18–40% for the "restricted land" response, when elasticities from developed regions were applied everywhere. As we discussed above, evidence on land expansion elasticities are scarce. It is likely that some of these estimates do not combined well with other elasticity values from literature selected here and estimated separately. The "land restricted" assumption might therefore be more relevant than the "long-term" one to reflect a marginal response in line with the average observed trend.

5.4.3   FROM INDIRECT LAND USE CHANGES TO ILUC FACTORS

So far, we have been expressing all the uncertainty in our results by focusing on the economic responses, and analyzing the land use change associated to biofuel production. This allowed investigating the uncertainty ranges behind the Net Displacement Factor. However, as illustrated by Plevin et al. (2010), the outcome of the policy depends on a last source of uncertainty, emission factors, according to the formulas expressed in subsection 5.2.4.

Emission factor uncertainty relates first to the emissions flows associated to the conversion of one type of land cover, but also to the composition effect between the different types of land cover in which cropland expand, and to the composition of region. Calculating an average emission factor therefore requires to make assumptions on these different parameters. Plevin et al. (2010), for instance, use some probability range on the allocation of expanded cropland across land cover (15% to 50% for forests, 0% to 2% for wetlands and the rest for grassland). They review estimates of emissions for each land use type (350 to 650 tCO_2 ha^{-1} for forests, 75 to 200 tCO_2 ha^{-1} for

Table 5.3. Mean and standard deviation of the decomposition parameters for ILUC and NDF uncertainty exploration based on literature elasticities.

Scenario	Demand		Reallocation		Expansion		Yield		Co-products		Exp /Sup
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	
Ethanol wheat											
Short-term - Random	0.23	0.09	-0.01	0.03	0.23	0.11	0.13	0.06	0.42	0.06	0.66
Short-term - Uniform	0.19	0.07	-0.01	0.03	0.28	0.09	0.08	0.04	0.45	0.06	0.80
Short-term - Normal	0.19	0.04	-0.01	0.02	0.29	0.05	0.08	0.02	0.45	0.03	0.81
Long-term - Random	0.17	0.06	-0.01	0.02	0.26	0.08	0.16	0.06	0.42	0.06	0.64
Long-term - Uniform	0.15	0.05	-0.01	0.02	0.20	0.06	0.21	0.05	0.45	0.06	0.50
Long-term - Normal	0.15	0.03	-0.01	0.02	0.20	0.03	0.21	0.03	0.45	0.03	0.50
Restr. land - Random	0.22	0.07	-0.01	0.03	0.14	0.03	0.22	0.07	0.42	0.06	0.40
Restr. land - Uniform	0.19	0.06	-0.01	0.02	0.10	0.02	0.27	0.06	0.45	0.06	0.28
Restr. land - Normal	0.19	0.03	-0.01	0.02	0.10	0.01	0.27	0.03	0.45	0.03	0.28
Biodiesel rapeseed											
Short-term - Random	0.22	0.08	0.08	0.04	0.26	0.10	0.10	0.06	0.35	0.04	0.59
Short-term - Uniform	0.16	0.05	0.08	0.03	0.33	0.08	0.08	0.04	0.36	0.03	0.67
Short-term - Normal	0.15	0.03	0.08	0.03	0.34	0.05	0.08	0.02	0.35	0.02	0.69
Long-term - Random	0.14	0.05	0.07	0.03	0.27	0.06	0.17	0.04	0.35	0.04	0.53
Long-term - Uniform	0.14	0.03	0.07	0.03	0.25	0.05	0.18	0.03	0.35	0.03	0.50
Long-term - Normal	0.14	0.02	0.07	0.02	0.26	0.03	0.18	0.02	0.36	0.02	0.51
Restr. land - Random	0.23	0.06	0.08	0.04	0.08	0.04	0.27	0.05	0.35	0.04	0.18
Restr. land - Uniform	0.19	0.04	0.09	0.03	0.13	0.02	0.25	0.03	0.35	0.03	0.27
Restr. land - Normal	0.19	0.02	0.09	0.03	0.12	0.01	0.25	0.02	0.35	0.02	0.27

grassland and 1000 to 3000 tCO_2 ha^{-1} for wetlands), and obtain possible emission factors in the range 116–481 tCO_2 ha^{-1}. However, they do not rely on historical data to calculate their allocation but only on two model sources (Searchinger et al., 2008, Hertel et al., 2010a). Additionally, no geographic dimension is taken into account, although forest conversion in the US and in Brazil induce different carbon flows.

We follow here a similar approach but keep the emission factors used in Chapter 4 and based on IPCC (2006). Our emission factors assume a complete loss of carbon stock in above and below-ground forest biomass, or in soil for other natural land, taking into account heterogeneity of data across agro-climatic zone (see appendix C for more details). For allocation across land use (parameter θ_i in equation (5.26)), we base our analysis on the historical parameters used by EPA from the Winrock database and presented in Figure 4.4. The shares that we apply are therefore region specific.[28] To take into account uncertainty on allocation to natural forests and plantations, we vary this share from $\theta_i/2$ to $\max(2\theta_i, 1)$. As a result, we obtain for each region a range of aggregate cropland expansion emission factors corresponding to $\sum_c \theta_c e_c$ in formula (5.26). The minimum, average and maximum value for each region is displayed in Table 5.4. The world cropland area-

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[28]   In the case of Brazil, six subregions are furthermore distinguished to take into account the heterogeneity of land use change patterns.

Table 5.4. Emission factors associated to cropland expansion (Mg CO_2e ha^{-1})

Region	Lower bound	Median	Upper bound
Brazil	138	197	290
Central America Caribbeans	143	214	354
China	67	78	101
CIS	44	53	70
EU27	84	95	117
Indonesia and Malaysia[a]	264	440	780
South America	107	148	228
Canada, Australia and other OECD	58	70	93
Rest of the world	47	54	67
Sub-saharan Africa	79	101	145
USA	63	72	91
World (cropland-weighted)	**74**	**95**	**134**
World (expansion-weighted)[b]	**137**	**204**	**332**

[a] Emissions from peatland drainage are not taken into account in this estimate.

[b] Expansion is taken for harvested areas of 18 most cultivated crops from FAOSTAT between 1995 and 2010. Total expansion is 79 million ha on the period for these crops.

weighted aggregate is quite low, ranging from 74 to 134 tCO$_2$ ha^{-1} with an average at 94 tCO$_2$ ha^{-1} ("average EFs"). However, when taking into account the dynamics of expansion over the last 15 years, this magnitude is doubled because most expansion of the world harvest took place in tropical regions, with higher carbon stocks. We in that case obtain a range of 137–332 tCO$_2$ ha^{-1} with a mean at 204 tCO$_2$ ha^{-1} ("marginal EFs").

We apply the emission factors above to the ILUC effects obtained in Subsection 5.4.2. For this, we apply log-uniform distribution on the two samples to take into account the skewness of the distribution. The emissions obtained are divided by 20 years, in line with the EU methodology for direct land use emission (EP, 2009). Results are displayed in Figure 5.8 for wheat and rapeseed biofuels, applied to the distribution of ILUC obtained through random selection of parameters. We also report in this figure with a red line the level of emissions associated to consumption of fossil fuel in the EU (i.e. production, distribution and combustion). A blue line indicates the maximum level of emissions that lead to GHG emission levels lower than fossil fuel, once emissions from biofuel production and distribution are taken into account, using the most efficient technology (see EP, 2009, appendix tables). Last, the green line represents the maximum level of emissions for ILUC to comply with the EU sustainability criteria of −35% of minimum savings. These levels are 15 tCO$_2$ ha^{-1} for wheat and 8 tCO$_2$ ha^{-1} for rapeseed, which makes them very difficult to achieve (see Ros et al., 2010, for a discussion).[29]

[29] Best technology selected here for wheat is combined heat and power plants with natural gas as a process fuel

We observe that under the "short-term" and "long-term" settings, none of the fuel save GHG emissions under the current marginal EFs, when compared to average fossil fuels. More worryingly, most of the results are on the right side of the red line, which means that land use change emissions alone are higher than emission from fossil fuels. If we take the average emission factors, we obtain more ambiguous outcome with most of the distribution on the right side of the blue line, but a part of the distribution left-tail leads to GHG savings, in particular for wheat in the "short-term" setting. Restricted land scenarios under marginal EFs also give mixed results. Most of the distribution for wheat is on the right side of technological threshold, whereas for rapeseed, the results are distributed around this threshold, and a large share of ILUC factors are now below the level of emission of fossil fuels. Only if we take the "land restricted" scenarios with average emission factors, we come to a situation where the distribution of ILUC can lead to some GHG savings, under the condition that the best technologies are used. However, most of the distribution remains beyond the level of 35% allowed by the sustainability criteria (green line).

5.5 CONCLUSION

Many large scale models have been used so far to calculate ILUC values. They produced different results and all performed sensitivity analyses to some extent. But they were difficult to compare and for publicly accessible ones, not easy to manipulate for a non-specialist. We showed in this chapter that a simple decomposition approach allow for representing all the most important parameters discussed in the debate on model behaviours. Their relative contribution can be explored in a tractable framework and help to better understand implications of their respective uncertainty. This approach in particular helps to directly link results to elasticity values provided in the literature.

On the basis of econometric estimates currently available, we have shown that land, yield and demand responses, as well as co-product return rates were the most significant determinants of final land use change effects. This is in line with the findings from the past literature. However, we obtained here some much larger ranges of uncertainty than those derived from applied modelling exercises. This is due to the fact that cumulating uncertainty in two or more parameters significantly widens the range of possible ILUC values, but also because the full range of literature estimate is usually not considered. Our findings support Plevin et al. (2010) arguments that the right-tail of distribution of possible emissions could reach high values, in a more economic analytical approach. We did not reach the upper bound of their estimates, but we only considered one reference period of 20 years – versus 15 years for their higher ILUC values. We did not either incorporate possible wetland emissions, that represent around one third of rapeseed ILUC emissions in Laborde (2011).

At the same time, the level of confidence in the final range produced remains as good as the econometric literature on which it is based. We identified that some parameters were not well known

(typical saving 53% in the Renewable Energy Directive). For rapeseed biodiesel, we use the typical saving coefficient of 45% (see EP, 2009).
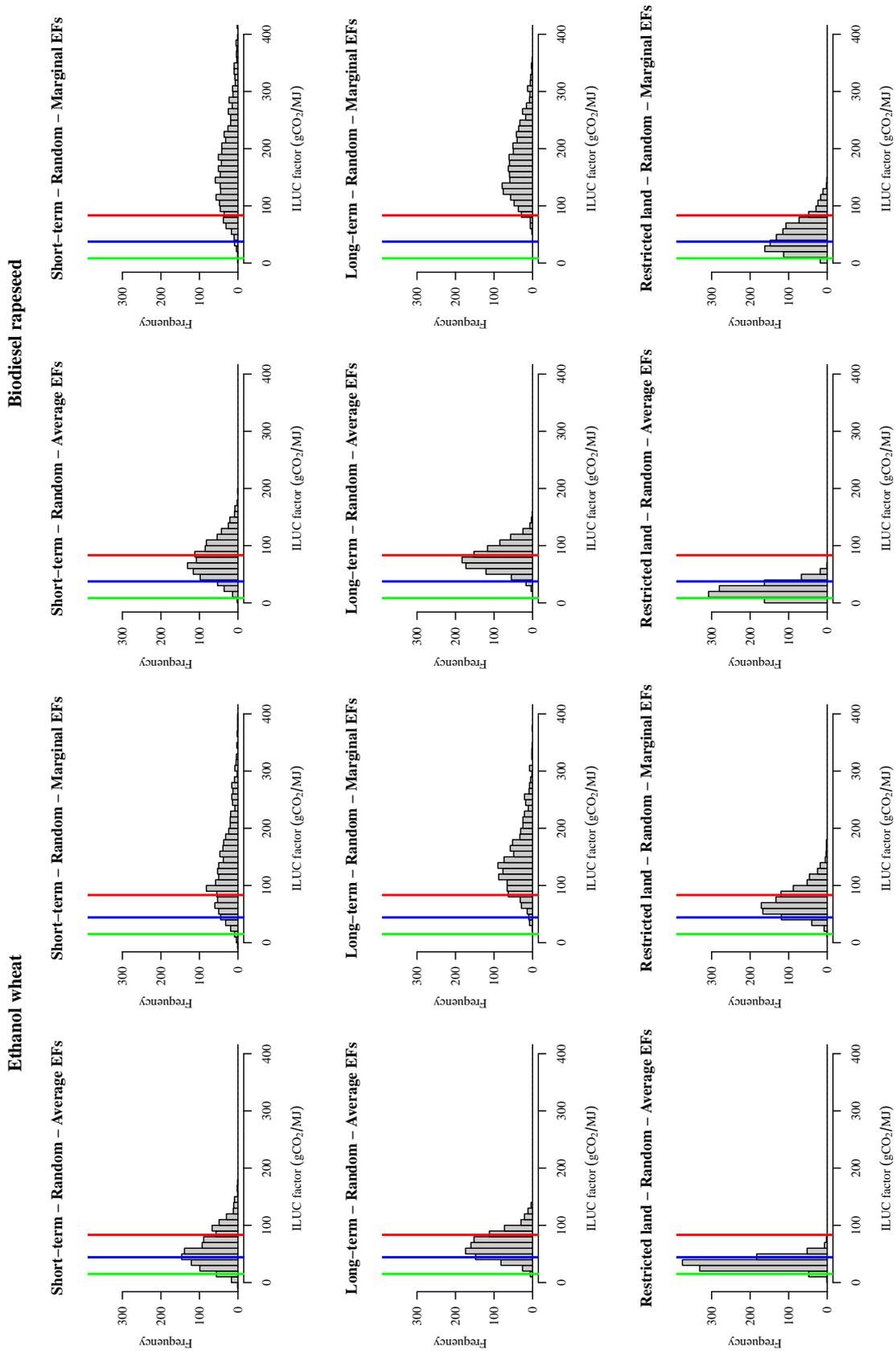
Figure 5.8. ILUC factors for wheat ethanol and rapeseed biodiesel with two different possible distributions of emission factors (average and marginal EFs) and three scenario settings ("long-term", "short-term" and "restricted land"). Land use change emission are divided by 20 years, according to the EU standard methodology, to obtain annual emissions factors. The red line indicates the level of emissions of fossil fuel consumption, according to the EU Renewable Energy Directive. The blue line indicates the maximum level of ILUC factor that still allows emitting less than fossil fuels, once LCA emissions are added to ILUC. The green line indicates the maximum level of ILUC factor that still allows complying with the sustainability criteria of 35% reduction of emissions, once biofuel LCA emissions are added to ILUC.

and supported by only by a few papers. Yield elasticities, in particular, are very controversial and have strong implications on the results. Land expansion elasticities are also crucial but based on scarce assessments. Articles on cropland elasticities show very unstable elasticities over time (Barr et al., 2011) and focus on a limited number of regions (Ahmed et al., 2008, Barr et al., 2011), which requires simplified extrapolation assumptions (Baldos and Hertel, 2013). When combining the full span of possible elasticity values, the contribution of land expansion revealed substantially higher than what has been seen on average in the agricultural sector. At the same time, the part of yield expansion over time associated to total factor productivity is certainly more indirectly linked to prices than intensification through additional fertiliser or capital. The marginal effect would then be less sensitive to this contribution, which showed significantly important in most recent developments (Fuglie, 2010).

Overall, these results try to provide the most transparent picture of what ILUC effects can be, on the basis of the current econometric literature. In the current state of knowledge, our current findings is that pathways such as rapeseed or wheat are likely to emit more than fossil fuel, and have a very high probability not to quality under the sustainability criteria defined by the EU legislation. We find some parameter configuration where the outcome is more favorable but this represent a limited part of the distribution, and the average magnitude of results reinforces the previously established concerns on GHG savings from biofuels (including those raised Chapter 4).

Our findings however do not lead us to claim that this type of framework should substitute with more in-depth exploration through large scale economic model. Our framework remains here very simple and misses many of the structural details present in simulation models, like the different sectors and regions, the role of livestock, etc. Also our approach remains based on a linear development, whereas for large scale deployment of biofuel, some non-linear responses are likely to occur. On the contrary, the present framework appears to us as a very suitable way of testing model parameterisation and behaviours and of comparing the results across models. But it also emphasizes that the level of confidence in the results obtained today in the literature remain limited. Although some current uncertainties are well characterised, some others need more empirical investigations because of the too small number of estimates available to provide a robust assessment. Agricultural supply and demand behaviours have been investigated at the level of some crops, but too little empirical analyses looked at the overall dynamics of land in link with agricultural prices. We only used here econometric estimates available today but our approach is integrative. New empirical studies will help to improve the current elasticity dataset and update our results. Such progress will be necessary to reduce the currently high uncertainty around these types of assessment.

CHAPTER 6

GENERAL CONCLUSION

SOME new concerns arise today on how agricultural policies influence land use changes globally through market responses. I brought with this work three concrete illustrations where these effects can be of significant magnitude and deserve some closer consideration.

MAIN FINDINGS

First of all, agricultural intensification has been praised for its potential to reduce land related GHG emissions while at the same time resolving food availability issues. However, as emphasized in Chapter 2, the overall mitigation outcomes could be more or less beneficial, depending on the implementation pathway and the trade-offs with food demand response. I have shown in particular that the rebound effect on the demand side could offset 60% to 80% of the GHG emission savings. These results confirm the need to more carefully take into consideration the response of land use to intensification, as also raised in the Borlaug versus Jevons paradox (Hertel, 2012, Villoria et al., 2013) – does intensification save land (Borlaug, 2007) or generate further expansion (Jevons, 1865, in the case of coal)? Agricultural investments should therefore be scrutinised not only under the perspective of their social achievements but also their environmental implications, an objective ambitioned through the new concept of "Climate Smart Agriculture" (FAO, 2010a, Beddington et al., 2012). Sustainable intensification in regions where environment is already under high pressure should promote more GHG efficient production methods but also pay attention to land management in order to deliver their full mitigation potential.

Intensifying trade with regions where land use change generates significant greenhouse gases is also likely to prove in the long term detrimental. The EU-MERCOSUR example from Chapter 3 clearly illustrates the adverse effect of liberalising some specific agricultural products, closely connected to land use change dynamics, in regions where agricultural land expansion is used as a source of development. The magnitude of the final impacts remains small when compared to total deforestation emissions. But they are large enough to jeopardise the expected benefits of the agreement. In spite of the economic wealth created in the short run, I showed that in a case with little intensification responses, opening EU markets to MERCOSUR agricultural products would

take 3 years to be beneficial at a price of US\$ 100 per tonne carbon (US\$ 27 per tCO_2-eq), and that after 6 years, the benefits would still be halved after integrating the environmental externality. Intensification of practices would be key to avoid this adverse effect, provided they respect conditions raised in Chapter 2. Sustainable intensification accompanying the trade agreement could reduce the payback time to one year. Higher value associated to avoided carbon would bring much higher results, especially for ruminant meat, for which 25 years are necessary for a high level of price close to estimate from the Stern Review. These findings show that sustainability provisions are important for bilateral trade agreements. The attention on carbon embodied in trade of industrial goods (Davis et al., 2011b) should expand to agricultural products (West et al., 2010, Karstensen et al., 2013, EC, 2013) to improve the environmental sustainability of our consumption patterns.

Last, land use change is confirmed with Chapters 4 and 5 as a major concern for biofuel policies. I showed that the level of emissions associated to EU biofuels can be substantially high. The results are however subject to significant uncertainty with a magnitude in Chapter 4 from 1 to 10 depending on the assumption on behavioural parameters. In Chapter 5, explorations of the various elasticity values showed some even larger range of results. As for the case of a trade agreement, the impacts remain relatively small when compared with the overall land use change patterns occurring in certain regions. But the levels of emission are still large enough to question the expected GHG savings from the direct life cycle analysis of biofuels. These findings echo those from a larger body of literature (De Cara et al., 2012). As illustrated in Chapter 5, magnitude of response in yield and demand are, similarly to supply and trade policies, the most important factors shaping the results of these demand shocks.

Dealing with parameter uncertainties

All the chapter of this thesis showed that results around market mediated land use change responses were subject to significant uncertainty. Chapter 5 is certainly the place where I developed this idea the furthest, emphasizing the role played by some critical behavioural parameters for the estimation of these responses. Beyond the description of mechanisms at play and the potential impact they can generate, a better understanding of most plausible responses magnitude is crucial to progress in the analysis of the market-mediated effect of agricultural shocks. This is essential for better informing agricultural policies, but also to understand the future reactions of the food systems to other exogenous shocks (see for instance Nelson et al., 2013, for response to climate change shocks).

The biofuel debate has been the most sensitive forum for such discussion. A Subgroup on Elasticity Values has even been set up in the context of the California Air Resource Board consultation of experts (CARB, 2011) to tackle this important question. Values of yield elasticities have in particular been one of the most contentious points. Keeney and Hertel (2009) showed that estimates from Searchinger et al. (2008) were too high. Berry and Schlenker (2011) strongly criticised these latter findings arguing that these elasticities were close to zero. Last in date, Gohin (2013) argues for much higher values of elasticities than previous authors. As reflected by the different elastic-

ities values collected in Chapter 5, possible values indeed vary significantly depending on region and period of estimation, and econometric technique (Keeney and Hertel, 2008). The difficulties raised around parameter choice pushed several authors to qualify ILUC "difficult to compute" and "unstable" (Zilberman et al., 2011, p. 413), when not "impossible to measure" (de Gorter and Just, 2010, p. 21), "unmeasurable" (Babcock, 2009a, p. 5). Bruce Babcock, who participated to the EPA Impact Assessment modelling exercise, indeed explains:

> The precision with which life-cycle analysts can estimate the greenhouse gas emissions that are associated with the growing, transporting, and processing of the feedstock is relatively high, although the estimates are quite sensitive to the assumptions being used. The precision with which models can estimate emissions associated with market-induced land use changes is low. If Congress and individual states want to be able to estimate with any degree of confidence how expanded production of biofuels changes greenhouse gas emissions, then significant improvements are needed in our understanding of the dynamics of crop and livestock production around the world. (Babcock, 2009a, p. 3)

The conclusion of Babcock is that more research should be pursued, a wish also formulated by Zilberman et al. (2011) who however warns, "but research is costly and should be conducted only if the expected benefit from improved decision making is greater than the extra cost of the research" (p. 422).

Future directions to improve estimation of land use responses

One value of the investigation pursued here is definitely to have emphasized some of the potential damages associated to the different types of policies. In that sense, I adhere to Babcock's statement: "Perhaps economists' greatest social contribution is their ability to anticipate unintended consequences of seemingly good policy ideas. A classic unintended consequence is the market response of producers and consumers to a price change" (p. 6). "Markets work!" stress Hertel and Tyner (2013) about market-mediated impact of biofuels, but "obtaining tightly bounded estimates of these impacts is likely beyond the reach of current models and data" (p. 6). Determining the next steps forward for more precise assessment is a challenging task. It should go, in my opinion, into five different parallel directions.

First of all, econometric works will remain a fundamental approach to investigate historical data and feed models with the parameters estimates. As Babcock (2009a) notes:

> Given the lack of data and detailed knowledge about exactly how the world's producers and consumers will respond to a change in US policy, the models used to estimate land-use changes are populated with parameters that reflect judgment calls, modeller insights, and economic wisdom rather than hard data. (p. 6)

Because applied economic models are very data intensive, such task will never be comprehensive, and even less with the increasing level of details such models can incorporate. But even for a

simplified framework as used in Chapter 5, I have shown that ranges of input were significantly wide and uncertain. The heterogeneity in databases based on literature estimates makes their use difficult for global modelling (see for instance USDA, 1998, for demand elasticities). More comprehensive estimation, performed at the same time on different products, regions and variables appear as the best way to progress. The more recent USDA demand elasticity estimates based on cross-section analysis (Seale et al., 2003, Muhammad et al., 2011) appear as a more useful dataset even if underlying assumptions on the demand structure are stricter. On the supply side, it is also worth mentioning the work from Huang and Khanna (2010), who estimate US elasticities of corn, wheat and soybeans at the same time for endogenous yield response and expansion response, and this with two different time periods. From all the elasticities distinguished in Chapter 5, land expansion elasticity is certainly the one on which robust information has been the least gathered. And Zilberman et al. (2011) and Barr et al. (2011) demonstrated how strongly these elasticity values can vary depending on the time period considered. Considering the poor quality of usual land use change data and the complexity of land use change drivers (Geist and Lambin, 2002), such estimations are moreover likely to be of limited robustness. Only two sources were used among the elasticities I collected and only for limited sets of regions (Barr et al., 2011 for the US and Brazil and extrapolation approaches based on US data from Ahmed et al., 2008). However, as highlighted again in Chapter 5, only relative magnitude of the different elasticities matters to assess the contribution of land use change among other market responses. Therefore, approaches focusing on decomposition of production and demand responses should certainly be more explored. Fuglie (2010) for instance show that land response has been contributing on average much less than other inputs and productivity increase to the expansion of production than what is suggested by the combination of the literature elasticities I inventoried. Similarly, Nelson et al. (2013) identified how different distribution of market responses can be from one model to another when applying a climate change shock. The current gap between the modelling capacities deployed for such important challenges and the knowledge on underlying structural parameters to be used for calibration appears quite untenable. The elasticity inventory initiated in Chapter 5 needs to be expanded, in particular in terms of geographical coverage and estimation period, but also requires some quality enhancement that could come from more standardisation in the estimation techniques, or even better, in the times series and cross-sectional datasets, in particular for land use for which too few estimates are known. Several research communities would have the capacity to coordinate such efforts (GTAP, AgMIP, Global Land Project) and the benefits of such an investment would certainly quickly pay off in terms of increased quality of modelling results.

Second, approaches to better deal with uncertainties in the input data should be more developed. Some progress have been observed on this matter over recent years, with move to simpler approaches in ILUC modelling (Plevin et al., 2010, Rajagopal and Plevin, 2013) or more general land use change approaches (Baldos and Hertel, 2013). For large applied models, uncertainty analyses based on sensitivity testing around mean values remain the norm, and the explorations from Chapters 2 to

4 above are additional illustrations of it. In Chapter 4, I used a uniform distribution of parameters instead of normal or triangular distribution around the mean value.[1] I also tried in that chapter to investigate the uncertainty related to model specifications, which cannot be addressed by just adjusting some of the model parameters. However, only Chapter 5 stepped away from the bias of having to choose a specific model and a central estimate. I only relied in that last chapter on a decomposition of the effects and tested the results on different possible distributions (normal and uniform) but also on a random selection of elasticities that removes the bias to mean value of these former distributions. This does not mean that some stylised distribution of parameters should not be assumed and I here avoided the difficult task of inferring one. But the full information reflected by econometric findings should be used when possible due to the instability of the elasticity estimates. A further step would be to better assess the quality of the input information to refine estimations. The parameter inventory from Chapter 5 is a living dataset that will be improved in the future. My hope is that expanding this dataset will reinforce the relevance of the estimations performed in Chapter 5 but also possibly new ones on different topics. And beyond methodological development to address uncertainty, there is also a need for more relevant ways of communicating results associated to these approaches. The usual bar plot approach needs to be replaced by graphs more oriented towards results distribution, from error-bars approach (Chapter 2)[2] to more complete whisker and box plot (Chapter 4) or distribution histograms (Chapter 5). Exploring more efficient ways of presenting results under uncertainty is certainly not a minor topic, as it is fundamental to acknowledge the current limitations in state of knowledge and at the same time preserving the relevance of the results.

The third track I foresee as an opportunity to improve land use response description is model comparisons (Smith et al., 2010, Edwards et al., 2010, De Cara et al., 2012) and model intercomparisons – modellers compare their own model with each another (von Lampe et al., 2014, Nelson et al., 2014). This type of exercise are not likely to generate new research breakthrough as such but more to tighten the estimates provided by the literature by identifying abnormal deviations from well characterised results, refining modelling approaches in different models by sharing of knowledge and experience, and creating synergies on data gaps to fill. Model comparisons also encourage modellers to look more closely into some of their model responses and define metrics to better trace their model behaviours. That is for instance the role of the Net Displacement Factor (Chapters 4 and 5) or the decomposition of contribution from various market adjustment mechanism (Chapter 5, see also Nelson et al., 2013). The long-term efforts around the Energy Modelling Forum (Huntington et al., 1982) provide an example of intercomparison experiment for applied energy economic mod-

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[1]   For instance, Laborde (2011) runs the same model with a Monte-Carlo approach, assuming normal distribution on parameters. This leads to a smaller standard deviation than in the estimations from Chapter 4 results. Hertel et al. (2010a) rely on triangular distribution for their sensitivity analysis.

[2]   Note that error bars were used in Chapter 2 to describe uncertainties in the emission factors, according to the methodology on uncertainty in emissions from IPCC (2006). Although it seems difficult in economics to attribute a 95% confidence interval on a behavioural parameter, a characterisation of uncertainty range can hardly be avoided.

els. Some more recent initiatives have been launched by the agricultural economics community on global model comparison (AgMIP, see Rosenzweig et al., 2013, von Lampe et al., 2014). A natural follow-up of this thesis would be to explore in more details differences in results provided by CGE and partial equilibrium (PE) models, that were used together in Chapter 3. Some fundamental specifications can lead to different outcome for the modelling of land use change policies, such as trade representation (Villoria and Hertel, 2011). I already started to look at model specifications comparison on the demand side (Valin et al., 2014), and contributed to parallel explorations on the supply side (Schmitz et al., 2014, Robinson et al., 2014). Such efforts should be pursued although they can only be complementary to the first two tracks of research raised earlier. They however remain inescapable to tackle what is called "model uncertainty", i.e. the part of uncertainty still tied to the choice of a specific model, even when all input data and parameters variability is explored (Draper, 1995).

Beside and probably in synergy with comparison efforts, land use models should progress further in their validation approach, as a way to improve the consistency of their specifications and the relevance of their calibration. I did not tackle this question upfront in the present work although it was several times underlying the modelling. Most of the time, I focused the discussion around the values of econometric estimates for elasticities (Chapters 3 to 5). Only in Chapter 2, with the GLOBIOM model, the calibration was tested by comparing land use change emissions from the model with past observations, and the model was able to reproduce consistent trends related to deforestation in a certain number of regions. For some other regions however, non-market drivers also play a role, and their description is required to represent how they can interact with market-related effects. Baldos and Hertel (2013), using a more stylised model, also experienced difficulties to reproduce regional trends of land use change, while validating their calibration to represent global trends. More generally, simplified frameworks such as developed in Chapter 5 can be useful to check complex model behaviours and provide back of the envelop consistency checks and improve behavioural parameters. Validation is not yet an obligatory device but starts to develop for economic models of global land use change Lotze-Campen et al. (2008), Baldos and Hertel (2013), Souty et al. (2013). Such attempts should be more systematic in the future and I wish I will have opportunity to contribute further on this matter on the basis of the accumulated experience from this work. Validation by results however remains one side only of the overall validation requirements. It does not prevent thorough examination of model specifications and their testing, i.e. what McCarl (1984) calls "validation by assumption".

The last track of research I would like to raise is the most methodological. It relates to the modelling techniques and the progress still to be done with this respect considering the requirements of some sound representation of land use change dynamics. Because this field is relatively recent, current tools have been adapted to the research question raised. CGE approaches using the GTAP framework were extended to land use change issues Hertel et al. (2009b) but are constrained by the aggregated level of the GTAP database, a problem that has been partially tackled in Chapter

4 by adding some products. A model like GLOBIOM is much younger (Havlík et al., 2011) and benefits for a more flexible structure and a detailed supply-side representation. However, land use change modelling brings some very specific challenges (Rindfuss et al., 2004) that these models cannot address alone at the moment. One of them is the integration of scales and the role of geography. Another example is the consideration of the full extent of land use change drivers, including non-market related ones. I started in Chapter 3 to combine a CGE and a PE model to gather the macroeconomic consistency of the first one and the level of details on the production side of the second one. However, the linkage explored there remained top-down. In a different paper, I tested a hard-linkage between a PE and a non-linear demand module, using an iterative procedure to have all variables common to the two models converge (Valin et al., 2010b). These model linkages are not always the most flexible framework to operate but allow to bridge across scales. Other development options to progress into that direction are achievable, for instance, introducing a fully spatially explicit modelling in the linear programming model (Mosnier et al., 2012). Or representing general equilibrium effects in a grid-cell based model of agriculture (Costinot et al., 2012). The fast development of computation technologies should certainly open the way to new modelling possibilities combining the modelling approaches developed above.

All the efforts listed above will be important to make the modelling of land use change more consistent and relevant. They however will not remove some range of uncertainty in this type of modelling. Therefore, this uncertainty will need to be dealt with in the interpretation and use of results from this modelling.

Policy making under uncertainty

Considering all the limitations outlined above, how should these land-use change impacts from agricultural policies be addressed at the policy level? The academic community today agrees that these market-mediated interactions are a concern. The case of biofuels policy is certainly the one where the question has been raised the most directly. Findings on this matter have produced a consistent understanding of the matter and, in spite of the debate on their magnitude (De Cara et al., 2012, Broch et al., 2013), ILUC emissions are today well acknowledged. The risk of extreme effects responses raised even more concern (Plevin et al., 2010) but uncertainty remains an issue for a sound legislation. As Babcock testified in 2009 in front of the US House Committee on Agriculture:

> Congress and the California legislature have good justification for wanting to account for emissions caused by market-induced changes in land use when determining whether expansion of biofuels will increase or decrease global greenhouse gas emissions. The key question is whether we can accurately predict how an expansion of US biofuels will affect land use both here and abroad. (Babcock, 2009b, p. 2)

For Zilberman et al. (2011), "the uncertainty and variability of ILUC estimates do not imply that they should not be incorporated in biofuel regulation" (p. 429). But they add: "When the

estimated ILUC parameters have significant variance, however, there is high probability that they may result in solutions that are far from the best" (Zilberman et al., 2011, p. 429).

In spite of estimation uncertainties, the US EPA took into account the land use impact of biofuels, directly in the life cycle analysis of biofuels (Farber, 2011). This mandate was however temporarily removed through the American Clean Energy and Security Act of 2009 proposing a more comprehensive US climate policy (Waxman-Markey bill, US Congress, 2009). ILUC finally remained when that bill was defeated in the Senate in 2010 but results were then more favourable to corn ethanol. The California Air Resource Board also kept ILUC factors in its ruling (CARB, 2009) with possibility to update estimates, and set up large consultation of experts to understand how to reduce uncertainties (CARB, 2011).

On the EU side, the best way to include ILUC was initially let opened in the Renewable Energy Directive. The European Commission had proposed a larger set of policy options among which a) monitoring and postponing decision, b) increasing the threshold for GHG emission savings of biofuels, c) introduce some additional sustainability criteria on some fuels, and d) allocate an ILUC factor similar to EPA's (EC, 2010). Instead of including ILUC factors in the LCA, it was finally proposed, as a "precautionary approach" to set up stricter rules for saving requirements and to cap first generation biofuel targets. However, since the rejection at the end of 2013 by the European Council of the proposals of the Commission and the Parliament (proposing on his side to include ILUC factors), any measure on this subject have been postponed.

The case of ILUC illustrates well the difficulty to take into account in the legislation estimates of market-mediated land use change impacts. Uncertainties paralyse the policy making and have been largely exploited in many past issues to differ decisions (Oreskes and Conway, 2010). The biofuel debate attracts a lot of attention as it opens the door to new types of ruling that could reshape our conception of climate change policy. With respect to trade, for instance, several countries have already warned that sustainability criteria would not be acceptable under the World Trade Organization rules and Argentina in May 2013 requested first consultation with WTO to complain against EU Renewable Energy Directive provisions (WTO, 2013). Indeed, academics have already emphasized the inherent flaws of such mechanisms under the WTO rules (Mitchell and Tran, 2009, de Gorter and Just, 2010), in particular if ILUC is included (Schaus and Lendle, 2010, Ackrill and Kay, 2011). The questions at stake are indeed close to the debate on carbon embodied in trade and the potential compatibility of border tax adjustments (BTA) with international trade law (Ismer and Neuhoff, 2007, WTO, 2009). Provisions to implement trade restriction related to emissions from production of traded goods are in principle possible. But if they come to apply differentiated coefficients to imported goods, they must be scientifically sound and robust. For that reason, considering the uncertainties illustrated above, it seems clear that no land use change related restrictions could be imposed at the border in the case of biofuels or for a more general list of products in the context of a trade agreement as tried to be reached between the EU and MERCOSUR.

ADDRESSING LAND USE CHANGE EMISSIONS FROM AGRICULTURAL POLICIES: AT WHAT LEVEL?

For the reasons above, land use change emissions associated to agricultural policies require appropriate responses, but at a different level than those experimented so far with the biofuel policies. As de Gorter and Just (2010) or (Zilberman et al., 2011) emphasize, the major caveat of the different scheme of land use change accounting is that they attempt to monitor emissions at a different location from where they have been emitted. All the current schemes indeed deviate from an approach targeting GHG emissions directly at their source, i.e. on the production side, as organised around the Kyoto protocol. As discussions on global agreement on climate change stall since many years, various provisions for limiting emissions associated to product consumption appear in the legislation, but losing consistency across each other. These *ad hoc* policy fixes make final legislation fragile internationally and without insurance of real effectiveness. For instance, beside ILUC, inefficiency of the sustainability criteria in Europe has already been emphasized in the literature (de Gorter and Just, 2010, Frank et al., 2013). Accounting for land use change in a trade agreement with MERCOSUR is also challenging due to fast changing land use change patterns in Brazil (Nepstad et al., 2009).

However, in the absence of a global regulation of GHG emissions, some second best policies need to be adopted. Several alternative options could be attempted, that would lead to some effects while departing from product-related carbon accounting. One possibility would be upscale the certification rules that started to be proposed for some specific sectors. In their current implementation framework, shuffling and leakage make them inefficient. But if such voluntary agreements could expand to more products and consuming markets, they could exert a strong pressure on the supply side (Khanna et al., 2011). In the most extreme case, instead of regulating one specific use of some goods, a complete ban of a product could be envisaged, as it is currently the case for some endangered species under the Convention on International Trade in Endangered Species of Wild Fauna and Flora (CITES), to which most countries adhere. Lessons from the forestry sector, the most advanced in that domain, could in particular be taken as a source of inspiration (Auld et al., 2008). Under the pressure of EU sustainability criteria, some other sectors started to organise. For instance, the Roundtable on Sustainable Palm Oil,[3] created in 2004 and gathering most important retailing groups, has been quite active recently to demonstrate better cultivation practices. In 2012, companies and non-governmental organisations (NGOs) also decided to create a Roundtable on Sustainable Beef,[4] with in particular producers from North America, Brazil and Argentina.

An important complementary area of effort is the expansion of activities within the REDD+ framework (Pistorius, 2012). Initiatives under REDD+ constitute today the main mechanism to limit deforestation emissions in forest and could deliver important co-benefits (Visseren-Hamakers et al., 2012). But the direct contribution of the agricultural sectors to these schemes may gain to be

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[3] www.rspo.org
[4] www.grsbeef.org

reinforced (Olander et al., 2012). Climate-Smart Agriculture could integrate to this scheme through its emphasis on landscape approach and the promotion of more carbon efficient production systems. The potential for sustainable intensification benefits and their trade-offs have been well illustrated in Chapter 2, and in particular the role that the livestock sector can play due to its high heterogeneity in productivities (Herrero et al., 2013). Well-tailored supply-side measures would allow achieving much more efficiently mitigation objectives than policies targeting consumption patterns (Havlík et al., 2014).

Last, agricultural trade policies could reveal as an efficient tool to leverage the measures above, as long as they do not enter trade restrictive measures based on quantitative land use change related factors, whose robustness could be easily challenged at WTO. Trade policies could instead be used to encourage countries to join international climate mitigation efforts by introducing climate-related provisions in trade agreements. I have just discussed the limitations of too narrow certification criteria on specific products. Free trade zones could be used to coordinate more stringent environmental provisions on larger sets of products and production processes if not possible at a World Trade Organization (WTO) level. For instance, the presence of environmental criteria in the European Generalised Scheme of Preferences "plus" (GSP+) is an interesting example of environmental standards taken into account in trade regulation. Trade with environmentally vulnerable regions should in particular be subject to a particular attention. Obviously, such criteria should be used with some pragmatism, because economic growth and rural development can for a certain number of cases reveal the best direction to better land carbon stocks management. At the same time, encouraging trade with regions currently expanding production through degradation of their natural resources should be imperatively avoided.

Through this work, I gathered enough arguments to demonstrate that land use change responses to global agricultural market shocks can jeopardise the benefits of a certain number of policies, from high-input intensification (Chapter 2) to trade liberalisation (Chapter 3) or biofuels use for substituting fossil fuel (Chapter 4). Emission associated to these policies can be quantified using numeric simulation methods but the estimate cannot be precise enough to allow a direct use of modelling results as emission factors for a carbon pricing scheme (Chapter 5). *Ad hoc* provisions directly implementing such estimates in regulations therefore risk to lead to arbitrary choices and stack of inconsistent measures. More comprehensive approaches should be preferred, such as land use oriented supply-side policies or, as a second best option, market-wide demand-side measures, internationally coordinated, to tackle the adverse effect of market-mediated land use change emissions from agriculture.

APPENDIX A

YIELD PROJECTION SCENARIOS FOR CHAPTER II

A.1 Crop yield

A.1.1 Yield extrapolation in scenarios

The crop yield baseline from Chapter 2 ("TREND") is built around the assumption than future yields will follow the past trend with a linear extrapolation (Fischer, 2009). Historical trend is estimated on the period 1980–2010 using FAOSTAT data, except for Eastern Europe and Former Soviet Union countries where we took the 1995–2010 period to take into account the change in farming structure during the 1990s. As illustrated in Figure 2.1 of Chapter 2, average crop yield in developed regions keep a slow pace increase (0.4% p.a. on average) to reach a total yield of 4.9 dry matter (DM) tons per ha by 2050 for the bundle of the 17 crops considered. Latin America, starting slightly lower, succeeds to take a leader position in 2050 at 5 t DM/ha. The good performance of this region can be explained by favorable environmental conditions but also different composition of crops with higher yields (such as sugar cane). Emerging Asia catches up even faster at a growth rate of 1% per year and reaching 4.6 t DM/ha in 2050. This contrasts with the situation in Eastern Europe and Former USSR ("REUR") that started from similar level in the 70s but hardly exceeds 3.6 t DM/ha in 2050 if the current trend continues. Last, Africa, starting from a lower level, remains largely behind other continents with only 40% of the average level of Latin America by 2050. In order to provide more insight on how these trends decompose across regions, Figure A.1 represents the trend for each region in blue, which can be compared with past record. Results per crops are furthermore displayed in Figure A.2.

Projecting a continuation of such past trends can appear as an optimistic assumption. Some regions currently show for specific crops a slow-down in their growth rate (e.g. wheat in Northern Europe or rice in China; see Cassman et al., 2010). At the same time, there is little ground to impose a plateau on a certain number of crops when projecting up to 2050, considering possibility that new varieties may offer potential to further yield improvements (Fischer, 2009). Our "SLOW" scenario therefore reflects an intermediate situation where future yields do not materialise as in the past and some stagnation occurs in developing regions. However, we did not apply this alternative
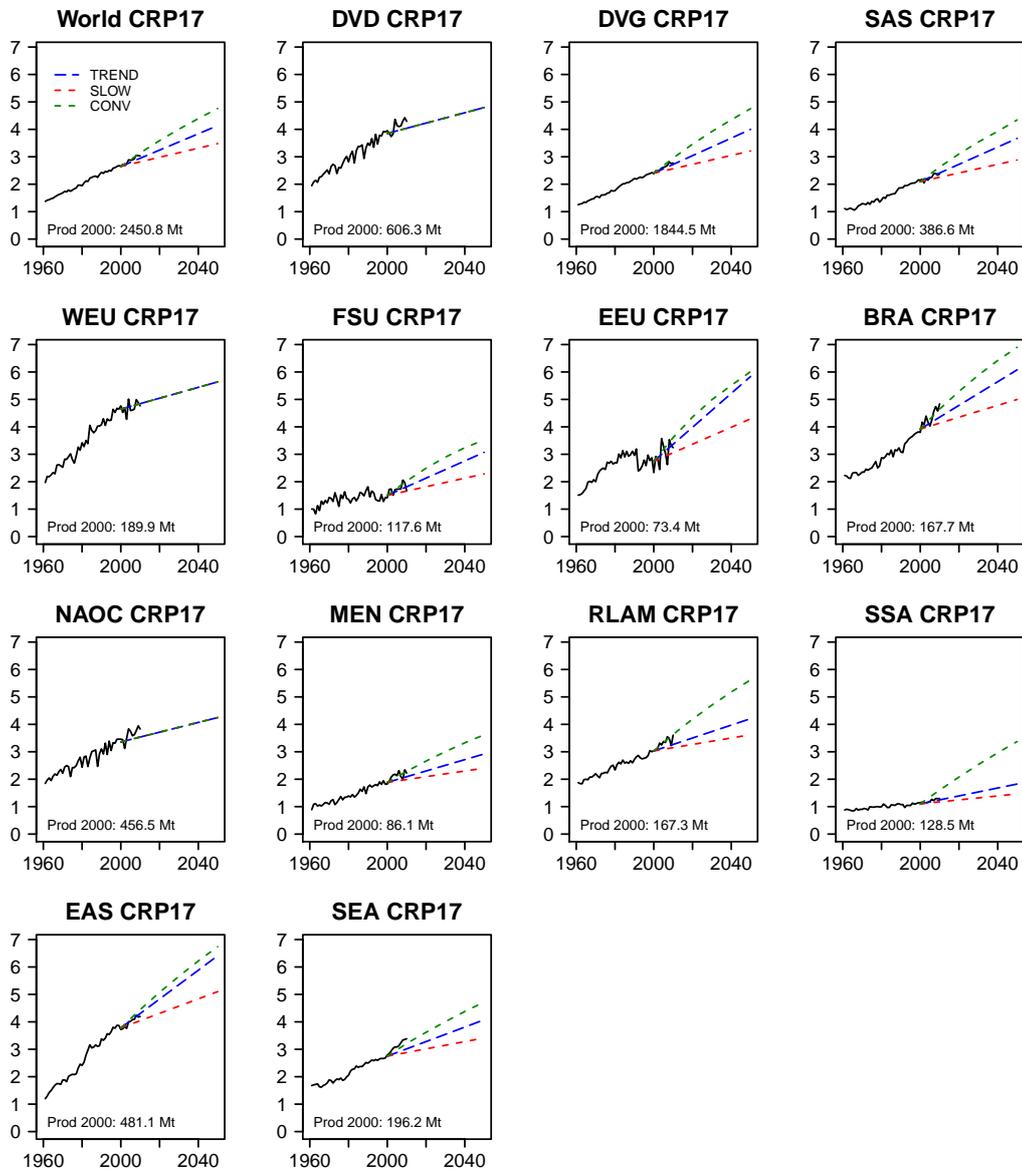
Figure A.1. Historic yield and yield projections according to the TREND, SLOW and CONV scenario for the average of 17 crops in GLOBIOM modeled with EPIC (t DM/ha). DVD= Developed; DVG=Developing. Region codes are the same as in figure 2.3.

assumption to developed regions considering the point of focus of this article is developing regions. This case is explored in a separate sensitivity analysis in section 2.3.3 of the paper. The "SLOW" trend is visible in red in Figures A.1 and A.2.

Our last scenario ("CONV") explores the possibility of exploiting yield gaps that were not closed in the "TREND" scenario. Indeed the yield gap observed in 2000 for some regions can be closing as a business as usual situation if past trends prolong. For example, in the case of China, the yield gap for rice is very limited (see section A.1.2). With the "TREND" scenario, we therefore assume
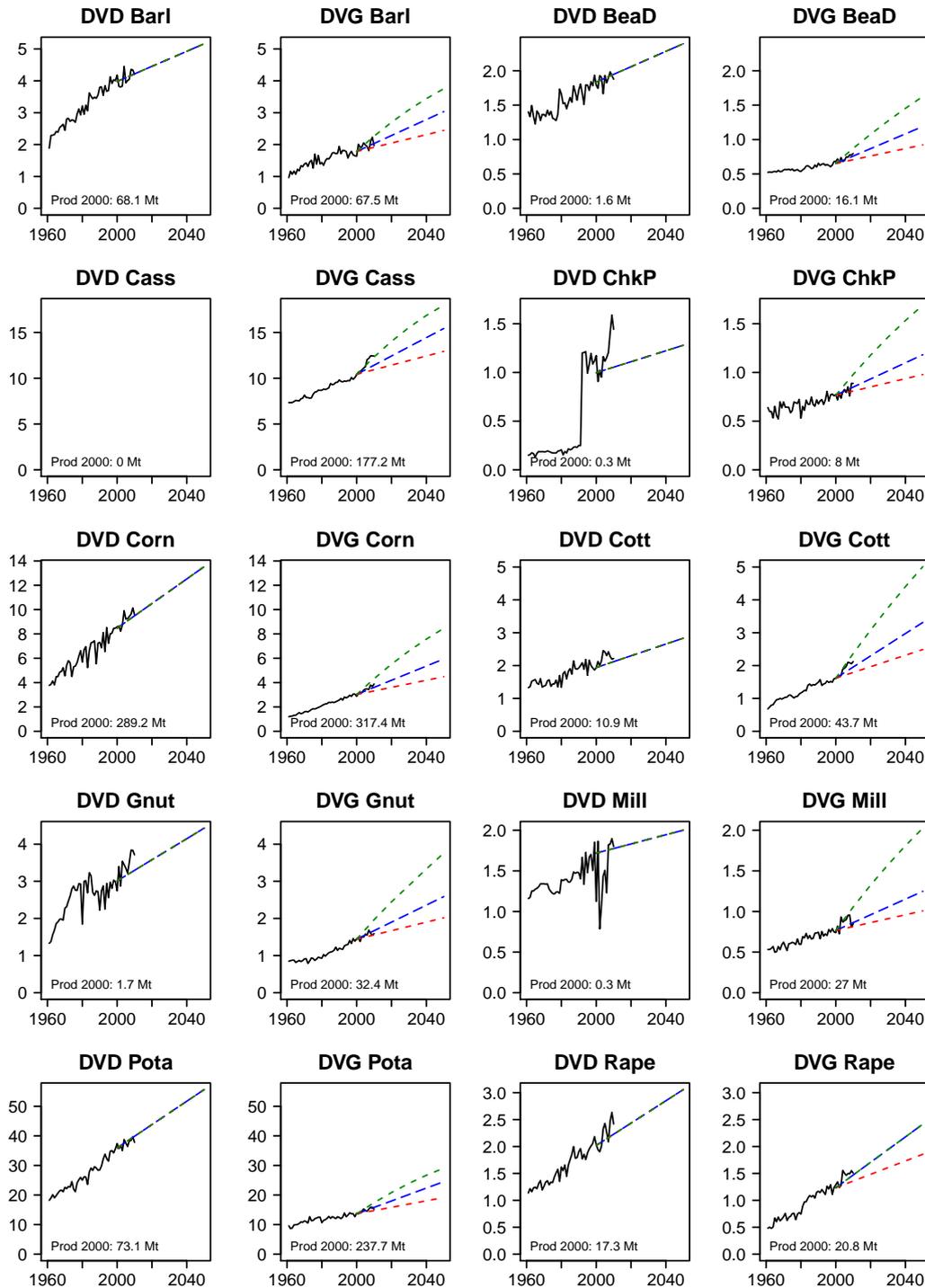
Figure A.2.   Historic yield and yield projections according to the TREND, SLOW and CONV scenario for each of the 17 crops in GLOBIOM modeled with EPIC. DVD= Developed; DVG=Developing. Crops: Barl = barley; BeaD = Dry beans; Cass = Cassava; ChkP = Chick peas; Cott = Cotton; Gnut = Groundnut; Mill = Millet; Pota = Potatoes; Rape = Rapeseed.
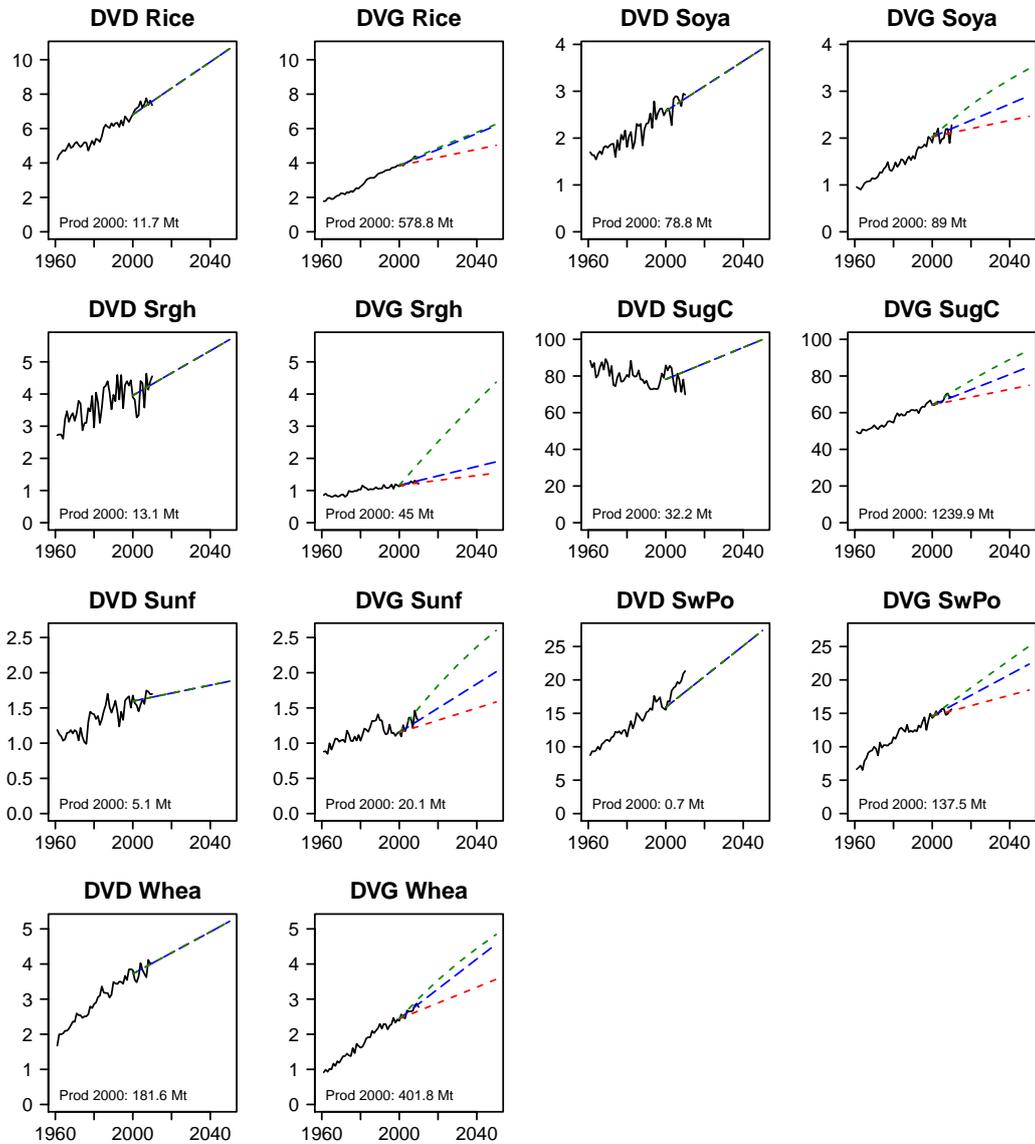
Figure A.2. (continuation of previous page) Historic yield and yield projections according to the TREND, SLOW and CONV scenario for each of the 17 crops in GLOBIOM modeled with EPIC. DVD= Developed; DVG=Developing. Crops: Soya = Soybeans; Srgh = Sorghum; SugC = Sugar cane; Sunf = Sunflower; SwPo = Sweet potatoes; Whea = Wheat.

that additional yield gain will be obtained through other technologies than just intensification under current varieties, in particular through breeding. The "CONV" scenario therefore does not assume additional yield increase due to gap closure, because the historical yield growth is kept as the low bound for yield growth increase for such cases. On the opposite, in Sub-Saharan Africa, extrapolating the past trend let yield potential for most crops largely unexploited under "TREND". In that case, the additional yield increase following the yield gap closure by 50% in "CONV" makes a significant difference with the baseline.

Obviously, projecting yield towards 2050 remains a very arbitrary exercise. For that reason, we chose the simplest possible baseline with a linear trend to avoid any country or crop specific treatment that would make the process less transparent. Are the future yield projections obtained all biophysically feasible? For developed regions, this remains an opened question, but in a case where the full set of new technologies is used, further yield improvement can be expected. For example, Fischer (2009) list a different track of research to improve potential yield (conventional breeding, increased photosynthetic rates, genetic enhancement through use of wild species, stress tolerance, etc.). Additionally, they reports some potential yield obtained in specific regions much higher than current average farm yield. They also remind that Monsanto has set an objective of doubling maize yield between 2000 and 2030. On the other hand, a caveat of our approach is that we do not take into account possible negative impact of climate change that appears of one of the main challenger of a continuation of past trends. That is why we developed the "SLOW" scenario to explore how such effect could affect the results.

However, when coming to developing countries, it can be seen that our projections hardly lead to greater yields than the current level observed in developed regions. This ensures that projected yield for these regions are feasible from a crop physiology perspective, although each region has its own growing environmental conditions. Only two crops appear to have yield notably higher than recorded in developed regions. First, cotton is projected in our best scenario as reaching on average 5 t/ha in developing regions in "CONV" by 2050. This would obviously require good irrigation conditions but does not seem biophysically infeasible as some yield greater than 4 t/ha are regularly reported in some countries like Turkey or Syria (FAOSTAT). The second case is sunflower that we project to levels at 2.5 t/ha on average in developing regions, also for "CONV". These also appear biophysically feasible, as average yields over 2.5 t/ha are reported for some regions (eg. Mercau et al., 2001, in Argentina).

A.1.2   IDENTIFYING CROP YIELD GAPS

Our crop productivity scenario "CONV" relies on an assumption of closing yield gap by 50% for crops in developing countries. In order to assess yield gaps for crops, we rely on the crop model EPIC. This model is used to assess for each region potential yield under different management systems: rain-fed cultivation with high level of input (potential water-constrained yield) or irrigated systems with high level of input (pure potential yield). We calculate the average potential yield by applying
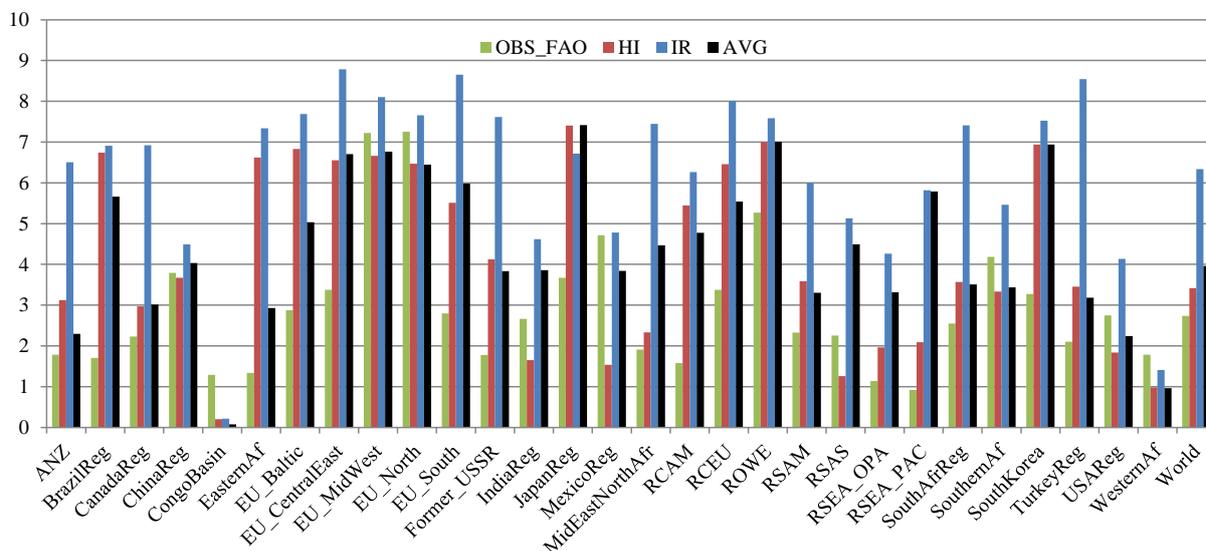
Figure A.3. FAO average wheat yield in 2000 (OBS_FAO), and attainable wheat yield through high input (HI), irrigated (IR) and combined (AVG) systems on the base of current crop location.

our high input system to all rain-fed crops and keeping irrigated systems fixed. The gap between this average potential yield at the country level and the FAO reported yield is used as a proxy for yield gap.

The EPIC model is run for the 17 different crops on a world mosaic of homogenous response units (HRUs) defined as the intersection of GIS layers of slope, altitude and soil, at a 5 arcminute resolution, and fit within a grid of 0.5 x 0.5 degree resolution (largest unit area possible; for more information on the concept of HRU, see Skalský et al., 2008. The high input system (HI) considered is obtained by parameterizing the model with an automatic nitrogen fertilisation assumption: N-fertilisation rates are automatically applied based on N-stress levels (N-stress free days in 90% of the crop growing period). The upper limit of N application is set at 200 kg/ha/yr. For irrigated systems (IR), N and irrigation rates are based on stress levels (N and water stress free days in 90% of the crop growing period. N and irrigation upper limits are 200 kg/ha/yr and 300 mm/yr. We also run a subsistence farming system for which no fertiliser or irrigation is considered. Information on crop location and management system are source from SPAM (You and Wood, 2006).

We display below the difference in observed FAO yield and attainable yield obtained with the EPIC runs for the three major cereals: wheat, rice and maize. As can be seen on Figure A.3, our estimated wheat yield gap is at the world level relatively small, with little margin of improvement in Europe or in China that appear close to their potential. Rice is in an even more extreme situation (Figure A.4), considering that many observed yields are above the values obtained with the crop model. This suggests that no easy improvement can be achieved in those regions for this crop. However, the case of maize (Figure A.5) shows much more potential with large margin to exploit in Africa, South America or China.
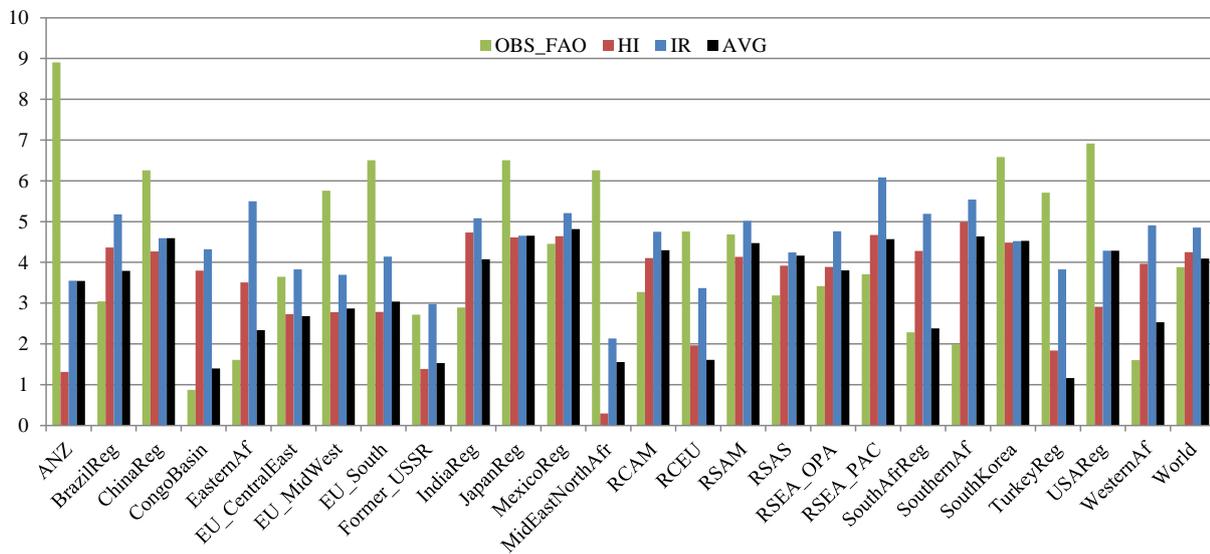
Figure A.4. FAO average rice yield in 2000 (OBS_FAO), and attainable rice yield through high input (HI), irrigated (IR) and combined (AVG) systems on the base of current crop location.
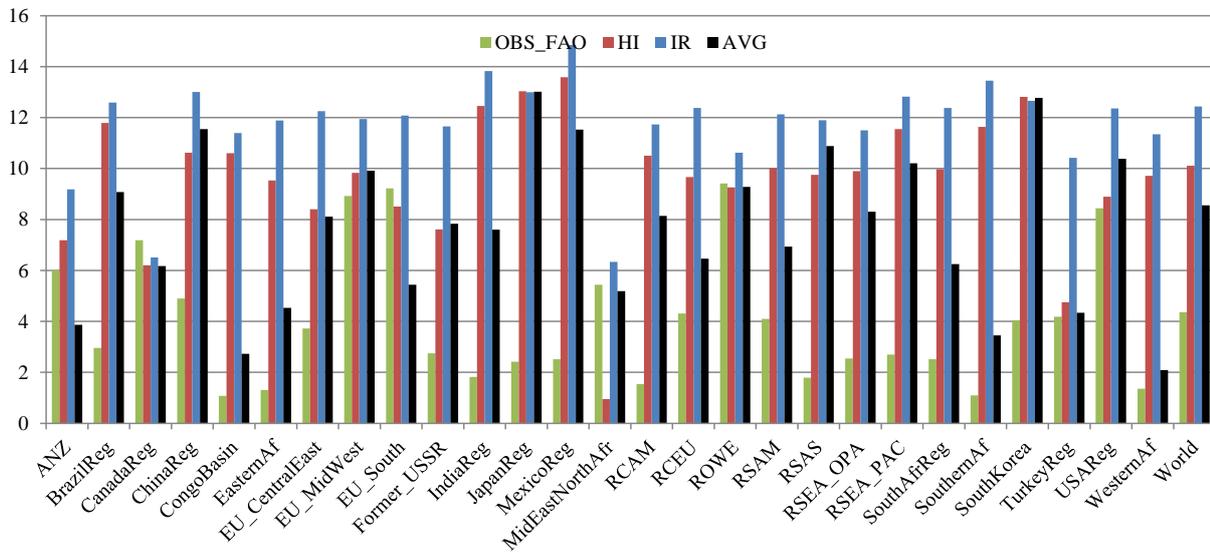
Figure A.5. FAO average maize yield in 2000 (OBS_FAO), and attainable maize yield through high input (HI), irrigated (IR) and combined (AVG) systems on the base of current crop location.

A.1.3 COMPARISON OF CROP YIELD GAP RESULTS WITH THE LITERATURE

In order to assess the relevance of our CONV scenario, we compare our yield gap assessment with some other findings from the literature. The results are presented below in Table A.1. Two other studies have been used to compare our estimates. Mueller et al. (2012) provide estimates of attainable yield gap under available technologies in different regions of the world. The results

presented here are sourced from the Figure 2 of their paper, and we reaggregated our results using their regional nomenclature (similar code to this study except for ANZ, Australia-New Zealand, aggregated to South-East Asia, and NAM, North America, separated). These authors in particular calculate what would be the production in different parts of the world if 100% of attainable yield was reached. The other paper used for the comparison is from Licker et al. (2010), who provide some maps of yield gaps identified by different coloured pixels. As no summary statistics were provided in this paper, we derived from map visual interpretation the range of values for reported yield gaps.

EPIC estimate are reported in Table A.1 for the potential average yield gap, water constrained for rain-fed agriculture location (see previous section), and for the yield gap corresponding to the closure of half this potential gap, which is the gap used for the CONV scenario in the paper. Looking first at the potential estimated yield gaps, we can see some differences between the EPIC potential yield and the attainable yield from Mueller et al., but these differences are usually kept within the range of the value reported by Licker et al..

For maize, we find more important yield gap that in Mueller (57% versus 39%). At the same time, the values for North America appear conservative (13%) and yield increases after a decade are already over this level of attainable yield. Indeed yield gap analysis usually does not represent yield enhancement related to improvement of varieties as it assesses potential yield under current technologies. Considering that only 50% of the gaps are closed leads however to more comparable yield gap (40%) at the world level.

Wheat yield gap assessment is found relatively lower than in Mueller et al. (33% vs 42%). This is mainly due to a very different estimation of yield gaps for North America and Western Europe. As illustrated in the previous section, our EPIC simulations for wheat provide for these regions yield levels slightly lower than the levels currently reached. Therefore, we consider that the yield gap is closed already. In the case of other regions of the world (ROW), our yield gap estimate is however much closer to Mueller et al. (42% vs 47%). Considering only 50% of yield gap can be closed is equivalent to representing for wheat a yield gap of 27%.

With respect to rice, we also find a lower yield gap estimate (23% vs 32% for Mueller et al. mainly because of different assessment of the yield in Eastern Asia, where we consider there that yield are already closed. For South Asia and South-East Asia, our assessments are more in agreement. As a consequence, and considering our assumption of closing 50% of yield gap, only limited yield boost on rice can be considered for the CONV scenario, and it can only occur in South Asia and South-East Asia.

Table A.1. Crop yield gaps in our model and a selection of studies for three major cereals and underlying causes (production in Mt).

| Region | Crop | Mueller et al. (2012) | | | GLOBIOM/EPIC | | | Licker et al., 2010 | Main limiting factor[b] | |
		Prod 2000	Prod att.	Yield gap	Pot. yield gap	Yield gap 50%	Prod att. 50%	Yield gap	Müller et al., 2012	Neumann et al., 2010
NAM	Corn	260	300	13%	19%	10%	290	0%–25%	None	na
NAM	Wheat	80	130	38%	0%	0%	80	12%–62%	N + W	A + I
NAM	Rice	10	10	0%	0%	0%	10	na	None	na
LAM	Corn	75	140	46%	75%	60%	189	0%–75%[a]	N	I + M[c]
LAM	Wheat	20	35	43%	43%	27%	28	25%–50%	N	na
LAM	Rice	20	32	38%	24%	14%	23	na	N + W	na
WEU	Corn	45	60	25%	6%	3%	46	37%–62%	None	na
WEU	Wheat	95	120	21%	0%	0%	95	0%–25%	None	na
WEU	Rice	2	2	0%	0%	0%	2			
EEU+FSU	Corn	25	70	64%	60%	42%	43	25%–62%	N + W	na
EEU+FSU	Wheat	95	205	54%	56%	39%	155	25%–75%	N	A + L
EEU+FSU	Rice	0	0		0%	0%	0			
MEN	Corn	1	5	80%	3%	2%	1	na	na	na
MEN	Wheat	30	70	57%	59%	41%	51	na	N + W	M + A
MEN	Rice	0	0		0%	0%	0			
SSA	Corn	25	100	75%	86%	75%	102	25%–100%	N + W	M + A
SSA	Wheat	2	5	60%	64%	47%	4	na	N + W	na
SSA	Rice	10	30	67%	63%	46%	18	na	N	I
SAS	Corn	15	35	57%	85%	74%	58	0%–62%	N + W	M + I
SAS	Wheat	90	170	47%	39%	24%	118	12%–75%	N + W	na
SAS	Rice	175	280	38%	37%	22%	226	12%–50%	Variable	na
EAS	Corn	120	225	47%	58%	40%	201	25%–50%	N	na
EAS	Wheat	100	140	29%	8%	4%	104	0%–75%	None	S + I
EAS	Rice	195	245	20%	0%	0%	195	0-37%	None	na
SEA+ANZ	Corn	15	20	25%	75%	59%	37	0-25%	None	na
SEA+ANZ	Wheat	20	45	56%	45%	29%	28	12%–50%	N + W	na
SEA+ANZ	Rice	140	205	32%	21%	12%	159	25%–50%	Variable	I + L[d]
WORLD	Corn	581	955	39%	57%	40%	968			
WORLD	Wheat	532	920	42%	33%	20%	663			
WORLD	Rice	552	804	31%	23%	13%	633			
DVLG	Corn	276	595	54%	72%	56%	632			
DVLG	Wheat	357	670	47%	42%	27%	488			
DVLG	Rice	540	792	32%	23%	13%	621			
NAM+WEU	Corn	305	360	15%	17%	9%	337			
NAM+WEU	Wheat	175	250	30%	0%	0%	175			
NAM+WEU	Rice	12	12	0%	0%	0%	12			

[a] 0%–37% in South America; 37%–75% in Central America.
[b] Limiting factors codes: N = Nutrient; W = Water; M = Market Influence; S = Slope; I = Irrigation; L = Labor; A = Accessibility.
[c] For Central America.
[d] Specific information for Indonesia: M + A + L.
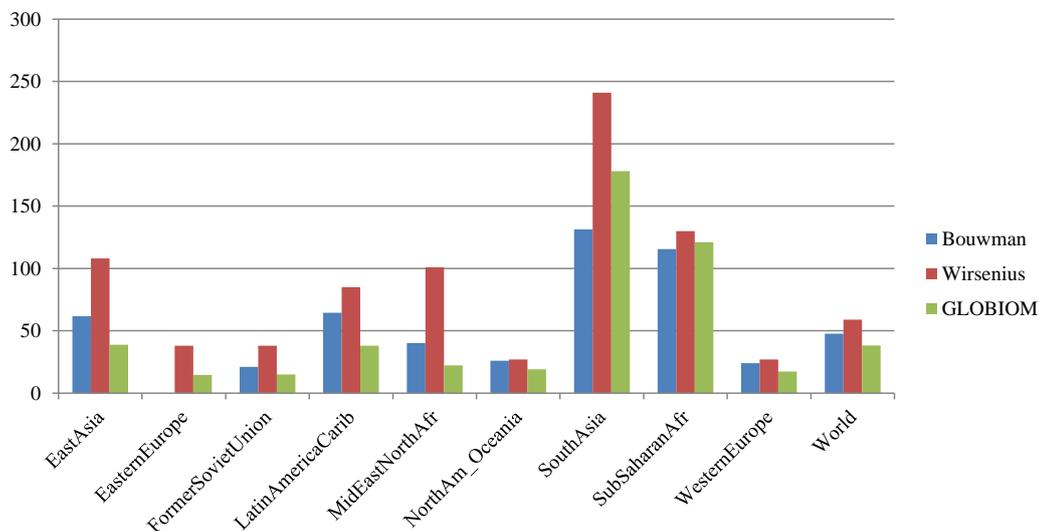
Figure A.6. Feed use per unit of cattle beef according to different sources (kg dry matter feed per kg output). Source: Bouwman et al. (2005), base year: 1995; Wirsenius et al. (2010), base year:1992/94; base year for the present work: 2000.

A.2   Livestock productivity

A.2.1   Feed conversion efficiency calculation

In this study, we look at the improvement of livestock productivity measured as feed conversion efficiency, i.e. feed requirements (in total DM t) by animal product output. All livestock productivity data in GLOBIOM are based on a validated dynamic digestion and metabolism model (Herrero et al., 2002, RUMINANT,), as described in Thornton and Herrero (2010) and Herrero et al. (2013). The model estimates productivity (milk, meat), methane emissions and manure and N excretion.

In order to reconcile process-based model and national accounts in a consistent framework, bovine and small ruminants' productivities estimation follows a three steps process which consists of first, specifying a plausible feed ration, second, calculating in RUMINANT the corresponding yield, and finally confronting at the region level with FAOSTAT (Supply Utilization Accounts) data on production. These three steps are repeated in a loop until a match with the statistical data in FAOSTAT was obtained (Herrero et al., 2013, Havlík et al., 2014, see details in). For monogastrics, information on feed quality is used to estimate feed intake, productivity and feed use efficiency using standard nutrient requirements guidelines from the National Research Council.

The heterogeneity in ruminant productivity across regions seems wider for livestock products than for crops (see Figure A.6 to A.8) and this is an inherent function of the quality of the diet for ruminants in different regions (Herrero et al., 2013). We compare our base year figures sourced from Herrero et al. with some other estimates from the literature (Wirsenius et al., 2010, Bouwman et al., 2005).
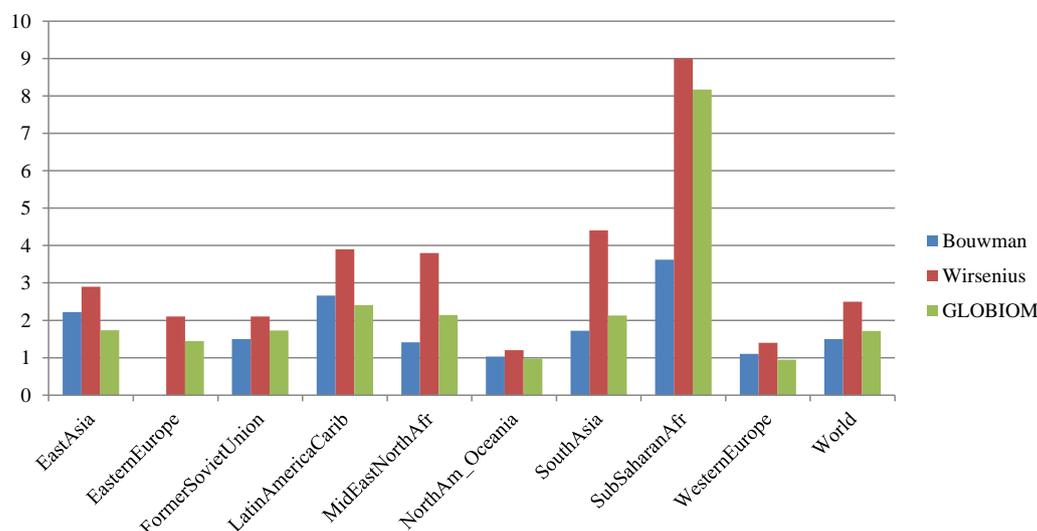
Figure A.7. Feed use per unit of cattle milk according to different sources (kg dry matter feed per kg output). Source: Bouwman et al. (2005), base year: 1995; Wirsenius et al. (2010), base year:1992/94; base year for the present work: 2000.
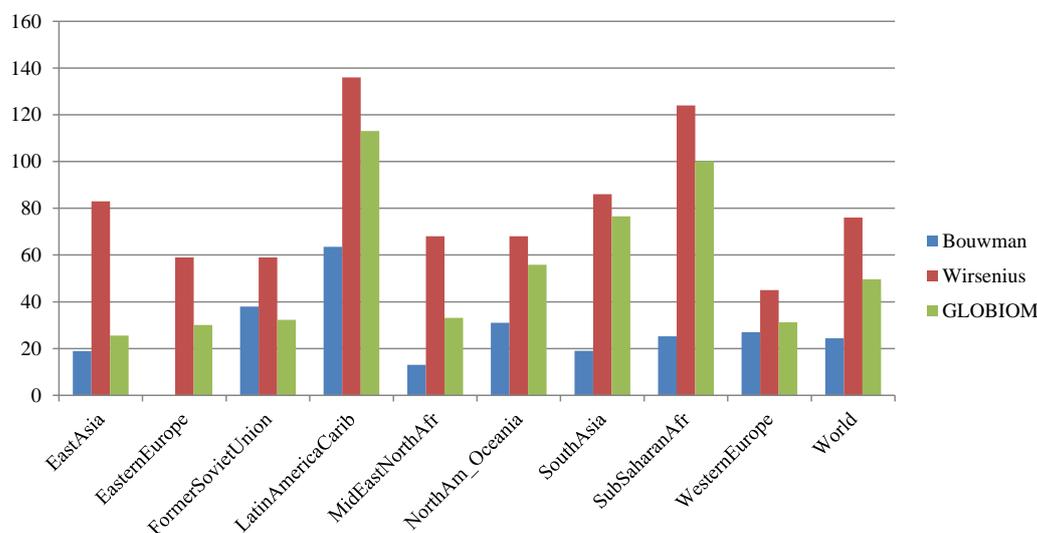
Figure A.8. Feed use per unit of small ruminant meat according to different sources (kg dry matter feed per kg output). Source: Bouwman et al. (2005), base year: 1995; Wirsenius et al. (2010), base year:1992/94; base year for the present work: 2000.

The estimates obtained appear fully consistent with other sources, however, they also vary for some specific regions, which illustrates the difficulty to precisely characterise the average livestock productivity with the current data available on feed consumption. As can be clearly observed on the different figures, we sometimes tend to agree with Wirsenius et al. (2010) for some regions and for some others with Bouwman et al. (2005). However, these figures all illustrate the gap between the production efficiency during developing and developed regions. It is the effect of reducing this
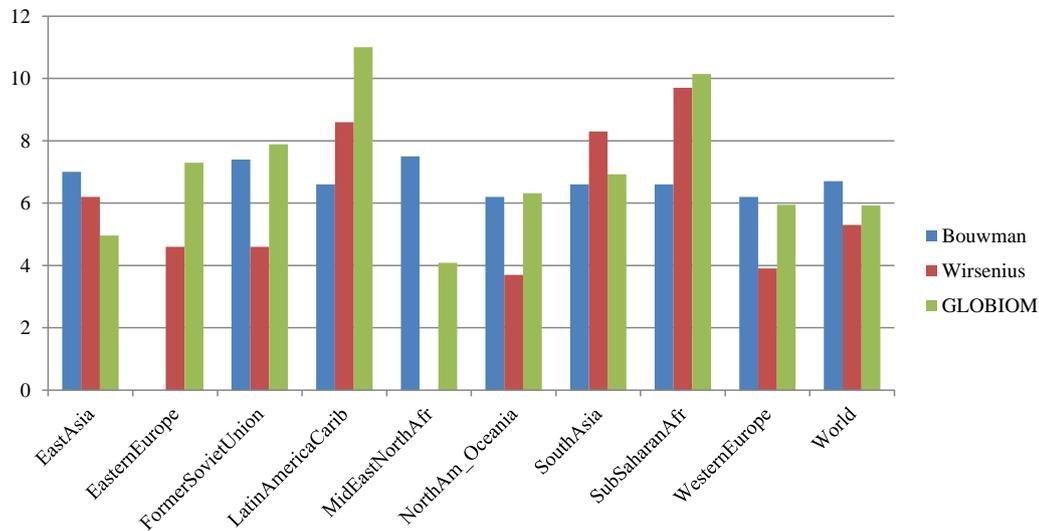
Figure A.9. Feed use per unit of pig meat according to different sources (kg dry matter feed per kg output). Source: Bouwman et al. (2005), base year: 1995; Wirsenius et al. (2010), base year:1992/94; base year for the present work: 2000.
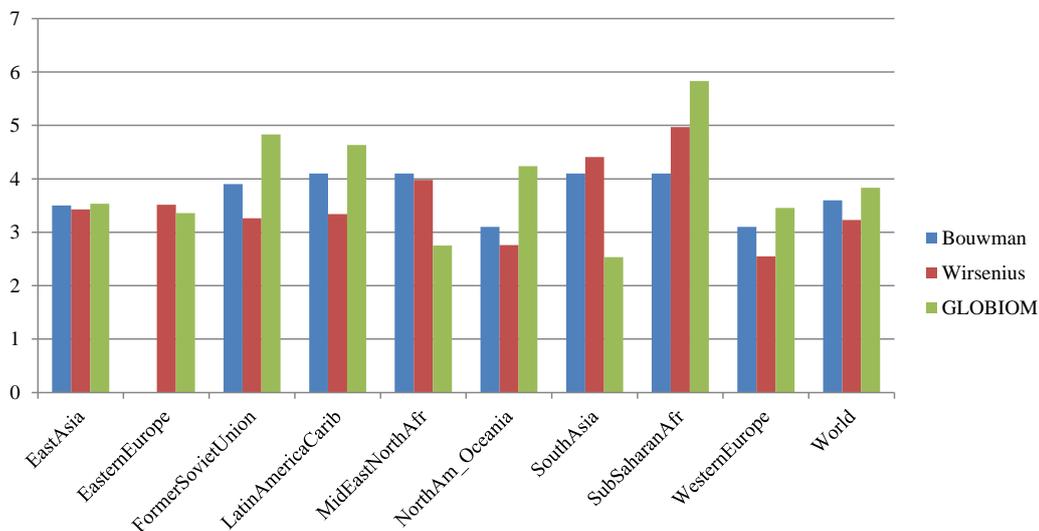
Figure A.10. Feed use per unit of poultry meat and eggs according to different sources (kg dry matter feed per kg output). Source: Bouwman et al. (2005), base year: 1995; Wirsenius et al. (2010), base year:1992/94; base year for the present work: 2000.

gap that will be at the basis of our scenario on livestock productivity.

For monogastrics, the contrast between developing and developed regions is however much less clear (see Figure A.9 and A.10). According to Bouwman et al. (2005), most regions are already at the efficiency frontier for pigs, whereas Wirsenius shows more disparity, but also sometimes much higher efficiency (i.e. lower feed use per unit of output). Data used for GLOBIOM are also inconclusive on a difference between these regions (see Herrero et al., 2013, for more details).

Following these observations, in the absence of reliable productivity data, we did not consider here any yield gap scenarios for pigs and poultry. This should not affect the conclusions of this work for two reasons. First, livestock direct emissions are emitted for 91% by ruminant (Herrero et al., 2013). Second, non-ruminant are not directly linked to land, only indirectly through grain feed whose land requirements are at global level evaluated to 320 Mha, i.e. 10 times less than the grassland occupation (3.5 Gha according to FAO, from which about 2 Gha are grazed in GLOBIOM).

A.2.2   BASELINE AND CONVERGENCE SCENARIO FOR FEED EFFICIENCY

We take for our baseline assumption the livestock productivity trends from (Bouwman et al., 2005). In their paper, they propose a trend for livestock productivity until 2030, defined per system. We implement these trends directly in our livestock systems, by animal and category (mixed or grass-fed), and prolong them up to 2050.

An overview of the productivity trend obtained for ruminant meat and milk is provided in the Figure 2.2 of Chapter 2. We observe that these productivity trends are in continuation of the assumed historical trends (also sourced from Bouwman et al.). Feed conversion efficiency for meat (panel A) is less than half the efficiency from OECD and Eastern Europe countries and sometimes much lower (almost 10 times lower for Asia in the years 1970).[1] However, some regions have been catching up at considerable pace, such as Asia that reaches half of the level of Latin America today. Following Bouwman et al. trends, we assume in our baseline that Asia gets very close to current Latin America yield by 2050. The catching up patterns are similar in the case of milk products (panel B).

For the catching up scenario, we assume that 25% of the gap between the present yield and the yield of OECD regions is bridged. For this, we compute a feed conversion efficiency level of reference for each of the animals, and follow the convergence path, except if the baseline scenario is higher; in this latter case, we remain on the baseline path, so that the convergence scenario is always higher or equal in trend than the baseline.

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[1]   There is significant uncertainty in characterizing average feed efficiency at the world level at the different period of time. Here, we backcast present productivities such as computed in GLOBIOM from FAOSTAT using the trends of Bouwman et al. (2005).

APPENDIX B

GHG EMISSIONS IN GLOBIOM

Greenhouse gas emissions are at the core of Chapter 2 analysis. We provide in this appendix more details on GHG accounts in GLOBIOM and the underlying emission factors and compare with other sources in the literature.

B.1   GHG EMISSION ACCOUNTS IN GLOBIOM

As explained in the Table 2.3 of Chapter 2, GLOBIOM accounts for a wide range of sources, in the crop and in the livestock sectors, but also emissions related to land use changes.

B.1.1   LIVESTOCK SECTOR

In GLOBIOM, we assign the following emission accounts to livestock directly: CH_4 from enteric fermentation, CH_4 and N_2O from manure management, and N_2O from excreta on pasture (N_2O from manure applied on cropland is reported in a separate account linked to crop production). The estimation of these emissions follows an IPCC Tier 3 approach for enteric fermentation thanks to the use of the RUMINANT model (see Section A.2 in Appendix A) to compute emissions for each species and system by region. For other livestock sources, we use a Tier 2 approach. Detailed description of how these coefficients are calculated is provided in Herrero et al. (2013). In brief, CH_4 from enteric fermentation is a simultaneous output of the feed-yield calculations in the RUMINANT model, as well as nitrogen content of excreta and the amount of volatile solids. The assumptions about proportions of different manure management systems, manure uses, and emission coefficients are based on detailed literature review.

B.1.2   CROP SECTOR

Crop emissions sources accounted in the paper are N_2O fertilisation emissions, from synthetic fertilizer and from organic fertilizers, as well as CH_4 methane emissions from rice cultivation.

Synthetic fertilizers are calculated on a Tier 1 approach, using the information provided by EPIC on the fertilizer use for each management system at the simulation unit level and applying

the emission factor from IPCC AFOLU guidelines. Synthetic fertilizer use is therefore built in a bottom-up approach, but upscaled to the International Fertilizer Association statics on total fertilizer use per crop at the national level for the case where calculated fertilizers are found too low at the aggregated level. This correction allows a full consistency with observed fertilizer purchases.

Organic fertilizer emissions are calculated with RUMINANT, following a methodology similar to what was applied for livestock allocated emissions. In the case of rice, we only apply a Tier 1 approach, with a simple formula where emissions are proportional to the area of rice cultivated. Emission factor is taken from FAO.

B.1.3 Land use change

Land use change emissions are computed based on the difference between initial and final land cover carbon stock. For forest, above and below-ground living biomass carbon data are sourced from Kindermann et al. (2008), who provide geographically explicit allocation of the carbon stocks. The carbon stocks are consistent with the Forest Assessment Report (FAO, 2010b). Therefore, our emission factors for deforestation are in line with those of FAO.

Additionally, carbon stock from grasslands and other natural vegetation is also taken into account using the above and below ground carbon from the biomass map of Ruesch and Gibbs (2008).

When forest or natural vegetation is converted into some agricultural use or short rotation plantation, we consider in our approach that all below and above ground biomass is released in the atmosphere. However, we do not account for litter, dead wood and soil organic carbon.

B.2 Comparison with the literature

GLOBIOM incorporates main sources of GHG emissions for agricultural and land use change. These sources are all listed in Table 2.3 of Chapter 2. In this section, we compare our emission estimates with those of some other inventories and observations.

B.2.1 Agriculture

For emissions from agriculture, we compare our base year emissions with those of three sources: FAOSTAT (Tubiello et al., 2013), non-CO_2 emission database from EPA (2012), and EDGAR v4.2 from JRC and PBL (2009). As can be observed in Table B.1 below, organized following the 1996 UNFCCC reporting guidelines, these different databases report varying range of sources and emission values.

In terms of source coverage, we cover 94.1% of emissions sources reported by FAOSTAT (only missing non CO_2 emissions from soil and burning from agricultural residues and drained organic soil). Because they are not classified by UNFCCC as agricultural source, emissions from fertiliser production are not accounted by these different inventories and not reported in GLOBIOM. However, another important source of emissions missing in FAOSTAT is Savannah burning (5.9% of

Table B.1. Global GHG emissions from agriculture in 2000 under UNFCCC framework in GLOBIOM and different databases ($MtCO_2$-eq/yr).

UNFCCC 1996 CRF code			GLOBIOM	FAOSTAT[a]	EPA 2012	EDGAR v4.2
4A	**Enteric fermentation**		**1,502**	**1,863**	**1,811**	**2,283**
4B	**Manure Management**		**457**	**323**	**390**	**363**
		CH_4	251	168	216	271
		N_2O	207	155	174	92
4C	**Rice cultivation**		**487**	**490**	**495**	**839**
4D	**Agricultural soil**		**1,009**	**1,530**	**1,684**	**1,584**
	Synthetic fertilizer N_2O		522	521	na[b]	713
	Manure left on pasture		403	675	na[b]	528
	Manure applied on cropland		83	105	na[b]	236
	Other Soil emissions (CO_2)		na	na	na[b]	107
	Crop residues N_2O		na	132	na[b]	na
	Drained organic soils N_2O		na	97	na[b]	na
4E	**Prescribed burning of Savannas**		**na**	**na**	**na**	**306**
		CH_4	na	na	na	154
		N_2O	na	na	na	152
4F	**Field Burning of Agricultural Residues**			19		44
		CH_4	na	14	na	34
		N_2O	na	5	na	10
ND	**Other Agricultural emissions (EPA)[c]**				**1,043**	
		CH_4	nd	nd	344	nd
		N_2O	nd	nd	699	nd
	TOTAL GLOBIOM sources		**3,455**	**3,977**	**4,380**	**4,962**
	TOTAL Agriculture		**3,455**	**4,225**	**5,423**	**5,312**
	GLOBIOM Sources coverage			*94.1%*	*80.8%*	*93.4%*

[a] Accessed 14/05/2013

[b] Details not provided. For comparison of GLOBIOM source coverage, we assume the full aggregate covers GLOBIOM sources.

[c] EPA only reports an aggregate for Savanna burning, agricultural residues burning, and other agricultural soils

nd= not defined; na=not available.

agricultural emissions according to EDGAR v4.2 and up to 19.2% of emissions in EPA database, aggregated with agricultural residues and other agricultural soil emissions). Overall, Tubiello et al. (2013) estimate that the FAOSTAT GHG database represents 80–85% of all agricultural emissions.

Total emissions allocated to agriculture vary across databases not only because of the number of sources covered but also because of the level of emission reported for each source. However, because the intervals of confidence associated to each source are large, this does not reflect inconsistencies. Overall, emissions in GLOBIOM are 9% lower than FAOSTAT estimates for the same sources, 18% lower than EPA and 27% lower than EDGAR v4.2. A part of this difference is attributable to the way livestock emissions are computed. Herrero et al. (2013) use a Tier 3 approach for enteric fermentation and also disaggregated them into nine types of production systems for 28 regions. A large proportion of animals in the developed world are in systems of low productivity, which drive gross emissions downwards in comparison to other estimates based on Tier 1 methods, which use aggregated data. Our Tier 3 method also provides more realistic estimates of feed intake for low quality diets, which is a crucial factor driving the lower gross emissions of these large numbers of animals.

B.2.2 Land use change emissions

Land use change dynamics traced in the model also covers only a part of afforestation, land use and land use change emissions sources (AFOLU). Because the model does not monitor geographic reallocation at a finer scale that its grid cell resolution (in this study 2×2 degrees), deforestation measured is only net deforestation, calculated in each pixel as the difference between final and initial forest cover. Afforestation in developed regions is not modelled and supposed unaffected by agricultural expansion. Therefore, our deforestation figures need to be compared to net tropical deforestation statistics, which report lower deforestation and emission numbers than gross deforestation. Table B.2 presents the level of GHG emissions reported by a few assessments for land use change emissions. As can be seen looking at the EDGAR database, land use change emissions from forest biomass only account for a share of 32% of total emissions attributable to land use change. However, EDGAR assumes a low figure for biomass land use change emissions. If this figure was replaced by the FAOSTAT estimate, the share of emissions represented in GLOBIOM would be higher at 51%.

Emissions presented in the main scenario of this paper correspond to the release of living biomass carbon in forest and other natural land. Two important sources are therefore omitted:

- Carbon decay emissions, released from dead wood, litter and forest soil are not accounted, because, apart from forest, this information is not implemented in the model for other land use type—Ruesch and Gibbs (2008) maps only provide living biomass carbon stock. Additionally, soil carbon stocks in different biomes significantly depend on soil management practices that we do not explicitly represent here. Because the importance of soil carbon emissions follow-

Table B.2. Global CO$_2$ emissions for land use change according to different sources and in GLOBIOM (MtCO$_2$/yr).

Land use change sources	EDGAR v4.2 2000	FAOSTAT 1995–2000	FAOSTAT 2001–2005	FAOSTAT 2006–2010	Pan et al. (2011) 1990–2000	Pan et al. (2011) 2000–2007	GLOBIOM TREND 2000–2030	GLOBIOM SLOW 2000–2030
Net forest conversion (living biomass)[a]	1,622	3,599	2,634	2,616	na[c]	na[c]	1,306	1,588
Net tropical deforestation[b]	1,622	4,021	3,181	2,984			1,306	1,588
Forest cover rest of the world	na	–422	–546	–368	na	na	na	na
Other vegetation conversion	na	na	na	na	na	na	591	703
Decay of wetlands/peatlands	2,345	na	na	na	na	na	na	na
Forest fires-post burn decay incl. decomposition of peatlands due to drainage	1,172	na	na	na	na[c]	na[c]	na	na
TOTAL GLOBIOM sources	**1,622**	**3,599**	**2,634**	**2,616**	**na**	**na**	**1,897**	**2,291**
TOTAL reported	**5,139**	**3,599**	**2,634**	**2,616**	**5,353**	**4,033**	**1,897**	**2,291**

[a] Differently labelled depending on database: EDGAR: Forest fires inc. Peat fires – attributed by authors of this paper to tropical areas mainly; FAOSTAT: Converted forest – living biomass emissions; Pan et al.: Tropical land use change emissions account account for living biomass and loss in forest dead wood, litter and soil carbon.

[b] For a consistent match with tropical forest basin accounted for deforestation in GLOBIOM, the following regional aggregates were allocated in FAOSTAT to net tropical deforestation : Africa+, South America+, Central America+, South-Eastern Asia+;

[c] Pan et al. (2011) provide details on the different stock in living and dead carbon stock for various regions; however, this also includes the forest regrowth effect, therefore we only reported the total emissions associated to net tropical deforestation, including carbon decay.

ing forest conversion is widely acknowledged, we perform a sensitivity analysis on the forest emission factor, assuming that all the carbon from dead wood, litter and soil is also emitted.

- Peatland emissions are also not accounted in this work. This is mainly due to the difficulty of precisely allocating the share of agricultural expansion going into peatland and to limited information about peat land management. Due to the high uncertainty around the magnitude of peatland emissions Murdiyarso et al. (2010), we decided for this study not to consider this source.

Net tropical deforestation emissions trend for the period 2000–2030 is estimated in GLOBIOM around 1,300 $MtCO_2$/year (scenario "TREND"). This represents 44% of the total net tropical deforestation emissions attributed by FAO to the period 2006–2010. Three different reasons explain why we assume a lower level of deforestation emissions in our baseline:

(i)   We only represent in the model agricultural drivers of deforestation. These drivers represent around 80% of deforestation causes worldwide (Geist and Lambin, 2002, Hosonuma et al., 2012). Figure S12 illustrates how our deforestation emission estimates would be affected if we could account for other deforestation drivers and 30% of deforestation is due to subsistence agriculture, whose dynamics is difficult to trace in an economic equilibrium model, because disconnected from market evolutions.

(ii) The second cause of difference is the assumption that future agricultural expansion will occur more largely than before in non-forested area. Historically, it was estimated that 80% of agricultural expansion would take place in forest Gibbs et al. (2010). In our projections, only 50% of agriculture expansion is at the expense of forest on the period 2000–2030 and this share falls to 30% on the period 2030–2050. This decrease of deforestation is in line with current statistical reporting (see Figure S12) and policy evolution in regions such as Brazil where change in governance and enforcement have recently diminished pressure on the Amazon (Nepstad et al., 2009, Macedo et al., 2012, Nolte et al., 2013).

(iii) The third cause is related to our baseline assumptions that yield and feed efficiency will follow their historical patterns over the next 50 years. The sensitivity to this factor is well illustrated by the paper. When we assume in the "SLOW" scenario that yield growth is lower, emissions increase by 22%. An even more pessimistic scenario is explored with the same model in Havlík et al. (2013), where yield are maintained at their current level of 2000 when projecting in the future (scenario S0). Under such assumption, deforestation is doubled when compared to the baseline. Land use change emissions in our baseline are therefore to be interpreted in light of our baseline underlying assumption.

FAOSTAT trend and GLOBIOM projected values are compared in Figure S12. It can be seen that if all drivers are taken into account for deforestation, the FAO trend would reach GLOBIOM
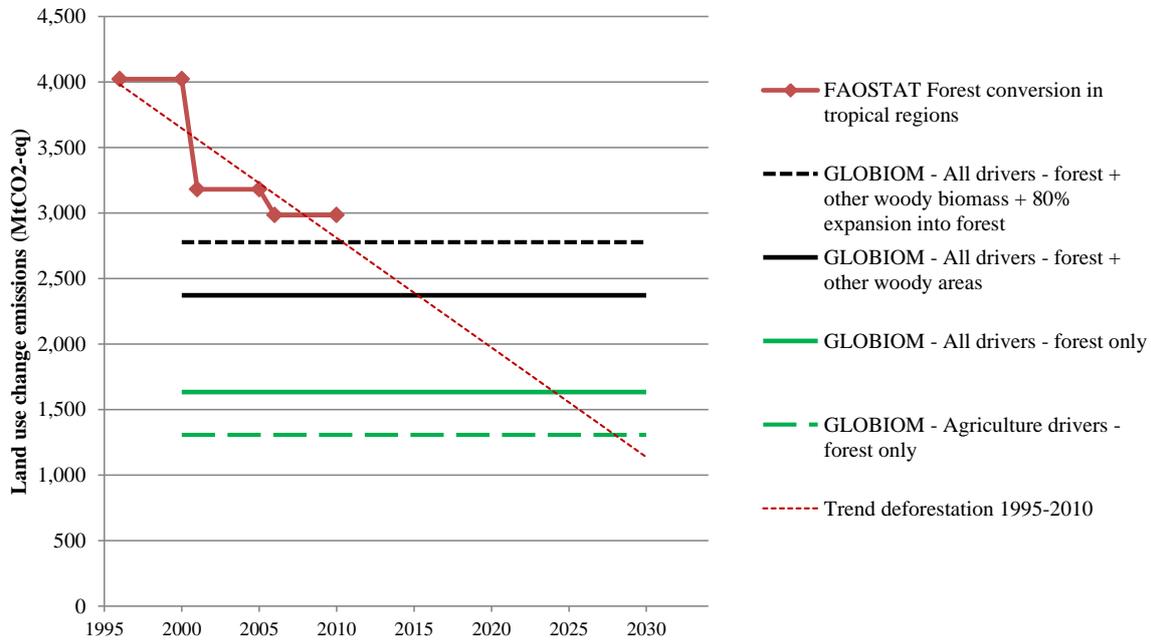
Figure B.1. Land use change related biomass emissions reported in FAOSTAT on the period 1995–2000, 2000–2005 and 2005–2010 for tropical forest, and GLOBIOM average projection for 2000–2030, under different accounting assumptions. FAO numbers come from Table B.2.

estimate between 2020 and 2025. If emissions from woody biomass are added, the level of emissions is much higher and reached around 2015. Last, if we assume that 80% of new agricultural land expands into forest, the level of emissions reaches almost the level observed on the period 2005–2010 by FAO.

B.3 GHG EMISSIONS UNCERTAINTIES

Emissions uncertainty can be related to two main factors: i) uncertainty in activity level, ii) uncertainty in emission factor (Tubiello et al., 2013). For Chapter 2, we chose to address activity level uncertainty through sensitivity analyses around the model results. Error bars on graphs reflect uncertainty in emission factors, with a 95% confidence interval, as provided by IPCC (2006) guidelines (see Table B.3). The only exception was made for enteric fermentation calculated from Herrero et al. (2013) and based on a Tier 3 approach. The uncertainty estimate for this source was evaluated at ±20%. For emissions from land use change, we directly used the uncertainty estimates from Pan et al. (2011) who report their results with an overall ±66% confidence interval. Uncertainty confidence intervals were applied at the level of the 10 regional aggregates and propagation of errors formula were applied when aggregating across sources. However, we did not apply propagation of errors across regions and simply summed uncertainty intervals to obtain the world level uncertainty.

Table B.3. Uncertainty intervals considered for the uncertainty analysis.

Sector	Source	GHG	Uncertainty
Crops	Rice methane	CH_4	$\pm 15\%$
Crops	Synthetic fertilizers	N_2O	$+200\%/-66\%$
Crops	Organic fertilizers	N_2O	$+200\%/-66\%$
Livestock	Enteric fermentation	CH_4	$\pm 20\%$[a]
Livestock	Manure management	CH_4	$\pm 30\%$
Livestock	Manure management	N_2O	$\pm 50\%$
Livestock	Manure grassland	N_2O	$+200\%/-66\%$
Forest	Land use conversion	CO_2	$\pm 66\%$
Other vegetation	Land use conversion	CO_2	$\pm 66\%$

[a] Uncertainty range based on Herrero et al. (2013) (Tier 3 approach for enteric fermentation).

APPENDIX C

PARAMETERS AND MODELLING FOR CHAPTER V

C.1 Elasticities from literature

A significant number of econometric studies have produced elasticity estimates. Our intent here is not to provide an exhaustive overview of them but to provide a large enough sample to inform on uncertainty margins. All elasticities mentioned below were used in our uncertainty analysis.

C.1.1 Demand elasticities

A first source of information was USDA that provides two large datasets of demand elasticities. The first one is a selection of elasticities collected in the literature (USDA, 1998). However, the high heterogeneity in methodologies, products and region covered makes its use quite delicate.[1] A generally more cited source is the estimation from (Seale et al., 2003), updated in 2011 (Muhammad et al., 2011). The database provides estimates of compensated and uncompensated elasticities for the year 2005 for a panel of 144 countries and 9 broad consumption groups from final consumers baskets. Food commodities unconditional elasticities are decomposed in 8 subgroups. Results for "cereals" show a mean value of -0.25 and range from -0.012 (Portugal) to -0.502 (Democratic Republic of Congo).[2] Germany and France have values of -0.014 and -0.026 respectively. For "Fat and oils", the world mean value is -0.28 ranging from -0.013 to -0.507. France is found at -0.069 and Germany at -0.076.

However, these values only concern final food consumption and food consumption is generally considered more inelastic than feed consumption. For an estimation of the aggregate agricultural good demand, these values may therefore be underestimated. That is why we also examine values from another database provided by FAPRI. This second source of data gives higher demand elasticities than the USDA database. Wheat demand elasticities is evaluated at -0.26 for food consumption in EU-15 and oilseeds are at -0.38. Similar variations as in Muhammad et al. (2011)

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[1]   This database can be found on http://www.ers.usda.gov/Data/Elasticities/Query.aspx
[2]   We do not consider the values of 8 countries for cereals and 4 countries for oils and fats – including the United States – whose elasticity values are found positive with the model used.

are displayed across regions. We can also compare values for different regions for a single crop. Wheat feed elasticitiy is evaluated across the world from -0.05 (Former Soviet Union) to -0.43 (Brazil) and food range from -0.05 (Former Soviet Union) to -0.39 (Argentina). In the case of oilseeds, rapeseed elasticity is the lowest for EU-15 (highest -0.25 for Japan, Canada and India), rapeseed meal elasticity is quite homogeneous (-0.35 for country listed except -0.23 for China and -0.25 for Japan), and rapeseed oil is for most countries at -0.38. FAPRI also provide elasticities for feed and industrial demand. As can be seen in Table C.1 for Western EU values, the order of magnitude for the different uses are similar according to this source.

Table C.1. Demand elasticities for EU-15 from the FAPRI database

	Food	Feed	Industry
Barley	-0.41	-0.14	
Corn	-0.44	-0.24	
Rapeseed		-0.08	
Rapeseed oil and meal	-0.38	-0.35	-0.25
Soybean	-0.25	-0.24	
Soybean oil and meal	-0.38	-0.45	-0.25
Sunflower		-0.20	
Sunflower oil and meal	-0.38	-0.3	-0.25
Wheat	-0.26	-0.33	

Such high values are also found in Gardner (1988) for short run responses. However, Roberts and Schlenker (2010) argue for much lower demand (and supply) elasticities than for these databases. On the basis of their econometric analysis, they estimate an order of magnitude of -0.05 to -0.08. These low values are also in line with estimates used in the GTAP model to calibrate the demand function (Hertel et al., 2009a). The different values collected in the database above can be seen in Table C.2.

Table C.2. Demand elasticities used for uncertainty analysis

Source	Reg	Comm	Value	Applied to
Roberts and Schlenker (2010)	World	cere & soyb	-0.08	Dom
	World	cere & soyb	-0.05	Dom
	World	cere & soyb	-0.08	For
	World	cere & soyb	-0.05	For
Gardner (1988)	US	wheat	-0.5	Dom
	US	corn	-0.6	Dom
	US	soybn	-0.7	Dom
FAPRI (2008)	EU15	barl	-0.41	Dom
	EU15	corn	-0.44	Dom
	EU15	rapoil	-0.38	Dom
	EU15	soyboil	-0.38	Dom
	EU15	whea	-0.26	Dom

(continued)

Source	Reg	Comm	Value	Applied to
	EUNew	wheat	−0.34	Dom
	EUNew	corn	−0.25	Dom
	EUNew	rapoil	−0.35	Dom
	EUNew	barl	−0.33	Dom
	Canada	barl	−0.36	Dom
	Canada	corn	−0.25	Dom
	Canada	rapoil	−0.35	Dom
	Canada	soyboil	−0.17	Dom
	Canada	whea	−0.22	Dom
	Brazil	barl	−0.4	For
	Brazil	corn	−0.39	For
	Brazil	soyboil	−0.15	For
	Brazil	whea	−0.27	For
	China	barl	−0.25	For
	China	corn	−0.14	For
	China	rapoil	−0.35	For
	China	soyboil	−0.38	For
	China	whea	−0.07	For
	India	corn	−0.22	For
	India	rapoil	−0.38	For
	India	soyboil	−0.38	For
	India	whea	−0.32	For
	Russia	corn	−0.37	For
	Russia	barl	−0.26	For
	Russia	whea	−0.15	For
	SouthAfrica	corn	−0.25	For
	SouthAfrica	barl	−0.09	For
Muhammad et al. (2011)	Canada	cere	−0.059	Dom
	Germany	cere	−0.026	Dom
	Brazil	cere	−0.27	For
	China	cere	−0.389	For
	India	cere	−0.393	For
	Congo, Dem Rep	cere	−0.502	For
Hertel et al. (2009a)	US	crops	−0.01	Dom
	EU	crops	−0.02	Dom
	Brazil	crops	−0.14	For
	China	crops	−0.14	For
	China	crops	−0.09	For

C.1.2 LAND SUPPLY ELASTICITIES PER CROP

Supply response of the production system has also been studied for long time by the econometric litterature. However, precision of estimates differ a lot across regions. Based on several reviews of litterature, the OECD investigated plausible values for supply elasticities in a 2001 report on market effects of crop support measures (OECD, 2001). Their review, based on two reports from Abler (2000) and Salhofer (2000) show that much uncertainty exist on the different supply elasticities, in particular land supply elasticities. We complemented here their analysis by a few additional sources. Looking at the EU27 (Table C.3), land own price elasticity range from 0.12 (FAPRI value for EU15) to 0.85 (CAPRI value) for wheat, from 0.08 (FAPRI value for EU15) to 0.72 (CAPRI value) for maize and from 0.23 (Guyomard et al., 1996) to 0.69 (CAPRI) for oilseeds. In the case of the US (Table C.4), values also show great variations across sources (from 0.05 to 0.95). OECD (2001) recommend using a range from 0.1 to 0.4 for the EU and 0.2 to 0.6 for the US but considering the values observed, we can see that this range remains conservative.

Land supply elasticities for crops in developing regions are less easily available. Among available sources, one can cite FAPRI (2008) database and Elobeid et al. (2012) who also use the FAPRI model. We report some of their estimate in Table C.5.

Table C.3. Land and production elasticities provided by the literature for the European Union

Land elasticities				
Crop	Source	with respect to price of
		Wheat	**Maize**	**Oilseeds**
Wheat	FAPRI: EU15	0.12		
	FAPRI: EU New members	0.29		
	CAPRI (Britz and Hertel, 2011)	0.85	−0.51	−0.16
	Guyomard et al. (1996) France	0.33	−0.11	0
	Ibáñez Puerta and Perez Hugalde (1994) Spain	0.57	−0.57	
	Burton (1992) UK	0.3		−0.21
	OECD (2001)	0.1 to 0.4		
Maize	FAPRI: EU15		0.08	
	FAPRI: EU New members		0.26	
	CAPRI (Britz and Hertel, 2011)	−0.55	0.72	−0.08
	Guyomard et al. (1996) France	−0.36	0.68	−0.12
	Ibáñez Puerta and Perez Hugalde (1994) Spain	−0.69	0.69	−0.27
	OECD (2001)		0.1 to 0.4	
Oilseeds	FAPRI: EU New members			0.26
	CAPRI (Britz and Hertel, 2011)	−0.3	−0.14	0.69
	Guyomard et al. (1996) France	−0.02	−0.03	0.23
	Burton (1992) UK			0.53
	OECD (2001)			0.1 to 0.4

Table C.4. Land and production elasticities provided by the literature for the US

Land elasticities

Crop	Source	with respect to price of		
		Wheat	**Maize**	**Oilseeds**
Wheat	Morzuch et al. (1980)	0.35		
	Gardner (1988)	0.5	−0.1	−0.05
	Chavas and Holt (1990)			
	Abler and Shortle (1992)	0.2	−0.15	−0.05
	Chembezi and Womack (1992)	0.05	−0.05	−0.1
	OECD (2001)	0.2 to 0.6		
	Lin and Dismukes (2007)	0.25 to 0.34		
	Huang and Khanna (2010)	0.067	0.306	−0.054
Maize	Gardner (1988)	−0.05	0.4	−0.2
	Chavas and Holt (1990)		0.15	−0.15
	Abler and Shortle (1992)	−0.05	0.15	−0.1
	Chembezi and Womack (1992)	−0.05	0.1	−0.05
	Miller and Plantinga (1999)		0.95	−0.45
	OECD (2001)		0.2 to 0.6	
	Lin and Dismukes (2007)		0.17 to 0.35	
	Huang and Khanna (2010)	−0.345	0.51	−0.118
Oilseeds	Gardner (1988)	−0.05	−0.5	0.8
	Chavas and Holt (1990)		−0.3	0.45
	Abler and Shortle (1992)	−0.05	−0.15	0.2
	Miller and Plantinga (1999)		−0.4	0.95
	OECD (2001)			0.2 to 0.6
	Lin and Dismukes (2007)			0.3
	Huang and Khanna (2010)	0	−0.295	0.487

Table C.5. Land supply elasticities for different crops outside the EU and US.

Source	Reg	Comm	Value	Applied to
FAPRI (2008)	Canada	barl	0.37	Dom
	Canada	corn	0.18	Dom
	Canada	rape	0.26	Dom
	Canada	soyb	0.25	Dom
	Canada	whea	0.39	Dom
	Brazil	barl	0.11	For
	Brazil	corn	0.42	For
	Brazil	soyb	0.34	For
	Brazil	whea	0.43	For
	China	barl	0.25	For
	China	corn	0.13	For
	China	rape	0.26	For
	China	soyb	0.45	For
	China	whea	0.09	For
	India	corn	0.21	For
	India	rape	0.34	For
	India	soyb	0.36	For
	India	whea	0.29	For
	Russia	corn	0.31	For
	Russia	barl	0.35	For
	Russia	whea	0.19	For
	SouthAfrica	corn	0.28	For
	SouthAfrica	barl	0.44	For
Elobeid et al. (2012)[a]	Brazil	corn	0.18	For
	Brazil	corn	0.22	For
	Brazil	soyb	0.43	For
	Brazil	soyb	0.48	For

[a] Elasticities reported here with respect to crop returns. Conversion to elasticities to price are then performed using return to price elasticities from Barr et al. (2011).

C.1.3   Yield elasticities

As we have seen in our sensitivity analysis, yield elasticities are crucial parameter for the estimation. Some recent publications investigated ranges of plausible values for the US (see Table C.6. Keeney and Hertel (2009) looked at six studies on US crops with time series between 1951 and 1973 Houck and Gallagher (1976), Lyons and Thompson (1981), Menz and Pardey (1983) and one more recent on the period 1964–1988 (Choi and Helmberger, 1993). The elasticities proposed range from 0.22 to 0.76 with the lowest value for the most recent study. Some other estimates reviewed in Keeney and Hertel (2008) find even lower yield elasticities (Ash and Lin, 1987, Love and Foster, 1990). More recently, Huang and Khanna (2010) estimated elasticities for the US and found also some small response for maize but higher elasticity for wheat. Roberts and Schlenker (2010) and Berry (2011) argue that such elasticity would be close to zero, an assumption also reflected in the elasticities of the model developed by Stout and Abler (2004) and cited in Dumortier et al. (2011). On the basis of its own literature survey and expertise, the expert group from the California Air Resource Board formulated some recommendations on yield elasticities with values in the range 0.05–0.3 (CARB, 2011).

Table C.6. Yield response elasticities reported in the literature

Source	Reg	Comm	Value	Applied to
Roberts and Schlenker (2010)	World	cere & soyb	0	Dom
	World	cere & soyb	0	For
Elobeid et al. (2012)[a]	US	corn	0.013	Dom
	US	corn	0.074	Dom
	Brazil	corn	0.184	For
Stout and Abler (2004)	US	corn	0.02	Dom
(cited by Dumortier et al., 2011)	US	soyb	0.1	Dom
	US	whea	0	Dom
	EU	corn	0.15	Dom
	EU	soyb	0.17	Dom
	EU	whea	0.09	Dom
	Canada	corn	0.15	Dom
	Canada	soyb	0.07	Dom
	Canada	whea	0.18	Dom
	Australia	corn	0.21	Dom
	Australia	soyb	0.097	Dom
	Australia	whea	0.2	Dom
	Brazil	corn	0.11	For
	Brazil	soyb	0.218	For
	Brazil	whea	0.11	For
	China	corn	0.11	For
	China	soyb	0.071	For
	China	whea	0.11	For
	Argentina	corn	0.12	For
	Argentina	soyb	0.217	For

(continued)

Source	Reg	Comm	Value	Applied to
	Argentina	whea	0.12	For
	RoW	corn	0.12	For
	RoW	soyb	0.01	For
	RoW	whea	0.12	For
Choi and Helmberger (1993)	US	corn	0.27	Dom
	US	soyb	0.03	Dom
	US	whea	0.13	Dom
Houck and Gallagher (1976)	US	corn	0.76	Dom
	US	corn	0.69	Dom
	US	corn	0.28	Dom
	US	corn	0.24	Dom
Lyons and Thompson (1981)	US	corn	0.22	Dom
Ash and Lin (1987)	US	corn	0.05	Dom
Love and Foster (1990)	US	soybean	0.1	Dom
	US	wheat	0	Dom
Huang and Khanna (2010)	US	corn	0.15	Dom
	US	soyb	0.06	Dom
	US	whea	0.43	Dom
Menz and Pardey (1983)	US	corn	0.61	Dom
OECD (2001)[b]	US	whea	0.63	Dom
	US	corn	0.67	Dom
	US	soyb	0.72	Dom
	Mexico	whea	0.67	For
	Mexico	corn	0.69	For
	Mexico	soyb	0.54	For
CARB (2011)	US	crops, short term (min)	0.05	Dom
	US	crops, short term (max)	0.2	Dom
	US	crops, long term (min)	0.1	Dom
	US	crops, long term (max)	0.25	Dom
	Brazil	double crop, long term	0.3	For
	RoW	crops, long term	0.175	For

[a] Elasticities reported here with respect to crop returns. Conversion to elasticities to price are then performed using return to price elasticities from Barr et al. (2011).
[b] Elasticities from the PEM model as reported by Keeney and Hertel (2008).

C.1.4 AGRICULTURAL LAND EXPANSION ELASTICITIES

These elasticities also obviously crucial for the problem of land use change. As we have seen in the exploration of sensitivity analyses, assuming a null value for expansion means that ILUC will be zero, if not negative. This assumption seems however excessive, as cropland area change over time and agricultural markets are part of the drivers of land use change, especially in tropical areas (Geist and Lambin, 2002, Morton et al., 2006, Hosonuma et al., 2012).

However, this parameter has been little documented so far. We present in Table C.7 some of the available estimates. Barr et al. (2011) represent an interesting effort to bridge this gap by looking at agricultural land expansion in the US and in Brazil. Using a farmer's decision model on expected returns from land conversion, they measure that land expansion elasticities for US cropland would range from 0.007 to 0.029 where as it would be much higher in Brazil (0.382–0.895). However, if agricultural land as a whole is tracked (pasture included), the elasticity for Brazil falls within the range (0.007–0.245), with upper bound on the period 1997–2003 and lower bound on 2004–2006. This definitely reflects the inherent uncertainty related to policy context. During the five most recent years, Brazil protection of the rainforest has been more successfully implemented and deforestation rate has decreased. Other estimates available in the literature for cropland expansion are based on the GTAP model that rely on estimation from Ahmed et al. (2008) on the U.S. and on which CARB (2011) bases its recommendations. Baldos and Hertel (2013) extended this framework with elasticities extrapolated from Gurgel et al. (2007) and distinguish short term and long term elasticities for different regions of the world. These elasticities are however calculated with respect to land rent, and need to be increased to get the value with respect to commodity price (see formula in Salhofer, 2000, eq. 9, p. 13).

Table C.7. Elasticity of agricultural land expansion from the literature.

Source	Reg	Comm	Value	Applied to
Barr et al. (2011)	US	cropland	0.007	Dom
	US	cropland	0.02	Dom
	US	cropland	0.029	Dom
	Brazil	cropland	0.664	For
	Brazil	cropland	0.895	For
	Brazil	cropland	0.382	For
	Brazil	cropland	0.477	For
	Brazil	cropland+pasture	0.201	For
	Brazil	cropland+pasture	0.245	For
	Brazil	cropland+pasture	0.007	For
	Brazil	cropland+pasture	0.082	For
Elobeid et al. (2012)[a]	Brazil	cropland+pasture	0.13	For
Baldos and Hertel (2013)[b]	China	cropland+pasture	0.04	For
	Europe	cropland+pasture	0.04	Dom
	Brazil	cropland+pasture	0.2	For
	MENA	cropland+pasture	0.11	For
	US	cropland+pasture	0.04	Dom
	India	cropland+pasture	0.1	For
	Africa	cropland+pasture	0.2	For

[a] Elasticities reported here with respect to crop returns. Conversion to elasticities to price can then be performed using return to price elasticities from Barr et al. (2011).

[b] Only 2001–2006 elasticities reported here. These elasticities are expressed with respect to land rent. They can be converted to elasticities to price using formula from Salhofer (2000).

C.1.5   Marginal yield elasticities

This parameter also play a role in the modelling and has been discussed in the literature (see in particular developments in CARB, 2011). We report here in particular the work from Tyner et al. (2010) who used the TEM model to estimate this parameter for most regions of the world. Some other values reported for Brazil by UNICA are also mentioned by the expert group from CARB. All the values discussed so far are reported in C.8.

Table C.8. Marginal yield values reported in the literature.

Author	Reg	Comm	Value	Applied to
Elobeid et al. (2012)	Brazil	corn	0.81	For
UNICA (2009)	Brazil	cropland	0.9	For
	Brazil	cropland	1.05	For
Tyner et al. (2010)	US	cropland	0.71	Dom
	US	cropland	1	Dom
	EU	cropland	0.83	Dom
	EU	cropland	1	Dom
	Brazil	cropland	0.88	For
	Brazil	cropland	1	For
CARB (2011)	US	wheat	0.82	Dom
	US	soyb	1.23	Dom
	US	corn	0.95	Dom

C.2   Co-product substitution

The contribution of coproduct is critical to determine the level of displacement associated to crops because DDGSs and oilseed meals can replace some large quantities of other feed crops in the livestock sector and save land. We have been using substitution rates from an updated version of Edwards et al. (2004) in our analysis (v3.0, from november 2008). However, some other sources also exist and suggest different displacement ratios that the one we used in our central case. We report here in particular the values from Croezen and Brouwer (2008) and Hoffman and Baker (2011). Because our framework is simplified, we cannot represent explicitly the dynamics related to coproducts. Therefore, we have to distinguish two assumptions for substituted soybean meals: our default assumption is to consider that soybean meals displaced decrease cultivated areas of soybean used for their production by 82% (i.e. the share of soybean mass changed into meal). Another assumption with higher substitution rates corresponds to the case when all the soybean used is replaced (i.e. oil co-product is neglected). All substitution rates used for the uncertainty analysis are summarised in Table C.9.

Table C.9. Possible coproduct substitution ratios based on the literature.

	Cereals[a]			Rapeseed[b]		
	Cereals[a]	Soybean meal		Cereals[a]	Soybean meal	
Oil not displaced						
Edwards et al. (2004)	0.94	0.12	kg/kg DDGS	0.48	0.4	kg/kg rape meal
	0.32	0.04	kg/kg wheat	0.28	0.24	kg/kg rapeseed
	0.32	0.06	kcal/kcal[c]	0.13	0.17	kcal/kcal[d]
Croezen and Brouwer (2008)	0.66	0.50	kg/kg DDGS	0.26	0.66	kg/kg rape meal
(average on sectors)	0.22	0.17	kg/kg wheat	0.15	0.39	kg/kg rapeseed
	0.22	0.26	kcal/kcal[c]	0.07	0.28	kcal/kcal[d]
Hoffman and Baker (2011)	0.71	0.29	kg/kg DDGS			
Low assumption	0.21	0.09	kg/kg corn			
(average on sectors)	0.21	0.14	kcal/kcal[c]			
Hoffman and Baker (2011)	0.81	0.34	kg/kg DDGS			
High assumption	0.24	0.10	kg/kg corn			
(average on sectors)	0.24	0.16	kcal/kcal[c]			
Oil displaced[e]						
Edwards et al. (2004)	0.94	0.12	kg/kg DDGS	0.48	0.4	kg/kg rape meal
	0.32	0.04	kg/kg wheat	0.28	0.24	kg/kg rapeseed
	0.32	0.08	kcal/kcal[c]	0.13	0.21	kcal/kcal[d]
Croezen and Brouwer (2008)	0.66	0.50	kg/kg DDGS	0.26	0.66	kg/kg rape meal
(average on sectors)	0.22	0.17	kg/kg wheat	0.15	0.39	kg/kg rapeseed
	0.22	0.33	kcal/kcal[c]	0.07	0.34	kcal/kcal[d]
Hoffman and Baker (2011)	0.71	0.29	kg/kg DDGS			
Low assumption	0.21	0.09	kg/kg corn			
(average on sectors)	0.21	0.17	kcal/kcal[c]			
Hoffman and Baker (2011)	0.81	0.34	kg/kg DDGS			
High assumption	0.24	0.10	kg/kg corn			
(average on sectors)	0.24	0.20	kcal/kcal[c]			

[a] Wheat in Edwards et al. (2004) and Croezen and Brouwer (2008), corn in Hoffman and Baker (2011). Wheat is assumed to generate 0.34 tonne DDGS per tonne fresh matter (Edwards et al., 2004) and corn to produce 0.30 tonne per tonne fresh matter (Croezen and Brouwer, 2008, EPA, 2010).

[b] Rapeseed is considered to generate 0.59 tonne meal and 0.41 tonne oil per tonne seed (Edwards et al., 2004)

[c] 4,240 kcal/kg assumed for soybean meal (10% H_2O) and 2,720 kcal/kg for cereals.

[d] 4,240 kcal/kg assumed for soybean meal (10% H_2O) and 5,900 kcal/kg for rapeseed.

[e] Full soybean displaced. We consider 1 kg soybean contains 0.188 kg oil and 0.812 kg meal.

C.3   Land use allocation and emission factors

Hertel et al. (2010a) use more precise interval ranges for their computations. Supplementary materials of their article display interval of confidence concerning their emissions for three land cover types and 18 regions.

C.3.1   Forest emission factors

Our forest emission factors are calculated based on the methodology exposed in Bouët et al. (2010) and used in chapter 4. This approach relies on IPCC Tier 1 approach (IPCC, 2006). We use data on average estimate of forest above and below provided per agro-climatic zone in these accounting guidelines. This gives us estimates for natural forests ranging from 169 to 709 tCO_2e ha^{-1} in warm areas, from 159 to 463 tCO_2e ha^{-1} for temperate areas and around 112 tCO_2e ha^{-1} in cold areas. This is consistent with the range from Plevin et al. (2010) of 350–650 tCO_2e ha^{-1}. Values of plantation forests are between 20% and 50% lower depending on the region.

C.3.2   Pasture conversion emission factors

For pasture, we do not account carbon loss from above and below ground biomass because this would involve taking a precise account of carbon sequestered in the cultivated crops as well. We only concentrate on soil carbon losses from pasture conversion to cropland. Our range of possible losses vary across agro-climatic zones from 28 tCO_2e ha^{-1} (warm temperate, dry) to 110–115 tCO_2e ha^{-1} (cold temperate, moist and tropical, wet). This shows the potentially high role of composition. However, as we do not take into account above ground vegetation, and because error intervals are wide for these intervals, these latter emissions factors taken alone could underestimate conversion of pastures. Plevin et al. (2010) use a range of 75 to 200 tCO_2e ha^{-1} and they find that shrubland conversion could release up to 348 tCO_2e ha^{-1} according to the literature.

Emission factors associated to each landcover type is summarised in Table C.10.

Table C.10. Emission cover of the different land cover type across the world (Mg CO$_2$e ha^{-1})

Land cover type	Lower bound	Area-weighted average	Upper bound
Natural forest - Boreal	34	69	112
Natural forest - Temperate or subtropical	159	309	463
Natural forest - Tropical	169	602	709
Plantation forest - Boreal	34	75	90
Plantation forest - Temperate or subtropical	68	239	294
Plantation forest - Tropical	72	252	354
Peatlands		1000	
Pasture and other cultivable land	28	63	114

C.4 Summary of parameters and indicator formulas

Index

Name	Dim.	Description
i, j	n	Crop categories
i_0	1	Crop used as biofuel feedstock
r, r'	–	Regions
r_0	1	Region implementing the biofuel program
c	–	Land cover types converted to cropland

Parameters

Parameters are defined in scalar (lower-case), vector (upper-case) and matrix (bold upper-case) format to allow for easier insertion in the various formula. Dimension n used corresponds to the number of crops. Note that index r is sometimes omitted in the formula, to help the reading when no confusion is possible. Quantities are expressed in tonnes of cereals equivalent, in kilocalorie basis (noted "t eq."). Bar notation is used in section 5.2.5 to represent parameters of the foreign regions.

Name	Dim.	Description	Unit
$l_{i,r}$	1	Land use of crop i in region r	[ha]
$L_{(r)} = (l_{i,r})_i$	n	Land use vector of region r	[ha]
$\mathbf{L}_{(r)} = \mathrm{diag}(l_{i,r})_i$	$n \times n$	Diagonal matrix notation of $L_{(r)}$	[ha]
$y_{i,r}$	1	Average yield of crop i in region r	[t eq./ha]
$Y_{(r)} = (y_{i,r})_i$	n	Average yield vector of region r	[t eq./ha]
$\mathbf{Y}_{(r)} = \mathrm{diag}(y_{i,r})_i$	$n \times n$	Diagonal matrix notation of $Y_{(r)}$	[t eq./ha]
$y_{m\,(i,r)}$	1	Marginal yield of crop i in region r	[t eq./ha]
$Y_{m\,(r)} = (y_m\,(i,r))_i$	n	Marginal yield vector of region r	[t eq./ha]
$\mathbf{Y}_{\mathbf{m}\,(r)} = \mathrm{diag}(y_{m\,(i,r)})_i$	$n \times n$	Diagonal matrix notation of $Y_{m\,(r)}$	[t eq./ha]
$s_{i,r}$	1	Supply of crop i in region r	[t eq.]
$S_{(r)} = (s_{i,r})_i$	n	Supply vector of region r	[t eq.]
$\mathbf{S}_{(r)} = \mathrm{diag}(s_{i,r})_i$	$n \times n$	Diagonal matrix notation of $S_{(r)}$	[t eq.]
$d_{i,r}$	1	Demand of crop i in region r	[t eq.]
$D_{(r)} = (d_{i,r})_i$	n	Demand vector of region r	[t eq.]
$\mathbf{D}_{(r)} = \mathrm{diag}(d_{i,r})_i$	$n \times n$	Diagonal matrix notation of $D_{(r)}$	[t eq.]
$p_{i,r}$	1	Price index of crop i in region r	[index]
$\varepsilon^d_{i,j,r}$	1	Demand elasticity of crop i w.r.t. price $p_{j,r}$ in region r	[%/%]
$\mathbf{E^d}_{(r)} = (\varepsilon^d_{i,j,r})_{i,j}$	$n \times n$	Demand elasticity matrix of region r	[%/%]
$\varepsilon^s_{i,j,r}$	1	Land supply elasticity for substitution of crop i w.r.t. price $p_{j,r}$ in region r	[%/%]

Name	Dim.	Description	Unit
$\mathbf{E^s}_{(r)} = (\varepsilon^s_{i,j,r})_{i,j}$	$n \times n$	Land substitution elasticity matrix in region r	[%/%]
$\varepsilon^e_{i,r}$	1	Own-price land expansion elasticity of crop i in region r	[%/%]
$\mathbf{E^e}_{(r)} = \mathrm{diag}(\varepsilon^e_{i,r})_i$	$n \times n$	Land expansion elasticity diagonal matrix of region r	[%/%]
$\varepsilon^y_{i,r}$	1	Own-price yield elasticity of crop i in region r	[%/%]
$\mathbf{E^y}_{(r)} = \mathrm{diag}(\varepsilon^y_{i,r})_i$	$n \times n$	Yield elasticity diagonal matrix of region r	[%/%]
α_{i,r,r_0}	1	Elasticity of price $p_{i,r}$ w.r.t. price p_{i,r_0}	[%]
$\mathbf{A}_{r,r_0} = \mathrm{diag}(\alpha_{i,r,r_0})_i$	$n \times n$	Diagonal matrix of price transmission from region r_0 to r	[%]
F	n	Demand vector for biofuel feedstock in region r_0	[t eq.]
P	n	Co-product return from biofuel processing in region r_0	[t eq.]
$B = F - P$	n	Biofuel related shock in region r_0	[t eq.]
$U_B = B/\|B\|$	n	Biofuel shock normalized vector in region r_0	[no unit]
ρ_{i_0}	1	Energy yield efficiency of biofuel feedstock i_0	[MJ/t eq.]
$y\_Fuel = \rho_{i_0} y_{i_0,r_0}$	1	Energy yield of feedstock i_0 in region r_0	[MJ/ha]
$N = (1)_i$	n	Vector unity	[no unit]
$\theta_{c,r}$	1	Share of land cover c converted to cropland in region r	[%]
$e_{c,r}$	1	Emission factor of land cover c conversion in region r	[tCO$_2$/ha]
t_{ref}	1	Reference period for land use change emissions	[years]

INDICATORS

Name	Dimension	Description	Unit
$\mathbf{\Gamma}_r$	$n \times n$	Matrix of domestic market responsiveness to price in region r	[t. eq/%]
$\tilde{\mathbf{\Gamma}}_{r_0}$	$n \times n$	Matrix of global market responsiveness to price in region r_0	[t. eq/%]
$\mathbf{\Phi}_{r_0}$	$n \times n$	Global land expansion sensitivity matrix of region r_0	[t eq./t eq.]
$\mathbf{W}_{r_0,r}$	$n \times n$	Diagonal matrix of share of ILUC from region r_0 occurring in region r	[%]
$\tilde{\mathbf{Y}}_{r_0,r}$	$n \times n$	Diagonal matrix of average marginal yield of ILUC from region r_0	[t. eq/ha]
NDF	n	Net displacement factor	[ha/ha]
ILUC	n	Indirect land use change	[ha/TJ]
EF$_{r_0}$	n	ILUC emission factors of crops in region r_0	[tCO$_2$/ha]
ILUC factor	1	Indirect land use change factor	[gCO$_2$ MJ^{-1} yr^{-1}]

INDICATOR FORMULAS

$$\boldsymbol{\Gamma}_r = \mathbf{YLE}^y + \mathbf{Y}_m\mathbf{LE}^s + \mathbf{Y}_m\mathbf{LE}^e - \mathbf{DE}^d \tag{C.1}$$

$$\tilde{\boldsymbol{\Gamma}}_{r_0} = \sum_r \mathbf{A}_{r_0,r}\boldsymbol{\Gamma}_r \tag{C.2}$$

$$\boldsymbol{\Phi}_{r_0} = \left[\sum_r \mathbf{Y}_m \cdot \mathbf{A}_{r_0,r}\mathbf{L}_r\mathbf{E}_r^e\right] \tilde{\boldsymbol{\Gamma}}_{r_0}^{-1} \tag{C.3}$$

$$\mathbf{W}_{r_0,r} = \mathbf{A}_{r_0,r}\mathbf{L_r}\mathbf{E}_r^e \cdot \left[\sum_{r'} \mathbf{A}_{r_0,r'}\mathbf{L}_{r'}\mathbf{E}_{r'}^e\right]^{-1} \tag{C.4}$$

$$\tilde{\mathbf{Y}}_{r_0} = \sum_r \mathbf{W}_{r_0,r}\mathbf{Y}_m \tag{C.5}$$

$$\text{ILUC} = \tilde{\mathbf{Y}}_{r_0}^{-1}\boldsymbol{\Phi}_{r_0}U_B/\rho_{i_0} \tag{C.6}$$

$$\begin{aligned}\text{NDF} &= \rho_{i_0}\, y_{i_0,r_0}\, \text{ILUC} \\ &= \frac{y_{i_0,r_0}}{\tilde{\mathbf{Y}}_{r_0}} \cdot \boldsymbol{\Phi}_{r_0} \cdot U_B\end{aligned} \tag{C.7}$$

$$\text{EF}_{r_0} = \sum_{c,r} \theta_{c,r}\ e_{c,r}\ \mathbf{W}_{r_0,r}\, N \tag{C.8}$$

$$\text{ILUC factor} = \frac{\text{ILUC} \cdot \text{EF}_{r_0}}{t_{ref}} \tag{C.9}$$

$$\tag{C.10}$$

C.5   Model code in R language

```
1    ##
     ## Model reduced form for ILUC
     ## Example paper uncertainty: R code
     ##
     ## Contact: valin@iiasa.ac.at
6    ## Time-stamp: <2014-01-27 07:16:14 HV>
     ##

     ## Variables

11   ## 1) PARAMETERS DECLARATION

     reg=c('Dom','For')
     crops=c('Cer','Osd','Oth')
     #
16   S =list()
     L =list()
     Y =list()
     D =list()
     A =list()
21   rm = list()

     ESval=list()
     ESvalc=list()
     ES=list()
26   ED=list()
     ES0=list()
     ED0=list()
     EY=list()
     EE=list()
31
     ## Initial supply and demand

     L[['Dom']] = diag(c(  60,  10,   10))
     L[['For']] = diag(c( 500, 200,  400))
36
     S[['Dom']] = diag(c(  300,  60,   30))
     S[['For']] = diag(c( 1250, 600,  800))

     D[['Dom']] = diag(c(  310, 140,   55))
41   D[['For']] = diag(c( 1240, 520,  775))

     for(i in 1:2){
         rownames(S[[reg[i]]]) <- crops
         colnames(S[[reg[i]]]) <- crops
```

```
46          rownames(L[[reg[i]]]) <- crops
            colnames(L[[reg[i]]]) <- crops
            rownames(D[[reg[i]]]) <- crops
            colnames(D[[reg[i]]]) <- crops
            Y[[reg[i]]] = S[[reg[i]]] %*% solve(L[[reg[i]]])  }
51
      ## Marginal to mean yield

      rm[['Dom']] <- diag(rep(.75,3))
      rm[['For']] <- diag(rep(.75,3))
56

      ## Land substitution elasticities

      ESval[['Dom']] = array(
61     c( 0.15,     0.9,     0.05),
       dim=c(3,1),
       dimnames = list(crops,'NULL'))
      ESvalc[['Dom']] = -0.15

66     ESval[['For']] = array(
       c( 0.2,     0.6,     0.1),
       dim=c(3,1),
       dimnames = list(crops,'NULL'))
      ESvalc[['For']] = -0.2
71

      ## Compute substitution matrix

      for(r in 1:2){
76        ES[[reg[r]]]= array(NA,c(3,3))
          for(k in 1:3){
              ES[[r]][k,k]      = ESval[[r]][k]}
          ES[[r]][1,2]     = ESvalc[[r]]
          ES[[r]][1,3]     = - ES[[r]][1,1] - ES[[r]][1,2]
81        ES[[r]][2,3]     = (- ES[[r]][1,3]*L[[r]][1,1]
                              - ES[[r]][3,3]*L[[r]][3,3])/L[[r]][2,2]
          ES[[r]][2,1]     = - ES[[r]][2,2] - ES[[r]][2,3]
          ES[[r]][3,2]     = (- ES[[r]][1,2]*L[[r]][1,1]
                              - ES[[r]][2,2]*L[[r]][2,2])/L[[r]][3,3]
86        ES[[r]][3,1]     = - ES[[r]][3,2] - ES[[r]][3,3]
      }
      ES0 <- ES


      ## Demand elasticities
91
      ED0[['Dom']] = t(array(
```

```
        c (  −0.10 ,   0.01 ,  0.01 ,
              0.05 ,   −0.1 ,   0.01 ,
              0.05 ,       0.05 ,  −0.1) ,
96      dim=c ( 3 , 3 ) ,
        dimnames = l i s t ( crops , crops ) ) )


        ED0 [ [ ' For ' ] ] = t ( array (
          c (  −0.25 ,   0.01 ,   0.01 ,
101           0.05 ,  −0.25 ,   0.01 ,
              0.05 ,   0.05 ,  −0.25) ,
         dim=c ( 3 , 3 ) ,
          dimnames = l i s t ( crops , crops ) ) )


106     ED <− ED0


        ## Endogenous   y i e l d   response

        EY [ [ 'Dom ' ] ] <− diag ( c ( 0 . 2 5 , 0 . 2 5 , 0 . 2 5 ) )
111     EY [ [ ' For ' ] ] <− diag ( c ( 0 . 2 5 , 0 . 2 5 , 0 . 2 5 ) )



        ##    Expansion   e l a s t i c i t y

116     EE [ [ 'Dom ' ] ] <− diag ( c ( 0 . 0 5 , 0 . 0 5 , 0 . 0 5 ) )
        EE [ [ ' For ' ] ] <− diag ( c ( 0 . 1  , 0 . 1 ,  0 . 1 ) )
        #
        for ( i  in  1 : 2 ) {
             rownames (EE [ [ r e g [ i ] ] ] ) <− crops
121          colnames (EE [ [ r e g [ i ] ] ] ) <− crops
             rownames (EY [ [ r e g [ i ] ] ] ) <− crops
             colnames (EY [ [ r e g [ i ] ] ] ) <− crops
        }


126
        ## Trade   s e t t i n g

        A [ [ 'Dom ' ] ] = diag ( 1 , 3 , 3 )
        A [ [ ' For ' ] ] = diag ( 1 , 3 , 3 )
131     for ( i  in  1 : 2 ) {
             rownames (A [ [ r e g [ i ] ] ] ) <− crops
             colnames (A [ [ r e g [ i ] ] ] ) <− crops
        }


136
        ## Leakage   y i e l d   ( Y  t i l d e )

        e   =  c ( 1 , 1 , 1 )
```

```r
      LY = solve(A[['Dom']] %*% L[['Dom']] %*% EE[['Dom']]
141               +A[['For']] %*% L[['For']] %*% EE[['For']])
           %*% (A[['Dom']] %*% S[['Dom']] %*% EE[['Dom']]
                    +A[['For']] %*% S[['For']] %*% EE[['For']])


146
      ## 2) MARKET RESPONSES ##

      gamma = function(ES,ED,EY,EE,rm,r){
          S[[r]] %*% EY[[r]] + rm[[r]] %*% S[[r]] %*% ES[[r]]
151       + rm[[r]] %*% S[[r]] %*% EE[[r]] - D[[r]] %*% ED[[r]]
      }
      #
      Gamma = function(ES,ED,EY,EE,rm,A){
          gamma(ES,ED,EY,EE,rm, 'Dom') %*% A[['Dom']]
156       + gamma(ES,ED,EY,EE,rm, 'For') %*% A[['For']]}
      #
      Phi = function(ES,ED,EY,EE,rm,A) {
          (   Y[['Dom']] %*% rm[['Dom']] %*% L[['Dom']]
              %*% EE[['Dom']] %*% A[['Dom']]
161        + Y[['For']] %*% rm[['For']] %*% L[['For']]
              %*% EE[['For']] %*% A[['For']] ) %*%
          solve(Gamma(ES,ED,EY,EE,rm,A))}


166   ## 3) POLICY EVALUATION TEST ##


      ## Biofuel policy

171   F <- c( 1, 0, 0)
      P <- c(0.32, 0.06, 0)

      ub <- function (F,P) (F - P) / sum(F)

176   rho <- c(8.72,6.58, 0) # Source JRC
      ## for energy intensity of 1 ton of feedstock in EU
      ## (corrected for oilseeds to fit ton eq of cereals in kcal)

      ILUC = function(ES,ED,EY,EE,rm,A,BF,P){
181       t((L[['Dom']] %*% EE[['Dom']] %*% A[['Dom']]
              + L[['For']] %*% EE[['For']] %*% A[['For']])
          %*% solve(Gamma(ES,ED,EY,EE,rm,A)) %*% ub(BF,P)) %*% e }

      ILUC.DOM = function(ES,ED,EY,EE,rm,A,F,P){
186       t((L[['Dom']] %*% EE[['Dom']] %*% A[['Dom']]  )
```

```r
        %*% solve(Gamma(ES,ED,EY,EE,rm,A)) %*% ub(F,P)) %*% e }

ILUC.FOR = function(ES,ED,EY,EE,rm,A,F,P){
    t((L[['For']] %*% EE[['For']] %*% A[['For']] )
        %*% solve(Gamma(ES,ED,EY,EE,rm,A)) %*% ub(F,P)) %*% e }

NDF  = function(ES,ED,EY,EE,rm,A,F,P){
    ILUC(ES,ED,EY,EE,rm,A,F,P) * (t(Y[['Dom']] %*% e) %*% F) }

ILUC.TJ = function(ES,ED,EY,EE,rm,A,BF,P){
    c(ILUC.DOM(ES,ED,EY,EE,rm,A,BF,P),ILUC.FOR(ES,ED,EY,EE,rm,A,BF,P))
    / (rho %*% BF) * 1000 }

Prices = function(ES,ED,EY,EE,rm,A,F,P){
    A[['Dom']] %*% solve(Gamma(ES,ED,EY,EE,rm,A)) %*% ub(F,P)


## 4) Resultats

Phi(ES,ED,EY,EE,rm,A)

ILUC(ES,ED,EY,EE,rm,A,F,P)

NDF(ES,ED,EY,EE,rm,A,F,P)

ILUC.TJ(ES,ED,EY,EE,rm,A,F,P)

Prices(ES,ED,EY,EE,rm,A,F,P)


## 5) Decomposition of effects

lab_decomp <- c("Demand_drop","Reallocation",
                "Expansion","Yield_increase",
                "Coproduct","All")

Decomp <- function(ES,ED,EY,EE,rm,A,F,P){
    decompt <- array(0,
                    dim=c(4,3,6),
                    dimnames=list(c(crops,"All"),
                    c(reg,"World"),lab_decomp)
                    )
    for (r in 1:2){
        decompt[crops,r,1]
            = - D[[r]] %*% ED[[r]] %*% A[[r]]
            %*% solve(Gamma(ES,ED,EY,EE,rm,A)) %*% ub(F,P)
        decompt[crops,r,2]
```

```
               = rm[[r]] %*% S[[r]] %*% ES[[r]] %*% A[[r]]
               %*% solve(Gamma(ES,ED,EY,EE,rm,A)) %*% ub(F,P)
236          decompt[crops,r,3]
               = rm[[r]] %*% S[[r]] %*% EE[[r]] %*% A[[r]]
               %*% solve(Gamma(ES,ED,EY,EE,rm,A)) %*% ub(F,P)
             decompt[crops,r,4]
               =   S[[r]] %*% EY[[r]] %*% A[[r]]
241            %*% solve(Gamma(ES,ED,EY,EE,rm,A)) %*% ub(F,P)
             decompt[crops,1,5] =   P
             decompt[,"World",] = apply(decompt[,-3,],c(1,3),FUN=sum)
             decompt["All",,]    = apply(decompt[-4,,],c(2,3),FUN=sum)
             decompt["All","World",] = apply(decompt[-4,-3,],3,FUN=sum)
246          decompt[,,"All"]    = apply(decompt[,,-6],c(1,2),FUN=sum)
        }
        decompt = round(decompt,6)
      return(decompt)
      }
251
      Decomp(ES,ED,EY,EE,rm,A,F,P)


      ## End of file
```

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AUTHOR INDEX

Résumé – La contribution des changements d'usage des sols aux émissions de gaz à effet de serre d'origine anthropique est estimée à 17% pour la décennie 2000, en grande partie liée à la déforestation. L'un des facteurs principaux de ces changements est l'expansion des terres agricoles pour les besoins locaux de développement, mais également sous l'effet des exportations stimulées par la mondialisation. Pour cette raison, des préoccupations nouvelles surgissent quant aux effets des politiques sur l'usage des sols par le biais des marchés internationaux. Ce travail présente trois illustrations concrètes où ces effets peuvent être d'ampleur conséquente : i) l'intensification de l'agriculture dans les pays en voie de développement, ii) les accords commerciaux, et iii) les politiques d'agrocarburants. Les résultats montrent que pour chacune de ces politiques, les réponses des marchés sont susceptibles de jouer un rôle déterminant dans le bilan des gaz à effet de serre. L'atténuation du changement climatique par l'intensification des cultures conduit à des réductions d'émissions, mais l'effet rebond de la demande pourrait annuler une part substantielle des bénéfices attendus sur les surfaces de terres cultivées. L'exemple d'un possible accord entre l'Union européenne et le Mercosur montre les effets négatifs que peut induire la libéralisation de certains produits agricoles, si des mesures d'accompagnement adéquates ne sont pas mises en place. Enfin, l'effet des changements indirects d'affectation des sols est susceptible d'effacer une part substantielle des réductions d'émissions alléguées aux agrocarburants. Les réponses de l'affectation des sols aux différentes politiques dépendent néanmoins de nombreux paramètres comportementaux, et il est difficile d'en fournir une estimation chiffrée précise. Plusieurs approches de modélisation sont utilisées ici pour quantifier ces effets et explorer les intervalles de confiance découlant des estimations actuelles de la littérature économétrique. La prise en compte de cette externalité dans l'évaluation des politiques publiques nécessite des approches nouvelles prenant en compte les différents niveaux d'incertitude sur ces effets.

Abstract – *Land use change is estimated to have generated 17% of anthropogenic greenhouse gas emissions in the 2000s, a large part coming from deforestation. The main driver of these emissions is expansion of agricultural activities, for the need of local development in tropical regions. However, they have also been caused by the dynamics of globalisation which has stimulated agricultural trade flows. Thus, today, there are new concerns with respect to how agricultural policies are influencing land use changes in other parts of the world through international market responses. In this work I consider three concrete illustrations of where these effects can be of significant magnitude: i) agriculture intensification in developing countries, ii) trade agreements, and iii) biofuel policies. I find that for each of these policies, market responses are likely to play a significant role in the final greenhouse gas emission balance. Mitigation of emissions through agricultural intensification could have quite beneficial outcomes, but the rebound effect on the demand side would offset a large part of greenhouse gas emission savings attributable to the land sparing effect. With the example of a possible EU-MERCOSUR trade agreement, I also show the adverse effect of liberalising certain specific agricultural products closely connected to land use change dynamics without adequate accompanying measures. Last, the indirect land use change effect of biofuels is likely to offset a large part of their alleged GHG emission savings. Land use change responses depend on many behavioural parameters, however, and providing precise estimates constitutes a challenge. I use different modelling approaches to quantify their magnitude and extensively explore the level of confidence on the basis of current state of econometric findings. New approaches should be elaborated to take account of this externality in public policy assessments, together with an appropriate consideration of the uncertainty ranges associated with these effects.*