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Data-driven approach for addressing global agricultural issues: application to assess productivity of conservation agriculture under current and future climate

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Synthèse de données pour l'analyse des enjeux agricoles mondiaux : application pour évaluer la productivité de l'agriculture de conservation dans les conditions climatiques actuelles et futures
Data-driven approach for addressing global agricultural issues: application to assess productivity of conservation agriculture under current and future climate

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Data-driven approach for addressing global agricultural issues: application to assess productivity of conservation agriculture under current and future climate

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This dissertation is submitted for the degree of Doctor of Philosophy

Preface

This thesis was supported by the ANR under the "Investissements d'avenir" program with the reference ANR-16-CONV-0003 (CLAND)



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Résumé

L'évaluation des pratiques agricoles est devenue un enjeu majeur en raison des préoccupations croissantes concernant la sécurité alimentaire mondiale et les effets négatifs de l'agriculture sur l'environnement. La méta-analyse est devenue une approche standard pour de telles évaluations basées sur des données expérimentales collectées à partir de travaux publiés. Elle fournit des informations synthétiques précieuses aux scientifiques et aux décideurs politiques sur la base de l'estimation de la taille d'effet moyen. Cependant, résumer de grandes quantités d'informations par une seule valeur d'effet moyen n'est pas toujours satisfaisant, en particulier lorsque nous considérons les pratiques agricoles et leurs impacts sur les rendements des cultures. Ces impacts varient considérablement en fonction d'un certain nombre de facteurs, notamment les propriétés du sol et les conditions climatiques locales. Nous présentons ici une Machine Learning Pipeline qui produit des cartes mondiales alimentées par des données décrivant la distribution spatiale de la productivité des pratiques agricoles. Notre approche couvre la sélection et la comparaison d'algorithmes issus du Machine Learning (ML), la formation du modèle, le réglage avec validation croisée, les tests et la projection globale des résultats. Nous démontrons sa pertinence à l'aide d'un jeu de données mondial que nous avons réalisé et qui compare les rendements des systèmes d'agriculture de conservation (CA) et de la technique culturale sans labour (NT) par rapport au travail du sol conventionnel (CT) avec un large éventail d'espèces de cultures, de pratiques agricoles, de caractéristiques du sol et de conditions climatiques pendant la saison de croissance des cultures. Cet ensemble de données contient 4403 observations de rendement appariées entre 1980 et 2017 pour huit cultures de base majeures dans 50 pays. Ces données ont été collectées à partir de 413 articles publiés que nous avons identifiés par le biais d'une étude bibliographique et de la sélection d'articles. L'analyse de cet ensemble de données nous aide à mieux comprendre les principaux facteurs expliquant la variabilité de la productivité des CA et NT, et les conséquences de leur adoption sur le rendement des cultures.

Grâce à ce Machine Learning Pipeline, divers modèles de classification, de régression et de régression quantile sont développés sur la base de 12 algorithmes ML couramment utilisés. Après avoir été testés, les modèles les plus précis sont utilisés pour cartographier la productivité des cultures de la CA et de ses variantes par rapport au CT à l'échelle mondiale dans différentes pratiques agricoles et conditions climatiques dans les scénarios passé (1981-2010), actuel (2011-2020) et futur (2051-2060). Les variations de la productivité de la CA et de la NT dans les régions géographiques et climatiques selon les scénarios climatiques passé, actuel et futur ont été illustrées sur des cartes mondiales.

Nous identifions de grandes différences dans la probabilité de gains de rendement avec la CA entre les types de cultures, les pratiques agricoles, les zones climatiques et les régions géographiques. Nous montrons que les résidus de culture ont l'impact positif le plus fort sur la performance productive des systèmes de la CA et de la NT par rapport aux autres pratiques agricoles. Nos résultats montrent également que pour la plupart des cultures, la CA a donné de meilleurs résultats dans les régions continentales, sèches et tempérées que dans les régions tropicales. Dans les conditions climatiques futures, les performances de la CA devraient surtout augmenter pour le maïs par rapport aux zones tropicales, améliorant ainsi la compétitivité de la CA pour cette culture. Nous montrons également que la CA a de meilleures performances productives que la NT, et qu'elle a plus de 50% de chances de surpasser le CT dans les régions sèches du monde, en particulier avec des pratiques agricoles appropriées. En conclusion, la CA apparaît comme une pratique agricole durable si elle est ciblée sur des régions climatiques et des espèces de cultures spécifiques.

Abstract

Assessing agricultural practices has become a major issue due to growing concerns about global food security and the negative effects of agriculture on the environment. Meta-analysis has become a standard approach for such assessments based on experimental data collected from the published works. It provides valuable synthetic information to scientists and policy makers based on mean effect size estimation. However, summarizing large amounts of information by way of a single mean effect value is not always satisfactory, especially when considering agricultural practices and their impacts on crop yields. These impacts vary widely depending on a number of factors, including soil properties and local climate conditions. Here, we present a machine learning (ML) pipeline that produces data-driven global maps describing the spatial distribution of the productivity of farming practices. Our approach covers the selection and comparison of ML algorithms, model training, tuning with cross-validation, testing, and results global projection. We demonstrate its relevance using a global dataset we conducted which comparing the crop yields of conservation agriculture systems (CA) and no tillage systems (NT) vs. conventional tillage systems (CT) with a wide range of crop species, farming practices, soil characteristics and climate conditions over the crop growing season. This dataset contains 4403 paired yield observations between 1980 and 2017 for eight major staple crops in 50 countries. Analyzing this dataset can help us gain insight into the main drivers that can explain the variability of the productivity of CA and NT vs. CT and the consequence of their adoption on crop yields.

Through this ML pipeline, various models for classification, regression and quantile regression are trained based on 12 mainstream ML algorithms. And through the model tuning and model testing, the most accurate models are selected and used to map the crop productivity of CA and NT vs. CT at the global scale under different farming practices and under the past (1981-2010), current (2011-2020) and future (2051-2060) climate conditions. The variations in the productivity of CA and NT vs. CT with different farming practices, and across geographical and climatical regions under the past, current and future climate scenarios were illustrated on the global maps.

We reveal large differences in the probability of yield gains with CA and NT across crop types, agricultural management practices, climate zones, and geographical regions. We show for most crops, CA performed better in continental, dry and temperate regions than tropical ones. While under future climate conditions, the performance of CA is expected to mostly increase for maize over its tropical areas, improving the competitiveness of CA for this staple crop. Here we also show that CA has better productive performance than NT, and it stands a more than 50% chance to outperform CT in dryer regions of the world, especially with proper agricultural management practices. In conclusion, CA appears as a sustainable agricultural practice if targeted at specific climatic regions and crop species.

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Throughout the PhD study and the writing of this dissertation, I have received a great deal of support and assistance.

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List of abbreviations

AFOLU – Agriculture, forestry and other land uses
AI – Artificial intelligence
BECCS – Bioenergy with carbon capture and storage
CA – Conservation agriculture
CMIP6 – Coupled Model Intercomparison Project Phase 6
CT – Conventional tillage
ESL – extreme sea level
FAO – Food and Agriculture Organization
GHGs – Greenhouse gases
Gt – Gigatons
LSAT – land surface air temperature
IPCC – Intergovernmental Panel on Climate Change
MAP - Mean annual precipitation
MAT – Mean annual temperature
ML – Machine learning
NT – No tillage
SDGs – Sustainable Development Goals
SOC – Soil organic carbon
SOM – Soil organic matter
USDA – United States Department of Agriculture
yr-1 – per year

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Part I

—

Land-based Climate Change Mitigation and Adaptation

Chapter 1 General introduction

1.1 Climate change and agriculture

The world is facing increasing challenges under climate change ¹. The global temperature has increased around 1 degree above pre-industrial levels due to human activities (Figure 1.1) and is likely to reach 1.5 degree between 2030 and 2052 at current increasing rate ². The impact of climate change is multi-sectoral ¹. Evidences have shown an increase in the frequency and intensity of weather extremes, such as extreme heat waves, heavy precipitations, and droughts ². The increasing warming also accelerates sea level rise and associated risks to the habitants and ecological systems in coastal areas ² (Figure 1.2). The warming temperature also leads to the species loss and extinction, which decreases the biodiversity and resilience of ecosystem to climate change ².

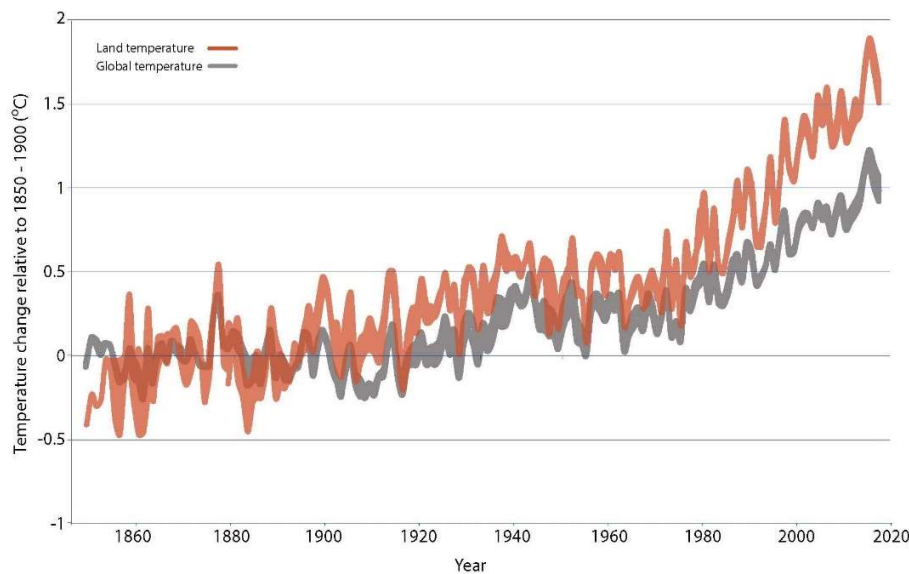


Figure 1.1 | Evolution of land surface air temperature (LSAT) and global mean surface temperature (GMST) over the period of instrumental observations (IPCC 2019 ³).

Scientists attribute the observed global warming trend since mid of 20th century to anthropogenic greenhouse gases (GHGs) emission ⁴. Those emissions will also largely determine the level of global warming by the late 21st century or even beyond. As one of the main contributors to GHGs emission ³, agriculture, along with forestry and other land uses (AFOLU), contributes 23% of total anthropogenic emissions of CO₂, CH₄ and N₂O in the year between 2007 and 2016 ³. It is also a net source of CH₄ and N₂O ³. In 2010, the total non-CO₂ GHGs emitted from agriculture sectors is around 5.2-5.8 gigatons (Gt) of CO₂ equivalent, making up 10-12% of global anthropogenic emissions of GHGs ⁵⁻⁷. In the meanwhile, agriculture also plays an important role in atmosphere CO₂ removal. It is reported that 11.2 ± 2.5 GtCO₂ yr⁻¹ was removed through managed and unmanaged land ³. Thus, a range of adjustments in farming practices, such as using green fertilizer, reducing fossil fuel usage with no tillage, etc. can be undertaken to reduce the GHG emission from agricultural systems and mitigate climate change.

Agriculture is also vulnerable to climate change⁸, actions need to be taken to increase the resilience of agriculture to climate change in order to ensure a stable global food supply. The changing climate pattern (Figure 1.3) is and will continue affecting the productivity and yield stability dramatically in some regions by decreasing availability of water resources, flooding, heat waves, etc. It will increase local and global food insecurity and force farmers to adjust the agronomic practices with current crop types or switch to

different crop types⁸⁻¹⁰. It has been estimated that climate change already decreased the global yield of maize and wheat¹¹, however, there is still a wide gap in the understanding of its impacts related to food and resources, especially at the regional level. Thus, it is necessary and urgent to design or exam the “climate-smart” agriculture systems to adapt climate change and ensure the food security.

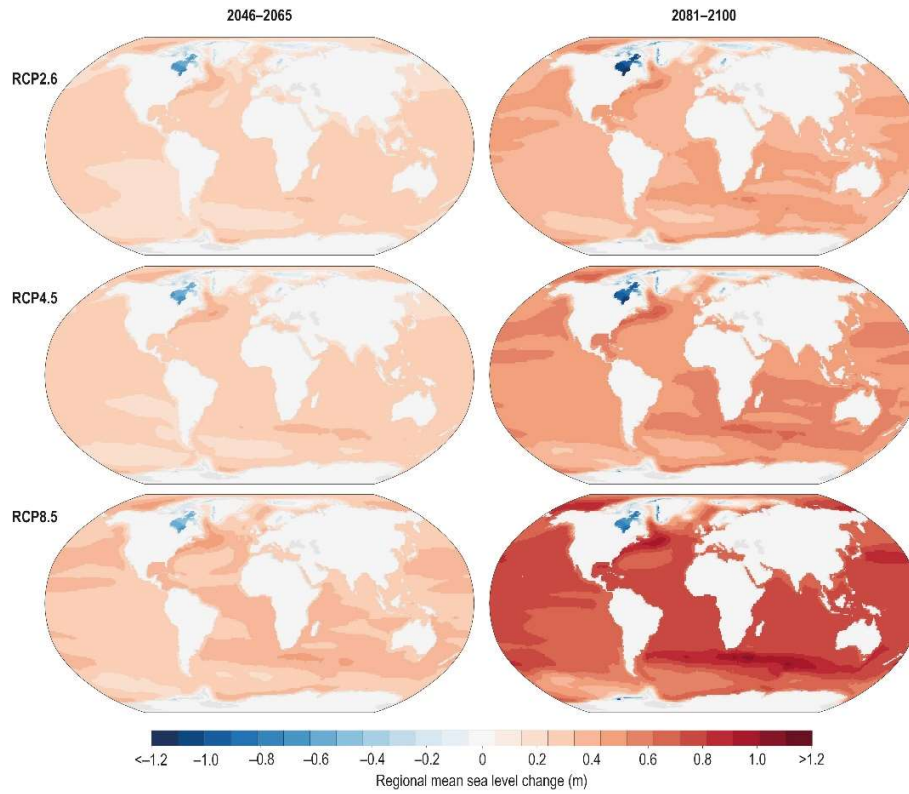


Figure 1.2 | Regional sea level change for RCP2.6, RCP4.5 and RCP8.5 in meters as used in this report for extreme sea level (ESL) events. The left column is for the time slice 2046–2065 and the right column for 2081–2100 (IPCC 2019¹²).

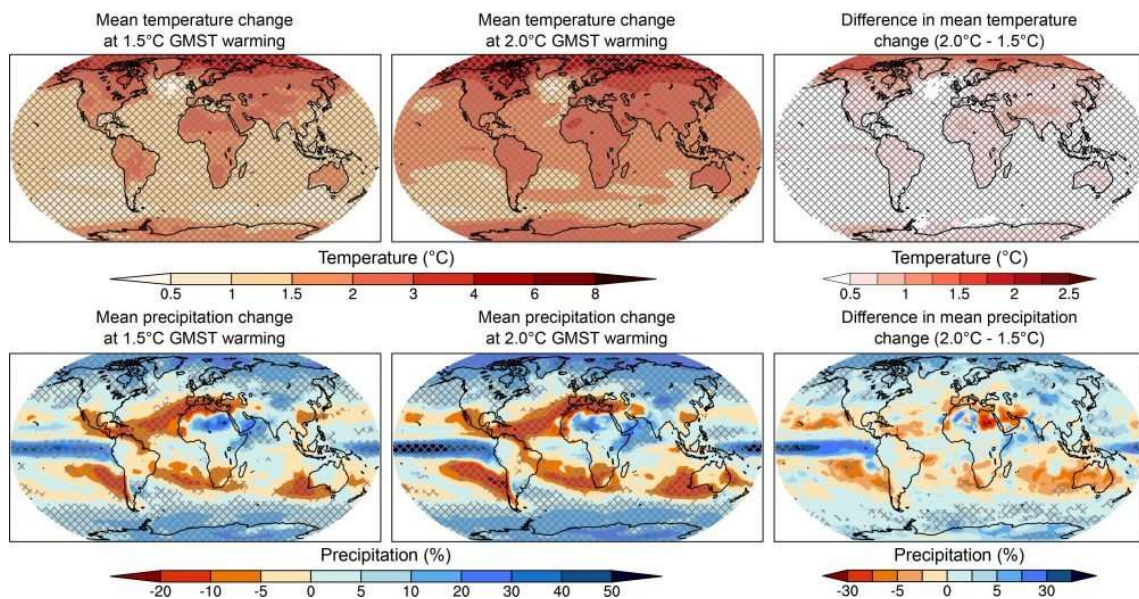


Figure 1.3 | Projected changes in mean temperature (top) and mean precipitation (bottom) at 1.5°C (left) and 2°C (middle) of global warming compared to the pre-industrial period (1861–1880), and the difference between 1.5°C and 2°C of global warming (right) (IPCC 2018 ¹³).

1.2 Food security

The world population is expected to increase to 9.7 billion in 2050 ¹⁴, ensuring a stable food supply for global population would be a great challenge especially under the climate-related risks. Food security is fundamental to human existence and is one of the essential elements for global security and stability, economic growth, and poverty reduction ¹⁵. But our ability to increase the production in current agricultural systems is limited by land degradation, water scarcity, the increasing climate variability, and more and more frequent extreme events associated with climate change ¹⁶.

Observed climate change already negatively affected the food systems and food security ¹⁷. Food production, prices, and stability (Figure 1.4) are affected by the changing climate, which increases the pressure on food resources, and makes millions of people, especially in underdeveloped countries, more vulnerable to hunger ¹⁸. Thus, adaptation measures must be taken to reduce negative impacts of climate change on the food system and ecosystems, and to boost the existing agricultural systems a higher productivity with greater sustainability.

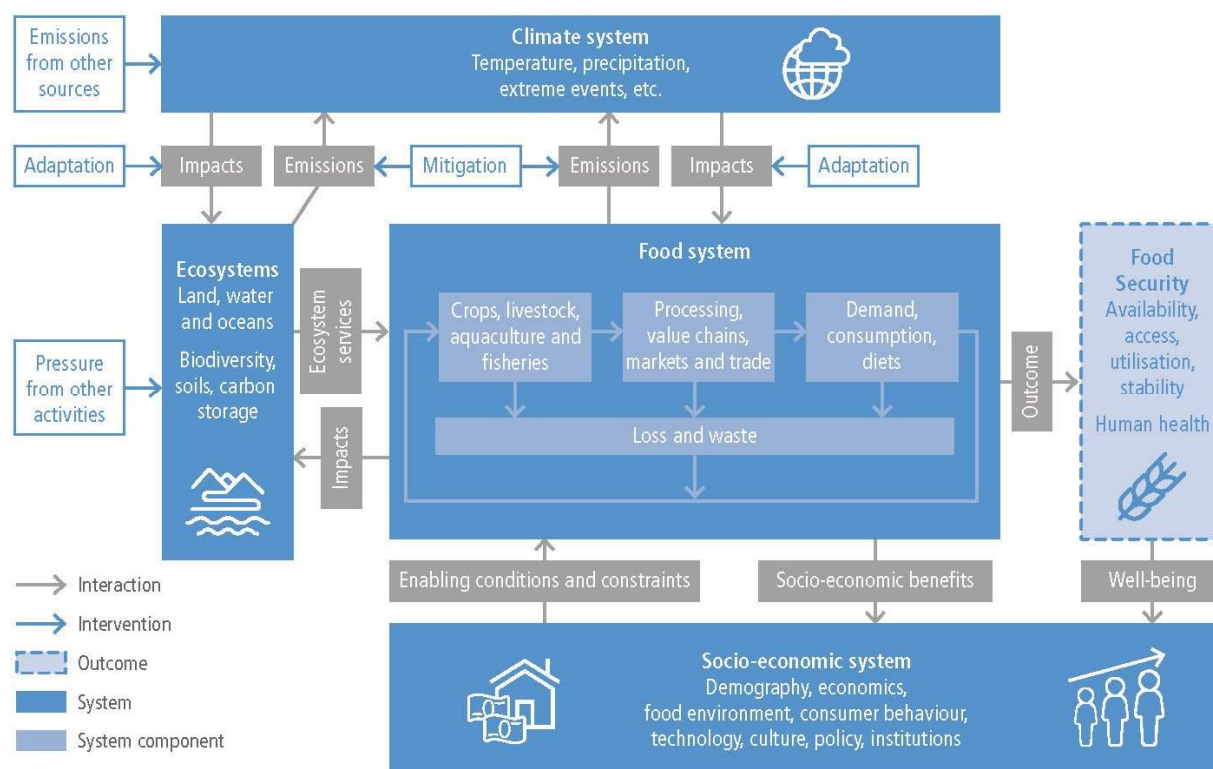


Figure 1. 4 | Interlinkages between the climate system, food system, ecosystems (land, water, and oceans) and socio-economic system (IPCC 2019 ¹⁷).

1.3 Climate change mitigation and adaptation measures

Continuing high level of GHGs emission will lead to further warming and climate changes, it will increase the likelihood of severe and irreversible impacts on human and ecosystems. Mitigating climate change and

reducing climate-related risks are imminent. There are multiple mitigation pathways (e.g., Table 1.1), such as Representative Concentration Pathways (RCPs) and shared socioeconomic pathways (SSPs), that are likely to limit warming to below 2°C relative to pre-industrial levels with a substantial reduction in GHGs emissions over the next few decades ¹⁹.

Table 1. 1 | World population and temperature rise (relative to the pre-industrial baseline) projected by different demographic and climate scenarios around the year 2070 ²⁰. The RCPs was combined with the SSPs to simulate the emission scenarios with socioeconomic assumptions.

Shared Socio-economic Pathways (SSPs)	World population growth [billion]	World population [billion]	Climate scenarios		
			RCP 2.6	RCP 4.5	RCP 8.5
Zero growth	0	7.26	1.06 ± 0.30	1.62 ± 0.42	2.37 ± 0.43
SSP1	0.98	8.24	1.20 ± 0.34	1.84 ± 0.48	2.69 ± 0.49
SSP2	2.20	9.46	1.38 ± 0.39	2.12 ± 0.55	3.09 ± 0.56
SSP3	3.88	11.14	1.63 ± 0.46	2.49 ± 0.65	3.64 ± 0.66
SSP4	2.20	9.46	1.38 ± 0.39	2.12 ± 0.55	3.09 ± 0.56
SSP5	1.21	8.47	1.24 ± 0.35	1.89 ± 0.49	2.76 ± 0.50

Anthropogenic GHGs emissions are mainly from energy, building, transportation, industry, and AFOLU ⁷. To reduce the GHGs emissions from those sectors, a lot of mitigation measures can be implemented, and some examples are listed here (Table 1.2). In energy sector, thermal energy could be replaced by renewable energy, nuclear energy, or bioenergy with carbon capture and storage (BECCS). In transportation, fossil fuel can be replaced with low-carbon fuels (e.g., electricity) and eco-driving should be promoted. In buildings, energy efficiency can be considered and integrated in building design and construction stage. In industry, green energy can be used in the production; Flue gas, wastewater and other emission should be strictly controlled. As for AFOLU, afforestation, reforestation, biochar, etc. should be implemented to increase the carbon pools.

As for climate change adaption measures, it refers to the actions that can be taken to manage the risks or reduce the negative impacts of climate change⁷. Depending on the local condition, it often consists of vulnerability reduction, disaster risk management or proactive adaptation planning. There are limitations on its effectiveness, especially with greater magnitudes of climate change. Thus, climate adaptation and mitigation should be integrated in planning and decision-making stage to create climate-resilient pathways for sustainable development.

Table 1.2 | Sectoral CO₂ emission and examples for sectoral mitigation measures ⁷.

Sectoral CO ₂ emissions and related energy system changes				Examples for sectoral mitigation measures		
Sector	CO ₂ emission (GtCO ₂ , 2050)	Low-carbon fuel share (% 2050)	Final energy demand (EJ, 2050)	Key low-carbon energy options	Key energy saving options	Other options
Energy supply^a				<p>Renewables (wind, solar bioenergy, geothermal, hydro, etc.), nuclear, CCS, BECCS, fossil fuel switching</p>	<p>Energy efficiency improvements of energy supply technologies, improved transmission and distribution, CHP and cogeneration</p>	<p>Fugitive CH₄ emissions control</p>
Baselines						
530–650 ppm CO ₂ -eq						
430–530 ppm CO ₂ -eq						
Transport				<p>Fuel switching to low-carbon fuels (e.g., hydrogen/electricity from low-carbon sources), biofuels</p>	<p>Efficiency improvements (engines, vehicle design, appliances, lighter materials), modal shift (e.g., from LDVs to public transport or from aviation to HDVs to rail), eco-driving, improved freight logistics, journey avoidance, higher occupancy rates</p>	<p>Transport (infrastructure) planning, urban planning</p>
Baselines						
530–650 ppm CO ₂ -eq						
430–530 ppm CO ₂ -eq						
Building				<p>Building integrated RES, fuel switching to low-carbon fuels (e.g., electricity from low-carbon sources, biofuels)</p>	<p>Device efficiency (heating/cooling systems, water heating, cooking, lighting, appliances), systemic efficiency (integrated design, low/zero energy buildings, district heating/cooling, CHP, smart meters/grids), behavioural and lifestyle changes (e.g., appliance use, thermostat setting, dwelling size)</p>	<p>Urban planning, building lifetime, durability of building components and appliances, low energy/GHG intensive construction and materials</p>
Baselines						
530–650 ppm CO ₂ -eq						
430–530 ppm CO ₂ -eq						
Industry				<p>Process emissions reductions, use of waste and CCS in industry, fuel switching among fossil fuels and switch to low-carbon energy (e.g., electricity) or biomass</p>	<p>Energy efficiency and BAT (e.g., furnace/boilers, steam systems, electric motors and control systems, (waste) heat exchanges, recycling), reduction of demand for goods, more intensive use of goods (e.g., improve durability or car sharing)</p>	<p>HFC replacement and leak repair, material efficiency (e.g., process innovation, re-using old materials, product design, etc.)</p>
Baselines						
530–650 ppm CO ₂ -eq						
430–530 ppm CO ₂ -eq						
AFOLU				<p>Emissions reduction measures: Methane (e.g., livestock management), nitrous oxide (e.g., fertilizer use), conservation of existing carbon pools (sustainable forest management, reduced deforestation and forest degradation, fire prevention, agroforestry), reduction in emissions intensity</p>	<p>Sequestration options: Increasing existing carbon pools (e.g., afforestation, reforestation, integrated systems, carbon sequestration in soils)</p>	<p>Substitution options: Use of biological products instead of fossil/GHG intensive products (e.g., bioenergy, insulation products)</p>
Baselines						
530–650 ppm CO ₂ -eq						
430–530 ppm CO ₂ -eq						

1.4 Land-based mitigation and adaptation measures

Land plays a key role as both a source and a sink of GHGs and is very important in the exchange of water, energy, and aerosols between land and atmosphere. It is essential in human development and provides us key products and ecosystem services such as food, shelter and water ²¹. Land-based mitigation and adaptation measures refers to the mitigation and adaptation measures related to land use management. It also often associated with improving the land degradation and food security. Sustainable land management can reduce the negative impacts of climate change and provide a healthier and more sustainable local ecosystems ⁷.

The IPCC special report on land ² outlines several land-based mitigation measures with large potentials on carbon sequestration: reforestation and forest restoration, afforestation, agroforestry, conservation agriculture (CA), BECCS, and biochar. All these measures enhance the carbon sink and could be implemented in large scale and different climate conditions.

In this thesis, we mainly focus on CA because it often has higher amounts of soil organic carbon (SOC) comparing with conventional tillage system, especially in the topsoil profile, while it can also sustain the crop long-term productivity and ensure the food stability and food security ^{16,22}.

1.5 Conservation agriculture as a land-based mitigation and adaption measure

1.5.1 Introduction to conventional tillage system and conservation agriculture

Conventional tillage-based intensive agricultural systems (CT) damage the soil structure, expose the soil to the wind and rain, and have caused the soil erosion, loss of biodiversity, water table decreasing, and high energy consumption ²³. Large areas of agricultural land were abandoned over recent decades due to the land degradation and nutrient loss and created dysfunctional and degraded ecosystems. CT systems also have negative impacts on food production in a long run, and often have poor resilience to climate change. To ensure a sustainable production and ecosystem services of agricultural systems, CA was promoted to address those issues ²⁴.

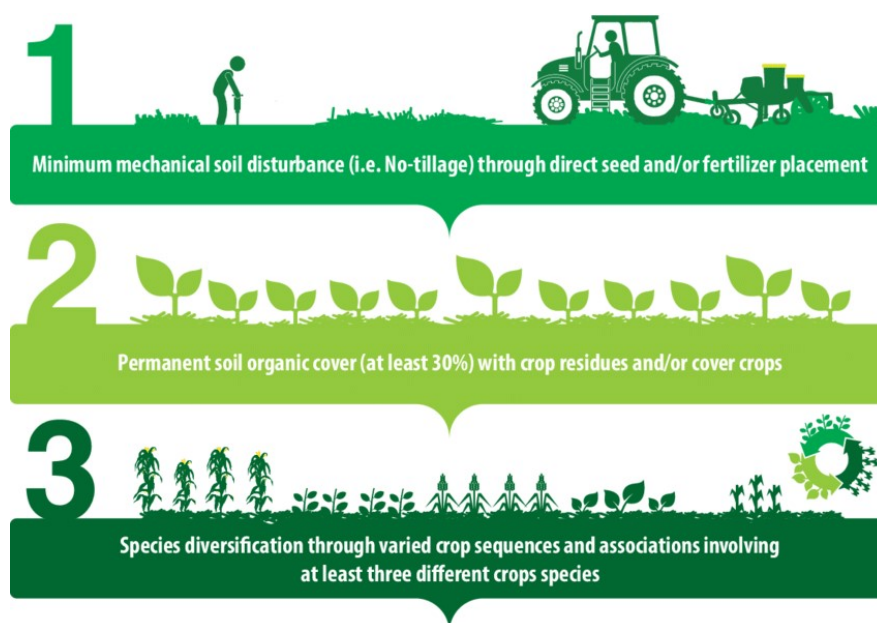


Figure 1. 5 | Three principles of conservation agriculture ²⁵.

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Based on the definition of²⁶ (FAO), CA refers to a sustainable farming system that promotes minimum soil disturbance, in practical terms, farmers grow crops with no-tillage (NT); Maintains a permanent soil cover by crop residues or cover crops with a covered rate at least 30%; Diversifies crop species (Figure 1.5). It is often reported that decreasing the soil disturbance from tillage can improve soil structure, reduce soil erosion, and potentially decrease the SOC loss^{16,23,27}. Without machinery tillage practice, CA systems can have one quarter to one half lower energy consumption and lower CO₂ emissions comparing with CT systems²⁸. The greater amount of residue retained on the bare soil indicates a greater amount of soil organic matter (SOM) input, which can potentially lead to greater SOC storage and better soil health¹⁶. Those soil covers also protect the soil surface from wind and raindrops, decrease the soil erosion^{27,29}. Moreover, soil cover can also prevent the evaporation of soil water and increase the ability of soil water storage³⁰, which can potentially increase the crop production in dry regions. However, in some situations CA can still lead to a reduction in plant growth due to a lower soil temperature, weed and pest pressure from soil cover^{16,31}. As for crop rotation, it is often associated with the improvement in diversity of both fungal and bacterial populations³²⁻³⁵. Although this may vary with different crop species involved in the crop rotation, most microbe groups are in greater abundance in CA than in CT systems²⁸.

These above-mentioned benefits from the three principles of CA increase the resilience of CA against extreme climate events¹⁶, such as drought and heat waves, which makes CA as a promising agricultural system that can mitigate and adapt the climate change and provide a sustainable food production^{25,36}. Moreover, CA also brings economic benefits with the lower fossil fuel consumption and less labour work²⁵. Thus, CA has been adapted to in many regions to improve the sustainability of local cropping system. It is reported that CA has been implemented on more than 180Mha (Figure 1.6) that makes around 12.5% of total arable land³⁷. By 2015, CA is adapted in 78 countries for different cropping species, climate conditions and soil characteristics, large and small farm sizes^{25,37}. The leading countries on CA are the US, Brazil, Argentina, Australia, and Canada, while in recent years, the area under CA is rapidly increasing in Asia³⁷, especially in China due to the strong supporting from the government²⁵. (Table 1.3) The area under CA varies a lot for different crop species. It is reported that³⁸ the crops have been mostly produced under CA are soybean, followed by wheat and maize. These three crops are the most important agricultural goods, thus, the demands to reduce the operational costs is high³⁸. Peas and millet contributed a litter cropland to CA area because they are more drought resistant³⁹.

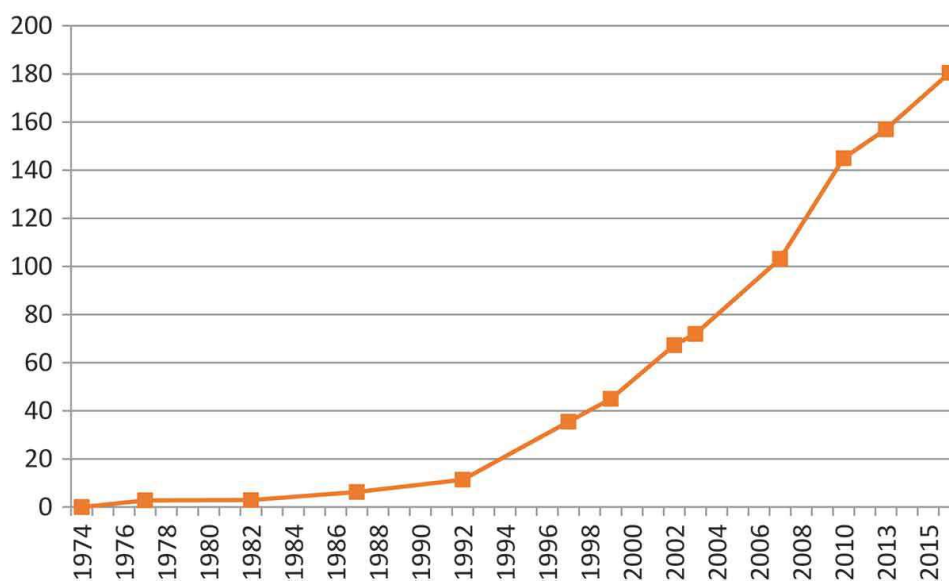


Figure 1. 6 | Global adaption area of CA in M ha of cropland ³⁷.**Table 1. 3 | The adaption area (unit in M ha) of conservation agriculture in the top 10 countries in 2008/09, 2013/13, and 2015/16 ³⁷.**

Ranking in 2015/16	Country	CA area in 2008/09	CA area in 2013/14	CA area in 2015/16
1	USA	26.5	35.6	43.2
2	Brazil	25.5	31.8	32.0
3	Argentina	19.7	29.2	31.0
4	Australia	12.0	17.7	22.3
5	Canada	13.5	18.3	19.9
6	China	1.3	6.7	9.0
7	Paraguay	2.4	3.0	3.0
8	Kazakhstan	1.3	2.0	2.5
9	Bolivia	0.7	0.7	2.0
10	Uruguay	0.7	1.1	1.3

1.5.2 The productive performance of conservation agriculture and the related data availability

The impact of CA and its variants (e.g., NT system) on crop productivity is still hotly debated ^{40–42}. A lot of experiments and studies have been conducted to assess the productivity of CA and its variant systems vs. CT systems under different farming practices, climate conditions, etc. Those experimental data offer an opportunity to identify the most efficient farming practices and climate conditions that can boost the performance of CA and its variants based on robust scientific evidence. In this context, meta-analysis has become a standard method for analysing experimental agricultural data from different publications, which summarizing the performance of different cropping systems by estimating the mean effect size based on random-effect model ⁴³.

Several meta-analyses have been conducted to study the performance of CA and its variants vs. CT systems (Table 1.6). It is shown that the performance of CA and NT systems varies a lot depending on crop species ^{41,42,44,45}, climate conditions ^{41,42,44–49}, and farming practices including crop rotation, residue management, fertilizer input, etc ^{41,42,47,49–51} (Table 1.6). Compared with CT, NT without crop rotation and without soil cover often results in a yield loss ^{41,42,45–47,50,52,53} (Table 1.6). It is reported that CA and NT systems perform better under dryer condition ^{40–42,44,48,54}, and it has the worst performance in tropical regions comparing with other regions ^{40,41,54} (Figure 1.7). As for the farming practices, depending on the crop species, both crop rotation and soil cover often boost the performance of NT systems ^{40–42,44,45,50,51,54} (Figure 1.8a, b). The success of CA system also requires the inputs of fertilizer ^{40,47,50,51,54}, herbicide and pesticide ^{40,49,54}.

These studies provide valuable insight into the overall performance of CA and NT systems compared with CT. However, the datasets used in these studies are often at a regional scale and only collected limited number of agricultural management practices. The climate conditions in these datasets were usually represented by the mean aridity indexes, mean annual precipitation (MAP), mean annual temperature (MAT), which do not represent the intra- and inter-annual variability of climate conditions. Moreover, most of the experimental yield data contained in the datasets were before the year 2014, which is not up to date. Thus, an up-to-date dataset, with a broader range of farming practices and climate conditions are needed.

In this thesis, we produced a global dataset ⁵⁵ based on the literature searching in the early 2020, which included the latest experimental data of crop yield of CA and its variants vs. CT, a broader range of farming practices, including crop residue retention and soil cover, crop species, crop rotation and its sequence,

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information about cover crops, crop irrigation, the type and amount of fertilizer applied, information related to weed and pest control, the year since NT implementation), soil characteristics, and climate conditions in the growing season (including precipitation, potential evapotranspiration, minimum air temperature, mean air temperature and maximum air temperature) at the year of experiment been conducted. The new global dataset enables us the ability of analyse how the productive performance of CA and its variant systems vary with climate variables and their intra-annual variabilities, and a broader range of farming practices.

Table 1. 4 | List of meta-analyses available that studied the impact of CA and its variant systems on crop yield

No.	Author	Publishing year	Main focused crop species	Main focused regions	Climate variables included	Main conclusions
1	An Van den Putte et al. ⁴⁶	2010	Maize, cereals	Europe	Seasonal water balance	<ul style="list-style-type: none"> • The yield of NT < CT. • NT performs worse under drier climatic conditions. • On clay and sandy soils, CA and NT perform better under drier climatic conditions
2	Leonard Rusinamhodzi et al. ⁵⁰	2011	Maize	Southern Africa, America	Mean annual precipitation (MAP)	<ul style="list-style-type: none"> • The yield of maize is less in NT without (-) rotation (R) compared with CT but more with (+) rotation (R). • The success of CA required high input of nitrogen fertilizer.
3	Marc Corbeels et al. ⁵¹	2014	Maize, soybean, sorghum, wheat	Sub-Saharan Africa	Three classes of seasonal rainfall (low, medium, high)	<ul style="list-style-type: none"> • Yield in NT + soil cover (SC) > NT + R + SC > NT. • Potential conflicts between crop residue retention and the feed for livestock. • The use of fertilizer enhances the crop productivity in CA system.
4	Chengyan Zheng et al. ⁴⁴	2014	Maize, rice, wheat	China	MAP, MAT, Aridity index	<ul style="list-style-type: none"> • Significant positive effects found of CA practices under relative dryer regions. • The impact of CA on crop yield is highly varied for different climates and crop types. • Yield in NT + SC > CT + SC.
5	Sylvie M. Brouder et al. ⁵²	2014	Maize, rice, cowpea, sorghum	Sub-Saharan African, Asia	NA	<ul style="list-style-type: none"> • Short-term yield of NT < CT.
6	Cameron M. Pittelkow et al. ⁴¹	2015	Maize, wheat, miscellaneous cereals,	Global	Aridity index	<ul style="list-style-type: none"> • Maize yield of NT < CT in tropical regions.

			legumes, rice, cotton, etc.			<ul style="list-style-type: none"> • Yield of NT > CT in arid regions. • Productive performance of NT is affected by crop species, farming practices, and climate conditions.
7	Cameron M. Pittelkow et al. ⁴²	2015	Maize, wheat, miscellaneous cereals, legumes, rice, cotton, etc.	Global	Aridity index	<ul style="list-style-type: none"> • Yield of NT < CT • Yield of NT < NT+R < NT+SC < NT+R+SC (CA) • In dry regions, yield of CA > CT. • Number of years since NT/CA implementation will affect their performance.
8	Xin Zhao et al. ⁴⁵	2017	Maize, rice, soybean, wheat, etc.	China	MAP, MAT	<ul style="list-style-type: none"> • Yield of NT < CT • Yield of NT+SC > CT+SC • Productive performance of NT is highly affected by crop species and climates.
9	Peter R. Steward et al. ⁴⁸	2018	Maize	Regions between the latitude of -38 to 38 degrees	Precipitation balance, Heat stress risk	<ul style="list-style-type: none"> • Maize yield in CA is better under the increasing drought severity or higher temperature. • The performance of CA is affected by soil moisture and heat stress, and this impact is affected by soil clay content.
10	T.M. Kiran Kumara et al. ⁴⁷	2019	Maize, rice, wheat	South Asia	Climate types, MAP	<ul style="list-style-type: none"> • Yield in NT < CT • Irrigation, soil cover, inputs of nitrogen are crucial in improving the performance of CA.
11	T.M. Kiran Kumara et al. ⁵⁶	2020	Maize, rice, wheat	South Asia	Climate types, MAP	<ul style="list-style-type: none"> • Yield of wheat, maize, legumes and oilseeds in CA > CT, while yield of rice in CA < CT.
12	Marc Corbeels et al. ⁴⁹	2020	Maize, sorghum, wheat, etc.	Sub-Saharan Africa	Average temperature and precipitation in the growing season	<ul style="list-style-type: none"> • Yield of CA > CT • The best performance of CA occurred when the rainfall is low, and the herbicides are applied.
13	Awais Shakoor et al. ⁵³	2021	Barley, maize, rice, wheat	Europe, China	Climate types	<ul style="list-style-type: none"> • Yield of NT > CT. • Yield of NT < CT in fine soil, while yield of NT > CT in coarse soil. • Yield of NT < CT when soil C:N ratio ≤ 10, while yield of NT > CT when soil C:N ratio > 10.

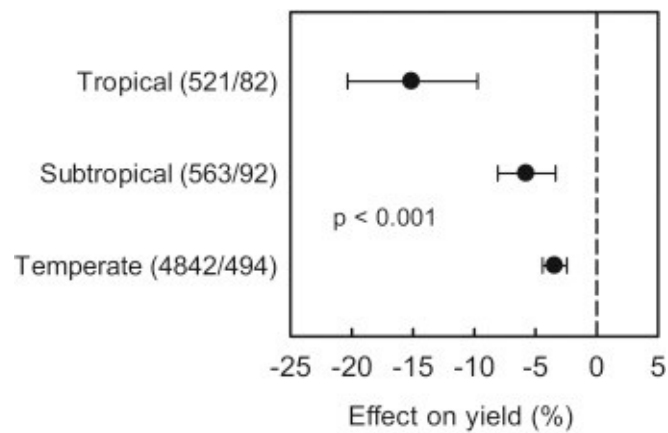


Figure 1. 7 | Yield impacts of no-till relative to conventional tillage in tropical, subtropical, and temperate latitudes ⁴¹. The number of observations and total number of studies included in each category are displayed in parentheses. Error bars represent 95% confidence intervals. Significant differences by latitude categories are indicated by p-values based on randomization tests.

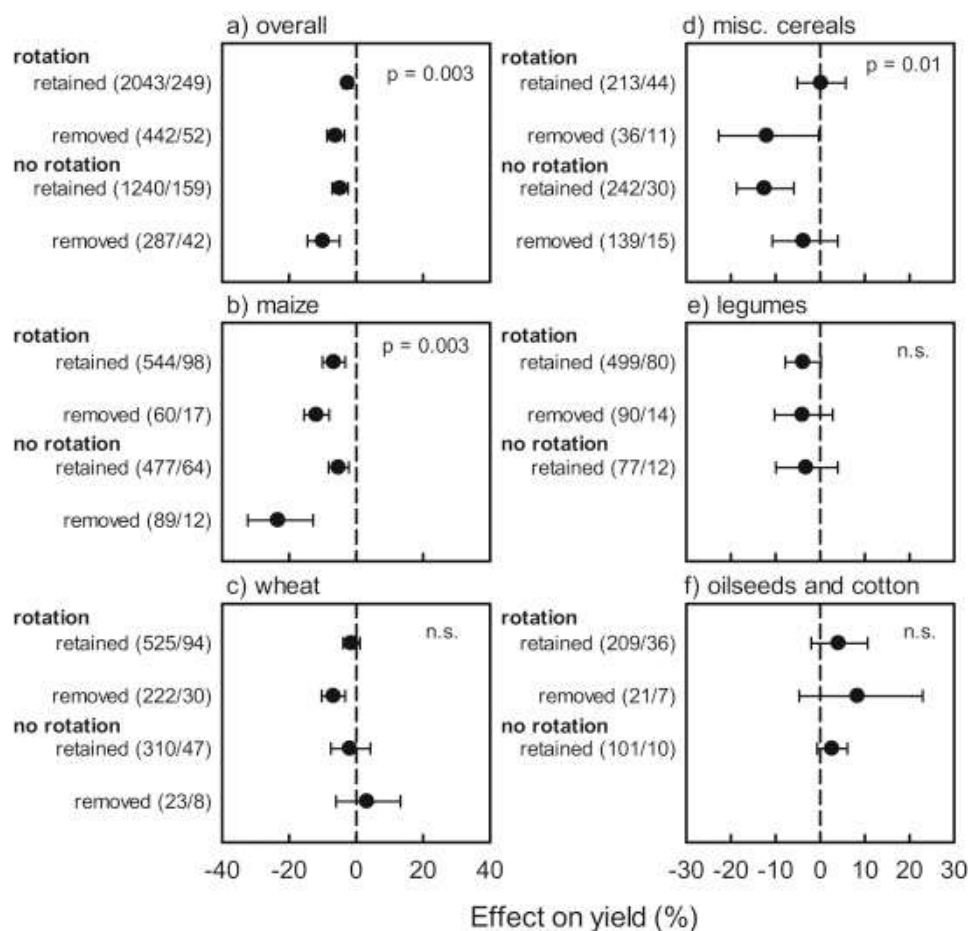


Figure 1. 8 | The influence of crop rotation and residue management practices on the yield impacts of no-till relative to conventional tillage for different crop categories ⁴¹. Misc. cereals include barley,

millet, oat, rye, sorghum, tef, and triticale. The number of observations and total number of studies included in each category are displayed in parentheses. Error bars represent 95% confidence intervals. Significant differences by crop rotation and residue management are indicated by p-values based on randomization tests. Note, several categories did not contain sufficient observations and were excluded from further analyses. n.s. = non-significant.

1.5.3 Meta-analysis and its limitation in agricultural sector

Meta-analysis is defined as a statistical analysis that collect the results of individual studies for the purpose of integrating the findings from the experiments conducted in, sometimes, very distant geographic regions^{57,58}. Meta-analysis can be used to estimate the mean size of a treatment effect (e.g., with vs. without tillage) on a variable of interest (e.g., crop yield)^{57,59} and to reveal the relationship between a response variable and one or more explanatory variables^{57,60,61}. A well-designed meta-analysis is an excellent tool to analyse such large experimental datasets and can highlight the correlations between studies or variables that may not be readily apparent. However, this approach also has several limitations⁶²⁻⁶⁴. One of them is that, although mean effect sizes can summarize experiments conducted in contrasting conditions and estimate the average performance of a practice or system, they do not provide a detailed description of the variability induced by local conditions⁶⁵⁻⁶⁷. This is an important limitation for its application in agricultural sectors since the crop yields are highly dependent on the climate conditions^{41,42,68}, soil characteristics^{24,69,70}, farming practices^{24,40-42,71}, which often vary in time and space. This makes it hard to use a meta-analysis to predict the crop production accurately for a given geographical region.

In this thesis, to map the productive performance of CA and its variant systems vs. CT systems accurately at the global scale, and to estimate how climate variables and farming practices will affect the performance of CA and NT systems, we develop a machine learning pipeline (Figure 3.1) to compare different machine learning (ML) algorithms and use these trained ML models to predict, analyse and map the performance of CA and its variant systems vs. CT systems based on the farming practices, soil and climate conditions based on a global dataset of crop yield of CA and its variant systems vs. CT systems. This pipeline can be easily adapted to analyse a diverse of outcomes, these may involve the effects of crop management practices on soil organic carbon dynamics, greenhouse gas emissions, biodiversity, etc. for different types of cropping systems, such as organic agriculture or agroforestry, and thus provide valuable information on the local performance of sustainable farming practices together with a global perspective. The maps created from this ML pipeline can provide detailed geographical information about the performance of one system compared to a reference.

1.5.4 Machine learning algorithm and its application in agricultural sector

Machine learning is a very important component of data science and artificial intelligence (AI). It uses the data to train a ML model to uncover key insights within the data⁷², and it becomes more accurate and effective as the increase of size of training dataset. In this thesis we will mainly use supervised learning, which is a branch of machine learning. It is defined by its use of labelled datasets to train models that to make accurate classifications or predictions. When input data is fed into the model, it adjusts the weights to fit the model appropriately, and tunes the model hyperparameters through cross-validation process to avoid overfitting or underfitting. Some methods often used in supervised learning include neural networks, random forest, generalized linear regression, support vector machine, etc.⁷³.

In order to meet the global food demand in the future sustainably, it is very necessary for us to increase crop production while conserving the environment. ML technology can optimize the farming practices and significantly reduce the yield loss and the running cost of a farm. For example, it can be used to analyse the experimental data and local weather patterns to find out the most suitable crops for planting. Combining with the data from soil, temperature and humidity sensors, it can help us determine the exact amount of

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irrigation, fertilizer, pesticide and herbicide needed for crops at different growing stages, which could minimize the resources used in agricultural activities while maximum the crop yield. Besides optimizing the farming practices, in agriculture sector, ML can be also used in weed and disease detection, yield prediction based on weather forecast, global food price prediction based on global yield prediction, which could help us match the crop supply with demand and manage the risk.

In this thesis, ML is used to analyse the global crop yield data from conservation agriculture (CA) and conventional tillage (CT). We identified preferable and unpreferable regions and climate conditions for CA implementation and analysed the performance of CA and its variant systems under different farming practices. We also predicted the change of this performance in the future under the trend of global warming.

1.6 Summary of research questions

In this thesis, with the dataset we collected and the ML pipeline we created, we would like to address these questions:

- Concerning of the method, will the machine learning pipeline give us more valuable information than meta-analysis? Which machine learning algorithm is more suitable to analyse the crop yield dataset?
- Regarding to the performance of different farming systems, does CA performs better than NT systems? And can CA and NT systems outperform CT systems in terms of yield production?
- For farming practices, how farming practices affect the productive performance of CA and NT systems? What should be done in order to boost the performance of CA and NT systems?
- Regarding to the crop species, which crop species is more suitable to grow in CA and NT systems?
- For climate conditions, how climate variables affect this performance? What condition is preferable for the implementation of CA and NT systems? And how this performance will change under climate change.

1.7 Structure of the papers

- In chapter 2, we presented a global dataset of crop yield that compares CA and NT systems vs. CT systems.
- In chapter 3, we introduced a machine learning pipeline which can train, tune, test and compare different ML models to predict the productive performance of CA and NT systems vs. CT systems, and map this performance at a global map.
- In chapter 4, we studied how this performance vary with different farming practices, assessed the geographical regions that preferred by CA and NT systems, and estimated the performance of CA and NT systems under past scenario (mean climate conditions between 1981 to 2010).
- In chapter 5, we focused on the performance and performance change of CA and NT systems vs. CT systems under current scenario (mean climate conditions between 2011 to 2020) and future scenario (mean climate conditions between 2051 to 2060).
- In chapter 6 and 7, we summarized our work during the thesis, discussed about the research questions proposed in last section, the limitations of this work and the outlooks of future study.

1.8 References

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Part II

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Machine Learning and Big Data in Agricultural Sector

Chapter 2 A global crop yield meta-dataset of conservation agriculture vs. conventional tillage

This chapter is published in Scientific Data, 8, 33 (2021), and can be accessed through this link <https://doi.org/10.1038/s41597-021-00817-x>. In this chapter, we presented a global dataset of crop yield of no tillage systems versus conventional tillage systems under different farming practices, climate conditions and soil characteristics.

This dataset can be accessed through the link: <https://doi.org/10.6084/m9.figshare.12155553>.

A global dataset for crop production under conventional tillage and no tillage systems

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2.1 Abstract

No tillage (NT) is often presented as a means to grow crops with positive environmental externalities, such as enhanced carbon sequestration, improved soil quality, reduced soil erosion, and increased biodiversity. However, whether NT systems are as productive as those relying on conventional tillage (CT) is a controversial issue, fraught by a high variability over time and space. Here, we expand existing datasets to include the results of the most recent field experiments, and we produce a global dataset comparing the crop yields obtained under CT and NT systems. In addition to crop yield, our dataset also reports information on crop growing season, management practices, soil characteristics and key climate parameters throughout the experimental year. The final dataset contains 4403 paired yield observations between 1980 and 2017 for eight major staple crops in 50 countries. This dataset can help to gain insight into the main drivers explaining the variability of the productivity of NT and the consequence of its adoption on crop yields.

2.2 Background & Summary

Often featured among promising climate change mitigation measures, NT systems, including conservation agriculture (CA), contributes to environmental preservation and sustainable agricultural production¹². NT is expected to mitigate soil degradation, improve soil structure and water retention properties³⁻⁵. Several studies indicate that this cropping system can provide a large range of positive environmental externalities such as increased biodiversity, enhanced carbon sequestration and improved soil quality through an increase in soil organic matter⁶⁻¹⁰. However, the productivity of NT systems compared to conventional cropping systems is still controversial. Since the productivity of NT depends on several interacting factors such as climatic conditions¹¹, soil characteristics^{1,12}, and other agricultural management activities¹³⁻¹⁹, the potential of NT to increase agricultural productivity remains highly uncertain.

Several studies^{1,12,20-22} have been conducted to synthesize the current evidence on the productivity in NT systems. Some of these studies relied on global datasets including results of field experiments comparing

NT and CT cropping systems over a large range of soil and climate conditions. However, these datasets do not include the most recent published experiments, and provide no or limited information on soil characteristics, climate variables, and management practices. In particular, information on fertilizer inputs, weed and pest control, and intra- and inter- annual climatic variability are frequently missing. Other studies comparing NT and CT rely on a limited number of experiments, are only conducted at a regional scale, or did not make their data fully available^{23–25}. Thus, a global dataset reporting findings from the most recent field experiments and including information about a wide range of climatic parameters, soil characteristics and agricultural management practices is still lacking.

To address this gap, we present an updated and extended dataset comparing CT and NT productivity including the most recently published experimental studies, and a detailed description of their environmental characteristics and management practices. Our dataset contains 4403 paired (NT vs. CT) yield observations collected between 1980 and 2017 for eight major staple crops in 50 countries. For each experiment, we provide information on soil texture, pH, the year and month of crop planting and harvesting, the location of the experiment, fertilization, weed and pest control practices, crop type, crop rotation, crop residue management, and crop irrigation. Besides soil characteristics and information on management practices, we also report a large range of climate variables derived from several external databases. These include precipitation, potential evapotranspiration, average temperature, maximum temperature, and minimum temperature during the crop growing season. This dataset can prove useful to disentangle the effects of soil, climate and agronomic drivers of crop yields when comparing NT with CT systems.

2.3 Methods

2.3.1 Data collection

The literature search was done in February 2020 using the following keywords ‘Conservation agriculture / No-till / No tillage / Zero tillage’ & ‘Yield / Yield change’ in the websites ‘ScienceDirect’, ‘Science Citation Index (web of science)’. A total of 1012 potentially relevant papers were identified by reviewing the title and abstract, and these papers were then screened according to the procedure summarized in Figure 2.1. Papers not reporting yield data for CT and NT systems were excluded, as well as papers reporting experiments on reduced tillage (RT) systems. Papers reporting only mean yield data across different years or sites were also excluded. We then checked whether information on fertilization, weed and pest control, crop irrigation, crop rotation and crop residue management were reported for both CT and NT practices. After these screening and selection steps, all relevant data were manually extracted from the selected papers, including general information about the paper, location and year of the experiment, the number of years under NT when the crop was sown, soil characteristics, crop growing season, crop type, crop management practices and crop yield of CT and NT. However, due to a large number of missing data, the crop growing season, climatic variables and soil characteristics were finally collected through several external databases (Table 2.1). The growing season information was generated from a crop calendar database^{26,27} based on the crop type and the locations of the experiments reported in the papers. The precipitation, average temperature in the growing season were extracted from the UDel_AirT_Precip data provided by NOAA/OAR/ESRL PSL²⁸. The maximum and minimum air temperature during the growing season were generated from CPC Global Temperature data provided by NOAA/OAR/ESRL PSL²⁹ and the potential evapotranspiration data over the growing season were extracted from GLEAM database^{30,31}. Soil textures were collected from the HWSD database³² using the locations of the experimental sites reported in the selected papers (see Table 2.1 for additional details). The experiments for which it was not possible to obtain the requested information from the external databases were excluded. The final dataset includes the results extracted from 413 papers (published between 1983 to 2020), 4403 paired yield observations from NT and CT for 8 major crop species, including 370 observations for barley (232 observations for spring barley and 138 for winter barley), 94 observations for cotton, 1690 observations for maize, 195 observations for rice, 160 observations for

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sorghum, 583 observations for soybean, 61 observations for sunflower, 1250 observations for wheat (1041 observations for winter wheat and 209 observations for spring wheat) in 50 countries from 1980 to 2017 (Figure 2.2).

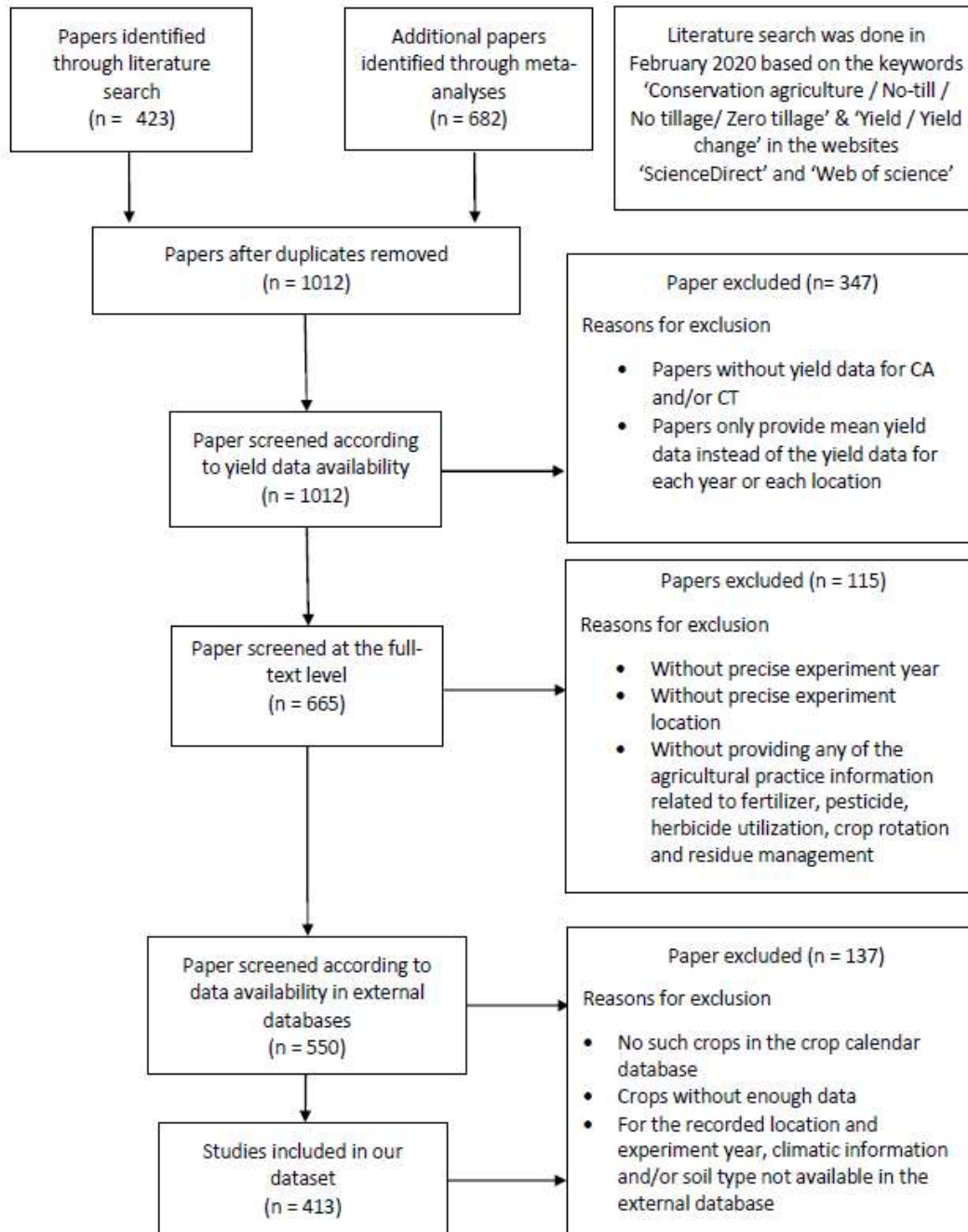


Figure 2.1 | Flow chart of paper collection and selection.

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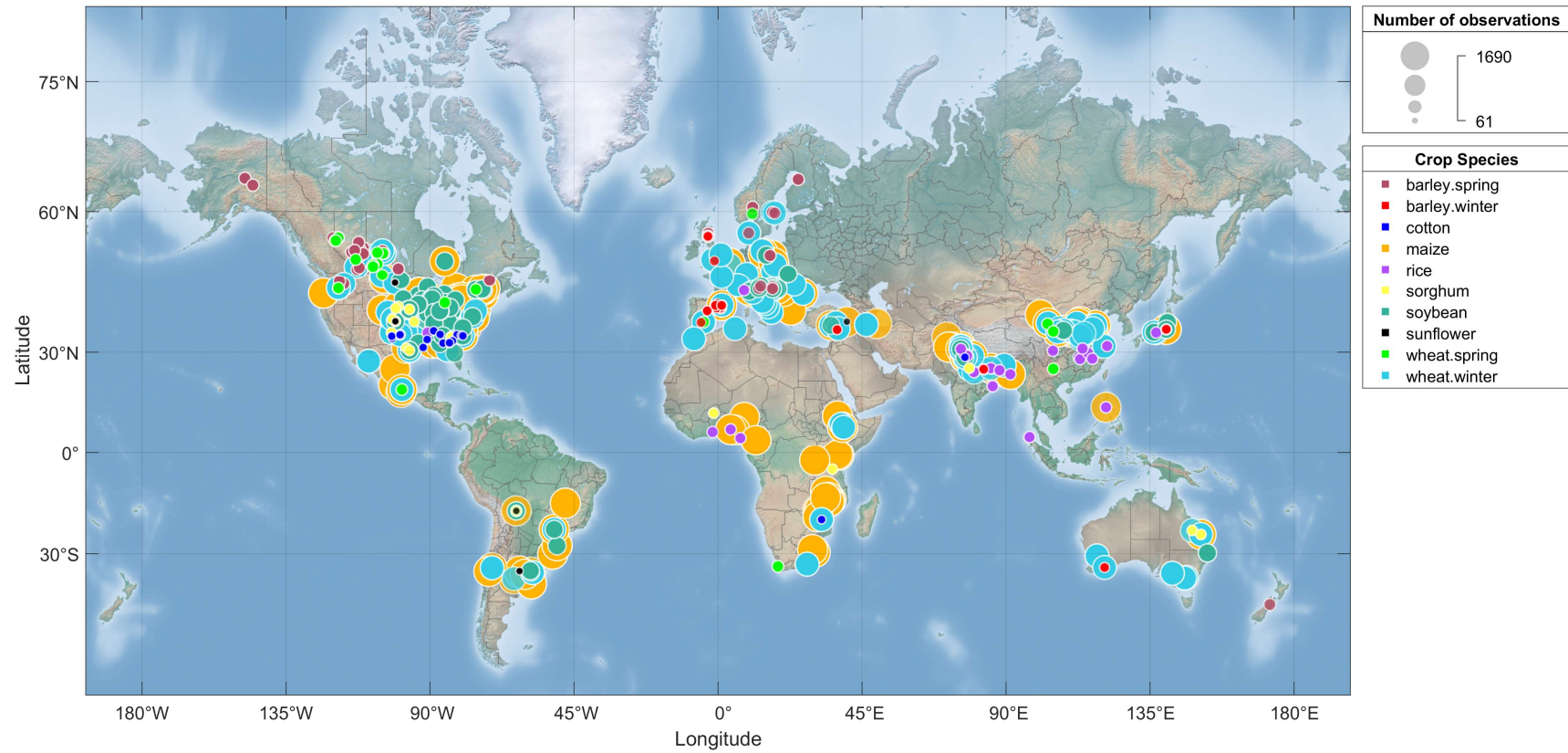


Figure 2.2 | Distribution of experimental sites. The size of the circle indicates the number of observations, and the colors indicates the crop species.

Table 2.1 | Metadata of the dataset

Category	Column	Data collected	Units	Notes	Source / Formula
I. General information of the paper	A	Author			Paper
	B	Journal			
	C	Publish year			
II. Experiment information	D	Country of experimental site			
	E	Location of experimental site			
	F	Latitude of experimental site	Degree		
	G	Longitude of experimental site	Degree		
	H	Soil type or texture			
	I	Surface pH of experimental site			
	J	Number of experiment replications			
	K	Crop type		Including 8 crops: barley (spring & winter barley), cotton, maize, rice, sorghum, soybean, sunflower, wheat (spring & winter wheat).	
	L	Initial year of NT practice	Year	If not mentioned in the paper, then this is assumed to be the initial year of the experiment.	
	M	Crop sowing year	Year		
N	Crop harvesting year	Year			
O	Years since NT started	Year		$Year_{sowing} - Year_{NT,initial} + 1$	
P	Crop planting month and harvesting month	Month	Crop growing season reported in the paper.	Paper	
III. Information about agricultural management activities	Q	Crop rotation with at least 3 crops involved in CT practice			Here we set crop rotation as “Yes” only when the crop species (including the cover crops) involved in the crop rotation sequence is more than 2 species in accordance with the FAO’s definition of Conservation Agriculture. More

				details about the crop sequence can be found in column S.
	R	Crop rotation with at least 3 crops involved in NT practice		Two categories: “Yes”, “No”.
	S	Details of crop rotation sequence		
	T	Cover crop before sowing		Set to “Yes” if a cover crop is present in the experiment
	U	Soil cover in CT practice		Four categories: “Yes”, “No”, “Mixed”, “Not reported”. Here we set soil cover as “Yes” when more than 30% of the soil is covered even after tillage, or when plastic/residue mulch exists. We set soil cover as “Mixed” for yield data corresponding to the average yields of both categories “Yes” and “No”.
	V	Soil cover in NT practice		Four categories: “Yes”, “No”, “Mixed”, “Not reported”. Here we set soil cover as “Yes” only when more than 30% of the soil is covered in current cropping season and residues from current cropping season are retained. We set soil cover as “Mixed” for yield data corresponding to the average yields of both categories “Yes” and “No”.
	W	Details of residue management of previous crop in CT practice		
	X	Details of residue management of previous crop in NT practice		

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	Y	Weed and pest control in CT practice		Three categories: “Yes”, “No”, “Not reported”.
	Z	Weed and pest control in NT practice		Three categories: “Yes”, “No”, “Not reported”.
	AA	Details of weed and pest control in CT practice		
	AB	Details of weed and pest control in NT practice		
	AC	Field fertilization in CT practice		Four categories: “Yes”, “No”, “Mixed”, “Not reported”. We set field fertilization as “Mixed” for yield data corresponding to the average yields of both categories “Yes” and “No”.
	AD	Field fertilization in NT practice		Four categories: “Yes”, “No”, “Mixed”, “Not reported”. We set field fertilization as “Mixed” for yield data corresponding to the average yields of both categories “Yes” and “No”.
	AE	N input		Four categories: “Yes”, “No”, “Mixed”, “Not reported”. We set N input as “Mixed” for yield data corresponding to the average yields of both categories “Yes” and “No”.
	AF	N input in details with the unit kg N ha ⁻¹		
	AG	Details about field fertilization		
	AH	Crop irrigation in CT practice		Four categories: “Yes”, “No”, “Mixed”, “Not reported”. We set crop rotation as “Mixed” for yield data corresponding to the

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				average yields of both categories “Yes” and “No”.	
	AI	Crop irrigation in NT practice		Four categories: “Yes”, “No”, “Mixed”, “Not reported”. We set crop rotation as “Mixed” for yield data corresponding to the average yields of both categories “Yes” and “No”.	
	AJ	Details of water applied in CT practice		Water applied in the field with the unit mm/ha/year	
	AK	Details of water applied in CT practice		Water applied in the field with the unit mm/ha/year	
IV. Other detailed information	AL	More detailed information about the experiment setting and the agricultural activities			
V. Information about crop yield	AM	Crop yield under CT practice	kg/ha		
	AN	Crop yield under NT practice	kg/ha		
	AO	Relative yield change			$\frac{Yield_{NT} - Yield_{CT}}{Yield_{CT}}$
	AP	Yield increase with NT practice?		Yes = yield increased with NT No = yield not increased with NT	
	AQ	Outlier of crop yield in CT practice		Set to “Yes” if it is an outlier for corresponding crop species	
	AR	Outlier of crop yield in NT practice		Set to “Yes” if it is an outlier for corresponding crop species	
VI. Information from external databases: climatic variables and soil texture	AS	Crop growing season start month	Month	Crop growing season was extracted from the external crop calendar databases of spring barley, winter barley, cotton, maize, rice, sorghum, soybean, sunflower, spring wheat and winter wheat based on the crop type and location	University of Wisconsin-Madison ^{26,27}

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	AT	Crop growing season end month	Month	Crop growing season were extracted from the external crop calendar databases of spring barley, cotton, maize, rice, sorghum, soybean and winter wheat based on the crop type and location	University of Wisconsin-Madison ^{26,27}
	AU	Precipitation over the growing season	mm	Precipitation was extracted from the external database based on the location, year of the experiment and crop growing season from the external database. The precipitations in each month were added together.	NOAA/OAR/ESRL PSL ²⁸
	AV	Potential evapotranspiration over the growing season	mm	Potential evapotranspiration was extracted from the external database based on the location, year of the experiment and crop growing season from the external database. The potential evapotranspiration rates in each month were added together.	GHENT university/ESA GLEAM ^{30,31}
	AW	Precipitation balance	mm	Indicated the amount of available water in the growing season for rainfed field	$P - E$
	AX	Average air temperature during the growing season	°C	Average temperature was extracted from the external database based on the location, year of the experiment and crop growing season from the external database. The temperature in each month were averaged.	NOAA/OAR/ESRL PSL ²⁸

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	AY	Maximum air temperature during the growing season	°C	Maximum temperature was extracted from the external database based on the location, year of the experiment and crop growing season from the external database. The temperatures in each month of the growing season were compared, the maximum one was recorded.	NOAA/OAR/ESRL PSL ²⁹
	AZ	Minimum air temperature during the growing season	°C	Minimum temperature was extracted from the external database based on the location, year of the experiment and crop growing season from the external database. The temperatures in each month of the growing season were compared, the minimum one was recorded.	NOAA/OAR/ESRL PSL ²⁹
	BA	Soil texture		Soil texture was extracted from the external database based on the location of the experiment from the external database. Categories included in this database: Sandy Loam; Loam; Silt Loam; Sandy Clay Loam; Clay Loam; Sandy Clay; Clay	The University of Tokyo ³²

A global crop yield meta-dataset of conservation agriculture vs. conventional tillage

2.3.2 Data records

All data are available on the figshare repository³³, which can be accessed through the link: <https://doi.org/10.6084/m9.figshare.12155553>. Four files are provided:

1. “Database.csv” includes the data.
2. “Summary of the database.docx”, includes the summary of dataset which explains the definition or assumption for each column in the dataset.
3. “List of references.docx” reports the references of the studies from which data were extracted.
4. “Code.zip”, includes all the codes used in this study.

Table 2.1 shows the metadata of our dataset. Six main categories of data are provided:

Category I covers authors, publishing journal and the publishing year.

Category II reports general information about the experiments, including country, location (villages or cities), latitude, longitude of experiment site, soil type and pH at experimental sites, number of replicates, crop types, the initial year of NT practice, crop planting/harvesting month/year, and the period since the initial year of NT practice.

Category III covers information about agricultural management activities under both NT and CT systems (data availabilities of those activities were shown in Figure 2.3):

- Crop rotation with at least 3 crops involved (based on the crop rotation principle of CA defined by FAO³⁴): “Yes”, “No”, “Not reported”. The details of crop sequence are also provided .
- Soil cover: “Yes”, “No”, “Mixed”, “Not reported”. Details of residue management for the previous crops are also provided .
- Weed and pest control: “Yes”, “No”, “Mixed”, “Not reported”.
- Field fertilization: “Yes”, “No”, “Mixed”, “Not reported”. The details of N input and other fertilizer input are also provided .
- Crop irrigation: “Yes”, “No”, “Mixed”, “Not reported”. The details of the amount of water applied are also provided.

Category IV contains detailed information about the experiment site, experiment setting, management activities, depending on the papers, it may also include the type and quantity used of fertilizer, herbicide, or pesticide.

Category V corresponds to data related to crop yield. It includes the paired crop yields under CT ($Yield_{CT}$) and NT ($Yield_{NT}$) systems. The relative yield changes is defined as $\frac{Yield_{NT}-Yield_{CT}}{Yield_{CT}}$. The column “Yield increase with NT” reports whether the differences between $Yield_{CT}$ and $Yield_{NT}$ are positive or negative (“Yes” indicates that crop yield is increased with NT practice, while “No” indicates that yield is not increased).

Category VI includes data extracted from the external databases, including crop growing season, climate variables (including precipitation, potential evapotranspiration, minimum/average/maximum temperature) during the growing season, and soil texture.

Crop growing season is defined by a start month and end month, which were extracted from the external crop calendar databases²⁶ of spring barley, winter barley, cotton, maize, rice, sorghum, soybean, sunflower, spring wheat and winter wheat based on the crop type and study sites. Data on the crop calendar corresponds

to averaged data and does not change intra-annually, thus the growing season extracted may be different from the actual growing season.

The climatic variables from the external databases are:

- Accumulated precipitation (P) during the growing season (sum of monthly precipitations during the growing season),
- Accumulated potential evapotranspiration (E) (sum of monthly evapotranspiration rates during the growing season),
- Precipitation balance (PB), defined as $PB = P - E$ ¹²,
- Average air temperature (Tave) during the growing season,
- Maximum air temperature (Tmax): the maximum value among the daily temperatures in the growing season,
- Minimum air temperature (Tmin): the minimum value among the daily temperatures in the growing season.

Soil texture was extracted from an external database based³² on the experiments' locations. In total seven texture classes were included: sandy loam, loam, silt loam, sandy clay loam, clay loam, sandy clay and clay.

2.4 Technical Validation

To ensure the reliability of the information collected from the papers, we carefully checked and compared all the collected data with the original paper several times. Quality control of the database was conducted based on outlier detection. For each crop, the outliers of crop yield in CT system and NT system were identified based on the Interquartile Rule³⁵ outlier detection method. For each crop species, an interquartile range (IQR) is defined as the difference between the first and third quartile of crop yield, and a threshold is calculated by adding 1.5 IQR to the third quartile. Any yield data beyond this threshold is flagged as an outlier for the crop species considered. The ratio of crop yield in NT and CT systems ($\frac{Yield_{NT}}{Yield_{CT}}$) were also calculated. All outliers and all the observations with a ratio higher than 2 were checked and compared with the values reported in the original papers one more time.

The crop yield values reported in our dataset are consistent with results of previous published studies. Comparing crop yield data of NT and CT, the adoption of NT practice overall leads to a yield decrease (Figure 2.4a). A similar trend of crop production decrease with NT was reported in previous studies^{1,12,20,36}. We also find that the combination of NT with crop rotation and soil cover (known as CA) trends to increase crop yield compared to NT practice without rotation and soil cover (Figure 2.4a), which is also in line with previous studies^{1,16,37}. Further analysis conducted on each crop confirms that NT tends to decrease the yield of maize¹, rice²¹, and wheat¹ (Figure 2.4b). The productivity of NT is found higher under dry conditions compared with wetter conditions (Figure 2.4c), and similar trends were reported in previous studies^{1,12}.

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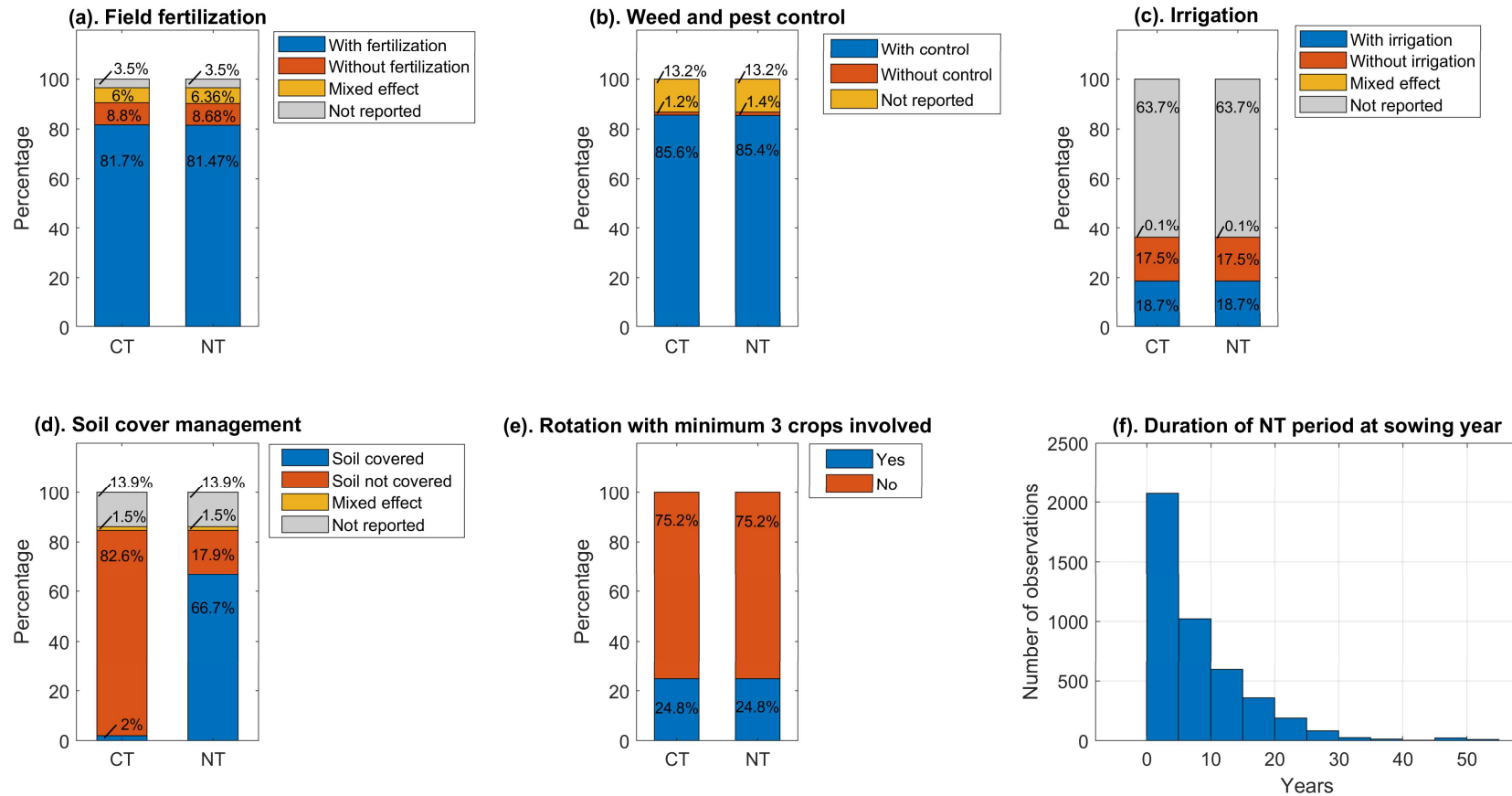


Figure 2.3 | Data availability and break-down of the different crop management practices and NT implementation periods reported in the dataset.

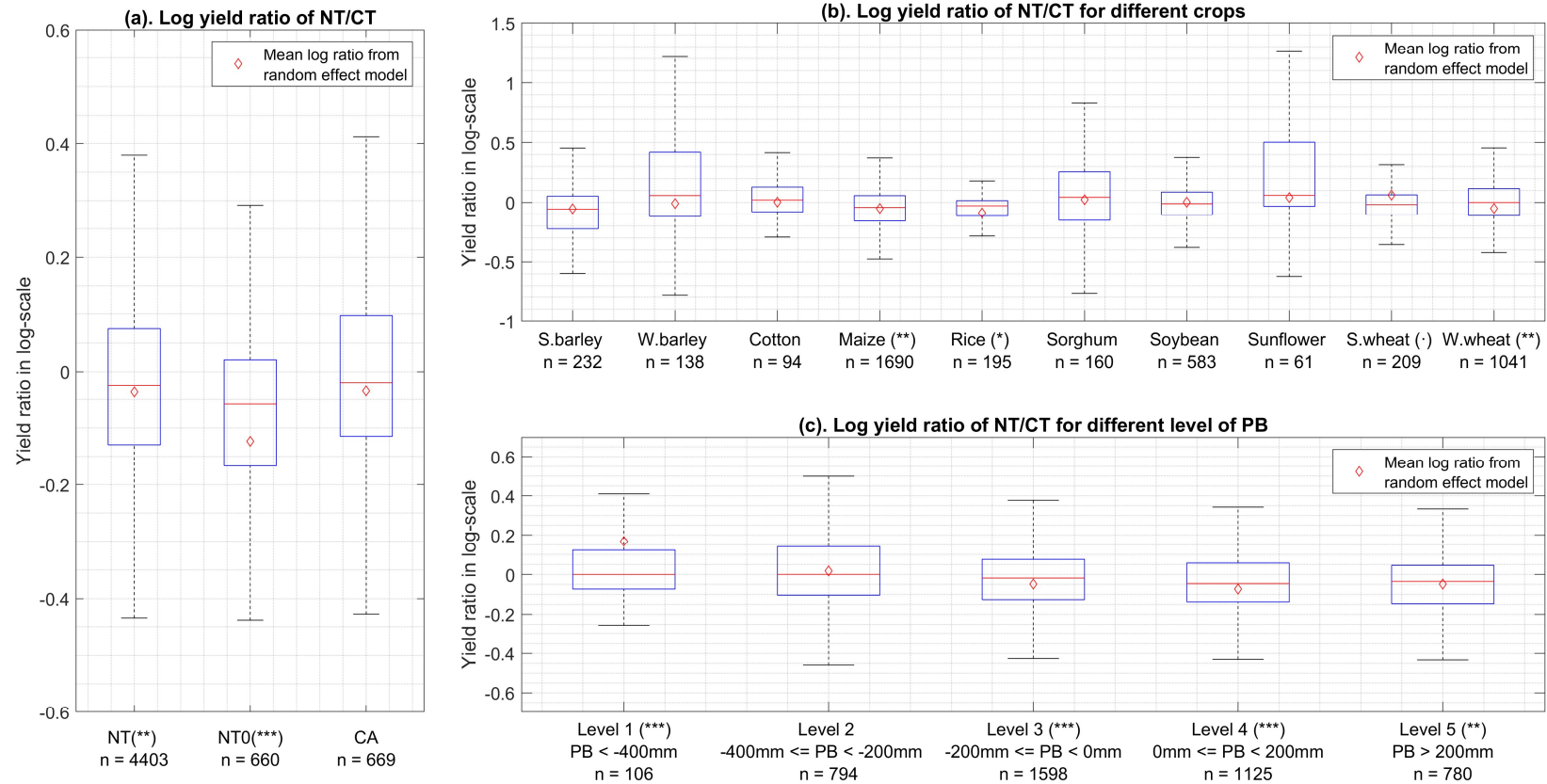


Figure 2.4 | Comparison of crop yield between NT and CT systems. The boxplots indicate the distributions (min, 1st quartile, median, 3rd quartile, max) of the log yield ratio of NT to CT. The mean log yield ratios of NT to CT were calculated based on a linear mixed effect model and marked as the red diamonds in the boxplots. Statistical tests were conducted to test the significance of the estimated values, *** indicates P-value < 0.001, ** indicates P-value < 0.01, * indicates P-value < 0.05, · indicates P-value < 0.1. Plot (a) shows the mean log ratios for different types of NT systems vs. CT systems. $NT_{overall}$ represents all the experiments involving NT systems in the dataset, NT_{-R-SC} represents the NT systems without crop rotation and without soil cover, and NT_{+R+SC} represents the CA systems or NT systems with both crop rotation and soil cover. Plot (b) shows the mean log ratios for different crop species. S. indicates spring, while W. indicates winter. Plot (c) shows the mean log ratios for different levels of PBs, corresponding to different level of water stress.

3.5 Usage notes

Our dataset can be used to analyze the factors influencing the productivity of NT (or CA) vs. CT. It is possible to train machine learning models to predict the probability of yield increase with NT (or CA) system (e.g. Appendix A figure 1 and Appendix A figure 2) or the range of yield changes resulting based on the soil type, climate and agronomic inputs provided by this dataset. Global maps of probability of yield increase with NT (or CA) or the range of yield changes can be generated based on the outputs of machine learning models trained with our dataset and enable policymakers or agricultural advisors to identify the most promising regions for CA implementation. Details of how to train machine learning models with our dataset are provided in Appendix A.

The crop yield data for 2018 and later can be extracted from the identified papers, but since some key climatic variables are missing in the external database for this time period (in particular, evapotranspiration), those data are not listed in the dataset provided. We will update the dataset once we have the latest data access to the missing climate variables.

Importantly, our dataset could be easily updated using data produced by new experiments. We welcome anyone interested to share data or papers not included in this meta-database to send them to the corresponding author (YS, yang.su@inrae.fr). We will maintain and add the new observations in the future to expand our dataset with the latest experimental data.

2.6 Code Availability

Scripts using the R and MATLAB programming language are provided to produce figures and extract data from external databases. The code is available from the corresponding author upon request.

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A machine learning pipeline to map the performance of cropping systems on a global scale

Chapter 3 A machine learning pipeline to map the performance of cropping systems on a global scale

This chapter is submitted to journal. In this chapter, we presented a machine learning pipeline that can train, tune, test and compare different machine learning models based on the dataset collected from published papers. We use the dataset presented in chapter 2 to illustrate the effectiveness of this machine learning pipeline, we compared 12 machine learning algorithms in its classification, quantitative prediction, and quantile regression ability. The best models were used to map the performance of CA and NT systems versus CT systems at the global scale.

A machine learning pipeline to map the performance of cropping systems on a global scale

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3.1 Abstract

Assessing agricultural practices has become a major issue due to growing concerns about global food security and the negative effects of agriculture on the environment. Meta-analysis has become a standard approach for such assessments based on experimental data. It provides valuable synthetic information to scientists and policy makers based on mean effect size estimation. However, summarizing large amounts of information by way of a single mean effect value is not always satisfactory, especially when considering agricultural practices. Indeed, their impacts on crop yields vary widely depending on a number of factors, including soil properties and local climate conditions. Here, we present a machine learning pipeline that produces data-driven global maps describing the spatial distribution of the productivity of farming practices. Our approach covers model selection, training, cross-validation, testing, and global projection. We demonstrate its relevance using a recent global dataset comparing the crop yields of conservation agriculture (CA) vs. conventional tillage (CT). Various models for classification, regression and quantile regression are trained based on 12 mainstream machine learning algorithms. After testing, the most accurate models are used to map the crop productivity of CA vs. CT at the global scale. The performance of CA vs. CT is characterized by a strong spatial variability, and the probability of obtaining a yield gain with CA is highly dependent on geographical locations. This result demonstrates that our approach is much more informative than simply presenting average effect sizes produced by standard meta-analyses, and paves the way for such probabilistic, spatially-explicit approaches in many other fields of research.

3.2 Main

Increasing food production and its stability over time becomes more difficult due to the negative effects of climate change on agricultural systems^{1,2}. The development of sustainable cropping systems, such as conservation agriculture (CA), has been proposed as a path to increase food security³, preserve biodiversity^{4,5}, and increase the resilience of agriculture to climate change^{6,7}. Numerous experiments have been

A machine learning pipeline to map the performance of cropping systems on a global scale

conducted to compare the productivity of different farming practices or cropping systems under a diversity of soil and climate conditions. The wealth of experimental data available offers an opportunity to identify the most efficient practices and systems based on robust scientific evidence. In this context, meta-analysis has become a standard method for analyzing experimental agricultural data and estimating mean effect sizes as a way of summarizing the performances of cropping systems. Specifically, several meta-analyses were conducted during the past decade to estimate the average performances of CA compared to CT⁸⁻¹⁰ showing conflicting results on the relative performance of CA vs. CT. Although meta-analysis is a powerful tool to analyze large experimental datasets, this approach has several limitations¹¹⁻¹³. One of them is that while mean effect sizes can summarize experiments conducted in contrasting conditions and account for the average performance of a practice or system, they summarize but do not provide a detailed description of the variability induced by local conditions¹⁴⁻¹⁶. This is an important limitation for the analysis of agricultural production because crop yields are highly dependent on the local climate conditions^{8,9,17}, soil characteristics¹⁸⁻²⁰, and agricultural management practices^{8,9,18,21,22}, which often vary in time and space. This makes it hard for standard meta-analyses to provide accurate predictions for a given geographical region.

To gain further insight and overcome this limitation, we define a new approach to analyze large experimental agricultural datasets based on standard machine learning algorithms. These algorithms have proven their usefulness over the last few years and are now widely used in numerous areas to process and analyze complex and high-dimensional data²³. We have relied on these algorithms to develop a machine learning pipeline (Figure 3.1) to standardize the process of comparing the performance of different cropping systems and mapping them at the global scale. The proposed framework includes several steps covering algorithms selection, model training, model hyperparameter tuning by cross-validation, model testing, and global projection.

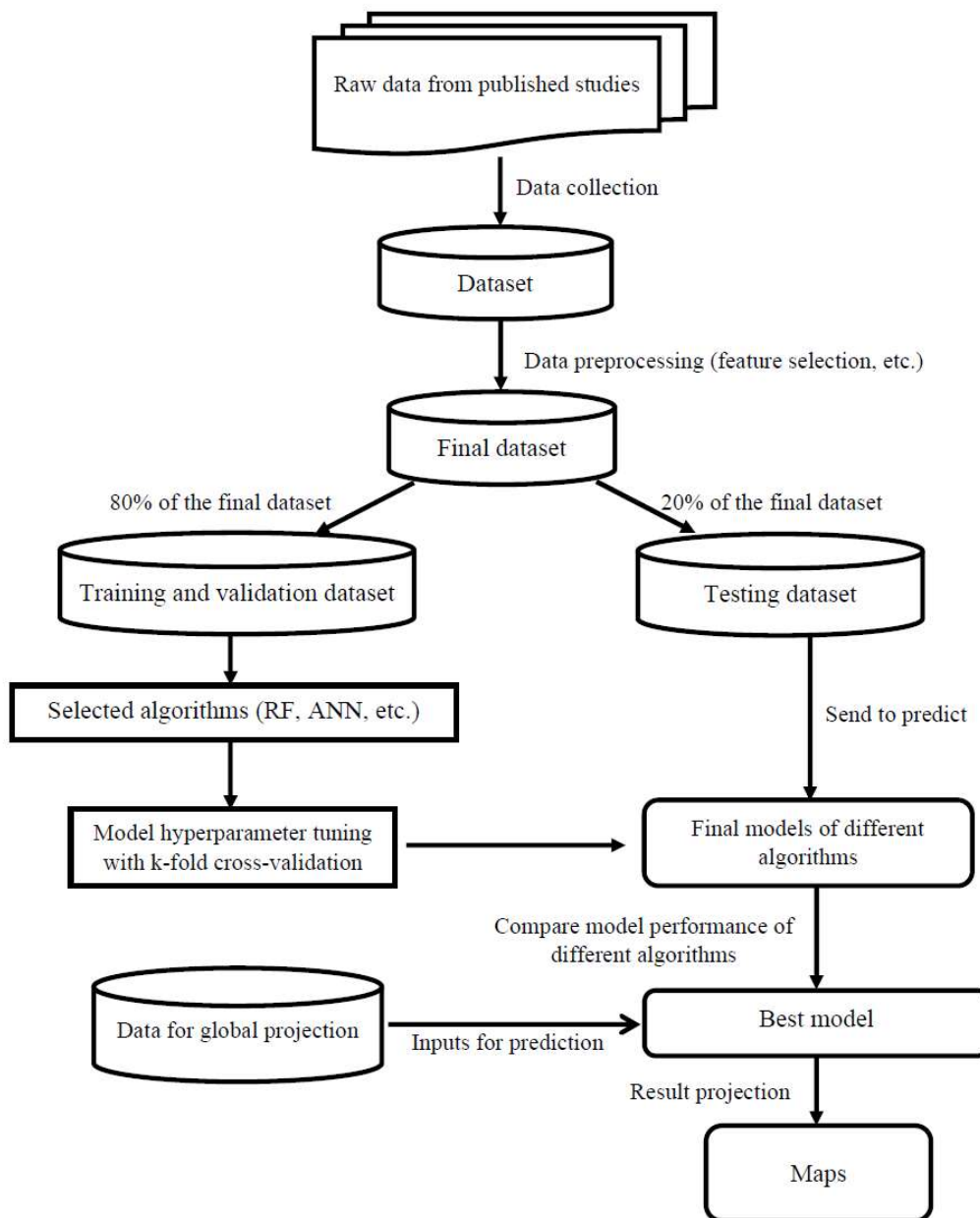
The value of this pipeline is illustrated using a recent global crop yield dataset²⁴ comparing cropping systems under CA and CT. Twelve different machine learning algorithms (See Appendix B table 1 for the details) are trained to analyze the yield ratio of CA vs. CT ($\frac{Yield_{CA}}{Yield_{CT}}$) as a function of climate variables, geolocations, soil characteristics, crop management practices. A first series of models are trained to classify yield gain ($\frac{Yield_{CA}}{Yield_{CT}} > 1$) versus yield loss ($\frac{Yield_{CA}}{Yield_{CT}} < 1$), namely random forest²⁵ (RF), random forest with spatial correlations²⁶ (RF with spaMM), gradient boosting^{27,28} (GBM), extreme gradient boosting²⁷⁻²⁹ (XGBOOST), artificial neural networks with different number of hidden layers^{30,31} (ANNs), k-nearest neighbors³² (KNN), support vector machines³³ (SVM), naïve bayes^{32,34} (NB), and generalized linear model³⁵ (GLM). A second series of models are trained for quantitatively predicting the ratio of relative yield change $\frac{Yield_{CA} - Yield_{CT}}{Yield_{CT}}$, namely RF, RF with spaMM, GBM, XGBOOST, ANNs, KNN, SVM, and GLM. Finally, a third series of models are trained to predict quantiles of this relative yield change, namely quantile regression forest³⁶ (QRF), quantile regression gradient boosting^{27,28} (QRGBM), quantile regression neural networks^{37,38} (QRNN). Thus, these models predict the ranges of relative yield change for different probability coverages.

The models' hyperparameters are tuned using a cross-validation procedure and the models are subsequently tested using an independent testing dataset (Figure 3.1). Classification models are tested based on the area under the receiver operating characteristics curve (AUC)³⁹. AUC corresponds to the probability that a classifier can rank a positive instance (yield gain in this case) higher than a negative one (yield loss), thus, a higher AUC indicates a superior classification performance by the model^{22,39}. Quantitative predictions are assessed using the coefficient of determination or R squared (R^2), which estimates how well the

A machine learning pipeline to map the performance of cropping systems on a global scale

predictions approximate the observations. Higher R^2 values indicate a better fit of the model⁴⁰. Ranges of values derived from the predicted quantiles are evaluated by computing an error score (ES), defined based on the area between the curve of coverage rates (CRs) for all prediction intervals and 1:1 line. Smaller ES indicates better model interval prediction ability. See **Method section** for the details of ES.

The best models are then used for classification (yield gain vs. loss), for quantitative prediction (ratio of relative yield change of CA vs. CT), and for computing intervals (intervals of relative yield change ratios). Model outputs are mapped at the global scale with climate data over the 1981-2010 time slice at a spatial resolution of 0.5° latitude \times 0.5° longitude. Details of model setting are available in Appendix B Table 5.



A machine learning pipeline to map the performance of cropping systems on a global scale

Figure 3.1 | Machine learning pipeline of predicting performance of cropping systems and comparing different algorithms.

Results

RF, GBM, and XGBOOST show better classification performance (with AUC values equal to 0.790, 0.786, 0.783, respectively), while the more traditional algorithms GLM and NB have lower performance (with AUC values of 0.644 and 0.647, respectively) (Figure 3.2, Appendix B table 2). With ANN, the best classification accuracy was obtained using 2 hidden layers, with an AUC value of 0.752 (Figure 3.2, Appendix B table 2).

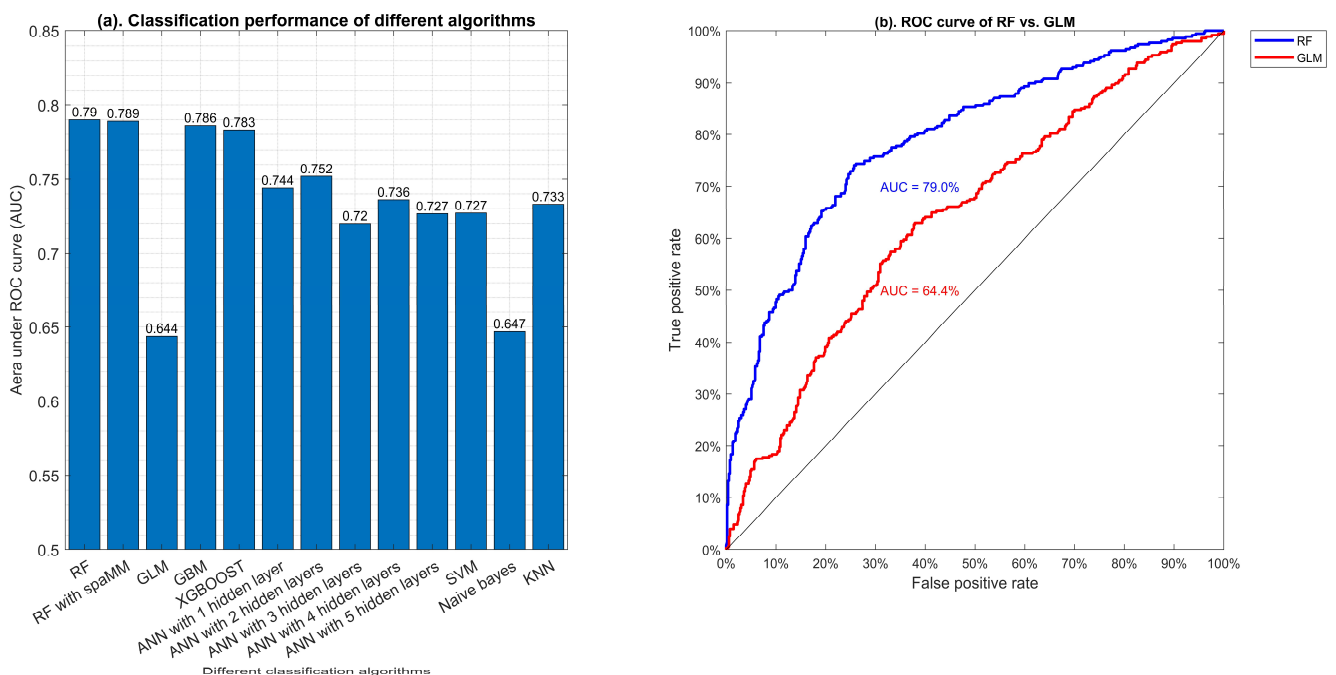


Figure 3.2 | Comparison of different classification algorithms based on AUC. Plot a shows the AUC of the final testing model of different algorithms. Plot b shows the ROC curve of the best (RF) and the worst (GLM) algorithms.

As regards regression models, the R^2 of all algorithms are smaller than 0.6 (Figure 3.3a, Appendix B table 3), revealing moderate explanatory powers. Among these algorithms, the best performance is achieved by RF, with a R^2 equal to 0.52, while GLM has the worst performance, with a R^2 equal to 0.12 (Figure 3.3a, Appendix B table 3). Figure 3.3b and 3.3c show the scatterplot of observations versus predictions of relative crop yield change from the RF and GLM models, respectively. The results show that GLM predictions are poorly related to observations, while RF is able to explain a substantial fraction of the total variability.

For range regression models, different rankings are obtained depending on whether outliers in the dataset were included or not (Figure 3.4). With outliers included, the best performance is obtained with QRF (ES=1.73%), while QRGBM performs better when the outliers were filtered (ES=1.38%). QRNN performs better with one than with two hidden layers, but never outperforms QRF and QRGBM (with ES equals to 5.35% and 15.69% without and with outliers, respectively).

A machine learning pipeline to map the performance of cropping systems on a global scale

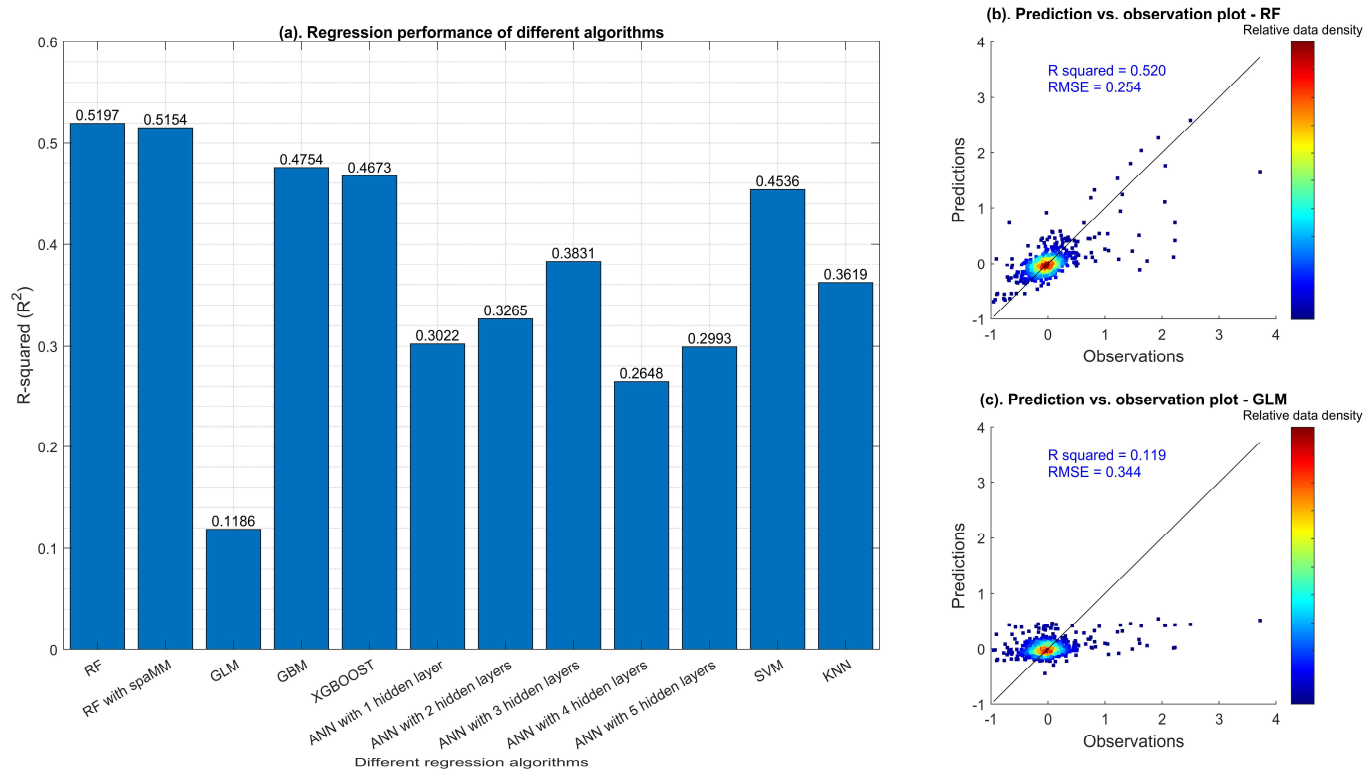


Figure 3.3 | Comparison of different regression algorithms based on R^2 . Plot a shows the R^2 in the final testing step for the various algorithms after model tuning. The number after ANN indicates the number of hidden layers in the neural networks. Plots b and c are the scatterplots of observations and predictions of relative crop yield change from the best (RF) and the worst (GLM) algorithms, respectively. All the models were trained with the training dataset in which the outliers (data points outside the 95% confidence interval) were filtered.

The productivity of CA vs. CT systems for spring barley was mapped at the global scale. To reveal the differences among models, we mapped this performance based on the results obtained with the best (RF) and the worst algorithms (GLM). Results obtained with both algorithms show that - with fertilizer inputs and an appropriate control of weeds and pests - the probability of yield gain with CA vs. CT is higher than 0.5 in western North America, central Asia, and many regions in the east and central Africa, while the probability is lower in eastern North America and Europe (Figure 3.5a, Figure 3.5b). However, there are many inconsistencies in the predictions of the two algorithms in other regions. For example, according to RF, the use of CA instead of CT would most likely lead to yield loss (probability of yield gain is lower than 0.5) in South America, and in most of the regions in eastern and southern Asia, while opposite results are provided by GLM in those regions (Figure 3.5a, Figure 3.5b, respectively). This contradiction reveals that the choice of an inappropriate model (such as GLM, here) would lead to wrong conclusions, highlighting the importance of the model selection step in our procedure. This is confirmed by the relative yield changes of CA vs. CT mapped with the RF and GLM models in Figure 3.5. According to RF, yield gains are expected when shifting from CT to CA in western North America, central Asia, and many regions in the east and central Africa, while yield losses are predicted in most part of Europe (Figure 3.5c). This is in line with the results from RF classification model (Figure 3.5a). Conversely, according to the results of the GLM regression model, yield gains are predicted in eastern North America and Europe, while yield losses are predicted in central Asia (Figure 3.5d), which is not consistent with the GLM classification model

A machine learning pipeline to map the performance of cropping systems on a global scale

(Figure 3.5b) and RF models (Figure 3.5a, 3.5c). Here again, the use of an inaccurate model like GLM would lead to misleading conclusions.

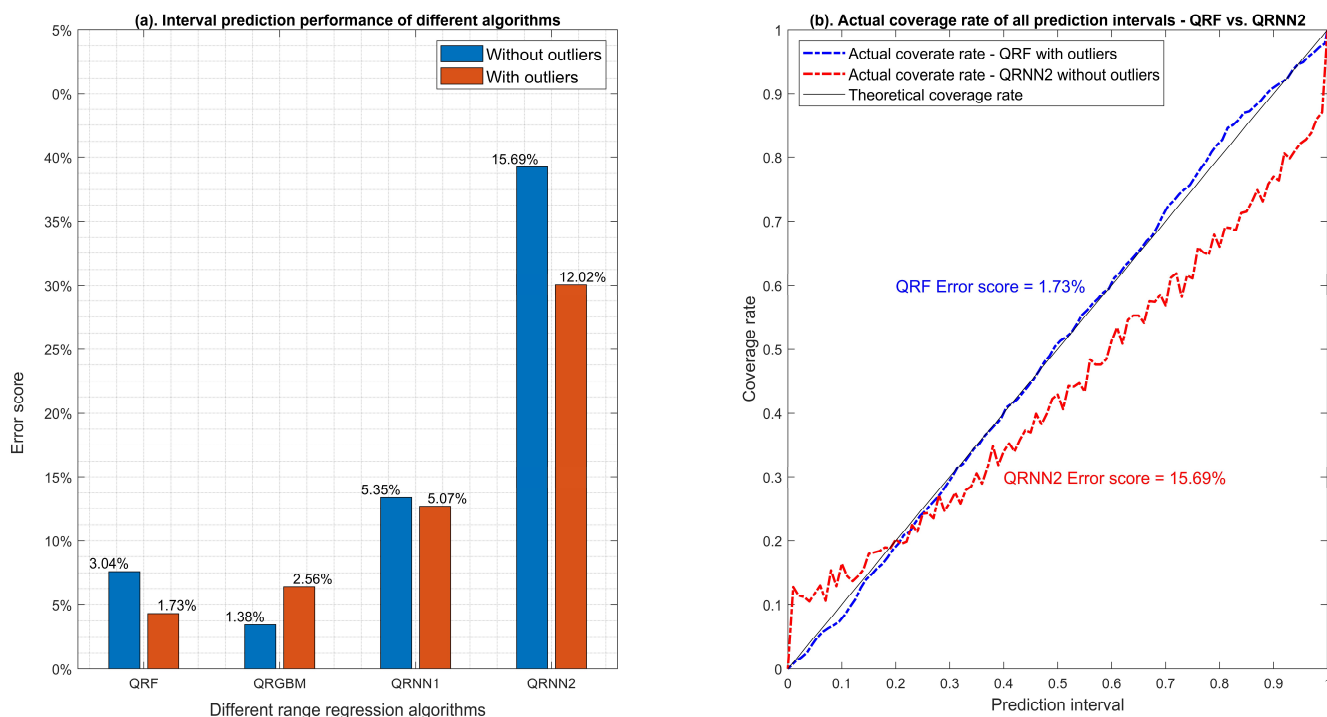


Figure 3.4 | Comparison of different range regression algorithms based on ES. Plot a shows the error score in the final testing step for the various algorithms after model tuning. Plots b and c show the actual coverage rates for all the prediction intervals of the best (QRF) and worst algorithm (QRNN2). The number after QRNN indicates the number of hidden layers in the quantile regression neural networks. All the models were trained both with and without the outliers (outside 95% confidence interval) in the original dataset filtered to check if the algorithms can handle outliers.

The predicted ranges (10th percentile and 90th percentile) of relative yield change of CA vs. CT are shown in Appendix B Fig. 1. We show that there is 10% chance that the relative yield change of CA vs. CT will be higher than 0.45 in western North America, southern South America, eastern and central Africa (Appendix B Figure 1b), while there is 10% chance that relative yield changes be lower than 0.35 in part of western North America, central Asia, and northern China (Appendix B Figure 1a). The uncertainty is higher in western North America, reflected by the broader yield gain range (between the 10th and 90th percentile predictions) in this region.

The Shapley value, which is the average marginal contribution of a feature value across all possible coalitions ⁴¹, is calculated for precipitation balance (PB) and years since no tillage was implemented (NTyear) to assess how PB and NTyear would affect the performance of CA. We show that a relative lower PB or a longer period of no tillage implementation is likely to improve the performance of CA compared to CT (Appendix B Figure 2, Appendix B Figure 3, respectively).

A machine learning pipeline to map the performance of cropping systems on a global scale

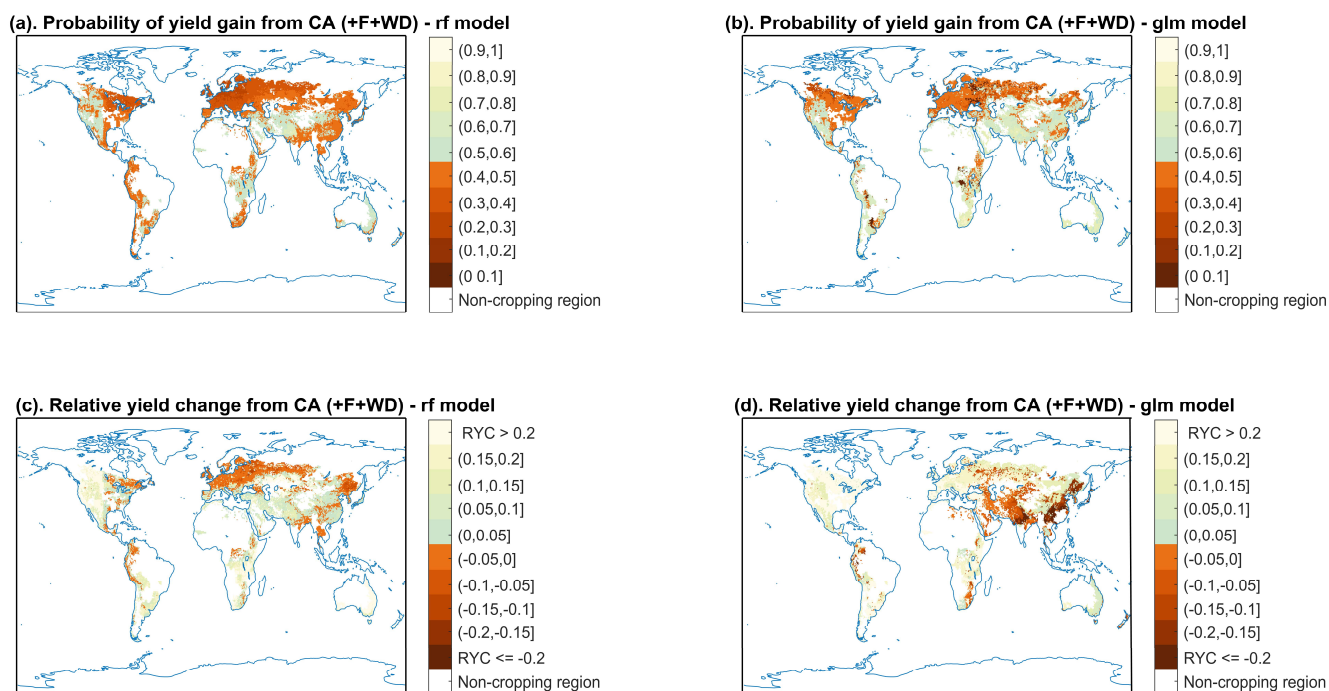


Figure 3.5 | Global projection of best and worst algorithms for classification and regression. Plot a and b show the maps of probability of yield gain with CA vs. CT based on RF and GLM algorithms, respectively. Regions with a probability of yield gain lower than 0.5 were highlighted in red. Plot c and d show the maps of relative yield change with CA vs. CT based on RF and GLM algorithms, respectively. Regions with negative relative yield change were marked in red.

3.3 Discussion

In this study, we trained a broad set of machine learning (ML) models for different purposes: classification, quantitative prediction, and range prediction. This is the first time that 12 ML algorithms are implemented and compared in an application dealing with a major, global issue for agriculture. The worldwide maps obtained with the most accurate algorithms reveal a strong geographical variation of the probability of yield gain with CA, and the relative yield change resulting from its adoption over conventional tillage. This result shows that the mere presentation of an average effect size - as often done in standard meta-analyses - does not provide sufficient information on the performance of one cropping system compared to another. Contrary to standard meta-analyses, our approach can be used to describe the variability of this relative performance and to identify geographical areas where one cropping system outranks the other with a higher spatial resolution. This is an important advantage in a context where the choice of cropping systems should be adapted to the local context to provide optimal performance. Here, the global maps generated from our pipeline indicate that CA can be competitive in western North America and central Asia, in particular in dry regions. This result is consistent with recent studies ^{8,9,22}.

Our comparative analysis show that, RF has the best performance for both classification and quantitative prediction, followed by GBM, XGBOOST, ANNs, SVM, and KNN, while GLM and NB have the worst performance compared to other algorithms. Other studies from agriculture-related sectors also reported similar trend in the performance of machine learning algorithms. For example, Cao et al. ⁴² reported that RF had better performance than ANNs in wheat yield prediction. Folberth et al. ⁴³ disclosed that RF and XGBOOST had similar performance for downscaling crop yields from model outputs. Rahmati et al. ⁴⁴ revealed that RF had better classification ability than SVM when predicting agricultural droughts in

A machine learning pipeline to map the performance of cropping systems on a global scale

Australia. Dubois et al. ⁴⁵ reported that RF and SVM had better quantitative prediction ability than ANNs for forecasting short-term soil moisture. In other fields, Uddin et al. ⁴⁶ unveiled that in disease detection, RF had the highest chance to show excellent classification capability (with an AUC over 0.8), followed by SVM, NB, ANNs, KNN. However, RF is not systematically ranked first in previous studies ⁴⁷⁻⁴⁹ and the performance of different algorithms may shift depending on the type of applications. It is therefore essential to evaluate a range of different candidate algorithms for each application, and not to systematically rely on the same approach. Our methodological framework appears very useful in this context because it allows the comparison of several algorithms on an objective basis.

Concerning interval prediction, David et al. ⁵⁰ reported that the performance of different algorithms varies depending on the quantiles considered. This highlights the importance of evaluating these algorithms for a wide range of quantiles. In this perspective, we used a new error score (ES) (See **method section** for more details) which is capable of assessing any quantile regression model over the whole range of quantiles. This criterion can be used to select algorithms performing well over a large range of quantiles and not only for specific quantile values.

In this study, we prove that the experimental data collected from published studies can be used to conduct more complex analyses via machine learning techniques than those done in standard meta-analyses, usually based on linear models. The maps created from the machine learning pipeline we proposed here provides detailed geographical information about the performance of one system compared to a reference, and this pipeline can be easily adapted to analyze a diversity of outcomes. These may involve the effects of crop management practices on soil organic carbon dynamics, greenhouse gas emissions, biodiversity, etc. for different types of cropping systems, such as organic agriculture or agroforestry, and thus provide valuable information on the local performance of sustainable farming practices together with a global perspective.

3.4 Methods

3.4.1 Dataset establishment

The literature search was conducted in February 2020 using the keywords ‘conservation agriculture or no-till or no tillage or zero tillage and ‘yield or yield change’ in the websites ‘ScienceDirect’ and ‘Science Citation Index’. The details of the paper screening and data collection procedure were described in previous publications ^{22,24}. The final dataset includes 4403 paired yield observations for no tillage (NT) and CT under different farming practices for 8 major crop species, which were extracted from 413 papers (published between 1983 to 2020). It includes 370 observations for barley, 94 observations for cotton, 1690 observations for maize, 195 observations for rice, 160 observations for sorghum, 583 observations for soybean, 61 observations for sunflower, 1250 observations for wheat. The experimental sites cover 50 countries from 1980 to 2017.

3.4.2 Model training

In classification models, pairs of yield data were used to compute the yield ratio $\left(\frac{Yield_{CA\ or\ NT}}{Yield_{CT}}\right)$. Data were then categorized in two categories corresponding to either yield gain or yield loss. These categories were then predicted from inputs describing climate conditions over crop growing season (precipitation balance, minimum temperature, average temperature, and maximum temperature), soil texture, agricultural management practices (crop rotation, soil cover, fertilization, weed and pest control, irrigation and CA/NT implementation year) and location (latitude and longitude) using different machine learning algorithms. Results were used to map the probability of yield gain with CA vs. CT (probability of yield ratio > 1). Note that CA is defined as NT with soil cover and with crop rotation based on the FAO’s definition⁵¹.

In regression models and range regression models, pairs of yield data were used to compute the relative yield change $\left(\frac{Yield_{CA\ or\ NT} - Yield_{CT}}{Yield_{CT}}\right)$. These relative yield changes were then related to the inputs listed

A machine learning pipeline to map the performance of cropping systems on a global scale

above. The models were used to predict the conditional mean of relative yield change with regression models, and the conditional quantiles of relative yield change with quantile regression models.

As shown in Figure 3.1, all the models were trained based on the 80% of the dataset. The brief description of algorithms and packages used were listed Appendix B Table 1.

3.4.3 Model tuning with 10-fold cross-validation

The hyperparameters of all algorithms except GLM were tuned using 10-fold cross-validation and grid search⁵². The settings of the grid search are presented in Appendix B table 6. For each hyperparameter setting in the grid search, the 10-fold cross-validation was implemented to calculate AUC³⁹ for classification models and R^2 ⁴⁰ in regression models, respectively. Model settings with the highest AUC and R^2 were selected for the model testing step.

For quantile regression, cross-validation was implemented to calculate the coverage rate (CR) of the 80% prediction interval (the interval between 10% quantile and 90% quantile) for all the hyperparameters setting in the grid search (Appendix B Figure 4). The model with the CR value closest to 0.8 was selected as the final model setting used in the model testing step.

For GLM, the final model was selected with a stepwise algorithm⁵³ implemented using the step function (from 'stats' package, version 4.0.4 in R) run with AIC⁵⁴.

3.4.4 Model testing

The performances of the trained algorithms were determined using an independent testing dataset including 20% of the total number of data (Figure 3.1) with the criteria AUC³⁹ and R^2 ⁴⁰ for classification models and regression models, respectively. For quantile regression models, the criterion used to assess the final model performance was the error score (ES). In previous studies⁵⁵⁻⁵⁷, quantile regression models were assessed by comparing the coverage rate (CR) of the range of values defined by the quantiles from $\frac{\alpha}{2}$ and $(1 - \frac{\alpha}{2})$ to its nominal target value (α). In these studies, this assessment was done for a limited number of values (α) (sometimes, a single one). Here, we generalized this approach by plotting CR vs. its corresponding α for all values of α between 0 and 1, then compared the resulting curve to the reference line (1:1 line) as shown in **Figure 3.4b**. The ES was then defined by Formula 1 and represents the area between the curve of CRs vs. α and the 1:1 line, then divided by 0.5, which serves here as a benchmark. This value of 0.5 is indeed reached when the CR is independent from α . The criterion ES measures the overall performance of the model over all quantiles.

$$\text{Error Score} = \frac{\text{Area between the curve of CRs vs. } \alpha \text{ and 1:1 line}}{0.5} \times 100\% \quad (1)$$

The final performance of those algorithms was presented in Appendix B Table 2 – 4.

3.4.5 Global projection

The algorithms with the best final model performance were selected to do global projection, the model setting for global projection was presented in Appendix B table 5. To predict the global productivity of CA vs. CT, the trained models were fed by the numerical explanatory variables, such as climatic variables, latitude, longitude, number of years since NT implementation, and categorical explanatory variables, including crop types, soil textures, agricultural management practices.

The model outputs included the probabilities of yield gain with CA vs. CT for the classification models, the relative yield change with CA vs. CT for regression models, and the 10th and 90th percentiles of relative

yield change for the range regression models. The results indicated the CA productivity at the global scale under the averaged climate conditions of the 1981-2010 time slice. All maps in the paper were generated with MATLAB R2020a (Version 9.8.0.1451342, <https://fr.mathworks.com/products/matlab.html>).

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Part III

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Conservation Agriculture from a Climate Change and Food Security Perspective

Chapter 4 The productive performance of conservation agriculture under past climate conditions (1981-2010)

This chapter is published in Scientific Reports, 11, 3344 (2021), and can be accessed through this link: <https://doi.org/10.1038/s41598-021-82375-1>. In the chapter, we trained the classification and quantile regression model based on the random forest and quantile regression forest model, which are the best models selected through the machine learning pipeline presented in chapter 3. Here we mapped the probability of yield increase with CA systems and the range of yield change at global scale, and how they vary with different farming practices under the mean climate condition between 1981 to 2010.

High probability of yield gain through conservation agriculture in dry regions for major staple crops

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4.1 Abstract

Conservation Agriculture (CA) has been promoted to mitigate climate change, reduce soil erosion, and provide a variety of ecosystem services. Yet, its impacts on crop yields remains controversial. To gain further insight, we mapped the probability of yield gain when switching from conventional tillage systems (CT) to CA worldwide. Relative yield changes were estimated with machine learning algorithms trained by 4403 paired yield observations on 8 crop species extracted from 413 publications. CA has better productive performance than no-till system (NT), and it stands a more than 50% chance to outperform CT in dryer regions of the world, especially with proper agricultural management practices. Residue retention has the largest positive impact on CA productivity comparing to other management practices. The variations in the productivity of CA and NT across geographical and climatical regions were illustrated on a global map. CA appears as a sustainable agricultural practice if targeted at specific climatic regions and crop species.

4.2 Introduction

Conservation Agriculture was originally designed to decrease soil erosion while sustaining crop productivity in the long run ¹. It consists of three principles: preserving a permanent soil cover, minimizing soil disturbance (going as far as NT), and diversifying crop species (at least three crops involved) ². CA system provides positive environmental externalities such as increased biodiversity, enhanced carbon sequestration and improved soil quality through an increase in soil organic matter^{3,4}, and is expected to enhance soil fertility, soil structure and water retention properties over time ⁵⁻⁷, thereby CA could increase crop yields in particularly in regions experiencing water scarcity ⁸. Nonetheless, its impacts on crop yield remains controversial. It is also reported that CA may lead to a yield reduction ^{1,9} especially when the principles of Conservation Agriculture are only partially applied (e.g. in NT system without soil cover or

without rotation)^{1,9,10}. Further analyses were conducted to reveal how the productive performance of CA and NT system varies as the function of several interacting factors such as agricultural management practices^{1,9,11}, soil characteristics¹¹, crop species^{1,12} and climatic conditions^{1,9,11,13}. However, the dataset used in those analyses only provide no or limited information on soil characteristics, climate variables, and management practices. In particular, information on fertilizer inputs, weed and pest control, and intra- and inter- annual climatic variability were frequently missing. To date, a comprehensive synthesis of the productivity of CA and NT system at the global scale, including multiple crops, a wider range of climatic parameters on yields, and a map showing the local productivity of CA and NT vs. CT at the global scale, is still lacking.

In this paper, we compared the productive performance of CA and NT vs. CT under different climate conditions and different agricultural managements based on a new, global dataset¹⁴. This dataset contains yield comparisons of NT vs. CT, and CA vs. CT, where CA was defined as NT with crop rotation and soil cover based on the FAO's definition¹⁵. In contrast with previous papers, we used here a probabilistic approach to analyze the dataset. Machine learning models^{16,17} were built to estimate the probability that CA (and NT) can outperform CT, and to compute plausible ranges of relative yield change when shifting CT to CA (or NT) system for eight major crops, including spring barley, cotton, maize, rice, sorghum, soybean, sunflower, and winter wheat. Unlike previous studies, we included a wider range of climate drivers (with their inter- and intra-annual variabilities) in the model predicting the impact of CA and NT on crop yields, rather than relying on aridity indices or broad climate zones. This provided further insight into the effects of climate on the comparison with conventional agricultural systems.

4.3 Data collection and analysis

A systematic literature review was performed in February of 2020 (see Appendix C1). We collected the papers cited in above mentioned meta-analyses^{1,9,11}, supplemented them by the most recently published experimental studies. The yield data of NT and CT, details of experimental site and agricultural management practices were extracted from those papers, with a broader set of climatic parameters from external databases. In the end, 4403 paired yield comparisons between NT (or CA when NT is implemented with soil cover, and crop rotation which involves at least three crops species) and CT were collected from 413 papers, along with the information of crop types, years and locations of the experiments, and the detailed agricultural management practices such as crop irrigation, field fertilization, the control of weed and pest, crop rotation, the management of crop residue and soil cover. Additional data were extracted from several external databases, including crop growing season^{18,19}, soil texture²⁰ and climate factors such as precipitation balance (precipitation²¹ – potential evapotranspiration^{22,23}), minimum temperature²⁴, average temperature²¹, maximum temperature²⁴ throughout the growing season in a particular year. The observations covered 50 countries (See Appendix C2) and 8 crops. Pairs of yield values were used to compute the yield ratios of CA (or NT) to CT $\left(\frac{Yield_{CA(or NT)}}{Yield_{CT}}\right)$ and the relative yield change ratios $\left(\frac{Yield_{CA(or NT)} - Yield_{CT}}{Yield_{CT}}\right)$.

Machine learning models, namely random forest and quantile regression forest were developed to analyse the database. The inputs of both models were the climatic conditions throughout growing season, crop type, soil texture, and the agricultural management practices. The output of the random forest model was the probability yield gain of CA (or NT) vs. CT (yield ratio > 1). The performance of this model was assessed by estimating the area under the ROC curve by leave-one-out cross validation (LOOCV) (AUC=0.786, see Appendix C3). The output of quantile regression forest model was the 1st and 3rd quartile of relative yield change ratios, corresponding to levels of losses and gains achieved in 25% and 75% of the cases. The performance of this model was assessed using a specific LOOCV procedure to check that the proportion of

The productive performance of conservation agriculture under past climate condition

yield ratio in the observation within the predicted intervals defined by the two quartiles (25th and 75th quartiles) was close to 50% (51.3%, see Appendix C4) ²⁵.

To predict the global performance of CA (and NT) vs. CT, the two trained machine learning models were supplemented with global climate data (the average of 1981-2010), agricultural management practices (NT: without crop rotation and without soil cover, CA: with crop rotation and with soil cover), the masks of crop presence ²⁶, irrigation ²⁶ and soil texture²⁰. Details of model setting are available in Appendix C5. Model results were then projected on map.

4.4 Results

The functional relationship among the probability of yield gain from CA (and NT) vs. CT, the climatic factors, the agricultural management practices were demonstrated through partial dependence plot ^{27,28}. The results showed that CA has better performance than NT due to the positive effects of soil cover and crop rotation on crop yield (Figure 4.1a, b). Fertilizer application increased the productivity of CA and NT systems as well (Figure 4.1c). The probability of yield gain from CA was slightly higher with weed and pest control under the dry condition, while there was no significant effect of weed and pest control on NT system (Figure 4.1d). Irrigation improved the performance of NT system, but decreased the competitiveness of CA vs. CT (Figure 4.1e). Our results also showed that both CA and NT practices were likely to result in a better productivity in regions where water stress prevails compared to wetter conditions (Figure 4.1). Here we defined a relatively dry region (region #1) and a relatively wet region (region #2) based on the precipitation balance: region #1 indicates that the accumulated precipitation balance throughout the growing season is lower than 0 mm, while region #2 indicates a positive balance. Further analyses on the probability of yield increase and 1st and 3rd quartile of relative yield change for different crops in relatively dry (region #1) and wet (region #2) regions also showed that, in general, CA outperformed NT, and that CA and NT have better performance in regions that were relatively dry (Figure 4.2d, Appendix C8d, C11d, C14d, C16d, C19d, C22d, C25d). For winter wheat, the mean probability of yield gain with CA vs. CT is 56% and 47% in region #1 and region #2, respectively (Figure 4.2b); The plausible range of yield change when shifting from CT to CA in region #1 is from -0.11 to 0.51, and -0.2 to 0.17 for region #2 (Figure 4.2d).

The productive performance of conservation agriculture under past climate condition

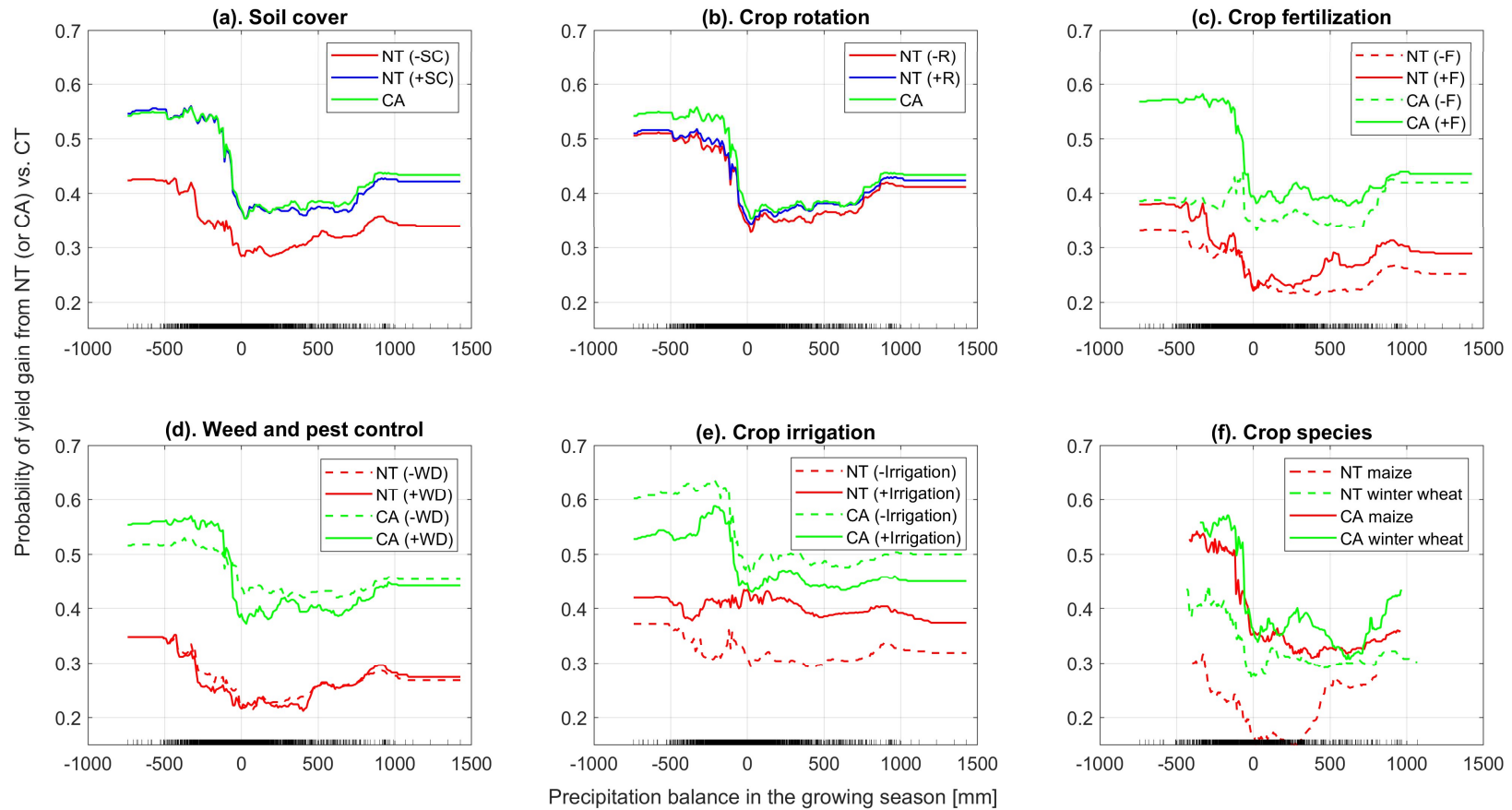


Figure 4.1 | Impact of crop management practices on CA performance, shown in 1-D partial dependence plot of the probability of yield gain as a function of precipitation balance (mm). The tick marks on the x-axis showed the distributions of observations of precipitation balance in the dataset.

The productive performance of conservation agriculture under past climate condition

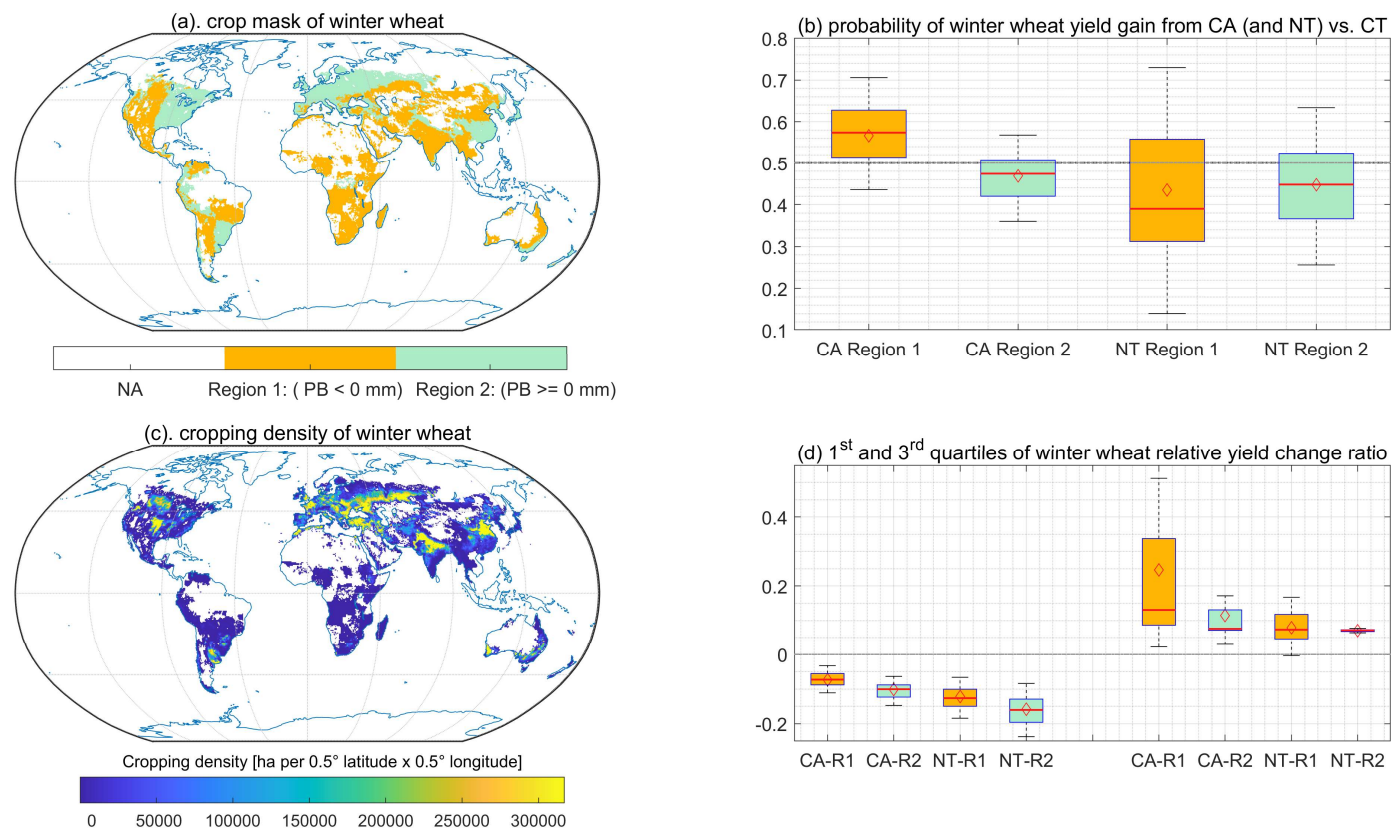


Figure 4.2 | Productivity of Conservation Agriculture for winter wheat in a relatively dry (region #1) and a relatively wet (region #2) region. (a) Illustration of the two regions on a global map with the two different colors showed in the sub-legend of plot a, while the blank area indicated the non-cropping region of winter wheat. (b) The probability of winter wheat yield gain (CA and NT vs. CT). (c) Wheat cropping density²⁶ on global map, the yellow shades indicated the higher density, and vice versa. The yellow color in this map indicated the crop density is equal or higher than 20% of maximum density in the cell of 0.5° latitude × 0.5° longitude at the global scale. (d) The 1st and 3rd quartiles of winter wheat relative yield change under CA and NT vs. CT practice in the two regions, and the x axis tick label in plot d: R1, R2 indicated the two different regions, and the left part of plot d indicated the yield change ratios at the 1st quartile, while the right part were the yield change ratios at 3rd quartile. The colors in plot a, b and d indicated the same regions. In plot b and d, the mean value of relative yield change in its region is marked by the red diamond, while the median value is depicted by the red horizontal line.

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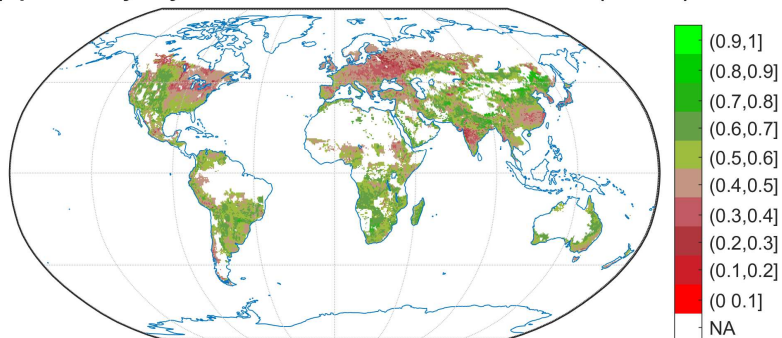
Probabilities of yield gain show important geographical variations. CA, in particularly when associated with fertilization and weed and pest control, is likely to lead to a yield gain compared to CT in North-western America for spring barley (Appendix C9a, b), maize (Figure 4.4a, b), sorghum (Appendix C20a, b), sunflower (Appendix C26a, b) and winter wheat (Figure 4.3a, b); In Pakistan and the west of India for spring barley (Appendix C9a, b), cotton (Appendix C12a, b), maize (Figure 4.4a, b), sorghum (Appendix C20a,b) and winter wheat (Figure 4.3a, b); In north of China for cotton (Appendix C12a, b), sorghum (Appendix C20a, b), sunflower (Appendix C26a, b), and winter wheat (Figure 4.3a, b). On the other hand, CA, especially without fertilization and the control of weed and pest, has lower probability of yield gain in tropical region for rice (Appendix C17a, b), sorghum (Appendix C20a, b), soybean (Appendix C23a, b), sunflower (Appendix C26a, b); In south of China for sorghum (Appendix C20a, b), soybean (Appendix C23a, b), winter wheat (Figure 4.3a, b); In North-eastern America, and Europe for spring barley (Appendix C9a, b), maize (Figure 4.4a, b), soybean (Appendix C23a, b), and winter wheat (Figure 4.3a, b).

Here we showed that, with proper management, CA has a 25% chance of producing large yield gains (more than 30%) compared to CT in most of the Africa for spring barley (Appendix C10b), cotton (Appendix C13b), maize (Appendix C15b), sorghum (Appendix C21b), soybean (Appendix C24b), sunflower (Appendix C27b), winter wheat (Figure 4.5b); In some part of South America for spring barley (Appendix C10b), cotton (Appendix C13b), maize (Appendix C15b), sorghum (Appendix C21b), soybean (Appendix C24b), sunflower (Appendix C27b), winter wheat (Figure 4.5b); In some part of Southeast of the US for spring barley (Appendix C10b), maize (Appendix C15b), sorghum (Appendix C21b), soybean (Appendix C24b), sunflower (Appendix C27b). Conversely, NT has a 75% chance of increasing yield by more than 5% for winter wheat in northeast of China (figure 4.5c).

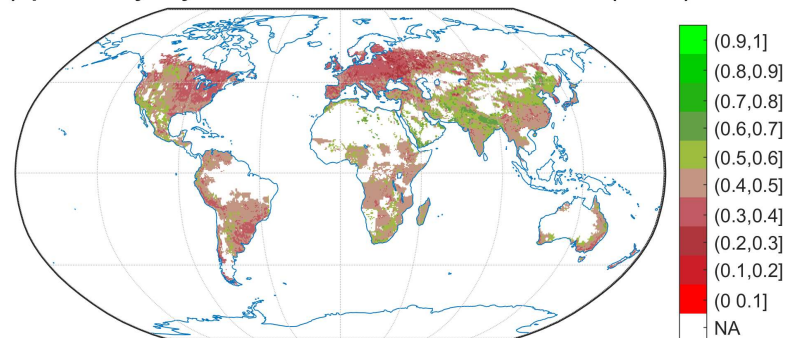
However, even with proper agricultural management practices, there is a 75% chance that NT will lead to a yield decrease in some part of the tropical regions for cotton (Appendix C13d), maize (Appendix C15d), rice (Appendix C18d), sorghum (Appendix C21d), soybean (Appendix C24d), and sunflower (Appendix C27d); In some part of China for rice (Appendix C18d), sorghum (Appendix C21d), soybean (Appendix C24d), and sunflower (Appendix C27d); In eastern EU for maize (Appendix C15d), sorghum (Appendix C21d), and soybean (Appendix C24d); And in North-eastern America for maize (Appendix C15d).

The productive performance of conservation agriculture under past climate condition

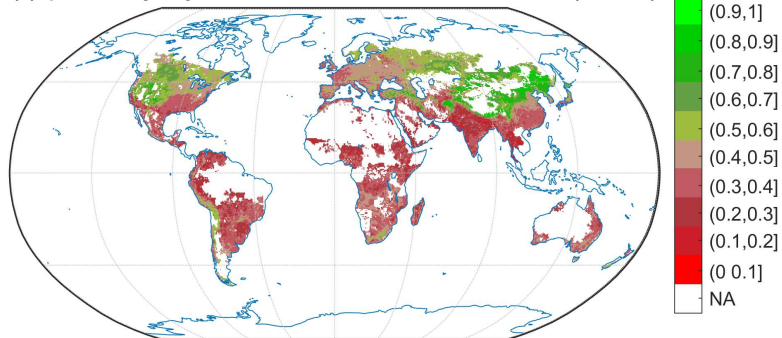
(a). probability of yield increase for winter wheat with CA (+F+WD)



(b). probability of yield increase for winter wheat with CA (-F-WD)



(c). probability of yield increase for winter wheat with NT (+F+WD)



(d). probability of yield increase for winter wheat with NT (-F-WD)

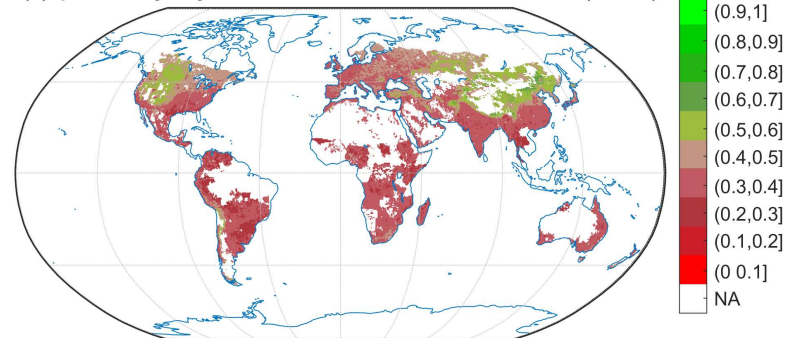


Figure 4.3 | Probability of yield gain with CA and NT vs. CT winter wheat. Only the cropping regions were presented. The different colors indicated different probabilities of yield gain from CA and NT comparing to CT system. The greener color indicated a higher probability of yield gain. +/- F indicated NT or CA and CT with/without field fertilization. +/- WD indicated NT or CA and CT with/without weed and pest control.

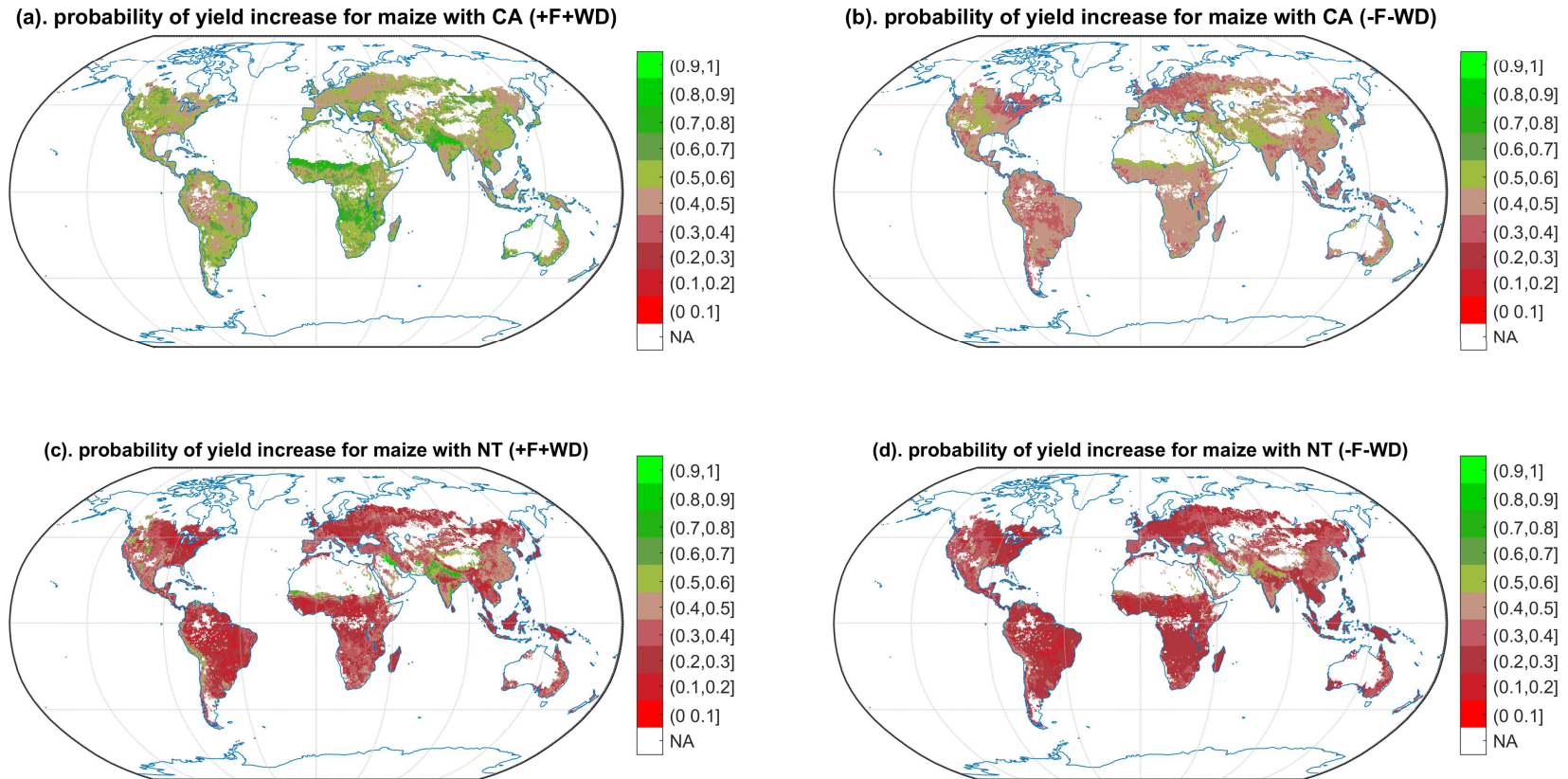
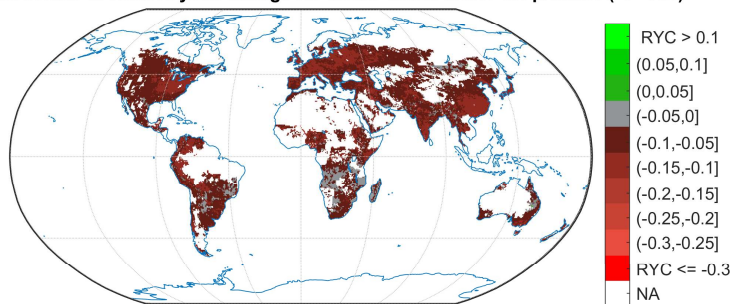


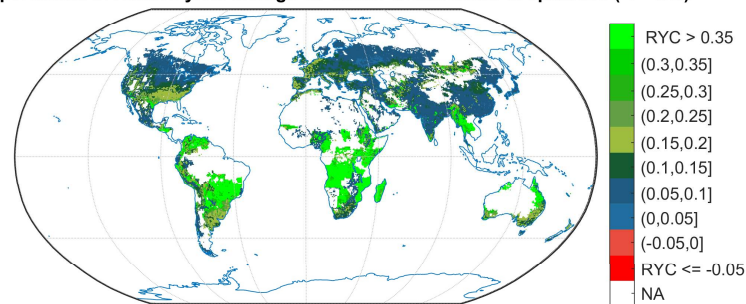
Figure 4.4 | Probability of yield gain with CA and NT vs. CT maize. Only the cropping regions were presented. The different colors indicated different probabilities of yield gain from CA and NT comparing to CT system. The greener color indicated a higher probability of yield gain. +/- F indicated NT or CA and CT with/without fertilization. +/- WD indicated NT or CA and CT with/without weed and pest control.

The productive performance of conservation agriculture under past climate condition

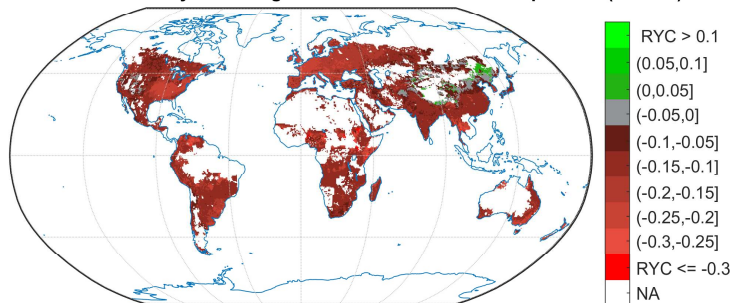
(a). 25th percentile of relative yield change for winter wheat under CA practice (+F+WD)



(b). 75th percentile of relative yield change for winter wheat under CA practice (+F+WD)



(c). 25th percentile of relative yield change for winter wheat under NT practice (+F+WD)



(d). 75th percentile of relative yield change for winter wheat under NT practice (+F+WD)

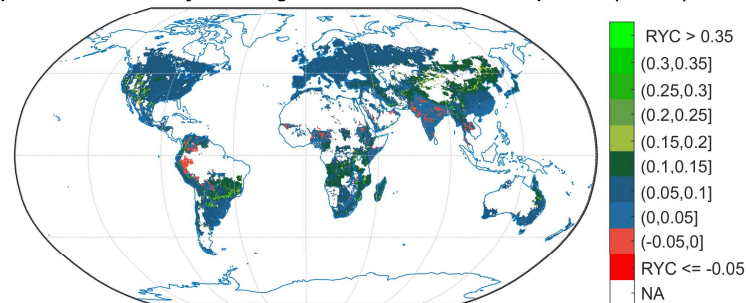


Figure 4. 5 | Relative yield change probability (1st and 3rd quartile estimate) of shifting CT to CA/NT for winter wheat, with fertilization and weed and pest control (+F+WD). There was a 75% chance that the relative yield change will be higher than the ratio shown on the map in plot a and c, and conversely a 25% chance that the relative change will be lower. There was a 75% chance that the relative yield change will be lower than the ratio shown on the map in plot b and d, and conversely a 25% chance that the relative change will be higher. The colors indicated different levels of yield change ratio, and the reddish colors indicated the negative yield change or yield loss.

4.5 Discussion

As the probabilities and plausible ranges of yield gain and loss with CA and NT systems have not been mapped in previous meta-analyses^{1,9,11}, our results bring meaningful and novel information to policymakers and agricultural extension services. In this study, we were able to identify the regions that have higher or lower probability of yield gain from shifting CT to CA and NT for eight major field crops. The magnitude of these gains was assessed, as well as the potential yield losses.

Although based on an expanded dataset, our study has several limitations. Most of the data collected pertains to humid climates rather than arid regions. Crop irrigation was considered only as a categorical variable here due to a lack of global data on this practice, but still proved meaningful in terms of yield impacts. Finally, to deal with missing climate and soil data in the selected papers, we used climate and soil data from external databases on a systematic basis. Consequently, crop growing season, precipitation, potential evapotranspiration, minimum temperature, average temperature, maximum temperature throughout the growing season, and soil texture may not always match local records. However, the use of external databases allowed us to analyse the effects of the inter-annual and intra-annual climate variabilities on CA and NT productivity.

Our study revealed large differences in the likelihood of yield gains associated with the adoption of CA (or NT) across crops, crop management practices, geographical regions, and climatic conditions. Based on our results, NT appeared more likely to increase yields in dry conditions compared to wet conditions, especially when it combined with soil cover. The potential benefits of such practice are well known.

The layer of crop residues retained on the soil surface in no-till systems reduces soil evaporation and water runoff^{29,30}, fosters the build-up of organic matter in soils³¹, preserves soil water resources for crops³², increases soil water retention capacity and mitigates drought effects³³⁻³⁵. These factors all contribute to increase the probability of yield gain. Conversely, in humid regions, the comparative advantages of CA or NT with soil cover were no longer evident and can even be detrimental in the case of soils prone to waterlogging¹. In some other conditions, such as winter crop in cold region, we did notice that not covering the soil increased the chance of yield gain compared to continuous soil cover. We showed that winter wheat in northeast of China, NT has better performance than CA, this might be because the soil cover reduced the mean soil temperature³⁶, which delayed the crop establishment and growth^{4,37,38}. However, it is also reported that residue cover could decrease the rate of soil temperature change³⁶, increase the minimum soil temperature in extreme cold conditions³⁹⁻⁴¹, and provide a buffer layer that can increase the crop resistance to the increasing climate variability and the occurrence of extreme events⁴. Therefore, soil cover reduces the risk of crop failure and increased yield stability. The fact that soil cover management had the largest positive impact on the productivity of NT, compared to other management practices including crop rotation and the control of weed and pest, was also reported in previous studies^{1,42}. Despite the recognized positive effects of residue cover and crop rotation, these two practices were not always implemented with NT systems⁴³.

Our results also showed that, with integrated weed and pest management, CA systems tend to perform slightly better than without (Figure 4.1d), which might indirectly suggest that the crop residue cover used in CA may increase the weed or pest pressure in dry conditions^{44,45}. While in humid condition, CA might have a slightly higher probability of yield gain in the absence of weed control. This may be due to a greater competition for water resources between crops and weeds when weeds were not controlled^{46,47}, leading to dryer conditions and to an increased probability of yield gain with CA. Our results showed again that CA and NT had a higher probability of yield gain under fertilized conditions¹.

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Overall, we showed that CA has a better productivity than NT, especially when combined with the proper agronomical practices of fertilization and integrated weed and pest management. Therefore, we recommend that NT systems should be implemented with soil cover, crop rotation (thus following the definition of Conservation Agriculture by the FAO), crop fertilization, integrated weed and pest management, and all the other good agronomic practices like good seed, water management. Although CA may not always outperform CT concerning on crop yield, CA can provide a range of ecosystem services far beyond biomass production, those ecosystem services included improve the soil health, reduce the soil erosion risk, etc.⁴⁸, while the present traditional tillage systems are resulting in serious land degradation, which will increase the risk of food insecurity in the future, and it will increase emissions and reduce carbon sinks⁴⁹. Therefore, CA is a promising practice that can be promoted to sustain the long-term food production.

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Chapter 5 The productive performance of conservation agriculture under climate change

This chapter is published in Nature Climate Change (2021) and can be accessed through this link: <https://doi.org/10.1038/s41558-021-01075-w>. In the chapter, we trained the classification model based on the random forest which the best classification model based on the machine learning pipeline presented in chapter 3. Here we mapped the productive performance of CA and NT systems vs. CT systems at global scale, and how this performance change under climate change (current scenario: 2011 – 2020, future scenario: 2051-2060).

The impact of climate change on the productivity of conservation agriculture

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5.1 Abstract

Conservation agriculture (CA) is being promoted as a set of management practices that can sustain crop production while providing positive environmental benefits. However, its impact on crop productivity is hotly debated, and how this productivity will be affected by climate change remains uncertain. Here we compared the productivity of CA systems and their variants based on no tillage (NT) vs. conventional tillage (CT) systems for 8 major crop species under current and future climate conditions using a probabilistic machine-learning approach at the global scale. We reveal large differences in the probability of yield gains with CA across crop types, agricultural management practices, climate zones, and geographical regions. For most crops, CA performed better in continental, dry and temperate regions than tropical ones. Under future climate conditions, the performance of CA is expected to mostly increase for maize over its tropical areas, improving the competitiveness of CA for this staple crop.

5.2 Main

Conservation agriculture is a crop production system based on three principles: minimum soil disturbance (going as far as NT), permanent soil cover with crop residues, and diversified crop rotation (with at least three crop species involved)¹. In compliance with sustainability goals, CA is designed to sustain crop production on the long-term while improving crop resilience to climate change and protecting the environment. Benefits of CA have been demonstrated in terms of enhancing soil carbon sequestration, improving soil quality, reducing soil erosion, and increasing biodiversity^{2,3}. However, since crop yield depends on many interacting factors including local climate conditions⁴, soil characteristics⁵, and management practices⁶, it is difficult to assess the potential of CA to increase agricultural productivity. Besides CA (as defined according to the above principles, which follow the Food and Agriculture Organization's (FAO) approach of CA⁷), this issue also applies to its variants such as NT without crop rotations and soil cover, NT with soil cover but no rotation, and NT with rotation but no soil cover. Based on the findings of recent meta-analyses^{5,6,8}, these systems are likely to lead to a yield reduction⁶ compared to CT, except for regions facing water limitations. However, the heterogeneity of the experimental results on CA (and their variants) vs. CT is very large, and their outcome varies as a function of climate conditions⁶ and management practices^{6,8,9}. The studies of Pittelkow et al.^{6,8} relied on a synthetic aridity index to characterize the characteristics of climate, which makes it hard to analyze the response of CA productivity to inter-annual weather variability or to predict the impact of future changes in climate. To date, a

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comprehensive, global synthesis of the impact of climate change on the productivity of CA with respect to CT systems is still lacking.

Here, we compared the crop yields of CA systems (and their variants) vs. CT under current and future climate conditions based on a new, global database^{10,11} of paired yield observations of CA (and their variants) vs. CT. This dataset includes the most recently published experimental studies on this topic, a detailed description of agricultural management practices (including crop irrigation, fertilization, weed and pest control, soil cover management and crop rotation), and a broad set of climatic variables from external databases, such as precipitation (P)¹², minimum air temperature (Tmin)¹³, average air temperature (Tave)¹², maximum air temperature (Tmax)¹³ and potential evapotranspiration (E)^{14,15} over the crop growing seasons¹⁶. As an indicator of water availability for crops, the precipitation balance (PB) was defined as (P – E) over the growing season⁵.

A machine learning model based on random forest¹⁷ was trained and cross-validated based on 4403 paired yield data of CA (and its variants) vs. CT from the dataset. The model was used to map the probability of yield gain from CA like systems vs. CT systems, i.e. $\left(\frac{Yield_{CA\ or\ variants}}{Yield_{CT}} > 1\right)$, considering different agricultural management practices successively (with/without soil cover, rotation, weed and pest control, irrigation, fertilization). The analysis was conducted at a spatial resolution of $0.5^\circ\ latitude \times 0.5^\circ\ longitude$ based on current (2011-2020) and future (2051-2060) average climate conditions for eight major crops worldwide (spring barley, cotton, maize, rice, sorghum, soybean, sunflower, and winter wheat). For each crop, maps were then produced and compounded to derive the accumulated fractions of the cropping area achieving a given yield gain probability of CA vs. CT under current climate conditions. Similarly, the accumulated fractions of the cropping area achieving a given level of change in this probability under future climate conditions were calculated. These fractions show the proportions of cropping area with low to high probabilities of yield gain from CA vs. CT, and with low to high changes for this probability under climate change. Both proportions were computed at the global scale and across different climate zones¹⁸. The results were used to evaluate the impact of crop management practices on the performance of CA, to identify the favorable and unfavorable climate zones for CA, and to assess the climate change impact on the productivity of CA in different climate zones. The details of model setting for global projection are explained in the **Methods** section and further detailed in Appendix D table 1.

Our results show that, under current climate conditions, NT (in the absence of soil cover and rotation) is associated with a very low probability of yield gain compared to CT (Appendix D figure 1.a4-h4, Appendix D figure 1.a5-h5). CA shows better performance than NT due to the presence of soil cover and use of crop rotation but does not systematically outperform CT (Appendix D figure 1.a1-h1, Appendix D figure 1.a4-h4). With well managed field fertilization and integrated weed and pest control, CA stands high chances of outperforming CT except in tropical regions (Figure 5.1, Appendix D figure 1.a2-h2). The performance of CA is also slightly improved in non-irrigated fields, except in tropical regions (Figure 6.1, Extended data figure 1).

For most of the studied crops, the overall probability of yield gain from CA is higher in continental, dry, and temperate regions than in tropical regions (Figure 5.1a, Figure 7.1d-g, Appendix D figure 1.a2-g2). The probability of yield gain with CA is particularly low for rice. For this crop, the probability of yield increase/gain is lower than 0.5 (which indicates a higher probability of yield loss) over about 60% of its global cropping area, and in about 85% of its cropping area in the tropics (Figure 5.1d, Appendix D figure 1.d2).

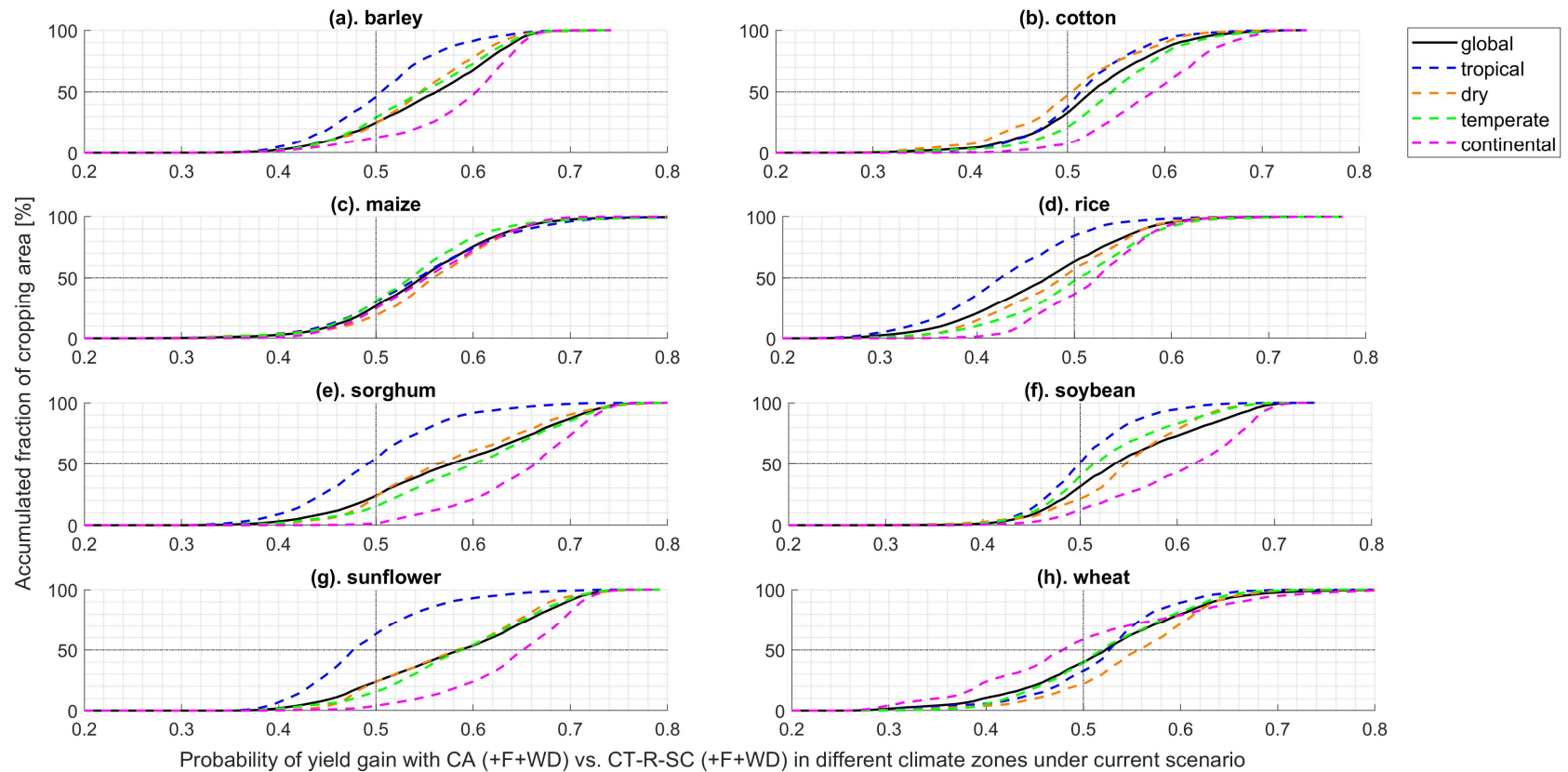


Figure 5.1 | Accumulated fraction of cropping area as a function of the probability of yield gain with CA (+F+WD) vs. CT-R-SC (+F+WD) for eight major crops (a-h) and different climate zones. The results are based on the average climate conditions over 2021-2020 simulated by the Ipsi-cm5a-lr climate model and RCP 4.5 scenario.

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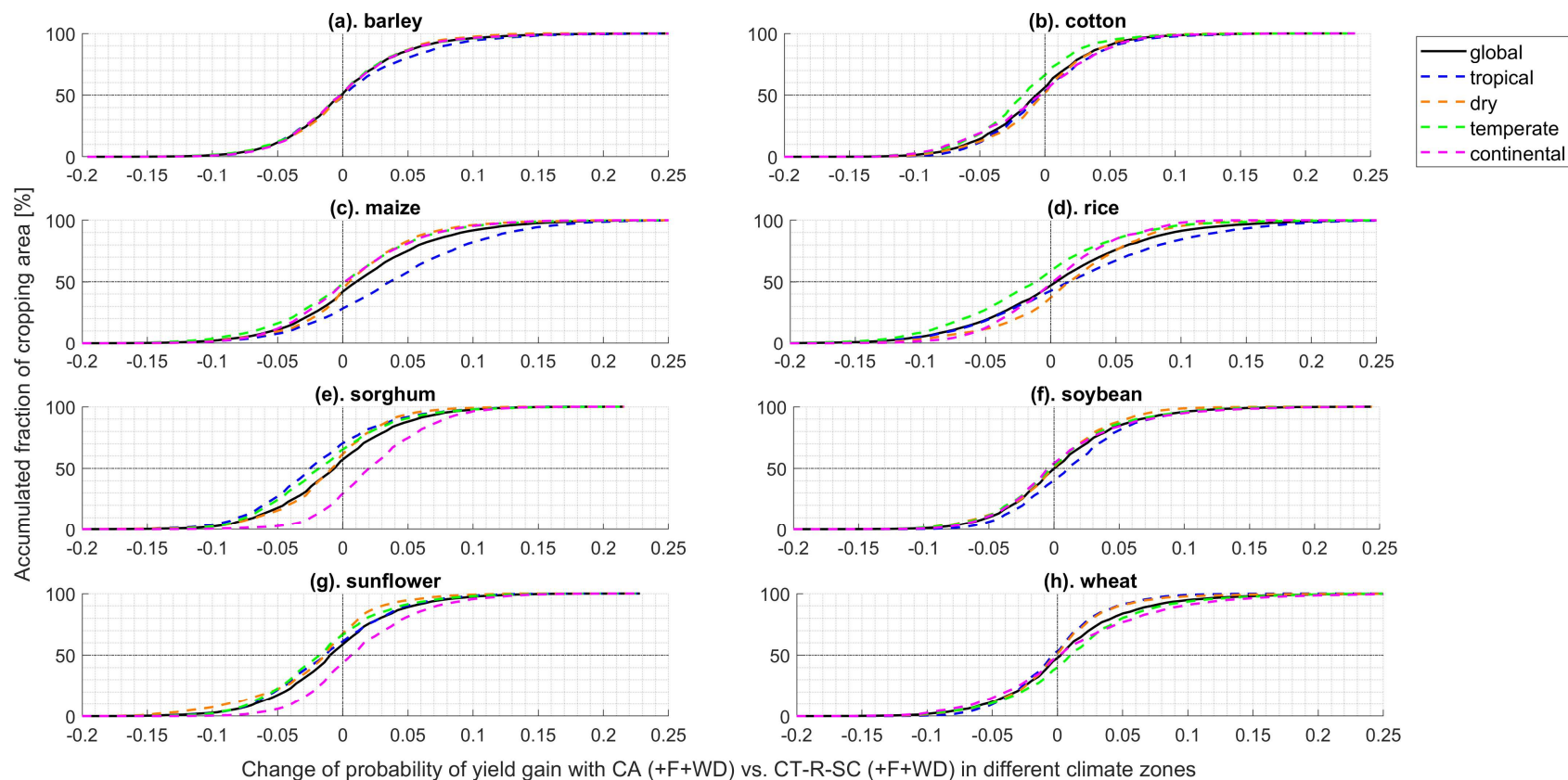


Figure 5.2 | Accumulated fractions of the cropping area for different levels of change in the probability of yield gain with CA (+F+WD) vs. CT-R-SC (+F+WD). The results are based on the mean climate conditions in 2021-2020 for the current scenario and 2051-2060 for the future scenario (Ipsl-cm5a-lr climate model and RCP 4.5 scenario). Change of probability corresponds to the difference between the probability under future climate and the probability under current climate.

For several crops and climate regions, the estimated effect of climate change on the probability of yield increase with CA is relatively moderate. Over approximately half of the cropping areas, a decrease of up to 10% in this probability is expected, while in the other half an increase of up to 15% may be anticipated (Figure 5.2). However, in some important cases the effect of climate change is stronger, especially for maize in tropical regions where the probability of yield gain with CA increases in about 70% of the cropping area. Besides, for more than 20% of the maize cropping area in this climate zone, the increase on the probability of yield increase is higher than 10% (Figure 5.2c). An increase in yield gain is also expected for more than 60% of the cropping area for rice in dry regions and for soybean in tropical regions (Figure 5.2d, Figure 5.2f). This fraction rises to more than 70% of the cropping area for sorghum in continental regions (Figure 5.2e).

Probabilities of yield gain with CA show important geographical variations under both current and future climate conditions for maize (Figure 5.3, Figure 5.4) but also for other crop species (Appendix D figure 2). Yield gains with CA systems and their variants are more likely in relatively higher latitude regions (> 40 Deg.) than lower latitudinal bands for barley, cotton, rice, sorghum, soybean, and sunflower (Appendix D figure 3), in line with the results showed on Figure 5.1. CA systems and their variants perform better in northwestern America, northwestern India, northern sub-Saharan Africa, and southern Russia than in northeastern America, western and central Europe, and central part of sub-Saharan Africa (Figure 5.3, Appendix D figure 2). For maize, in the absence of fertilizer inputs and integrated weed and pest control, the probability of yield gain from CA is higher than 0.5 in dry areas of western US, southern Russia, northern India, and North China Plain. The yield gain probability drops to 0.4 in the Laurentian Plateau of Canada, northcentral and northeastern US, and part of western and central Europe (Figure 5.3b). For other crop species, CA has a higher chance to lead to a yield loss compared to CT in the tropical regions (Appendix D figure 2.a2-h2), southern China (Appendix D figure 2.e2-h2), northeastern America, western and central Europe (Appendix D figure 2.a2, Appendix D figure 2.e2, Appendix D figure 2.f2, Appendix D figure 2.h2). Conversely, when implemented with field fertilization and integrated weed and pest control, CA has a higher chance to outperform CT in the major cropping areas for barley, sunflower and wheat (Appendix D figure 2.a1, Appendix D figure 2.g1-h1; Appendix D figure 5).

Our results also show that soil cover has a stronger (and positive) effect on yield gain probability than other management practices such as fertilizer inputs, weed and pest control, and crop rotation. Thus, without soil cover, NT systems show a lower probability of yield gain than full-blown CA (Appendix D figure 2), which in line with the input importance ranking obtained with our model (Extended data figure 2). Note that, although management practices have a substantial impact on yield gain probabilities, they have limited influences on the geographical variations of these probabilities (Appendix D figure 1, Appendix D figure 2).

The maps reporting the differences of yield gain probabilities between current (2010-2020) and future (2051-2060) climate conditions (see Appendix D table 1 for projection details, see Figure 5.5 and Appendix D figure 4 for results) reveal important geographical disparities in the effects of climate change on the odds of yield gain with CA systems and their variants, and we have noticed that climate change could have a positive effect in some regions for certain crop species. However, although the probability of yield gains with CA systems and their variants vs. CT systems tended to increase under future climate scenarios, it remained below 0.5 in many regions. Under climate change scenario RCP 4.5, the probability of yield gain is expected to increase in most of the northcentral and northeastern US for barley, maize, sorghum, soybean, and sunflower (Appendix D figure 4.a1, Figure 5.5a, Appendix D figure 4.e1-g1); In most of the central-western region in Brazil together with the Amazon basin, western Africa, and Asia-Pacific for maize, rice, and soybean (Figure 5.5a, Appendix D figure 4.d1, Appendix D figure 4.f1); In many parts of India for

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cotton, maize, rice, sorghum, soybean, sunflower (Appendix D figure 4.b1, Figure 5.5a, Appendix D figure 4.d1-g1); In most of Europe for barley, maize, sorghum, soybean, sunflower and wheat (Appendix D figure 4.a1, Figure 5.5a, Appendix D figure 4.e1-h1); In northeastern China for rice, sorghum (Appendix D figure 4.d1-e1). Conversely, the overall performance of CA will decrease in the future in most temperate regions in South America, including Uruguay, southern Brazil, and northern Argentina for barley, cotton, rice, sorghum, and sunflower (Appendix D figure 4.a1-b1, Appendix D figure 4.d1-e1, Appendix D figure 4.g1); In the south of Russia and northwest of Asia for barley, cotton, soybean, sunflower (Appendix D figure 4.a1-b1, Appendix D figure 4.e1, Appendix D figure 4.g1); In southern China for cotton, maize, rice, sorghum, sunflower (Appendix D figure 4.b1, Figure 5.5a, Appendix D figure 4.d1-e1, Appendix D figure 4.g1). Crop management practices have limited influence on the estimated impact pattern of climate change on yield gain probability (Appendix D figure 1).

To assess the model sensitivity to climate models and climate change scenarios, we plotted the fractions of global cropping areas corresponding to increasing levels of yield gain probability (from -0.1 to 0.2) for four different climate models and RCP scenarios (Extended data figure 3). The choice of the climate models had very little impact on the results (Extended data figure 3i-p), although the results obtained with Hadgem2-es, and Ipsi-cm5a-lr are somewhat more extreme than those obtained with Gfdl-esm2m and Miroc5. The sensitivity to the climate change scenarios was more important (Extended data figure 3a-h). Although the main conclusions remain similar across all RCP scenarios, the stronger changes in yield gain probability are obtained under RCP 8.5 compared to RCP 6.0, RCP 4.5, and RCP 2.6 (Extended data figure 3a-h). In particular the changes of yield gains become larger for maize and rice under RCP 8.5.

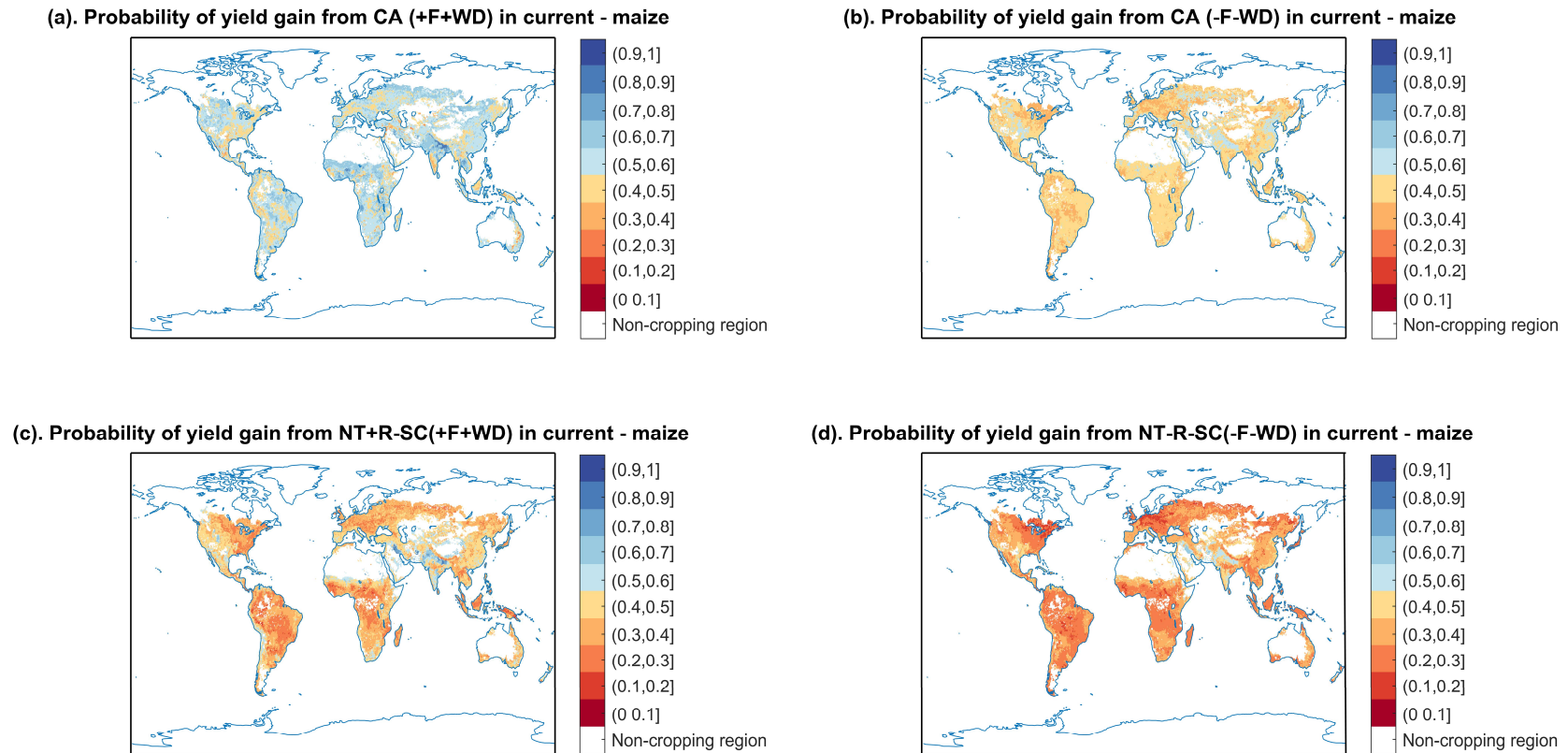


Figure 5.3 | Probability of yield gain with CA systems (a, b) and NT variants (c, d) vs. CT without soil cover (-SC) and without crop rotation (-R) for maize under current climate conditions (average climate conditions over 2011-2020 simulated by the Ipsi-cm5a-1r climate model and for the RCP 4.5 scenario). Regions with a probability of yield gain lower than 0.5 were highlighted in red (and in blue shades when the probability was higher). Non-cropping region indicated both the regions without maize crops and regions where climate data were unavailable. Plot a compares the performance of CA (+F+WD) vs. CT-R-SC (+F+WD); Plot b compares the performance of CA (-F-WD) vs. CT-R-SC (-F-WD); Plot c compares the performance of NT+R-SC (+F+WD) vs. CT-R-SC (+F+WD); Plot d compares the performance of NT-R-SC (-F-WD) vs. CT-R-SC (-F-WD).

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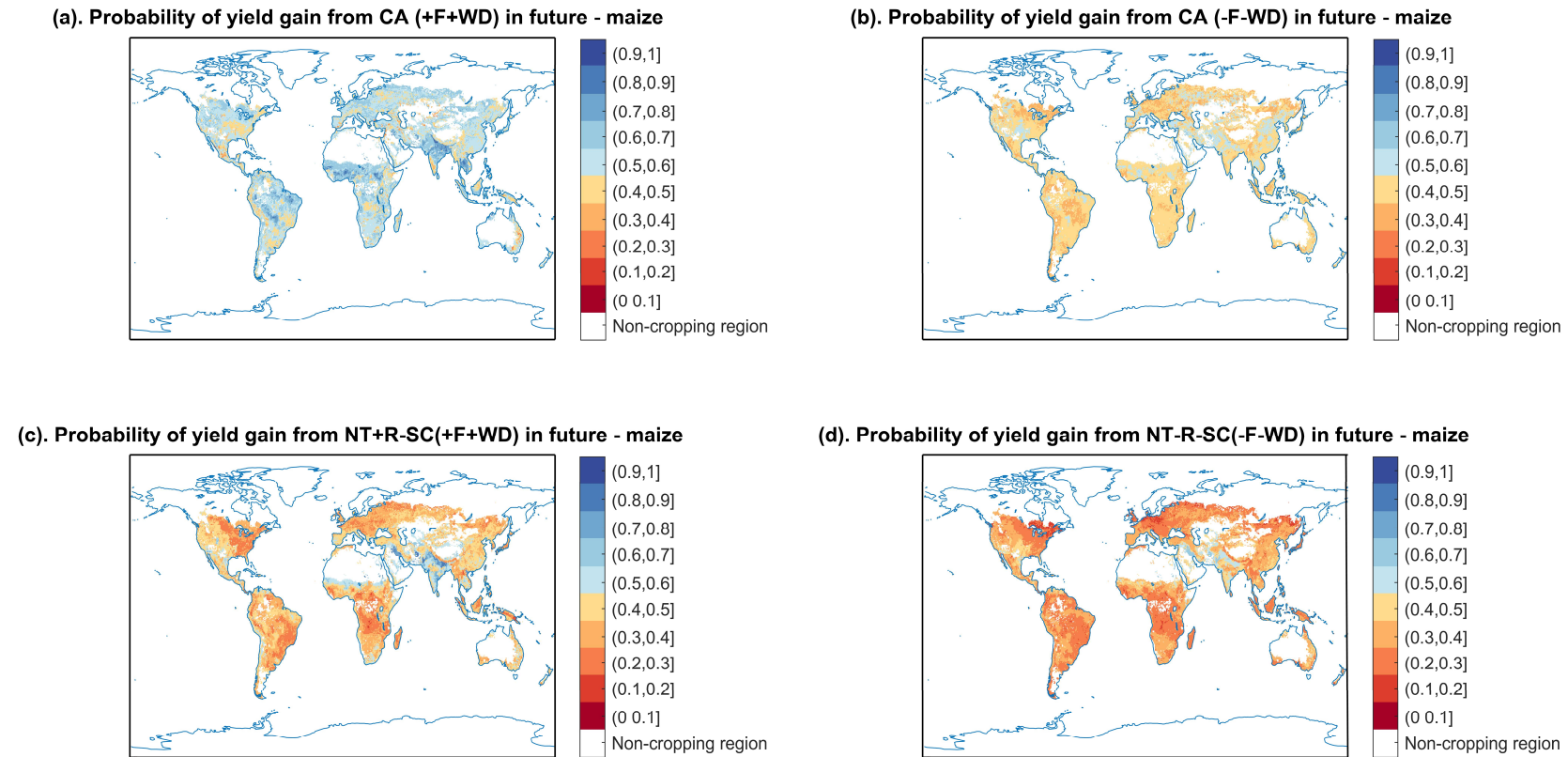


Figure 5. 4 | Probability of yield gain with CA systems (a, b) and NT variants (c, d) vs. CT without soil cover (-SC) and without crop rotation (-R) for maize under future climate conditions (average climate conditions over 2051-2060 simulated by the Ipsl-cm5a-lr climate model and for the RCP 4.5 scenario). Regions with a probability of yield gain lower than 0.5 were highlighted in red (and in blue shades when the probability was higher). Non-cropping region indicated both the regions without maize crops and regions where climate data were unavailable. Plot a compares the performance of CA (+F+WD) vs. CT-R-SC (+F+WD); Plot b compares the performance of CA (-F-WD) vs. CT-R-SC (-F-WD); Plot c compares the performance of NT+R-SC (+F+WD) vs. CT-R-SC (+F+WD); Plot d compares the performance of NT-R-SC (-F-WD) vs. CT-R-SC (-F-WD).

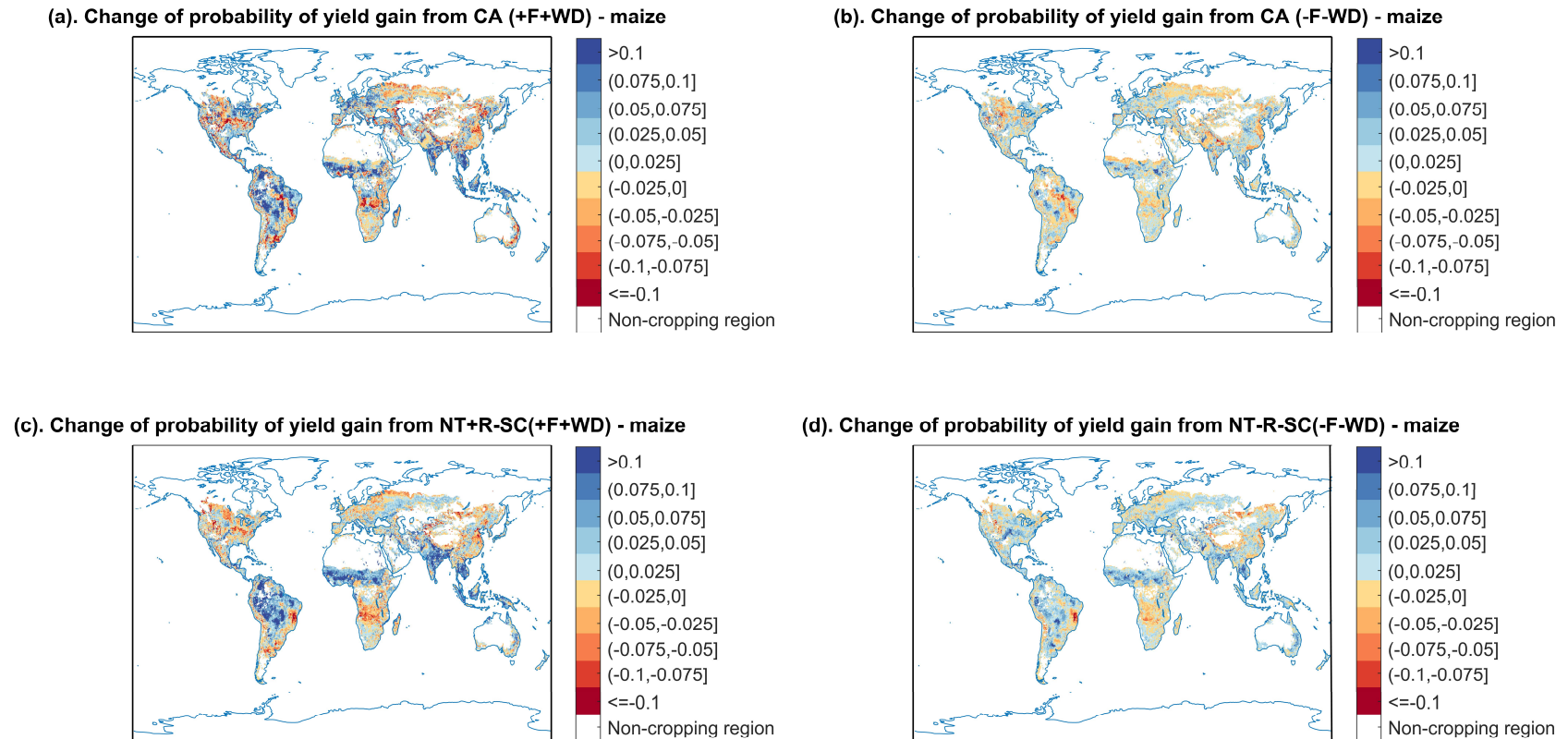
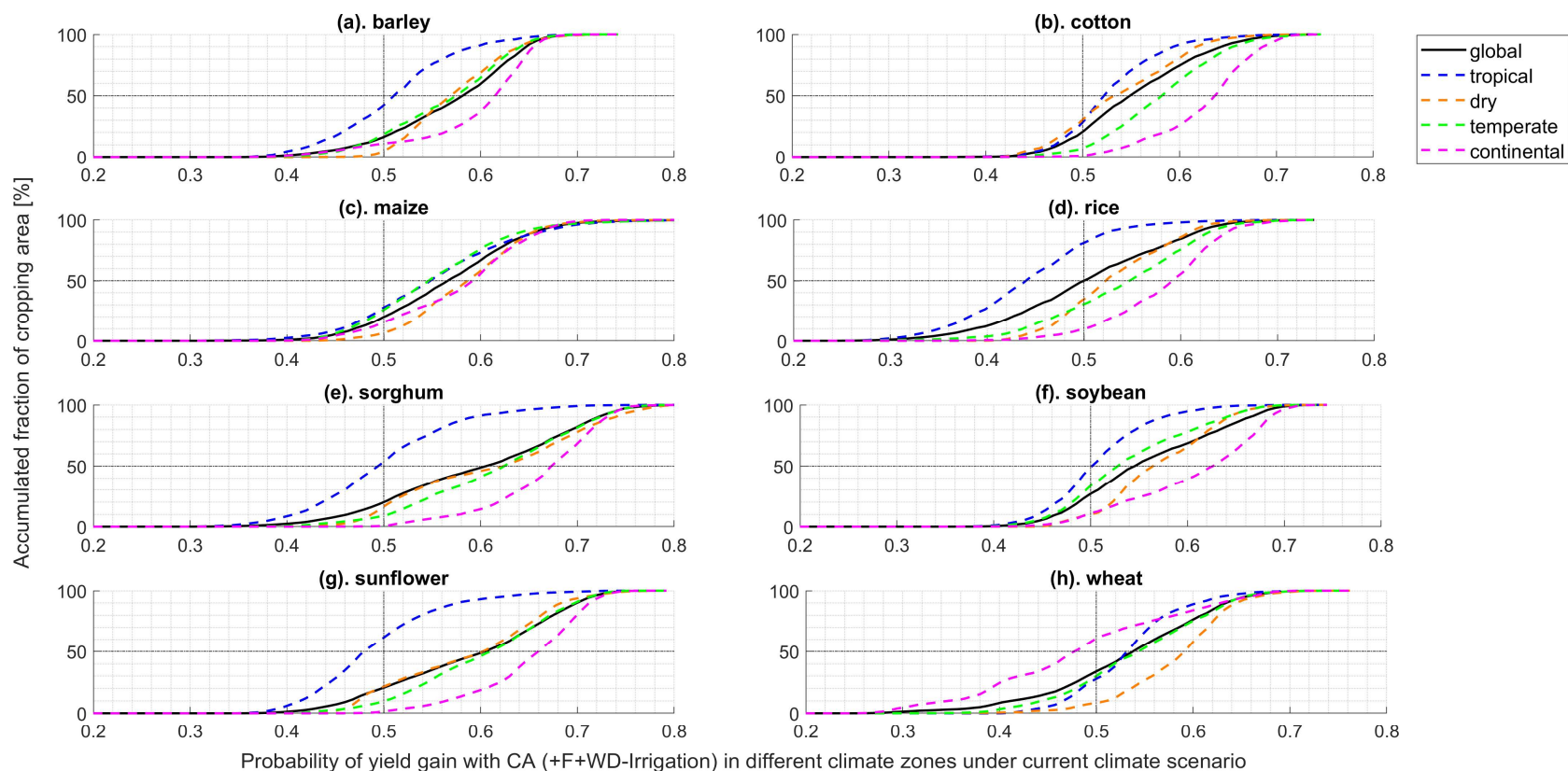
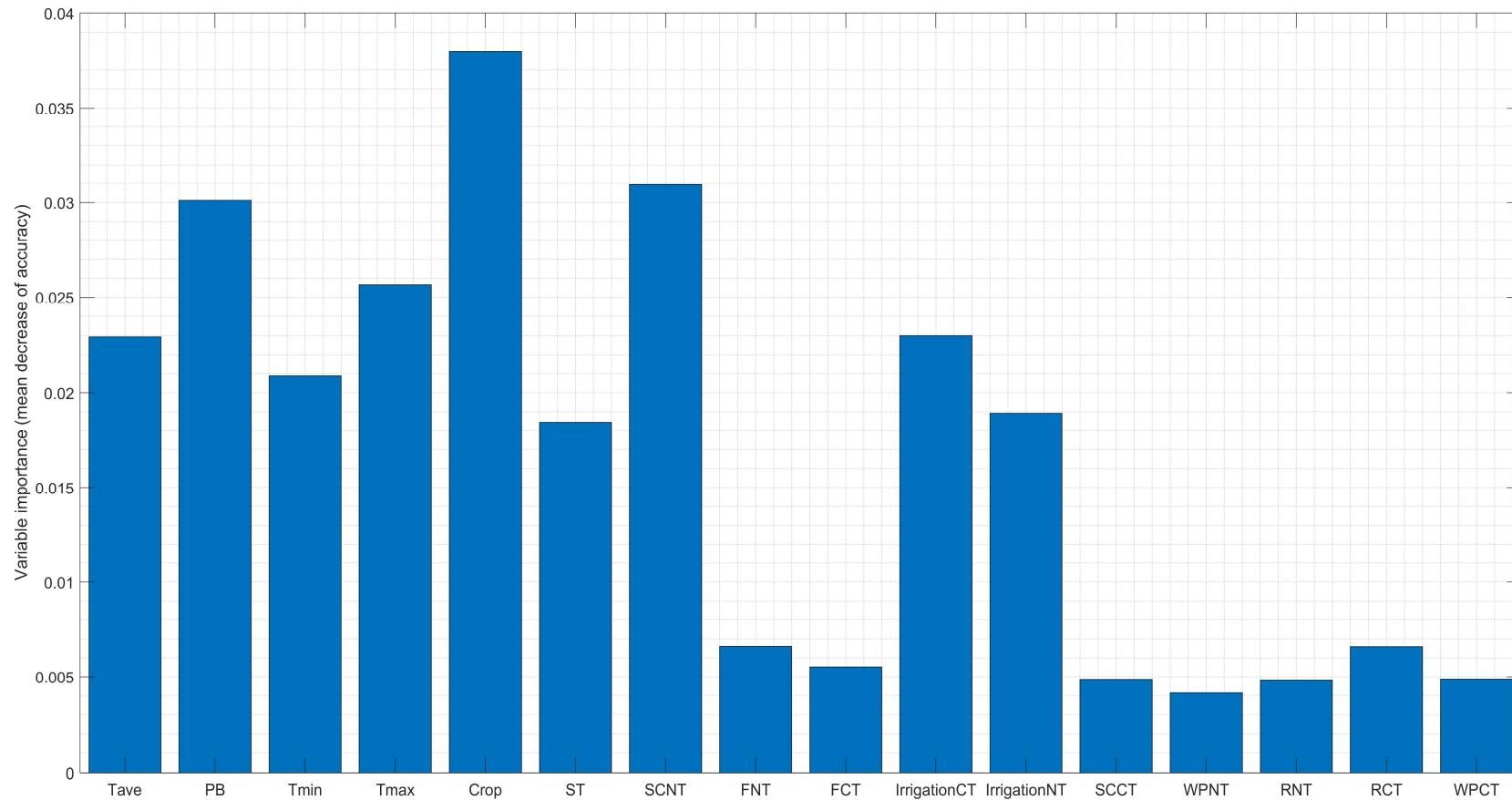


Figure 5.5 | The change of probability of yield gain with CA systems (a, b) and NT variants (c, d) vs. CT without soil cover (-SC) and without crop rotation (-R) for maize under climate change (future vs. current). regions with a decreasing trend were depicted in red, while those with an increase in yield gain probability were depicted in blue. The results are based on the average climate conditions over 2011-2020 (current) and over 2051-2060 (future) simulated by Ipsl-cm5a-lr climate model and for the RCP 4.5 scenario. Non-cropping region indicated both the regions without maize crops and regions where climate data were unavailable. Plot a shows the change of probability of yield gain with CA (+F+WD) vs. CT-R-SC (+F+WD) under climate change; Plot b shows the change of probability of yield gain with CA (-F-WD) vs. CT-R-SC (-F-WD) under climate change; Plot c shows the change of probability of yield gain with NT+R-SC (+F+WD) vs. CT-R-SC (+F+WD) under climate change; Plot d shows the change of probability of yield gain with NT-R-SC (-F-WD) vs. CT-R-SC (-F-WD) under climate change.

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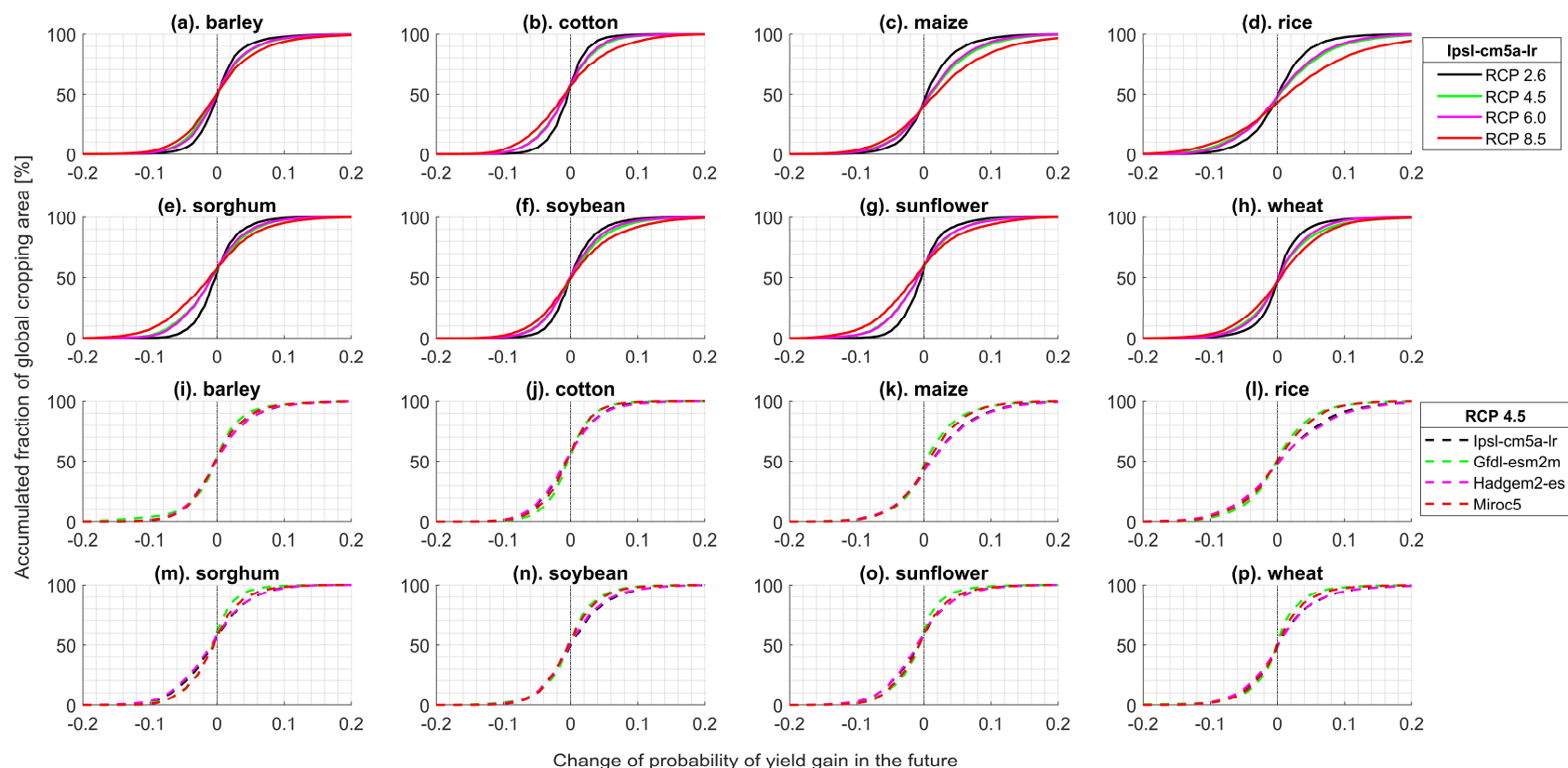


Extended data figure 1 | Accumulated fraction of the cropping area as a function of the probability of yield gain under CA (+ F+WD - Irrigation) vs. CT-R-SC (+F+WD -Irrigation) systems in different climate regions. Accumulated fraction of the cropping area as a function of the probability of yield gain under CA (+F+WD - Irrigation) vs. CT-R-SC with fertilization (+F) and weed and pest control (+ WD) without irrigation (-Irrigation) for eight major crops (a-h) and different climate zones. The results are based on the average climate conditions over 2021-2020 simulated by the Ipsi-cm5a-lr climate model and RCP 4.5 scenario.



Extended data figure 2 | Relative importance ranking of the model inputs. The importance was defined by the mean decrease in accuracy in ‘cforest’ model. Where ‘PB’ indicates precipitation balance over crop growing season; ‘Tmax’ indicates maximum temperature over crop growing season; ‘Tave’ indicates average temperature over crop growing season; ‘Tmin’ indicates minimum temperature over crop growing season; ‘Crop’ indicates the crop species; ‘ST’ indicates soil texture; ‘SCNT’ indicates soil cover management under the variants of no tillage systems; ‘SCCT’ indicates soil cover management under CT systems; ‘RNT’ indicates crop rotation management under the variants of no tillage systems; ‘RCT’ indicates crop rotation management under CT systems; ‘FNT’ indicates management of crop fertilization under the variants of no tillage systems; ‘FCT’ indicates crop management of crop fertilization under CT systems; ‘WDNT’ indicates management of weed and pest control under the variants of no tillage systems; ‘WDCT’ indicates crop management of weed and pest control under CT systems.

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Extended data figure 3 | The accumulated fraction of the cropping area in different level of change on the probability of yield gain under CA (+F+WD) vs. CT-R-SC (+F+WD) under different crops, climate models and RCP scenarios. The accumulated fraction of the cropping area in different level of change on the probability of yield gain under CA (+F+WD) vs. CT-R-SC (+F+WD) for different crops, climate models and RCP scenarios. The results are based on the average climate data in different RCP scenarios (RCP2.6, RCP 4.5, RCP 6.0, RCP8.5) in Ipsi-cm5a-lr model, and RCP 4.5 scenario in different climate models (Ipsi-cm5a-lr, Gfdl-esm2m, Hadgem2-es, Miroc5) for both current (2021-2020) and future (2051-2060) scenarios.

5.3 Discussion

Compared to previous studies on the productivity of CA^{5,6,8,19}, this is the first time that the probabilities of yield gain resulting from a shift from CT to several variants of CA systems have been mapped for current and future climate scenarios. Thus, our results offer meaningful and new information for policymakers, agricultural extension services and farmers. Relying on a global experimental dataset, we were able to identify favorable and unfavorable climate conditions and geographical regions for the implementation of CA systems for eight major staple crops under current and future climate conditions. Some of the most promising geographical regions in our analysis had also been identified in previous studies¹⁹, but we were able to report information on yield gains as probabilities instead of simpler increase or decrease categories. More importantly, we addressed the impacts of future climate change scenarios and different agricultural management practices on the performance of CA systems and their geographical patterns.

However, there are also limitations in our study. Due to the lack of global quantitative data on crop irrigation, this study was taken into account in our models as a categorical variable. Although a large part of the data considered in this study was collected under humid climate conditions, a significant proportion was obtained in dry regions under rainfed or irrigated conditions. In this study, climate and soil data were extracted from external databases and not from the collected articles because these data were missing or not reported consistently in the individual articles. Consequently, these data might not always match experimental records. The use of external databases has the added benefit of helping us understand how inter- and intra-annual climate variability affects the productivity of CA systems and their variants vs. CT. It is also required to predict the performance of these systems under future climate conditions. Data availability may affect model accuracy. Due to the limited number of observations for these crops, the conclusions obtained for rice and sunflower are more uncertain compared to other crops (Appendix D figure 7). Despite these limitations, the results of our model assessment via the cross-validation are overall satisfactory (See **Methods** and Appendix D figure 7).

We showed that soil cover has a strong positive effect on probability of yield gain. Without soil cover, NT systems are likely to lead to a yield loss compared to CT (Appendix D figure 2.a3-h3). Soil cover reduces soil evaporation and surface runoff and maintains a high level of soil moisture content²⁰⁻²⁸, thus increasing the competitiveness of CA systems especially for dryer climate conditions²⁹⁻³⁴. Therefore, keeping the soil covered by crop residues appears to be an important factor for the success of CA systems. However, in practice, maintaining crop residues might be challenging in some regions, such as Africa, where the crop residues are used to feed livestock³⁵. In such situations, a possible solution would be to rely on alternative sources of plant materials, e.g. residues from cover crops, grass, leaf litter from trees, sawdust, etc.³⁵. Without soil cover, NT has low chance to entail yield gains compared to CT. Under future climate scenarios, the performance of NT is expected to improve in the north of sub-Saharan Africa for maize (Figure 5.5c) and sorghum (Appendix D figure 4.e1), but the probability will remain lower than or close to 0.5.

Although less influential, other farming practices appear to increase the probability of yield gain of CA, in particular fertilization and weed and pest control. Thus, for most crops, CA with field fertilization and weed and integrated pest control outperformed CT in continental, dry and temperate regions, but proved less suitable in tropical regions (Appendix D figure 1.a1-h1, Appendix D figure 2.a1-h1). This overall pattern is in line with previous work⁶, and our results are also consistent with the study of Corbeels et al. (2020)³⁶ who showed that higher productive performance of CA systems in Africa can be expected when CA principles are implemented concomitantly in combination with herbicide application, especially for maize (Appendix D figure 2.c1). However, we also need to note that part of the regional variability in the performance of CA and NT might be related to the diversity of farm characteristics in the different regions under consideration, in particular the level of mechanization and size of farm.

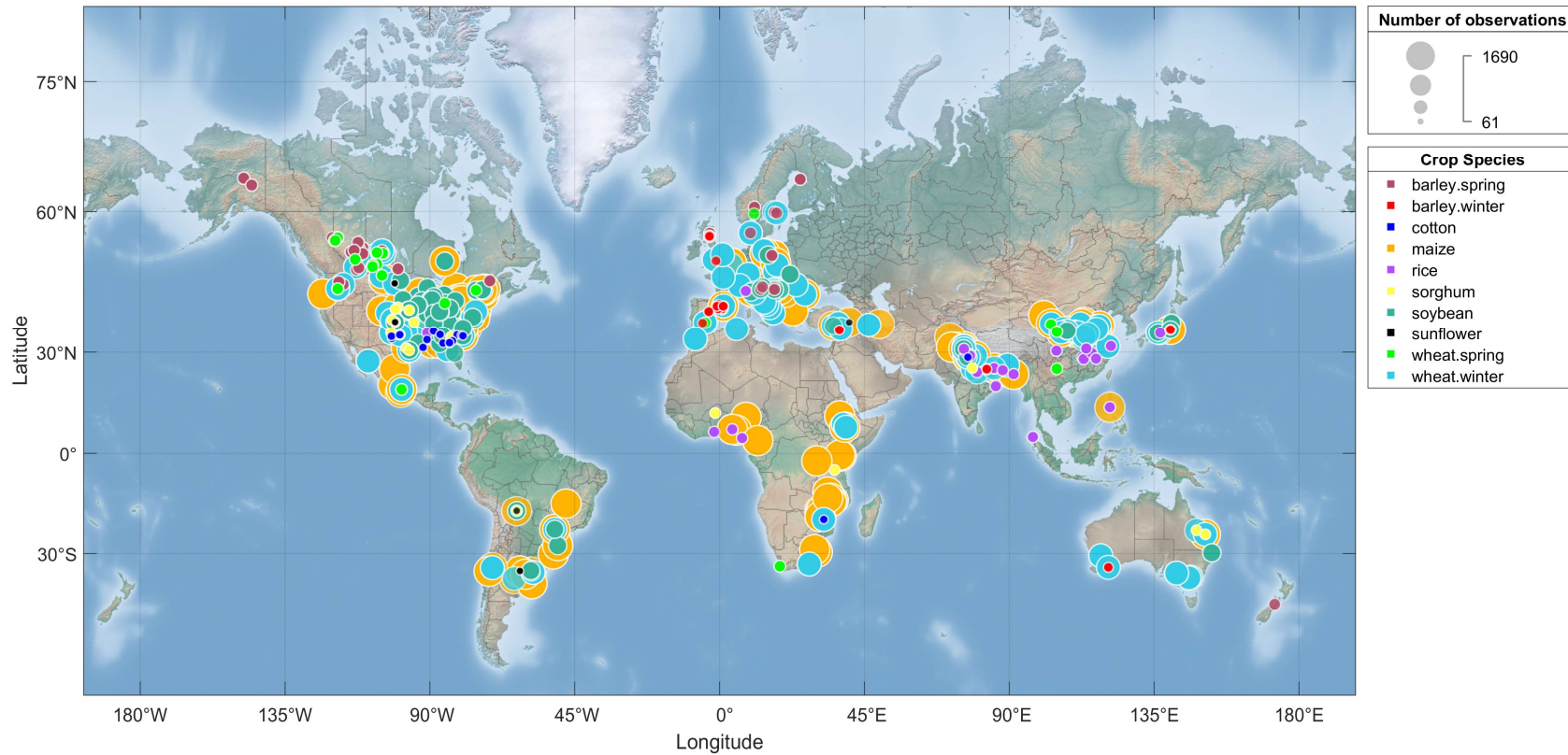
In addition to increasing crop yield, CA systems can potentially improve biodiversity, increase the soil organic matter, and bring about positive environmental externalities such as reduced soil erosion, improved soil quality and enhanced carbon sequestration^{2,3,37}. Moreover, CA could improve the resilience of cropping systems towards the changing climate and increase the stability of crop yields^{38,39}. Although several variants of CA systems may be associated with a high probability of yield loss in many regions, we also showed that, under future climate conditions and with good agricultural management practices, the relative productive performance of CA is expected to increase for several crop species. This is especially true for maize in tropical regions, which further strengthens the competitiveness of CA for this staple crop. Thus, our results support the idea that CA will be a relevant option for cropping systems in the future, capable of ensuring a long-term, sustainable agricultural production for some key cropping areas^{40,41}.

5.4 Methods

5.4.1 Data collection

The literature search was done in February 2020 using the following keywords ‘Conservation agriculture / No-till / No tillage / Zero tillage’ & ‘Yield / Yield change’ in the websites ‘ScienceDirect’ and ‘Science Citation Index (web of science)’. We also collected the papers cited in previous meta-analyses^{5,6,8}, supplemented them by the most recently published experimental studies. A total of 1012 potentially relevant papers were identified by reviewing the title and abstract, these papers were then screened according to the procedure summarized in Appendix D figure 6. More details about this screening and selection procedure were presented in previous studies^{11,42}. In the end, 422 papers were retained (published between 1983 to 2020). From these papers, we were able to extract 4403 paired yield observations from NT and CT for 8 major crop species, including 370 observations for barley (232 observations for spring barley and 138 for winter barley), 94 observations for cotton, 1690 observations for maize, 195 observation for rice, 160 observations for sorghum, 583 observations for soybean, 61 observations for sunflower, 1250 observations for wheat (1041 observations for winter wheat and 209 observations for spring wheat) in 50 countries from 1980 to 2017 (Extended data figure 4). We also retrieved from the papers the information of crop type, year and location of the experiments, and agricultural management activities for both NT and CT systems, including crop irrigation (yes vs. no), the field fertilization (yes vs. no) and the details of the type and amount of fertilizer used, integrated weed and pest control (yes vs. no) and the type of herbicide and pesticide used, crop rotation (yes vs. no) and details of crop sequence and information of cover crops, soil cover (yes vs. no) and the details of residues retention from previous crops or cover crops. Based on this information, we were able to define CA as the combination of NT with soil cover and rotation and to distinguish this system from other variants (NT without soil cover and rotation, NT with rotation but without soil cover, NT with soil cover but without rotation). Additional data were extracted from several external databases, pertaining to crop growing season¹⁶, soil texture⁴³ and climate factors such as precipitation (P)¹², minimum temperature (Tmin)¹³, average temperature (Tave)¹², maximum temperature (Tmax)¹³ and potential evapotranspiration (E)^{14,15} in the growing season¹⁶ in the particular year of the experiment, and the precipitation balance (PB) was defined as precipitation minus total evapotranspiration, which indicated the water availability in the growing season. These data were obtained at a spatial resolution of $0.5^\circ \text{ latitude} \times 0.5^\circ \text{ longitude}$, and if the source data were in a finer spatial resolution, they were downscaled to the resolution of $0.5^\circ \text{ latitude} \times 0.5^\circ \text{ longitude}$.

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Extended data figure 4 | Distributions of experiment site for each crop. This map and the corresponding dataset are presented in ref. 11, 42. This figure was generated by MATLAB R2020a (Version 9.8.0.1451342, <https://fr.mathworks.com/products/matlab.html>). In this meta-dataset¹¹, 4403 paired yield observations were extracted from NT and CT for 8 major crop species, including 370 observations for barley (232 observations for spring barley and 138 for winter barley), 94 observations for cotton, 1690 observations for maize, 195 observation for rice, 160 observations for sorghum, 583 observations for soybean, 61 observations for sunflower, 1250 observations for wheat (1041 observations for winter wheat and 209 observations for spring wheat) in 50 countries from 1980 to 2017.

5.4.2 Model training and cross-validation

The machine learning algorithm random forest¹⁷ was trained to analyze the yield ratios of NT vs. CT as the function of climatic variables, crop types, soil textures, and agricultural management activities. The climatic variables during the growing season such as PB, Tmin/Tave/Tmax were defined as numerical inputs, while crop type, soil texture, and agricultural management activities including crop irrigation, field fertilization, integrated weed and pest control, crop rotation and soil cover management were defined as categorical inputs. The model output was expressed as the probability of yield gain from NT vs. CT. When training, each tree in a random forest learns from a random sample of the data points. The samples are drawn with replacement (bootstrapping), only a subset of all the inputs is considered for splitting each node in each decision tree. Predictions are made by averaging the predictions of all decision trees⁴⁴. The performance of the algorithm was assessed by estimating the area under the ROC curve by leave-one-out cross validation (LOOCV). The procedure and results of cross-validation are presented in detail in Appendix D figure 7 and in ref.⁴². Since crop rotation, soil cover management and other agricultural management practices were included as model inputs, it is possible to map the probability of yield gain for CA (NT with crop rotation and soil cover) and variants systems (NT partly or not implemented with crop rotation and soil cover) vs. CT. Maps were generated for all crop species at a spatial resolution of $0.5^\circ \text{ latitude} \times 0.5^\circ \text{ longitude}$.

5.4.3 Global projection

The fitted random forest model was used to estimate the probability of yield gain from CA system and their variants vs. CT without crop rotation (-R) and without soil cover (-SC) for each grid cell located in cropping regions under current (2011-2020) and future (2051-2060) climate scenarios. This variant of CT was chosen as a baseline comparator because it prevails in the training dataset^{10,11}. The monthly-average values of the climatic variables (PB, Tmin/Tave/Tmax) were calculated in each grid cell over the two time periods considered, and then these data were used to calculate the climatic variables during the growing season based on the crop calendar database¹⁶ (assume no change in current and future scenario). All the climatic data in both current and future scenarios were obtained from four climate models: Gfdl-esm2m, Hadgem2-es, Ipsi-cm5a-lr, and Miroc5, and 4 RCP scenarios: RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5. This results in 32 combinations (4 climate models \times 4 RCP scenarios \times 2 periods). We mainly focused on the Ipsi-cm5a-lr model and RCP 4.5 scenario in the baseline simulations, because of their importance and similar role in the protocol of ISIMIP2b project⁴⁵. However, results from all combinations were analyzed and shown in Extended data figure 3. All the climatic data can be downloaded through the website of Lawrence Livermore National Laboratory⁴⁶.

We did not change the categorical inputs describing cropping practices between current and future scenarios. The global soil texture was set based on HWSO dataset⁴³. To compare the performance across different cropping systems, we mapped the probability of yield gain, and the change of yield gain probability under climate change with the systems of CA (+F+WD) vs. CT-R-SC (+F+WD), CA (-F-WD) vs. CT-R-SC (-F-WD), NT+R-SC (+F+WD) vs. CT-R-SC (+F+WD), NT-R-SC (+F+WD) vs. CT-R-SC (+F+WD), NT-R-SC (-F-WD) vs. CT-R-SC (-F-WD), where +/- R indicated crop rotation set as “yes” / “no”, +/- SC indicated soil cover set as “yes” / “no”, +/- F indicated fertilization set as “yes” / “no”, and +/- WD indicated weed and pest control set as “yes” / “no”. As for crop irrigation, it was set based on the crop irrigation mask from MIRCA2000 dataset⁴⁷. When more than 50% of the area in a grid cell were under rainfed conditions for a given crop in the MIRCA2000 database, this cell was then considered as non-irrigated for this crop, and vice versa. See Appendix D table 1 for the details of model settings. The model outputs were mapped at a spatial resolution of $0.5^\circ \text{ latitude} \times 0.5^\circ \text{ longitude}$ based on the MIRCA2000 crop mask database⁴⁷. Accumulated area fractions under different levels of yield gain probability and different levels of probability change between current and future scenarios were computed at the global scale and in different climate regions.

5.4.4 Climate regions

The “global” indicated the global cropping region for each crop²⁵. According to the Köppen-Geiger classification¹⁸ and its nomenclature (Appendix D figure 8). The “tropical climate” included the regions with the climate types Af, Am, As, Aw¹⁸. The “dry climate” included the regions with the climate types BWk, BWh, BSk, BSh¹⁸. The “temperate climate” included the regions with the climate types Cfa, Cfb, Cfc, Csa, Csb, Csc, Cwa, Cwb, Cwc¹⁸. The “continental climate” included the regions with the climate types Dfa, Dfb, Dfc, Dfd, Dsa, Dsb, Dsc, Dsd, Dwa, Dwb, Dwc, Dwd¹⁸.

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Part IV

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General Discussion on Conservation Agriculture

Chapter 6 General discussion

The world is facing new challenges under the changing climate, the increasing pressure on land and resources, and the growing food demanding. There are persistent difficulties in achieving a climate secure future ^{1,2}. Given these challenges related to climate change, food insecurity and ecosystem instability, the livelihoods of millions of people in developing countries are at risk. Achieving food security and maintaining ecosystem resilience to climate change are therefore prominent priorities. There is a wide gap in the understanding of climate change impacts related to agricultural production and food, especially at the regional level. Therefore, ensuring food security is challenging, and climate change makes it even more difficult, in turn affecting the achievement of Sustainable Development Goals (SDGs).

This thesis has shed light upon some concept farming systems, i.e., conservation agriculture and its variant systems, to achieve climate mitigation and adaptation. Through the machine learning pipeline, the productive performance of CA (and its variants) vs. CT under past, current and future climate were assessed and mapped. The preferable geographical regions, climate conditions and farming practices for CA (and its variants) implementation were identified, which could help the researchers to have a further understanding on how climate change affect the performance of CA and CT systems. The maps could also help policymakers to select the regions with high probability of yield increase to promote CA system.

6.1 Practical value of this machine learning pipeline and how to adapt it into other type of cropping systems

Machine learning is the science of making computer acts without being explicitly programmed. In the past decade, machine learning algorithms have been utilized in self-driving car, speech recognition, web search, and to process and analyze complex and high-dimensional data ³. In this thesis, we proved that the data collected from the publications are capable of doing more complex analyses than standard meta-analysis, e.g., through machine learning approaches. Meta-analysis refers to the statistical analysis of a large collection of analysis or experimental results from individual studies for the purpose of integrating the findings ⁴, it has been widely used in agronomic data analysis, and a well-designed meta-analysis can provide valuable synthetic information to scientists and policy makers based on mean effect size estimation. However, summarizing large amounts of information by way of a single mean effect value is not always satisfactory, especially when considering agricultural practices. To overcome this disadvantage of meta-analysis and gain further insight in the hidden relationship among the data, in chapter 3, we presented a machine learning pipeline, that train the machine learning models for different usage, including predicting the probability yield increase or decrease (classification), predicting the conditional mean of yield change (regression), and estimating the range of yield change (quantile regression). Through this pipeline, we also compared and mapped the productive performance of different cropping systems.

In general, to use this machine learning pipeline to train the machine learning model that can predict the performance of different cropping systems at the global scale, we need to prepare a training dataset that contained the target variable, e.g., crop yield, of target cropping systems, e.g., CA vs. CT; The locations of experimental site, e.g., latitude and longitude; The farming practices used in the experiment, e.g., the management of crop residue, rotation, irrigation, fertilizer, pesticide, herbicide, etc. And to ensure the consistency among the experimental records, we suggest that the local climate conditions at that year or growing season could be collected from the external datasets based on the locations, such external datasets include the products of Coupled Model Intercomparison Project Phase 6 (CMIP6) which can be accessed through Lawrence Livermore National Laboratory ⁵.

The amount of data needed and the requirement of its distribution for this pipeline to train a good model with high accuracy are unknown. But based on the results of this thesis, we suggest that the larger amount

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of the data could potentially give a better performance of model, and as for the distribution of the data, we are able to train the model with good performance with unbalanced dataset, because this pipeline can compare different machine learning algorithms and find the best algorithms and their hyperparameters to reach a high accuracy.

And to use the trained model from this machine learning pipeline to predict and project the differences between cropping systems on a global map, we need to prepare to gridded dataset that can be sent to the trained model for prediction. It should contain the gridded climate data at global scale, farming practices, and other variables that are the inputs in the trained model. Here the gridded climate data can be also gain from the products of CMIP6, the performance of different cropping systems under different time-slices can be discussed here (past, current and future scenario). By defining different scenarios of farming practices used in the experiment, the impact of different farming practices on the performance of cropping systems can be also assessed, e.g., with vs. without crop rotation, with vs. without crop residue retention etc.

This pipeline can be easily adapted in many other studies and can be used to analyze a diversity of outcomes. These may involve the effects of crop management practices on crop yield, soil organic carbon dynamics, greenhouse gas emissions, biodiversity, etc. for different types of cropping systems, such as conservation agriculture, organic agriculture or agroforestry, thus, provide valuable information on the local performance of sustainable farming practices together with a global perspective. And what we need to prepare to adapt this pipeline to those studies is to collect the data from the published studies or find the dataset that contains the target variable of target cropping systems, locations, and other farming practices as described above. As for the prediction and projection stage, what we mainly need to do is to define different scenarios of climate conditions and farming practices to study the impact of climate and farming practices on the performance of cropping systems.

Concerning the first research question proposed in this thesis, here, based on the crop yield dataset of CA and its variants vs. CT systems presented in chapter 2 and the machine learning pipeline described in chapter 3, we trained and compared 12 different machine learning algorithms through this pipeline to assess the performance of CA and its variants vs. CT. We identified that random forest algorithm is best algorithm for this study. And we mapped the performance of CA and its variants vs. CT systems at the global scale based on the results from this algorithm. Those maps provide more detailed geographical information than mean effect size in standard meta-analysis, which is very important in the analysis of agricultural production as it is highly dependent on the local climate conditions⁶⁻⁸, soil characteristics⁹⁻¹¹, and agricultural management practices^{7-9,12,13}, that often vary in time and space. And it proves that machine learning pipeline indeed give us more valuable information than meta-analysis.

6.2 The productive performance of conservation agriculture

Concerning the other research questions about the performance of CA and its variants vs. CT systems, based on the maps generated from this ML pipeline, in this thesis, we do reveal large differences in the productive performance associated with the adoption of CA and its variants across crops, farming practices, geographical regions, and climatic conditions.

We show that CA has a better performance than NT, especially when combined with the proper agronomical practices (Appendix D figure 1, Appendix D figure 2). We reveal that soil cover has a stronger positive effect on this performance than other management practices such as fertilizer inputs, weed and pest control, and crop rotation (Appendix D figure 1, Appendix D figure 2). Therefore, keeping the soil covered by crop residues appears to be an important factor for the success of CA systems. However, in practice, maintaining crop residues might be challenging in some regions, such as Africa, where the crop residues are used to feed livestock^{14,15}. In such situations, a possible solution would be to rely on alternative sources of plant

materials, e.g., residues from cover crops, grass, leaf litter from trees, sawdust, etc.¹⁴. Although less influential, our results show that other farming practices, such as the management of fertilization and the control of weeds and pests, can also boost the probability of yield gain of CA and its variants^{7,8,16–19}.

As for the impact of climate variables affect the productive performance, our results show that CA and its variants have better productive performance under relatively dry conditions (Figure 4.1), and this is consistent with previous work^{6–8,17,20,21}. We reveal the spatial variance of the performance of CA. The overall performance of CA is better in continental, dry, and temperate regions than in tropical regions (Figure 5.1a, Figure 5.1d-g, Appendix D figure 1.a2-g2, Appendix D figure 2.a1-h1). This pattern is also in line with previous work⁷.

This productive performance also varies from different crop species. In this thesis, we show that the performance of CA and its variants are particularly poor for rice. For this crop, the probability of yield increase is lower than 0.5 (which indicates a higher probability of yield loss) over about 60% of its global cropping area, and in about 85% of its cropping area in the tropics (Figure 5.1d, Appendix D figure 1.d2).

The productive performance change of CA and its variants under climate change also show important geographical variations, but the magnitude of this change is relatively moderate. Over approximately half of the cropping areas, a decrease of up to 10% in this probability is expected, while in the other half an increase of up to 15% may be anticipated (Figure 5.2). However, in some important cases the effect of climate change is stronger, especially for maize in tropical regions where the probability of yield gain with CA increases in about 70% of the cropping area. Besides, for more than 20% of the maize cropping area in this climate zone, the increase on the probability of yield increase is higher than 10% (Figure 5.2c). An increase in yield gain is also expected for more than 60% of the cropping area for rice in dry regions and for soybean in tropical regions (Figure 5.2d, Figure 5.2f). This fraction rises to more than 70% of the cropping area for sorghum in continental regions (Figure 5.2e).

Although several variants of CA systems may be associated with a high probability of yield loss in many regions, we show that, under future climate conditions and with good agricultural management practices, the relative productive performance of CA is expected to increase for several crop species. This is especially true for maize in tropical regions, which further strengthens the competitiveness of CA for this staple crop. Thus, in this thesis, we support the idea that CA will be a relevant option for cropping systems in the future, capable of ensuring a long-term, sustainable agricultural production for some key cropping areas^{22,23}.

6.3 Conservation agriculture from a sustainability perspective

In addition to the potential benefits CA can bring in food security, it is also proved that CA can reduce soil erosion and improve soil structure and soil quality, which is essential for a sustainable production. In CA systems, crop residues reduce the risk of crop failure and increased yield stability since it could decrease the rate of soil temperature change²⁴, increase the minimum soil temperature in extreme cold conditions^{25–27}, and provide a buffer layer that can increase the crop resistance to the increasing climate variability and the occurrence of extreme events²⁸. It is also reported that the residues retained on the soil surface reduce soil evaporation and water runoff^{29,30}, increase soil water content³¹, soil water retention capacity and mitigates drought effects^{32–34}, and increase soil organic matter³⁵. These factors all contribute to increase the probability of yield gain. Therefore, CA reduces the risk of crop failure and increased yield stability.

CA and NT systems have been proposed to ensure a more sustainable land use, however, the increased weed pressure is often an impediment to their adoption³⁶. It is reported that the demand of herbicides increases in CA and NT systems comparing with CT systems^{37,38}. To limit the over-reliance of herbicides for weed control in CA and NT systems, several alternative methods have been proposed, including manual

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and hoe weeding, etc.³⁹. Such alternative methods could reduce the herbicides usage in CA and NT systems, but also increase the time and labor demands by up to 50%⁴⁰. Thus, sustainable weed managements are needed in CA systems. Designing a proper crop rotation in CA systems could be a successful approach to reduce weed pressure. Weeds are often associated with specific crop species. By changing the sequence of crop species can reduce the chances of the infestation of particular weed, thus, reduce the weed pressure^{41,42}. Soil cover during fallowing is also key to suppress different weeds by impeding light and air^{43,44}. Thus, we recommend that NT systems should be implemented with proper agricultural management practices, such as permanent soil cover, dynamic crop rotation, crop fertilization, weed and pest control, and all the other good agricultural management practices like seed selection, irrigation management.

6.4 Novelty of this thesis

We conducted a new global dataset of crop yield of CA systems and its variants versus CT systems under a wide range of farming practices, soil characteristics and climate conditions over the growing season in different experimental years. The inclusion of climate variables from external datasets allows us to analyze the effects of the intra-annual climate variabilities on the productive performance of CA and its variants. And it is also the first time that the performance of conservation agriculture is discussed under the future climate.

As for the methods we used in this thesis, we developed a machine learning pipeline to analyze these data collected from the published papers, which is able to map and compare different cropping systems at the global scale based on machine learning algorithms. And it is also the first time 12 machine learning algorithms were compared based on the same dataset for different usages: classification, quantitative prediction and quantile regression. In classification, we use the probabilistic approach to analyze the dataset, instead of predicting the categories of yield increase or decrease. In quantile regression, we created a new approach, error score, to evaluate the overall performance of the model's interval prediction ability for all quantiles, which is more comprehensive than traditional coverage rate.

In this thesis, through the machine learning pipeline, we mapped the productivity of CA and its variants under different climate scenarios and different farming practices. The maps give us a better understanding in geographical variety of the performance of CA and its variants under different local conditions and help us identify the regions that have higher or lower probability of yield gain from shifting CT to CA and its variants for eight major field crops, which bring meaningful and novel information to policymakers and agricultural extension services.

6.5 Limitations

This thesis has several limitations. First, the data is unbalanced in this dataset. Most of the data collected pertains to humid climates rather than arid climates, which might cause the model has higher accuracy in humid regions than arid regions. The number of yield observations for different crop species are also very different, which may be linked to the different accuracies for different crop species. As mentioned in chapter 2, 4403 paired yield observations are recorded in the final dataset, and among those observations, there are 1690 observations for maize and 1041 observations for winter wheat, while there are only 195 observations for rice and 61 observations for sunflower. The model accuracies for different crop species are shown in Appendix D Figure 7. As shown in the results, the AUC of maize and wheat are 0.797 and 0.766, respectively, while the accuracies of rice and sunflower are 0.696 and 0.64, respectively. It may suggest that a larger number of observations can contribute positively to a higher model accuracy. But it does not mean that a smaller number of observations cannot train a model with high accuracy, for instance cotton, the number of observations of cotton yield is quite limited, but it still has a good model performance.

As for farming practices, crop irrigation was considered only as a categorical variable here due to a lack of global data on this practice, even though it still proved meaningful in terms of yield impacts. The type of fertilizer, herbicide and pesticide applied is not included in the model, the usage of fertilizer, herbicide and pesticide is not quantified, in this thesis, we consider them as categorical variables (with / without the usage of fertilizer, herbicide and pesticide). The area that covered by crop residues, and the amount of residues left on the field, and the type of residues are not considered in this study, while may potentially have a high impact on the crop yield. In this study, the soil is considered as covered as long as the area of the field is covered by at least 30% of the total area. Including the quantitative values of farming practices might increase the model accuracy.

Finally, to deal with missing climate and soil data in the selected papers, we used climate and soil data from external databases on a systematic basis. Consequently, crop growing season, precipitation, potential evapotranspiration, minimum temperature, average temperature, maximum temperature throughout the growing season, and soil texture may not always match local records. The mismatch of the records and external databases from the climate models may increase the model uncertainty, especially for the instance of outliers. The climate condition we discussed in this thesis is the mean or accumulated condition over the crop growing season, comparing with previous studies ^{7,8} which use the average climate condition over years, it helps us to reveal the impact of intra-annual and part of inter-annual variability of climate conditions on crop yield. However, besides the mean or accumulated climate condition over the crop growing season, the distributions of those variables in the crop growing season also have a large impact on the crop yield. For example, a low temperature during the plant's germination stage might damage the cytoplasmic membranes of seeds that rich in protein ⁴⁵, in turn affecting the yield. Thus, the crop yield may be very different even when the average temperature in two sites is the same. Therefore, the results showed in the thesis might not be as accurate as the analysis that uses the daily or monthly climate variables and cannot fully reveal the impact of inter-annual variability of climate variables on crop yield.

6.6 Perspectives

There are still a lot of knowledge gaps related to CA and NT systems that are worth to be addressed in future studies.

6.6.1 Proposal 1: The impact of different type of soil covers on crop yield and soil organic carbon

In this thesis we show that soil cover is important to boost the productive performance of CA system, however, maintaining crop residues as soil cover might be challenging in some regions, such as southern Africa, where the crop residues are usually used as the feed of livestock ^{14,15,46}. In such situation, a possible solution would be to rely on alternative sources of plant materials, e.g., residues from grass, leaf litter from trees, sawdust, bark mulch, etc. ^{14,46}. Few studies have been conducted to study the impact of different type of soil covers on crop yield and soil organic carbon, thus, experiments can be designed to compare and analyze the potentials of different type of soil covers in boosting the crop yield and soil organic carbon sequestration.

6.6.2 Proposal 2: The impact of NT system on soil temperature

Soil temperature is also one of the most important environmental factors that can affect the plant development and growth ^{47,48}, control the biological and biochemical reactions in the soil, and in turn affecting the organic matter formation and decomposition, and fertilizer efficiency ⁴⁷⁻⁵⁰. A higher level of soil organic matter and organic carbon content will improve the soil structure, reduce the erosion, increase the potential crop productivity, and mitigate the climate change ⁵¹⁻⁵³.

NT practice will change the soil structure, soil water content, soil oxygen content and heat conductivity ^{54,55}, resulting in a different soil oxygen content, moisture, temperature at different levels of soil depth, which

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will change the decomposition rate of soil organic matter. There are several experiments conducted to study how NT will affect the soil temperature at regional scale ⁵⁶⁻⁶⁰, the data can be extracted from such publications to analyze and map how this impact varies with different soil characteristics and air temperatures. It is important to map the impact of NT on soil temperature at the global scale in both current and future climate conditions since it can have a big influence on crop growth and decomposition rate of soil organic matter in some regions and is very important to achieve the local SDGs.

6.6.3 Proposal 3: The economic viability of CA and NT systems at the global scale

Conservation agriculture is economically attractive because it demands less labor and machinery inputs ^{61,62}, however, the yearly productivity from CA varies a lot under different local climate conditions, soil characteristics, and farming practices ^{7,8,13,46}, therefore, the economic viability of CA remains uncertain. The implementation of CA is depending on its economic viability because it is one of the main concerns of farmers when considering whether they should adapt CA systems to replace the CT systems. The local government might provide subsidies to promote CA systems, however, this varies dramatically in different regions with different policies. Moreover, the market price for agricultural products also varies a lot depending on the food demands and supply in that year, which makes it hard to estimate accurately the economic viability of CA systems at the global scale.

The models generated from this thesis can be used to predict the productive performance of CA and its variant systems vs. CT systems under different farming practices and climate conditions in different years, thus, it is possible to estimate the economic viability and reduce its uncertainty when combining with the price data of global agricultural production trade.

6.6.4 Proposal 4: Compare the results from data-driven models and knowledge-driven models

Data-driven models and knowledge-driven models are complementary. The using of complex functions to fit data enables data-driven machine learning models to achieve a relatively higher accuracy, but one of major limitations is the difficulty to explain the results ⁶³. While the knowledge-driven models are developed based on the scientifically and biologically meaningful hypotheses that are examined by many experiments. Such hypotheses greatly simplified the learning process and can achieve a reasonable performance, but the parameter calibration can be challenging due to the complex structures of these models⁶⁴.

In this thesis, we trained a lot of data-driven models that are capable of predicting the crop yield under CA and NT systems vs. CT systems for different crop species and at the global scale. To know the more about the regional prediction performance, or to explain the results for a specific region, we can compare the results from those data-driven models to knowledge-driven models. And we can also use the results from the data-driven models to calibrate the knowledge-driven models if we want to apply the knowledge-driven models to the regions with limited experimental observations.

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Chapter 7 General conclusion

In this thesis, we proved that the experimental data collected from the publications are capable of doing more complex analyses, e.g., through machine learning approaches, than simply meta-analysis. We designed a machine learning pipeline that can be used to analyze the impacts of different cropping systems, such as agroforestry, organic agriculture, etc., on crop yield, soil organic carbon, greenhouse gas emission, biodiversity, etc. Our machine learning pipeline offers an opportunity to compare, analyze and map the performance of these cropping systems under different geographical regions, climate zones, and different farming practices, which can help the researchers and policymakers to have further understanding of them, and in turn enhance their adaption based on the local conditions.

In this thesis, we discussed the productive performance of CA and NT systems vs. CT systems under different farming practices and climate scenarios. Our results showed that CA performed better than NT practices, and keeping the soil covered is the most effective farming practice that can boost the performance of NT system. Thus, we highly recommend that no-till practice should be always integrated with soil cover and crop rotation. Although less influential, other farming practices also appear to increase the productive performance of CA, in particular fertilization and weed and pest control. Thus, we suggest that field fertilization, weed and pest control should be incorporated in CA system. Here, we provided the maps that revealed the performance of CA and NT systems vs. CT systems at different geographical regions, the suitable regions for the implementation of CA and NT systems can be identified. We proved that CA and NT systems have better performance in dryer regions, and we showed that tropical regions are less suitable for their implementation, however, for some crop species, such as maize, under future climate conditions, the performance of CA is expected to increase in this area, which improves the competitiveness of CA and NT systems for this staple crop.

We confirm that CA is one of the promising cropping systems that can ensure a long-term sustainable crop production and increase the food stability under climate change. Although CA may not always outperform CT concerning of crop yield, CA can provide a range of ecosystem services far beyond biomass production, those ecosystem services include improving the soil health, reducing the soil erosion risk, etc., while the present traditional tillage systems are causing serious land degradation, which will increase the risk of food security in the future, and increase emissions and reduce carbon sinks. Therefore, CA is a promising practice that can be promoted to sustain the long-term food production, while conserve the environment.

Appendixes

Appendix A

A global dataset for crop production under conventional tillage and no tillage practice

Authors

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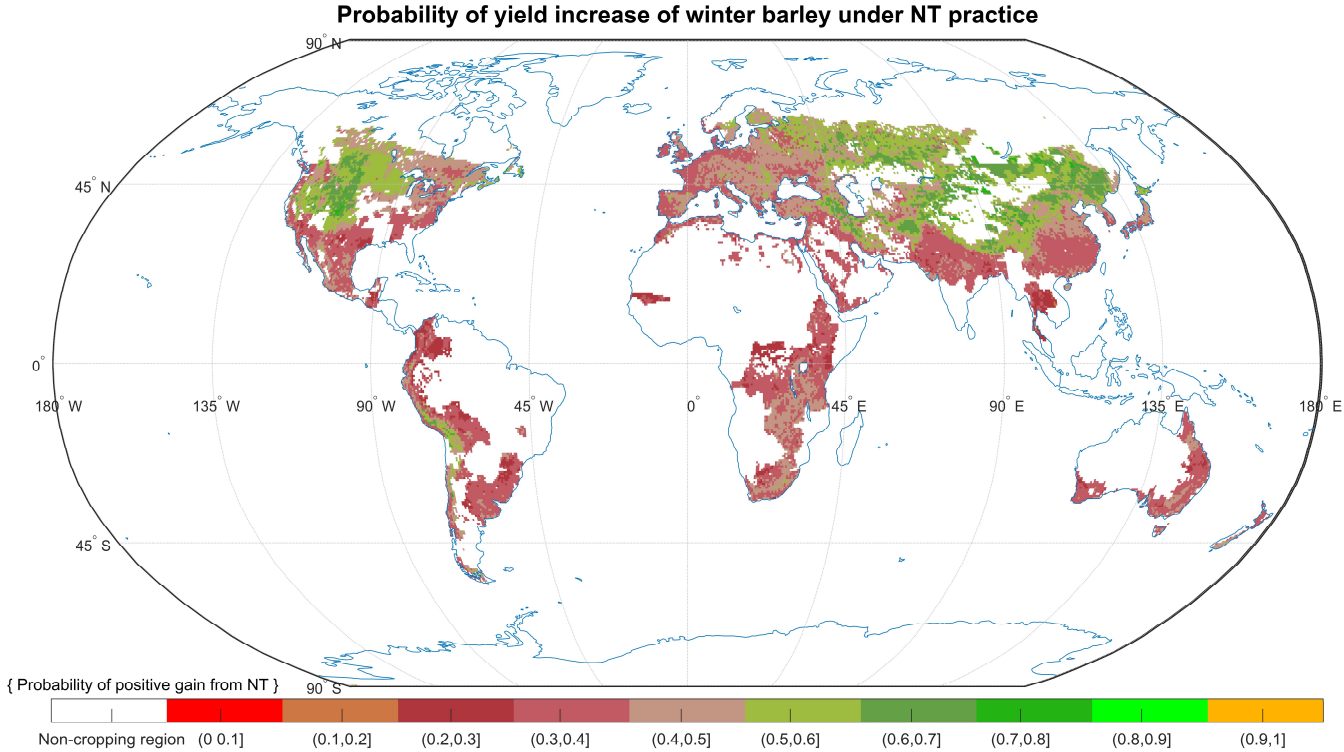
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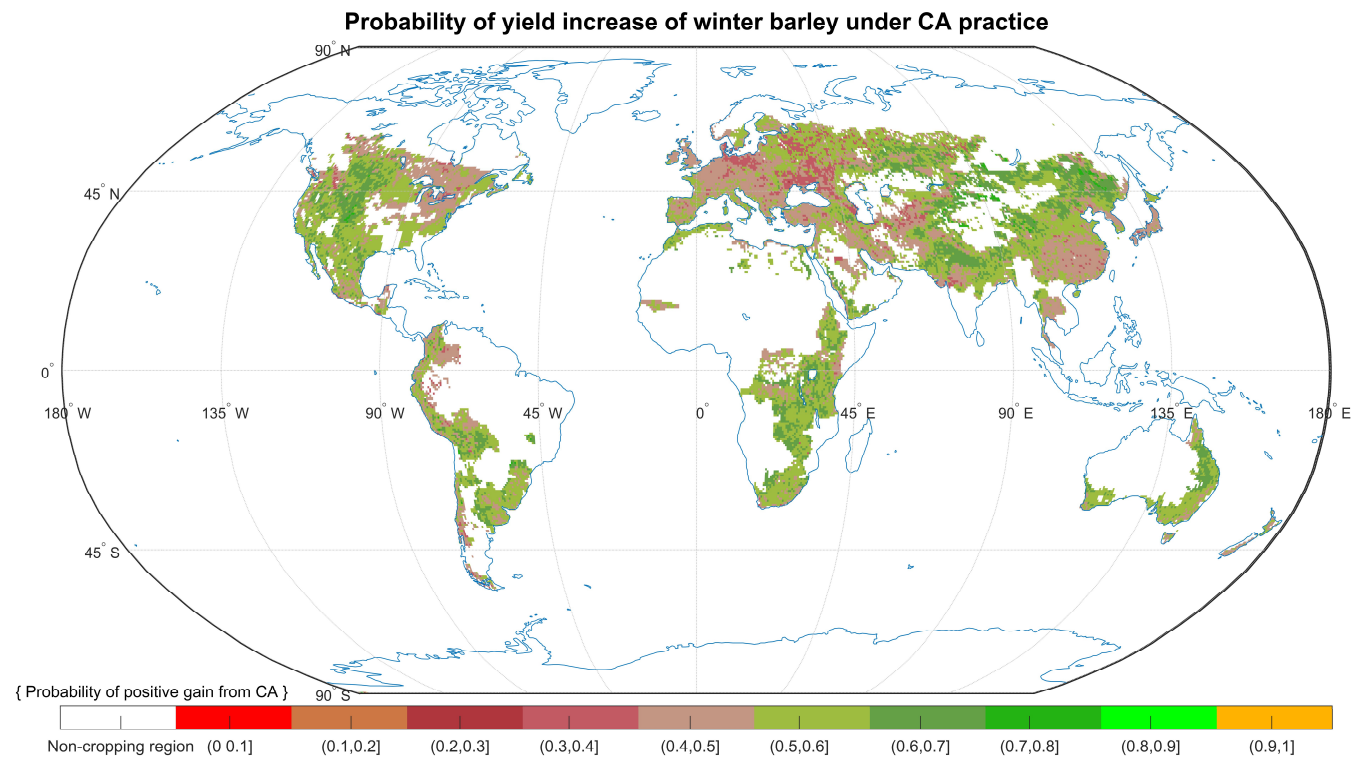
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Appendix A figure 1 | Probability of yield increase of winter barley under NT vs. CT practice in the average climate conditions of 1981-2010.



Appendix A figure 2 | Probability of yield increase of winter barley under CA vs. CT practice in the average climate conditions of 1981-2010.

Method to train machine learning models based on our dataset

The machine learning algorithms, e.g. random forest, can be trained based on the 4403 paired crop yield observations collected from papers¹⁻⁴¹³. It can be used to analyze the yield ratios of NT vs. CT as the function of climatic variables, crop types, soil textures, and agricultural management activities. And this can be done in R software with the package “randomForest”. To train the model, set the climatic variables during the growing season such as PB, Tmin/Tave/Tmax as numerical predictor variables; Set crop type, soil texture, and agricultural management activities including crop irrigation, field fertilization, control of pests and weeds, crop rotation and soil cover as categorical predictor variables; Set the column AP (Yield increase with NT) as response variable. When training, each tree in a random forest learns from a random sample of the data points, the samples are drawn with replacement (bootstrapping), only a subset of all the inputs are considered for splitting each node in each decision tree. Predictions are made by averaging the predictions of all decision trees.

The sample code for training the random forest model is available in “Code.zip” in figshare repository provided in the main manuscript. When setting the “proximity” as Ture, the model output is the probability of yield gain from NT vs. CT.

Method to producing the global maps of NT (or CA) vs. CT practices on our dataset

After the training the random forest model, supply the trained model the global climate variables and soil texture, plus the self-defined agricultural management activities, then the model can be used to predicting the performance of NT (or CA, when set with crop rotation and soil cover) vs. CT at the global scale under different agriculture management activities.

The sample codes for using the random forest model to predict (in R software) and map (MATLAB) the global performance of NT (or CA) vs. CT are available in “Code.zip” in figshare repository provided in the main manuscript. More codes can be requested by sending email to corresponding author.

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Appendix B

A machine learning pipeline to map the performance of cropping systems on a global scale

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Appendix B table 1 | Description of the machine learning algorithms used in this study

	Machine learning algorithms	Used in the models	R packages used to train the model	Brief description
1	Random forest (RF)	Classification (C) & regression (R)	ranger (version 0.12.1)	The random forest algorithm is a community-based algorithm that performs classification or regression tasks based on decision trees ¹ .
2	Random forest with spatial correlations (RF with spaMM)	C & R	ranger (version 0.12.1) & spaMM (version 3.6.0)	RF outputs are used as inputs in spaMM in order to take spatial correlation into account using Matern correlation matrix and a generalized linear mixed model ² .
3	Gradient boosting (GBM)	C & R	gbm (version 2.1.8)	GBM produces a strong learner in the form of an ensemble of weak learners fitted using a gradient descent optimization algorithm ³ .
4	Extreme gradient boosting (XGBOOST)	C & R	xgboost (version 1.3.2.1)	The XGBoost algorithm is an algorithm based on the decision tree approach and uses a gradient boosting system ⁴ .
5	Artificial neural networks (ANN)	C & R	RSNNS (version 0.4-12)	Artificial neural networks are computational systems developed which are inspired from neurons in the human brain and from the connections established by these neurons ⁵ .
6	Support vector machine (SVM)	C & R	e1071 (version 1.7-5)	The SVM algorithm is a discriminatory classification algorithm that attempts to make classification by producing a line, plane, or hyperplane that separates points at two or more dimensions from each other ^{6,7} .
7	K-nearest neighbor (KNN)	C & R	caret (version 6.0-86)	The k-Nearest Neighbor algorithm performs classification and regression tasks based on lazy learning ⁸ .
8	Generalized linear model (GLM)	C & R	stats (version 4.0.4)	The generalized linear model handles probability distributions from the exponential family (e.g., binomial) and is widely used for classification. Its parameters are estimated using iteratively reweighted least squares method for maximum likelihood estimation ⁹ .
9	Naïve Bayes (NB)	C	e1071 (version 1.7-5)	Naïve Bayes is a conditional probability model in which

				posterior is calculated as likelihood times prior then divided by normalization factor ¹⁰ .
10	Quantile regression forest (QRF)	Quantile regression (Q)	quantregForest (version 1.3-7)	Quantile random forests estimate conditional quantiles of response variables, which provides more information than conditional mean alone ¹¹ .
11	Quantile regression gradient boosting (QRGBM)	Q	gbm (version 2.1.8)	Quantile regression gradient boosting model is obtained from gradient boosting machines with quantile loss functions ¹² .
12	Quantile regression neural network (QRNN)	Q	qrnn (version 2.0.5)	Quantile regression neural network is an extension of linear quantile regression with an artificial neural network, which is capable of probabilistic predictions of mixed discrete-continuous variables ^{13,14} .

Appendix B table 2 | Performance of classification models

	Algorithms	CV AUC	Test AUC
1	Random forest (RF)	78.4%	79%
2	Random forest with spatial correlation (RF with spaMM)	77.3%	78.9%
3	Generalized linear model (GLM)	NA	64.4%
	Use step function to find the best model		
4	Gradient boosting (GBM)	77.1%	78.6%
5	Extreme gradient boosting (XGBOOST)	77.3%	78.3%
6.1	Artificial neural network (ANN with 1 hidden layer)	72.9%	74.4%
6.2	Artificial neural network (ANN with 2 hidden layers)	73.6%	75.2%
6.3	Artificial neural network (ANN with 3 hidden layers)	74.1%	72.0%
6.4	Artificial neural network (ANN with 4 hidden layers)	73.8%	73.8%
6.5	Artificial neural network (ANN with 5 hidden layers)	73.4%	72.7%
7	Support-vector machines (SVM)	68.8%	72.7%
8	Naive Bayes (NB)	60.8%	64.7%
9	k-nearest neighbours (KNN)	72.6%	73.3%

Appendix B table 3 | Performance of regression models. Outliers out of 95% confidence interval were excluded.

	Algorithms	CV R ²	Test R ²
1	Random forest (RF)	0.4937	0.5197
2	Random forest with spatial correlation (RF with spaMM)	0.4547	0.5154
3	Generalized linear model (GLM)	NA	0.1186
	Use step function to find the best model		
4	Gradient boosting (GBM)	0.4841	0.4754
5	Extreme gradient boosting (XGBOOST)	0.4704	0.4673
6.1	Artificial neural network (ANN with 1 hidden layer)	0.2842	0.3022
6.2	Artificial neural network (ANN with 2 hidden layers)	0.3033	0.3265
6.3	Artificial neural network (ANN with 3 hidden layers)	0.3098	0.3831
6,4	Artificial neural network (ANN with 4 hidden layers)	0.3164	0.26477
6.5	Artificial neural network (ANN with 5 hidden layers)	0.3043	0.2993
7	Support-vector machines (SVM)	0.3818	0.4536
8	k-nearest neighbours (KNN)	0.3224	0.3619

Appendix B

Appendix B table 4 | Performance of range regression models

Models/packages	With/Without outlier filter	CV CR 80%	Test CR 80%	Test area of CR curve above 1:1 line	Test area of CR curve below 1:1 line	Test Error Score
Quantile regression forest (QRNN)	With	81.57%	81.61%	0.0031	0.0056	1.73%
Quantile regression forest (QRNN)	Without	80.90%	81.19%	0.0129	0.0023	3.04%
Quantile regression GBM (QRGBM)	With	80.01%	80.36%	0.0014	0.0114	2.56%
Quantile regression GBM (QRGBM)	Without	79.99%	78.45%	0.0011	0.0059	1.38%
Quantile regression neural network with 1 hidden layer (QRNN)	With	78.53%	76.84%	0.0051	0.0203	5.07%
Quantile regression neural network with 1 hidden layer (QRNN)	Without	78.31%	77.31%	0.0057	0.021	5.35%
Quantile regression neural network with 2 hidden layers (QRNN2)	With	73.06%	72.87%	0.0097	0.0504	12.02%
Quantile regression neural network with 2 hidden layers (QRNN2)	Without	68.47%	66.02%	0.0082	0.0707	15.79%

Appendix B table 5 | Model setting for global projection

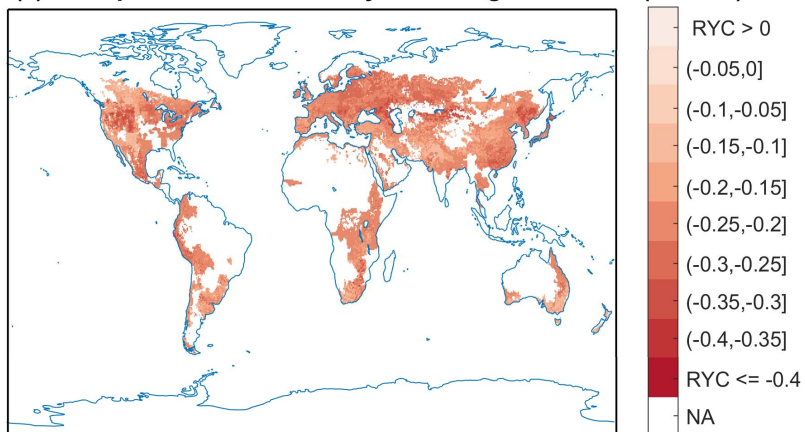
Model input	Setting (for each grid cell and each crop)	Source
Precipitation	Mean precipitation in the growing season of 1981-2010	National Oceanic and Atmospheric Administration (NOAA) ¹⁵
Evapotranspiration	Mean potential evapotranspiration in the growing season of 1981-2010	Data from GLEAM (Global Land Evaporation Amsterdam Model) ^{16,17}
Precipitation balance	Precipitation - Evapotranspiration	National Oceanic and Atmospheric Administration (NOAA) ¹⁵
Average temperature	Mean average temperature in the growing season of 1981-2010	National Oceanic and Atmospheric Administration (NOAA) ^{15,18}
Maximum temperature	Mean maximum temperature in the growing season of 1981-2010	National Oceanic and Atmospheric Administration (NOAA) ¹⁸
Minimum temperature	Mean minimum temperature in the growing season of 1981-2010	The University of Tokyo ¹⁹
Soil texture	HWSD data	University of Wisconsin-Madison ^{20,21}
Crop growing season	Month of planting to harvesting in the crop calendar dataset for each crop	Goethe University ²²
Crop mask	MIRCA2000 data	Goethe University ²²
Irrigation mask	MIRCA2000 data	
Crop type	Spring barley	
Fertilizer utilization in CA	Yes	
Fertilizer utilization in CT	Yes	
Control of weed and pest in CA	Yes	
Control of weed and pest in CT	Yes	
Crop rotation in CA	Yes	
Crop rotation in CT	No	
Soil cover in CA	Yes	
Soil cover in CT	No	Goethe University ²²
Crop irrigation in CA	Based on crop irrigation mask	Goethe University ²²
Crop irrigation in CT	Based on crop irrigation mask	National Oceanic and Atmospheric Administration (NOAA) ¹⁵
NT implementation year	5 years (the median value of NTyear in the dataset)	
Latitude	Latitude of the grid cell in the global map	
Longitude	Longitude of the grid cell in the global map	

Appendix B table 6 | Settings for model grid searching

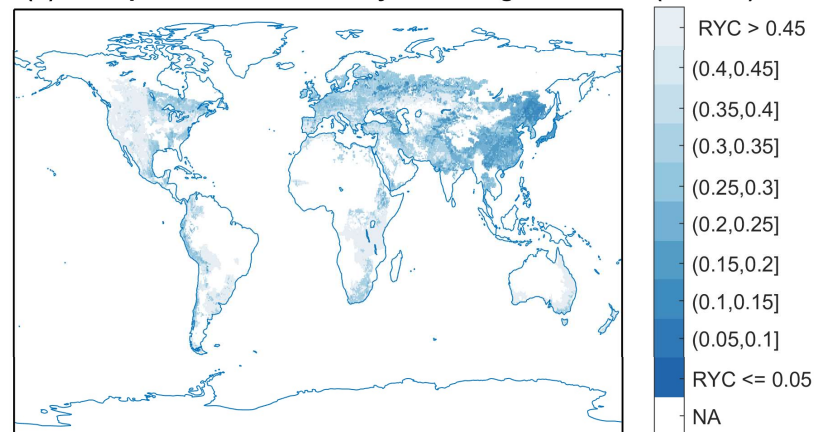
	Algorithms	Grid search setting
1	Random forest (RF)	mtry in (2,3,4,5,6,7,8,9,10,11) ntree in (300,400,500,600,700,800,900,1000)
2	Random forest with spatial correlation (RF with spaMM)	mtry in (2,3,4,5,6,7,8,9,10,11) ntree in (300,400,500,600,700,800,900,1000)
3	Generalized linear model (GLM)	Use stepwise algorithm ²³ based on step function for model selection
4	Gradient boosting (GBM)	ntree in (100,500,1000,2000,3000) shrinkage in (0.001,0.01,0.1,1) fraction in (0.1,0.5,1) depth in (1,5,10) node in (10, 30, 50) model in ("bernoulli") for classification model in ("tdist","gaussian") for regression
5	Extreme gradient boosting (XGBOOST)	max_depth in (3,5,7,9,11,13,15) eta in (0.001,0.01,0.05,0.1,0.5) nround in (50,100,500,1000)
6.1	Artificial neural network (ANN with 1 hidden layer)	layer 1 in (from 2 to 51) decay in (0.0001,0.001,0.01)
6.2	Artificial neural network (ANN with 2 hidden layers)	layer 1 in (15,20,15,30,35,40,45,50) layer 2 in (2,3,4,5,6,7,8,9,10,11)
6.3	Artificial neural network (ANN with 3 hidden layers)	layer1 in (35,40,45,50) layer2 in (12,14,16,18,20,22,24,26,28,30) layer3 in (2,3,4,5,6,7,8,9,10)
6.4	Artificial neural network (ANN with 4 hidden layers)	layer1 in (35,40,45,50) layer2 in (22,25,28) layer3 in (12,14,16,18,20) layer4 in (2,4,6,8,10)
6.5	Artificial neural network (ANN with 5 hidden layers)	layer1 in (35,40,45,50) layer2 in (25,28) layer3 in (15,18) layer4 in (8,10,12)

		layer5 in (2,4,6)
7	Support-vector machines (SVM)	gamma in (0.0005,0.001,0.01,0.05,0.1,0.5) cost in (from 1 to 20)
8	Naive Bayes (NB)	laplace in (from 0 to 20)
9	k-nearest neighbours (KNN)	k in (from 1 to 20) l in (from 0 to (k-1))
10	Quantile regression forest (QRF)	mtry in (2,3,4,5,6,7,8,9,10,11,12,13,14,15) ntree in (300,400,500,600,700,800,900,1000,2000,5000)
11	Quantile regression GBM (QRGBM)	ntree in (100,500,1000,2000,3000) shrinkage in (0.001,0.01,0.1,1) fraction in (0.1,0.5,1) depth in (1,5,10) node in (10, 30, 50) model in (“quantile”)
12.1	Quantile regression neural network (QRNN)	layer 1 in (from 2 to 51)
12.2	Quantile regression neural network (QRNN2)	layer 1 in (15,20,15,30,35,40,45,50) layer 2 in (2,3,4,5,6,7,8,9,10,11)

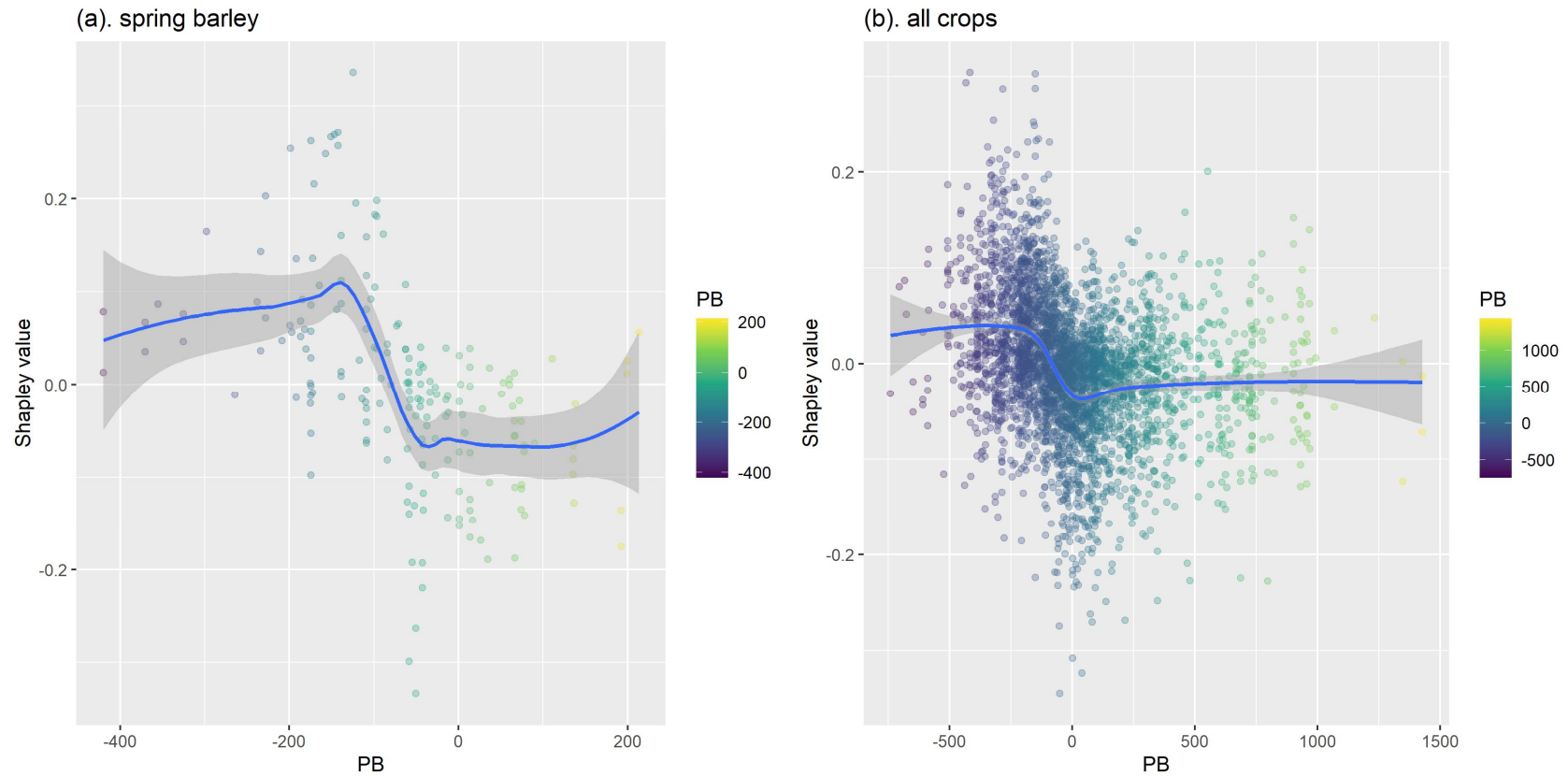
(a). 10th percentile of relative yield change under CA (+F+WD)



(b). 90th percentile of relative yield change under CA (+F+WD)

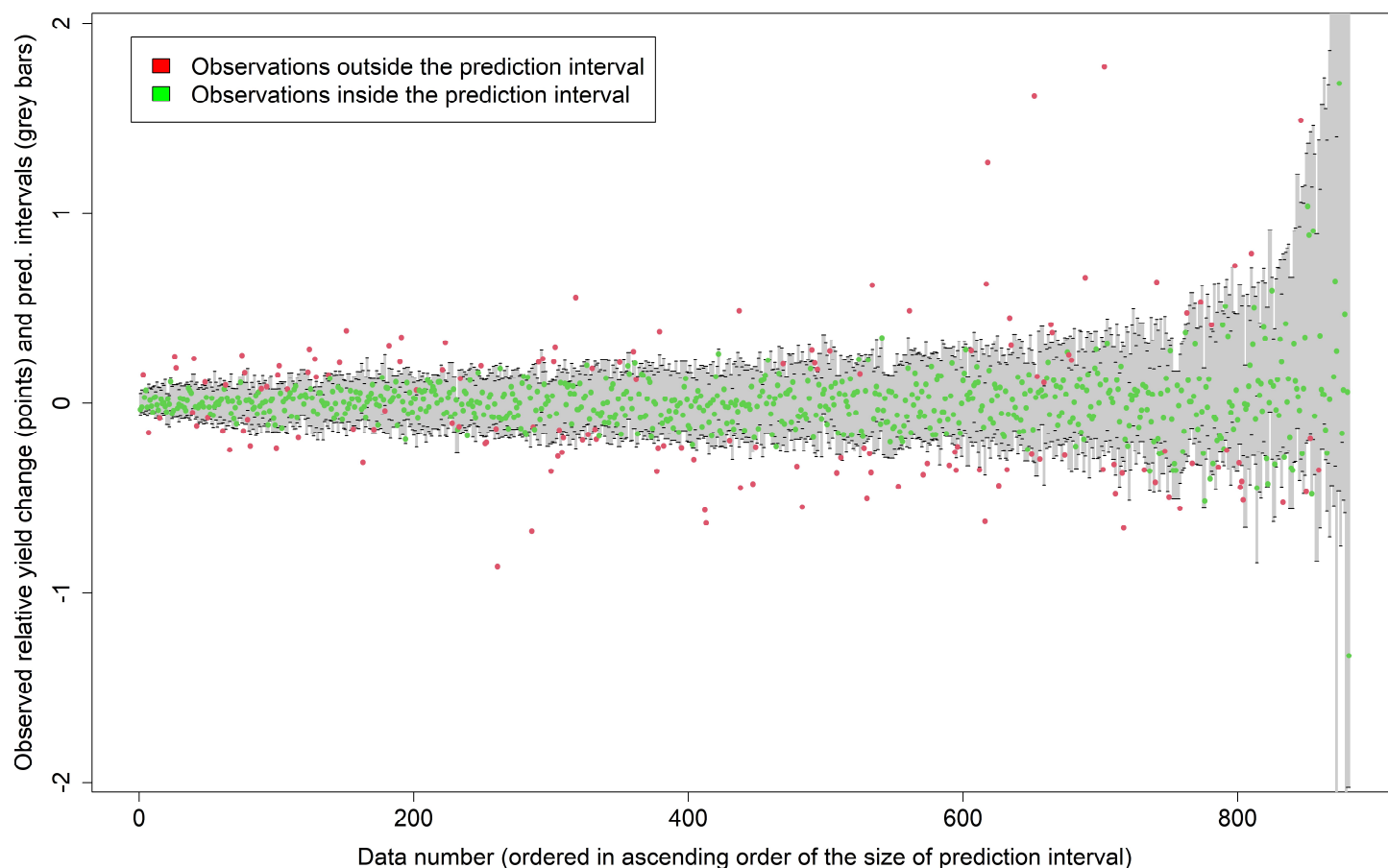


Appendix B Figure 1 | Maps of relative barley yield change of different quantiles. There was a 90% chance that the relative yield change will be higher than the ratio shown on the map in plot a, and conversely a 10% chance that the relative change will be lower. The maps were generated with MATLAB R2020a (Version 9.8.0.1451342, <https://fr.mathworks.com/products/matlab.html>).



Appendix B figure 2 | Shapley value of precipitation balance (PB). Plots a and b show that a lower PB contributes to a higher Shapley value, while indicates what CA has better performance when PB is lower or when climate is drier. Plots were generated based on the results from R package iml (version 0.10.1) and fastshap (version 0.0.5).

Coverage of the prediction intervals = 81.61% (nominal value = 80%)



Appendix B figure 4 | Interval prediction performance of quantile regression forest (QRF) with outliers when prediction interval is 80% (the range between 10th quantile and 90th quantile). This performance was evaluated by computing the proportion of data within the prediction intervals estimated by the model. When this proportion is close to the expected coverage probability, the intervals calculated by the quantile regression forest can be considered accurate. Model hyperparameters were tuned by 10-fold cross-validation. The final model was then used to compute the 10th and 90th percentiles of the relative yield change based on the independent testing dataset (20% of the whole dataset, Figure 1). The proportion of data within the prediction intervals was computed and compared to its expected value, 80% in this case. The vertical grey bars with two black dots correspond to the intervals defined by the 10th and 90th percentiles and the points correspond to observed relative yield changes. Data within the intervals are in green and data outside are in red.

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Appendix C

High probability of yield gain through conservation agriculture in dry regions for major staple crops

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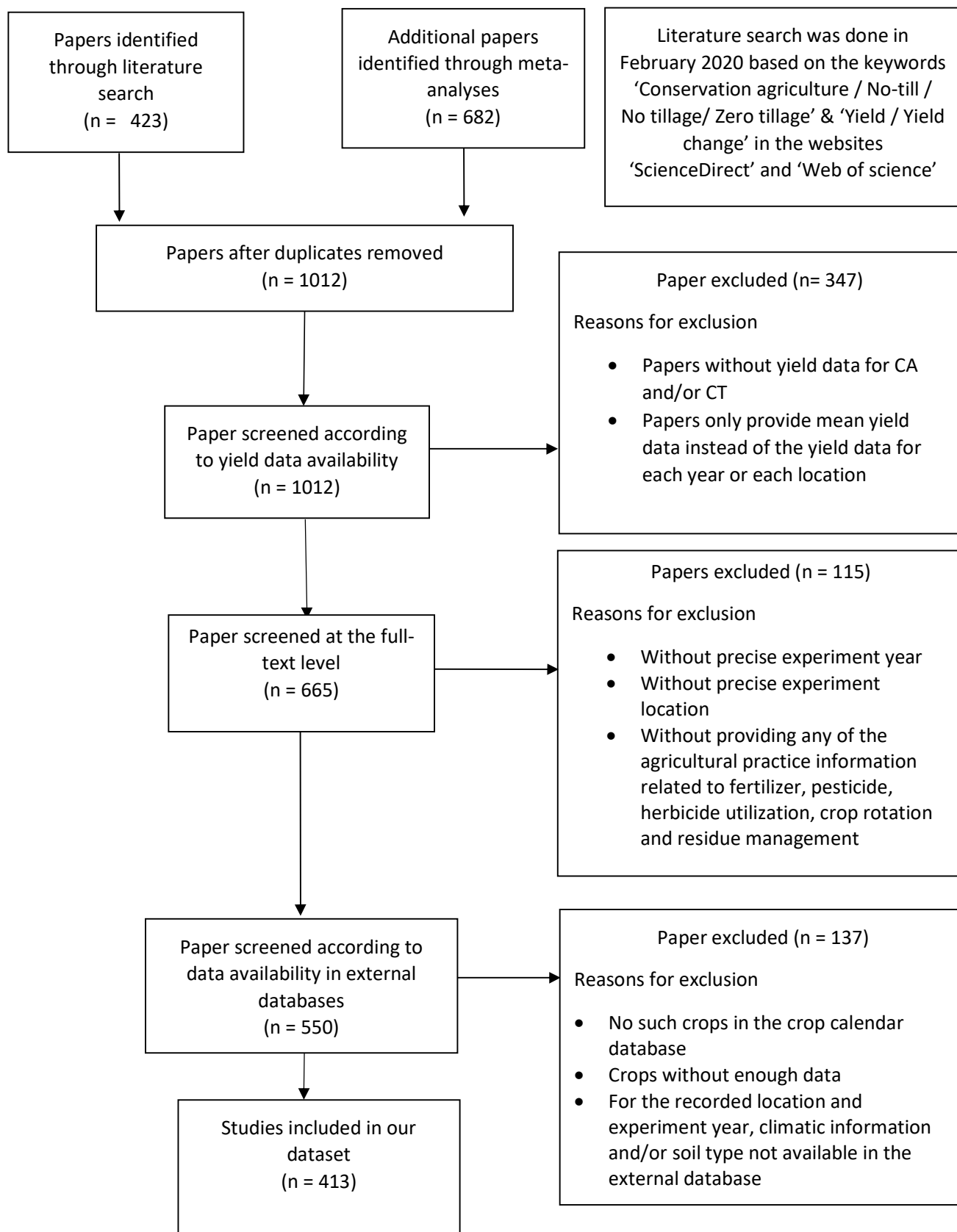
^d CIRAD, UPR HortSys, F-34398 Montpellier, France

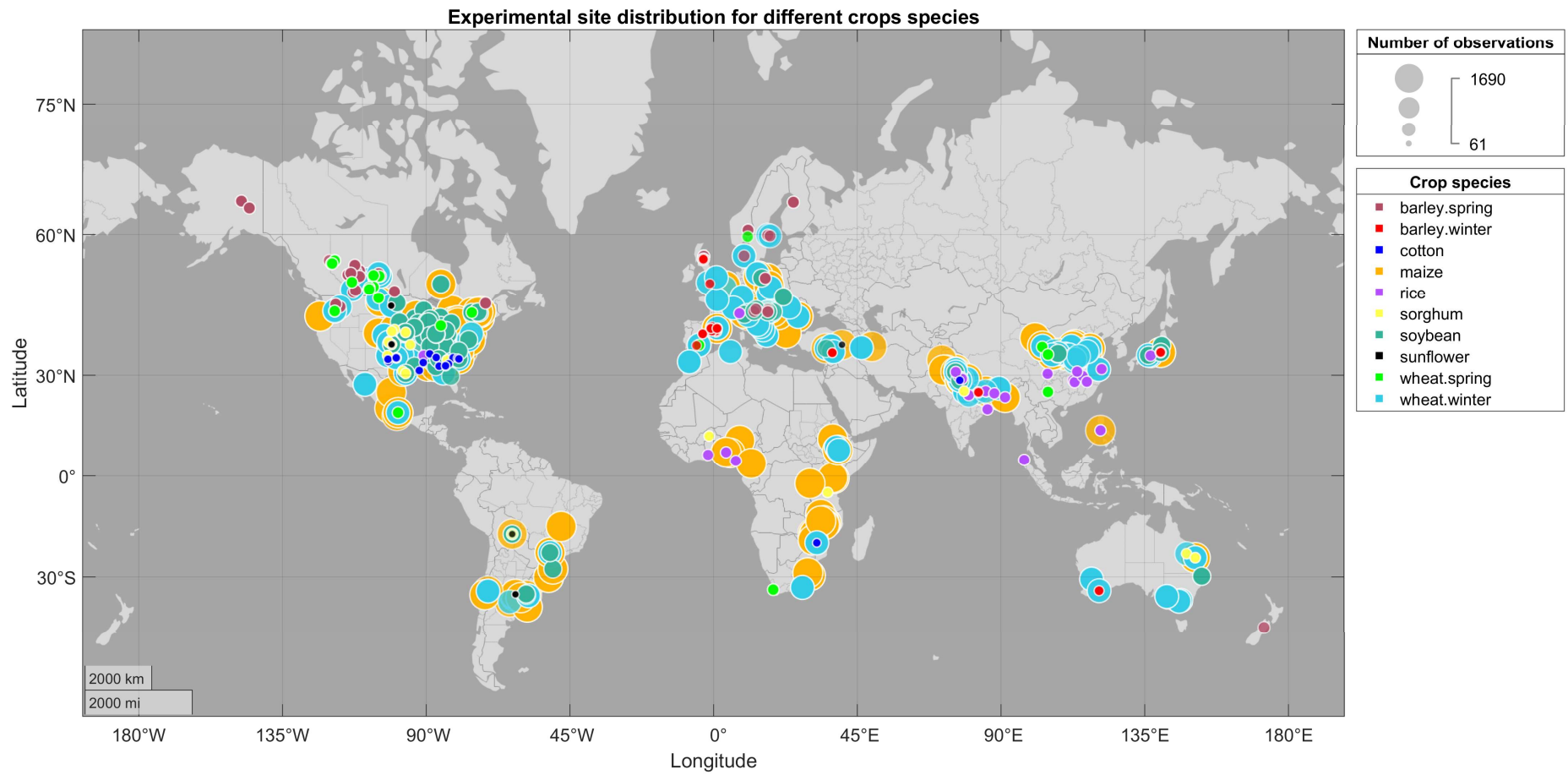
^e HortSys, Univ Montpellier, CIRAD, Montpellier, France

Corresponding Author

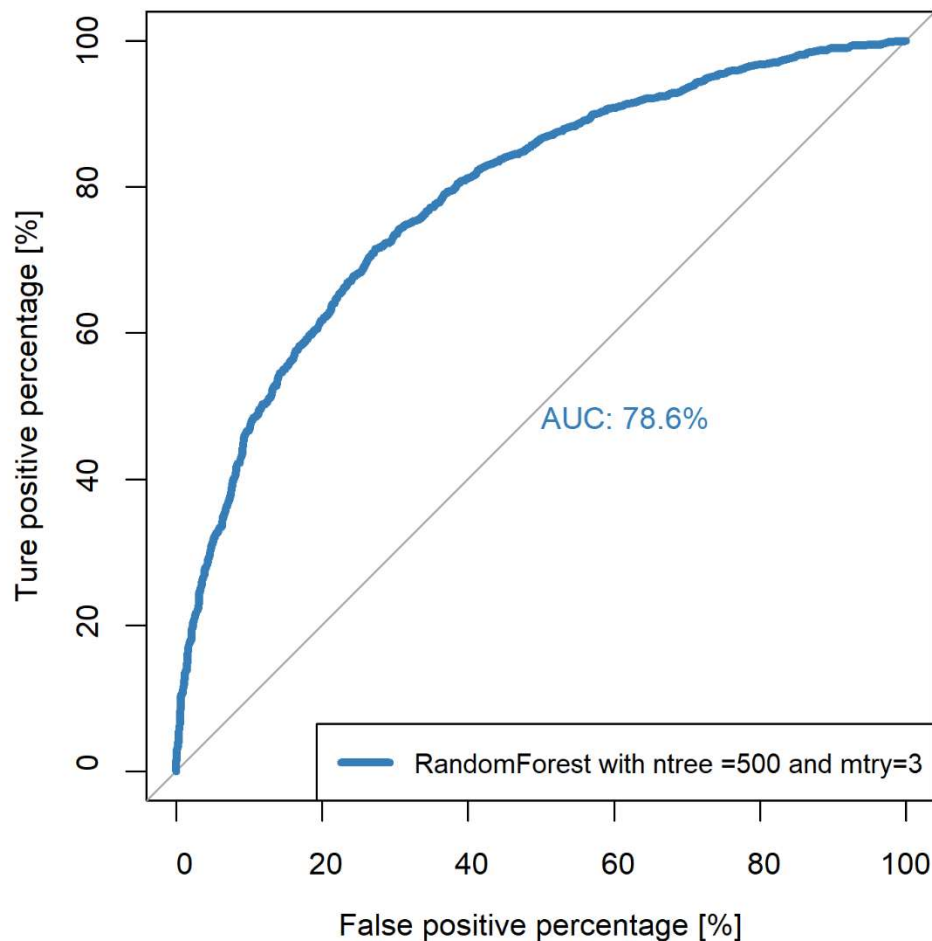
Yang SU yang.su@inrae.fr +33 1 30 81 55 51 INRAE AgroParisTech

Appendix C1 | Flow chart of literature search and data collection

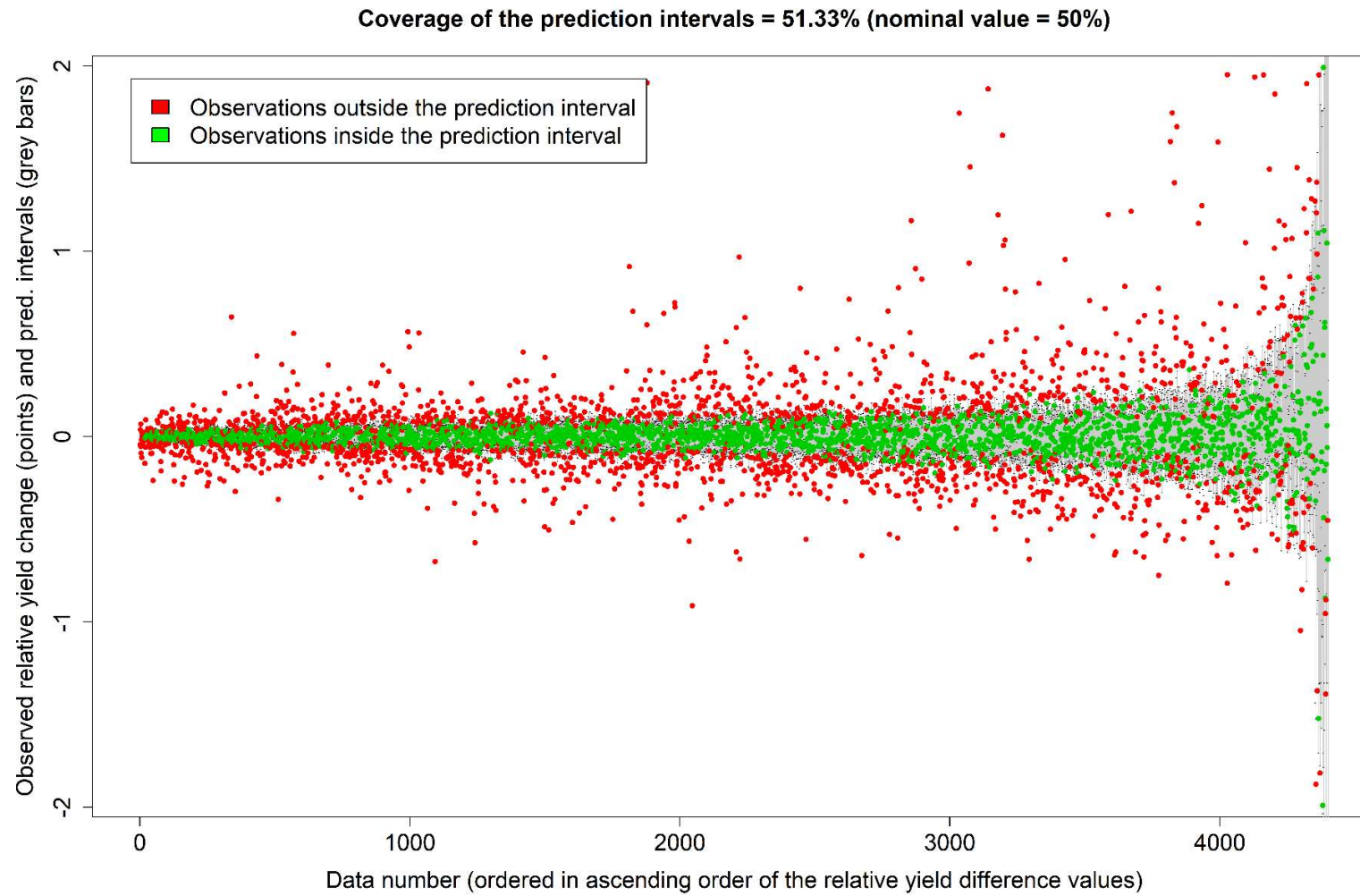




Appendix C2 | Locations of experiments included in the dataset



Appendix C3 | Ability of the random forest model to discriminate between yield ratio (CA and CA like systems vs. CT) higher and lower than one. ROC curves were computed by leave one out cross validation (LOOCV). Cross-validation procedure: One yield ratio (and its associated set of inputs) was removed from the dataset at each iteration of the LOOCV, and the rest of the dataset was used to train the random forest model. The trained model was then used to compute the probability of yield gain from the input data of the removed yield ratio. This procedure was repeated for all yield ratios. The R package “randomForest” was used. “randomForest” is a standard package for implementing ensemble of regression trees and is very robust ¹. The probabilities of yield gain computed by the package were used to compute the Area under the ROC curve (AUC) with the R package “pROC”. AUC is equal to the probability that the classifier (here the output of the random forest algorithm) will rank a random pair of positive (ratio>1) and negative (ratio<=1) cases correctly ², so a higher AUC means a better model classification performance. Here we see that AUC of “randomForest” is 78.6%, which indicates that the probability that random forest model can classify a pair of observed “yield gain” and “yield loss” correctly is 78.6%.



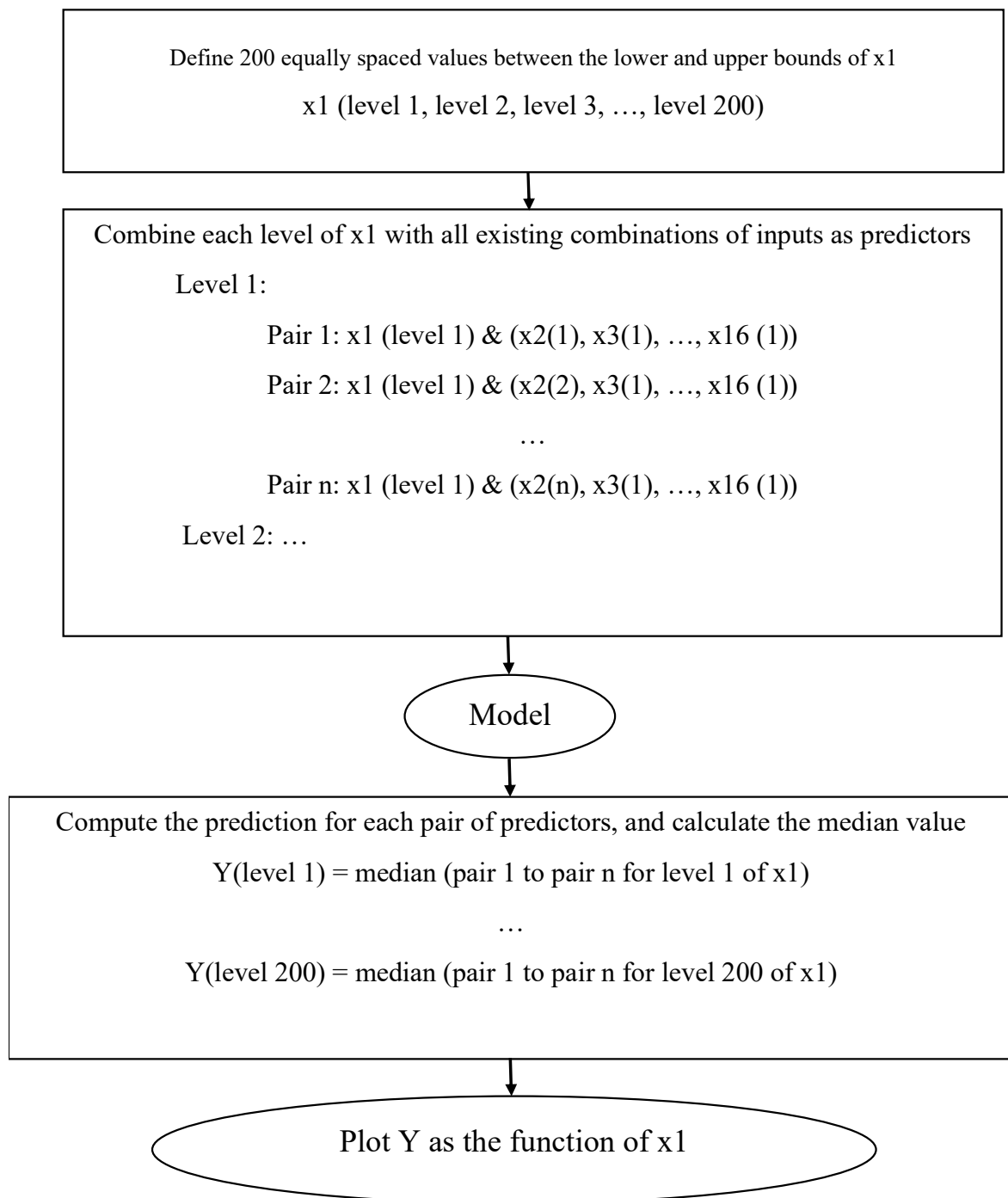
Appendix C4 | Ability of quantile regression forests model to predict the level of yield change from shifting CT to CA or CA like systems. Result based on leave one out cross validation (LOOCV) and the coverage probability. Cross-validation procedure: The performance of the quantile regression forest (based on “ranger” package in R) was evaluated by computing the proportion of data within the prediction intervals estimated by

the model. When this proportion is close to the expected coverage probability, the intervals calculated by the quantile regression forest can be considered accurate. This approach was implemented here by LOOCV. One relative yield change data (and its associated set of inputs) was thus removed from the dataset at each iteration of the LOOCV, and the rest of the dataset was used to train quantile regression forest model. The trained model was then used to compute the 25th and 75th percentiles of the relative yield change from the input values of the removed data. This procedure was repeated for all relative yield change data, and the proportion of data within the prediction intervals was computed and compared to its expected value, i.e. 50%. In S4, the vertical grey bars with two black dots correspond to the intervals defined by the 25th and 75th percentiles and the points correspond to observed relative yield changes. Data within the intervals are in green and data outside are in red.

Appendix C5 | Model setting for global projection of probability of yield grain and of the 1st and 3rd quartiles of relative yield change.

Model input	Setting (for each grid cell and each crop)	Source
Precipitation	Mean precipitation in the growing season of 1981-2010	National Oceanic and Atmospheric Administration (NOAA) ³
Evapotranspiration	Mean potential evapotranspiration in the growing season of 1981-2010	Data from GLEAM (Global Land Evaporation Amsterdam Model) ^{4,5}
Average temperature	Mean average temperature in the growing season of 1981-2010	National Oceanic and Atmospheric Administration (NOAA) ³
Maximum temperature	Mean maximum temperature in the growing season of 1981-2010	National Oceanic and Atmospheric Administration (NOAA) ^{3,6}
Minimum temperature	Mean minimum temperature in the growing season of 1981-2010	National Oceanic and Atmospheric Administration (NOAA) ⁶
Soil texture	HWSD data	The University of Tokyo ⁷
Crop growing season	Month of planting to harvesting in the crop calendar dataset for each crop	University of Wisconsin-Madison ^{8,9}
Crop mask	MIRCA2000 data	Goethe University ¹⁰
Irrigation mask	MIRCA2000 data	Goethe University ¹⁰
Crop type	Spring barley, cotton, maize, rice, sorghum, soybean, sunflower, winter wheat	
Fertilizer utilization in NT/CA	Yes (+F) or No (-F)	
Fertilizer utilization in CT	Yes (+F) or No (-F)	
Control of weed and pest in NT/CA	Yes (+WD) or No (-WD)	
Control of weed and pest in CT	Yes (+WD) or No (-WD)	
Crop rotation in NT/CA	With crop rotation for CA, without crop rotation for NT by default. In Figure 6.1b, NT (+/- R) indicated NT with/without crop rotation.	
Crop rotation in CT	Without crop rotation	
Soil cover in NT/CA	With soil cover for CA, without soil cover for NT by default. In Figure 6.1a, NT (+/- SC) indicated NT with/without soil cover.	
Soil cover in CT	Without soil cover	
Crop irrigation in NT/CA	Based on crop irrigation mask by default. In figure 6.1e, NT/CA/CT (+/- Irrigation)	Goethe University ¹⁰

	indicated NT/CA/CT with/without irrigation.	
Crop irrigation in CT	Based on crop irrigation mask by default. In figure 6.1e, NT/CA/CT (+/- Irrigation) indicated NT/CA/CT with/without irrigation	Goethe University ¹⁰

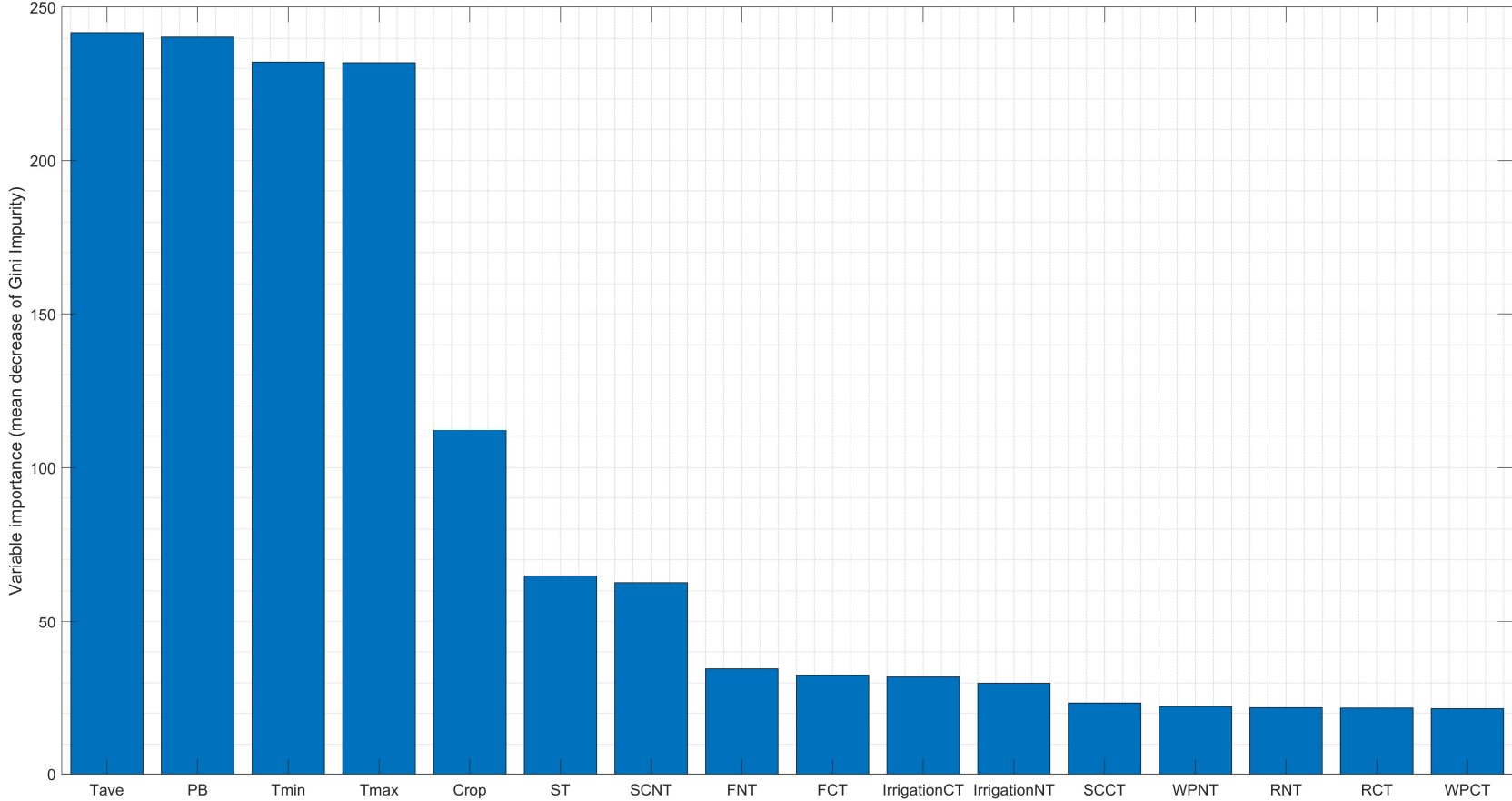


Appendix C6 | Flow chart showing the algorithm of making one-dimensional partial dependence plot.

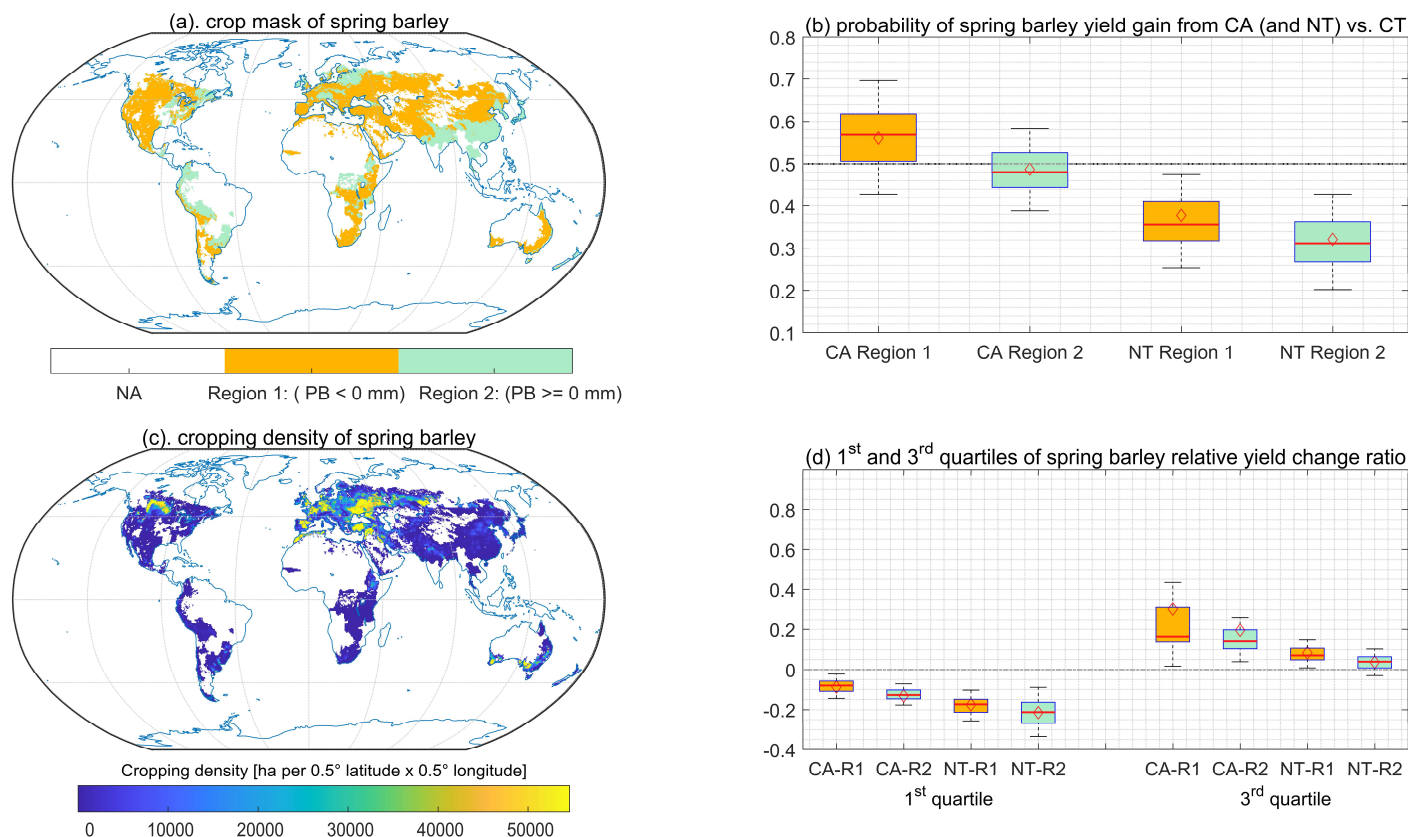
Here, x1 represented precipitation balance (PB). The ranges of PB values were divided into 200 values and the probability of yield gain resulting from CA or NT vs. CT was calculated using the random forest model for all combinations of the other input variables included in the dataset. The resulting probabilities were

then averaged for each level of PB, and the medians were plotted in a one-dimensional plot. The default setting of different crop systems is, NT: without crop rotation and without soil cover; CA: with crop rotation and with soil cover; CT: without crop rotation and without soil cover. And in Figure 6.1a NT: without crop rotation but with soil cover; In Figure 6.1b NT: with crop rotation but without soil cover. As for other crop managements such as fertilization, what is compared in this paper is CA with fertilization or NT with fertilization vs. CT with fertilization.

Appendix C

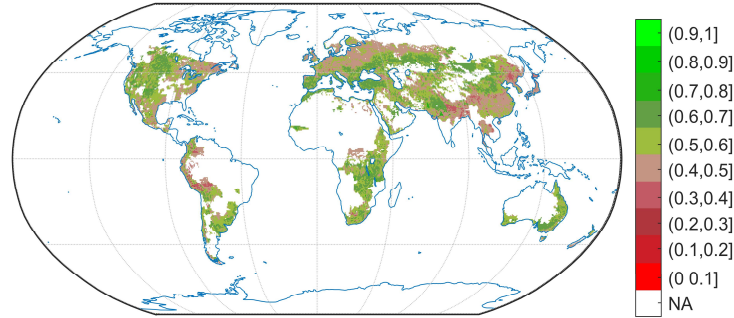


Appendix C7 | Relative importance ranking of the model inputs. The importance was defined by the mean decrease of Gini impurity in random forest model or quantile regression forest model.

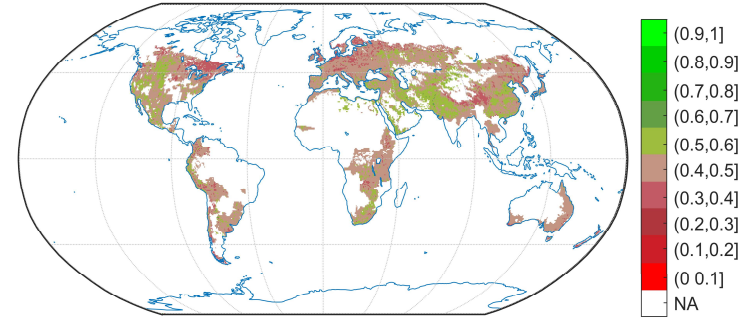


Appendix C8 | Productive performance of CA and NT vs. CT for spring barley in relatively dry and relatively wet regions. Productivity of Conservation Agriculture for spring barley in a relatively dry (region #1) and a relatively wet (region #2) region. (a) Illustration of the two regions on a global map with the two different colors showed in the sub-legend of plot a, while the blank area indicated the non-cropping region of spring barley. (b) The probability of spring barley yield gain (CA and NT vs. CT). (c) Barley cropping density on global map, the yellow shades indicated the higher density, and vice versa. The yellow color in this map indicated the crop density is equal or higher than 20% of maximum density in the cell of 0.5° latitude × 0.5° longitude at the global scale. (d) The 1st and 3rd quartiles of spring barley relative yield change under CA and NT vs. CT practice in the two regions, and the x axis tick label in plot d: R1, R2 indicated the two different regions, and the left part of plot d indicated the yield change ratios at the 1st quartile, while the right part were the yield change ratios at 3rd quartile. The colors in plot a, b and d indicated the same regions. In plot b and d, the mean value of relative yield change in its region is marked by the red diamond, while the median value is depicted by the red horizontal line.

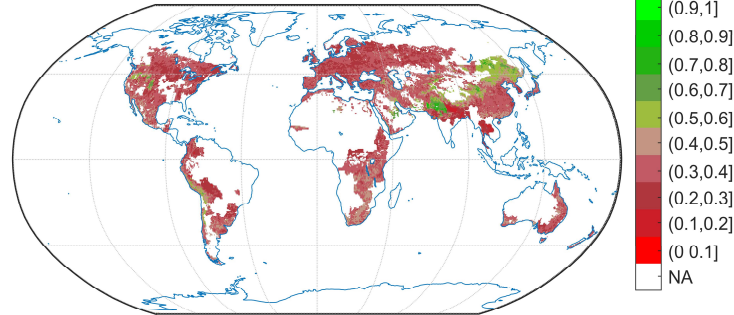
(a). probability of yield increase for spring barley with CA (+F+WD)



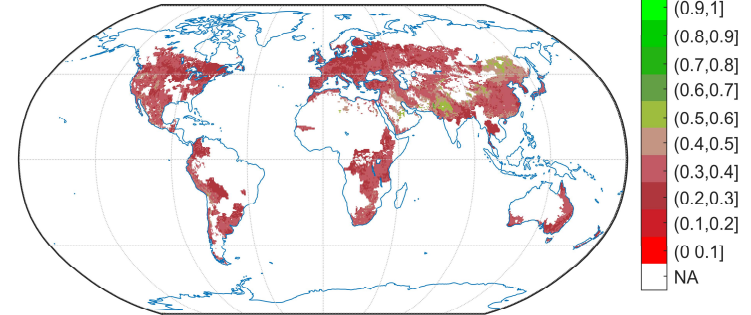
(b). probability of yield increase for spring barley with CA (-F-WD)



(c). probability of yield increase for spring barley with NT (+F+WD)

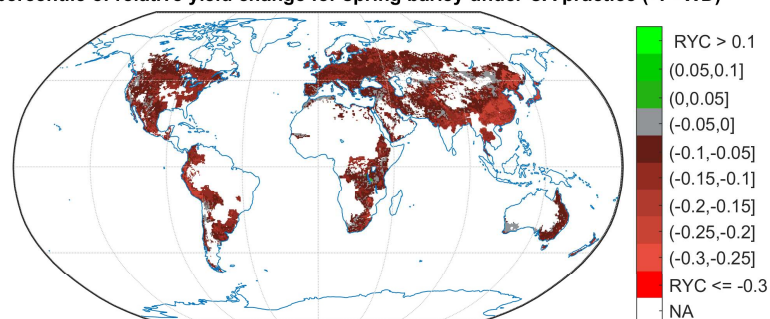


(d). probability of yield increase for spring barley with NT (-F-WD)

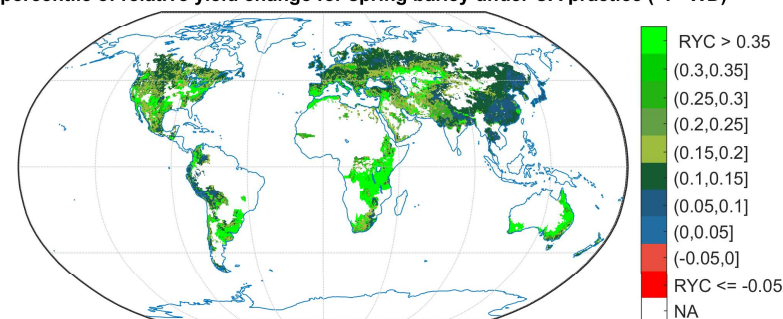


Appendix C9 | The probability of yield gain of spring barley with CA and NT vs. CT practice. Probability of yield gain with CA and NT vs. CT spring barley. Only the cropping regions were presented. The different colors indicated different probabilities of yield gain from CA and NT comparing to CT system. The greener color indicated a higher probability of yield gain. +/- F indicated NT or CA and CT with/without field fertilization. +/- WD indicated NT or CA and CT with/without weed and pest control.

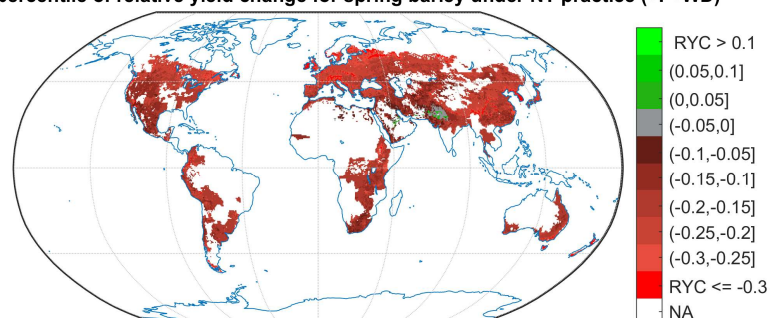
(a). 25th percentile of relative yield change for spring barley under CA practice (+F+WD)



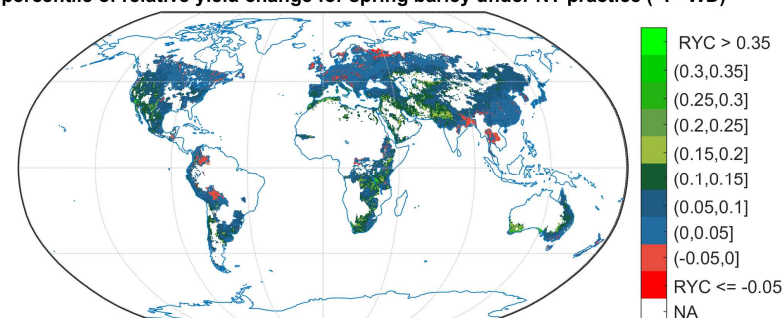
(b). 75th percentile of relative yield change for spring barley under CA practice (+F+WD)



(c). 25th percentile of relative yield change for spring barley under NT practice (+F+WD)

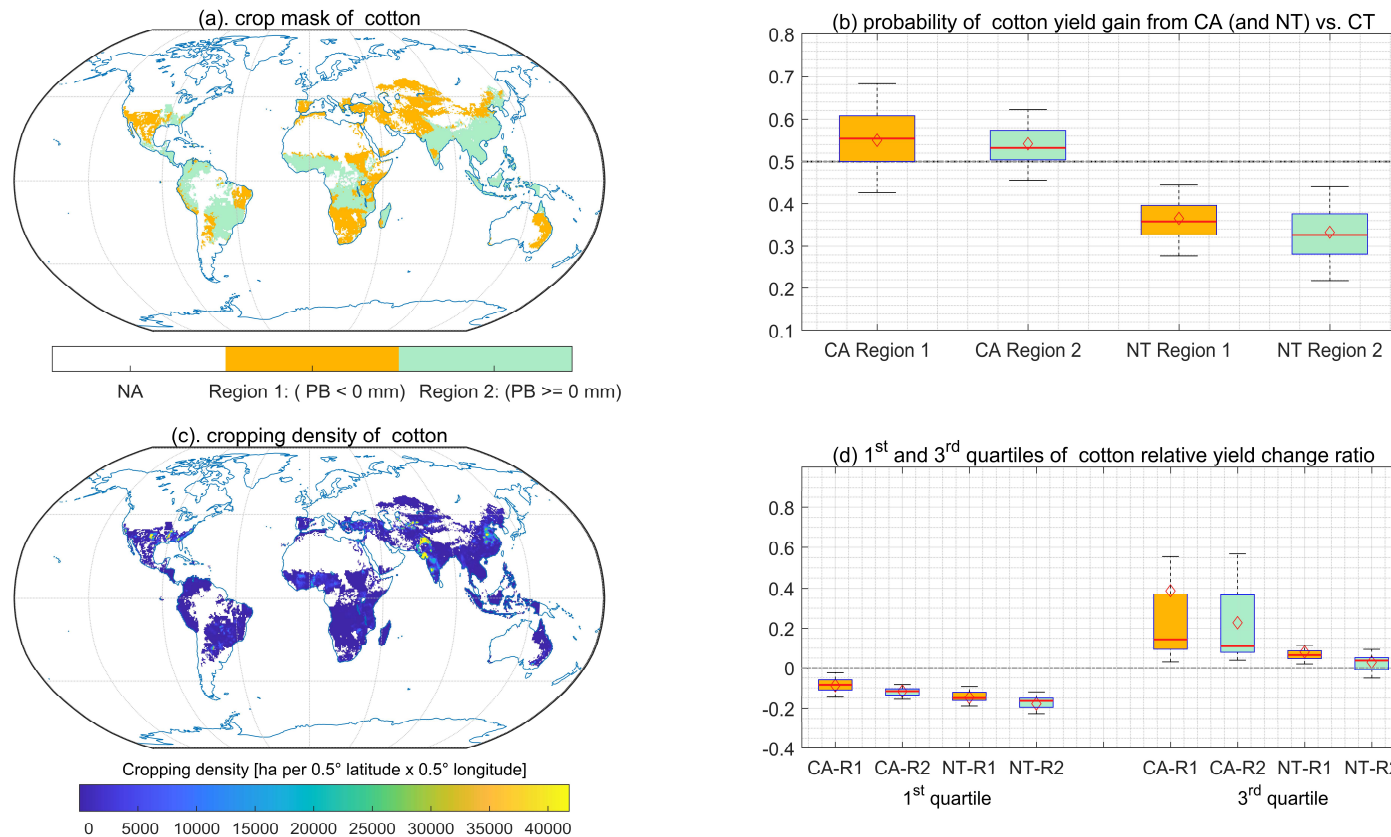


(d). 75th percentile of relative yield change for spring barley under NT practice (+F+WD)



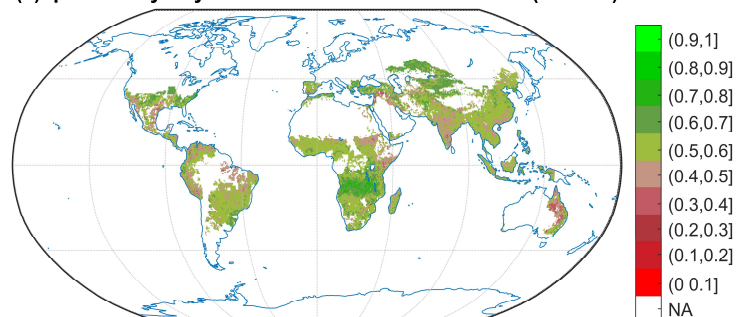
Appendix C10 | The relative yield change of spring barley with CA and NT vs. CT practice. Relative yield change probability (1st and 3rd quartile estimate) of shifting CT to CA/NT for spring barley, with field fertilization and weed and pest control (+F+WD). There was a 75% chance that the relative yield change will be higher than the ratio shown on the map in plot a and c, and conversely a 25% chance that the relative change will be lower. There was a 75% chance that the relative yield change will be lower than the ratio shown on the map in plot b and d, and conversely a 25% chance that the relative change will be higher. The colors indicated different levels of yield change ratio, and the reddish colors indicated the negative yield change or yield loss.

Appendix C

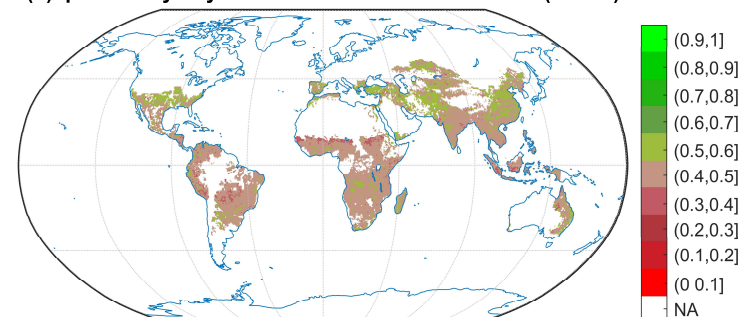


Appendix C11 | Productive performance of CA and NT vs. CT for cotton in relatively dry and relatively wet regions. Productivity of Conservation Agriculture for cotton in a relatively dry (region #1) and a relatively wet (region #2) region. (a) Illustration of the two regions on a global map with the two different colors showed in the sub-legend of plot a, while the blank area indicated the non-cropping region of cotton. (b) The probability of cotton yield gain (CA and NT vs. CT). (c) Cotton cropping density on global map, the yellow shades indicated the higher density, and vice versa. The yellow color in this map indicated the crop density is equal or higher than 20% of maximum density in the cell of 0.5° latitude × 0.5° longitude at the global scale. (d) The 1st and 3rd quartiles of cotton relative yield change under CA and NT vs. CT practice in the two regions, and the x axis tick label in plot d: R1, R2 indicated the two different regions, and the left part of plot d indicated the yield change ratios at the 1st quartile, while the right part were the yield change ratios at 3rd quartile. The colors in plot a, b and d indicated the same regions. In plot b and d, the mean value of relative yield change in its region is marked by the red diamond, while the median value is depicted by the red horizontal line.

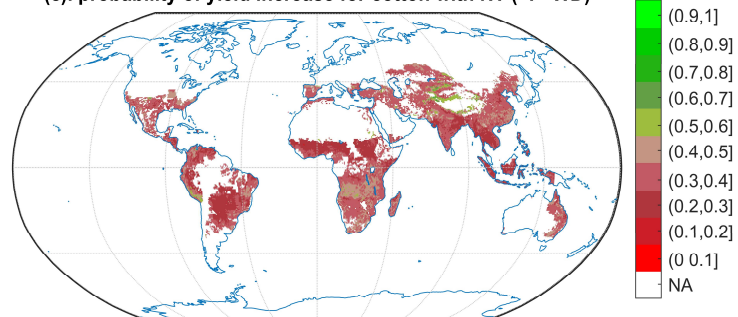
(a). probability of yield increase for cotton with CA (+F+WD)



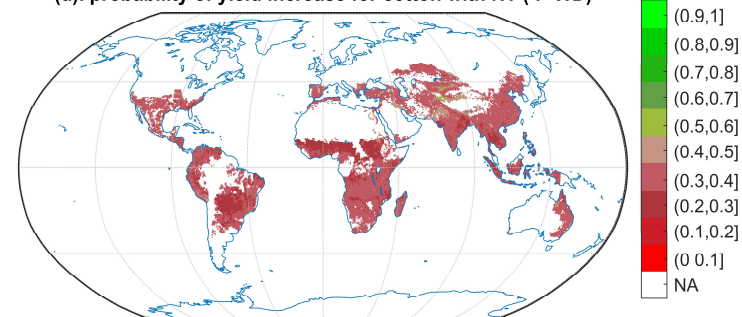
(b). probability of yield increase for cotton with CA (-F-WD)



(c). probability of yield increase for cotton with NT (+F+WD)

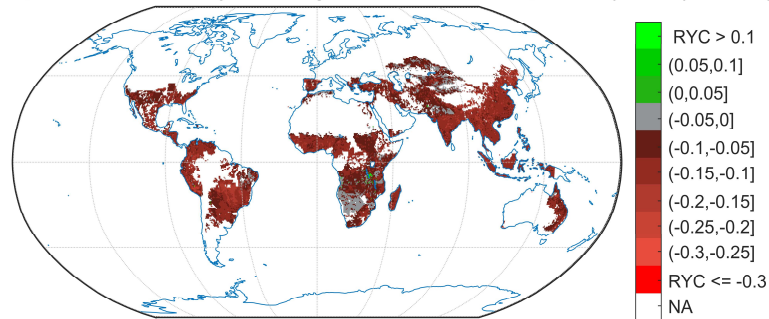


(d). probability of yield increase for cotton with NT (-F-WD)

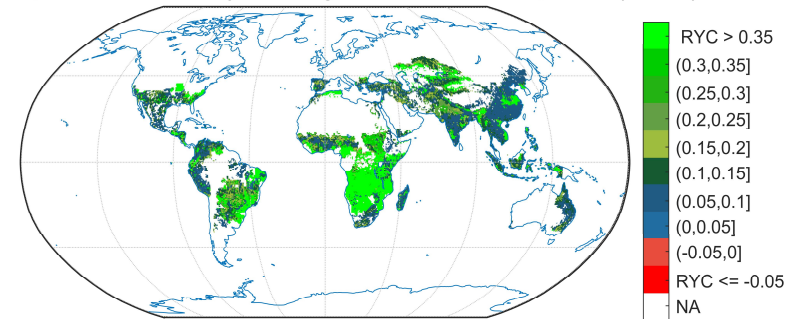


Appendix C12 | The probability of yield gain of cotton with CA and NT vs. CT practice. Probability of yield gain with CA and NT vs. CT cotton. Only the cropping regions were presented. The different colors indicated different probabilities of yield gain from CA and NT comparing to CT system. The greener color indicated a higher probability of yield gain. +/- F indicated NT or CA and CT with/without field fertilization. +/- WD indicated NT or CA and CT with/without weed and pest control.

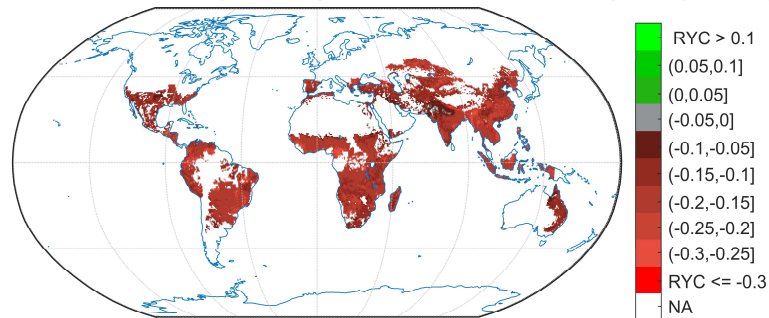
(a). 25th percentile of relative yield change for cotton under CA practice (+F+WD)



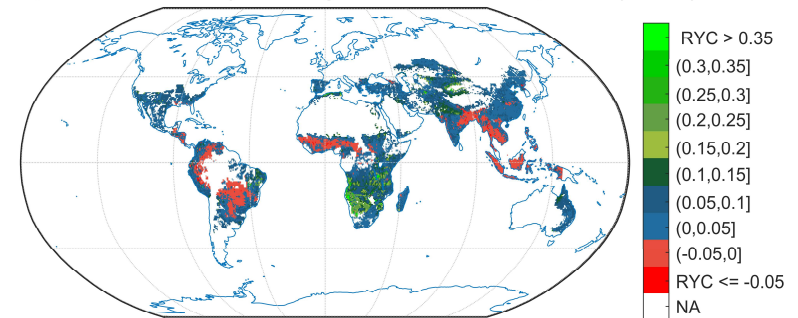
(b). 75th percentile of relative yield change for cotton under CA practice (+F+WD)



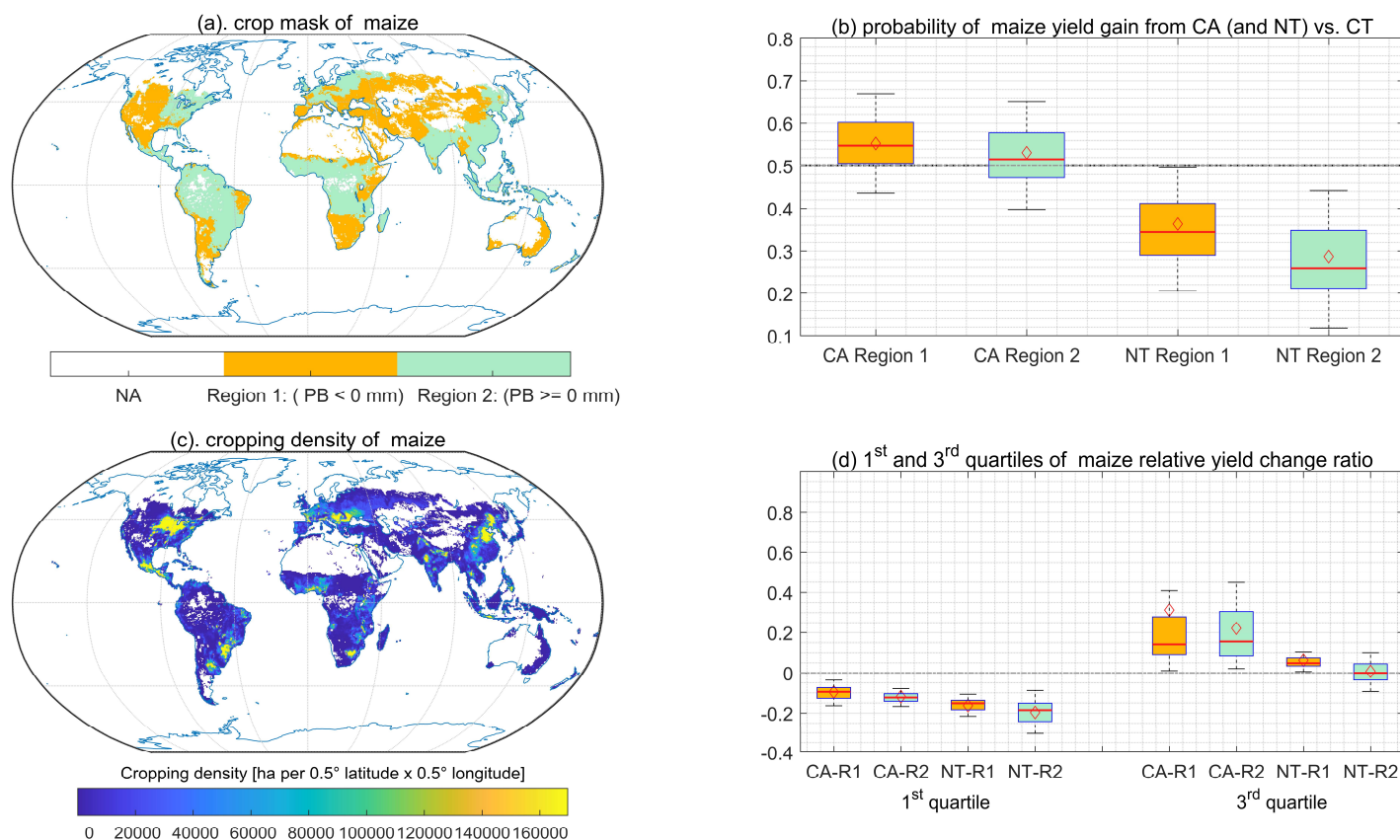
(c). 25th percentile of relative yield change for cotton under NT practice (+F+WD)



(d). 75th percentile of relative yield change for cotton under NT practice (+F+WD)

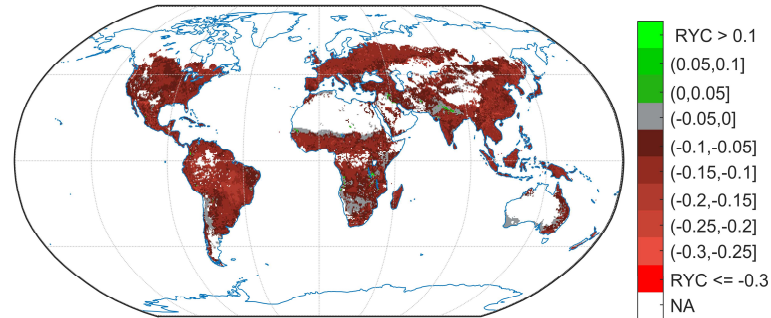


Appendix C13 | The relative yield change of cotton with CA and NT vs. CT practice. Relative yield change probability (1st and 3rd quartile estimate) of shifting CT to CA/NT for cotton, with field fertilization and weed and pest control (+F+WD). There was a 75% chance that the relative yield change will be higher than the ratio shown on the map in plot a and c, and conversely a 25% chance that the relative change will be lower. There was a 75% chance that the relative yield change will be lower than the ratio shown on the map in plot b and d, and conversely a 25% chance that the relative change will be higher. The colors indicated different levels of yield change ratio, and the reddish colors indicated the negative yield change or yield loss.

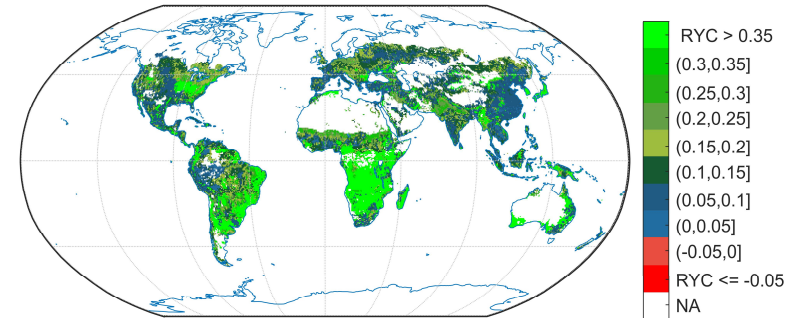


Appendix C14 | Productive performance of CA and NT vs. CT for maize in relatively dry and relatively wet regions. Productivity of Conservation Agriculture for maize in a relatively dry (region #1) and a relatively wet (region #2) region. (a) Illustration of the two regions on a global map with the two different colors showed in the sub-legend of plot a, while the blank area indicated the non-cropping region of maize. (b) The probability of maize yield gain (CA and NT vs. CT). (c) Maize cropping density on global map, the yellow shades indicated the higher density, and vice versa. The yellow color in this map indicated the crop density is equal or higher than 20% of maximum density in the cell of 0.5° latitude × 0.5° longitude at the global scale. (d) The 1st and 3rd quartiles of maize relative yield change under CA and NT vs. CT practice in the two regions, and the x axis tick label in plot d: R1, R2 indicated the two different regions, and the left part of plot d indicated the yield change ratios at the 1st quartile, while the right part were the yield change ratios at 3rd quartile. The colors in plot a, b and d indicated the same regions. In plot b and d, the mean value of relative yield change in its region is marked by the red diamond, while the median value is depicted by the red horizontal line.

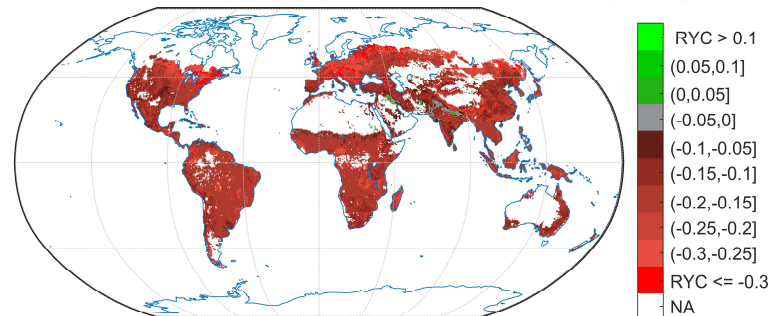
(a). 25th percentile of relative yield change for maize under CA practice (+F+WD)



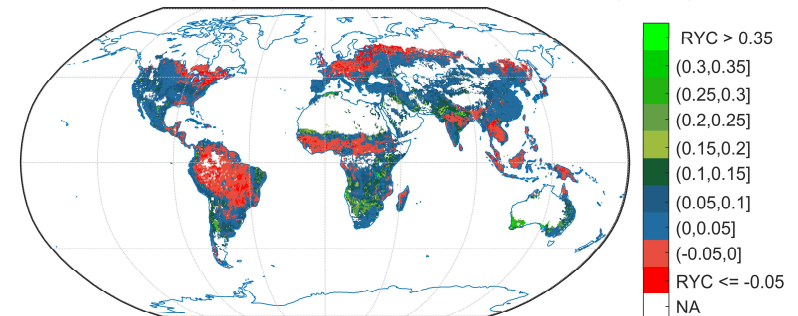
(b). 75th percentile of relative yield change for maize under CA practice (+F+WD)



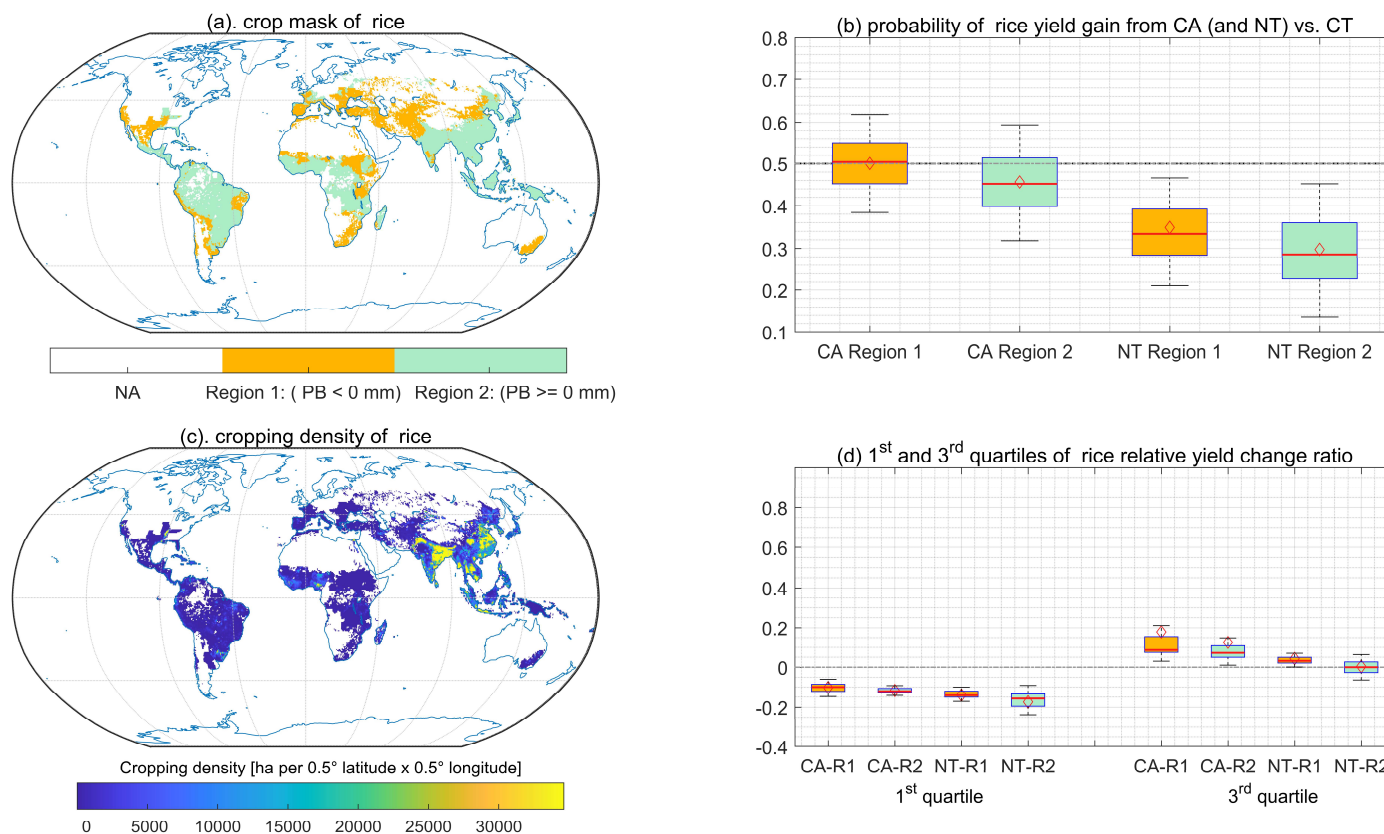
(c). 25th percentile of relative yield change for maize under NT practice (+F+WD)



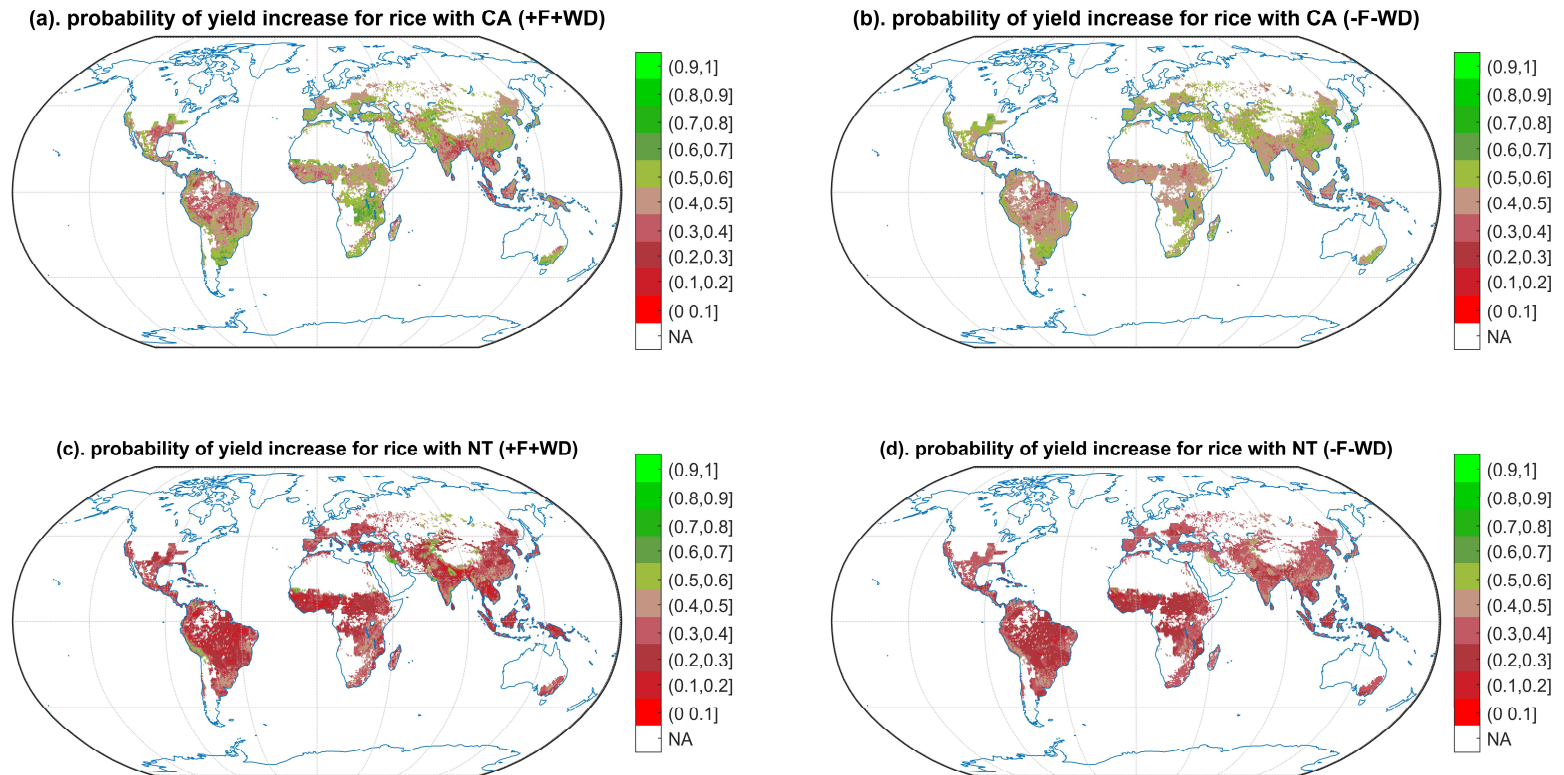
(d). 75th percentile of relative yield change for maize under NT practice (+F+WD)



Appendix C15 | The relative yield change of maize with CA and NT vs. CT practice. Relative yield change probability (1st and 3rd quartile estimate) of shifting CT to CA/NT for maize, with field fertilization and weed and pest control (+F+WD). There was a 75% chance that the relative yield change will be higher than the ratio shown on the map in plot a and c, and conversely a 25% chance that the relative change will be lower. There was a 75% chance that the relative yield change will be lower than the ratio shown on the map in plot b and d, and conversely a 25% chance that the relative change will be higher. The colors indicated different levels of yield change ratio, and the reddish colors indicated the negative yield change or yield loss.

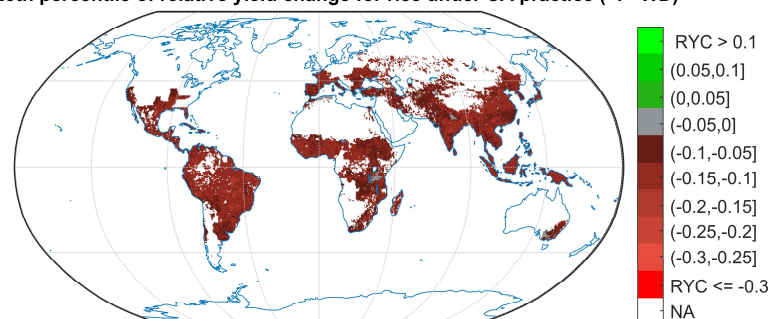


Appendix C16 | Productive performance of CA and NT vs. CT for rice in relatively dry and relatively wet regions. Productivity of Conservation Agriculture for rice in a relatively dry (region #1) and a relatively wet (region #2) region. (a) Illustration of the two regions on a global map with the two different colors showed in the sub-legend of plot a, while the blank area indicated the non-cropping region of rice. (b) The probability of rice yield gain (CA and NT vs. CT). (c) Rice cropping density on global map, the yellow shades indicated the higher density, and vice versa. The yellow color in this map indicated the crop density is equal or higher than 20% of maximum density in the cell of 0.5° latitude × 0.5° longitude at the global scale. (d) The 1st and 3rd quartiles of rice relative yield change under CA and NT vs. CT practice in the two regions, and the x axis tick label in plot d: R1, R2 indicated the two different regions, and the left part of plot d indicated the yield change ratios at the 1st quartile, while the right part were the yield change ratios at 3rd quartile. The colors in plot a, b and d indicated the same regions. In plot b and d, the mean value of relative yield change in its region is marked by the red diamond, while the median value is depicted by the red horizontal line.

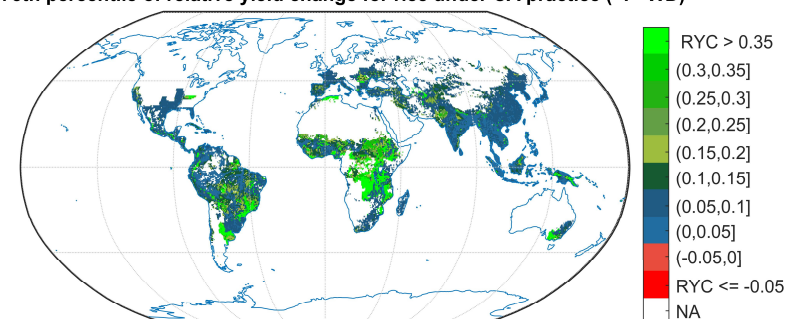


Appendix C17 | The probability of yield gain of rice with CA and NT vs. CT practice. Probability of yield gain with CA and NT vs. CT rice. Only the cropping regions were presented. The different colors indicated different probabilities of yield gain from CA and NT comparing to CT system. The greener color indicated a higher probability of yield gain. +/- F indicated NT or CA and CT with/without field fertilization. +/- WD indicated NT or CA and CT with/without weed and pest control.

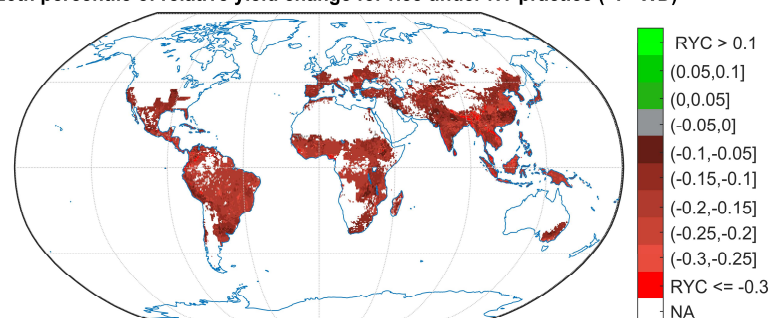
(a). 25th percentile of relative yield change for rice under CA practice (+F+WD)



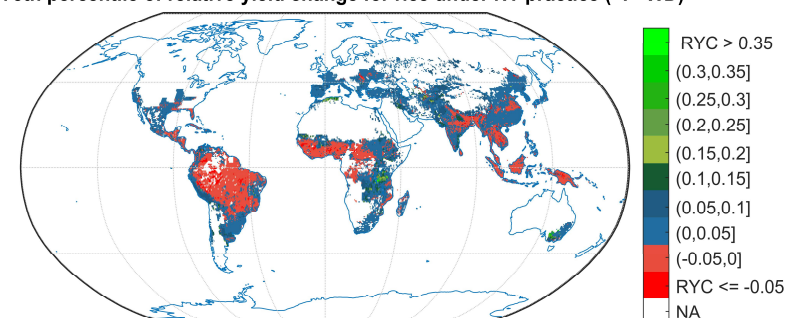
(b). 75th percentile of relative yield change for rice under CA practice (+F+WD)



(c). 25th percentile of relative yield change for rice under NT practice (+F+WD)

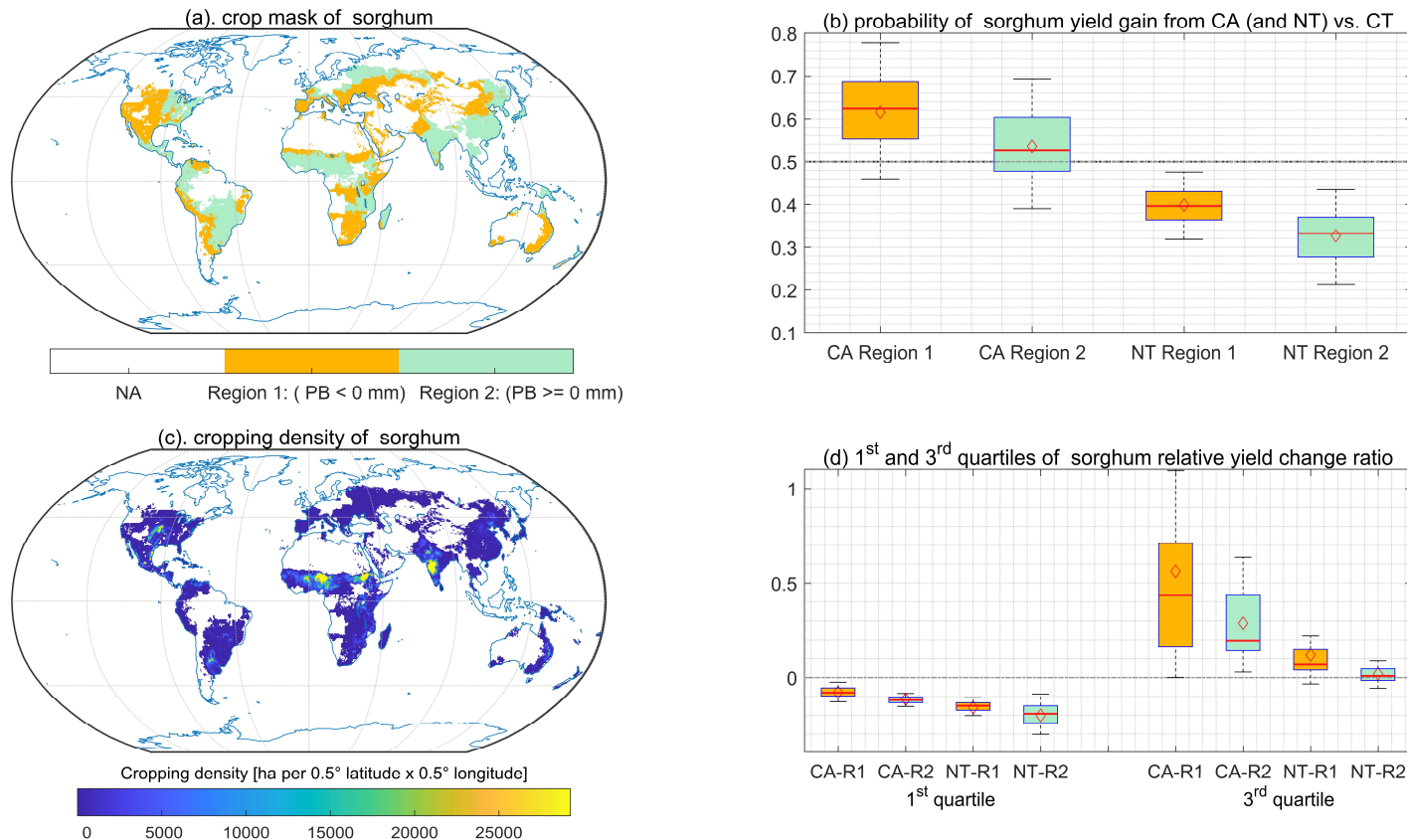


(d). 75th percentile of relative yield change for rice under NT practice (+F+WD)



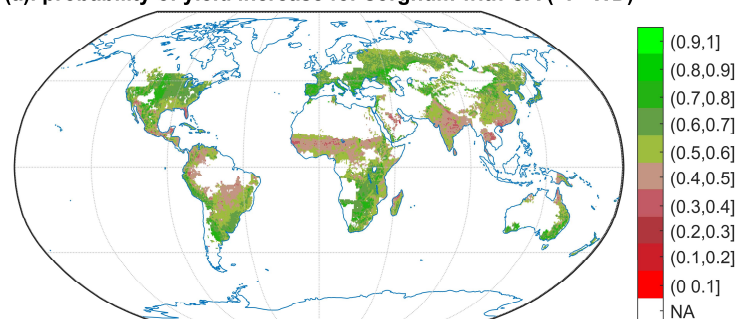
Appendix C18 | The relative yield change of rice with CA and NT vs. CT practice. Relative yield change probability (1st and 3rd quartile estimate) of shifting CT to CA/NT for rice, with field fertilization and weed and pest control (+F+WD). There was a 75% chance that the relative yield change will be higher than the ratio shown on the map in plot a and c, and conversely a 25% chance that the relative change will be lower. There was a 75% chance that the relative yield change will be lower than the ratio shown on the map in plot b and d, and conversely a 25% chance that the relative change will be higher. The colors indicated different levels of yield change ratio, and the reddish colors indicated the negative yield change or yield loss.

Appendix C

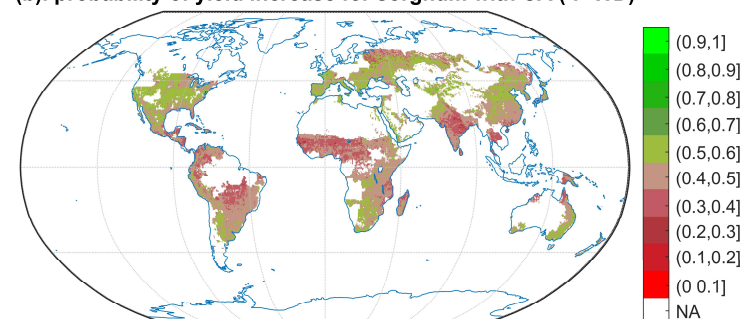


Appendix C19 | Productive performance of CA and NT vs. CT for sorghum in relatively dry and relatively wet regions. Productivity of Conservation Agriculture for sorghum in a relatively dry (region #1) and a relatively wet (region #2) region. (a) Illustration of the two regions on a global map with the two different colors showed in the sub-legend of plot a, while the blank area indicated the non-cropping region of sorghum. (b) The probability of sorghum yield gain (CA and NT vs. CT). (c) Sorghum cropping density on global map, the yellow shades indicated the higher density, and vice versa. The yellow color in this map indicated the crop density is equal or higher than 20% of maximum density in the cell of 0.5° latitude × 0.5° longitude at the global scale. (d) The 1st and 3rd quartiles of sorghum relative yield change under CA and NT vs. CT practice in the two regions, and the x axis tick label in plot d: R1, R2 indicated the two different regions, and the left part of plot d indicated the yield change ratios at the 1st quartile, while the right part were the yield change ratios at 3rd quartile. The colors in plot a, b and d indicated the same regions. In plot b and d, the mean value of relative yield change in its region is marked by the red diamond, while the median value is depicted by the red horizontal line.

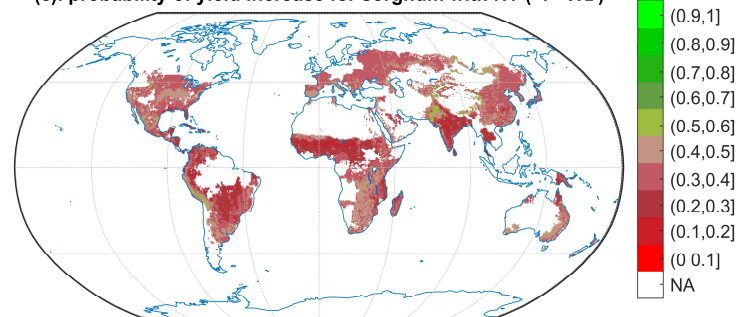
(a). probability of yield increase for sorghum with CA (+F+WD)



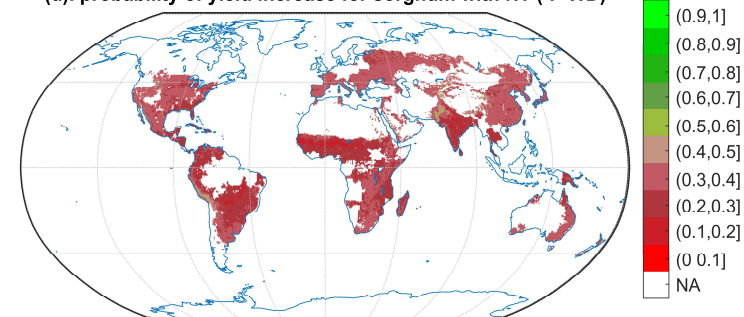
(b). probability of yield increase for sorghum with CA (-F-WD)



(c). probability of yield increase for sorghum with NT (+F+WD)

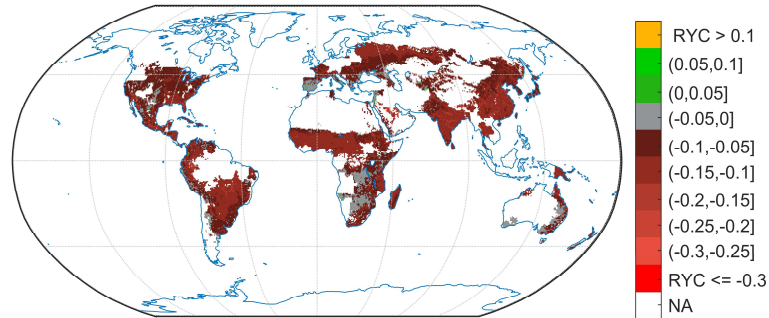


(d). probability of yield increase for sorghum with NT (-F-WD)

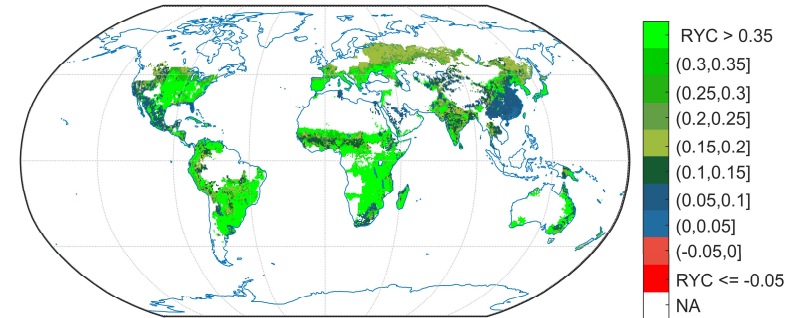


Appendix C20 | The probability of yield gain of sorghum with CA and NT vs. CT practice. Probability of yield gain with CA and NT vs. CT sorghum. Only the cropping regions were presented. The different colors indicated different probabilities of yield gain from CA and NT comparing to CT system. The greener color indicated a higher probability of yield gain. +/- F indicated NT or CA and CT with/without field fertilization. +/- WD indicated NT or CA and CT with/without weed and pest control.

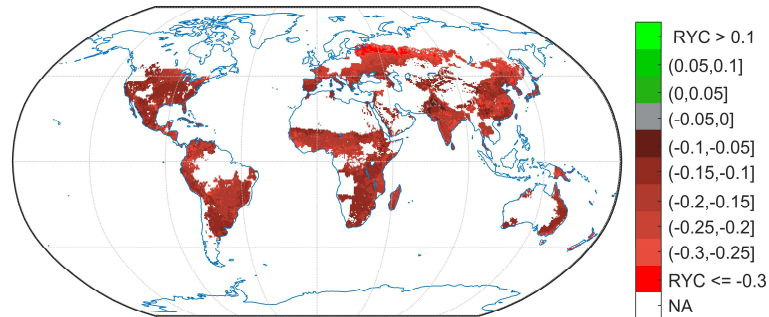
(a). 25th percentile of relative yield change for sorghum under CA practice (+F+WD)



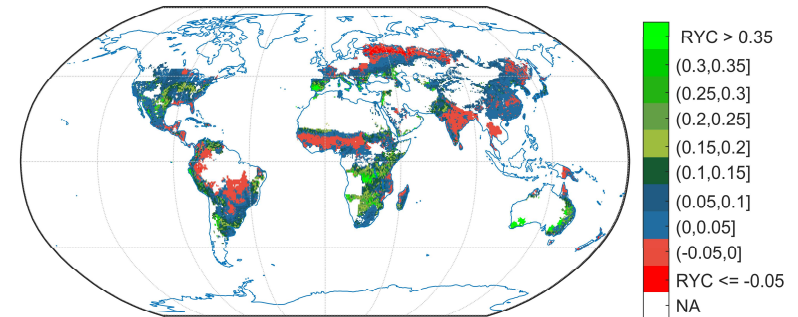
(b). 75th percentile of relative yield change for sorghum under CA practice (+F+WD)



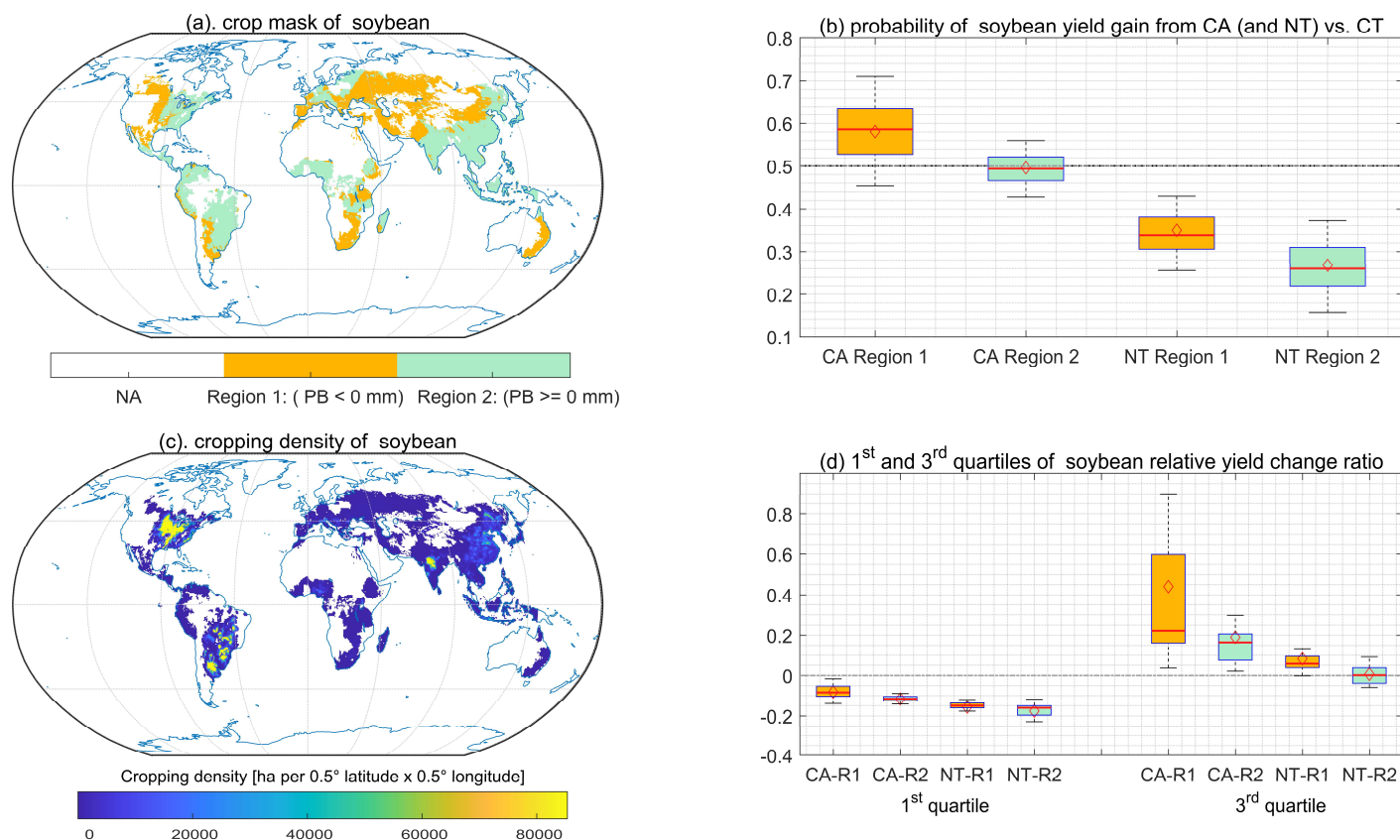
(c). 25th percentile of relative yield change for sorghum under NT practice (+F+WD)



(d). 75th percentile of relative yield change for sorghum under NT practice (+F+WD)

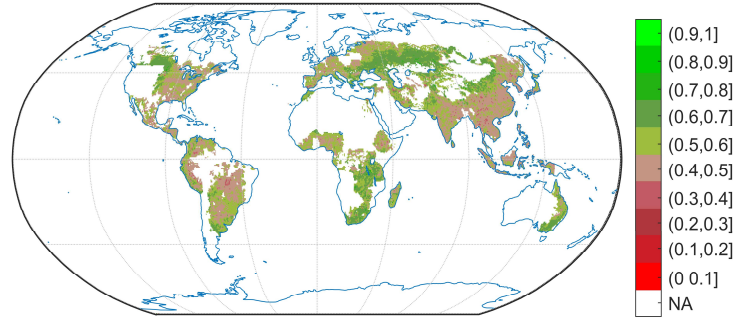


Appendix C21 | The relative yield change of sorghum with CA and NT vs. CT practice. Relative yield change probability (1st and 3rd quartile estimate) of shifting CT to CA/NT for sorghum, with field fertilization and weed and pest control (+F+WD). There was a 75% chance that the relative yield change will be higher than the ratio shown on the map in plot a and c, and conversely a 25% chance that the relative change will be lower. There was a 75% chance that the relative yield change will be lower than the ratio shown on the map in plot b and d, and conversely a 25% chance that the relative change will be higher. The colors indicated different levels of yield change ratio, and the reddish colors indicated the negative yield change or yield loss.

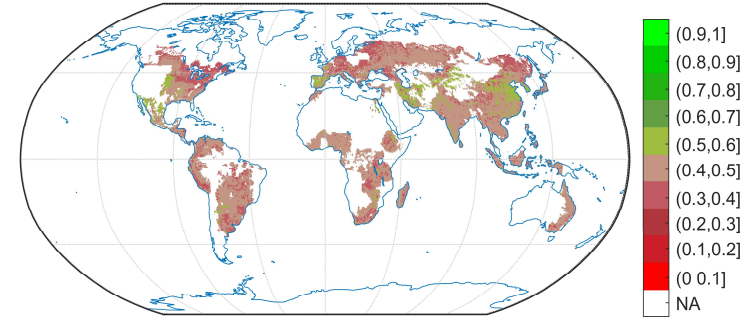


Appendix C22 | Productive performance of CA and NT vs. CT for soybean in relatively dry and relatively wet regions. Productivity of Conservation Agriculture for soybean in a relatively dry (region #1) and a relatively wet (region #2) region. (a) Illustration of the two regions on a global map with the two different colors showed in the sub-legend of plot a, while the blank area indicated the non-cropping region of soybean. (b) The probability of soybean yield gain (CA and NT vs. CT). (c) Soybean cropping density on global map, the yellow shades indicated the higher density, and vice versa. The yellow color in this map indicated the crop density is equal or higher than 20% of maximum density in the cell of 0.5° latitude × 0.5° longitude at the global scale. (d) The 1st and 3rd quartiles of soybean relative yield change under CA and NT vs. CT practice in the two regions, and the x axis tick label in plot d: R1, R2 indicated the two different regions, and the left part of plot d indicated the yield change ratios at the 1st quartile, while the right part were the yield change ratios at 3rd quartile. The colors in plot a, b and d indicated the same regions. In plot b and d, the mean value of relative yield change in its region is marked by the red diamond, while the median value is depicted by the red horizontal line.

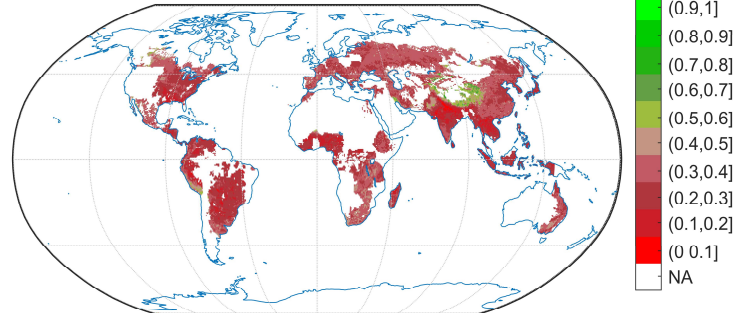
(a). probability of yield increase for soybean with CA (+F+WD)



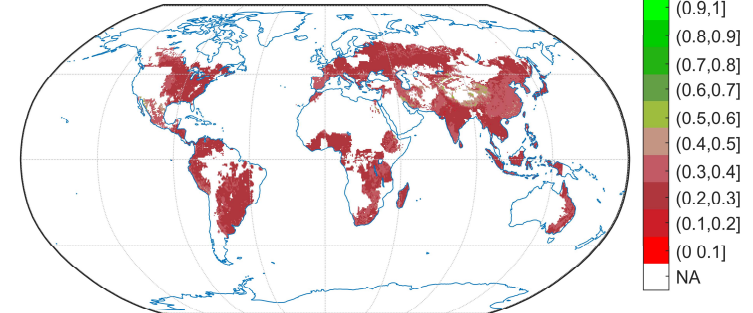
(b). probability of yield increase for soybean with CA (-F-WD)



(c). probability of yield increase for soybean with NT (+F+WD)

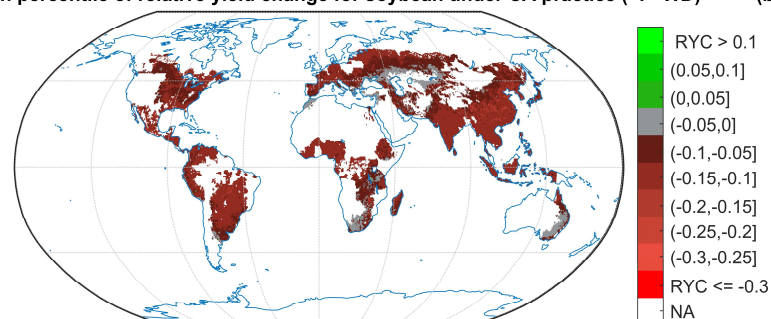


(d). probability of yield increase for soybean with NT (-F-WD)

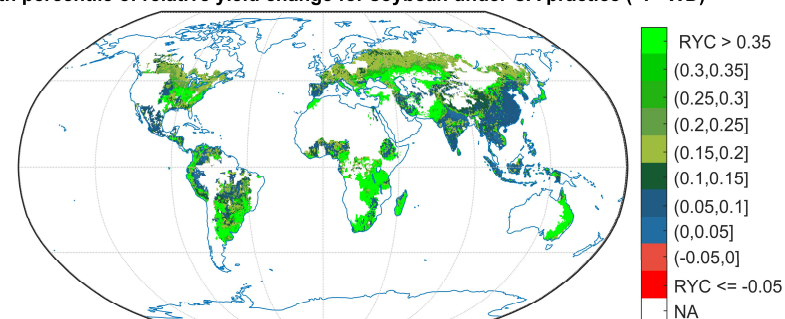


Appendix C23 | The probability of yield gain of soybean with CA and NT vs. CT practice. Probability of yield gain with CA and NT vs. CT soybean. Only the cropping regions were presented. The different colors indicated different probabilities of yield gain from CA and NT comparing to CT system. The greener color indicated a higher probability of yield gain. +/- F indicated NT or CA and CT with/without field fertilization. +/- WD indicated NT or CA and CT with/without weed and pest control.

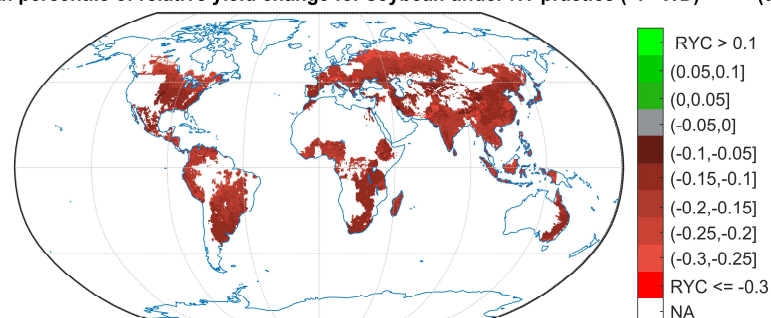
(a). 25th percentile of relative yield change for soybean under CA practice (+F+WD)



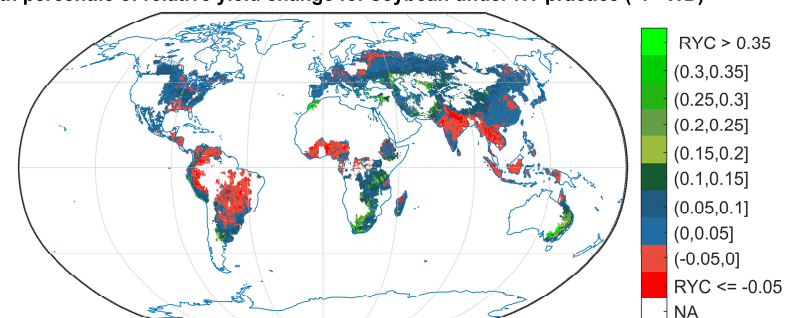
(b). 75th percentile of relative yield change for soybean under CA practice (+F+WD)



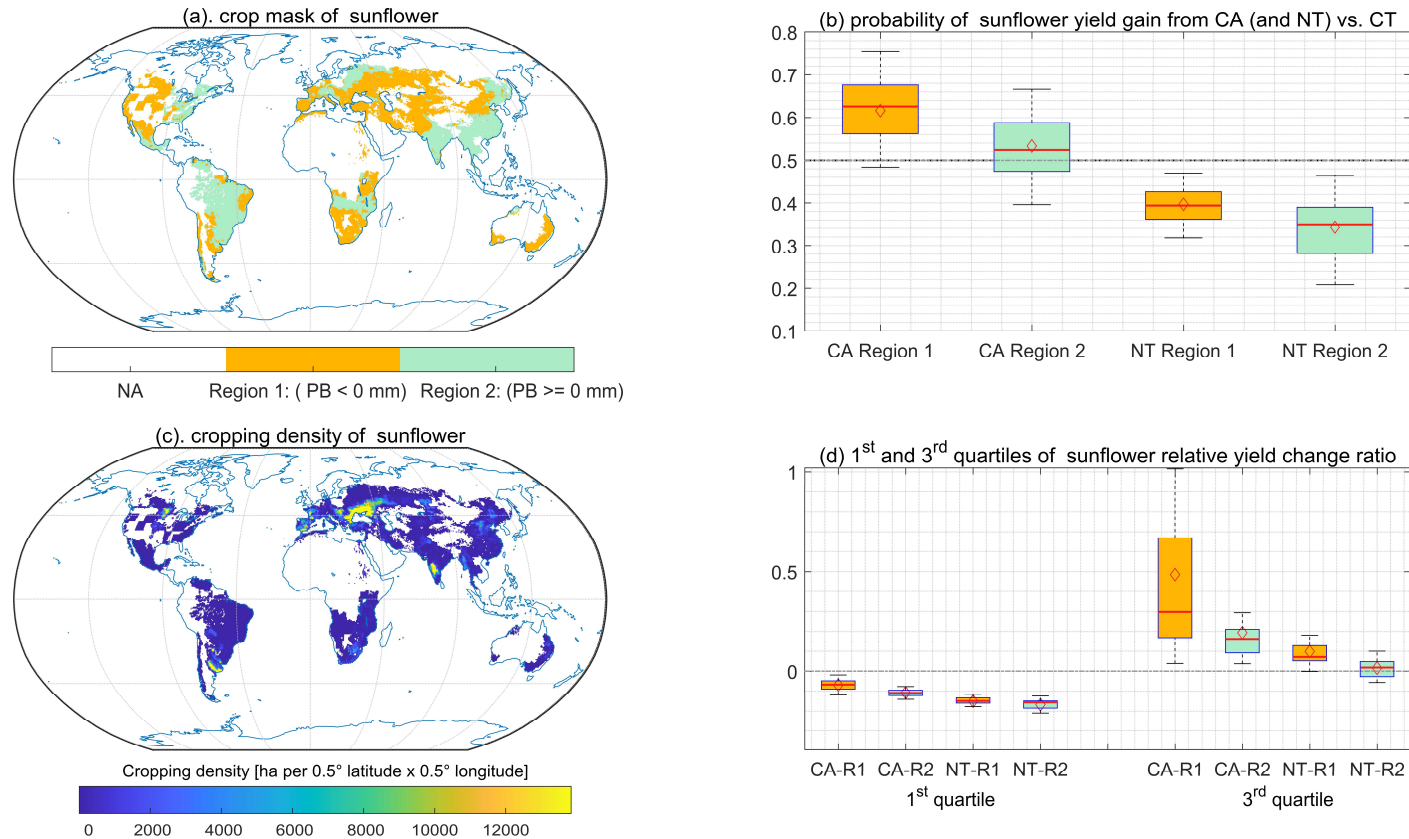
(c). 25th percentile of relative yield change for soybean under NT practice (+F+WD)



(d). 75th percentile of relative yield change for soybean under NT practice (+F+WD)

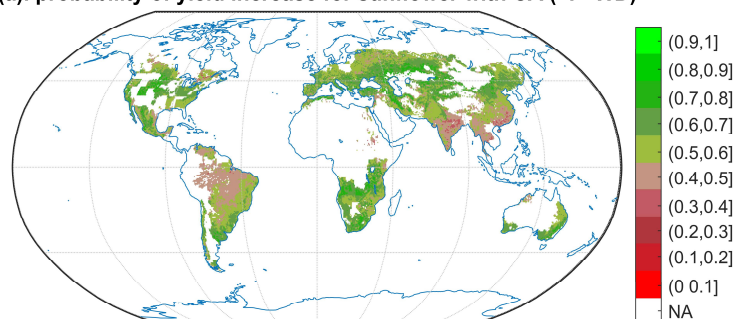


Appendix C24 | The relative yield change of soybean with CA and NT vs. CT practice. Relative yield change probability (1st and 3rd quartile estimate) of shifting CT to CA/NT for soybean, with field fertilization and weed and pest control (+F+WD). There was a 75% chance that the relative yield change will be higher than the ratio shown on the map in plot a and c, and conversely a 25% chance that the relative change will be lower. There was a 75% chance that the relative yield change will be lower than the ratio shown on the map in plot b and d, and conversely a 25% chance that the relative change will be higher. The colors indicated different levels of yield change ratio, and the reddish colors indicated the negative yield change or yield loss.

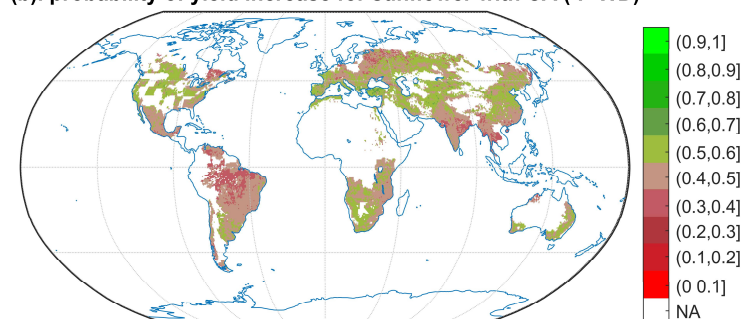


Appendix C25 | Productive performance of CA and NT vs. CT for sunflower in relatively dry and relatively wet regions. Productivity of Conservation Agriculture for sunflower in a relatively dry (region #1) and a relatively wet (region #2) region. (a) Illustration of the two regions on a global map with the two different colors showed in the sub-legend of plot a, while the blank area indicated the non-cropping region of sunflower. (b) The probability of sunflower yield gain (CA and NT vs. CT). (c) Sunflower cropping density on global map, the yellow shades indicated the higher density, and vice versa. The yellow color in this map indicated the crop density is equal or higher than 20% of maximum density in the cell of 0.5° latitude × 0.5° longitude at the global scale. (d) The 1st and 3rd quartiles of sunflower relative yield change under CA and NT vs. CT practice in the two regions, and the x axis tick label in plot d: R1, R2 indicated the two different regions, and the left part of plot d indicated the yield change ratios at the 1st quartile, while the right part were the yield change ratios at 3rd quartile. The colors in plot a, b and d indicated the same regions. In plot b and d, the mean value of relative yield change in its region is marked by the red diamond, while the median value is depicted by the red horizontal line.

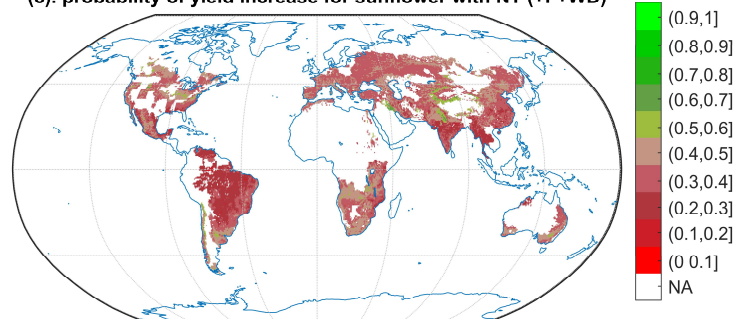
(a). probability of yield increase for sunflower with CA (+F+WD)



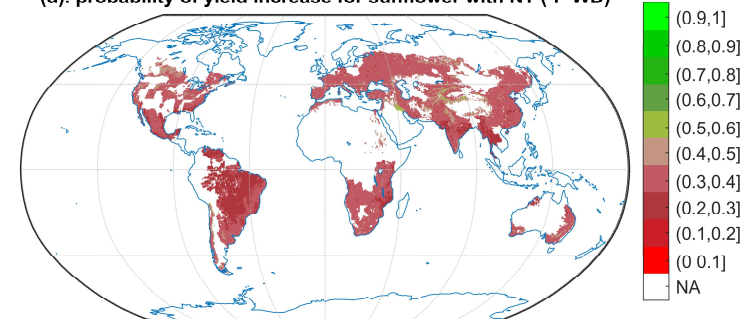
(b). probability of yield increase for sunflower with CA (-F-WD)



(c). probability of yield increase for sunflower with NT (+F+WD)

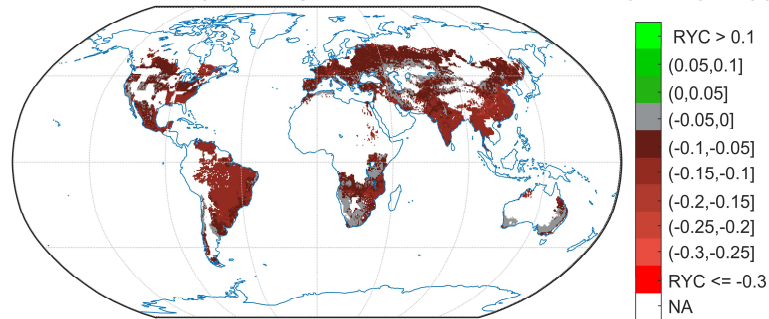


(d). probability of yield increase for sunflower with NT (-F-WD)

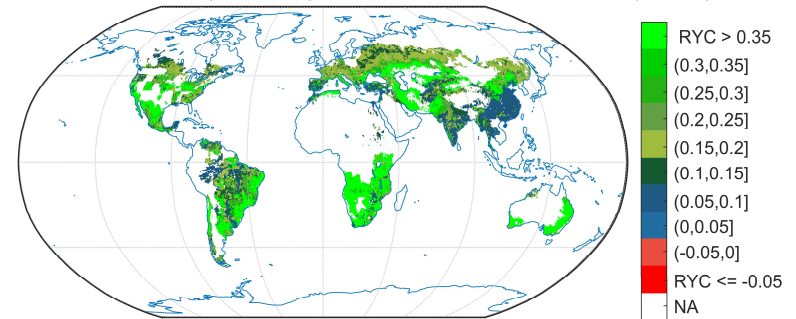


Appendix C26 | The probability of yield gain of sunflower with CA and NT vs. CT practice. Probability of yield gain with CA and NT vs. CT sunflower. Only the cropping regions were presented. The different colors indicated different probabilities of yield gain from CA and NT comparing to CT system. The greener color indicated a higher probability of yield gain. +/- F indicated NT or CA and CT with/without field fertilization. +/- WD indicated NT or CA and CT with/without weed and pest control.

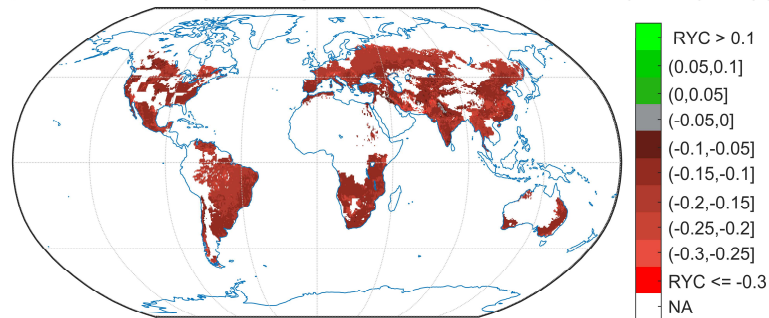
(a). 25th percentile of relative yield change for sunflower under CA practice (+F+WD)



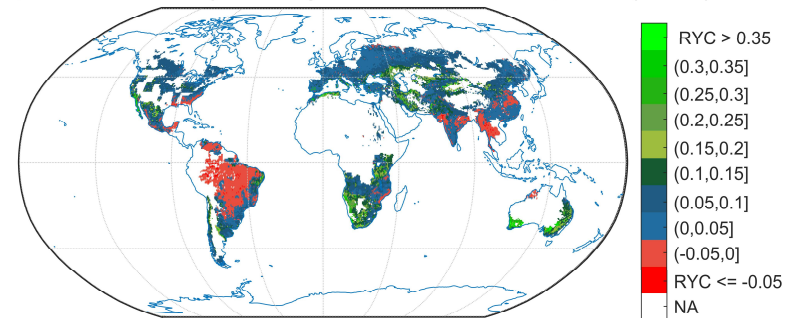
(b). 75th percentile of relative yield change for sunflower under CA practice (+F+WD)



(c). 25th percentile of relative yield change for sunflower under NT practice (+F+WD)



(d). 75th percentile of relative yield change for sunflower under NT practice (+F+WD)



Appendix C27 | The relative yield change of sunflower with CA and NT vs. CT practice. Relative yield change probability (1st and 3rd quartile estimate) of shifting CT to CA/NT for sunflower, with field fertilization and weed and pest control (+F+WD). There was a 75% chance that the relative yield change will be higher than the ratio shown on the map in plot a and c, and conversely a 25% chance that the relative change will be lower. There was a 75% chance that the relative yield change will be lower than the ratio shown on the map in plot b and d, and conversely a 25% chance that the relative change will be higher. The colors indicated different levels of yield change ratio, and the reddish colors indicated the negative yield change or yield loss.

Appendix C28 | Methods

Database establishment

The literature search was done in February 2020 using the following keywords ‘Conservation agriculture / No-till / No tillage / Zero tillage’ & ‘Yield / Yield change’ in the websites ‘ScienceDirect’, ‘Science Citation Index (web of science)’. A total of 1012 potentially relevant papers were identified by reviewing the title and abstract, and these papers were then screened according to the procedure summarized in S1. Papers not reporting yield data for CT and NT systems were excluded, as well as papers reporting experiments on reduced tillage (RT) systems. Papers reporting only mean yield data across different years or sites were also excluded. We then checked whether information on fertilization, weed and pest control, crop irrigation, crop rotation (at least three crops involved based on the definition of CA by FAO ¹¹) and crop residue management were reported for both CT and NT practices. After these screening and selection steps, all relevant data were manually extracted from the selected papers, including general information about the paper, location and year of the experiment, the number of years under NT when the crop was sown, soil characteristics, crop growing season, crop type, crop management practices and crop yield of CT and NT. However, due to a large number of missing data, the crop growing season, climatic variables and soil characteristics were finally collected through several external databases. The growing season information was generated from a crop calendar database ³ based on the crop type and the locations of the experiments reported in the papers. The precipitation, average temperature in the growing season were extracted from the UDel_AirT_Precip data provided by NOAA/OAR/ESRL PSL¹². The maximum and minimum air temperature during the growing season were generated from CPC Global Temperature data provided by NOAA/OAR/ESRL PSL ⁶ and the potential evapotranspiration data over the growing season were extracted from GLEAM database¹². Soil textures were collected from the HWSO database ⁷ using the locations of the experimental sites reported in the selected papers. The experiments for which it was not possible to obtain the requested information from the external databases were excluded. The final dataset includes the results extracted from 413 papers (published between 1983 to 2020), 4403 paired yield observations from NT and CT for 8 major crop species, including 370 observations for barley (232 observations for spring barley and 138 for winter barley), 94 observations for cotton, 1690 observations for maize, 195 observation for rice, 160 observations for sorghum, 583 observations for soybean, 61 observations for sunflower, 1250 observations for wheat (1041 observations for winter wheat and 209 observations for spring wheat) in 50 countries from 1980 to 2017 (Appendix C2).

Analysis

Pairs of yield data were used to compute two types of effect size, namely yield ratio $\left(\frac{Yield_{CA\ or\ NT}}{Yield_{CT}}\right)$ and relative yield change ratio $\left(\frac{Yield_{CA\ or\ NT} - Yield_{CT}}{Yield_{CT}}\right)$. The category of the yield gain and loss were then related to the inputs of climatic conditions, soil data, and agricultural management practices using a random forest algorithm in order to map the probability of yield gain with CA and NT vs. CT (probability that yield ratio > 1). Relative yield changes were related to the same input data using quantile regression forest to estimate the 25th and 75th percentiles of relative yield change in different climatic conditions.

The R package “randomForest” (version 4.6 - 14) was used to train the random forest model to analyse the yield ratios of CA or NT vs. CT as the function of climatic variables, crop types, soil textures, and agricultural management practices. To do so, set the climatic variables throughout the growing season such as PB, Tmin/Tave/Tmax as numerical explanatory variables; Set crop type, soil texture, and agricultural management activities including crop irrigation, field fertilization, control of pests and weeds, crop rotation and soil cover as categorical explanatory variables; Set the category of yield change (yield ratio $\left(\frac{Yield_{CA}}{Yield_{CT}}\right) > 1$ or ≤ 1) as response variable. The sample code for training the random forest

model is available in “Code.zip” in figshare repository provided in the main manuscript. When setting the “proximity” as Ture, the model output is the probability of yield gain from NT vs. CT. As for the quantile regression model, the R package “ranger” (version 0.11.2) was used to train a quantile regression forest model to analyse relative yield change of shifting from CT to CA or NT as the same explanatory variables as random forest. Both random forest model and quantile regression forest model were tree-based ensemble machine learning method using multiple deep decision trees to improve the accuracy and stability of their predictions¹². These methods did not make assumptions on the distributions of the input data and were able to deal with high-dimensional data. The importance ranking of the inputs were derived using the mean decrease of Gini impurity index ¹³(results available in Appendix C7).

Global projection of yield gain probability and relative yield change ratio

To predict the global productivity of CA and NT vs. CT, the trained machine learning models were fed by the numerical explanatory variables, such as climatic variables, and categorical explanatory variables, including crop types, soil textures, agricultural management practices. The details of the model input settings were available in Appendix C5. The global climatic variables were based on the latest NCEI’s three-decade averaged climatic conditions¹⁴, also called “1981-2010 U.S. Climate Normals”. The growing season information for each crop was defined as the period between seeding month and harvesting month from the crop calendar database^{8,9}. Mean precipitation and average temperature were calculated throughout the growing season for all the years from 1981 to 2010 using the global precipitation and air temperature database³. A similar approach was implemented for maximum and minimum temperature⁶, and potential evapotranspiration^{4,5}. As for the categorical explanatory variables, the global soil texture input data came from HWSD database¹⁵, the crop irrigation input data was based on the irrigation mask from MIRCA2000 database¹⁰, in each grid cell, crop irrigation was marked as yes if irrigation was the dominated practices in this region. Crop rotation and soil cover were set as “yes” for CA, and “no” for NT. Crop fertilization and integrated weed and pest control were set as “yes” for the scenario (+F+WD), while “no” for the scenario (-F-WD).

The model outputs were the probabilities of yield gain with CA or NT vs. CT, and 25th and 75th percentiles of relative yield change, which indicated the CA or NT productivity at the global scale under the averaged climate condition of 1981-2010. All maps in the paper were generated by MATLAB R2020a (Version 9.8.0.1451342, <https://fr.mathworks.com/products/matlab.html>).

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Appendix D

Appendix D

The impact of climate change on the productivity of conservation agriculture

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Appendix D table 1 | Model settings for global projection

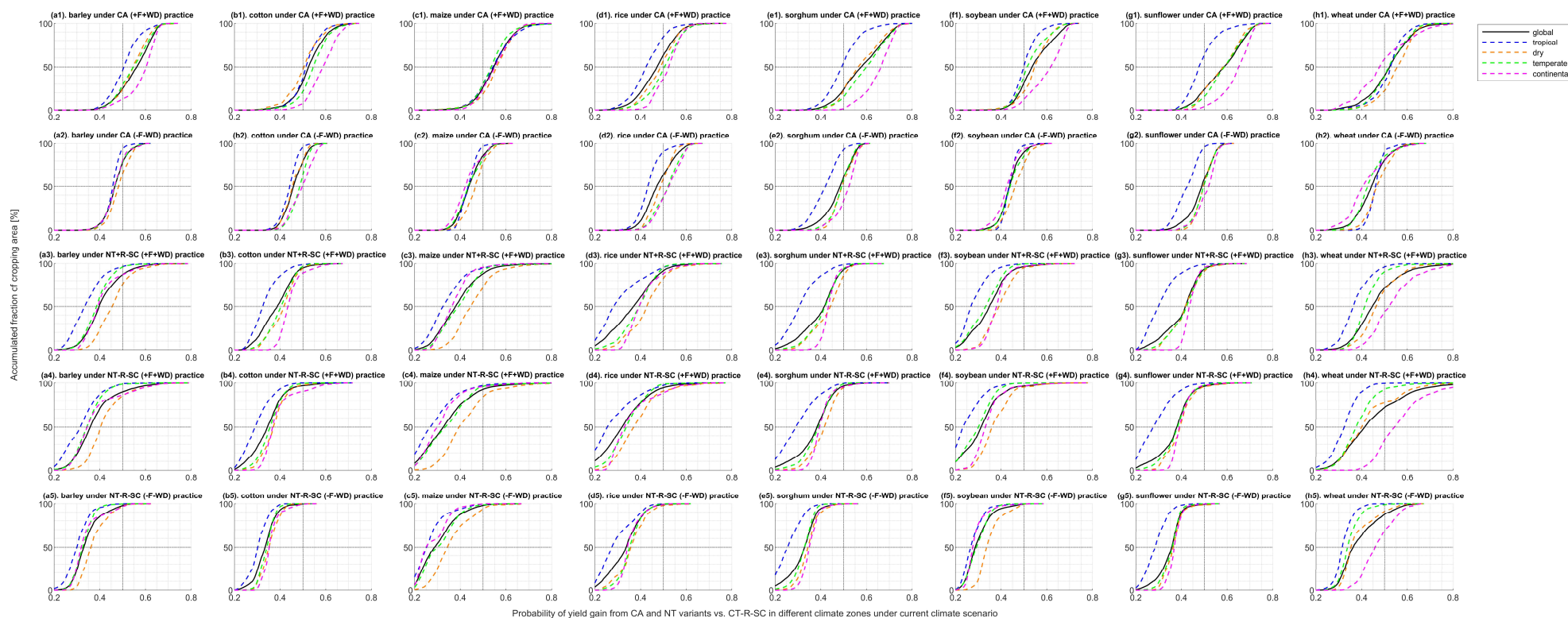
Category	Model input	Symbol in the model	Type	Setting	Notes
Climate variables	Precipitation over the growing season		Quantitative	Current: mean climate condition of 2011-2020; Future: mean climate condition of 2051-2060	The current and future climatic data ^{1,2} are based on the climate models: “Gfdl-esm2m”, “Hadgem2-es”, “Ipsl-cm5a-lr”, “Miroc5”, and the RCP scenarios: “RCP 2.6”, “RCP 4.5”, “RCP 6.0”, “RCP 8.5”, the ensemble method is “r1i1p1”, the EWEMBI dataset (Observed atmospheric climate) was compiled to support the bias correction of climate input data.
	Potential evapotranspiration over the growing season		Quantitative	Current: mean climate condition of 2011-2020; Future: mean climate condition of 2051-2060	The current and future climatic data ^{1,2} are based on the climate models: “Gfdl-esm2m”, “Hadgem2-es”, “Ipsl-cm5a-lr”, “Miroc5”, and the RCP scenarios: “RCP 2.6”, “RCP 4.5”, “RCP 6.0”, “RCP 8.5”, the impact model is “Water_GAP2”, the EWEMBI dataset (Observed atmospheric climate) was compiled to support the bias correction of climate input data.
	Precipitation balance over the growing season	PB	Quantitative	Precipitation – Potential evapotranspiration over the growing season	
	Average temperature over the growing season	Tave	Quantitative	Current: mean climate condition of 2011-2020; Future: mean climate condition of 2051-2060	The current and future climatic data ^{1,2} are based on the climate models: “Gfdl-esm2m”, “Hadgem2-es”, “Ipsl-cm5a-lr”, “Miroc5”, and the RCP scenarios: “RCP 2.6”, “RCP 4.5”, “RCP 6.0”, “RCP 8.5”, the ensemble method is “r1i1p1”, the EWEMBI dataset (Observed atmospheric climate) was compiled to support the bias correction of climate input data.

Appendix D

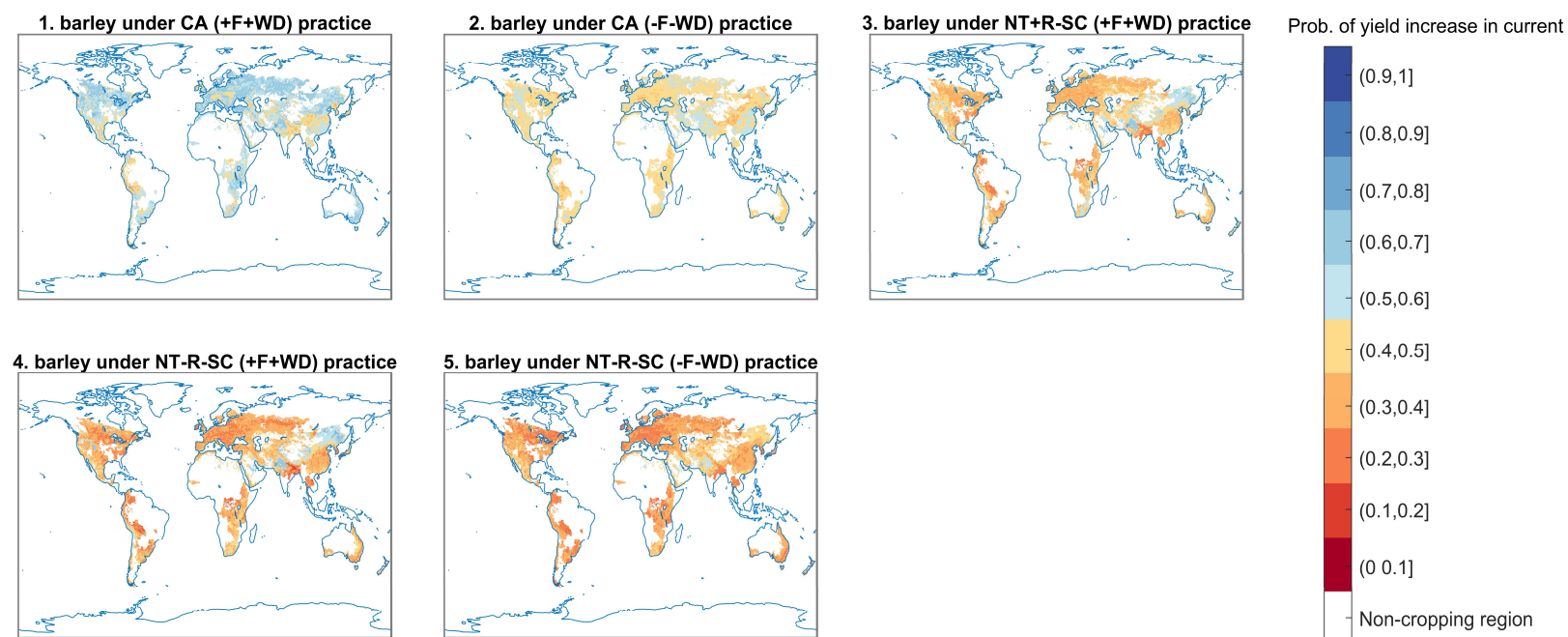
	Maximum temperature over the growing season	Tmax	Quantitative	Current: mean climate condition of 2011-2020; Future: mean climate condition of 2051-2060	The current and future climatic data ^{1,2} are based on the climate models: “Gfdl-esm2m”, “Hadgem2-es”, “Ipsl-cm5a-lr”, “Miroc5”, and the RCP scenarios: “RCP 2.6”, “RCP 4.5”, “RCP 6.0”, “RCP 8.5”, the ensemble method is “r1i1p1”, the EWEMBI dataset (Observed atmospheric climate) was compiled to support the bias correction of climate input data.
	Minimum temperature over the growing season	Tmin	Quantitative	Current: mean climate condition of 2011-2020; Future: mean climate condition of 2051-2060	The current and future climatic data ^{1,2} are based on the climate models: “Gfdl-esm2m”, “Hadgem2-es”, “Ipsl-cm5a-lr”, “Miroc5”, and the RCP scenarios: “RCP 2.6”, “RCP 4.5”, “RCP 6.0”, “RCP 8.5”, the ensemble method is “r1i1p1”, the EWEMBI dataset (Observed atmospheric climate) was compiled to support the bias correction of climate input data.
Agricultural management activities	Integrated weed and pest control	WD	Qualitative	Yes for +WD No for -WD	
	Field fertilization	F	Qualitative	Yes for +F No for -F	
	Soil cover management	SC	Qualitative	Yes for +SC No for -SC	CA: NT +R+SC Variants based on NT systems: NT - R+SC / NT +R-SC / NT -R-SC CT: CT-R-SC
	Crop rotation	R	Qualitative	Yes for +R No for -R	CA: NT +R+SC Variants based on NT systems: NT - R+SC / NT +R-SC / NT -R-SC CT: CT-R-SC
	Crop irrigation	Irrigation	Qualitative	No changes in current and future; Yes/No depends on the condition of irrigation for most of the cropping area inside each grid cell.	MIRCA2000 data from Goethe University ³

				But when generating the maps in S3, crop irrigation in each cell was manually set as No to simulate the field without crop irrigation.	
Others	Soil texture	ST	Qualitative	No changes in current and future	HWSD data from University of Tokyo ⁴
	Crop types	Crop	Qualitative	Spring barley, cotton, maize, rice, sorghum, soybean, sunflower, winter wheat	
	Crop growing season		Quantitative	No changes in current and future	Crop calendar data from University of Wisconsin-Madison ⁵

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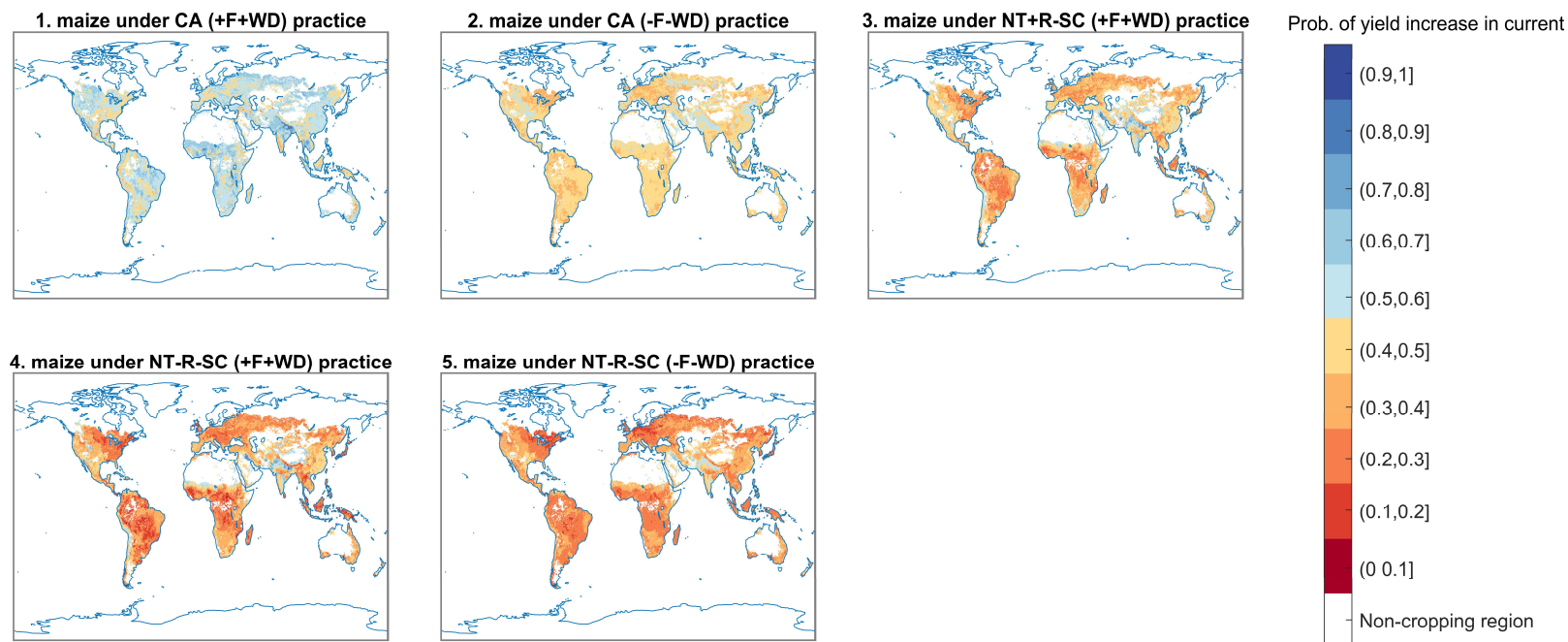


Appendix D figure 1 | Accumulated fraction of the cropping area as a function of the probability of yield gain under CA systems and NT variants vs. CT systems in different climate regions. The results are based on the average climate conditions over 2021-2020 simulated by the Ipsi-cm5a-lr climate model and RCP 4.5 scenario. Plots in row 1 show the accumulated fraction of cropping area as the function of probability of yield gain under CA (+F+WD) vs. CT-R-SC (+F+WD) systems in different climate regions. Plots in row 2 show the accumulated fraction of cropping area as the function of probability of yield gain under CA (-F-WD) vs. CT-R-SC (-F-WD) systems in different climate regions. Plots in row 3 show the accumulated fraction of cropping area as the function of probability of yield gain under NT+R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems in different climate regions. Plots in row 4 show the accumulated fraction of cropping area as the function of probability of yield gain under NT-R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems in different climate regions. Plots in row 5 show the accumulated fraction of cropping area as the function of probability of yield gain under NT-R-SC (-F-WD) vs. CT-R-SC (-F-WD) systems in different climate regions.

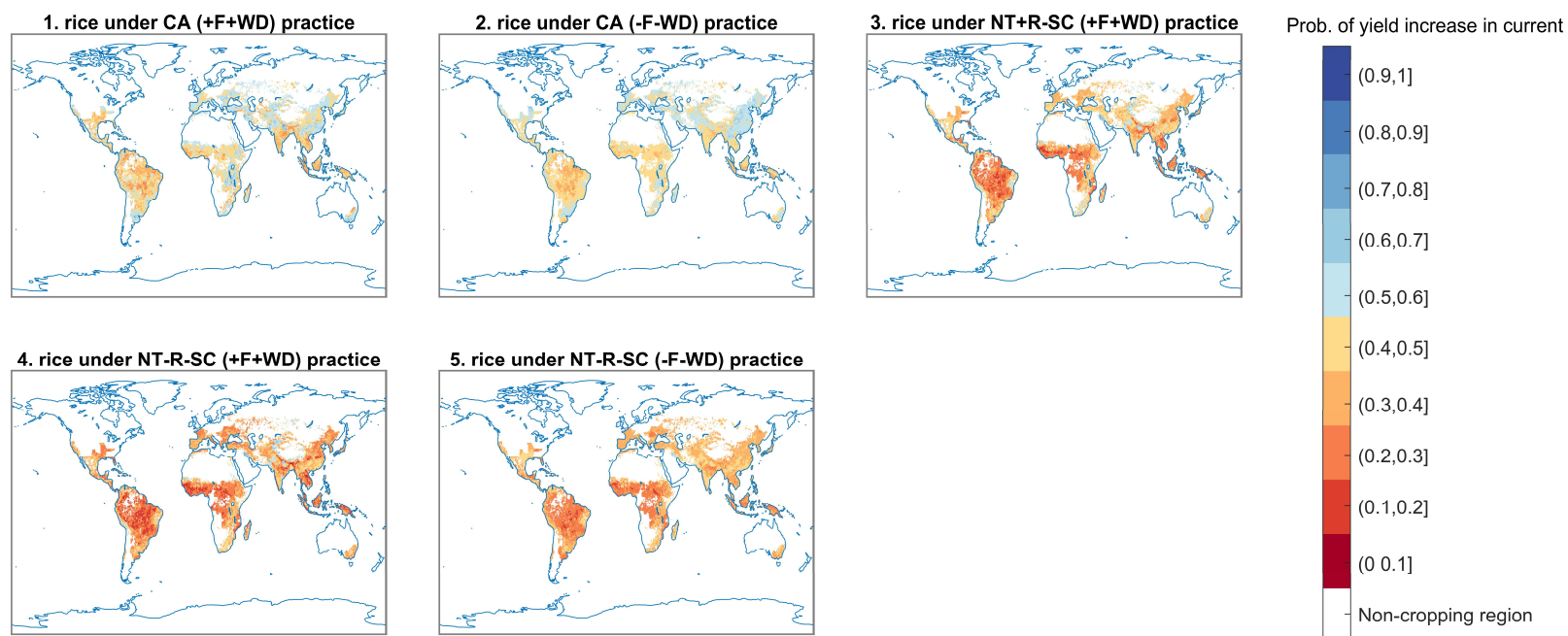


Appendix D figure 2a | Maps of probability of yield gain under CA systems and NT variants vs. CT systems under current climate scenario – barley. Regions with a probability of yield gain lower than 0.5 are highlighted in red (and in blue shades when the probability is higher). The results are based on the average climate conditions over 2011-2020 (current) simulated by Ipsi-cm5a-lr climate model and RCP 4.5 scenario. Plot 1 shows the probability of yield gain under CA (+F+WD) vs. CT-R-SC (+F+WD) systems under current climate conditions. Plot 2 shows the probability of yield gain under CA (-F-WD) vs. CT-R-SC (-F-WD) systems under current climate conditions. Plot 3 shows the probability of yield gain under NT+R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under current climate conditions. Plot 4 shows the probability of yield gain under NT-R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under current climate conditions. Plot 5 shows the probability of yield gain under NT-R-SC (-F-WD) vs. CT-R-SC (-F-WD) systems under current climate conditions.

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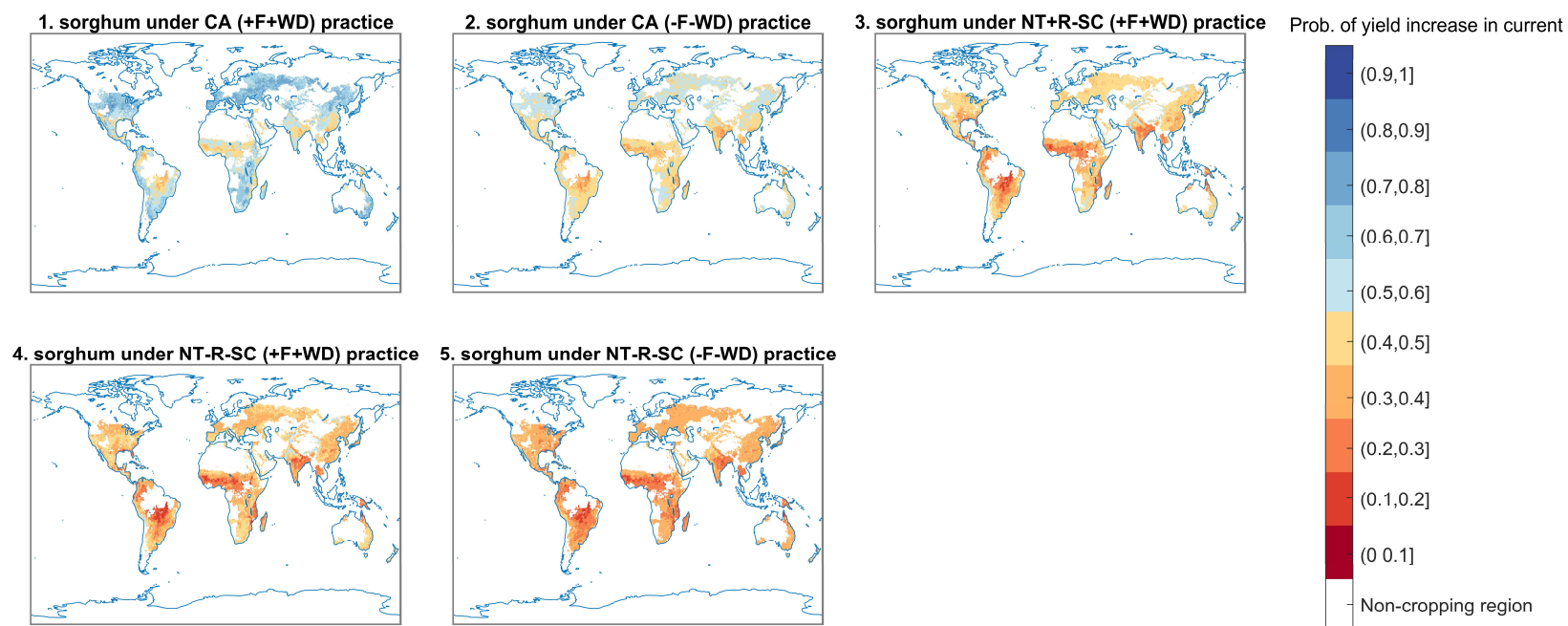


Appendix D figure 2c | Maps of probability of yield gain under CA systems and NT variants vs. CT systems under current climate scenario – maize. Regions with a probability of yield gain lower than 0.5 are highlighted in red (and in blue shades when the probability is higher). The results are based on the average climate conditions over 2011-2020 (current) simulated by Ipsi-cm5a-lr climate model and RCP 4.5 scenario. Plot 1 shows the probability of yield gain under CA (+F+WD) vs. CT-R-SC (+F+WD) systems under current climate conditions. Plot 2 shows the probability of yield gain under CA (-F-WD) vs. CT-R-SC (-F-WD) systems under current climate conditions. Plot 3 shows the probability of yield gain under NT+R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under current climate conditions. Plot 4 shows the probability of yield gain under NT-R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under current climate conditions. Plot 5 shows the probability of yield gain under NT-R-SC (-F-WD) vs. CT-R-SC (-F-WD) systems under current climate conditions.

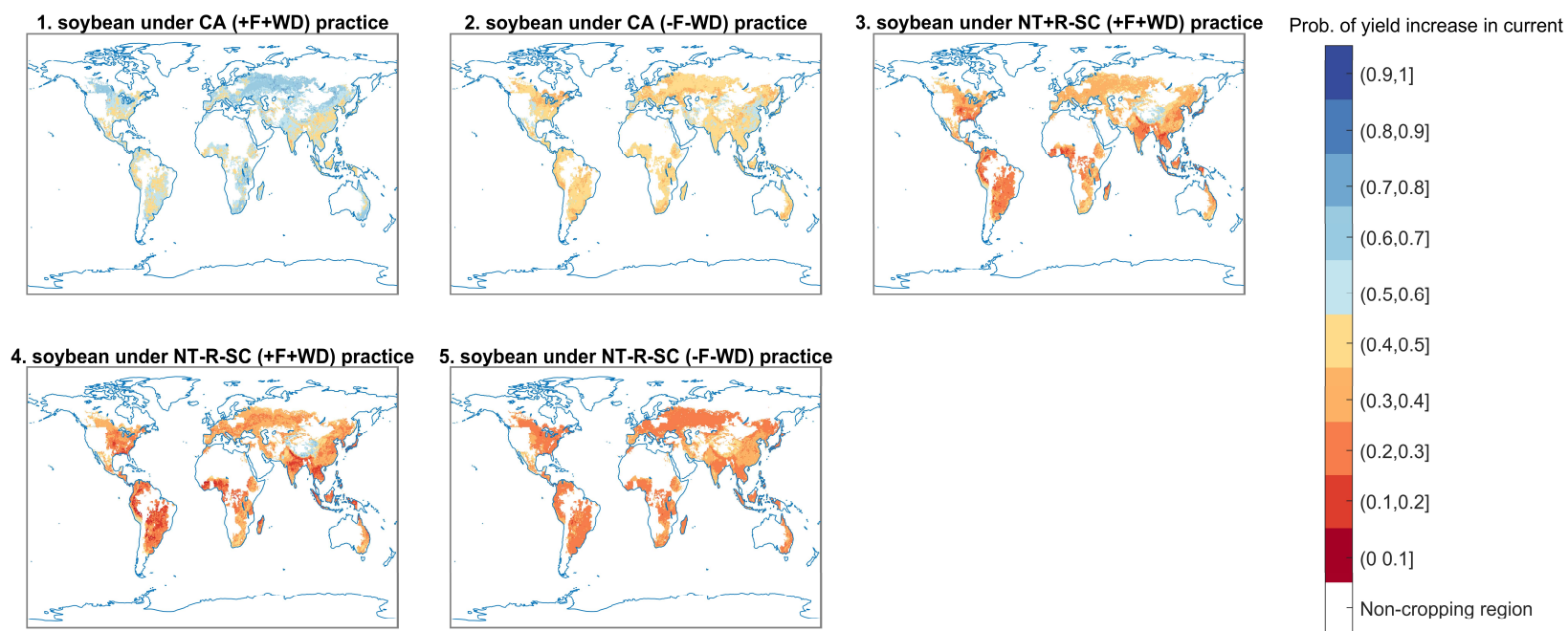


Appendix D figure 2d | Maps of probability of yield gain under CA systems and NT variants vs. CT systems under current climate scenario – rice. Regions with a probability of yield gain lower than 0.5 are highlighted in red (and in blue shades when the probability is higher). The results are based on the average climate conditions over 2011-2020 (current) simulated by Ipsi-cm5a-lr climate model and RCP 4.5 scenario. Plot 1 shows the probability of yield gain under CA (+F+WD) vs. CT-R-SC (+F+WD) systems under current climate conditions. Plot 2 shows the probability of yield gain under CA (-F-WD) vs. CT-R-SC (-F-WD) systems under current climate conditions. Plot 3 shows the probability of yield gain under NT+R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under current climate conditions. Plot 4 shows the probability of yield gain under NT-R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under current climate conditions. Plot 5 shows the probability of yield gain under NT-R-SC (-F-WD) vs. CT-R-SC (-F-WD) systems under current climate conditions.

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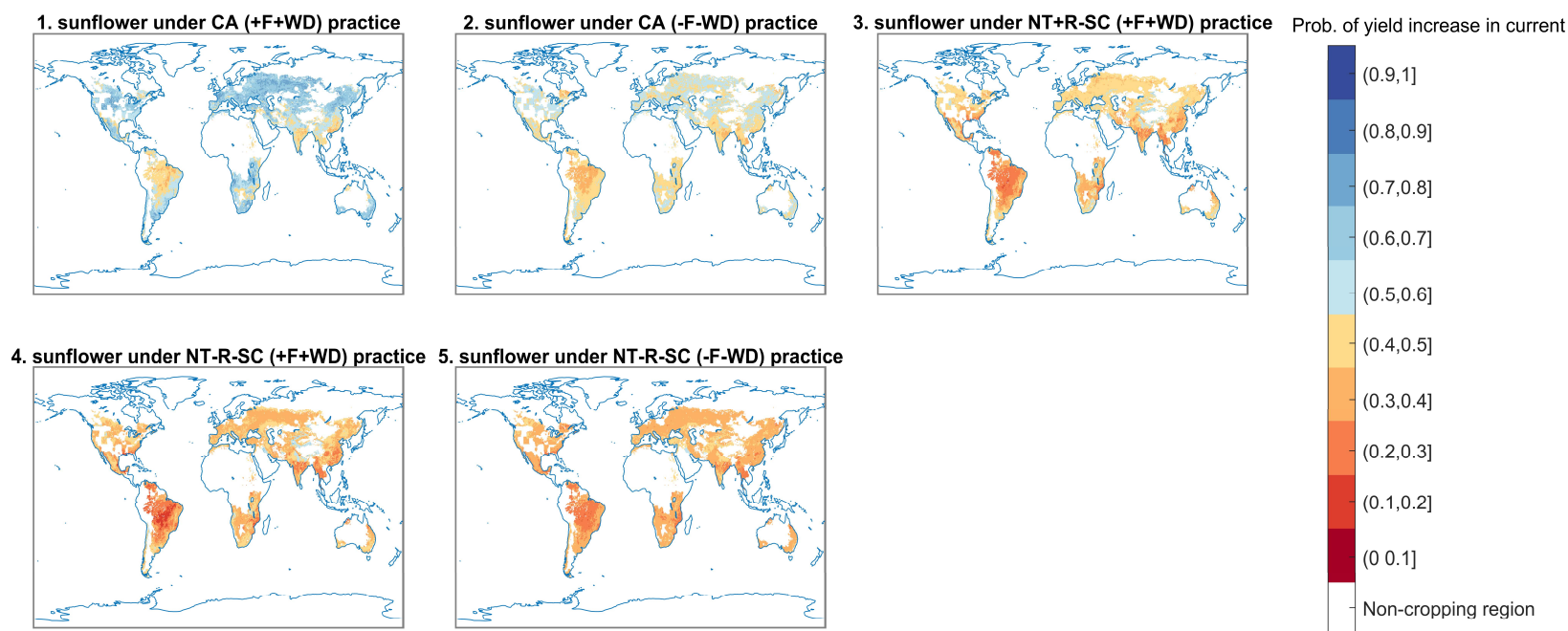


Appendix D figure 2e | Maps of probability of yield gain under CA systems and NT variants vs. CT systems under current climate scenario – sorghum. Regions with a probability of yield gain lower than 0.5 are highlighted in red (and in blue shades when the probability is higher). The results are based on the average climate conditions over 2011-2020 (current) simulated by Ipsi-cm5a-lr climate model and RCP 4.5 scenario. Plot 1 shows the probability of yield gain under CA (+F+WD) vs. CT-R-SC (+F+WD) systems under current climate conditions. Plot 2 shows the probability of yield gain under CA (-F-WD) vs. CT-R-SC (-F-WD) systems under current climate conditions. Plot 3 shows the probability of yield gain under NT+R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under current climate conditions. Plot 4 shows the probability of yield gain under NT-R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under current climate conditions. Plot 5 shows the probability of yield gain under NT-R-SC (-F-WD) vs. CT-R-SC (-F-WD) systems under current climate conditions.

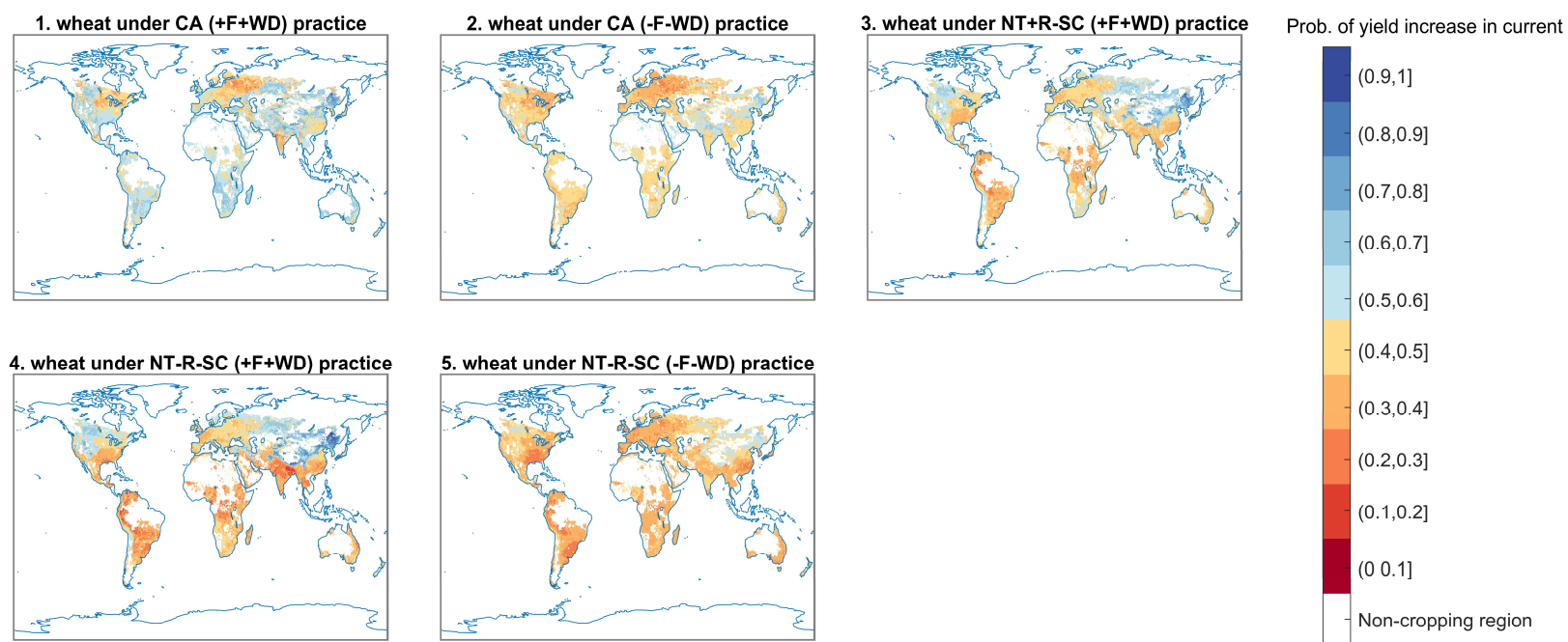


Appendix D figure 2f | Maps of probability of yield gain under CA systems and NT variants vs. CT systems under current climate scenario – soybean. Regions with a probability of yield gain lower than 0.5 are highlighted in red (and in blue shades when the probability is higher). The results are based on the average climate conditions over 2011-2020 (current) simulated by Ipsi-cm5a-lr climate model and RCP 4.5 scenario. Plot 1 shows the probability of yield gain under CA (+F+WD) vs. CT-R-SC (+F+WD) systems under current climate conditions. Plot 2 shows the probability of yield gain under CA (-F-WD) vs. CT-R-SC (-F-WD) systems under current climate conditions. Plot 3 shows the probability of yield gain under NT+R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under current climate conditions. Plot 4 shows the probability of yield gain under NT-R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under current climate conditions. Plot 5 shows the probability of yield gain under NT-R-SC (-F-WD) vs. CT-R-SC (-F-WD) systems under current climate conditions.

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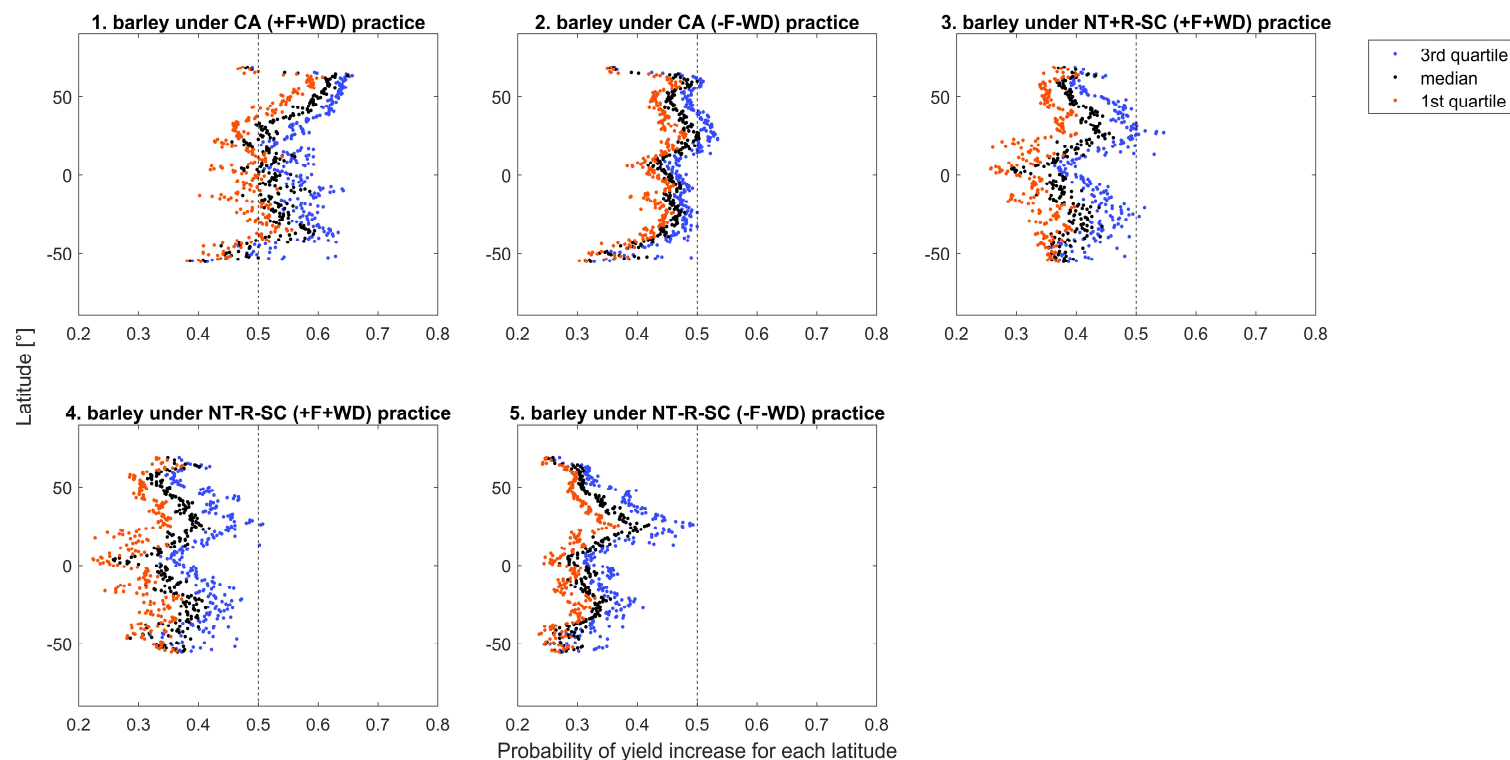


Appendix D figure 2g | Maps of probability of yield gain under CA systems and NT variants vs. CT systems under current climate scenario – sunflower. Regions with a probability of yield gain lower than 0.5 are highlighted in red (and in blue shades when the probability is higher). The results are based on the average climate conditions over 2011-2020 (current) simulated by Ipsi-cm5a-lr climate model and RCP 4.5 scenario. Plot 1 shows the probability of yield gain under CA (+F+WD) vs. CT-R-SC (+F+WD) systems under current climate conditions. Plot 2 shows the probability of yield gain under CA (-F-WD) vs. CT-R-SC (-F-WD) systems under current climate conditions. Plot 3 shows the probability of yield gain under NT+R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under current climate conditions. Plot 4 shows the probability of yield gain under NT-R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under current climate conditions. Plot 5 shows the probability of yield gain under NT-R-SC (-F-WD) vs. CT-R-SC (-F-WD) systems under current climate conditions.

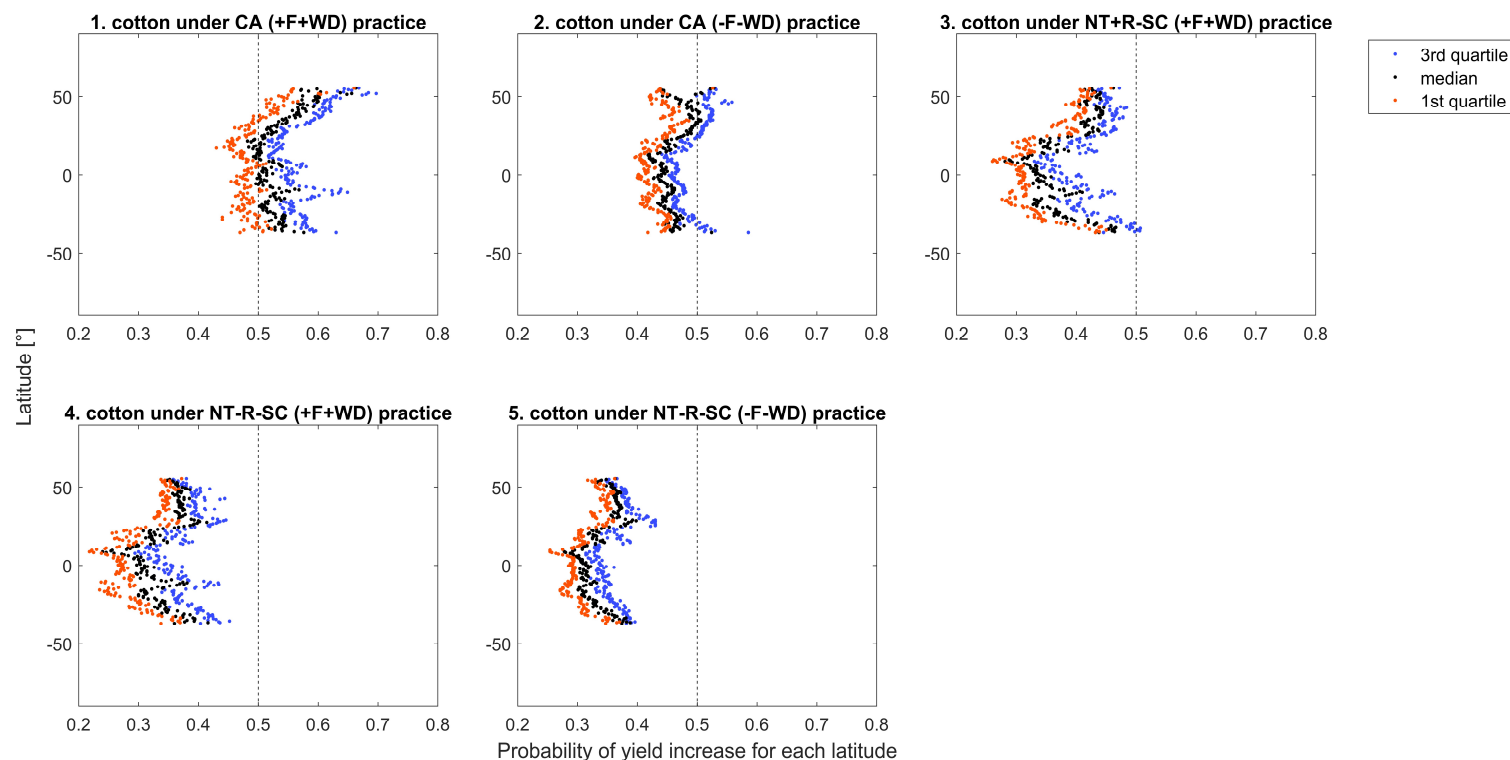


Appendix D figure 2h | Maps of probability of yield gain under CA systems and NT variants vs. CT systems under current climate scenario – wheat. Regions with a probability of yield gain lower than 0.5 are highlighted in red (and in blue shades when the probability is higher). The results are based on the average climate conditions over 2011-2020 (current) simulated by Ipsl-cm5a-lr climate model and RCP 4.5 scenario. Plot 1 shows the probability of yield gain under CA (+F+WD) vs. CT-R-SC (+F+WD) systems under current climate conditions. Plot 2 shows the probability of yield gain under CA (-F-WD) vs. CT-R-SC (-F-WD) systems under current climate conditions. Plot 3 shows the probability of yield gain under NT+R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under current climate conditions. Plot 4 shows the probability of yield gain under NT-R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under current climate conditions. Plot 5 shows the probability of yield gain under NT-R-SC (-F-WD) vs. CT-R-SC (-F-WD) systems under current climate conditions.

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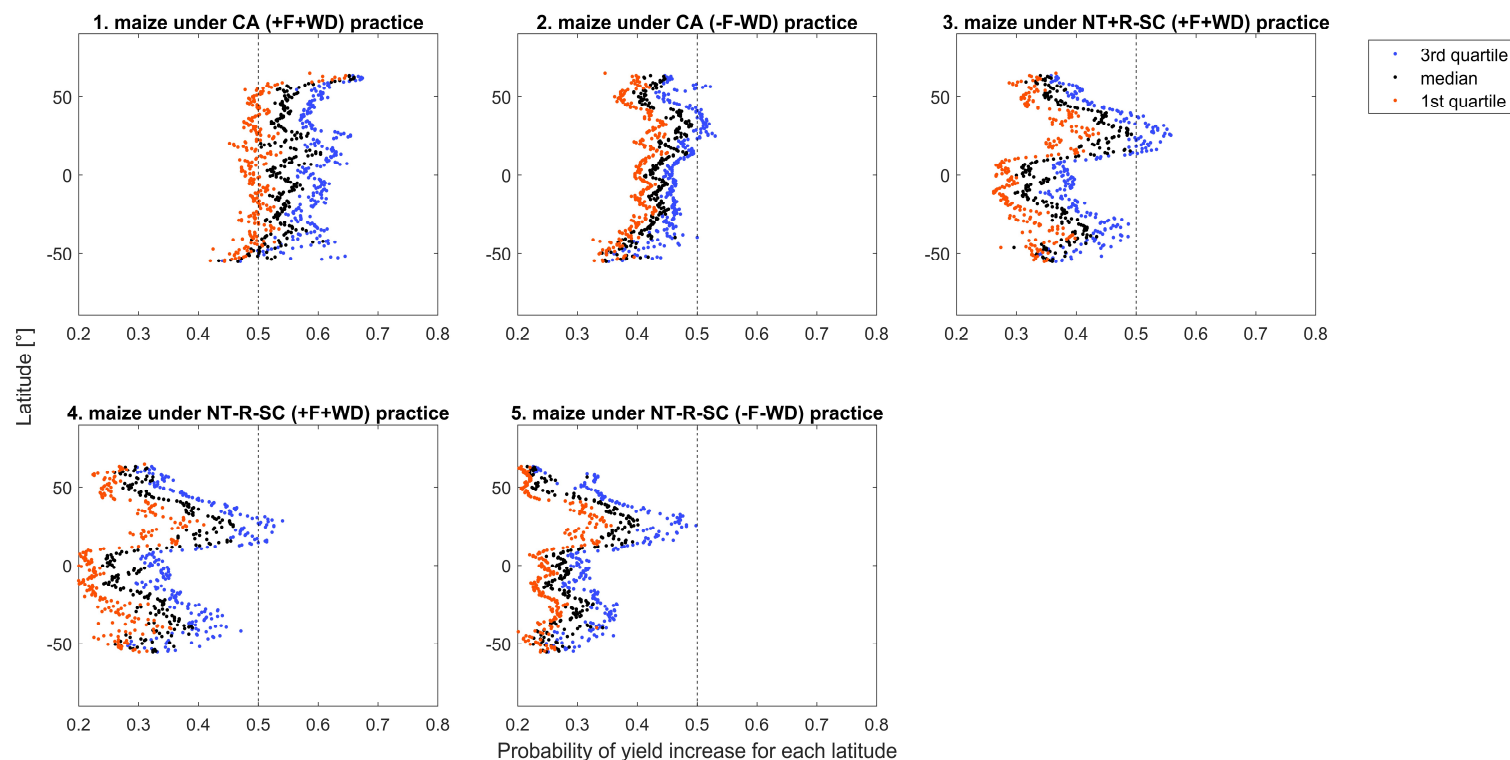


Appendix D figure 3a | Probability of yield gain under CA systems and NT variants vs. CT systems as a function of latitude under current climate scenario - barley. This figure shows the variations of 1st quartile (red), median (black), and 3rd quartile (blue) yield gain probability under CA systems and their variants vs. CT systems as a function of latitude. The results are based on the average climate conditions over 2011-2020 (current) simulated by Ipsi-cm5a-1r climate model and RCP 4.5 scenario. Plot 1 shows the probability of yield gain along latitude under CA (+F+WD) vs. CT-R-SC (+F+WD) systems under current climate conditions. Plot 2 shows the probability of yield gain along latitude under CA (-F-WD) vs. CT-R-SC (-F-WD) systems under current climate conditions. Plot 3 shows the probability of yield gain along latitude under NT+R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under current climate conditions. Plot 4 shows the probability of yield gain along latitude under NT-R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under current climate conditions. Plot 5 shows the probability of yield gain along latitude under NT-R-SC (-F-WD) vs. CT-R-SC (-F-WD) systems under current climate conditions.

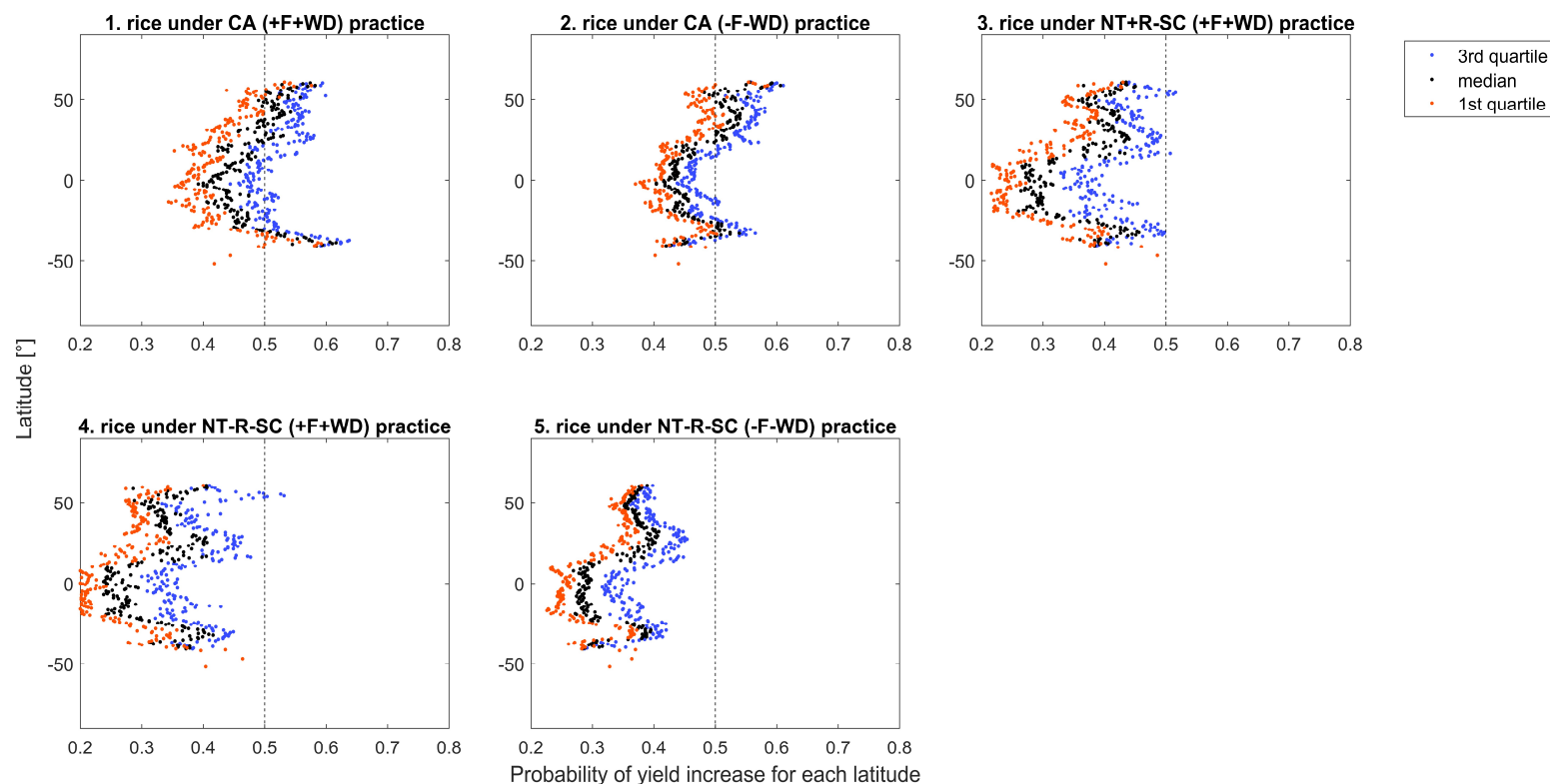


Appendix D figure 3b | Probability of yield gain under CA systems and NT variants vs. CT systems as a function of latitude under current climate scenario - cotton. This figure shows the variations of 1st quartile (red), median (black), and 3rd quartile (blue) yield gain probability under CA systems and their variants vs. CT systems as a function of latitude. The results are based on the average climate conditions over 2011-2020 (current) simulated by Ipsi-cm5a-1r climate model and RCP 4.5 scenario. Plot 1 shows the probability of yield gain along latitude under CA (+F+WD) vs. CT-R-SC (+F+WD) systems under current climate conditions. Plot 2 shows the probability of yield gain along latitude under CA (-F-WD) vs. CT-R-SC (-F-WD) systems under current climate conditions. Plot 3 shows the probability of yield gain along latitude under NT+R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under current climate conditions. Plot 4 shows the probability of yield gain along latitude under NT-R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under current climate conditions. Plot 5 shows the probability of yield gain along latitude under NT-R-SC (-F-WD) vs. CT-R-SC (-F-WD) systems under current climate conditions.

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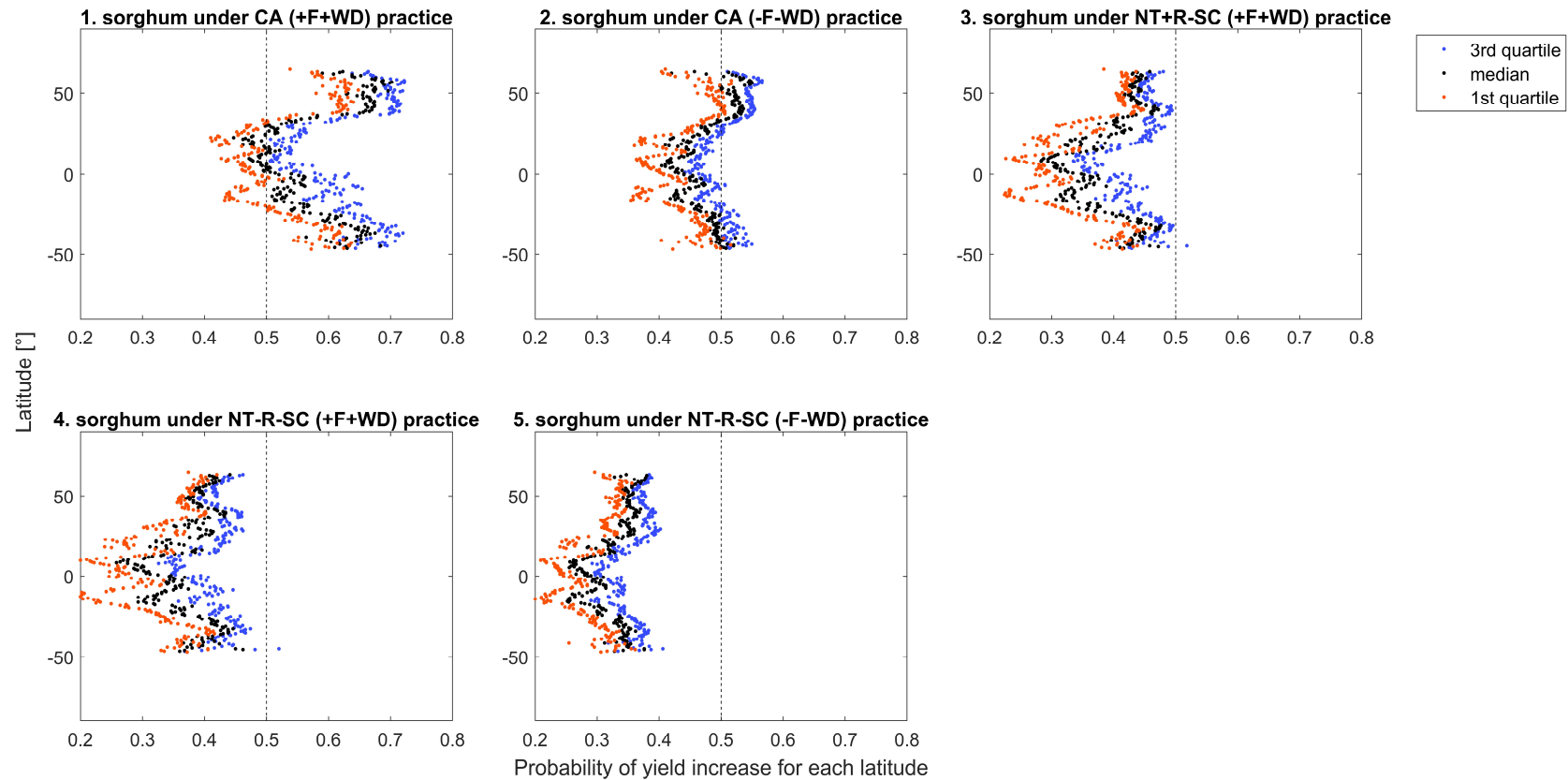


Appendix D figure 3c | Probability of yield gain under CA systems and NT variants vs. CT systems as a function of latitude under current climate scenario - maize. This figure shows the variations of 1st quartile (red), median (black), and 3rd quartile (blue) yield gain probability under CA systems and their variants vs. CT systems as a function of latitude. The results are based on the average climate conditions over 2011-2020 (current) simulated by Ipsi-cm5a-1r climate model and RCP 4.5 scenario. Plot 1 shows the probability of yield gain along latitude under CA (+F+WD) vs. CT-R-SC (+F+WD) systems under current climate conditions. Plot 2 shows the probability of yield gain along latitude under CA (-F-WD) vs. CT-R-SC (-F-WD) systems under current climate conditions. Plot 3 shows the probability of yield gain along latitude under NT+R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under current climate conditions. Plot 4 shows the probability of yield gain along latitude under NT-R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under current climate conditions. Plot 5 shows the probability of yield gain along latitude under NT-R-SC (-F-WD) vs. CT-R-SC (-F-WD) systems under current climate conditions.

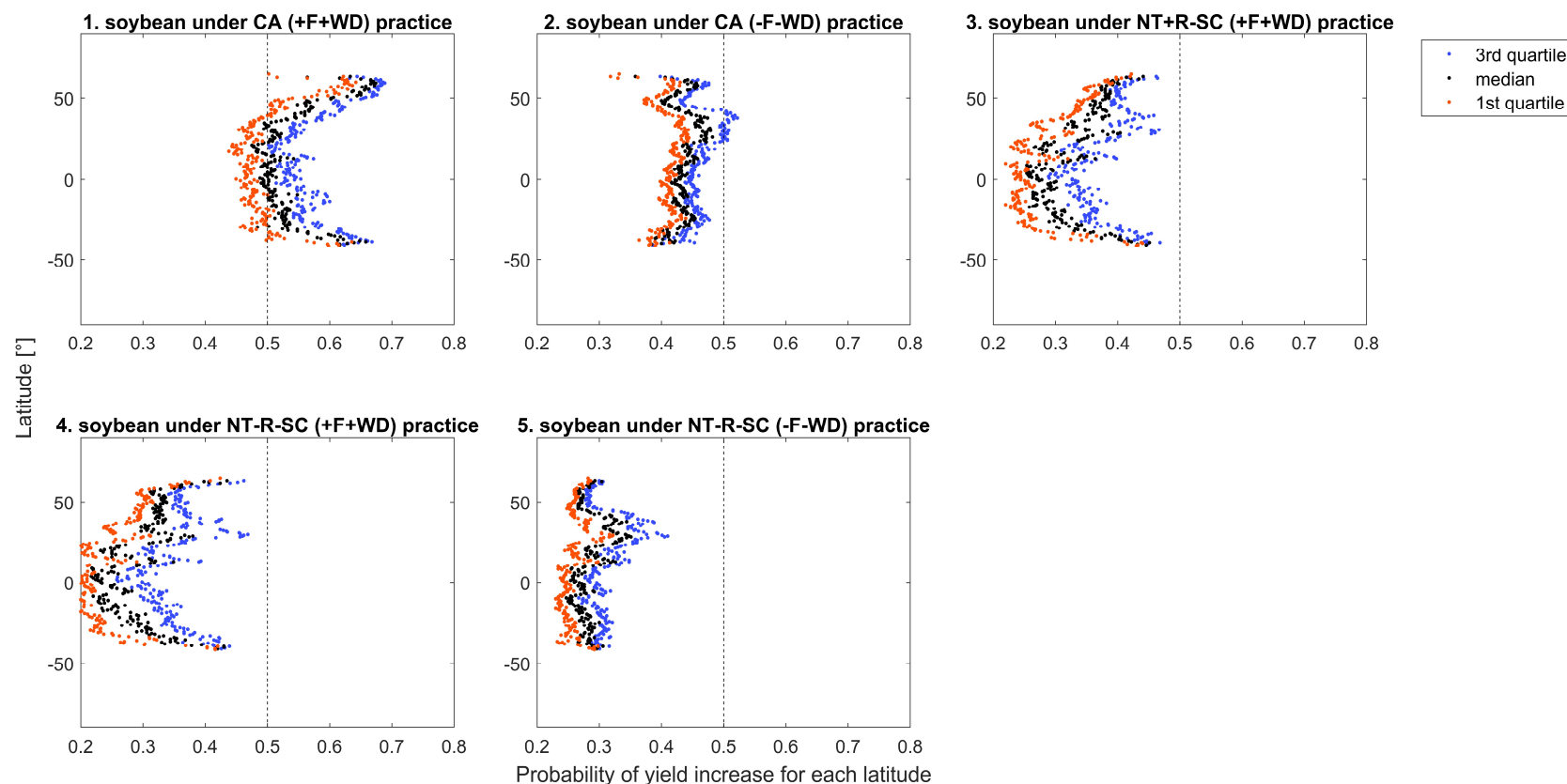


Appendix D figure 3d | Probability of yield gain under CA systems and NT variants vs. CT systems as a function of latitude under current climate scenario - rice. This figure shows the variations of 1st quartile (red), median (black), and 3rd quartile (blue) yield gain probability under CA systems and their variants vs. CT systems as a function of latitude. The results are based on the average climate conditions over 2011-2020 (current) simulated by Isp1-cm5a-1r climate model and RCP 4.5 scenario. Plot 1 shows the probability of yield gain along latitude under CA (+F+WD) vs. CT-R-SC (+F+WD) systems under current climate conditions. Plot 2 shows the probability of yield gain along latitude under CA (-F-WD) vs. CT-R-SC (-F-WD) systems under current climate conditions. Plot 3 shows the probability of yield gain along latitude under NT+R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under current climate conditions. Plot 4 shows the probability of yield gain along latitude under NT-R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under current climate conditions. Plot 5 shows the probability of yield gain along latitude under NT-R-SC (-F-WD) vs. CT-R-SC (-F-WD) systems under current climate conditions.

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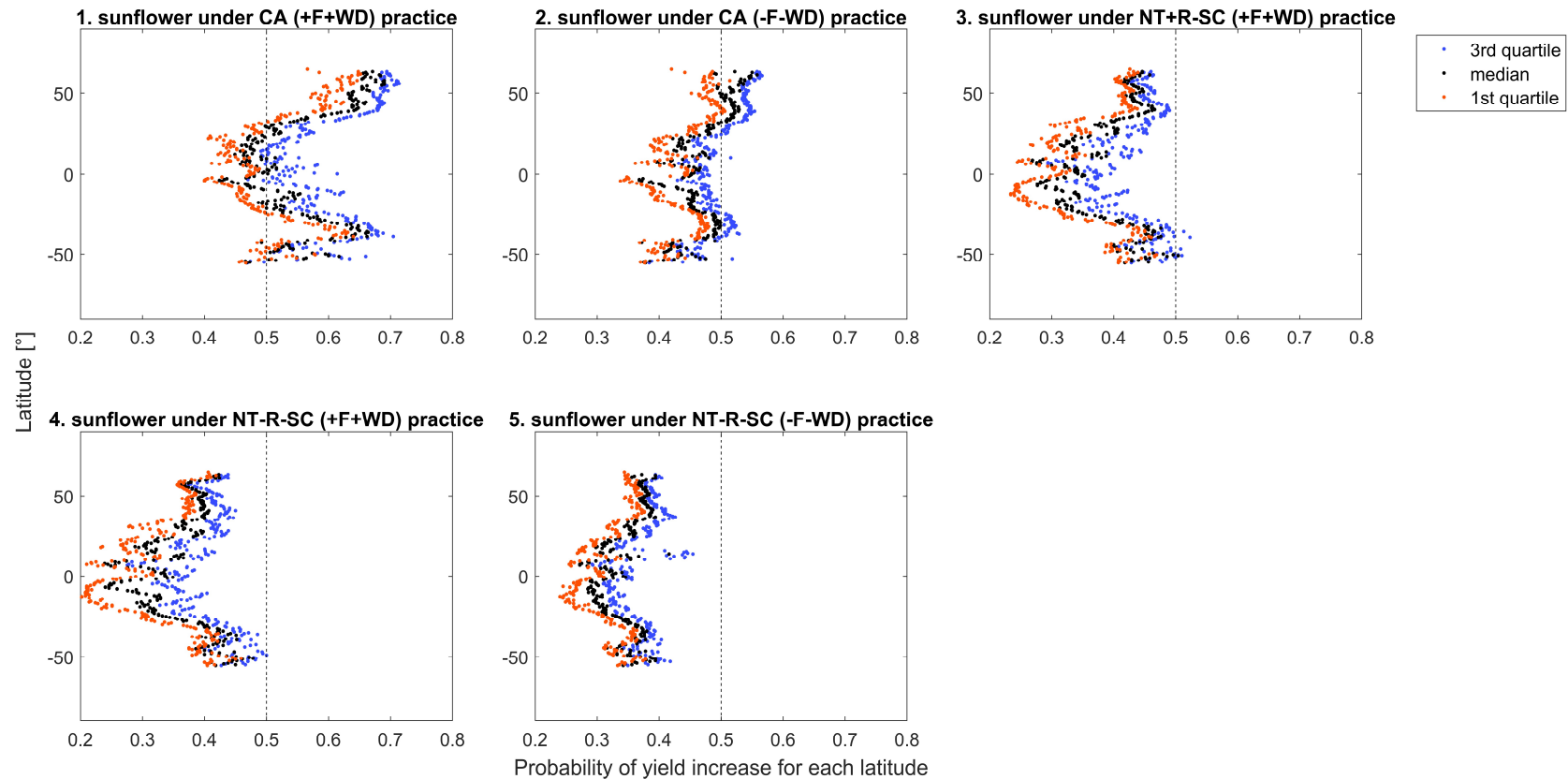


Appendix D figure 3e | Probability of yield gain under CA systems and NT variants vs. CT systems as a function of latitude under current climate scenario - sorghum. This figure shows the variations of 1st quartile (red), median (black), and 3rd quartile (blue) yield gain probability under CA systems and their variants vs. CT systems as a function of latitude. The results are based on the average climate conditions over 2011-2020 (current) simulated by Ipsl-cm5a-lr climate model and RCP 4.5 scenario. Plot 1 shows the probability of yield gain along latitude under CA (+F+WD) vs. CT-R-SC (+F+WD) systems under current climate conditions. Plot 2 shows the probability of yield gain along latitude under CA (-F-WD) vs. CT-R-SC (-F-WD) systems under current climate conditions. Plot 3 shows the probability of yield gain along latitude under NT+R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under current climate conditions. Plot 4 shows the probability of yield gain along latitude under NT-R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under current climate conditions. Plot 5 shows the probability of yield gain along latitude under NT-R-SC (-F-WD) vs. CT-R-SC (-F-WD) systems under current climate conditions.

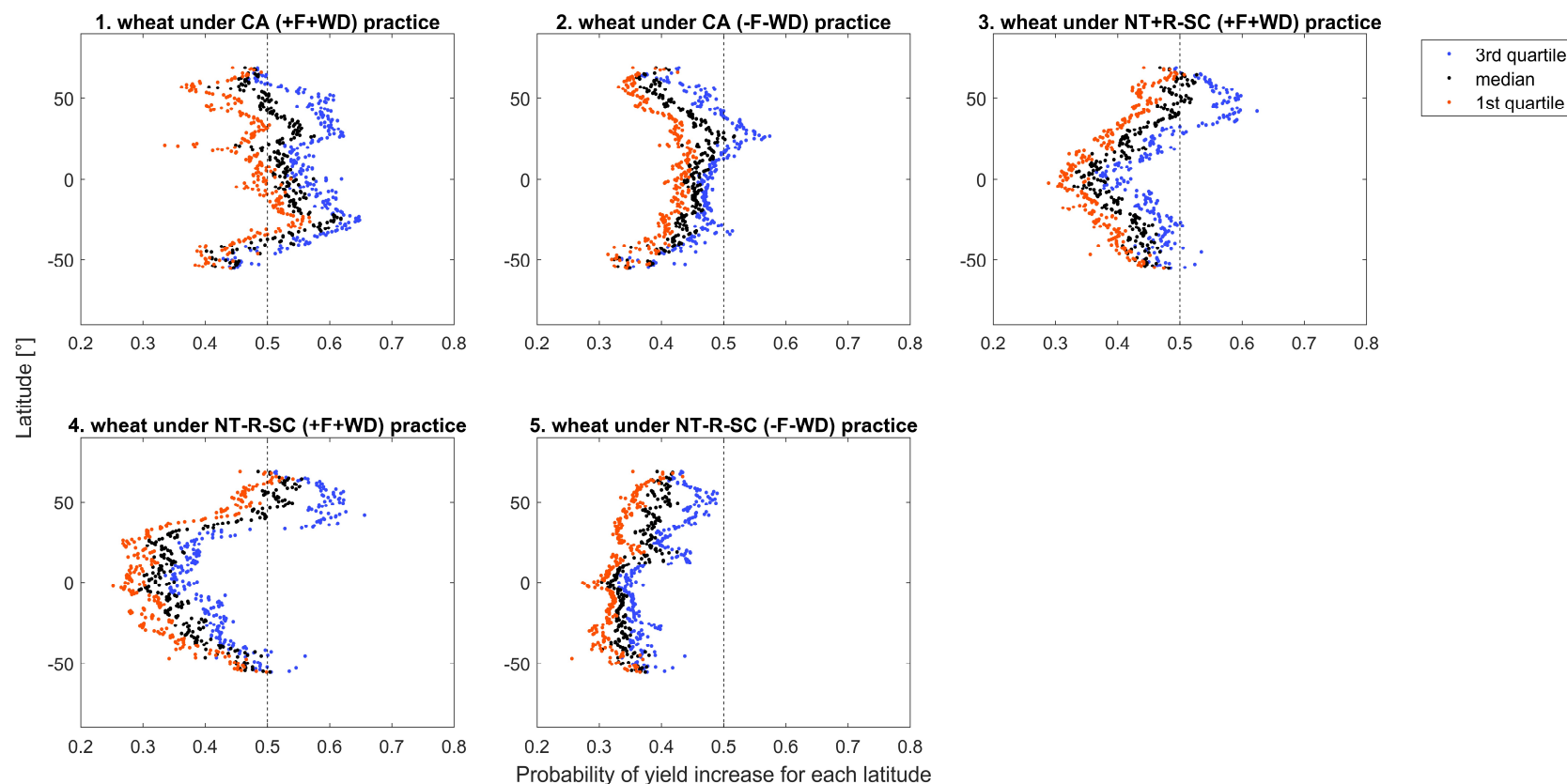


Appendix D figure 3f | Probability of yield gain under CA systems and NT variants vs. CT systems as a function of latitude under current climate scenario - sorghum. This figure shows the variations of 1st quartile (red), median (black), and 3rd quartile (blue) yield gain probability under CA systems and their variants vs. CT systems as a function of latitude. The results are based on the average climate conditions over 2011-2020 (current) simulated by Ipsl-cm5a-lr climate model and RCP 4.5 scenario. Plot 1 shows the probability of yield gain along latitude under CA (+F+WD) vs. CT-R-SC (+F+WD) systems under current climate conditions. Plot 2 shows the probability of yield gain along latitude under CA (-F-WD) vs. CT-R-SC (-F-WD) systems under current climate conditions. Plot 3 shows the probability of yield gain along latitude under NT+R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under current climate conditions. Plot 4 shows the probability of yield gain along latitude under NT-R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under current climate conditions. Plot 5 shows the probability of yield gain along latitude under NT-R-SC (-F-WD) vs. CT-R-SC (-F-WD) systems under current climate conditions.

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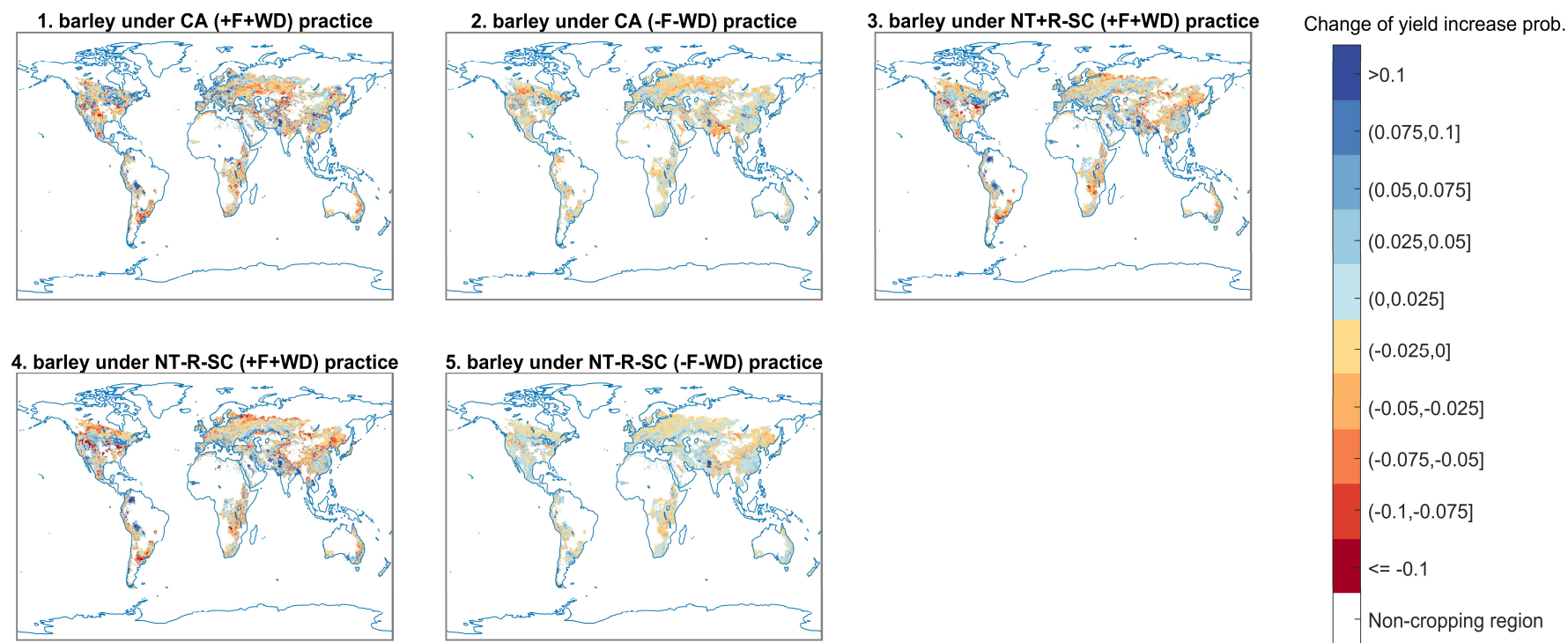


Appendix figure 3g | Probability of yield gain under CA systems and NT variants vs. CT systems as a function of latitude under current climate scenario - sunflower. This figure shows the variations of 1st quartile (red), median (black), and 3rd quartile (blue) yield gain probability under CA systems and their variants vs. CT systems as a function of latitude. The results are based on the average climate conditions over 2011-2020 (current) simulated by Ipsl-cm5a-lr climate model and RCP 4.5 scenario. Plot 1 shows the probability of yield gain along latitude under CA (+F+WD) vs. CT-R-SC (+F+WD) systems under current climate conditions. Plot 2 shows the probability of yield gain along latitude under CA (-F-WD) vs. CT-R-SC (-F-WD) systems under current climate conditions. Plot 3 shows the probability of yield gain along latitude under NT+R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under current climate conditions. Plot 4 shows the probability of yield gain along latitude under NT-R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under current climate conditions. Plot 5 shows the probability of yield gain along latitude under NT-R-SC (-F-WD) vs. CT-R-SC (-F-WD) systems under current climate conditions.

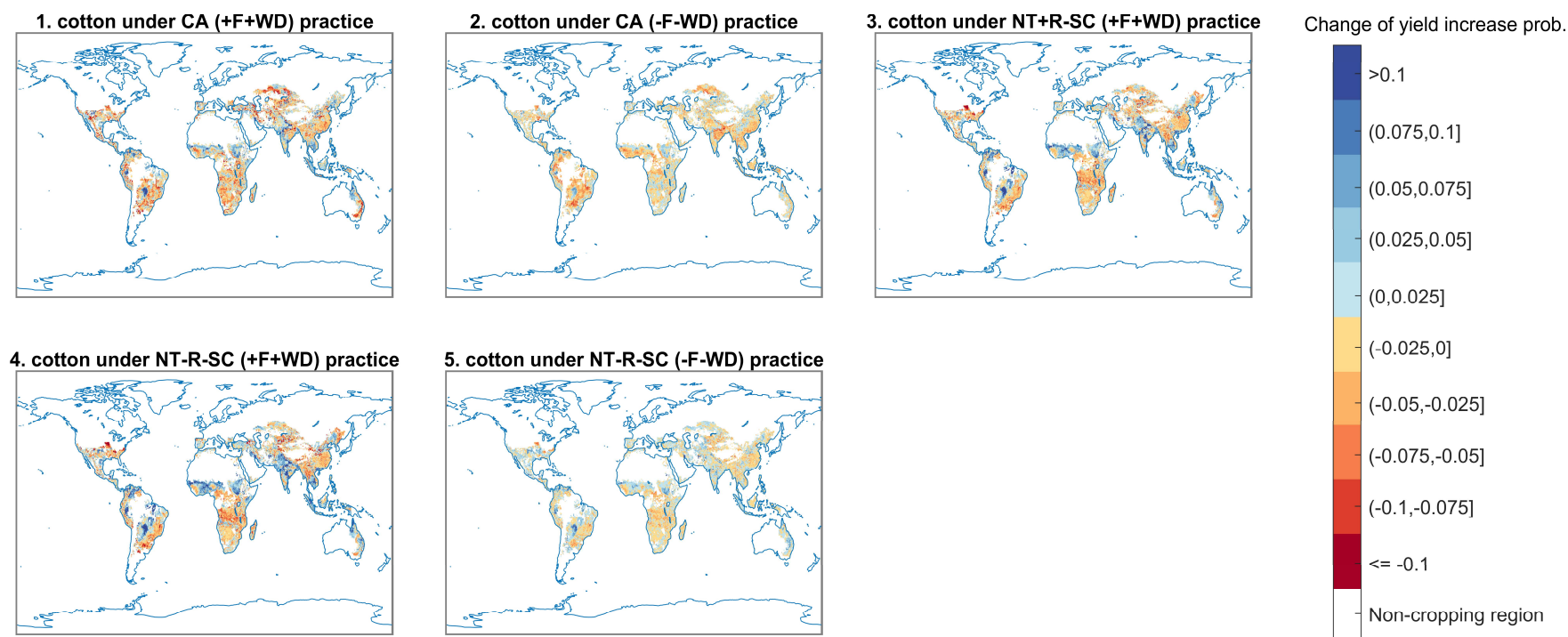


Appendix D figure 3h | Probability of yield gain under CA systems and NT variants vs. CT systems as a function of latitude under current climate scenario - wheat. This figure shows the variations of 1st quartile (red), median (black), and 3rd quartile (blue) yield gain probability under CA systems and their variants vs. CT systems as a function of latitude. The results are based on the average climate conditions over 2011-2020 (current) simulated by Ipsl-cm5a-lr climate model and RCP 4.5 scenario. Plot 1 shows the probability of yield gain along latitude under CA (+F+WD) vs. CT-R-SC (+F+WD) systems under current climate conditions. Plot 2 shows the probability of yield gain along latitude under CA (-F-WD) vs. CT-R-SC (-F-WD) systems under current climate conditions. Plot 3 shows the probability of yield gain along latitude under NT+R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under current climate conditions. Plot 4 shows the probability of yield gain along latitude under NT-R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under current climate conditions. Plot 5 shows the probability of yield gain along latitude under NT-R-SC (-F-WD) vs. CT-R-SC (-F-WD) systems under current climate conditions.

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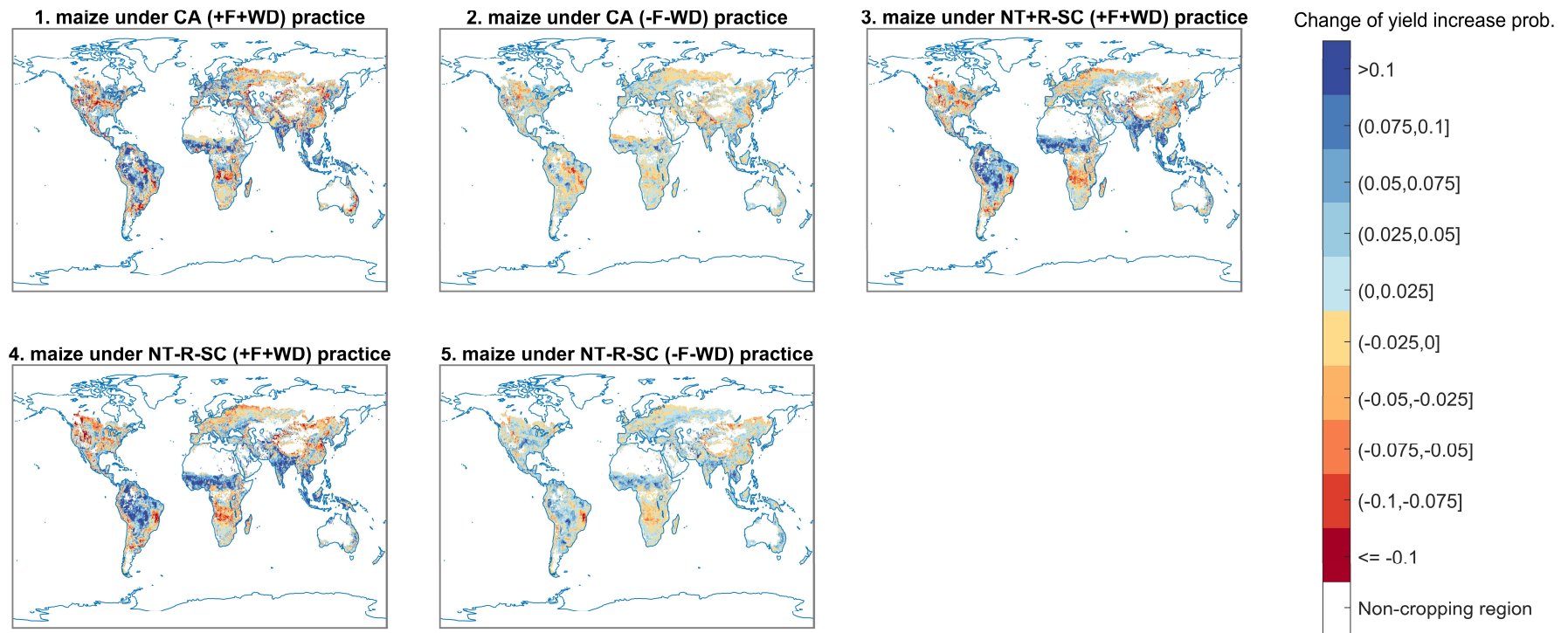


Appendix D figure 4a | Maps of the change of yield gain probability under CA systems and NT variants vs. CT systems under climate change – barley. Regions with a decreasing trend are depicted in red, while those with an increase in yield gain probability are depicted in blue. The results are based on the average climate conditions over 2011-2020 (current) and over 2051-2060 (future) simulated by Ipsi-cm5a-lr climate model and RCP 4.5 scenario. Plot 1 shows the change of yield gain probability under CA (+F+WD) vs. CT-R-SC (+F+WD) systems under climate change. Plot 2 shows the change of yield gain probability under CA (-F-WD) vs. CT-R-SC (-F-WD) systems under climate change. Plot 3 shows the change of yield gain probability under NT+R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under climate change. Plot 4 shows the change of yield gain probability under NT-R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under climate change. Plot 5 shows the change of yield gain probability under NT-R-SC (-F-WD) vs. CT-R-SC (-F-WD) systems under climate change.



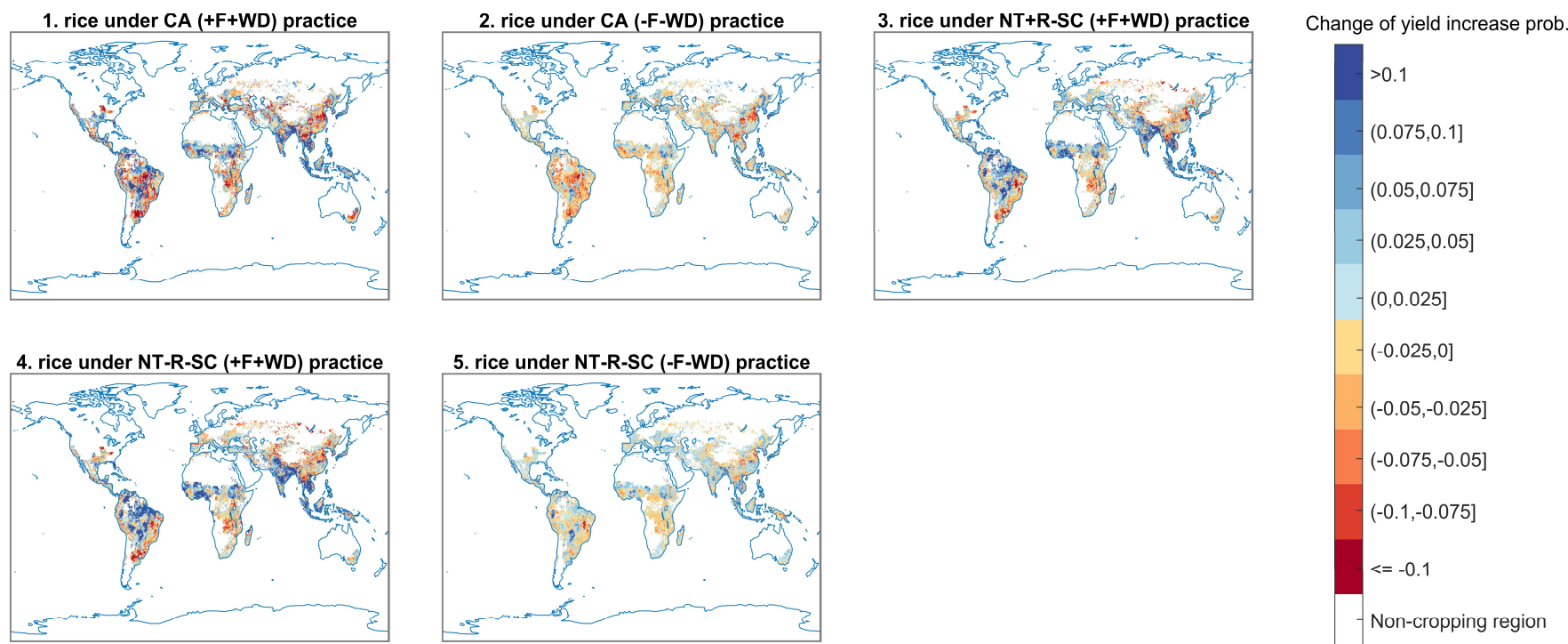
Appendix D figure 4b | Maps of the change of yield gain probability under CA systems and NT variants vs. CT systems under climate change – cotton. Regions with a decreasing trend are depicted in red, while those with an increase in yield gain probability are depicted in blue. The results are based on the average climate conditions over 2011-2020 (current) and over 2051-2060 (future) simulated by Ipsi-cm5a-lr climate model and RCP 4.5 scenario. Plot 1 shows the change of yield gain probability under CA (+F+WD) vs. CT-R-SC (+F+WD) systems under climate change. Plot 2 shows the change of yield gain probability under CA (-F-WD) vs. CT-R-SC (-F-WD) systems under climate change. Plot 3 shows the change of yield gain probability under NT+R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under climate change. Plot 4 shows the change of yield gain probability under NT-R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under climate change. Plot 5 shows the change of yield gain probability under NT-R-SC (-F-WD) vs. CT-R-SC (-F-WD) systems under climate change.

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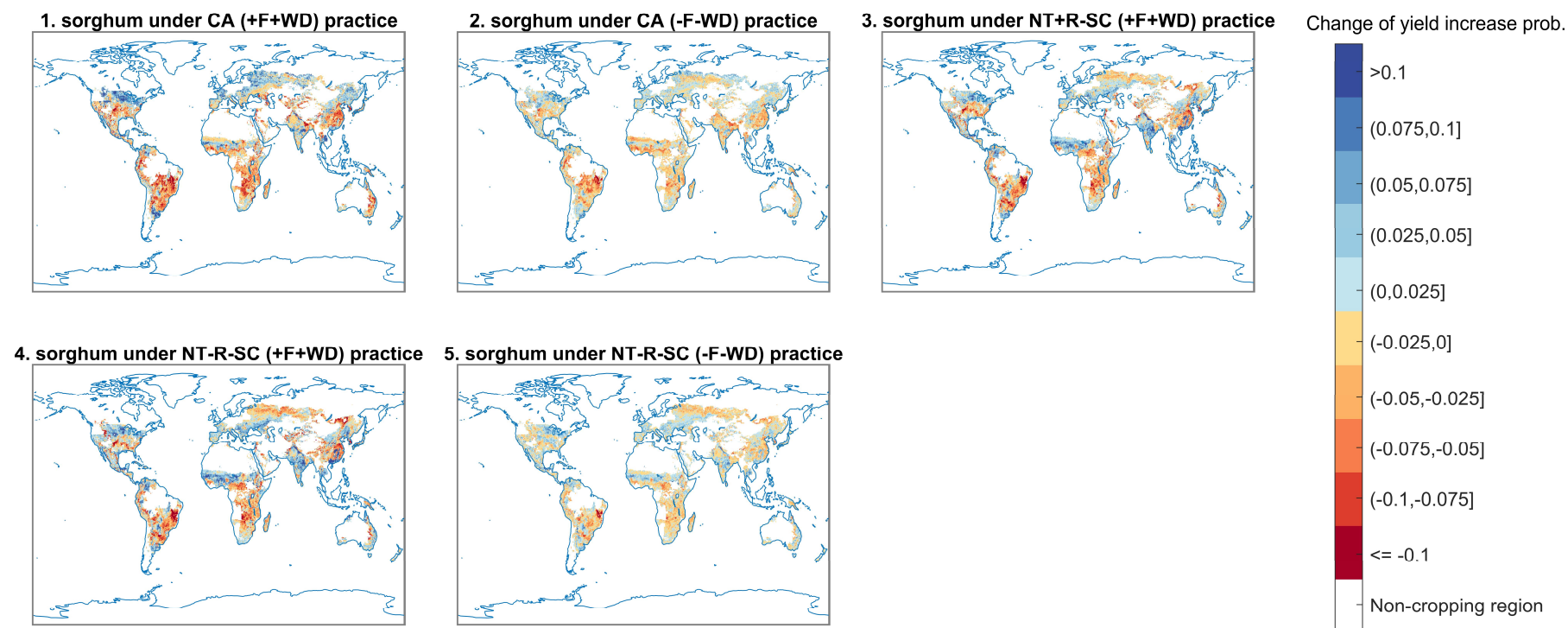
Appendix D figure 4c | Maps of the change of yield gain probability under CA systems and NT variants vs. CT systems under climate change – maize.

Regions with a decreasing trend are depicted in red, while those with an increase in yield gain probability are depicted in blue. The results are based on the average climate conditions over 2011-2020 (current) and over 2051-2060 (future) simulated by Ipsi-cm5a-Ir climate model and RCP 4.5 scenario. Plot 1 shows the change of yield gain probability under CA (+F+WD) vs. CT-R-SC (+F+WD) systems under climate change. Plot 2 shows the change of yield gain probability under CA (-F-WD) vs. CT-R-SC (-F-WD) systems under climate change. Plot 3 shows the change of yield gain probability under NT+R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under climate change. Plot 4 shows the change of yield gain probability under NT-R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under climate change. Plot 5 shows the change of yield gain probability under NT-R-SC (-F-WD) vs. CT-R-SC (-F-WD) systems under climate change.



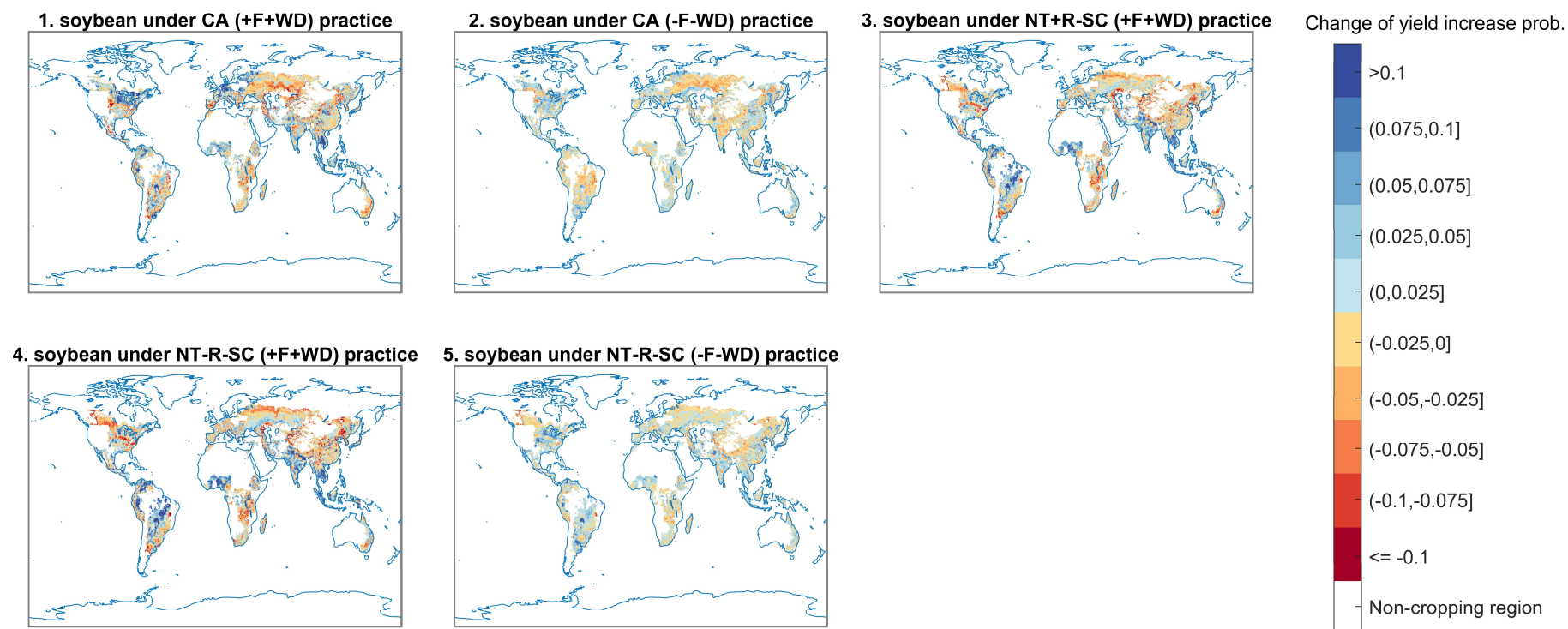
Appendix D figure 4d | Maps of the change of yield gain probability under CA systems and NT variants vs. CT systems under climate change – rice. Regions with a decreasing trend are depicted in red, while those with an increase in yield gain probability are depicted in blue. The results are based on the average climate conditions over 2011-2020 (current) and over 2051-2060 (future) simulated by Ipsi-cm5a-lr climate model and RCP 4.5 scenario. Plot 1 shows the change of yield gain probability under CA (+F+WD) vs. CT-R-SC (+F+WD) systems under climate change. Plot 2 shows the change of yield gain probability under CA (-F-WD) vs. CT-R-SC (-F-WD) systems under climate change. Plot 3 shows the change of yield gain probability under NT+R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under climate change. Plot 4 shows the change of yield gain probability under NT-R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under climate change. Plot 5 shows the change of yield gain probability under NT-R-SC (-F-WD) vs. CT-R-SC (-F-WD) systems under climate change.

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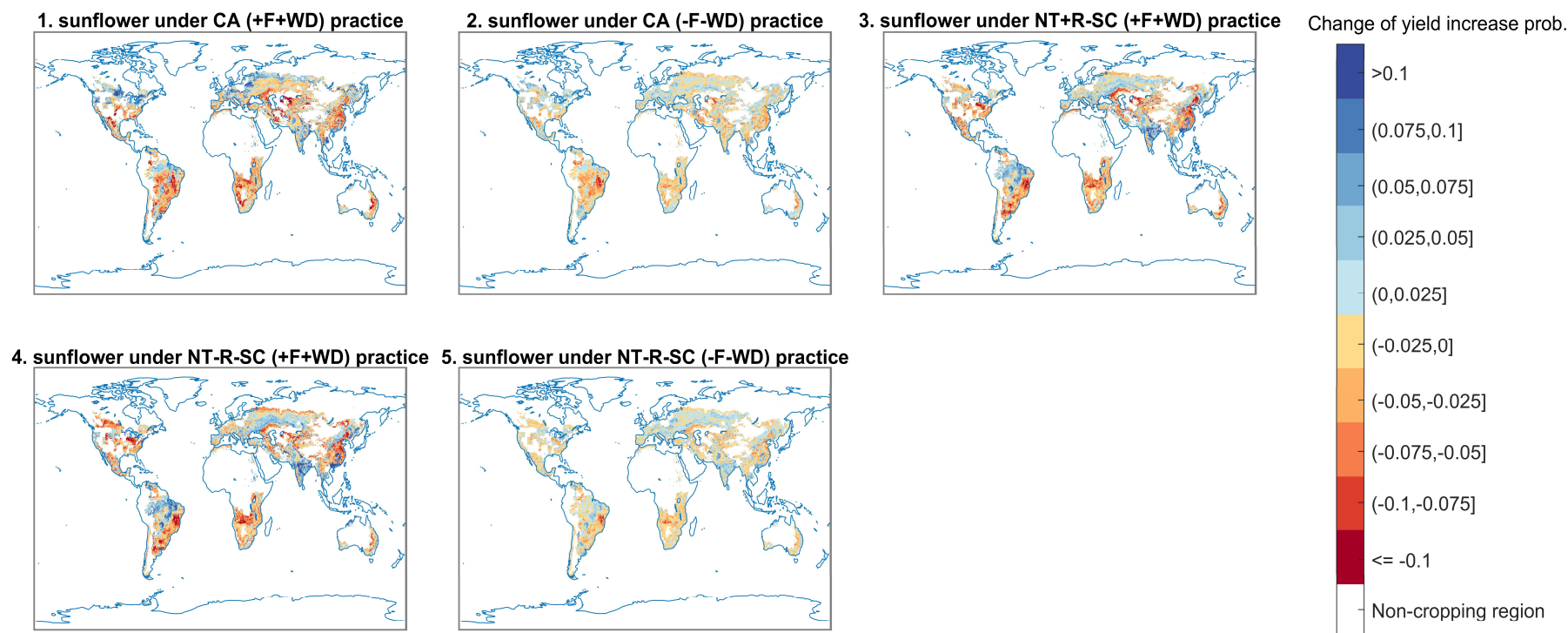
Appendix D figure 4e | Maps of the change of yield gain probability under CA systems and NT variants vs. CT systems under climate change – sorghum.

Regions with a decreasing trend are depicted in red, while those with an increase in yield gain probability are depicted in blue. The results are based on the average climate conditions over 2011-2020 (current) and over 2051-2060 (future) simulated by Ipsi-cm5a-lr climate model and RCP 4.5 scenario. Plot 1 shows the change of yield gain probability under CA (+F+WD) vs. CT-R-SC (+F+WD) systems under climate change. Plot 2 shows the change of yield gain probability under CA (-F-WD) vs. CT-R-SC (-F-WD) systems under climate change. Plot 3 shows the change of yield gain probability under NT+R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under climate change. Plot 4 shows the change of yield gain probability under NT-R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under climate change. Plot 5 shows the change of yield gain probability under NT-R-SC (-F-WD) vs. CT-R-SC (-F-WD) systems under climate change.

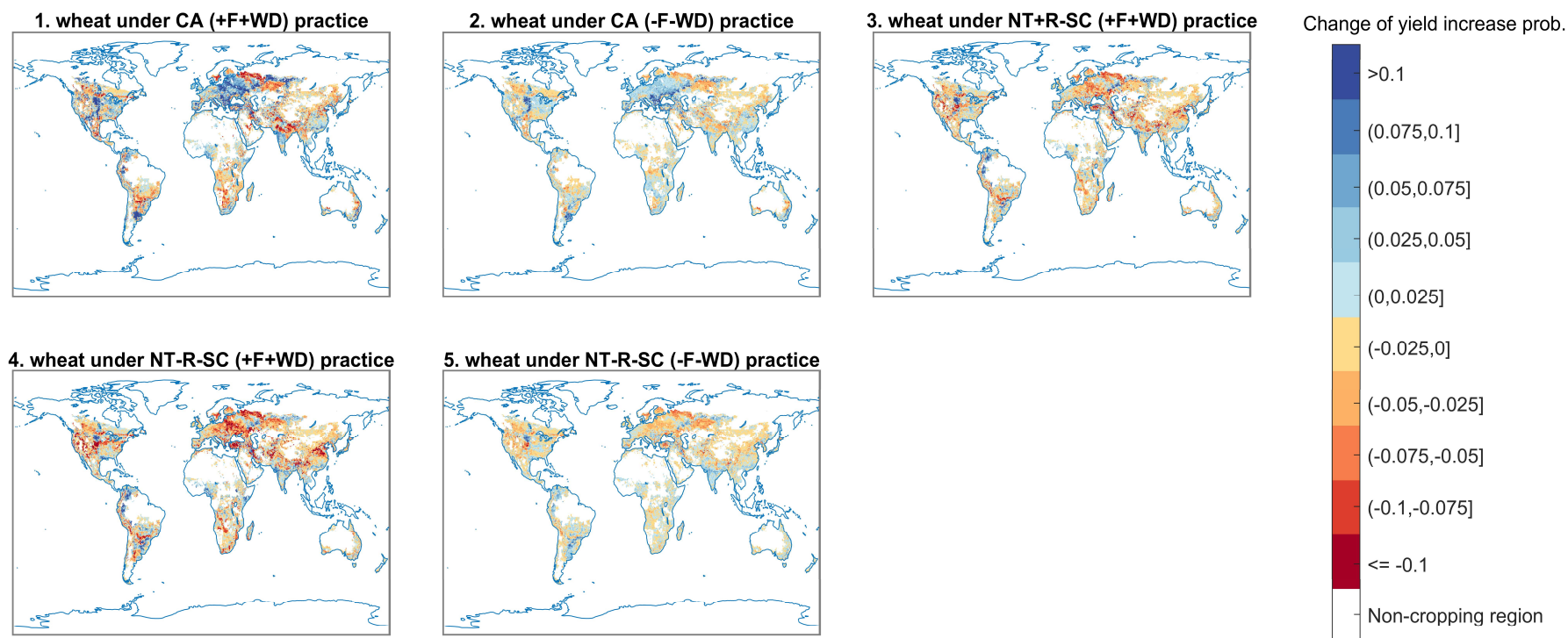


Appendix D figure 4f | Maps of the change of yield gain probability under CA systems and NT variants vs. CT systems under climate change – soybean. Regions with a decreasing trend are depicted in red, while those with an increase in yield gain probability are depicted in blue. The results are based on the average climate conditions over 2011-2020 (current) and over 2051-2060 (future) simulated by Ipsi-cm5a-lr climate model and RCP 4.5 scenario. Plot 1 shows the change of yield gain probability under CA (+F+WD) vs. CT-R-SC (+F+WD) systems under climate change. Plot 2 shows the change of yield gain probability under CA (-F-WD) vs. CT-R-SC (-F-WD) systems under climate change. Plot 3 shows the change of yield gain probability under NT+R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under climate change. Plot 4 shows the change of yield gain probability under NT-R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under climate change. Plot 5 shows the change of yield gain probability under NT-R-SC (-F-WD) vs. CT-R-SC (-F-WD) systems under climate change.

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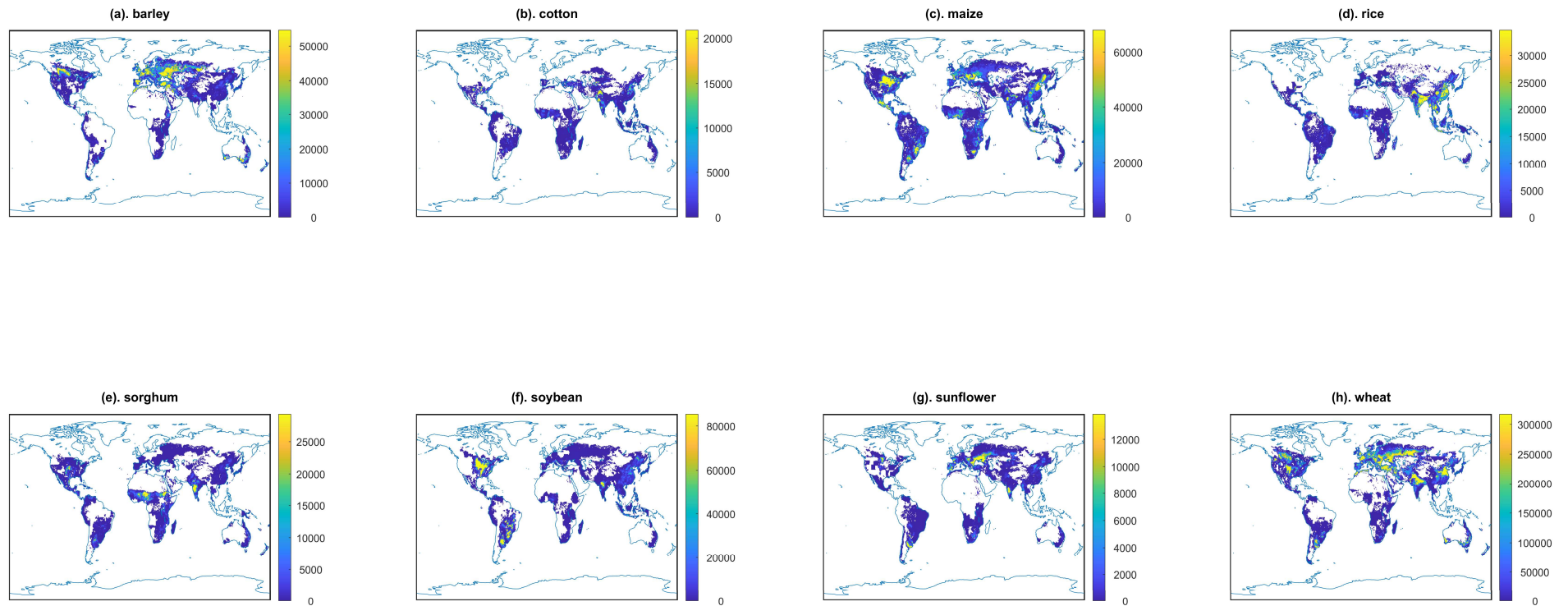


Appendix D figure 4g | Maps of the change of yield gain probability under CA systems and NT variants vs. CT systems under climate change – sunflower. Regions with a decreasing trend are depicted in red, while those with an increase in yield gain probability are depicted in blue. The results are based on the average climate conditions over 2011-2020 (current) and over 2051-2060 (future) simulated by Ipsi-cm5a-lr climate model and RCP 4.5 scenario. Plot 1 shows the change of yield gain probability under CA (+F+WD) vs. CT-R-SC (+F+WD) systems under climate change. Plot 2 shows the change of yield gain probability under CA (-F-WD) vs. CT-R-SC (-F-WD) systems under climate change. Plot 3 shows the change of yield gain probability under NT+R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under climate change. Plot 4 shows the change of yield gain probability under NT-R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under climate change. Plot 5 shows the change of yield gain probability under NT-R-SC (-F-WD) vs. CT-R-SC (-F-WD) systems under climate change.

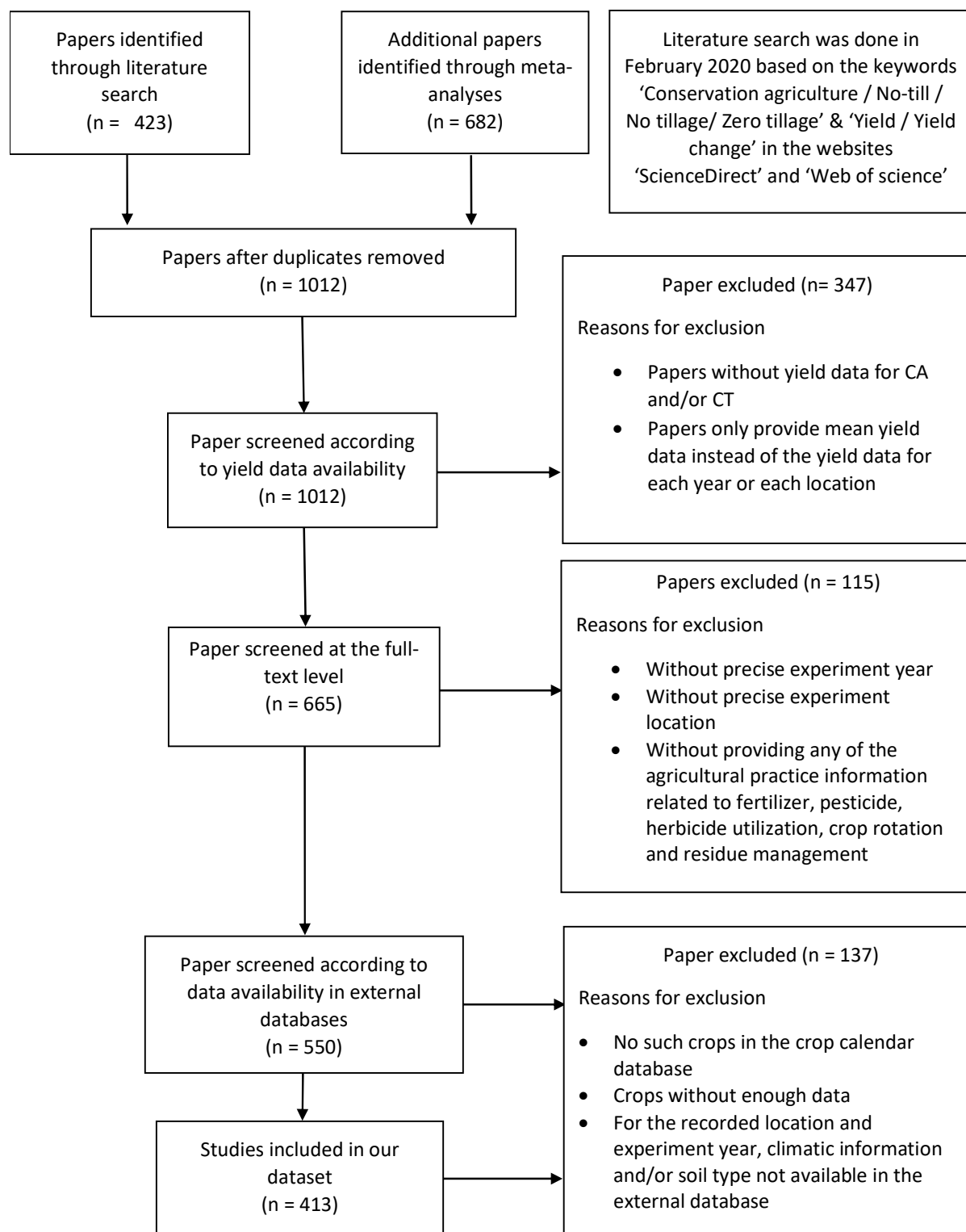


Appendix D figure 4h | Maps of the change of yield gain probability under CA systems and NT variants vs. CT systems under climate change – wheat. Regions with a decreasing trend are depicted in red, while those with an increase in yield gain probability are depicted in blue. The results are based on the average climate conditions over 2011-2020 (current) and over 2051-2060 (future) simulated by Ipsl-cm5a-lr climate model and RCP 4.5 scenario. Plot 1 shows the change of yield gain probability under CA (+F+WD) vs. CT-R-SC (+F+WD) systems under climate change. Plot 2 shows the change of yield gain probability under CA (-F-WD) vs. CT-R-SC (-F-WD) systems under climate change. Plot 3 shows the change of yield gain probability under NT+R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under climate change. Plot 4 shows the change of yield gain probability under NT-R-SC (+F+WD) vs. CT-R-SC (+F+WD) systems under climate change. Plot 5 shows the change of yield gain probability under NT-R-SC (-F-WD) vs. CT-R-SC (-F-WD) systems under climate change.

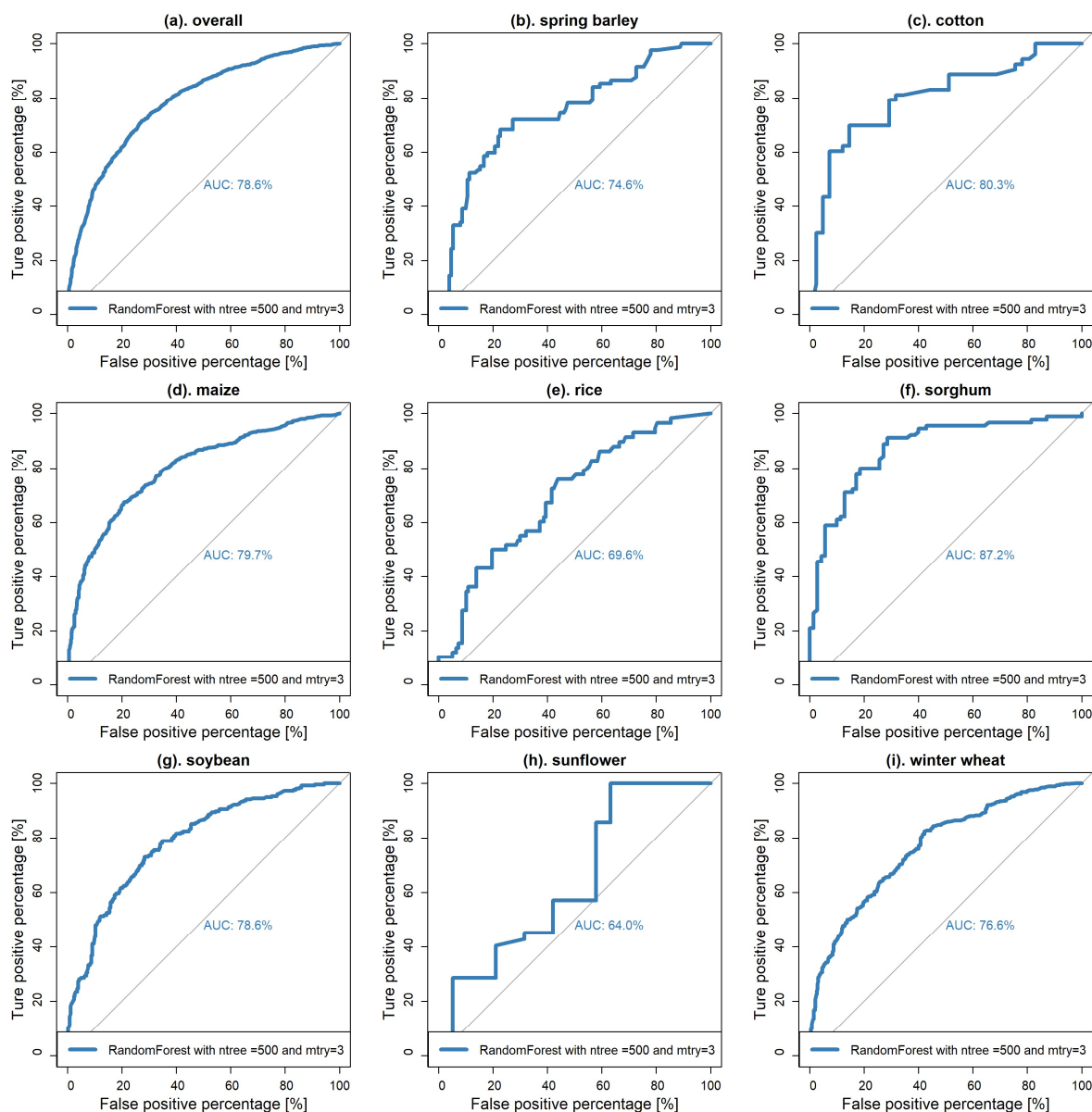
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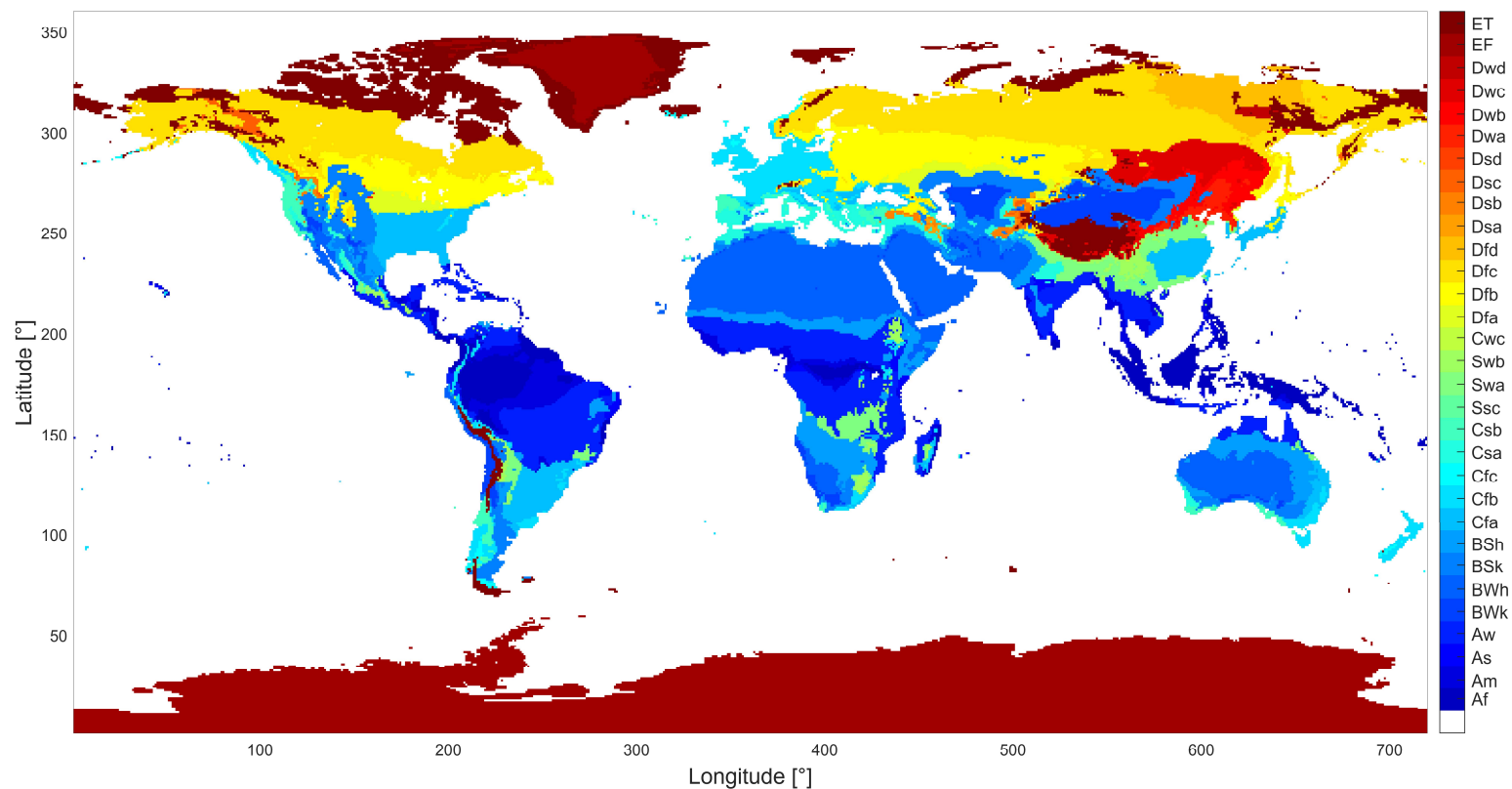
Appendix D figure 5 | Maps of crop density. These cropping density maps were generated based on MIRCA2000 dataset³ and were presented in ref. 6. The yellow shade indicates the higher density, and vice versa. To make the plots more contrast, the yellow color in the map is set to the crop density that equals to or is higher than 20% of maximum density worldwide. The unit for the color bar is [ha / 0.5° latitude × 0.5° longitude grid cell].



Appendix D figure 6 | Flow chart of paper section. The search strategy is described in detail in ref. 6,7.



Appendix D figure 7 | Model cross-validation – leave one out cross validation (LOOCV). Leave one out cross-validation procedure: The details of this cross-validation procedure are presented in ref. 6. One yield ratio (and its associated set of inputs) was removed from the dataset at each iteration of the cross-validation and used as testing sample. The rest of the dataset was used to train the random forest model. The trained model was then used to compute the probability of yield gain from the input data of the removed yield ratio. This procedure was repeated for all yield ratios. The R package “randomForest” was used to train the model. “randomForest” is a standard package for implementing ensemble of regression trees and is very robust ⁸. The probabilities of yield gain computed by the package were used to compute the Area under the ROC curve (AUC) with the R package “pROC”. AUC is equal to the probability that the classifier will rank a random pair of positive (yield ratio>1) and negative (yield ratio<=1) cases correctly ⁹, so a higher AUC means a better model classification performance.



Appendix D figure 8 | Koppen-Geiger climate regions¹⁰ used in this paper. The first part of the name indicates the main climates, A: equatorial; B: arid; C: warm temperate; D: snow; E: polar. The second part of the name indicates the precipitation conditions, W: desert; S: steppe; f: fully humid; s: summer dry; w: winter dry; m: monsoonal. The third part of the name indicates the temperatures, h: hot arid; k: cold arid; a: hot summer; b: warm summer; c: cool summer; d: extremely continental. While F indicates polar frost, T indicates polar tundra.

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Titre : Synthèse de données pour l'analyse des enjeux agricoles mondiaux : application pour évaluer la productivité de l'agriculture de conservation sous les climats actuels et futurs

Mots clés : L'agriculture de conservation, Changement climatique, Rendement des cultures

Résumé : Dans cette thèse, nous présentons un pipeline d'apprentissage machine (ML) qui produit des cartes mondiales générées par synthèse de données pour répondre aux enjeux agricoles mondiaux, tels que l'évaluation de la distribution spatiale de la productivité de l'agriculture de conservation (CA) par rapport au travail du sol conventionnel (CT) sous les climats actuels et futurs. Notre approche comporte la sélection et la comparaison d'algorithmes d'apprentissage automatique, l'entraînement du modèle, son optimisation avec validation croisée, les tests et la projection globale des résultats. Nous illustrons la démarche proposée à l'aide d'un jeu de données mondial pour comparer les rendements des systèmes d'agriculture de conservation (AC) et de non-travail du sol (NT) par rapport au travail du sol conventionnel (CT) avec un large éventail d'espèces de cultures, de pratiques agricoles, de caractéristiques du sol et de conditions climatiques pendant la saison de croissance

des cultures. Grâce à ce pipeline, une série de modèles de classification, de régression et de régression quantile sont développés sur la base de 12 algorithmes ML courants. Les modèles les plus performants sont utilisés pour cartographier la productivité des cultures de l'AC et de ses variantes par rapport au CT à l'échelle mondiale pour différentes pratiques agricoles et conditions climatiques dans les scénarios passés (1981-2010), actuels (2011-2020) et futurs (2051-2060). Nous révélons de grandes différences dans la probabilité de gains de rendement avec l'AC entre les types de cultures, les pratiques de gestion agricole, les zones climatiques et les régions géographiques. Nous montrons que l'AC a plus de 50% de chances de surpasser le CT dans les régions sèches du monde, en particulier avec des pratiques de gestion agricole appropriées. En conclusion, l'AC apparaît comme une pratique agricole durable si elle est ciblée sur des régions climatiques et des espèces de cultures spécifiques.

Title : Data-driven approach for addressing global agricultural issues: application to assess productivity of conservation agriculture under current and future climate

Keywords : Conservation agriculture, Climate change, Crop yield

Abstract : In this thesis, we present a machine learning (ML) pipeline that produces data-driven global maps to address the global agricultural issues, such as assessing the spatial distribution of the productivity conservation agriculture (CA) versus conventional tillage (CT) under current and future climate. Our approach covers the selection and comparison of ML algorithms, model training, tuning with cross-validation, testing, and results global projection. We demonstrate its relevance using a global dataset we conducted which comparing the crop yields of conservation agriculture (CA) and no tillage (NT) vs. conventional tillage (CT) systems with a wide range of crop species, farming practices, soil characteristics and climate conditions over crop growing season. Through this ML pipeline, various

models for classification, regression and quantile regression are trained based on 12 mainstream ML algorithms. The models are used to map the crop productivity of CA and its variants vs. CT at the global scale under different farming practices and climate conditions in the past (1981-2010), current (2011-2020) and future (2051-2060) scenarios. We reveal large differences in the probability of yield gains with CA across crop types, agricultural management practices, climate zones, and geographical regions. We show that CA stands a more than 50% chance to outperform CT in dryer regions of the world, especially with proper agricultural management practices. In conclusion, CA appears as a sustainable agricultural practice if targeted at specific climatic regions and crop species.