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Rice production in West Africa: Analyzing the impacts of risks and constraints on yields and rice farmers' food security

Offre de riz local en Afrique de l'Ouest : analyse des risques et contraintes affectant la production et de leur impact sur la sécurité alimentaire des riziculteurs

Thèse de doctorat de l'université Paris-Saclay

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Thèse soutenue à Paris-Saclay, le 27 avril 2023, par

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Titre : Offre de riz local en Afrique de l'Ouest : analyse des risques et contraintes affectant la production et de leur impact sur la sécurité alimentaire des riziculteurs

Mots clés : riz, rendements, pratiques agricoles, risques, bien-être des ménages

Résumé : Le riz, du fait de son importance croissante en tant qu'aliment de base, joue un rôle clé dans les régimes alimentaires ouest-africains, représentant près de 40 % du volume total de céréales consommées. Dans le contexte de la crise des prix alimentaires de 2008, plusieurs pays d'Afrique de l'Ouest ont proclamé leur objectif d'autosuffisance en riz d'ici 2050, par l'expansion des zones rizicoles et l'intensification de la riziculture. L'objectif de cette thèse est d'analyser les risques de production et de marché associés à une augmentation de la production de riz en Afrique de l'Ouest et d'évaluer leur impact sur le bien-être et sur la sécurité alimentaire des producteurs de riz.

Dans une première étude, l'impact potentiel de la réaffectation de ressources telles que la terre, le travail ou les capitaux vers la production de riz au détriment d'autres cultures vivrières de base comme le manioc, le maïs, le millet, le sorgho ou l'igname est examiné. En moyenne, sur toute la région, les rendements du riz sont plus variables, d'environ 20%, que ceux des cinq autres cultures alimentaires de base. Le riz tend à avoir des rendements plus variables que les autres cultures dans les régions où elles sont traditionnellement cultivées (i.e., les tubercules en zone guinéenne et le sorgho et le mil dans les zones sahélienne et soudanienne). Les rendements du riz, tous systèmes de culture confondus, ont tendance à être plus variables que ceux des autres cultures dans les régions où la variabilité des précipitations est la plus forte.

L'impact des pratiques agricoles et du risque climatique sur les rendements du riz est examiné dans une deuxième étude, via la construction de fonctions de production du riz pour quatre systèmes de culture représentatifs (i.e., système pluvial de bas-fond, système de bas-fond amélioré, système irrigué, système pluvial de hautes-terres). L'étude statistique des rendements montre que les pratiques intensives

(i.e., utilisation de fertilisants, de pesticides, de variétés améliorées, gestion de l'eau améliorée) augmentent significativement les rendements moyens mais ne conduisent pas à une stabilisation des rendements, à l'échelle d'une région administrative 1. Dans les zones guinéenne et soudanienne, où la pénurie d'eau et le risque de sécheresse sont moindres, c'est la fréquence de désherbage qui a le plus d'impact sur les rendements moyens. Au contraire, dans la zone sahélienne, la variabilité spatio-temporelle des précipitations explique environ 50% de la variance des rendements, dans le cas des systèmes non irrigués. Enfin, dans une troisième et dernière partie, l'impact des risques et contraintes agricoles et l'effet de changements du contexte économique sur la prise de décision des riziculteurs est évalué grâce à un modèle microéconomique. Les résultats de cette analyse montrent que la situation économique des ménages influence leur choix d'investissement dans la riziculture. Les producteurs piégés dans la trappe à pauvreté sont, par définition, contraints par le manque de capital disponible en début de cycle et n'ont donc pas la possibilité d'investir dans des intrants, contrairement aux ménages qui ont pu dégager un surplus et épargner une partie de leurs revenus. Cette trappe à pauvreté est fortement corrélée au contexte climatique, puisque dans les régions où l'eau est rare et le risque de sécheresse élevé (c'est-à-dire les zones sahélienne et Nord-soudanienne), les rendements sont faibles et l'eau est le facteur limitant, de sorte que l'ajout d'engrais ne génère pas de revenus significatifs.

L'amélioration de la production de riz est, dans le contexte actuel, fortement freinée par les risques et les contraintes auxquels sont confrontés les ménages producteurs de riz. Nos résultats montrent que l'autosuffisance en riz pourrait ne pas être efficace pour atteindre la sécurité alimentaire en Afrique de l'Ouest car la production peut varier considérablement en fonction des conditions climatiques.

Title : Rice production in West Africa: Analyzing the impacts of risks and constraints on yields and rice farmers' food security

Keywords : rice, yields, cropping practices, risks, households' welfare

Abstract : Rice, with its rapidly growing importance as a staple food, plays a key role in West African diets, accounting for nearly 40% of the total volume of cereals consumed. In the context of the 2008 food price crisis, several West African countries have proclaimed their goal of rice self-sufficiency by 2050, through expansion of cultivation areas and intensification of rice farming. The objective of this thesis is to assess the production and market risks associated with increased rice production in West Africa and to evaluate their impact on the welfare and food security of rice producers.

In a first study, the potential impact of reallocating resources such as land, labor or capital to rice production at the expense of other staple food crops such as cassava, maize, millet, sorghum or yam is examined. On average across the region, rice yields are more variable, by about 20%, than those of the other five staple food crops. Rice tends to have more variable yields than the other crops in areas where they are traditionally grown (i.e., tubers in the Guinean zone, and sorghum and millet in the Sahelian and Sudanian zones). Rice yields, across all cropping systems, tend to be more variable than those of other crops in areas where rainfall variability is greatest.

The impact of agricultural practices and climate risk on rice yields is examined in a second study, via the construction of rice production functions for four representative cropping systems (i.e., rainfed lowland system, improved lowland system, irrigated system, rainfed upland system). The statistical study of yields shows that intensive practices (i.e., use of fertilizers, pesticides, improved varieties, improved water increase

average yields but do not lead to a stabilization of yields, at the scale of an administrative region 1. In the Guinean and Sudanian zones, where water scarcity and drought risks are lower, it is the frequency of weeding that has the greatest impact on average yields. In contrast, in the Sahelian zone, the spatio-temporal variability of rainfall explains about 50% of the variance of yields, for non-irrigated systems.

Finally, the impact of agricultural risks and constraints, and the effect of changes in the economic context, on the decision making of rice farmers is assessed using a microeconomic model. The results of this analysis show that the economic situation of households influences their choice of investment in rice farming. Farmers locked into the poverty trap are, by definition, constrained by the lack of available capital at the beginning of the cycle, and thus have no opportunity to invest in inputs, unlike households that have been able to generate a surplus and save part of their income. This poverty trap is strongly correlated with the climatic context, since in regions where water is scarce and the risk of drought is high (i.e., the Sahelian and North-Sudanian zones), yields are low and water is the limiting factor, so that the addition of fertilizer does not generate significant income.

Improving rice production is, in the current context, strongly constrained by the risks and constraints faced by rice-producing households. Our results show that rice self-sufficiency may not be effective in achieving food security in West Africa, as production can vary considerably depending on climatic conditions.

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Résumé étendu

Avec une proportion de la population sous-alimentée en augmentation (de 10,5% en 2009 à 14,3% en 2019), l'Afrique de l'Ouest est l'une des régions du monde les plus concernées par les enjeux de sécurité alimentaire. Par conséquent, les trajectoires et scénarios de développement agricole y font l'objet d'un examen scientifique et politique approfondi. Le riz, dont l'importance en tant qu'aliment de base est fortement croissante, joue un rôle clé dans les régimes alimentaires ouest-africains, représentant près de 40 % du volume total de céréales consommées. Dans le contexte de la crise des prix alimentaires de 2008, plusieurs pays d'Afrique de l'Ouest ont proclamé leur objectif d'autosuffisance en riz d'ici 2050, par l'expansion des zones de culture et l'intensification de la riziculture.

L'objectif de ma thèse est d'évaluer les risques de production et de marché associés à une augmentation de la production de riz en Afrique de l'Ouest et d'évaluer leur impact sur la sécurité alimentaire des producteurs de riz. Des éléments de réponses sont donc apportés à la problématique générale suivante : **Dans quelle mesure les risques et contraintes qui pèsent sur la production de riz ont un impact sur la stabilité de la production, les stratégies de cultures, le bien-être et la sécurité alimentaire des ménages riziculteurs ?** Cet objectif est atteint à travers (i) une comparaison de la variabilité des rendements du riz avec la variabilité des rendements d'autres cultures vivrières majeures dans la région (i.e., manioc, maïs, mil, sorgho, ignames), (ii) l'estimation de la contribution des facteurs et des risques de production au niveau moyen et à la variabilité des rendements du riz pour quatre systèmes de culture représentatifs, (iii) l'analyse des stratégies de culture des riziculteurs, en considérant les risques et contraintes de production et de marché auxquels ils sont confrontés, et l'effet de changements du contexte économique sur ces stratégies.

Deux types d'approches sont développées dans cette thèse, mêlant agronomie et économie agricole : analyses statistiques et construction de fonctions de production et d'un modèle microéconomique. Pour les besoins de la modélisation, je définis quatre systèmes de culture de riz, représentatifs des systèmes ouest-africains, en fonction de l'environnement et du niveau de gestion de l'eau :

- (i) système pluvial de bas-fond (noté LLR), sans gestion de l'eau,
- (ii) système de bas-fond amélioré (noté IMP), avec des parcelles aplanies, endiguées, avec drains et canaux d'irrigation prélevant l'eau dans des cours d'eau temporaires,
- (iii) système irrigué (noté IRR), dans les plaines, les vallées intérieures, avec des parcelles aplanies, endiguées, avec drains et canaux d'irrigation prélevant l'eau dans des cours d'eau permanents et/ou de bassins de rétention en amont,
- (iv) système pluvial de plateau (noté ULR), sans gestion de l'eau.

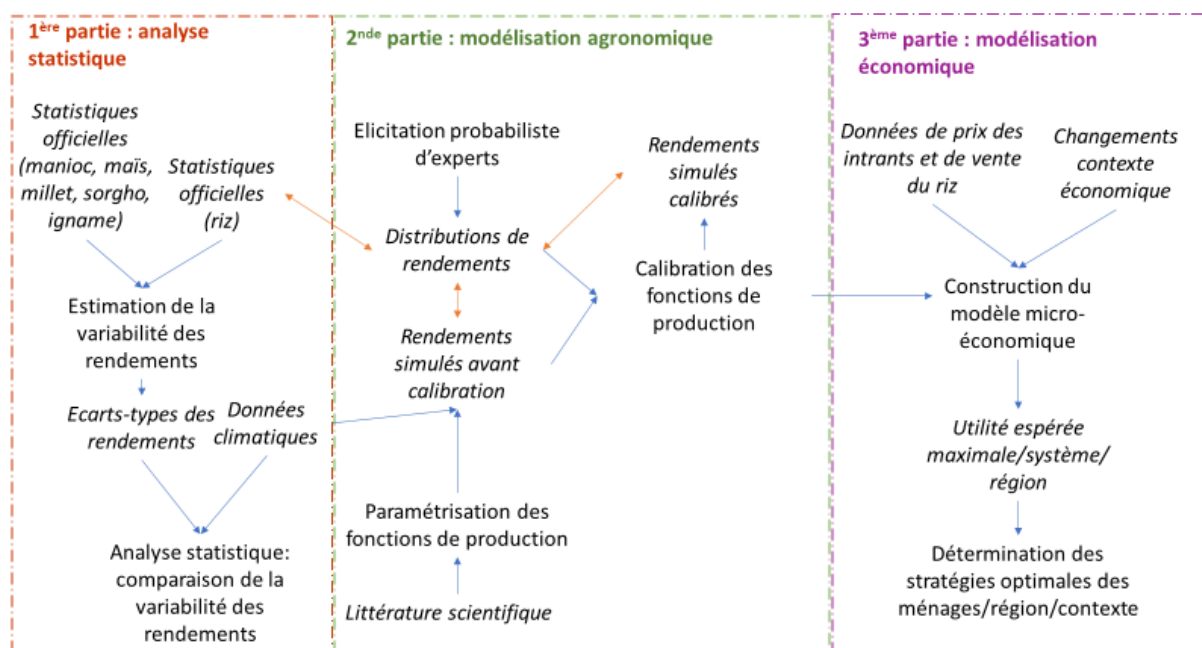


Figure 1. Représentation schématique des trois parties de ma thèse. Les lignes orange avec une double flèche représentent une comparaison entre deux ensembles de données. Les mots en italique font référence aux entrées ou aux sorties. Les mots non italiques font référence aux étapes du projet de thèse.

Dans une première étude, j'examine l'impact potentiel de la réaffectation de ressources telles que la terre, le travail ou les capitaux vers la production de riz au détriment d'autres cultures vivrières de base comme le manioc, le maïs, le millet, le sorgho ou l'igname. L'objectif est de déterminer si cette allocation peut être bénéfique à la fois pour la stabilité des moyens de subsistance des ménages agricoles et pour la sécurité alimentaire de la population. J'aborde les questions suivantes : Les rendements des cultures vivrières alternatives sont-ils plus ou moins stables par rapport à ceux du riz ? Quels sont les facteurs géographiques et climatiques qui impactent cette stabilité ? En analysant les données officielles de rendement de divers pays d'Afrique de l'Ouest au niveau administratif 1, en conjonction avec des données climatiques agrégées, cette étude fournit un aperçu des risques potentiels pour les riziculteurs qui pourraient choisir d'allouer leurs ressources au riz plutôt qu'à d'autres cultures de base, ainsi que de l'impact potentiel sur la sécurité alimentaire locale si la zone consacrée à la production de riz devait augmenter en Afrique de l'Ouest. En moyenne, sur toute la région, les rendements du riz sont plus variables, d'environ 20%, que ceux des cinq autres cultures alimentaires de base. Au niveau administratif 1, les rendements du riz sont significativement moins stables (et inversement, significativement plus stables) pour 33% (et pour 15%) des comparaisons avec les rendements d'autres cultures dans les régions pour lesquelles des données étaient disponibles (Figure 2).

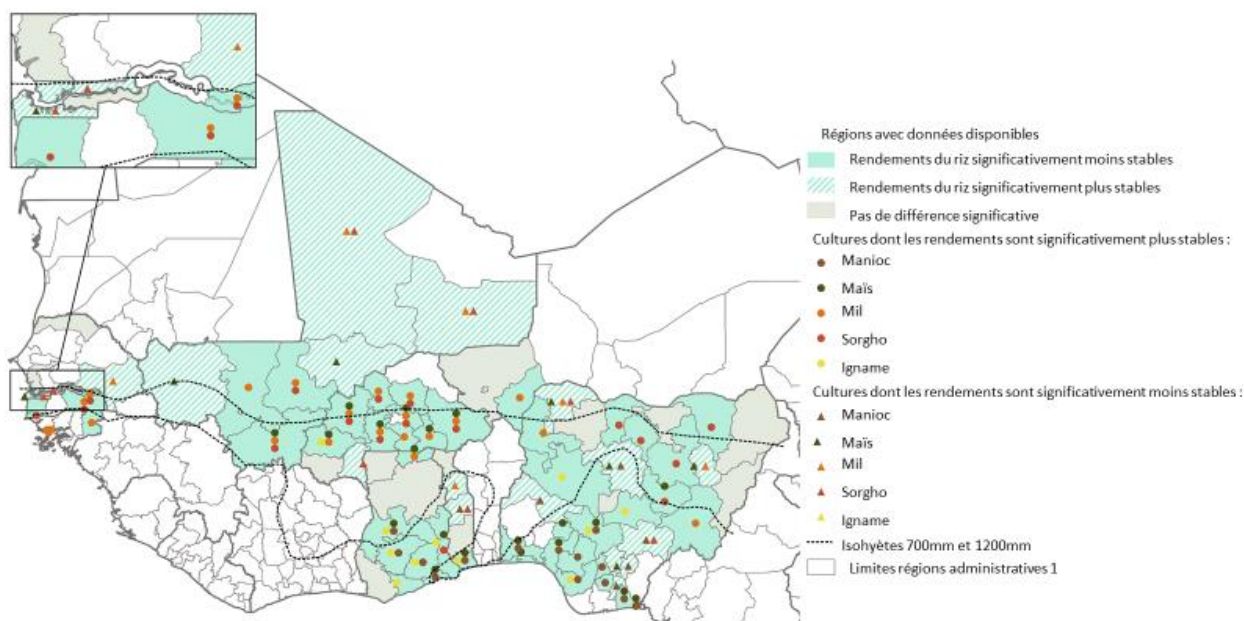


Figure 2. Schéma spatial des différences de variabilité des rendements en Afrique de l'Ouest. Les zones en vert délimitent les régions où les rendements d'au moins une culture alternative sont significativement plus stables que le riz. Les cercles remplis indiquent les espèces de cultures alternatives qui sont plus stables que le riz (brun pour le manioc, vert foncé pour le maïs, orange pour le millet, rouge pour le sorgho et jaune pour l'igname). Les zones vertes pointillées délimitent les régions où les rendements du riz sont significativement plus stables que ceux des autres espèces de cultures. Les triangles indiquent quelles espèces de cultures alternatives ont été comparées aux rendements du riz dans ces régions. Les délimitations entre les trois régions climatiques de l'Afrique de l'ouest sont indiquées par des lignes pointillées noires (l'isohyète 700mm est la frontière entre la région sahéenne au nord et la région soudanienne au sud et l'isohyète 1200 mm est la frontière entre la région soudanienne au Nord et la région guinéenne au Sud).

Le riz tend à avoir des rendements plus variables (d'environ 15-30%) que les autres cultures dans les régions où elles sont traditionnellement cultivées (Figure 2). Par exemple, dans la zone guinéenne, les tubercules (c'est-à-dire le manioc et les ignames) ont des rendements plus stables que le riz. Dans les zones sahéenne et soudanienne, les rendements du sorgho et du millet ont tendance à être moins variables que ceux du riz. En outre, la variabilité interannuelle et intra saisonnière des précipitations explique jusqu'à 17 % des différences de variabilité mesurées entre le riz et les cinq autres cultures. Les rendements du riz, tous systèmes de culture confondus, ont tendance à être plus variables que ceux des autres cultures dans les régions où la variabilité des précipitations est la plus forte. En conclusion, l'allocation de plus de terres au riz présenterait un risque pour la sécurité alimentaire régionale et pour la stabilité des moyens de subsistance des ménages producteurs de riz en raison de la variabilité de la production. Les résultats de cette étude encouragent la prise en compte de la stabilité des rendements dans les scénarios d'expansion des surfaces rizicoles et les stratégies d'approvisionnement alimentaire.

L'impact des pratiques agricoles et du risque climatique sur les rendements du riz est examiné dans une deuxième étude. L'objectif est de répondre aux questions suivantes : Comment les facteurs de production et les risques affectent-ils les rendements, en fonction de la région et du système de culture ? Dans un premier temps, les facteurs de production et les risques sont identifiés, puis leur effet sur les rendements du riz, en fonction des systèmes de culture, est évalué. Cette évaluation permet de déterminer le bénéfice agronomique de l'adoption d'une stratégie culturale plutôt qu'une autre, compte tenu du contexte climatique et du système de culture. Ainsi, la construction de fonctions de production est réalisée pour estimer la contribution des facteurs clés (i.e., engrais, types de semences, gestion de l'eau) et des risques (i.e., sécheresses et inondations) à la moyenne et à la variance des rendements du riz (i.e., distribution du rendement) dans les quatre systèmes de culture. L'étude statistique des rendements à l'aide de l'élicitation probabiliste d'experts montre que les pratiques intensives (c'est-à-dire l'utilisation d'engrais et de pesticides, la gestion de l'eau partielle ou totale) augmentent significativement les rendements moyens (Table 1).

Table 1. Relation entre les rendements moyens du riz et le recours aux engrais, aux pesticides et aux semences certifiées. (.)=p-value <0,1, (*) =p-value <0,05, (**) =p-value<0,01, (***) =p-value<0,001. "NA" signifie que le nombre de points est insuffisant pour estimer les trois coefficients pour le système IMP.

	Proportion d'utilisation de fortes quantités de fertilisants	Proportion d'utilisation de pesticides	Proportion d'utilisation de semences certifiées
Tous systèmes	2.17 (***)	1.64 (***)	1.12 ()
LLR	5.16 (***)	1.01 ()	0.88 ()
IMP	2.24 (**)	NA	1.87 (*)
IRR	8.95 (**)	0.59 ()	0.71 ()
ULR	1.36 ()	1.81 (**)	0.90 ()

Table 2. Relation entre les coefficients de variation des rendements du riz et le recours aux engrais, aux pesticides et aux semences certifiées. (.)=p-value <0,1, (*) =p-value <0,05, (**) =p-value<0,01, (***) =p-value<0,001. "NA" signifie que le nombre de points est insuffisant pour estimer les trois coefficients pour le système IMP.

	Proportion d'utilisation de fortes quantités de fertilisants	Proportion d'utilisation de pesticides	Proportion d'utilisation de semences certifiées
Tous systèmes	-0.21 (***)	0.13 (**)	0.17 (**)
LLR	-0.11 ()	0.27 (***)	0.29 (***)
IMP	-0.03 ()	NA	0.35 (**)
IRR	0.58 (*)	-0.44 (*)	0.30 (*)
ULR	-0.37 ()	0.37 (***)	0.36 (**)

Cependant, l'adoption de ces pratiques ne conduit pas à une stabilisation des rendements, au niveau administratif 1 (Table 2). L'utilisation de variétés améliorées est corrélée à une augmentation de la variabilité spatiale et temporelle des rendements.

L'analyse de la variance du modèle montre que dans les zones guinéenne et soudanienne, où la pénurie d'eau et le risque de sécheresse sont moindres, c'est la fréquence de sarclage qui a le plus d'impact sur les rendements moyens (Figure 3). Au contraire, dans la zone sahélienne, la variabilité spatio-temporelle des précipitations explique environ 50% de la variance des rendements, dans le cas des systèmes non irrigués.

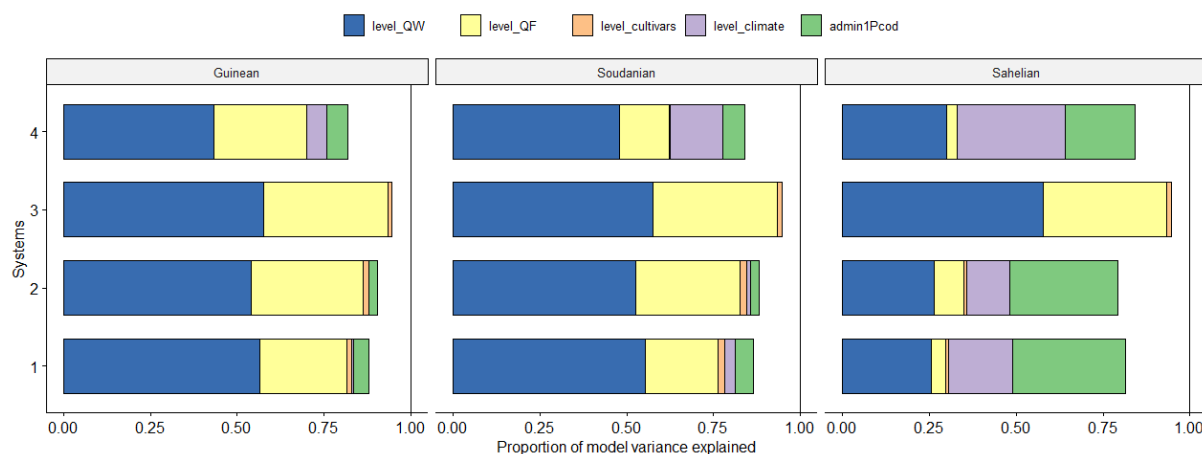


Figure 3. Décomposition de la variance des fonctions de production dans les trois principales zones climatiques d'Afrique de l'Ouest (i.e., guinéenne, soudanienne et sahélienne), pour les quatre systèmes de culture du riz. Le système 1 se réfère au système LLR, le système 2 se réfère au système IMP, le système 3 se réfère au système IRR et le système 4 se réfère au système ULR. Cinq facteurs sont analysés : les conditions climatiques (i.e., level_climat avec trois modalités : années humides, normales et sèches), type de semences utilisées (i.e., level_cultivars avec trois modalités : local, certifiées et mixte), la quantité d'engrais (i.e., level_QF avec trois modalités : faible, moyen et élevé), l'intensité du désherbage (c'est-à-dire, level_QW avec trois modalités : absent, partiel et total), les surfaces au niveau administratif 1 (c'est-à-dire, admin1Pcod avec 189 surfaces). L'axe des abscisses représente la proportion de la variance du modèle expliquée par chaque variable. La variance expliquée représentée n'atteint pas la valeur de 1 car les interactions entre les variables étudiées ne sont pas représentées.

En outre, l'adoption de ces pratiques agricoles par les riziculteurs dépend du contexte économique local dans lequel ils se trouvent (i.e., des risques et contraintes de marché et de production auxquels ils sont confrontés). En effet, le niveau et la stabilité des rendements du riz ne dépendent pas uniquement de la disponibilité de l'eau précipitée, ils dépendent également des facteurs de production (e.g., main-d'œuvre, nutriments, semences) ainsi que d'autres facteurs de risques (e.g., risques de marché, risques financiers, risques institutionnels, risques humains). Les producteurs de riz peuvent donc améliorer les rendements mais aussi atténuer les risques en misant sur la gestion de l'eau, sur le recours aux engrais ou à des variétés améliorées. Ces investissements peuvent contribuer à augmenter et à stabiliser la production en évitant les pertes de rendement dues aux ravageurs, au manque d'eau ou de nutriments. Mais ces stratégies, basées sur une intensification des systèmes de culture du riz, sont très coûteuses pour les producteurs et ont des impacts environnementaux importants. L'intensification de la production est également associée à une augmentation de la part de la production dans les ventes afin de couvrir ces coûts. L'intensification peut, de ce fait, accroître la

vulnérabilité aux risques du marché (les producteurs de riz doivent s'endetter pour investir et dépendent davantage de la vente de leur production pour rembourser leurs dettes). Dans les systèmes extensifs, à l'inverse, si les risques de production peuvent être plus importants, les risques de marché sont réduits par l'autoconsommation. Les choix d'allocation des ressources peuvent donc être vus, schématiquement, comme le résultat d'un arbitrage entre gestion des risques et rentabilité. Cependant, les stratégies culturelles adoptées par les petits exploitants riziculteurs pourraient ne pas s'aligner avec l'augmentation de la production locale de riz, comme le souhaitent les gouvernements ouest-africains. Des changements du contexte économique telles que l'accès au crédit ou l'augmentation du taux d'épargne pourraient encourager les producteurs de riz à adopter des stratégies d'intensification et/ou d'expansion.

Dans une troisième et dernière partie, j'explore l'impact des risques et contraintes agricoles sur la prise de décision des riziculteurs. Cette dernière partie répond aux questions suivantes : Comment les risques et contraintes de production et de marché affectent-ils les stratégies des agriculteurs ? Quels changements du contexte économique pourraient augmenter la production de riz tout en améliorant le bien-être et la sécurité alimentaire des ménages riziculteurs ? Je cherche à identifier les stratégies qui optimisent le bien-être des ménages rizicoles dans cinq régions différentes, et j'examine l'effet de l'accès au crédit et des différentes possibilités d'épargne sur ces stratégies et sur le bien-être des ménages. Les résultats de cette section permettent de comprendre dans quelle mesure les changements du contexte économique ont un impact sur les stratégies optimales des ménages représentatifs (c'est-à-dire l'intensification de la production ou l'expansion des surfaces rizicoles). Pour ce faire, j'ai construit un modèle microéconomique d'optimisation de l'utilité espérée pour un ménage représentatif, stratifié par système de culture et par région au niveau administratif 1. Pour représenter les facteurs de production et les impacts des risques sur les rendements, j'ai intégré les fonctions de production de riz précédemment construites dans un modèle microéconomique à l'échelle des petits riziculteurs, représentatifs des ménages ruraux au niveau des petites unités administratives (i.e. NUTS1). Les impacts de l'accès au crédit et de plusieurs taux d'épargne sont également testés dans le modèle.

Table 3. Utilité espérée maximale et pratiques culturales optimales associées pour chaque zone*contexte et pour deux options d'accès au crédit : sans accès au crédit et avec accès au crédit (avec un taux d'intérêt r de 0,15). Dans les deux cas, le taux d'épargne est fixé à 0,05. BF53 se réfère à la zone des Hauts-Bassins au Burkina Faso, GN05 se réfère à la zone de Kindia en Guinée, ML05 se réfère à la zone de Mopti au Mali, NG26 se réfère à la zone de Nassarawa au Nigeria et SN10 se réfère à la zone de Saint-Louis au Sénégal. Le texte vert foncé signifie que, dans le contexte d'un bas-fond sans irrigation, le système LLR est plus optimal par rapport au système IMP alors que le texte vert clair signifie le contraire. Le texte bleu correspond au système IRR. Le texte marron correspond au système ULR. Le texte en gras fait référence à l'utilisation de cultivars améliorés plus optimale que l'utilisation de cultivars traditionnels. r fait référence au taux d'intérêt dans le cas de l'accès au crédit.

	Contexte	BF53	GN05	ML05	NG26	SN10
Pas de crédit, $s = 0,05$	Bas-fonds sans irrigation	EU = 80.4 qF* = 0 S* = 1,74	EU = 147.1 qF* = 39 S* = 0.81	EU = 92.3 qF* = 0 S* = 1.42	EU = 120.8 qF* = 21 S* = 0.75	EU = 60.0 qF* = 0 S* = 4.25
	Bas-fonds avec irrigation	EU = 73.6 qF* = 0 S* = 1.20	EU = 133.5 qF* = 31 S* = 0.64	EU = 85.3 qF* = 0 S* = 0.89	EU = 107.2 qF* = 12 S* = 0.74	EU = 84.1 qF* = 0 S* = 2.23
	Hautes terres sans irrigation	EU = 75.9 qF* = 0 S* = 1.77	EU = 143.4 qF* = 32 S* = 1.05	EU = 86.0 qF* = 0 S* = 1.46	EU = 113.3 qF* = 17 S* = 0.88	EU = 58.9 qF* = 0 S* = 4.56
$r = 0,15, s = 0,05$	Bas-fonds sans irrigation	EU = 86.2 qF* = 68 S* = 1.33	EU = 158.7 qF* = 166 S* = 1.05	EU = 98.4 qF* = 22 S* = 1.78	EU = 128.1 qF* = 87 S* = 2.76	EU = 61.3 qF* = 9 S* = 3.43
	Bas-fonds avec irrigation	EU = 79.3 qF* = 69 S* = 1.14	EU = 143.5 qF* = 116 S* = 1.17	EU = 92.2 qF* = 81 S* = 1.10	EU = 110.8 qF* = 103 S* = 1.00	EU = 89.5 qF* = 77 S* = 2.09
	Hautes terres sans irrigation	EU = 80.6 qF* = 36 S* = 1,85	EU = 153.0 qF* = 105 S* = 1.76	EU = 93.8 qF* = 23 S* = 1.73	EU = 119.5 qF* = 59 S* = 1.55	EU = 63.4 qF* = 12 S* = 4.82

Les résultats de cette analyse montrent que la situation économique des ménages influence leur choix d'investissement dans la riziculture (Table 3). Les producteurs piégés dans la trappe à pauvreté sont, par définition, contraints par le manque de capital disponible en début de cycle et n'ont donc pas la possibilité d'investir dans des intrants, contrairement aux ménages qui ont pu dégager un surplus et épargner une partie de leurs revenus (i.e., dans les régions BF53, ML05 et SN10, où l'utilité espérée est faible). Cette trappe à pauvreté est fortement corrélée au contexte climatique, puisque dans les régions où l'eau est rare et le risque de sécheresse élevé (c'est-à-dire les zones sahélienne et soudanienne), les rendements sont faibles et l'eau est le facteur limitant, de sorte que l'ajout d'engrais ne génère pas de revenus significatifs, ne permettant pas aux riziculteurs d'atteindre une utilité espérée élevée. L'irrigation entraîne une augmentation significative de l'utilité espérée seulement dans le cas de la région de Saint-Louis. De plus, le piège de la pauvreté et la sécurité alimentaire des

ménages sont très liés, car les ménages ne peuvent pas viser une production élevée et donc un revenu suffisant, et sont dans l'incapacité d'acheter les calories nécessaires pour atteindre le seuil de sécurité alimentaire. L'accès au crédit permet, toutefois, une légère augmentation du bien-être des ménages producteurs, grâce à l'augmentation de la production moyenne, via l'ajout de fertilisants.

Enfin, une réponse à la problématique générale de ma thèse peut être apportée à partir des éléments issus des trois études réalisées. Les ménages riziculteurs sont confrontés à des risques et des contraintes importants qui les empêchent d'accéder aux ressources nécessaires dans le cadre de leur activité rizicole. Ainsi, l'extension des surfaces rizicoles peut entraîner une instabilité des moyens d'existence des ménages en raison de l'allocation des ressources au riz, au détriment des autres cultures de base. En outre, les pratiques d'intensification rendent les ménages producteurs vulnérables aux risques du marché, car les investissements nécessaires à leur mise en œuvre doivent être couverts par la vente d'une partie du riz produit. Ainsi, en cas de hausse du prix des intrants, de pénurie de main d'œuvre, ou de forte baisse du prix du riz, les producteurs peuvent se retrouver en situation d'endettement, sans possibilité de remboursement. L'utilisation d'intrants peut être un moyen intéressant d'augmenter la production dans les cas où l'eau n'est pas un facteur limitant, c'est-à-dire dans les zones où les précipitations sont abondantes et/ou dans les systèmes irrigués. En substance, la situation économique et la sécurité alimentaire des ménages riziculteurs dépendront du contexte économique (accès au crédit, prix de vente du riz, prix d'achat des engrais, etc.) et environnemental (régime pluviométrique, infrastructures d'irrigation) local. L'accès au crédit et le développement d'infrastructures d'irrigation peuvent permettre aux ménages bloqués dans la trappe à pauvreté de s'en sortir et d'assurer leur sécurité alimentaire grâce à une production accrue. L'augmentation du taux d'épargne peut encourager les ménages, dont la sécurité alimentaire est assurée, à augmenter leur production.

L'amélioration de la production de riz est, dans le contexte actuel, fortement freinée par les risques et les contraintes auxquels sont confrontés les ménages producteurs de riz. Pour cette raison, les initiatives de développement agricoles devraient se pencher simultanément sur des mesures facilitant la production de riz, telles que les subventions pour les engrais ou les variétés, les projets d'irrigation, et sur des mesures pour améliorer la chaîne de valeur du riz avec pour objectif de rendre le riz local compétitif avec le riz importé en termes de qualité, et ainsi atteindre un prix de vente plus élevé. Nos résultats montrent que l'autosuffisance en riz pourrait ne pas être efficace pour atteindre la sécurité alimentaire en Afrique de l'Ouest car la production peut varier considérablement en fonction des conditions climatiques. En plus de l'amélioration de la production, la constitution de stocks et la diversification de l'origine des aliments de base permettraient d'amortir les chocs de production locaux. En outre, l'évolution des régimes alimentaires vers des aliments de base traditionnels et robustes, tels que les tubercules, pourrait améliorer la sécurité alimentaire dans la région. Par ailleurs,

la durabilité de la production, qui doit être respectueuse de l'environnement et préserver les ressources - d'autant plus que la disponibilité de l'eau pourrait devenir une préoccupation majeure dans le contexte du changement climatique - est une préoccupation majeure pour éviter l'appauvrissement des ménages dû à la dégradation des ressources.

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CHAPTER 1

1 GENERAL INTRODUCTION

The second of the 17 Sustainable Development Goals (SDGs) adopted by all UN member states in 2015 as part of the 2030 Agenda for Sustainable Development was "Zero Hunger." However, the number of undernourished people, whose food energy consumption is less than their food energy needs, has only slightly decreased from 841.7 million in 2009 to 821.6 million in 2019. In West Africa, this number has actually increased from 31.5 million to 56.1 million, resulting in a higher ratio of undernourished people in the region (from 10.5% to 14.3%) (Soullier et al. 2020; Department of Economic and Social Affairs 2019).

In this introduction, I will first discuss why rice is a major food security issue in West Africa. Next, I will present how rice production is important for rural households to aim at being food secure. I will then establish an overview of various agronomic solutions studied to increase local rice production through yields increase and area under rice cultivation expansion. I will also show, based on existing literature, that the perception of risks and constraints by rice farmers¹ plays a significant role in their adoption of agricultural practices. I will then explain the general objective of my thesis, which is to examine the impact of the implementation of agricultural practices that aim to increase production with rice farmers food security, when considering production risks and constraints. Finally, some elements of framing and of methods used will be presented.

1.1 GENERAL CONTEXT: RICE, A MAJOR FOOD SECURITY ISSUE IN WEST AFRICA

Today, it is estimated that rice is the primary source of caloric intake for over half of the world's population, many of whom live in poverty (International Rice Research Institute 2023). This high level of consumption particularly affects vulnerable populations who do not have access to diverse sources of calories. In 2019-2020, out of the 493 million tons of the milled rice equivalent consumed globally, 84% were consumed in Asia, 7% in sub-Saharan Africa and 4% in Latin America (USDA 2020).

¹ Throughout this thesis, I use the following terms to refer to rice-producing (and consuming) households: "rice farmers," "smallholder rice farmers," or just "producers" or "households". These terms are used to describe farms, composed of a family - sometimes extended - that cultivate rice, among other crops or among other off-farm activities. The family manages capital and labor and self-consume a part of the production.

In sub-Saharan Africa, and particularly in West Africa, rice consumption is increasing, reaching 22 million tons (milled rice equivalent) in 2018 and accounting for 36% of total cereal consumption (Tondel et al. 2020; FAO 2020). West African rice demand has been growing at a rate of around 4.6% per year since the early 1990s, driven by several factors such as strong population growth, increasing urbanization, and shifts in dietary preferences towards rice (Mendez del Villar and Bauer 2013). Rice is the fourth most consumed staple in the region (after cassava, yams and maize in fresh weight) (FAO 2020) and constitute the basic component of the diet of numerous urban households.

Projections suggest that the demand for rice in sub-Saharan Africa will continue to rise in the coming decades, with estimates of 48 million tons in 2050 at constant average per capita consumption and 88 million tons with an annual growth in average per capita consumption of 1.5% (Chantal le Mouél et al. 2018).

However, local production has not been able to keep up with this growing demand, reaching only 13.3 million tons (milled rice equivalent) in 2018. From 1961 to 2009, rice yields in West Africa increased from 1 t/ha to 2.1 t/ha, while world average rice yield is 4 t/ha (Mendez del Villar and Bauer 2013). Besides differences in climate and soil, possible causes of these low yield gains include limited use of improved varieties, lack of access to good quality seeds, low input use, and poor adaptation of farming practices (Soullier et al. 2020). Additionally, rice requires a significant amount of water during its growth cycle, with 900m³ evapotranspired water for the production of one ton of rice (Bouman 2009). Water availability throughout the crop cycle probably plays a significant role in the low yield values achieved (Sultan et al. 2003).

Nigeria, Mali, and Guinea are the three leading rice producers in the region, accounting for 39%, 14%, and 12% of local supply, respectively (Mendez del Villar 2019). The increase in production of 9.8 million tons (milled rice equivalent) between 1980 and 2018 is primarily due to the allocation of more land to rice cultivation, with an annual increase in harvested area of about 7.5%, mostly in Nigeria, Senegal, Mali, Ghana, and Côte d'Ivoire (Chantal le Mouél et al. 2018; Soullier et al. 2020). Climate change could also exacerbate existing problems and further impede the increase in local production. Changes in temperature and precipitation, including changes in monsoon patterns, may have a significant impact on local rice production, depending on the cropping systems, varieties, or adaptation scenarios considered. A synthesis of experimental studies and model simulations at a global scale shows that rice yields could decrease by about 8.3% for each additional degree (Zhao et al. 2016).

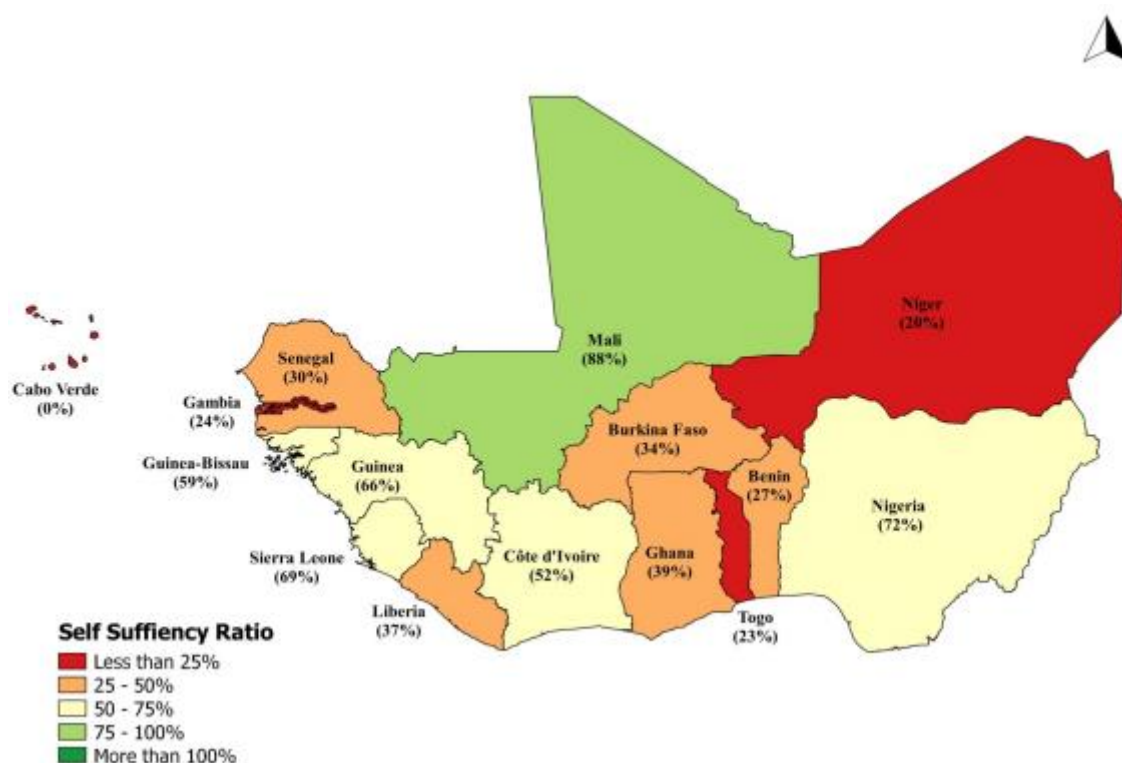


Figure 1.1. Rice self-sufficiency ratios in ECOWAS countries (%), in 2017 (extracted from Grow Africa, Rice Factbook (ECOWAS Commission 2019)). Self-sufficiency ratio is the ratio between locally produced rice and rice consumption in each country.

In an effort to address the gap between local rice supply and demand (see Figure 1.1), West Africa has increasingly turned to imported rice, primarily from India, Thailand, and Vietnam (Tondel et al. 2020). Imports from these countries have risen significantly over the past decades, increasing from 2 million tons in the early 1990s to 9.5 million tons (milled rice equivalent) in 2019 (Mendez del Villar and Bauer 2013; Adebawale et al. 2019). In 2018, these imports accounted for 40% of the region's consumption needs (Adebawale et al. 2019) and are expected to continue growing as production fails to keep pace with rising demand (FAO 2020). This has resulted in West African countries becoming highly dependent on the global rice market and vulnerable to international price fluctuations. A World Bank study in Liberia estimated that the poverty rate would increase by 3% with a rice price increase of 20% (Tsimpo and Wodon 2007). Haggblade et al. measured a decrease of about 8% of calories consumption in Sahelian West Africa induced by a 50% spike in world rice prices (Haggblade et al. 2017).

The 2008 food price crisis, during which rice prices tripled in a matter of months, reinvigorated interest in achieving self-sufficiency in rice production in West African countries. Rice is one of the five strategic products of the West African Economic and Monetary Union (UEMOA) and agricultural policies of the Economic Community of West African States (ECOWAS) consequently aim to achieve self-sufficiency in rice production by 2025 in order to ensure food security (Fofana et al. 2017).
PhD thesis Duvallet M.

al. 2015). At the international level, the Rice Offensive was launched by ECOWAS in 2021 with the ambitious objective to bridge the gap between local supply and demand by 2025. This program includes a number of projects aimed at increasing production through the development of agricultural strategies that promote the expansion of cultivation areas and/or increased yields. Examples include the CARD project (Coalition for Africa Rice Development), a policy framework, which aims to double rice production in sub-Saharan Africa (SSA) over the period from 2008 to 2018, the Partnership for Sustainable Rice Systems Development in SSA, which objective is to support scaling up of innovative policies such as System of Rice Intensification (SRI), rice processing and post-harvest management, the KAFACI initiative (i.e., Korea-Africa Food and Agricultural Development Initiative) and the NERICA dissemination project, which both promote the use of more productive and drought or flood resistant varieties (Adebowale et al. 2019).

To improve the competitiveness of local rice and decrease dependency on imports, several projects engage the entire rice value chain. Among these, the Competitive African Rice Initiative (CARI) aims to foster cooperation among various stakeholders in the rice sector, and the Continental Investment Plan on Rice Self-Sufficiency in Africa (CIPRISSA) supports national government-implemented projects. For instance, in 2008, Senegal launched at national level, the Great Agricultural Offensive for Food and Abundance, which included the National Rice Self-Sufficiency Program, with a goal of producing 1.6 million tons of paddy rice in 2017 (but only achieved a production of about 1 million tons of paddy rice (USDA)).

However, these public policies have, for the most part, failed to achieve significant and sustainable increases in productivity or the emergence of modernized and better coordinated value chains (Soullier et al. 2020; Mees 2016). On one hand, rice producers are encouraged to enhance production through productivity gains and area expansion. On the other hand, economic and environmental context dampens farmers' adoption of agricultural practices that allow them to move in that direction.

1.2 ECONOMICS OF LOCAL RICE PRODUCTION IN WEST AFRICA

1.2.1 Between subsistence farming and cash crop agriculture

In West Africa, the rural population represents more than half of the population. Agriculture constitutes an essential role in rural household's food security (World Bank 2023). Indeed, to supply their daily caloric needs, most rural households practice subsistence farming² and self-consume their

² Subsistence farming is defined as the integration of « crops and livestock, with most production used to maintain the farm households themselves and leaving little surplus, if any, for sale or trade » (Bisht et al. 2014)

production. However, Frelat et al. 2016 evaluated that 37% of sub-Saharan farm households were food insecure (Frelat et al. 2016). For instance, in northern Ghana, only 10% of households produce enough food to feed the family (Ken E. Giller et al. 2021).

Subsistence agriculture is mostly extensive and, thus, characterized by very low input use and low workforce productivity per produced rice unit and per land unit. Usually rainfed, subsistence farming is highly dependent on biotic and abiotic conditions. Smallholder farmers are, hence, very vulnerable to production risks that can lead to crop loss and even to crop failure. Because of the low access to cash and to production factors (i.e., land, labor, nutrients, water), household average production is low and variable, which leads to food insecurity (Seydou et al. 2014). Indeed, the low production could lead to insufficient staple crops for self-consumption and prevent the release of surplus from sales that could allow the purchase of missing calories on the market. To answer labor needs, farmers can rely on family labor or external labor. The choice of household members to work on the family farm rely on the opportunity cost of work, which is highly seasonal (Ken E. Giller et al. 2021). The use of external labor, however, is also constrained by cash availability to cover wages. In sub-Saharan Africa, the majority of farms are less than 1ha, and very few exceed 3ha, which is very small and represents a huge constraint to the farm viability (Harris 2018). Total land area has been determined as the key factor influencing food security (Douxchamps et al. 2016). Indeed, large land areas allow the production of more, and to spatially distribute production risks. However, because of land pressure, acquisition of more lands is not always possible, depending on the region. Investments in inputs or in cropping improvements such as irrigation infrastructures are limited by the lack of economic incentives (Ken E. Giller et al. 2021). Moreover, rural households would not invest in technology to increase yields if they are not profitable and positively impacting food security (Ken E. Giller et al. 2021). In West Africa, cash availability to purchase inputs is a huge constraint, especially because credit access is rare and saving rate is low.

Because of these constraints, households can be locked into this poverty situation. This phenomenon is called poverty trap and is defined by Azariadis and Stachurski (2005) as “any self-reinforcing mechanism which causes poverty to persist” (Azariadis and Stachurski 2005). For instance, the cash low availability constraint impedes households to invest enough in inputs or in external labor to achieve a good profitability. When selling their rice, because of low production, they cannot expect to earn enough cash to purchase inputs for the following growing cycle.

Credit access allows rice producers to intensify their production but as they have to reimburse the loan, rice production has to be sold at the end of the growing cycle. Thus, producers that invest in their production are more market oriented (Douxchamps et al. 2016). These households might be highly vulnerable to market risks and find themselves in over-indebtedness situation if input prices suddenly increase and rice prices decrease. In that case, if they are not able to access a new credit because of high interest rate or creditor distrust, they can be locked into the poverty trap. Moreover, even if intensive farming aims at mitigating production risks through irrigation, drainage or pesticides use, crop loss may occur, leading to negative net return for farmers.

Furthermore, the consideration of environment protection and resources safeguarding is an important issue for households. Indeed, resource degradation is a major factor of poverty in the agricultural sector because of the heavy dependence of smallholders on natural assets (Ruijjs and Dellink 2007). Sustainable resources use is, hence, primordial for household food security, especially in the context of climate change, that could lead to a decrease of available water.

In essence, productivity gains would increase household's food security. However, on one hand, constraints to production factors access dampen productivity enhancement. On the other hand, smallholder's vulnerability to risks can increase with increased use of production factors.

1.2.2 Local rice profitability and competitiveness

Rice profitability has mostly been studied in irrigated systems, as rice is intended to be sold as a cash crop in this type of system. Donovan et al. measured positive net return of fertilizer use with a cost/value ratio varying from 1.6 in Kou Valley in Burkina Faso to 3.6 in Office du Niger in Mali for irrigated systems in credit access conditions (Donovan et al. 1999). In Nigeria, Chidiebere-Mark et al. estimated return on investment of 13.03% for upland systems, 20.10% for lowland systems and of 29.37% for swamp systems³ with very intensive practices (i.e., certified seeds and agrochemicals use and very high fertilizer rate) (Chidiebere-Mark et al. 2019). For upland systems, improved cultivars (i.e., NERICA varieties) have shown higher gross margin than traditional cultivars (i.e., *O. glaberrima* variety) in Nigeria savannas, with positive impact of weeding frequency (Ekeleme et al. 2009). Coronel and Lançon have measured return cash ratio (i.e., net income/total cost) for several rice systems and different regions of Ghana (Coronel and Lançon 2008). They found ratios varying from 0.0 to 0.8 for irrigated systems, from 0.1 to 0.6 for banded lowlands and inland valleys, from 0.1 to 0.6 for unbanded lowland and inland valleys and equal to 0.9 for upland systems. In

³In the study mentioned, swamp systems refer to areas with permanent water table while lowland systems refer to hydromorphic, flood prone areas.

comparison, the return cash ratio of cassava cultivation in Côte d'Ivoire varies from 1.24 to 2.90 according to the commercialization circuit (Mendez del Villar et al. 2017). For maize, in Nigeria, this ratio has been measured to 1.26 (Oladejo and Adetunji 2012). Extensive system profitability is less studied than that of intensive systems. However, as extensive systems are intended to do subsistence agriculture, its economic interest relies on the opportunity cost of self-consuming instead of purchasing calories on the market. Recently, the System of Rice Intensification (SRI) has been developed in West African countries in the scope of the SRI-WAAPP project, which ran from January 2014 to June 2016. The SRI, consists of a set of practices adapted to particular agro-ecological and socio-economic settings. This farming method, labor intensive, has been claimed to improve rice productivity with low input use and thus, significantly improve West African poor households' incomes (Graf and Oya 2021; Styger and Traoré 2018).

In West Africa, in 2018, producer rice prices vary from 195 USD/ton in Guinea to 692 USD/ton in Benin (FAOSTAT 2018) depending on the commercial and geographical context of the country (e.g., imported rice ban in Nigeria to protect local production, landlocked countries with less accessibility to imported rice). A significant segmentation exists between local rice market and imported rice due to different quality attributes between both types of rice and local consumers preferences (Chohin-Kuper et al. 1999; Mendez del Villar and Lançon 2015). Indeed, local rice is processed by small-scale mills that are not able to achieve the quality of milled rice processed by industrial mills. Local rice has difficulties to be competitive against imported rice, especially in urban markets localized near import ports (Demont et al. 2017). At institutional level, several reasons can explain this low competitiveness: (i) low import protection with a Common External Tariff too low, that does not allow for local rice to be cost-competitive, (ii) rice importing firms arbitrary granted of tax exemption and (iii) weak application of quality norms that benefit to low quality imported rice (Tondel et al. 2020). The low competitiveness of local rice is reinforced by high dependency of West African countries to the international market. This dependency can lead to food insecurity for West African population in case of sudden international prices rise (e.g., food prices crisis in 2008) but it can also lead to large profit losses for local rice producers when international prices drop (Tondel et al. 2020).

To increase household's food security by increasing rice production and profitability, incentives to decrease constraints rice households are confronted with are needed.

1.2.3 Incentives for rice production increase through value chain upgrade

To facilitate rice production and support producers, measures can be taken to improve the organization of the rice value chain, specifically in terms of its management. The formation of producer groups can provide them with better access to resources and labor during times of high demand. Provisions can also be made at the level of the rice value chain, particularly in terms of

governance. The organization of producers into groups can make it easier for them to access inputs and labor during peak demand periods (Soullier et al. 2020). Additionally, forming partnerships between these groups and processing units through contractual agreements could, in theory, be mutually beneficial. For instance, the rice mill could provide high-quality seeds and possibly lend fertilizers, while producers could achieve higher yields and have the assurance that their rice will be sold to the mill with which they have a contract (Soullier et al. 2020). In reality, rice milling units have a lot of difficulties retrieving rice paddy intended in the contract. Furthermore, access to quality milling facilities could be a crucial factor in increasing the profitability of rice production, provided that milling units collect enough rice paddy to be cost-effective (Lançon and Erenstein 2002; Mendez del Villar and Lançon 2015). On the other hand, a lack of access to large market areas can limit a region's rice production. If the production is too high and cannot be sold locally, it will be wasted. Therefore, infrastructure improvements such as the construction of roads and the organization of a marketing chain for rice can serve as incentives for production as it allows to reduce marginal cost of transport for retailers and thus increase rice producer price (Emodi and Madukwe 2008).

1.3 ENHANCING PRODUCTION: AGRONOMIC CONSIDERATIONS OVERVIEW

Food security of both rural smallholders and urban households would benefit from production enhancement through yield gain and area expansion. As production increase relies on production factors impacts, I compile in this section an overview of the state of the art of agricultural practices impacts on production.

1.3.1 A local rice production characterized by low yields

The study of low rice productivity, in West Africa, has been extensively researched, mostly with an analytical approach through the concept of yield gap. The yield gap refers to the discrepancy between the potential yield, being the highest yield measured, in experimental stations, when water and nutrients are not limiting and biotic stresses are managed, and the actual yield (see Figure 1.2). Through this analytical framework, researchers have successfully pinpointed the factors that contribute to the yield gap.

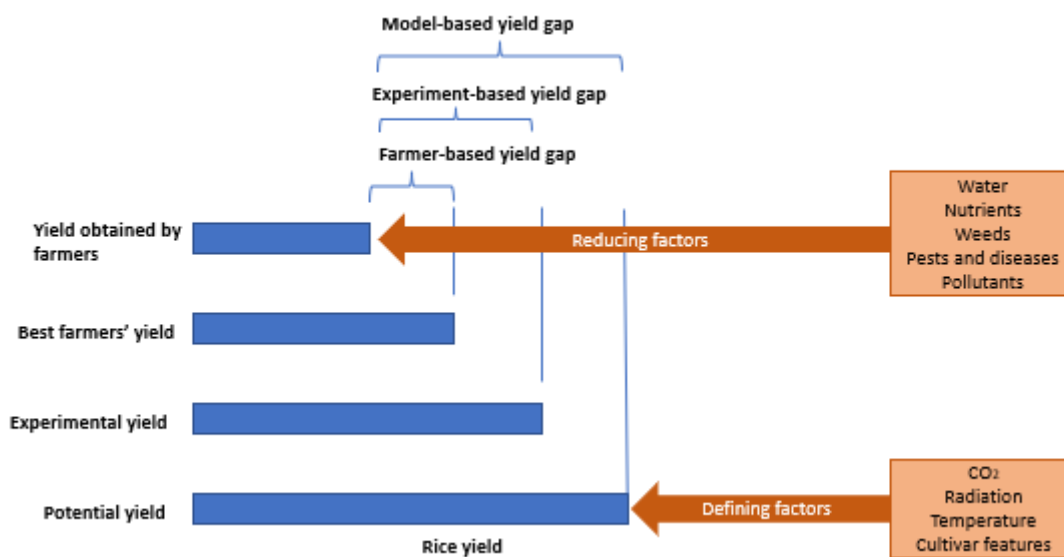


Figure 1.2. Framework for estimation of yield gap based on three different definitions of potential yields (model-based ‘potential yield’, maximum experimental field ‘experimental yield’ and on-farm maximum ‘best farmers’ yield’) (adapted from (Saito et al. 2017) and (van Ittersum et al. 2013)).

The values of average actual yield and potential yield are greatly influenced by the cropping system. In West Africa, rice is grown in a diverse range of environments such as alluvial plains, valley bottoms, hillsides, and mangrove swamps and is subject to varying degrees of water management, which can range from no management, partial management through plot leveling and bunding, implementation of drainage canals, to full management through irrigation infrastructure. Environment characteristics and water management level are typically used for the identification of various rice-growing systems, although the boundaries between them can sometimes be indistinct. Therefore, three main categories of systems are commonly distinguished in the literature: (i) Rainfed lowland, which pertains to a cropping system situated in a hydromorphic and generally flood-prone environment (such as alluvial plain, valley bottom), with no water management, (ii) Irrigated lowland, in which rice is grown in the same type of environment with full, albeit sometimes imperfect, water management, and (iii) Upland rainfed, referring to a cropping system with no water management and situated in a well-drained environment that is not prone to flooding (such as hillsides, plateaus). Diagne et al. (2013) estimated that rainfed lowland and upland systems accounted for 38% and 32% of the total rice-cultivated area in Africa, respectively, in 2009. The irrigated rice area is estimated to constitute 26% of the total rice-cultivated area (Diagne et al. 2013). According to Tanaka et al. (2017), the average yields per system in sub-Saharan Africa range from 1.1 to 5.2 tons per hectare for rainfed lowland rice, from 1.0 to 2.5 tons per hectare for rainfed upland rice, and from 2.2 to 5.8 tons per hectare for irrigated rice (Tanaka et al. 2017).

Potential yields can be estimated through simulations using plant growth models such as ORYZA 2000, or by determining the best yields achieved by farmers. These potential yields, as calculated from simulations, can be found in the Global Yield Gap Atlas (Global Yield Gap and Water Productivity Atlas). In the case of irrigated rice, potential yields can range from 7 t/ha in Burkina Faso to 10.4 t/ha in Mali. For rainfed rice, potential yields can range from 4.6 t/ha in Côte d'Ivoire to 9.8 t/ha in Nigeria. An Africa Rice (i.e., the Africa-wide Rice Agronomy Task Force) survey of rice-producing households, conducted in 2011, determined the best yields achieved by producers by analyzing the average yield of the upper 10th percentile of households in different cropping systems. The results showed that the best yields were: 4.8 t/ha for lowland rainfed systems, 3.5 t/ha for upland rainfed systems, and 5.9 t/ha for irrigated lowland systems (Saito et al. 2017). Yield gaps range tends to be wider when measured from simulated potential yield (see Table 1).

Table 1.1. Overview of yield gap ranges measured from two potential yield measurement methods.

Rice cropping system	Actual yield (Tanaka et al. 2017) (t/ha)	Farmer-based yield gap (Saito et al. 2017)		Model-based yield gap (GYGA)	
		Potential yield (t/ha)	Yield gap (t/ha)	Potential yield (t/ha)	Yield gap (t/ha)
Lowland rainfed	1.1 – 5.2	4.8	0 – 3.7	4.6 – 9.8	0 – 8.7
Irrigated	2.2 – 5.8	5.9	0.1 – 3.7	7 – 10.4	1.2 – 8.2
Upland rainfed	1.0 – 2.5	3.5	1 – 2.5	4.6 – 9.8	2.1 – 8.8

In 2022, Senthilkumar conducted a systematic review of the literature analyzing the possible causes of the rice yield gap in sub-Saharan Africa (Senthilkumar 2022). He ranked the recurrence of these yield loss factors in the literature. The most commonly cited cause of yield loss was weeds, regardless of the production system. Nutrient deficiencies due to insufficient fertilization or poor crop residue management were also widely mentioned, particularly for irrigated and rainfed lowland systems. Insufficiently robust or productive varieties, or those that are poorly adapted to the cropping calendar, can also lead to significant yield losses in both irrigated and rainfed systems. In the lowlands, poorly managed plots, such as lack of leveling or bunds to control water table level, were also cited as causes of low yields. Finally, less frequently mentioned causes of yield loss include iron toxicity and pests, such as granivorous birds and insects. According to Senthilkumar (2022), the average differences between actual yields and potential yields, as determined through farmer surveys or simulations, were 3.1 t/ha and 7.7 t/ha in rainfed lowlands, 2.0 t/ha and 6 t/ha in rainfed uplands, and 3.1 t/ha and 5 t/ha in irrigated lowlands. These figures suggest the existence of opportunities to significantly increase the production, through the implementation of agricultural practices.

1.3.2 Considered practices to increase rice yields

As mentioned above, increasing rice production can be accomplished by area expansion (i.e., increasing the area planted to rice) and/or intensification (i.e., increasing yields). There have been extensive studies on farming practices that increase yields and/or allow the use of previously unproductive land, and the effects of their implementation have been measured.

The utilization of improved rice varieties has been shown to have significant potential, particularly in the case of NERICA cultivars, which are the result of hybridization between Asian *Oryza sativa* and African *Oryza glaberrima*. This has been demonstrated in a study by Diagne et al. (2012), who observed a substantial yield gain of 276.4 kg/ha with the adoption of NERICA varieties in rainfed upland systems (Diagne et al. 2012). Improved varieties have also been found to exhibit greater weed competitiveness compared to traditional varieties, particularly in rainfed upland systems. Saito et al. (2010) estimated an average yield increase of 0.240 kg/ha between improved and traditional varieties without weed control, with an average gain of 80 kg/ha when weed control was implemented (Saito et al. 2010). In lowland systems, improved varieties have shown less adaptation than traditional varieties when conditions are unfavorable, such as anaerobic conditions and low soil fertility, but have exhibited better yields when these stress factors are absent (Saito et al. 2012).

The implementation of effective weed control (e.g., mechanical and/or chemical) can significantly increase rice yields. In rainfed upland systems in Nigeria, Ekeleme et al. showed yield increases ranging from 43% to 145%, depending on the varieties studied, between no weed control and single weed control (Ekeleme et al. 2009). Similarly, in lowland systems, studies have reported yield increases of up to 310 kg/ha under rainfed conditions and 230 kg/ha under water managed conditions with the implementation of total weed control compared to no weed control (Becker and Johnson 2001). Fertilization, either chemical or organic, is also necessary to address the lack of nutrients in areas where water is not limiting. According to a review of the literature by Senthilkumar (2022), the agronomic efficiency of nitrogen ranges from 12 kg/kgN in rainfed uplands, 18 kg/kgN in rainfed lowlands, to 21 kg/kgN in irrigated lowlands, regardless of whether it comes from chemical fertilizers or organic amendments (Senthilkumar 2022). Improving water management can also increase yields, particularly in the context of climate change (Ibrahim et al. 2021; Redicker et al. 2022). This can be achieved through the development of facilities such as leveling plots, building bunds, setting up drainage or irrigation canals – either run-of-river or from a reservoir located upstream – to reduce the risks of drought and flooding (Cassman and Grassini 2013).

Other possibilities include agroecological methods use such as increasing fallow periods (Lançon and Erenstein 2002), agroforestry (Rodenburg and Saito 2022) or conservation agriculture with crop rotations (Husson et al. 2022). Education and access to information, such as climatic and market data,

have also been shown to positively impact yield increases (Emodi and Madukwe 2008; Ibrahim et al. 2021).

1.3.3 Expanding rice areas

An alternative approach to increasing production is by expanding the area used for rice cultivation, without necessarily striving for high yields. This strategy can be viable as long as land pressure is not excessive (Lançon and Erenstein 2002). There are several methods for increasing the rice harvested area, such as utilizing previously unused land, converting land previously used for other crops, planting rice twice a year on the same land⁴, and reducing the amount of fallow time between cropping cycles. However, this last option, which has already been used extensively in rainfed upland systems, can lead to soil exhaustion and decreased productivity (Lançon and Erenstein 2002). One way to expand rice cultivation is to develop water managed perimeters in areas that were previously uncultivable due to a lack of water, drought, or major flooding. For instance, during the second half of the 20th century, irrigation development allowed new areas to be allocated to rice cropping in the Senegal River Valley in Senegal and Mauritania, and in the Office du Niger in Mali. Moreover, inland valleys are particularly well-suited for rice area expansion, as they are often difficult to use due to the risk of flooding. Indeed, rice is well-adapted to these environments and can grow in a water table that prevents weeds from invading the plots. In the early 2000s, it was estimated that only 10% to 25% of lowland areas were cultivated (Lançon and Erenstein 2002). Additionally, the use of labor-saving technologies such as mechanization, animal traction, or even herbicides can facilitate the expansion of lowland areas where labor cost is high (Rickman et al. 2013).

1.4 CULTIVATION STRATEGIES DETERMINED BY RISKS PERCEPTION AND CONSTRAINTS

1.4.1 A production under major stresses

Rice cultivation in West Africa faces numerous challenges and limitations that may impede the intensification of systems or the expansion of rice area. It is important to clarify the terms "risks" and "constraints" in order to distinguish between them. Risk refers to the uncertainty associated with a phenomenon or the lack of complete knowledge about it (Eldin and Milleville 1989). On the other

⁴The increase of the cropping index (i.e., more than one harvest per year) can also be seen as an increase in the production per unit of physical area over a year.

hand, "constraint" refers to a permanent limitation or obstacle. Understanding the difference between these two concepts requires considering the frequency and degree of uncertainty of the phenomenon in question. For example, in a region of the Sahelian zone that receives on average a low amount of cumulative rainfall, the lack of water would be considered a constraint. On the other hand, in a region of the Guinean zone that receives, on average, significant rainfall, the occurrence of an exceptionally dry year could be examined as a risk.

Several types of agricultural risks can be distinguished, linked to different hazards: (i) production risk, linked to external factors (biotic and abiotic), which can lead to a decrease or even loss of yields, (ii) market risk, linked to the unpredictability of input prices and product sales prices, (iii) financial risk, linked to the farm's ability to maintain its financial model, (iv) institutional risk, related to changes in public policy, international trade, agriculture, and the organization of different actors within the value chain, and (v) human risk, related to the use of human resources within the farm (Hardaker et al. 2004). Agricultural constraints can also be divided according to this same typology (Table 1.2).

Table 1.2. Examples of constraints and risk factors affecting rice production in West Africa

	Constraints	Risks
Production	Low annual precipitation Nutrient poor soils Soil acidification Soil salinization Iron toxicity	Droughts Floods Locust invasion Granivorous birds
Market	Lack of roads, lack of organized marketing chain leading to difficulties in accessing marketing centers, certified seeds, fertilizers	Decrease in the paddy rice sales price Increase in the price of fertilizers
Financial	Lack of cash flow Lack of crop failure insurance Low access to credit	Increase in interest rates
Institutional	Opening to the international market (competition with imported rice)	Sudden change in public policies leading to the end of input subsidies
Human	Rice farmers' lack of information about weather forecasts Insufficient knowledge of rice farmers regarding the management of irrigation infrastructure	Death, illness, injury of the producer or a member of his household Negligence of a farm worker or household member

Regional precipitation patterns are characterized by significant variability across decadal, interannual, and seasonal time scales (Sultan et al. 2003). Latitude also plays a role in determining the precipitation regimes, which can be either unimodal or bimodal (Herrmann und Mohr 2011). Additionally, dry spells or high-intensity rainfall events of varying duration can occur during the wet

(monsoon) season (Sultan et al. 2003). As rice production in West Africa is only rarely irrigated, it is therefore highly dependent on average climatic conditions and vulnerable to climatic risks.

1.4.2 Perception of risks and constraints

While various methods can enhance production through improved efficiency and the utilization of more land for rice cultivation, low actual yields indicate a low adoption rate of these practices. For instance, in West Africa, adoption rate of NERICA varieties was only equal to 50% in 2010 (Arouna et al. 2017). Several factors affect the adoption of agricultural practices by farmers, including their perception of the risks they face and the availability of resources that might be constraining (Duong et al. 2019). Research has shown that farmers' subjective preferences for new agricultural technologies play a significant role in the adoption of these technologies, especially with regards to improved varieties (Adesina and Baidu-Forson 1995). To mitigate the risks they face, farmers can adjust their cropping strategies, while considering the constraints they may face (e.g., lack of land, lack of information or knowledge, labor, water, financial resources).

Yield reducing climatic events such as flooding and drought are particularly influential in farmers' decision-making (Bossa et al. 2020). Rice producers associate these events with increased crop losses, food insecurity, and financial difficulties (Adaawen 2021). As a result, the perception, based on their observations, of climatic risk, can lead farmers to modify their cropping calendar, such as planting early to avoid a lack of rainfall at the end of the crop cycle or transplanting instead of direct seeding (Bossa et al. 2020). Agricultural experience, access to credit, and cooperative membership also play a significant role in the adoption of improved varieties (Ayinde et al. 2014). The adoption of fertilizer in Côte d'Ivoire was found to be influenced by several factors, including lowland cultivation, mechanization, farm size, land pressure, availability of off-farm income, distance to the nearest village or market, and the gender of the farm manager, as reported by (Adesina 1996). Another study revealed that the decision to adopt new fertilizer technologies was influenced by factors such as availability, land use and labor policies, food security, perceived profitability, and access to information (Enyong et al. 1999).

In essence, to mitigate these risks, rice farmers must implement strategies that are based on their perception of risks. Examples of risk management methods in semi-arid West Africa were studied by Matlon in 1990 (see Table 1.3) (Matlon 1990). However, the constraints faced by rice producing households, and especially the lack of available cash that lead to a poverty situation, can hinder producers' capability to manage risks (Lallau 2008).

Table 1.3. An inventory of risk management methods used by farmers in semi-arid West Africa (extracted from (Matlon 1990)).

Scale	Time frame
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	Ex ante	Interactive	Ex post
Plant	Varietal selection for stress resistance/tolerance	Replanting with earlier maturing varieties	
Plot	Early/staggered planting dates Low hill density High seeds rate Intercropping Run-off management Delayed fertilizer application	Changing crops with replanting Changing plot density through thinning or replanting	Grazing of failed plots for animal maintenance Late planting for forage production
Farm	Diversified cropping pattern Land type diversification Plot fragmentation	Shifting crops between land types	
Household, village, region	Cereal stocks Livestock/assets Social networks Non-farm employment networks	Farm wage labor	Cereal rationing Asset sales for food purchases Migration employment Food transfers

1.5 CONTRIBUTION OF MY THESIS: AN INCREASE IN PRODUCTION HINDERED BY RISKS AND CONSTRAINTS

On one hand, West African governments show interest in increasing rice production and thus reducing the vulnerability of rice consumers (mainly urban) to international price volatility. On the other hand, rice producer's food security could benefit from an increase in their production. However, to enhance production, smallholders have to adopt agricultural practices relying on production factors. The adoption of agricultural practices allowing rice production enhancement depends on the decisions made by individual rice producing households that aim to be food secure. Smallholder strategies are heavily influenced by their perception of the risks associated with rice farming, as well as being constrained by the availability of resources such as land, labor, and financial capital. These constraints and risks may discourage farmers from implementing practices that have the potential to increase production if they perceive that their welfare and food security would be negatively impacted.

In this thesis, we aim to explore the interest for smallholders to adopt cropping practices that allow production enhancement when considering rice cropping risks and constraints. Our central question is:

To what extent do risks and constraints affecting rice production impact production stability, households' cropping strategies, welfare and food security?

We focus on the role of risk in shaping household decisions and outcomes. The variability of yields and the crop failure risks threaten both the rice producing households and the regional population food security. Our investigation will consider risks as referring to the underlying causes of production variability – including pest and diseases, extreme climatic events – but also as the consequences of this production variability on rice producing households and regional population food security.

In a first study, I examine the potential impact of reallocating resources such as land, labor, or cash towards rice production at the expense of other staple food crops such as cassava, maize, millet, sorghum, or yam. The goal is to determine whether this allocation can be beneficial to both the food security of farm households and the population. I will address the following questions: **Do the yields of alternative staple food crops exhibit more or less stability compared to rice yield? And, what are the geographical and climatic factors that determine this stability?** By analyzing official yield data from various West African countries at the administrative level 1, in conjunction with aggregated climate data, this study provides insight into the potential risks for rice farmers who may choose to allocate their resources to rice over other staple crops, as well as the potential impact on local food security if the area devoted to rice production were to increase in West Africa.

Next, the impact of agricultural practices and of climatic risk on rice yields is examined in a second study. The aim is to answer the following questions: **How do production factors and risks affect yields, based on the region and cropping system? Conversely, how are rice farmers constrained in their choice of agricultural practices due to climatic conditions?** First, production factors and risks are identified, then their effect on rice yields, based on cropping systems, is assessed. This assessment allows us to determine the agronomic benefit of adopting one cropping strategy over another, considering the climatic context and cropping system. To conduct this study, an agronomic model was used, constructed and calibrated using the agronomic literature and results from a probabilistic expert elicitation.

Finally, in a third and final part, I explore the impact of agricultural risks and constraints on rice farmers' decision-making. This last part addresses the following questions: **How do production and market risks and constraints affect farmers' strategies? What economical context changes could increase rice production while enhancing the welfare and food security of rice-growing households?** I aim to identify strategies that optimize the welfare of rice-growing households, and I examine the effect of access to credit and varying savings opportunities on these strategies and on household welfare. The results of this section provide insights about the extent to which changes in the economic context impact representative households' optimal strategies (i.e., production intensification or rice area expansion). To achieve this, I constructed a microeconomic model of

expected utility optimization for a representative household, stratified by cropping system and region at the administrative level 1.

I relied on an interdisciplinary approach to investigate the link between rice production impacted by agricultural practices and risks and economic decision-making processes. The first part of the thesis focuses on agronomy, the second one relies on agronomic information to formalize production functions, usually used in economic analysis, and the third part incorporates agronomy and economics to consider both the agronomic risks and limitations that may affect yields and the economic factors that influence the strategies of rice-growing households.

Most studies that examine the effect of biotic and abiotic factors on yields focus on identifying agricultural practices that increase production and mitigate risks. However, these studies do not account for the economic reality of households and their ability to implement such practices. Conversely, studies on the economic viability of various rice cultivation practices in West Africa often neglect to consider the agricultural risks that result in yield variability. Most studies, realized at varying geographical level (i.e., subnational, national or international), measure efficiency of rice production factors through economic analyses (Nwaobiala and Adesope 2013; Ayambila et al. 2008; Odoemenem and Inakwu 2011; Ohaka et al. 2013; Adesina and Zinnah 1993; Adesina and Djato 1996; Kolawole and Michael 2021). Several studies measure the impact of economic incentives on cropping strategies, such as credit access, using rice producers' survey data (Donovan et al. 1999) and/or bioeconomic models (Barbier 1998). Economic analyses that determine the profitability of cropping strategies (e.g., improved varieties or fertilization) only use one-year variables so that interannual variability in climatic conditions, in incomes or outcomes prices are not considered (Donovan et al. 1999; Arouna et al. 2017).

1.6 METHODOLOGY

1.6.1 Definitions and framework

In this thesis, we consider the whole West African region as the ambition to increase local rice production is regional, with most programs launched at this level. Moreover, even if self-sufficiency ratios vary across countries, the whole region relies on imports to satisfy the rice demand. Hence, the study area encompasses all 14 member countries of ECOWAS in West Africa (excluding Cape Verde as it is an island nation) including Benin, Burkina Faso, Côte d'Ivoire, The Gambia, Ghana, Guinea, Guinea-Bissau, Liberia, Mali, Niger, Nigeria, Senegal, Sierra Leone, and Togo, with the inclusion of Mauritania. Data are systematically aggregated to administrative level 1, based on the Nomenclature of Territorial Units for Statistics. This level of analysis is consistent throughout the thesis.

To establish a comprehensive framework for analyzing cropping systems in the study area, an overview of the literature was conducted (as detailed in the Supplements section 6.1.1). As a result, four main categories of systems were identified: (i) rainfed lowlands without water management, localized in hydromorphic, flood-prone areas (e.g., valley bottom, river side, mangrove swamp) (ii) improved lowlands, which are an intermediate system between rainfed lowlands and irrigated lowlands, in which plots are leveled, bunded, drained and sometimes irrigated from a temporary stream (iii) irrigated lowlands, in which plots are leveled, bunded, drained and irrigated from a permanent source of water (i.e., rivers or water retention located upstream) and (iv) rainfed uplands, localized in well-drained or steep, never flooded areas (e.g., plateaus, hillside). Note that, for simplicity, the term "lowlands" henceforth encompasses all hydromorphic zones, including alluvial plains (Albergel and Claude 1994). Additionally, as upland systems in West Africa are rarely irrigated and never flooded, only the rainfed upland system is considered in this classification.

1.6.2 Data and models

One of the significant obstacles in this thesis was the availability of reliable yield data and information about rice systems covering the entire study area. I, hence, had to combine data from various sources (Figure 1.3).

For example, long-term time-series of yields at the administrative level 1 was missing for some regions. Nevertheless, a combination of official subnational datasets provided an adequate number of data points were obtained to carry out a statistical analysis of the relative variability of rice, cassava, maize, millet, sorghum, and yam.

Similarly, one of the major challenges in studying the impact of production factors and risks on rice yields was the scarcity of data on cultivated areas and farming practices of each system in each region. To overcome this challenge, probabilistic elicitation was employed with the help of rice experts from West Africa. This method, in combination with specialized literature, allowed for the correlation of yield distributions with agricultural practices and the creation of an agronomic model in the form of production functions, each representing a cropping system (i.e., rainfed lowlands, improved lowlands, irrigated lowlands, or rainfed uplands).

Finally, the production functions were incorporated into a microeconomic model to simulate the decision-making process of rice-producing households. This resulted in a bioeconomic model that measures the expected utility of a representative household in each region, considering the presence of production and market risks. Using this model, it was possible to evaluate the impact of various economic context change, such as varying savings rate and access to credit, on the welfare of households.

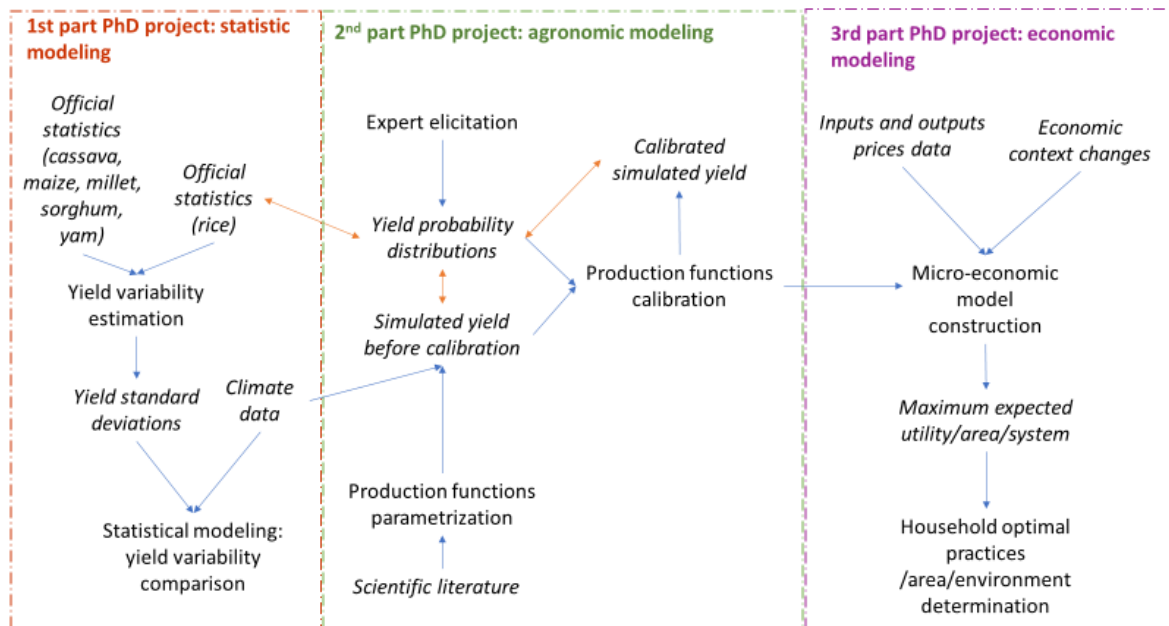


Figure 1.3. Schematic representation of the three parts of the PhD thesis. Orange lines with a double arrow represent a comparison between two datasets. Italic words refer to inputs or output of the models. Non-italic words refer to steps of the PhD project.

1.7 THESIS OUTLINE

In the present manuscript, each chapter, except the general introduction and conclusion, corresponds to an article. Table 1.4 provides an overview of the contents of each of these chapters.

In Chapter 2, the variability of rice yields is compared with that of the yields of the other major staple food crops in West Africa. The geographical and climatic determinants of these variability differences are examined. This chapter was published in November 2021 in the journal *Environmental Research Letters* (Duvallet et al. 2021).

Chapter 3 analyzes the contributions of different production factors and climate risks based on the construction of rice production functions. The manuscript for this chapter has been submitted to the *Agronomy Journal*.

Chapter 4 determines the optimal farming strategies of representative households at administrative level 1. The effect of several economic context change is also tested. This article is still in progress.

Table 1.4. Thesis content insight , GZ refers to the Guinean climatic zone, SOZ to the Sudanian climatic zone and SAZ to the Sahelian climatic zone (see Figure S2 13 for climatic zone delimitations).

Chapter	Issue	Material	Method	Main results	Implications
2	Are other staple crops more or less stable than rice yield? What are the geographical and climatic determinants of this stability?	<ul style="list-style-type: none"> Yield time series, covering time periods between 1984 and 2015, collected from official subnational datasets Climatic variables, post-processed from CHIRPS precipitation dataset 	Statistical analysis (linear mixed effect model)	<ul style="list-style-type: none"> On average rice yields are less stable than that of the other crops. The other crops tend to be more stable in climatic regions where they are traditionally grown: sorghum and millet in the SOZ and SAZ regions, tubers in the GZ regions. Rice yields relative variability is wider in areas where precipitation is more variable. 	<ul style="list-style-type: none"> At constant production systems, expanding rice production may impact the stability of the caloric supply mix locally produced. For producers, it can be riskier to produce rice instead of other crops.
3	How do production factors and risks impact yields, depending on the region and the cropping system? Conversely, how are rice producers constrained in their choice of agricultural practices by climatic conditions?	<ul style="list-style-type: none"> Specialized literature (with trials, surveys results) Expert probabilistic elicitation results (yield distributions and agricultural practices associated) Climatic variables, post-processed from CHIRPS precipitation dataset 	Bottom-up approach to build an agronomic model	<ul style="list-style-type: none"> Irrigated and improved lowland do not have higher yield relative stability than rainfed lowland. In the GZ and SOZ regions, weeding frequency is the main factor impacting yields, followed by fertilizer supply. In the SAZ regions, rainfall variability explains half of the spatial and interannual yield variability, for non-irrigated systems. Cultivar types (improved or traditional) have almost no impact on average yields due to low fertilizer use. 	<ul style="list-style-type: none"> Intensification in rainfed systems in SOZ and SAZ could not be interesting as water is scarce and drought risks are high. As intensification does not improve yield stability, households can be more vulnerable to crop loss.
4	How do production and market risks impact rice farmers' strategies? What economic context changes would increase rice production while improving the welfare of rice-producing households?	<ul style="list-style-type: none"> Inputs and outputs prices time series Climatic variables, post-processed from CHIRPS precipitation dataset 	Micro-economic modeling: expected utility optimization	<ul style="list-style-type: none"> Economic context changes show contrasted results according to the climatic zone: increase in saving rate enhances expected utility (EU) in GZ but not in SOZ and SAZ while credit access tends to enhance EU in SOZ and SAZ. Intensification is optimal in areas where water is not scarce (i.e., not the limiting factor). Intensification is promoted by credit access. Poverty trap translates into households' food insecurity because of low production. 	<ul style="list-style-type: none"> In water scarce environments, intensification is not of interest as no income gains can be expected. Constraints (lack of available production factors) limit the possibility for households to adapt to risks and thus decrease their ability to be food secure.

CHAPTER 2

This chapter has been published in Environmental Research Letters: Mathilde Duvallet et al 2021 *Environ. Res. Lett.* **16** 124005, available at: <https://iopscience.iop.org/article/10.1088/1748-9326/ac343a>.

2 RICE YIELD STABILITY COMPARED TO MAJOR FOOD CROPS IN WEST AFRICA

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KEYWORDS: yield variability, rice, West Africa, climate variability, land use

ABSTRACT

West Africa is one of the regions the most concerned with structural food and nutrition security. Consequently, agricultural development pathways and scenarios are under high scientific and political scrutiny in this region. Rice, as a rapidly growing staple plays a key role in the West African diet representing close to 40% of the total volume of cereal consumed in the region. In the context of the 2008 food price crisis several West African countries have since proclaimed rice self-sufficiency as a target. Here, we show that rice yields tend to be, on average over the entire region, less stable (by a range of 15% to 30%) than that of alternative crops, possibly substitutable in diets. The regions where yields of alternative crops are more stable than those of rice correspond to the climatic regions where these crops are grown: sorghum, millet in the Sahelian and Sudanian regions and tubers in the Guinean region. Rice yields are significantly less stable for 33% of the comparisons. Fewer areas, without clear latitudinal pattern, are characterized by rice yields significantly more stable than any alternative crop also cultivated in these regions. Rice yields are significantly more stable for 15% of the comparisons. We also show that yield variability differences between rice and alternative crops tends to widen in the areas where the monsoon precipitation is more variable between-years: rice yields are the most variable relative to alternative crops in regions where the monsoon varies strongly between years. Models accounting for climate variability explain up to 17% of yield stability differences. Our analysis advocates for an explicit account of yield stability in West African rice expansion scenarios and supply strategies.

2.1 INTRODUCTION

With a large fraction of structurally food insecure people (from about 11% in 2009 to 14% in 2019), West Africa is one of regions of the world most concerned about food availability and access. A combination of contextual factors underlies this situation (Fawole et al. 2015). Strong population growth (Zakari et al. 2014) and rapid urbanization (Matuschke 2009), international food prices volatility (Wossen et al. 2018), biotic and abiotic adverse conditions (Rattan Lal and B A Stewart 2010), climate variability and change (Pereira 2017; Clover 2003), and political instability or wars (Clover 2003), affect both food availability and access under continuous demand growth. This region is characterized by a relatively small diversity of plant-based foods (Dury and Bocoum 2012; Dabalén and Paul 2014), and staples (i.e., cereals and roots and tubers) form the basis of food security and represent about 68% of the daily West African caloric supply (FAO 2020). The relative share of rice in West African diets has been progressively growing in the last decades, and its consumption has reached about 22 million tons or about 36% of the total cereal consumed in the region in 2018 (FAO 2020; Tondel et al. 2020). The average annual rate of demand growth is about 4.6% since the early 1990s and is expected to continue growing in the near future (Mendez del Villar and Bauer 2013). This rapid growth, associated with the “rice diet transition” (Mendez del Villar and Bauer 2013; Lançon and David Benz 2007), now generates a structural imbalance between production and imports with imported rice volumes contributing to about 50% of the total rice supply in West Africa (Tondel et al. 2020). In the context of the 2008 food price crisis - in which international rice prices tripled in a few months (Headey 2011), this situation has been regularly questioned and several countries have since proclaimed rice self-sufficiency as a target (e.g., in Senegal and in Mali) (Mendez del Villar and Bauer 2013). More recently, the Economic Community of West African States (ECOWAS) proclaimed to target rice self-sufficiency in the region by 2025 (Fofana et al. 2014).

West African rice production has been steadily increasing from about 3.2 million tons in 1980 to 18.5 million tons in 2018 (FAOSTAT). This increase has primarily relied on an extension of agricultural land dedicated to rice production with an annual increase of harvested areas of about 7.5% (especially in Nigeria, Senegal, Mali, Ghana and Cote d’Ivoire) (Le Mouël et al. 2018; Soullier et al. 2020). Over roughly the same time period, yields increased from about 1 t/ha to 2.1 t/ha, i.e., reaching about half of worldwide average rice yields (Soullier et al. 2020). Unless the rice yield gaps are reduced within the coming decade, regional expansion of rice harvested areas seems unavoidable to meet self-sufficiency targets (van Oort et al. 2015). If allocating more agricultural land to rice would help increase average rice production in the region, one important unknown concerns the stability of the rice production especially compared to alternative crop species.

Climate variability has been shown to explain about one third of global maize, rice, wheat and soybean yield variability (Ray et al. 2015). In West Africa, the characteristics of the West African monsoon is a key determinant of precipitation levels, generating high variability from intra-seasonal to multi-decadal time scales (Sultan et al. 2003; Sylla et al. 2010), with impacts on rainfed crops, including rice (Diagne et al. 2013). Due to its important water needs, rice yields are known to be sensitive to water stress (Davis et al. 2019). The recurrently limited availability in surface water may disproportionately affect rice production compared to more resilient crop species, better adapted to sporadic water unavailability (e.g., millet and sorghum) (Hadebe et al. 2017). It has already been shown, for example, that rice yields are more sensitive to extreme climatic conditions (e.g., very high temperatures or droughts) than alternative crops yields (i.e., finger millet, sorghum, pearl millet and maize) in India (Davis et al. 2019). The comparative yield stability of rice to alternative crops (defined here as crop species that are as important as rice in annual volume of production and possibly substitutable in diets) is hence a salient element in this context. Are those crops more or less stable than rice? If so, what are the geographical and climatic determinants of this stability?

Contrary to the dynamics of average crop yields and farm profitability, which are widely studied (Haefele et al. 2003; Nhamo et al. 2019; Freduah et al. 2019; Srivastava et al. 2017; Srivastava et al. 2018; Niang et al. 2017; Katic et al. 2013), much smaller attention has been given to yield interannual variability. Several recent studies analyzed yield stability of one or several crop species in various parts of the world (Ray et al. 2015; Davis et al. 2019; Iizumi and Ramankutty 2016; Kumar et al. 2011; Cernay et al. 2015; Osborne and Wheeler 2013; Kukal and Irmak 2018; Chloupek et al.), with only a few including rice (Ray et al. 2015; Iizumi and Ramankutty 2016; Osborne and Wheeler 2013; van Oort et al. 2017) and only a few covering West African countries (Ray et al. 2015; van Oort et al. 2017; Faye et al. 2018; Parkes et al. 2018; Sultan et al. 2013). Hence, only two studies analyzed rice yield stability in West Africa (Ray et al. 2015; van Oort et al. 2017). These are based on (i) a downscaling of national data and (ii) simulations of yield potential. Hence, a data-based analysis of the comparative stability of rice over West Africa, at sub-national scales is still lacking in the literature. Here, to make progress, we compare the levels of yield variability of rice to five alternative major staple crops in West African regions and evaluate the impact of climate local features on these between-crops differences. We rely on yield time-series at the scale of small regions (administrative level 1) over the totality of the West African region. Our comparisons are based on normalized yield residuals standard deviation (henceforth referred to as SDR in the following, see method section). In the last section, we thrive to explain SDR variability based on the interannual variability of cumulated precipitation and indices of monsoon continuity.

2.2 MATERIALS AND METHODS

2.2.1 Yield data

We rely on publicly available data at subnational level 1 over the 15 countries defining West Africa as defined by the Food and Agriculture Organization of the United Nation (FAO) classification (excluding islands). These are Benin, Burkina Faso, Côte d'Ivoire, the Gambia, Ghana, Guinea, Guinea-Bissau, Liberia, Mali, Mauritania, Niger, Nigeria, Senegal, Sierra Leone, Togo. Two distinct datasets, based on public statistical offices, are available for time periods up to 23 consecutive years between 1984 and 2015 (i) FAOCountrySTAT (FAOCountrySTAT) and (ii) AgroMAPS (AgroMAPS). FAOCountrySTAT and AgroMAPS cover administrative levels 1 and 2 and inform annual production (in tons) and annual harvested areas (in ha). We compute yields from these two variables. In total, there are 201 geographical units at administrative level 1 over West Africa. The maximum number of available yield time-series is 1206 (i.e., number of units x number of alternative crops). The five most produced alternative crops to rice in the region (in fresh weight), according to FAOSTAT annual data are cassava, maize, millet, sorghum and yams (with 81, 19, 10, 12, 57 million tons per year respectively, on average in the last decade, see Figure S2 1).

We apply several selection criteria to the raw time-series collected based on (i) the precision of yield values (i.e., we select yield values informing at least two decimals); (ii) the coherency of yield values: we remove outliers above crop-dependent maximum potential yields estimated from the literature (see Table S1), we remove the geographical areas where yield, production and area harvested are equal to 0 or any duplicate; (iii) the length of the time-series (i.e., we select those with at least nine years with gaps of length inferior to three consecutive years). These three criteria are completed in 316 time-series from FAOCountrySTAT and 267 time-series from AgroMAPS. In a final step, we merge both datasets and remove redundant values, obtaining a total of 399 yield times series at administrative level 1 for time periods of length 9 to 23 years between 1984 and 2015 (see Figure S2 2). Note that in the merging process we have prioritized FAOCountrySTAT data because it is a more recent dataset. In the supplement we present the length, time-span and origin of each of the 399 selected time-series (see Table S2 2).

We detrend each yield time-series to remove any signal due to low frequency variability, for example expected from long-term technological changes or low-frequency climate variability. To this end, a polynomial regression of degree 1, 2 or 3 is fitted to each of the 399 time-series independently. The best model is selected according to the Akaike Information Criteria (AIC). To assess the sensitivity of our results to the detrending method, we also compute yield trends based on local regressions (spline and loess, see Figure S3) and compare with solutions obtained without any detrending (see Figure S2 4). We

rely on normalized yield values by dividing yields or yield residuals by average or expected yields, respectively. Normalized yield residuals are computed following:

$$\bar{Y}_{t,i,j} = \frac{Y_{t,i,j} - \hat{Y}_{t,i,j}}{\hat{Y}_{t,i,j}} \quad (1)$$

where i indicates crop species (i.e., rice, cassava, maize, millet, sorghum, yams) and j indicates the area (at administrative level 1). $Y_{t,i,j}$ is the observed yield at year t , for species i , in the area j . $\hat{Y}_{t,i,j}$ is the expected yield at year t (estimated from the fitted yield trends), for species i , in the area j . $\bar{Y}_{t,i,j}$ is thus the normalized yield residual at year t , for species i , in the area j . Note that in the main document we present the results obtained from polynomial detrending only, the results obtained with the other two methods or for non-detrended yields being presented in the supplements.

2.2.2 Climate data

We compute four annual precipitation variables based on the CHIRPS precipitation dataset. CHIRPS merges satellite information on cloud temperatures and rain gauge data to estimate daily precipitation from 1981 to 2020 at a $0.05^\circ \times 0.05^\circ$ resolution. We only use grid cells where at least 1% of the areas are cultivated (see Supplements section 6.2.1 for more detail on the method used) to compute the aggregated climate variables of interest at the administrative level 1. We consider (1) the yearly sum of precipitation based on the calendar year (mm^{-1}); (2) monsoon length, defined as the number of days between onset and retreat days. The onset monsoon day is defined as the day following a sequence of rainy events as in Diaconescu et al. (2015) (Diaconescu et al. 2015). If the onset day is estimated to have occurred after the 1st of October, it is filled out as missing value by default. The retreat day is computed as the last day of a sequence of rainy days, as defined by Diaconescu et al. (2015) (Diaconescu et al. 2015). When occurring after the end of the calendar year, it is replaced by the 31st of December. (3) Monsoon precipitation, defined as the sum of precipitation from onset to retreat; (4) the number of dry spells is calculated as the number of dry episodes of strictly more than 7 consecutive calendar days between onset and retreat. A day is defined as dry when it receives less than 1mm precipitation. These four precipitation variables are then spatially-averaged, over cultivated areas (with a threshold of 1%, see above), on each administrative area (level 1) for the time period corresponding to that of each SDR. We compute the average, interannual standard deviation and coefficient of variation for each climate time-series to obtain 12 climate indices in each considered area over the totality of West Africa. Note that these four precipitation variables tend to be strongly correlated (see Figure S8). For example, the average occurrence of dry spells is positively correlated to precipitation variability and to the variability of monsoon length.

2.2.3 Statistical analysis of ratios of yield standard deviation

We estimate a ratio of standard deviation of yield for each alternative crop i and region j as:

$$SDR_{i,j} = \frac{SD_{rice,j}}{SD_{i,j}} \quad (2)$$

where $SDR_{i,j}$ is the ratio of rice normalized yield residual standard deviation ($SD_{rice,j}$) to that of alternative crop i ($SD_{i,j}$) in area j . We only compute ratios for yield times series composed of the exact same years for rice and the alternative crop considered (i.e., cassava or maize or millet or sorghum or yams). We obtain 261 SDR in total over West Africa. We then estimate the SDR confidence intervals based on (i) a bootstrapping method with 500 resamples per couple of crop species and areas (ii) analytical estimations based on the Nakagawa et al. (2015) formulas for estimating the variance of standard deviations ratios (Nakagawa et al. 2015). Note that both of the above-mentioned methods chosen to estimate SDR confidence intervals do not rely on gaussian assumptions.

Next, we estimate SDR for each of the five alternative crops considered in our study over the totality of West Africa based on the following random-effect model:

$$\log(SDR_{i,j}) = \mu_i + b_j + e_{ij} \quad (3)$$

where μ_i is the mean log of SDR for crop i (i.e., cassava, maize, millet, sorghum or yams) and b_j is a random regional effect and e_{ij} is the residual error. Model (3) is fitted to the data using the method REML implemented with the function lmer of the package lme4 of R (Bates et al. 2015). During the fitting process, the values of SDRs are weighted by their variances relying on (Nakagawa et al. 2015). The fitted model is used to estimate the mean log variability ratio of rice to each alternative crop species. The estimated log ratios are then back transformed to estimate the variability ratios. The uncertainty is described by computing the 95% confidence interval. Rice to alternative crops yield variability are considered significantly different when the confidence intervals do not include 1. To assess the role played by irrigation in offsetting the effects of monsoon variability, we identify areas where irrigated rice is predominant (i.e., superior to 80% of the total rice area) according to the SPAM2000 dataset (You and Wood 2006) (see Supplements section 6.2.2 for details). We then assess the impact of 12 climate indices on relative rice yield variability (i.e., the SDR) in the areas where rainfed systems (i.e., lowland and upland) are predominant. We also identified the areas where irrigation is predominant according to two other datasets, namely MIRCA 2000 and GAEZv3, and compared the results obtained with these two alternative datasets. This sensitivity analysis does not reveal any substantial difference (see Supplements section B). When yield data for several alternative crops is available in one given area, several SDR can be computed (i.e., one per crop species). A random regional effect is included to relax

the assumption that SDR common to one area are independent. We test possible effects of the climate indices on the 261 SDR altogether based on a model with all the alternative crops together and location fixed effects:

$$\log(SDR_{i,j}) = \alpha + \beta \times x_j + b_j + e_{ij} \quad (4)$$

where α and β are fixed parameters (common to all species), x_j is one of the 12 climate indices measured in area j , b_j is a random regional effect and e_{ij} is the residual error. Model (4) is fitted to the data using the method REML implemented with the function `lmer` of the package `lme4` of R (Bates et al. 2015). During the fitting process, the values of SDRs are weighted by their variances relying on (Nakagawa et al. 2015).

We also build a model for each alternative crop i separately:

$$\log(SDR_{i,j}) = \alpha_i + \beta_i \times x_j + e_{ij} \quad (5)$$

where α_i and β_i are species-specific fixed parameters, x_j is one of the 12 climate indices measured in area j and e_{ij} is the residual error. The analysis is expanded by combining several factors (crop species and climate indices) with or without interaction. Note that, in all models, the data are weighted by their variances. Model's summaries are presented in Tables S7, S8, S12 and S15.

2.3 RESULTS

2.3.1 Inconsistent relative levels of rice yield variability

We estimate a yield variability difference between rice and each of the five alternative crops based on 261 SDR in 80 administrative level 1 areas over West Africa. We show that yields tend to be, on average over the entire region, more variable for rice than for the alternative crops (Figure 2.1). In other words, rice yields tend to be less stable than that of the alternative crops. The mean effect sizes are 1.15 (p-value = 0.25), 1.14 (p-value = 0.16), 1.25 (p-value < 0.05), 1.23 (p-value < 0.05) and 1.23 (p-value < 0.1) for cassava, maize, millet, sorghum and yams respectively, when irrigated areas are included. When excluded, the ratios are only marginally changed (Figure 2.1).

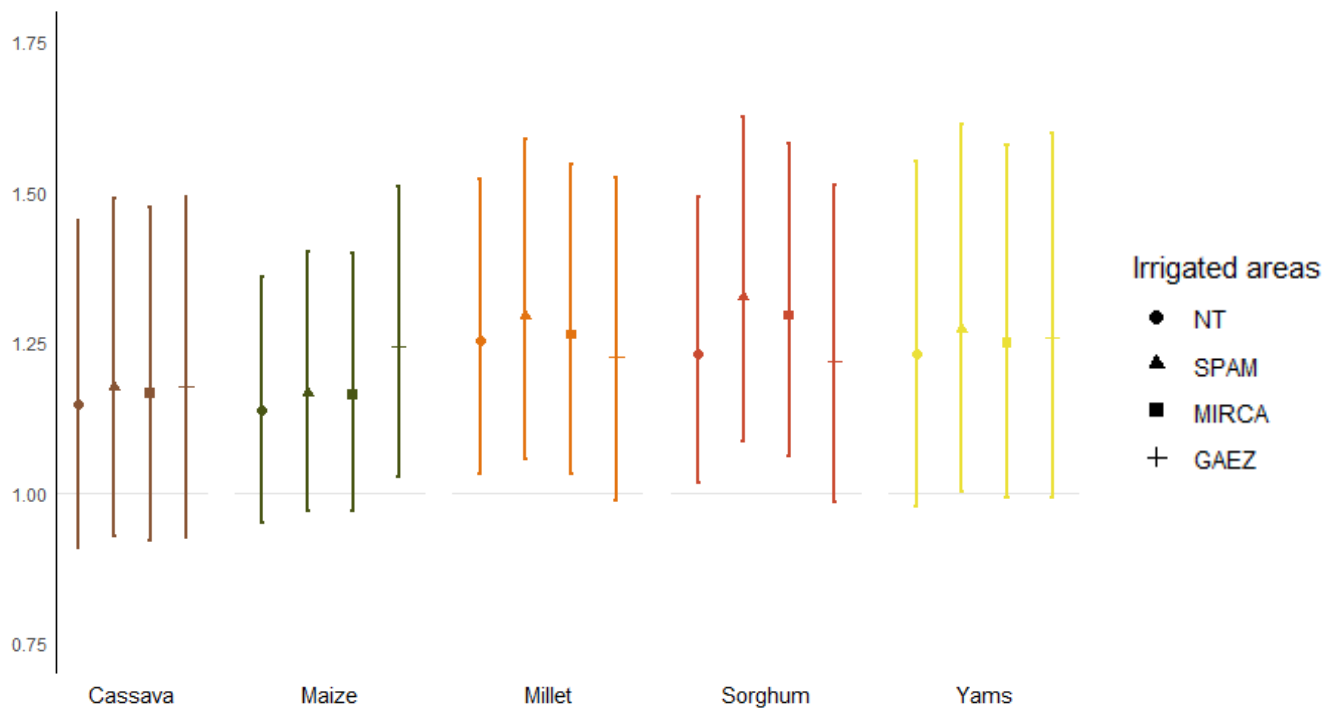


Figure 2.1. Mean effect sizes of rice yield variability compared to that of alternative crops over West Africa, measured without removing predominantly irrigated areas (i.e., ‘NT’) and measured after removing predominantly irrigated areas identified from SPAM2000 (i.e., ‘SPAM’), MIRCA2000 (i.e., ‘MIRCA’) and GAEZ v3.0 (i.e., ‘GAEZ’). Mean effect sizes are estimated from equation (3) for all regions of West Africa. Average yield variability of rice compared to alternative crops are represented in brown for cassava, in dark green for maize, in orange for millet, in red for sorghum and yellow for yams. 95% confidence intervals are estimated based on the standard error of each estimate. The grey horizontal bar delineates SDR equal to 1 (rice yield variability is equal to that of the other crop species). A ratio superior to 1 indicates that rice yield variability is higher than that of the other crop (i.e., rice is less stable than the alternative crop).

While millet, sorghum and yams exhibit a significant stability advantage over rice, there are no significant differences between alternative crops. Hence, we cannot rank the five alternative crops in terms of their relative stability. This explains the pattern shown in Figure 2.2 in which there is no evident systematic stability advantage for one given crop species over West Africa. Figure 2.2 also shows that 33% (when confidence intervals are estimated based on (Nakagawa et al. 2015) or 28% via bootstrapping, see methods) of the computed SDR are significantly higher than 1 (13 SDR for cassava, 19 for maize, 20 for millet, 17 for sorghum and 11 for yams). In these 45 regions (a few regions sometimes cumulate several SDR), rice yields are significantly more variable than the alternative crops. Fewer areas are characterized by rice yields significantly more stable than alternative crops with about 15% (or 9% via bootstrapping) of the SDR significantly lower than 1. A significant higher yield stability for rice is estimated for Sud-Ouest (Burkina Faso), North Bank, West Coast (Gambia), Gao, Kayes, Mopti, Tombouctou (Mali), Abia, Benue, Ebonyi, Enugu, Gombe, Kaduna, Kwara, Sokoto (Nigeria), Tambacounda (Senegal), Centrale, Kara (Togo) (Figure 2.3). There are also at least half of SDR regional confidence intervals which include 1 (about 52%, or 63% via bootstrapping). In these regions, rice yield

interannual variability is not significantly different from that of the alternative crops. This reflects a large uncertainty in the estimated regional stability ratios due to the relatively small number of yield data available within each region.

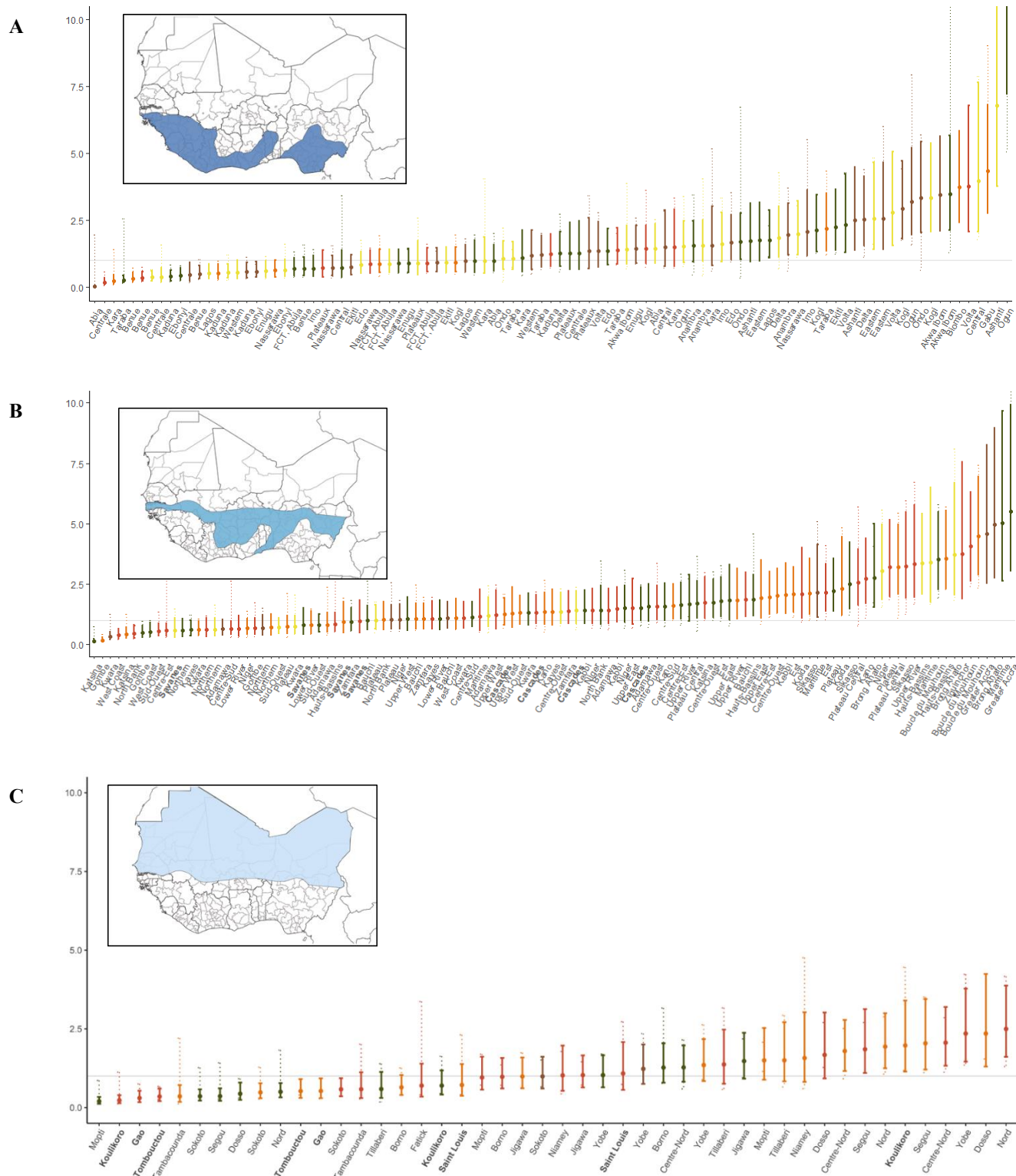


Figure 2.2. Standard deviation ratios (SDR) in the Guinean (A), Sudanian (B) and Sahelian (C) regions of West Africa. SDR are measured via equation (2). Results are presented per crop region combination for cassava

(brown), maize (dark green), millet (orange), sorghum (orange) and yams (yellow). Note that one area where several crops of interest are cultivated is represented several times. Confidence intervals estimated via bootstrapping (dotted lines) and based on Nakagawa et al (2015) [46] analytical approximations (bold lines). The areas written in bold refer to the predominantly irrigated areas (i.e., >80% of the total area is irrigated), identified from SPAM2000. The points are organized by ascending order for each of the three broad climatic regions with the Guinean region delineated by cumulative annual rainfall superior to 1200 mm, the Sudanian region with cumulative rainfall between 700 and 1200 mm and the Sahelian below 700mm (see Figure S13). Areas are split into the three climatic regions, according to the geographical position of their barycentre. Grey horizontal bar delineates SD ratio equal to 1 (rice yield variability is equal to that of the other crop species). A ratio superior to 1 indicates that rice yield variability is higher than that of the other crop (i.e., rice is less stable than its alternative). A confidence interval including 1 indicates non-significant results.

For clarity, we divide the area into three broad climatic zones defined by average cumulated precipitation since 1980. The Guinean, Sudanian and Sahelian regions correspond to average total precipitation above 1200 mm, between 700 and 1200 mm and below 700 mm, inspired by FAO definitions (Sigaud and Eyog-Matig 2001) (see Figure S2 13). Note that there is no systematic pattern in any of these broad climatic areas (Figure 2.2). Areas with SDR significantly superior (alt. inferior) to 1 are distributed on a large range of latitudes across the West African region, i.e., they are not spatially aggregated. For example, the areas where rice yields are significantly more stable than the alternative crops are dispersed among these three broad regions. The most intensive rice production basins, characterized by large-scale irrigation schemes, high meccanization level and intensive use of inputs (e.g., Senegal River Valley and Office du Niger in Segou, Mali (Mendez del Villar and Bauer 2013)) are not associated with SDR significantly lower than 1. In other words, intensive rice yields are not more stable than alternative crops in these regions. In Segou, millet and sorghum SDR are 2.04 and 1.85, respectively. This means that the yields of alternative crops are nearly twice as stable than rice yields, on average in this region. In Saint-Louis region, SDR are non-significant.

Noticeably, the areas where alternative crops have more stable yields than rice (i.e., $SDR > 1$) tend to be located in the climatic regions where these crops are mostly cultivated. In the Sahelian and Sudanian regions, where cereals constitute the larger share of the production, sorghum, millet and maize yields tend to be more stable while in the Guinean region, which produces large quantities of tubers cassava and yams tend to exhibit more stable yields (Figures 2.3 and S2 14).

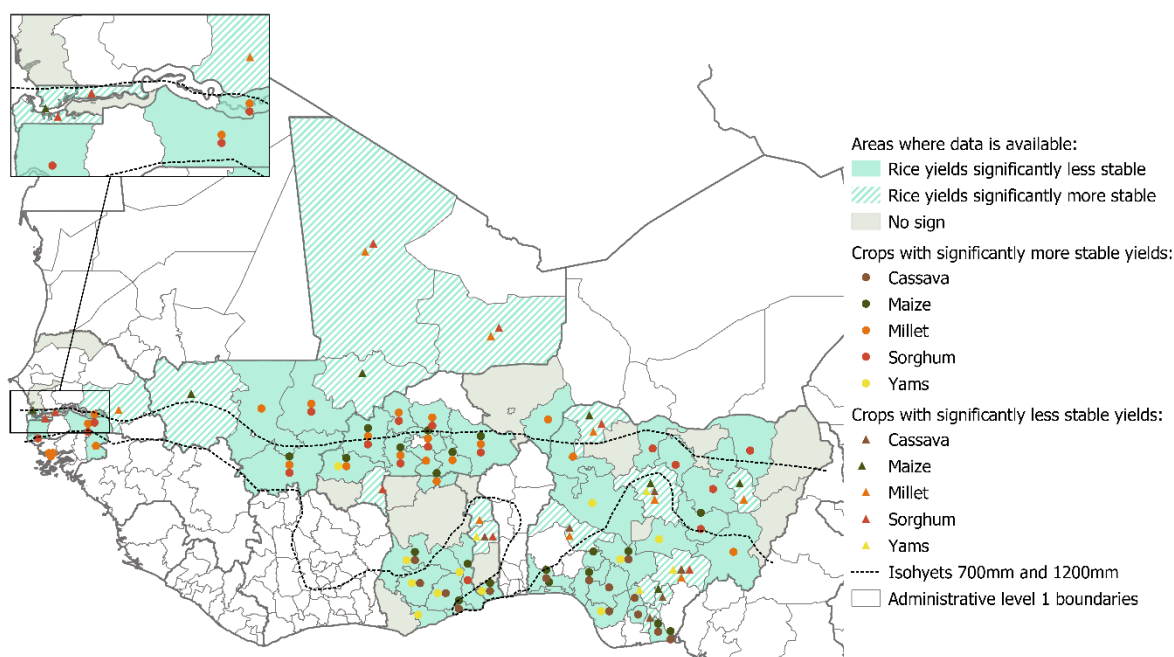


Figure 2.3. Spatial pattern of yield variability differences across west Africa. We present the spatial distribution of average ratios presented in Figure 1. Full green areas delineate the regions where the yields of at least one alternative crop is significantly more stable than rice (i.e., SDR superior to 1 with a probability of 95%). Filled circles indicate the alternative crop species which are more stable than rice (brown for cassava, dark green for maize, orange for millet, red for sorghum and yellow for yams). Dashed green areas delineate the regions where rice yields are significantly more stable than any alternative crop species. Open triangles indicate which alternative crop species were compared to rice yields in these regions. When the SDR are not significantly different from one (either superior or inferior to 1) the areas are colored in grey. A delimitation between three west African climatic regions are indicated with dashed black line (the isohyet 700mm is the frontier between the Sahelian region at the North and the Sudanian region at the South and the isohyet 1200 mm is the frontier between the Sudanian region at the North and the Guinean region at the South).

2.3.2 Monsoon patterns explains a significant but small fraction of yield variability differences

We look for climatic determinants of SDR variability across crops and areas. We analyze the relationship between a series of 12 monsoon indices and SDR variability. These indices measure monsoon interannual variability both in terms of cumulated precipitation and dry spells events. We show that the coefficient of variation of monsoon precipitation (measuring the interannual variability of monsoon cumulated precipitation, see Table S2 8) explains a small fraction of SDR variability across West Africa with the model including all alternative crops (model (4)). Monsoon precipitation coefficient of variation has a significant positive impact on SDR (p -value = $8e-4$, see Table S2 8). This means that yield variability differences between rice and alternative crops tends to widen in the areas where the monsoon precipitation is more variable between-years: rice yields are the most variable relative to alternative crops in regions where the monsoon varies strongly between years. When considering all alternative crops together, other precipitation indices (such as dry spell events) do not

significantly impact SDR. We also test model (5) independently for each alternative crop to rice ratio. Note that, because the areas considered in this study extend over a wide geographical area, the distribution of values for climate indices differ between alternative crop species (see Figure 2.4). More complex models do not explain a higher fraction of total variability (see Table S2 16).

For each rice-alternative crop comparison we select models with covariates that present smallest AIC and highest slope significance: monsoon precipitation coefficient of variation for cassava and yams, average and standard deviation of the number of dry spells occurring during the monsoon season for maize and sorghum respectively and monsoon length coefficient of variation for millet (Figure 2.4). Note that these models have very similar performances (see Table S2 15). Per-food crop selected models explain a relatively small share of the total variance, about 17% of the total variance for maize and millet, about 15% for cassava, about 10% for yams and less than 10% for sorghum. For yams, the slope is barely significant ($p= 0.0546$). The stability of cassava, maize and millet yields are significantly improved, relative to rice, in the areas where the monsoon is the most variable, either in terms of interannual variation of cumulated precipitation, monsoon duration, or occurrence of 7-day dry spell events (p -value= 0.0159 for cassava, p -value= $6e-4$ for maize and $p= 0.0027$ for millet see Table S2 12). This impact of monsoon precipitation variability is the highest for rice yield variability relative to millet: for a 0.1 unit increase in relative variability of monsoon duration (i.e., the coefficient of variation of interannual monsoon duration), the yield variability difference is doubled.

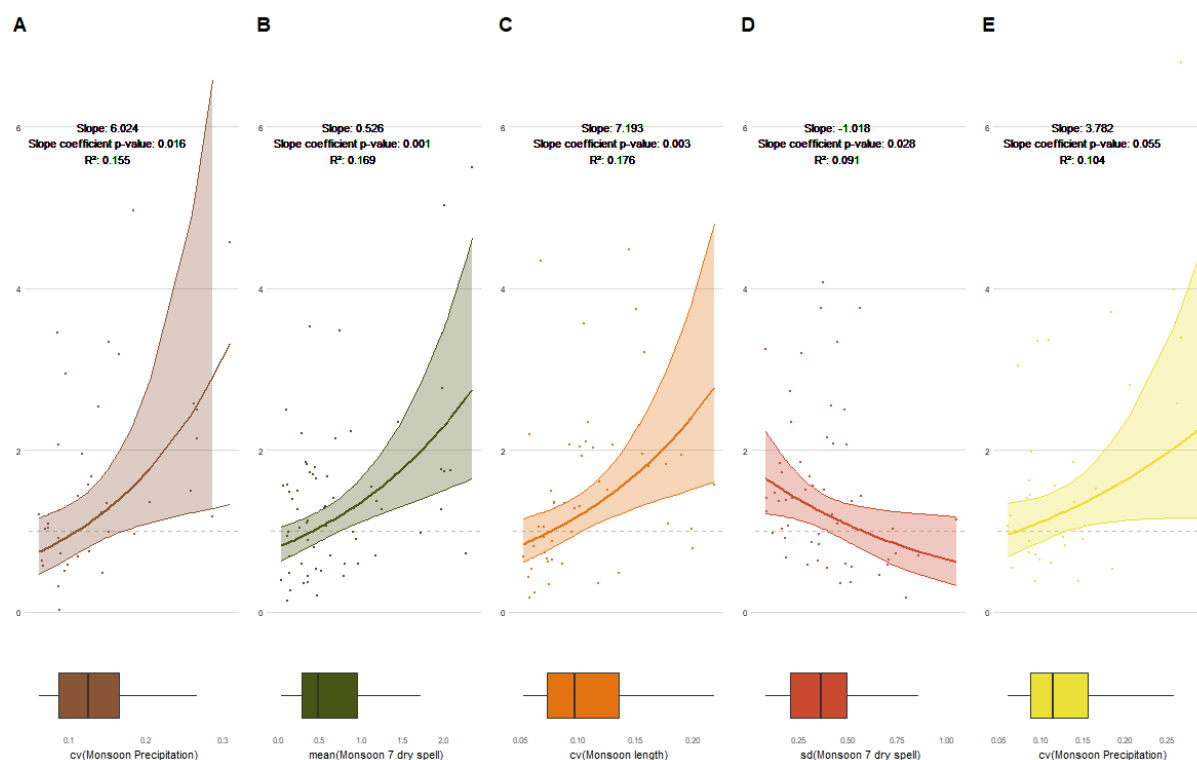


Figure 2.4. Relationship between climate indices, and the variability of rice yields compared to cassava (A), maize (B), millet (C), sorghum (D), and yams (E) yields variability, after removing areas where irrigated rice predominates (i.e., more than 80% of irrigated rice areas), identified from SPAM2000. Climatic indices are selected based on the AIC criteria. Selected best indices are the normalized variability of monsoon precipitation (CV(Monsoon Precipitation)) or of monsoon length (CV(Monsoon length)), the average or standard deviation of dry spells occurrences mean (Monsoon 7 dry spell) and sd(Monsoon 7 dry spell). Median relationship (bold lines) and 95% confidence intervals are computed based on model (5). Boxplot represents the distribution of the observed values of corresponding climate indices. Note that the time-periods on which these relationships are computed may vary between crops. Grey horizontal dotted lines indicate SD ratios equal to 1 (rice yield variability is equal to that of another crop species) with values above one indicating higher variability of rice yields (or lower stability) in comparison to alternative crops. AIC criteria, slope value and significance and R2 are informed for each model independently.

2.4 DISCUSSION AND CONCLUSION

Here, we show that, on average over the entirety of West Africa, alternative food crops yields tend to be more stable than rice. This stability difference is significant for millet and sorghum but not for maize, yams and cassava; these differences are somewhat affected by the inclusion or not of predominantly irrigated areas (Figure 2.1). This pattern and its robustness are heterogeneous across latitude (Figure 2.2). Fewer areas are characterized by rice yields significantly more stable than any alternative crop also cultivated in these administrative regions (Figure 2.2). While the areas characterized by more stable rice yields are located in diverse climatic regions, the areas where alternative crops have more stable yields than rice tend to be located in the climatic regions where these crops are mostly cultivated (Figures 2.2, 2.3 and S2 14). For example, sorghum and millet tend to have more stable yields than rice in the Sahelian and Sudanian areas, whereas cassava, tubers and yams yields tend to be more stable in the Guinean areas (Figure 2.3). This remains true when excluding irrigated areas (Figure 2.2). Monsoon precipitation

variability and mean dry spell occurrence explain a small part of these yields' variability differences (Figure 2.4).

The robustness of our results may suffer from two types of impediments. The first ones pertain to the quality and availability of the data and the second, to the statistical methods on which we base our analysis. This study relies on statistical data collected by the FAO according to national declarations. Hence, the consistency of the data depends on national survey or estimation methodologies (which sometimes includes indirect estimates from harvested or planted areas and corrections based on cropping conditions, com. pers.). Note though, that our initial data treatment and selection procedure addresses such possible heterogeneities (see methods). We also compared our dataset with data from alternative sources to assess the consistency of our yield standard deviations estimates. We relied on simulated rice and maize from a global gridded yield dataset (Iizumi and Sakai 2020) and qualitatively compared the distribution of yield variability estimated from these data to (i) the ones estimated from our administrative level 1 data and (ii) national estimates from USDA (USDA - Foreign Agricultural Service) and FAOSTAT (FAOSTAT) datasets (see Figure S2 15). We find that the mean standard deviations measured from (Iizumi and Sakai 2020) are similar to the ones estimated with administrative level 1 data when grouped by countries. Yield variability distribution estimated from (Iizumi and Sakai 2020) noticeably tends to be narrower. This is perhaps due to the fact that (Iizumi and Sakai 2020) simulations are based on a secondary disaggregation from national and satellite data, i.e., the subnational variability is estimated. Yield standard deviations estimated from the aggregation of administrative level 1 time-series are similar to the ones estimated at national level with FAOSTAT and USDA yield data. Mean yield variability tends to be smaller at national level than at subnational level (see Figure S2 15): yield interannual variability tends to decrease when the area of the geographical units studied increase, consistent with previous findings (Popp et al. 2005; Marra and Schurle). Note that despite our efforts, we did not succeed in collecting data over the totality of West Africa (for data availability see Figure S16, e.g., no data is available for the western part of the Guinean sub-region). Finally, standard deviation ratios (SDR) are based on normalized detrended yields. Note that detrending or the detrending method chosen has little to no effect on our estimates since the time-span of yield time-series is rather short (see Table S2 and Figure S4). Climate indices are also associated with uncertainties in particular regarding observed precipitation datasets for observation-poor regions such as West Africa (Donat et al. 2016; Bador et al. 2020b). Satellite retrievals are useful in that context, especially when corrected with in situ observations, but also present some challenges (Prigent 2010). Different datasets can be used in order to characterize observational uncertainties (Bador et al. 2020a), but there is no other available dataset at the high spatial and temporal resolution needed in this study.

The estimated yield variability differences we find here may be due to the fact that the areas encompassed by rice cultivation cover the entire West African sub-continent, i.e., there is an absence of

geographical specialization for rice while on the other hand, traditional crops are cultivated in narrower agroecological areas. These differences may also be the result of a stronger adaptation to precipitation variability or more broadly, higher resistance of traditionally cropped species such as millet and sorghum in arid and semi-arid areas (Hadebe et al. 2017; Sultan et al. 2013) or tuber species such as yam and cassava in more humid areas (Daryanto et al. 2016). Sorghum and millet farmers are, for example, known to develop strategies designed to cope with precipitation uncertainty (Mortimore and Adams 2001). A small negative impact of monsoon precipitation variability on the rice to sorghum SDR measured here, tends to support this hypothesis.

The width of administrative level 1 regions typically spans from 100 km in the Guinean region to 1000 km in the Sahelian region. The regions studied are composed of a large diversity of cropping systems (e.g., different types of soil, hygrometric conditions, topography). West African rice cropping systems can be classified according to local hydrological and topographic conditions and water management practices. The most commonly found rice cropping systems are rainfed upland systems (about 43% of the total west African rice area in 1990-2000), followed by rainfed lowland and irrigated lowland systems (40% and 12% respectively) (Diagne et al. 2013). The relative proportion of these systems varies spatially (Diagne et al. 2013). The effects of monsoon characteristics on the relative stability of rice to alternative crop species is significant but small (i.e., from about 9 % to less than 18%). This means that the bulk fraction of the differences in stability between rice and alternative crop species is due to other factors. Topographic conditions (i.e., plateaus, hydromorphic slopes, valley bottom, floodplains, rivers, lagoons and deltas) cropping systems (in particular water management practices) and agronomic factors (e.g., fertilizers, pesticides or crop cultivars) certainly explain part of these differences. The effects of these factors may be direct (e.g., precipitation accumulation in valley bottom) or indirect (increased yield average and variance through fertilization). Note that results with and without areas with predominant irrigation reveal negligible to small effects on our conclusions. Geographically explicit information on the use of fertilizers and pesticides would obviously be needed to formally test the response of yield variability to increased input use. A unified database at the scale of West Africa would be very relevant to precisely evaluate the direct and indirect effects of agronomic practices on the relative stability of rice. Such a database may be built from, national and subnational statistics, field or farm scale surveys and quantitative expert elicitation.

Our results suggest that, at constant production systems, expanding West African rice production may impact the stability of the caloric supply mix produced in this region. This stability may be enhanced or hindered depending on regional stability and climatic specificities. For example, rice production may be enhanced in the areas where rice yield stability is significantly higher. Similarly, we have shown that alternative food crops may, for some species-regions combinations, improve the relative stability of the regional caloric supply, including when climatic conditions are less favorable. In terms of imports, the

three biggest rice suppliers of West Africa (i.e., India, Thailand and Vietnam) tend to have a higher relative stability (see Figure S2 17) which may give them a competitive advantage. But, the relationship between domestic production stability and the stability of exports is complex and perhaps nonlinear as exports are the result of public policies which depend on domestic or global economic shocks. Hence, our results advocate for an explicit account of yield stability in West African rice expansion scenarios and supply strategies.

CHAPTER 3

This chapter is under review at *Agronomy Journal*.

3 BUILDING RICE PRODUCTION FUNCTIONS FOR WEST AFRICA FROM TRIAL AND SURVEY DATA AND EXPERT ELICITATION

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KEYWORDS: Crop systems, Nutrient management, Rice, Water management, Agroclimatology

HIGHLIGHTS

- We build production functions for the four rice cropping systems represented in West Africa.
- Thus, we represent the contributions of several production factors and of two climatic risks to rice yield.
- In Guinean and Sudanian zones, weeding frequency is the main factor impacting yields.
- In the Sahelian zone, rainfall variability explains half of the spatial and interannual yield variability.
- We offset the lack of unified subnational data on yields distributions associated with cropping practices.

ABSTRACT

In West Africa, rice yields can be highly variable. Producers rely on various cropping strategies to balance the need to minimize production risks, including climatic risks, with the goal of achieving high yields. In the present study, we analyze the contributions of a variety of management and cropping strategies (i.e., seed origin, fertilization and weeding) and biophysical conditions (i.e., water availability, drought and flood risks) to rice yield levels and variability for four rice cropping systems across West Africa (i.e., rainfed upland, rainfed lowland, improved lowland – levelled, banded, and drained lowland – and irrigated lowland). We build a production function to model rice yield levels and variability for each of the four defined cropping systems separately, covering all agro-ecological zones. According to probabilistic expert elicitation, intensive cropping practices (i.e., water management, high use of fertilizers and pesticides) increase regional average yield but do not seem to decrease yield spatial and

temporal variability. According to the model variance analysis, rainfall has the largest impact on average rice yields in the Sahelian zone for all systems, except the irrigated system (precipitation variability explains about 50% of interannual and spatial simulated yield variability). The variance analysis also suggests that weeding number is the main factor impacting average simulated yield, especially in regions where water is not scarce (in Guinean and Sudanian zones). Seeds types have almost no significant impact on average yields for all systems across West Africa.

3.1 INTRODUCTION

Recent international production concerns for the availability of key staples maintain food security tensions in net importing countries. To reduce their dependence on the global market, West African governments have shown, for several decades, a renewed interest to achieve rice self-sufficiency before 2025 (Fofana et al. 2014). But, a commonly accepted difficulty, among others, is that local rice production is characterized by low and variable yields (Soullier et al. 2020). Rice yield frequency distributions are determined by (i) the availability and application of limiting production factors (ii) production risks, which can be important in water-limited systems. In fact, rice water requirements are substantial (i.e., about 909m³ of evapotranspired water to produce 1 ton of paddy, (Bouman 2009)). In West Africa, precipitation shows strong variability at decadal, interannual or seasonal time scales (Sultan et al. 2003). Moreover, dry spells or intense rainfall events of variable duration can occur during the monsoon or wet season (Sultan et al. 2003). Since the topography and water management of rice cropping systems largely differ across landscapes and may mitigate or increase the effects of adverse rainfall conditions it is necessary to consider the variety of rice cropping systems (Bezançon 1995). Additionally and similarly to other cereals, rice yields can suffer from pests and diseases, weeds or lack of access to other production factors such as inputs or labor (Hardaker et al. 2004; Platform for Agricultural Risk Management 2019).

Recently, Senthilkumar conducted a systematic review of the literature analyzing the impact of several production factors on rice yield gap in sub-Saharan Africa (Senthilkumar 2022). Fertilization rate (Asai et al. 2021; Tsujimoto et al. 2019), weeding frequency (Ekeleme et al. 2009; Saito et al. 2010; Ogwuiké et al. 2014), water management improvement such as bunding or levelling (Worou et al. 2012; Touré et al. 2009; Becker and Johnson 2001) and cultivar choice (Touré et al. 2009; Saito et al. 2012) are the most studied yield gap causes (Senthilkumar 2022). Rice production risks is mostly studied through climatic risks (i.e., drought or floods) impacts on yield (Bossa et al. 2020; Serpantié et al. 2020). At global scale, Savary et al., developed a map of five potential rice diseases occurrence risks (Savary et al. 2012). More occasionally, pests risks (Lecoq 1998; Treca 1989) and iron toxicity (Audebert and Fofana 2009) have been studied at large scale.

To find a trade-off between mitigating production risks and achieving high yields, producers can rely on an array of strategies such as: seeds types, water management, use of fertilizers, and weeding. The impact of production risks on yield is different according both to the rice cropping systems (e.g., rainfed versus irrigated) and to the cropping strategies adopted by rice growers. To estimate what strategies are optimal for rice producers according to this variance-average trade-off, a necessary first step is to develop a methodology that enables the estimation of the contribution of various risks and production factors to rice yield average and variability. The aim of this study is to represent and to assess these contributions. More precisely, we try to answer the following questions: How do production factors and risks impact yields according to the region and cropping system? Conversely, how are rice producers constrained by climatic conditions in their choice of cropping strategies?

Here, we build production functions specific to West African rice production systems, with an explicit representation of the effects of production factors and risks on yields (bottom-up approach). Our production functions are calibrated on agronomic literature and, to offset insufficient information on rice cropping practices over the West African region, we also relied on probabilistic expert elicitation to build a database of yield frequency distributions for each cropping system. This method, based on expert knowledge, is used to collect data at regional (i.e., administrative levels 1 or 2) level and to build a database of production system shares, cropping practices (i.e., inputs use) and yield frequency distributions per system. Finally, we then decompose the contributions, in the model, of a variety of management and cropping strategies (i.e., seeds types, fertilization and weeding) and biophysical conditions (i.e., water availability) to rice yield levels and variability across West Africa.

A handful of studies have built rice production functions, mostly using econometric approaches based on (i) linear or nonlinear regressions (Bapari and Joy 2017) and on (ii) stochastic frontier production functions (Kyi and von Oppen 1999). Stochastic frontier production functions have been applied, for example, to estimate rice production technical efficiency in Asia (in Sri Lanka for irrigated rice (Karunaratne and Herath 1989), for irrigated, lowland and upland rice (Villano and Fleming 2004), in North Africa (all systems together (Fan et al. 1997) and in West Africa, especially in Nigeria (all systems together (Onyenweaku and Nwaru 2005). In West Africa, Niang et al. used a boundary function to estimate attainable yields for 3 systems: irrigated lowland, rainfed lowland and rainfed upland. Based on a random forest algorithm, they identify the factors determining yield gap and yield variability for each of these three systems (Niang et al. 2017). Djagba et al. relied on the same methodology to estimate the production potential of inland valleys rice production (Djagba et al. 2018). But, if frontier production functions allow us to estimate production levels at given input, it does not allow us to analyze and compare the efficiency of different production factors. More generally, econometric methods require large datasets and are most often available only for a very small region or in specific production contexts. Another category of existing methods to simulate the effects of cropping practices and climate variability

on crop yields are mechanistic crop models. For rice, the CERES-Rice model has, for example, been used for model evaluation with field data in one Nigerian region (Akinbile 2013), ORYZA2000 in the Agricultural Production System Simulator (APSIM) modeling framework to assess climate change impacts on rice yields in the whole West African region (van Oort and Zwart 2017) and the EPIC model to compare cropping strategies on lowlands in West Africa (Worou et al. 2012). The results of these models can also be used as inputs in bioeconomic models such as ANDERS-CELSIUS (Ricome et al. 2017) to determine optimal crop strategies at farm scale. One important caveat regarding their use in the present context is the size of the gap between the potential yields simulated by these models, especially in Africa, and actual or even best yields from the agronomic literature, which would require prior developments to reconcile agronomic studies and crop model results (Niang et al. 2017; Global Yield Gap and Water Productivity Atlas). However, these models do not explicitly represent weeding, pesticide use and improvements in lowland systems or important processes such as local lowland hydrologic contexts, flooding, and risks of labor shortages. Analyzing the relative contributions of production factors and climatic risks to rice yields levels and variability, requires to explicitly model their impact separately for each cropping system.

In the following, we (i) describe the expert elicitation methodology and results, (ii) build and adjust production functions for each cropping system, (iii) compare the results obtained via the model with elicited yield distributions and (iv) perform an analysis of variance to study the impact of each production factor and risk effect on yields in the model.

3.2 MATERIAL & METHOD

3.2.1 Building production functions from heterogeneous sources of information for four rice cropping systems

To study the impact of rice cropping management strategies on yield average levels and variability across systems and areas, we collect the information available in the scientific literature and/or expertise. We rely on expert elicitation to (i) estimate the relative proportion of rice cropping systems per areas, (ii) characterize and quantify input and type of seed used in cropping management strategies and (iii) gather yield frequency distributions for each cropping system in an array of selected areas in West Africa. We rely on peer-reviewed and grey literature, together with climatic reanalysis data to build production functions in order to simulate rice yields distributions. These two sources of information are then combined to calibrate production functions (Figure 3.1). Our calibration is based on averaged elicited yields since experimental or survey data on yields, cropping systems and management strategies is sparse and incomplete. The calibrated production functions hence correspond, for each rice cropping system, to an average farm for an average year. In a final step, we add stochasticity to the production functions using stochastic climatic variables as inputs. This allows us to estimate the fraction of yield

variability which can be attributed to climate variability. Figure 3.1 presents the different steps of the construction of production functions.

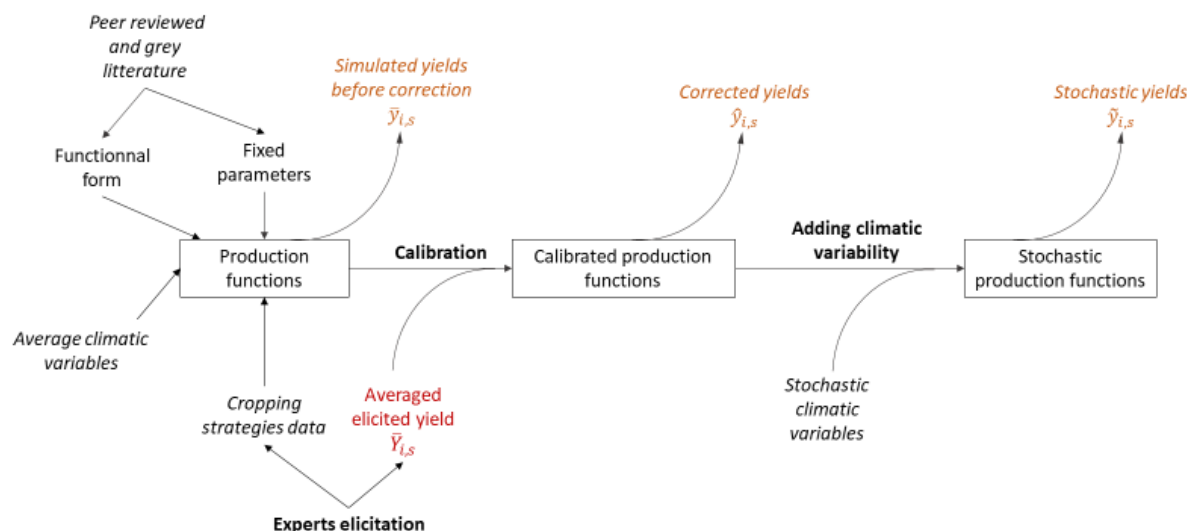


Figure 3.1. Schematic representation of the main methodological steps to build stochastic rice production functions. Inputs are noted in italic, simulated yields (output) in orange.

We consider four different cropping systems: rainfed lowland (i.e., rice cultivated with no water management in lowland environments), improved lowland (i.e., water partially managed through bunding, levelling and draining), irrigated lowland (i.e., advanced water management through irrigation from a permanent source of water, bunding, levelling and draining) and rainfed upland (i.e., no water management in upland environments) (see Table S3 1). Thereafter, we refer to these four systems respectively as LLR, IMP, IRR, ULR. Probabilistic expert elicitation is performed for each of those four systems independently; elements of production functions and parameterization are also specific to each of these four rice cropping systems.

3.2.2 Experts' elicitation of rice cropping systems and yield frequency distribution

Expert elicitation consists of the extraction of expert's knowledge through the determination of the probability distribution of an unknown variable of interest. This method is often used in the context of data scarcity (Karvetski et al. 2013) and applied to agricultural research (Chen et al. 2019; Andriamampianina et al. 2018; Makowski et al. 2020). According to the European Food Safety Authority, probabilistic elicitation requires a capacity to associate a probability to the range of values that can be taken by a variable of interest (European Food Safety Authority 2014). Expert elicitation here aims at (i) gathering information on management strategies differences between rice cropping

systems and areas (i.e., fertilizers and cultivars uses, weeding habits) and (ii) estimating probability distributions of rice yields per system and per area (at administrative levels 1 or 2).

Probabilistic elicitation enables the estimation of both yield average and yield variability because it relies on the description of a probability distribution (or frequency distribution). This is the most relevant here since rice yields are known to be very variable across West Africa (Gaya et al. 2018).

We here defined an expert as a researcher who has worked on rice production in at least one West African country. The first sample of experts is obtained through the *French Agricultural Research Center for International Development (CIRAD)* rice researchers and additional local experts were obtained iteratively (i.e., AfricaRice, Agronomic Research Institute of Guinea, Houphouët-Boigny Polytechnique National Institute). At the end of the elicitation campaign, 12 experts are interviewed and among them 7 accept to participate in the elicitation (3 agronomists and 4 economists). Experts are asked to locate their yield distributions in regions, defined geographically with a GIS tool. These regions can be included in or encompass several administrative areas. Overall elicited data span, 26 regions covering 40 areas, at the administrative levels 1 or 2 over 7 countries, for time periods ranging from 1995 to 2021 depending on the expert and on the region (see Figure S3 1).

It should be noted that, in some of the regions, elicitation are performed by more than one expert (e.g., Saint Louis area in Senegal or Guinea regions). For the purpose of calibrating and evaluating the production function, when a region is elicited by two experts or more on different periods of time, we keep all data collected. Moreover, for one region, one expert informs yield distributions over two different periods of time because he considers that there had been important changes in the cropping practices between these two periods. All data (i.e., cropping system weight, cropping practices, yields distributions) are available online at <https://doi.org/10.18167/DVN1/44ZJEV>.

Each session has been conducted as follows: the objective and methodology of the study are presented openly, and questions are answered if necessary. The interview then proceeds in two consecutive steps. The first step consists of an iterative process to precisely delineate the regions of expertise, knowledge sources and the time range covered in each region. A region is defined as a geographical entity characterized by a relatively homogeneous landscape, distribution of rice cropping practices and average climate (e.g., Maritime Guinea, Office du Niger). Elicited regions can encompass one or several administrative level 1 areas or be delimited by a smaller area, for example at the administrative level 2. The second step focuses on targeted regions: (i) the weight of each rice cropping system is estimated (i.e., the area proportion covered by cropping systems), (ii) for each system identified, management strategies are quantified (i.e., proportion of rice growers using high quantities of fertilizers, proportion of rice growers using high quantities of pesticides, proportion of rice growers using improved cultivars),

(iii) the level and variability of rice yields are determined via the definition of a frequency yield distribution from a graphical interface (via the online, open-source, research-based elicitation tools *Licite*, see Figure S3 2). Note that both spatial and temporal variability are tangled. Regarding inputs, experts are asked to differentiate qualitatively between two opposite situations: ‘high’ quantity of fertilizers (or pesticides, or certified seeds) and a non-use of fertilizers (or pesticides, or certified seeds)

3.2.3 Production functions

We rely on a bottom-up approach to build production functions, by explicitly representing agronomic and biophysical constraints. We represent (i) the effects of main production factors (i.e., seeds type, nitrogen and water supply and weeding frequency) and (ii) climate-induced yield loss causes (i.e., drought and flood). The other factors that can reduce yields (e.g., labor shortage, pests and diseases, or information level of the producer) are not integrated in the model because of insufficient consistent data allowing to quantify their impact on yield. These factors are not explicitly considered in the production functions but they are implicitly integrated during the calibration procedure based on average elicited yields, and should also ultimately be present in the residual temporal and spatial variability of the elicited yield distributions that is not explained by the model.

In West Africa, two broad types of seeds are used: (i) traditional local seeds, predominant in extensive systems and (ii) conventional seeds most often used in intensive systems (Bèye and Wopereis 2014). In the cropping systems which rely on local seeds of traditional cultivars, farmers save seeds from one year to the other. Conversely, with conventional seeds, farmers buy certified seeds of improved cultivars on the market, and replicate these seeds for one or two generations. Here, we represent both seed types because, although potential yields may vary within each cultivar type, according to the cultivar, the average potential yields of traditional and improved cultivars are significantly different (i.e., for a given cropping system, yields tend to be higher for improved cultivars than for traditional cultivars).

The yield function is based on a potential yield with water and nitrogen as limiting factors. Effects of competition with weeds and of extreme climatic events are expressed as percent loss of yields. Simulated yield before calibration in region i , for system s is thus expressed as:

$$\bar{y}_{i,s} = \left((1 - \alpha_{i,s}) \times Y_{s,loc} \times \bar{\theta}_{i,s,loc}^F \times P_{i,s,loc}^d \times P_{i,s,loc}^f + \alpha_{i,s} \times Y_{s,imp} \times \bar{\theta}_{i,s,imp}^F \times P_{i,s,imp}^d \times P_{i,s,imp}^f \right) \times \theta_s^W \quad (1)$$

With,

$\alpha_{i,s}$: the proportion of rice producers using certified seeds in region i , for system s

$Y_{s,loc}$: the potential yield for system s, for local seeds

$Y_{s,imp}$: the potential yield for system s, for certified seeds

$\bar{\theta}_{i,s,loc}^F$: the mean effect of fertilization in region i, for system s, for local seeds

$\bar{\theta}_{i,s,imp}^F$: the mean effect of fertilization in region i, for system s, for certified seeds

$P_{i,s,loc}^d$: the effect of dry spells occurrences in region i, for system s, for local seeds

$P_{i,s,imp}^d$: the effect of dry spells occurrences in region i, for system s, for certified seeds

$P_{i,s,loc}^f$: the effect of flood episodes in region i, for system s, for local seeds

$P_{i,s,imp}^f$: the effect of flood episodes in region i, for system s, for certified seeds

θ_s^W : the effect of weeding for system s

$$\theta_s^W = \min \{a^W \times Q_s^W + b^W; 1\} \quad (2)$$

With,

Q_s^W : the number of weedings done by rice producers for system s

a^W : the slope of the linear relation between the number of weedings and the effect on yield

b^W : the intercept of the linear relation between the number of weedings and the effect on yield

Expert elicitation informs on the proportion of rice producers using a high level of fertilizer. We compute the effect of fertilizer as an average between the high level and the low level of fertilizer effects on yield, the effect on yields being represented by the $\theta_{s,c}^F$ () fertilizer response function:

$$\bar{\theta}_{i,s,c}^F = \gamma_{i,s} \times \min \{ \theta_{s,c}^F(Q_{high}^F), \theta_{i,s}^P \} + (1 - \gamma_{i,s}) \times \min \{ \theta_{s,c}^F(Q_{low}^F), \theta_{i,s}^P \} \quad (3)$$

With,

$\gamma_{i,s}$: the proportion of rice producers using a high quantity of fertilizer, in region i, for system s

Q_{high}^F : the quantity of nitrogen considered as high, it is here fixed to 100kgN/ha

Q_{low}^F : the quantity of nitrogen considered as low, it is here fixed to 20kgN/ha

$\theta_{i,s}^P$: the effect of precipitations in region i, for system s

Fertilization effect here follows a dose-response relationship: the more nitrogen is applied, the more yield increases, but with decreasing returns, using an exponential function. We assume that the yield with zero nitrogen input and the slope at zero nitrogen input depend only on the system:

$$\theta_{s,c}^F(Q^F) = a_{s,c} \times e^{-b_{s,c} \times Q^F} + 1 \quad (4)$$

$$a_{s,c} = \frac{y_s^N(0)}{Y_{s,c}} - 1 \quad (5)$$

$$b_{s,c} = \frac{\frac{y_s^{N'}(0)}{Y_{s,c}}}{1 - \frac{y_s^N(0)}{Y_{s,c}}} \quad (6)$$

With,

$y_s^{N'}(0)$: the slope at the origin of the relation between the quantity of nitrogen and the yield, for system s

$Y_{s,c}$: the potential yield for rice in system s, depending on seed type c (i.e., local or certified)

$y_s^N(0)$: the yield with 0 nitrogen supplied, for system s

Note that the equations relating the effect function parameters $a_{s,c}$ and $b_{s,c}$ are simply derived from the definition of the effect function in 0, $\theta_{s,c}^F(0) = \frac{y_s^N(0)}{Y_{s,c}}$, and $\theta_{s,c}^{F'}(0) = \frac{y_s^{N'}(0)}{Y_{s,c}}$.

$$\theta_{i,s}^P = \min \{A_s \times Q_{i,s}^P; 1\} \quad (7)$$

With,

$Q_{i,s}^P$: the cumulated rainfalls over the rice growing cycle in region i, for system s

A_s : the slope of the linear relation between the cumulated rainfalls in region i and the effect on yield

$$P_{i,s,c}^d = 1 - \{\beta_{i,s} + p_c^d \times N_{i,s}^d; 1\} \quad (8)$$

With,

$\beta_{i,s}$: the proportion of dry spells during the cropping cycle in region i, for system s

p_c^d : the daily loss due to a day of dry spell occurring during the reproductive phase, for seeds c

$N_{i,s}^d$: the cumulated days of dry spell occurring during the reproductive phase

$$P_{i,s}^F = 1 - \min \{p_c^f \times N_{i,s}^f; 1\} \quad (9)$$

With,

p_c^f : the daily loss due to a day of flood occurring during the vegetative phase, for seeds c

$N_{i,s}^f$: the cumulated days of flood occurring during the vegetative phase

The minimum relation between precipitations and fertilization effects corresponds to a representation of the limiting factors relationship between those two inputs. We differentiate the daily losses coefficients

of drought or flooding events between local seeds and certified seeds to incorporate the stylized fact of robustness of local seeds.

All parameters are fixed according to the literature (see Tables S3 2, S3 3 and S3 4).

We finally rely on CHIRPS reanalysis data, aggregated at the administrative level 1, from 1980 to 2020 at $0.05^\circ \times 0.05^\circ$ resolution. We removed from our dataset all grid cells with below 1% of cultivated areas.

3.2.4 Production functions post-processing

We rely on probabilistic elicitation data to calibrate our yield model. As yield distributions elicited by experts entangle both spatial and interannual variability, we only rely on average elicited yields to calibrate the production functions in the different areas and for each system. We adjust simulated yields via a linear regression:

$$lm(\bar{Y}_{i,s} \sim \bar{y}_{i,s} - 1) \quad (10)$$

With,

$\bar{Y}_{i,s}$: the average elicited yield in area i , and system s

$\bar{y}_{i,s}$: the predicted yield measured from the production function applied to area i , and system s

The effect of climate interannual variability of the mean is negligible in our model, as checked by prior simulations (see Figure S3 3). Therefore, we use the ten years average climate variables in the calibration. To avoid mismatch between elicited and predicted years we rely on the last ten years of climate data preceding the end of the expertise period.

We obtain a proportional relation between these two sources of mean yield values (simulated yield and averaged elicited yield). It allows to readjust predicted yields with the following relation:

$$\hat{y}_{i,s} = a \times \bar{y}_{i,s} \quad (11)$$

The estimated coefficient (a) is equal to 0.782 (with a p -value < 0.001 , and an R-squared of 0.94). As the relation is linear, the correction coefficient has proportionally more impact on high yields. Thus, it permits to correct the tendency of our model to overestimate intensive systems yields (i.e., IMP and IRR) (see Figure S3 4).

In a final step, to add stochasticity to the production functions, we use stochastic climate variables as inputs in the calibrated production functions. We run our model on the ten last year climate data

preceding the end of the expertise period of time. This gives us ten values of simulated yields for each system*area combination.

Finally, we decompose simulated yield variance to test the sensitivity of the model to a change in input values.

For this part, we use the model for the four systems in each area at administrative level 1 in West Africa – under the condition that climate data is available. The experimentation design contains 81 runs per system*area (4*189 combinations) (see Table 3.1).

Table 3.1. Variables and modalities tested during the variance decomposition.

Inputs	Levels		
Fertilizers use	Weak (QF = 20 kgN/ha)	Medium (QF = 60 kgN/ha)	High (QF = 100 kgN/ha)
Weeding number	Absent (QW = 0)	Partial (QW = 1)	Total (QW = 2)
Climate	Dry year	Average year	Wet year
Seeds used	Local (100% local)	Mixed (50% local + 50% certified)	Certified (100% certified)

For each area, we identify (i) the driest year, (ii) the average year and (iii) the wettest year in the period 1980 – 2019 by calculating the cumulated rainfall on the growing cycle. We do that computation for each system as the cycle lengths differ and estimate the seeding date as the onset of the monsoon for each year. Because climatic conditions vary across areas including at administrative level 1, the variable ‘area’ also somehow reflects the sensitivity of our model to spatial precipitation variability. For this reason, we choose to integrate this variable in the variance analysis of our model.

3.3 RESULTS

3.3.1 Intensive cropping practices does not seem to decrease yield spatial and temporal variability, according to experts

Highest average rice yields are achieved by IRR systems (3.58 t/ha), followed by IMP systems (2.46 t/ha), LLR systems (1.53 t/ha) and ULR (1.04 t/ha). ULR yields are significantly lower than the three other systems. Similarly, IRR systems are significantly higher than the three other systems. LLR yields are significantly lower than the two other lowlands systems. In terms of relative variability (i.e., regional interannual and spatial yield variance), ULR yield coefficients of variation tend to be significantly higher than that of the three other systems (with a p-value < 0.001 when comparing with LLR, and p-value < 0.05 when comparing with IMP and IRR systems). There is no significant difference in the yield coefficients of variation between the three lowland systems.

High use of inputs and of certified seeds is correlated to the level of water management. In IMP and IRR systems, the mean proportion of rice producers using high fertilizer quantities are respectively equal to 60% and 95% while for rainfed systems, LLR and ULR, they are equal to 23% and 8%. In LLR and ULR systems, about 23% of rice growers use high quantities of pesticides, while these proportions are 48% and 86% in IMP and IRR systems. Certified seeds are used by 26%, 47%, 65%, 96% and of rice producers in ULR, LLR, IMP and IRR systems respectively.

Table 3.2. Relationship between average rice yields and the reliance on fertilizers, pesticides and certified seeds. (.)= p-value <0.1, (*) =p-value <0.05, (**) =p-value<0.01, (***) =p-value<0.001). “NA” means that there are insufficient points to estimate the three coefficients for the IMP system.

	High use of fertilizers proportion	High use of pesticides proportion	Certified seeds use proportion
All systems	2.17 (***)	1.64 (***)	1.12 (.)
LLR	5.16 (***)	1.01 (.)	0.88 (.)
IMP	2.24 (**)	NA	1.87 (*)
IRR	8.95 (**)	0.59 (.)	0.71 (.)
ULR	1.36 (.)	1.81 (**)	0.90 (.)

The use of fertilizers, of pesticides or of certified seeds has a positive effect on average yields for all systems (see Table 3.2). However, the effect of certified seeds is not or almost not significant. In the case of ULR the use of pesticides tends to significantly increase mean yields while in the case of lowland systems (i.e., LLR, IMP, IRR), it is the use of fertilizers that tends to significantly increase mean yields. A reason can be that, in these three systems, water is often not limiting (LLR systems are most often found in rainy areas) so the increase of fertilizer supply can improve average yields. On the contrary, in ULR systems, the effect of fertilizers may be limited by the low quantity of available water.

Table 3.3. Yield coefficient of variation relation with fertilizers, pesticides and certified seeds use. (.)= p-value <0.1, (*) =p-value <0.05, (**) =p-value<0.01, (***) =p-value<0.001). “NA” means that there are insufficient points to estimate the three coefficients for the IMP system.

	High use of fertilizers proportion	High use of pesticides proportion	Certified seeds use proportion
All systems	-0.21 (***)	0.13 (**)	0.17 (**)
LLR	-0.11 (.)	0.27 (***)	0.29 (***)
IMP	-0.03 (.)	NA	0.35 (**)
IRR	0.58 (*)	-0.44 (*)	0.30 (*)
ULR	-0.37 (.)	0.37 (***)	0.36 (**)

The use of certified seeds tends to increase the relative variability of yields for all systems (see Table 3.3). A reason could be that the use of certified seeds may increase the range of values taken by yield more than it improves average yields and thus increase yield variability. The impact of the use of fertilizers on yield variability is negative and not significant for LLR, IMP and ULR. However, for IRR,

the use of fertilizers tends to increase yield variability while the use of pesticides tends to decrease it. The use of pesticides significantly impacts LLR and ULR yields coefficients of variation by increasing it.

3.3.2 Consistency between simulated yields and elicited yields in terms of mean level and variability

We first perform a correction of simulated yield based on averaged elicited yields based on linear regression (see section 2.4.). To evaluate the accuracy of this calibration, we compare simulated yields after correction with those elicited for each area*system (see Figure 3.2).

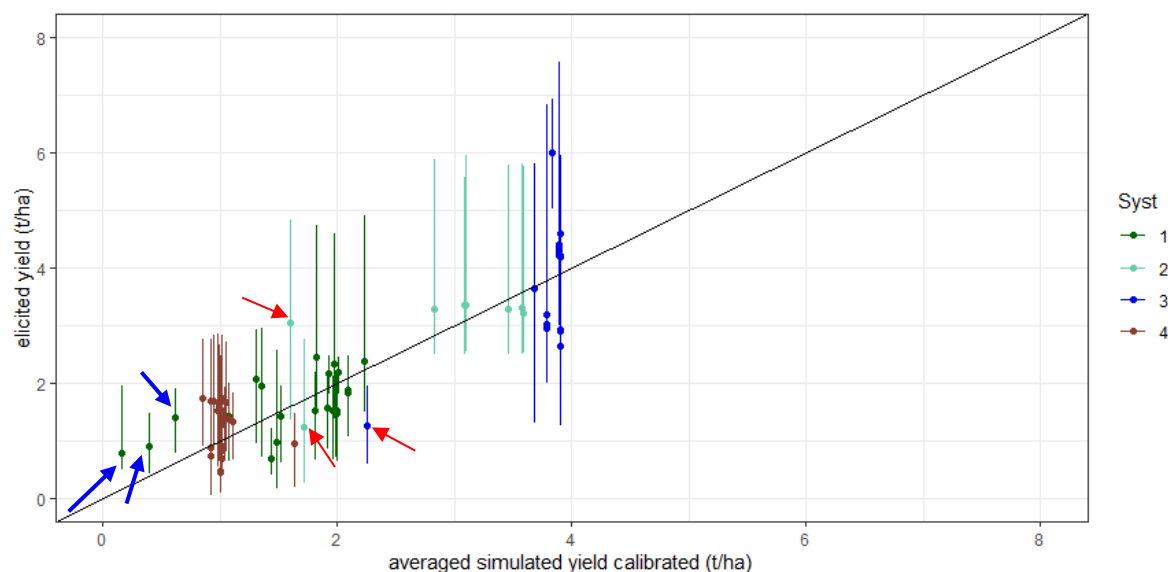


Figure 3.2. Comparison between averaged simulated yield calibrated and elicited yield, per cropping system, at the administrative level 1. Syst 1 refers to LLR, Syst 2 to IMP, Syst 3 to IRR and Syst 4 refers to ULR. The error bars represent the range between maximal and the minimum elicited yields. Red arrows highlight three points that have a lower simulated yield than the majority of the other points associated with their respective system, see the text for the analysis (section 3.2). The blue arrows highlight three points with the lowest simulated yields.

In LLR and ULR systems, simulated yields are consistent with average elicited yields (e.g., in the Bere area, in Côte d'Ivoire, our model simulates a corrected yield equals to 2.27 t/ha for LLR system while the average elicited yield is equal to 2.44 t/ha and in the Kaolack area, in Senegal, our model simulates a corrected yield equal to 0.89 t/ha for ULR system while the average elicited yield is equal to 0.82 t/ha for the same system). But our model tends to overestimate irrigated yields compared to elicited yields in the corresponding systems. This is perhaps because we assume that IRR systems are independent of water constraints and only dependent on cropping practices (i.e., fertilizers supply, weeding number and certified seeds choice). However, IRR systems can be limited by water even when there is enough supply from hydraulic infrastructures (e.g., because of imperfect water management or defective equipment). Also, and similarly in all the cropping systems, our production functions do not include other production risks such as pest losses, labor shortage at critical periods such as transplantation or harvest. Simulated

yields in the IMP system (light blue in Figure 3.2) also tend to be overestimated. The three points, highlighted with red arrows in Figure 3.2, associated for two of them to the IMP system and for the last one to the IRR system are characterized by a very low use of fertilizer. For the points highlighted with blue arrows, simulated yields are very low. These points correspond respectively to the Saint-Louis, the Fatick and the Kaolack regions, in Senegal, for the LLR system. The model tends to under estimate yields in lowland rainfed systems in the Sahelian zone as precipitation is low and drought risk is high.

The described above linear calibration used to correct simulated yields has a larger effect on highest yields and smaller on lower yields (dominant in LLR and ULR systems). We simulate yields over a period of 10 years for each system x area combination. In these simulations climatic variability is the only source of interannual variability considered. We then compare the coefficient of variation of simulated yields to that of the elicited yields based on their probability distribution. Note that elicited yields mingle, by construction, both temporal and spatial variability.

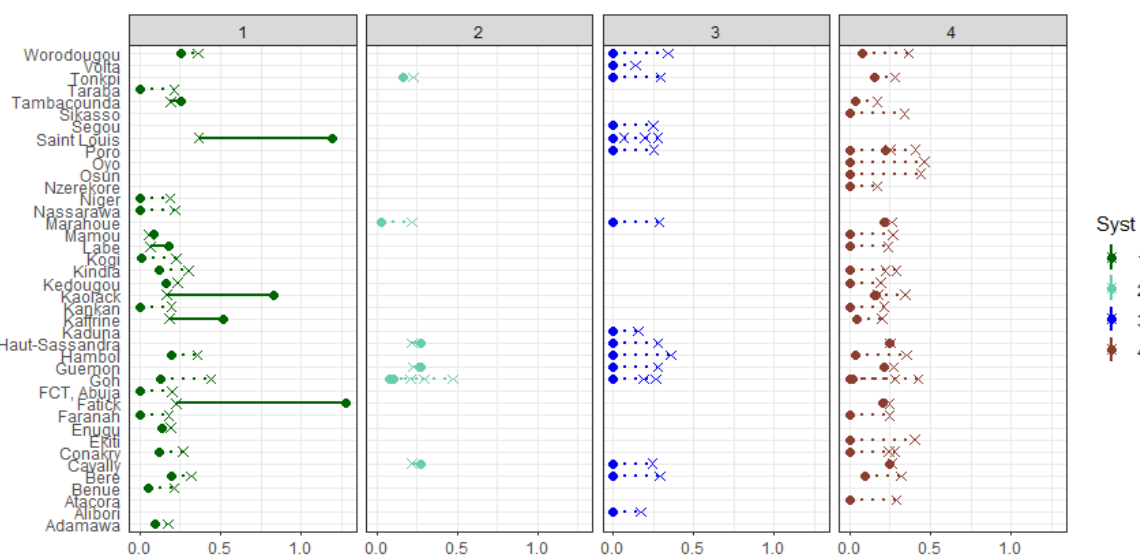


Figure 3.3. Comparison between elicited yields and simulated yields coefficient of variation for 10 years in each of the 4 rice cropping systems. Syst 1 refers to LLR, syst 2 refers to IMP, syst 3 refers to IRR and syst 4 refers to ULR. Each dot represents the coefficient of variation of simulated yield with 10 years of climatic data. Each cross represents the coefficient of variation of elicited yields. Note that in some areas*system combinations, there are more than one elicited yield distribution because more than one expert has provided elicited yield values for this specific combination (e.g., in the Goh region for IMP, IRR and ULR systems). Plain lines indicate the few situations where the coefficient of variation of simulated yield are higher than that of elicited yields. On the contrary, dotted lines correspond to a simulated yield coefficient of variation lower than the elicited yield coefficient of variation.

To evaluate the correspondence between climate-based variability in simulated yields and the probability distributions of elicited yields, we perform a one-by-one comparison between the corresponding coefficient of variation (see Figure 3.3). It is visible that, in a large majority of cases, the relative variability of simulated yield is smaller than that of elicited yields. This is largely due to the entanglement of both temporal and spatial variability in the latter and outlines that there are no major

inconsistencies. Note that simulated yield variability is only due to interannual rainfall variability (climate-based) and more specifically to the heterogeneity of rainfall distribution during the rice growing cycles (i.e., drought and flooding periods). For this reason, simulated yield variability might be lower for each system*area than elicited yield distributions variability. Because water constraints are not considered in the IRR system, coefficient of variation of simulated yield for this system appears to be equal to 0. We expected higher simulated yield variability for the ULR system, which is the most limited by water. This low simulated yield variability can be due to the fact that ULR system yields are elicited by experts in regions where rainfalls are mostly abundant (i.e., only about 19% of the areas where rainfed upland rice yields were elicited received less than 1000 mm per year on average). For the same reason, in the areas where LLR yields have been elicited, precipitation is rarely the limiting factor because fertilizers use is very low.

In the LLR system, there are three areas where simulated yield variability is higher than elicited yield variability. These areas are localized in the northern half of Senegal, a region characterized by low precipitation and frequent dry spell events. Moreover, because we define flooding relatively to an average year in our model; in the areas where precipitation is low on average, intensity rainfall events are more frequently classified as floods in our time series.

3.3.3 Contributions of cropping practices and climatic conditions to yield simulations across West Africa

We perform an analysis of variance to study the relative effects of the considered production factors and of precipitation variability effects on yields in our model (see Figure 3.4).

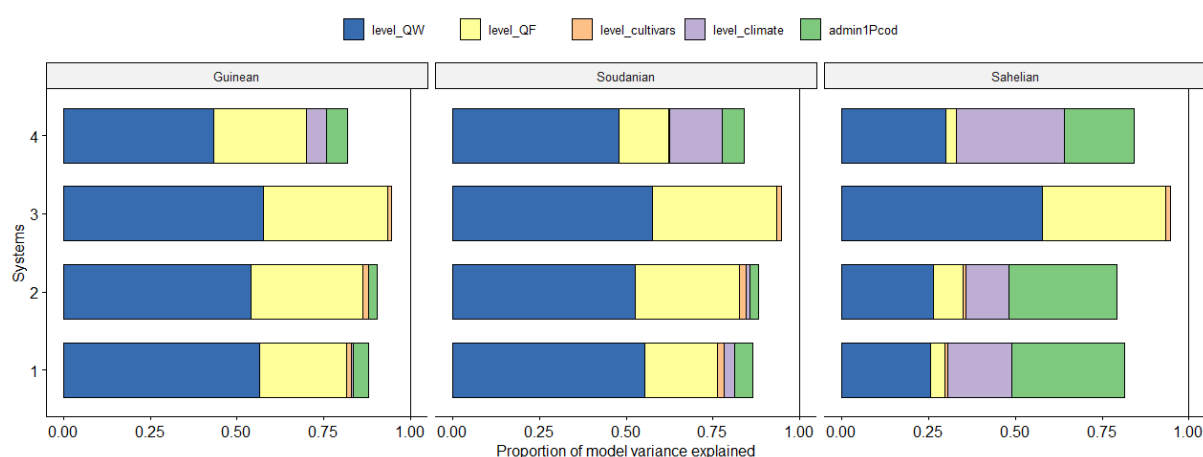


Figure 3.4. Variance decomposition of production functions in the three main climatic zones of West Africa (i.e., Guinean, Soudanian and Sahelian), for the four rice cropping systems. System 1 refers to LLR, system 2 refers to IMP, system 3 refers to IRR and system 4 refers to ULR. Five factors are analyzed: climatic conditions (i.e., level_climate with three modalities: wet, normal and dry years), certified seeds use (i.e., level_cultivars with three modalities: local, certified and mixed), fertilizers quantity (i.e., level_QF with three modalities: low, medium and high), weeding intensity (i.e., level_QW with three modalities: absent, partial and total), areas at administrative

level 1 (i.e., admin1Pcod with 189 areas). The X-axis represents the proportion of the model variance explained by each variable.

In IRR systems there is no effect of the climate zone considered on yield variance decomposition. This is due to the hypothesis of yield independence from precipitation conditions in irrigated systems (see section 3.2). On the other hand, a change of the variance proportion explained by climate can be observed from the Guinean zone to the Sahelian zone for the three other systems and in particular for the rainfed ones (i.e., LLR and ULR). While, in the Guinean zone, climatic conditions variability explains less than 10% of the model variance for extensive systems (i.e., LLR and ULR), it explains about 50% of the model variance in the Sahelian zone, for the same systems. The zone considered impacts greatly on simulated yields especially in the Sahelian zone. In this zone, precipitation is the lowest of all three zones. Hence, water is the most limiting factor while, in the other two climatic zones, nitrogen is the most important limiting factor. Moreover, the occurrence of dry spells and flooding events are higher in the Sahelian region. This implies that precipitation variability differences between areas have more impact on yields in the Sahelian region than in the two other regions. Finally, the effect of weeding on simulated yield variance is much greater than that of seeds types. Note that with low fertilization use (i.e., $QF = 20\text{kgN/ha}$ and $QF = 60\text{kgN/ha}$), yield differences between the two types of seeds is very low (i.e., from 0 to 0.4 t/ha). The effect of fertilization has a higher impact on model variance for intensive systems (i.e., IRR and IMP) and it explains more model variance when precipitation is not the most important limiting factor (i.e., in Guinean and Sudanian zones).

3.4 DISCUSSION AND CONCLUSION

We build novel rice production functions for West Africa explicitly accounting for the disparities due to cropping systems and large-scale climatic zones. Although they rely on a simplified description of rice yield formation, these production functions thrive to represent essential production factors and production risks in order to assess their relative contributions. We find that the contribution of production factors to yields and yield interannual variability strongly vary according to rice cropping systems. Overall, our estimates suggest that weeding frequency is a strong determinant of average yields in all cropping systems especially in the Guinean and Sudanian zones, where water is not a limiting factor. In these situations, because of the competition between weeds and rice plants, increasing weeding frequency can impact yield more than in areas where water is scarce. Cumulated rainfall and the duration of drought and floods within the monsoon season have the largest effect on yield levels and variability, for all cropping systems, except the IRR system, in the Sahelian zone where climate risks are high and water is scarce.

Several methodological impediments need to be examined. These are principally related to a recurring data scarcity on rice production in West Africa, whether on yields, cropping systems or management

practices, at subnational level. The first one pertains to the construction of new data from alternative sources, the second to the difficulties of relying on existing models, third, to the limited number of processes implemented in our model and the fourth to its evaluation with independent information. The lack of independent and consistent detailed data hence leads us to a number of methodological choices that we discuss in the following paragraphs.

A small number of yield and/or cropping practices data sources exist for West Africa: (i) official data (e.g., FAOCountrySTAT and AgroMAPS), which provide yield time-series with no information on rice cropping systems, at administrative level 1, for time periods varying regionally and all comprised between 1980 and 2012), (ii) survey data (i.e., LSMS-ISA with information on cropping systems in Mali for the time periods 2014-2015 and 2017-2018, in Niger for the time periods 2011-2012 and 2014-2015 and in Nigeria for the time periods 2010-2011, 2012-2013, 2015-2016 and 2018-2019) and (iii) agronomic trial data providing cropping practices and cropping systems information together with yields data, but only at a local scale, from a valley bottom (Touré et al. 2009) to a latitudinal gradient of selected plots in Côte d'Ivoire (Becker and Johnson 2001). To summarize, a variety of data exists but none qualify in terms of spatial resolution (that is at the scale of administrative level 1 regions), temporal resolution (that is with information covering several consecutive years) and explicit cropping system information. In the following we detail how we rely on these data to evaluate our data construction, methodological choices and results. We first rely on probabilistic expert elicitation to overcome structural data scarcity at the scale of rice cropping systems. This method, which is still underused, has already been successfully applied in similar contexts (Andriamampianina et al. 2018; Chen et al. 2019). Experts are selected via a research network to have access to scientists with extensive field experience. While this is an efficient strategy to target specific experts, it can also limit access to a diversity of opinions and knowledge sources. Our panel of experts is selected to cover the largest geographical area, with several experts having knowledge of contrasted countries and zones. This explains the relatively small number of experts. An additional difficulty pertains to the differences in the definitions of cropping systems and their boundaries between experts. Finally, the evaluation of expert knowledge, one important limitation in expert elicitation, is made difficult by the lack of independent data. Alternatively, one may rely on an elicitation protocol ensuring that the knowledge of experts is accurate, independent and precise enough (European Food Safety Authority 2014). Here, comparing elicited yield distributions to country scale yield time-series (FAOCountryStat and AgroMAPS1), requires re-aggregating the elicited yields across all systems in each region. We do not observe a robust relationship between these two sources of data (see Figure S3.5). This is not surprising though because both the cropping system and temporal time periods are not consistent between them. We also compare elicited yields and the relatively scattered information on yield values found in the literature. We find that average elicited yields per cropping system tend to be slightly lower in intensive systems, and similar for other systems. For instance, Lançon and Erenstein (2002) estimate that current average yield in the Sahelian zone for

irrigated systems can reach 4.5 t/ha and we obtain an average elicited yield for IRR of 4.48 t/ha in Office du Niger, which is very similar, but a lower yield of 3.77 t/ha in Senegal River valley. Average elicited yield in irrigated systems in the Sahelian zone is equal to 3.95 t/ha (i.e., measured from three yield distributions elicited in Saint-Louis region, for different periods of time, and one yield distribution elicited in Office du Niger). Fall (Fall 2018) estimates that the average irrigated yield in Office du Niger and Senegal River valley is close to 5 to 6.5 t/ha. In rainfed systems, average yields are about 1.85 t/ha for LLR and 1.3 t/ha for ULR according to Fall (Fall 2018), which is only 0.3 t/ha higher than average elicited yields. This underlines a high level of consistency between elicited yields and reported yields at similar spatio-temporal scales in the literature.

We build production functions of intermediate complexity, for an average rice farm in West Africa, for the four main rice cropping systems to analyze production factors and climatic risk effects on rice production. We choose to only represent key production factors, and we discuss below the limitations associated with our production functions, and the evaluation of their impact on our results. Our production functions explicitly account for weeding frequency, nitrogen and water supply, seed types and the magnitude of drought and flooding. Seed types and variety, nitrogen supply and weeding frequency have been shown to be the most important ones for rice yields in West Africa (Niang et al. 2017) and precipitation variability (i.e., annual cumulated rainfall and number of dryspell episodes) has been shown to influence rice yield interannual variability (Duvallet et al. 2021). But, because of the absence of data, we do not model the effects of pests and diseases or of adaptation through late seeding (i.e., in our model, seeding deterministically occurs on the onset of the monsoon).

To simplify, we made a decision to set the rice growing cycle length at 140 days for Irrigated (IRR) and Improved (IMP) systems, 130 days for Rainfed Lowland (LLR) systems, and 100 days for Rainfed Upland (ULR) systems, regardless of the climate conditions. The impact of dry spells on yield is taken into account and hence, indirectly, late seedings. The explicit effects of other fertilizers such as potassium, phosphates are also not included in our production functions because we assume that their use is highly correlated to the use of nitrogen. Similarly, we do not explicitly represent alternative sowing methods (i.e., broadcasting, per seed holes, with or without transplanting). But sowing methods are usually associated with cropping systems: for example, in intensive systems (i.e., IRR and IMP), rice producers tend to transplant seedlings while in extensive systems (i.e., LLR and ULR), they tend to use a direct seeding method. In our model the parametrization of weeding is constant across the four rice cropping systems considered although weed quantity and weeding may be impacted by flooding conditions. This is because available field trial information is divergent between available sources (Saito et al. 2010; Ekeleme et al. 2009; Touré et al. 2009; Bandaogo and Arzouma 2010; Ogwuie et al. 2014). We model the interaction between water availability and nitrogen supply as a minimal effect between these two factors. However, when the effect of one of these factors is limiting, the quantity of the other

can interact and increase the effect of the factor (Niang et al. 2017). We choose to represent fertilization impacts on yields through a dose-response functions parametrized with nitrogen balances instead of considering fertilizer trials to offset the inconsistency of yields observed with no fertilization on control plots. In most cases, these yields are higher than expected with nitrogen balances, probably because of other fertilizers supply sources (i.e., fertilizers remaining from previous years or fertilizers used on upstream plots) (Becker and Johnson 2001a; Touré et al. 2009a).

The production functions were parameterized using trial and survey data from both published and non-published sources. The potential yields were estimated based on cultivar technical catalogs and differentiated based on cropping system and seed type. The estimated potential yields range from 4.6 t/ha in Côte d'Ivoire to 9.8 t/ha in Nigeria for rainfed rice, and from 7.0 t/ha in Burkina Faso to 10.4 t/ha in Mali for irrigated rice (according to the Global Yield Gap and Water Productivity Atlas). The best yields achieved by rice-producing households, as determined by Saito et al. (2017), are 4.8 t/ha for lowland rainfed, 3.5 t/ha for upland rainfed, and 5.9 t/ha for irrigated lowland. Our estimated potential yields align with those obtained through crop modeling or rice producer surveys (Senthilkumar 2022).

We then rely on the production functions to simulate yield distribution from climatic information aggregated at administrative level 1. These simulated yield averages are then calibrated on average elicited information. This step, although essential, conveys approximations since all agronomic processes are not represented. Also note that our calibration is based on existing managements for each given cropping system. Indeed, there are theoretical combinations that do not exist in reality (e.g., high fertilization with no water management). This illustrates the adaptation of rice producers to their environment and in particular to water constraints (e.g., there is almost no rainfed upland rice production over the isohyet 900).

Finally, and to assess the consistency of our results, we rely on yield values and cropping practices from surveys and trial information when available even for very short time periods at local scale. Namely, we compare simulated yields with LSMS-ISA surveyed yields, in Mali, for 2014-2015 (Cellule de Planification et de Statistiques et al. 2014-2015) based on cropping practices declared by rice producers (see Figure S3 6). To this end, we simulate yields with our production functions from input information provided by surveyed rice producers at plot scale. Many yield points in LLR and ULR systems in LSMS-ISA data appear to be implausibly high, while some yields in IRR systems are implausibly low. When removing all surveyed yields superior to 7.5 t/ha - as a cap to separate possible yield values from obvious errors - the correlation coefficient between these two yield sources is equal to 0.3 with a p-value < 0.05. Reported nitrogen levels are also often implausible, especially in relation to reported yields. Even though the resulting surveyed yields include many erroneous data, we could not proceed to additional corrections, as there would be no clear basis to do so without a model. Variability ranges of simulated

and declared yields are similar, but the correlation is rather low. This comparison cannot easily be interpreted since (i) the LSMS-ISA dataset includes many implausible values and seems to be very noisy, (ii) the farmers are sometimes surveyed and asked to estimate yields before harvest, such that the reported levels are predictions and not observations. Given that the model is applied at regional level, it misses intra-regional heterogeneity. This limitation is not clearly visible in the comparison with the LSMS-ISA dataset, since the variability ranges are similar. The low correlation could relate partly to missing intra-regional variability, but it is more likely that it points to missing or incorrectly modeled processes, although the difficulties of comparison of the two datasets precludes concluding with certainty. We also compare our simulated yields with information from agronomic trials (see Figure S3 7, (Becker and Johnson 2001; Touré et al. 2009)). Our model shows a similar response to changes in management (i.e., water level, type of seeds, fertilizer supply, number of weeding) than in trial data. But our model tends to simulate lower yield than trial data for absent or low fertilizer use. This is perhaps related to the fact that in trial, rice plants can benefit from nitrogen residuals resulting, for example, from former fertilizer supply. On the contrary, for higher fertilizer supply levels, the response of simulated yield to high nitrogen application is somewhat higher than reported in field trials. One possible explanation lies in the fact that our model does not simulate all yield loss causes (e.g, iron toxicity, pest and diseases).

The construction of production functions has allowed us to represent the relative contribution of a series of cropping strategies to yield level and variability. The lack of available and consistent data, at subnational level, hinders the explicit representation of other production risks. Comparisons with diverse data sources - expert elicited yields, official data, literature on yields, farmer plot surveys and agronomic trials- give mixed results, but the different data sources are not consistent and might not be very reliable. Obtaining similar results to one source would mean disagreeing with another. Our simulations furthermore hide important heterogeneity in yields due to local scale hydrological conditions. One improvement perhaps lies in the combination of production functions with local hydrology models (Hector et al. 2018) to more finely represent the spatial variability of key processes. Our production functions could be integrated in a bioeconomic model, at farm scale, to represent the impact of cropping strategies on producer income (see for example the combination of a crop and bioeconomic models, (Ricome et al. 2017)). Such a framework can allow modeling the cropping strategies adopted by a given rice producer to maximize income (assuming rational behavior) despite a range of agricultural risks (i.e., production, financial, market, institutional and human).

CHAPTER 4

This article is still in progress.

4 IDENTIFYING OPTIMAL RICE CROPPING STRATEGIES IN WEST AFRICA CONSIDERING PRODUCTION AND MARKET RISKS

KEYWORDS: Rice cropping, household welfare, food security, resources management

4.1 INTRODUCTION

Rice is one of the most commonly consumed staples in West Africa, but the region's dependence on imports is growing. To reduce reliance on international markets, especially after the 2008 food price crisis, West African governments have renewed their interest in achieving rice self-sufficiency by 2050. Although regional consumption has steadily increased over the past few decades (from 3.4 million tons in 1980 to 22 million tons of milled rice equivalent in 2018 (FAO 2020)), local production has not kept pace with this demand (from 2.1 million tons in 1980 to 13.3 million tons of milled rice equivalent in 2018, according to the USDA). The increase in West African rice production can be attributed mostly to rice cropping areas expansion, with yield increases playing a smaller role. Rice yields in West Africa are generally low (with an average yield of 2.1 tons per hectare, about half the global average for rice (Soullier et al. 2020), besides differences in climate and soil conditions) and exhibit high interannual variability, especially compared to other staple crops (Duvallet et al. 2021).

Several explanations to these low yields have been proposed in the specialized literature. These include a lack of production factors such as fertilizers, improved cultivars, and water, caused by environmental and economic constraints, as well as uncertain conditions leading to production risks such as climatic conditions, pests, and disease. The term "risk" refers to the uncertainty associated with a phenomenon or a lack of complete knowledge about it (Eldin and Milleville 1989). In contrast, "constraint" refers to a permanent limitation or obstacle. The differentiation between these two concepts requires to consider both the frequency and the degree of uncertainty associated with the phenomenon in question.

Numerous studies in this region have identified factors leading to rice yield gaps (Awio et al. 2022; Senthilkumar 2022; van Oort 2018). This literature shows that implementing efficient agricultural practices, such as using improved varieties, managing water resources, efficient weeding, and providing nutrients, should reduce yield gaps and increase average rice production (Senthilkumar, 2022). However, constraints on credit access and very low savings rates impede rice growers from purchasing inputs or external labor (Ken E. Giller et al., 2021). Additionally, rice crops have significant water requirements, needing about 909m³ of evapotranspired water to produce 1 ton of paddy (Bouman 2009),

and are mainly rainfed in West Africa, with about 83% of the total rice cropped area being rainfed in 1990-2000, compared to about 12% in irrigated systems (Diagne et al. 2013). Rainfalls in this region are highly variable at decadal, interannual, or seasonal time scales, and extreme events such as dry spells and floods often occur during the wet season (Sultan et al. 2003). Furthermore, rice yields may be affected by other production risks such as pests and diseases, iron toxicity, and soil salinity (Van Oort, 2017). While rice production risks are mostly studied through climatic risks such as drought or floods (Bossa et al., 2020; Serpantié et al., 2020; Sultan et al., 2020), Savary et al. developed a map of five potential rice disease occurrence risks at the global scale (Savary et al. 2012). Pests' risks (Lecoq, 1998; Treca, 1989) and iron toxicity (Audebert and Fofana, 2009) have also been studied at a large scale. A wide range of literature on agricultural risk management strategies in West Africa is available (Duong et al., 2019; Bossa et al., 2020; Hardaker et al., 2004; Ayinde et al., 2014). Several strategies are possible to avoid (e.g., irrigation, plot bunding) or mitigate risks (e.g., late seeding, drought or flood-tolerant cultivars, crop production diversification). In 1990, Matlon compiled an inventory of risk management methods used by farmers in semi-arid West Africa (Matlon, 1990). For instance, at the production stage, producers can choose to sow cultivars resistant to major risks occurring in the area (e.g., drought tolerance, pest resistance), modify the expected sowing date to adapt to rain precipitation, replant with earlier maturing varieties, or delay fertilizer application. Limited access to information and formal low-interest loan systems hinders the implementation of these risk management strategies (Duong et al., 2019).

However, these cropping practices require investments in either cash or labor, which may not be economically advantageous for rice growers who are facing agricultural risks and may be constrained by limited household resources. Additionally, market risks such as rising fertilizer prices and decreasing rice paddy prices, financial risks like increasing interest rates, human risks such as negligence leading to yield loss or injury, and institutional risks such as changes in agricultural policies are often added to production risks (Hardaker et al. 2004). These factors may decrease the willingness of rice producers to make investments in efficient agricultural practices.

In order to evaluate whether the West African governments' ambition to increase local rice production through intensification aligns with the economic interests of rice producers, it is necessary to determine optimal cropping strategies. These strategies should enable rice producers to mitigate risks according to the environmental and economic constraints they are dealing with, while taking into account the variety of agricultural risk sources. Several economic analyses estimate the efficiency of rice production factors at subnational level (e.g., in several Nigerian states (Odoemenem and Inakwu 2011; Nwaobiala and Adesope 2013; Falola et al. 2013; Ohaka et al. 2013)), at national level (e.g., in Ghana (Ayambila et al. 2008), in Côte d'Ivoire (Adesina et al. 1996), in Sierra Leone (Adesina et al. 1993) and at international level (e.g., over the Sahel and Savanna regions of West Africa (Donovan et al. 1999)). These studies

allow to determine what agricultural practices are preferred by rice growers, and, for a few, the impact of credit access to purchase inputs, using rice producers' surveys data (Donovan et al. 1999) and/or bioeconomic models (Barbier 1998). However, these studies generally only consider smallholders' rice farm incomes, with (Donovan et al. 1999) or without (Kolawole and Michel 2021) considering risks, and do not integrate the household welfare into their analyses.

To address this gap, we propose to answer the following questions: How do production and market risks and constraints affect farmers' strategies, and what economic context changes could increase rice production while enhancing the welfare and food security of rice-growing households?

To make progress, we determine optimal rice cropping practices that maximize household welfare at the administrative level 1 for the entire West African region. These practices include fertilizers supply, rice plot area, water management level, and improved cultivars use. We also analyze the impacts of economic context changes, such as credit access and increased saving rates, on these cropping practices.

4.2 MATERIAL AND METHOD

4.2.1 Rice producing household program

We rely on a bottom-up approach to build a conceptual model to determine optimal cropping practices for a representative rice producer household (representative at administrative level 1). A rural household, simultaneously consumer and producer, allocates its resources rationally to maximize its welfare. Thus, the model details a household program that consists in the optimization of its expected utility. Here, representative household refers to a rural household, whose composition, in terms of gender and age, varies according to each country.

We, first, define the cropping practices (i.e., fertilizers supply quantity, weeding frequency, certified or local seeds use, water management level) and explicitly represent their impact on yields in the household program together with climatic conditions and risks (i.e., available water provided by rainfalls, extreme events – dry spells and floods – occurrence and magnitude) (see Chapter 3, section Materials and methods, for details). We also represent the opportunity costs of the use of family workforce (instead of external workforce), the use of certified seeds purchased on the market (instead of re-use of local seeds). The possibility for the household to self-consume on-farm rice is also considered.

To build the conceptual model, we formulate several hypotheses: (i) producer household can rely on its own workforce and on the incomes earned and saved from previous year, (ii) cash spending on household rice plots is fully covered by income from the previous year (when there is no credit access), (iii)

household workforce and available cash are preferentially used to reach, in priority, a food security threshold (and if possible, a poverty threshold).

We define four different rice cropping systems, for all West African agro ecological zones, characterized by (i) environment type and (ii) water management level:

- Rainfed lowland (LLR), regroups all rice cropping systems located on lowlands (i.e., alluvial plain, estuaries, inland valleys, rivers bank and seashore) with no water management.
- Improved lowland (IMP), refers to rice cropping systems also located on lowlands with partial water management (i.e., leveled and bunded fields, drainage canals, irrigation canals with no water storage and derived from episodic stream).
- Irrigated (IRR), refers to rice cropping systems located on lowlands with total water management (i.e., leveled and bunded fields, drainage canals, irrigation canal with water storage upstream or derived from permanent river).
- Rainfed upland (ULR), regroups rice cropping systems located on uplands (i.e., plateaus, slopes) with no water management.

In the following we present the model of household rice production (detailed equations can be found in Supplements section 6.4.1.1).

a) Household resources and consumption

A household is composed of active and inactive members. Active members can work on a rice plot and be involved in income generating activities. The work capacity is in adult equivalent time. The adult's work capacity is different according to the time invested in domestic duty (e.g., women work capacity is weighted by 0.75 as they also take care of domestic duties). We also assume that teenagers' work capacity is weighted by 0.5 as they might be less efficient than adults due to their young age (Aboudou et al. 2021). The food and non-food consumption of household members are also weighted as every member does not have the same needs (e.g., teenagers and young children's needs are weighted by 0.5 while all adults' needs are weighted by 1).

The total workforce needed for the household activity is fulfilled with family workforce and, if necessary, external workforce. There are two constraints to allocate this labor need: (i) family labor availability (i.e., the proportion of family workforce working on the rice plot) cannot be superior to the available family workforce and (ii) priority to family labor (i.e., the household employs external workforce only if the entire family workforce capacity is already used on the rice plot). Workforce needed for harvest depends on the quantity of rice produced so its value is proportional to yield. The

external workforce working during harvest can be paid in kind (with rice), so it is not constrained by cash.

The minimum food requirement for an adult is defined by the food security threshold. We decompose it in two parts: (i) calories provided by staples crops (e.g., cassava, maize, millet, rice, sorghum, yam) and (ii) calories provided by oil, meat, vegetables and fruits. Calories supply can be provided by produced rice self-consumption. The quantity of self-consumed rice depends on rice production. This quantity is bounded by rice production or by a fixed rice maximal consumption of a representative household. The opportunity cost of self-consumption is defined as the avoided cost of buying other staple food. We suppose a perfect substitution between calories provided by rice and that provided by other staples. This calorie's supply is bought on the market at an average price for calories. To achieve food security, the representative household needs to complete its non-staples calories needs. The achievement of the poverty threshold requires the consumption of non-food goods and services.

b) Production costs

Rice smallholder farms have to cover several costs if they use external inputs: (i) fertilizers, (ii) seeds⁵ (certified seeds are purchased on the market) and (iii) external workforce. We formulate the hypothesis that the relationship between costs and rice plot areas is linear (i.e., no economy of scale). Fixed costs that are independent to the plot area also have to be covered. In the model, we explicitly represent reimbursement of existing loans, with interests. However, we do not represent capital depreciation because we assume that, in a wide majority, investments in irrigated perimeters or in improvement of lowland are supported by external organizations (e.g., governments, World Bank, NGOs). In some cases, these costs are fed back into households through water fees or obligation for rice producers to maintain irrigated perimeters or improved lowland with their own resources. However, water fees are very rare in West Africa and we implicitly consider maintenance needs in IRR and IMP with higher labor needs, especially in land preparation.

c) Incomes

The household might earn incomes from (i) rice cropping and (ii) other activities (either agricultural or off-farm activities). Rice self-consumption is subtracted from paddy sales. To estimate yield, and thus rice production, achieved by the rice producer, production functions, associated with seeds type (i.e., local or certified) and cropping system (i.e., LLR, IMP, IRR or ULR), are used (see Chapter 3, section

⁵ We formulate the hypothesis that certified seeds (i.e., purchased on the market) refer to improved cultivars and that local seeds (i.e., reused from one year to another) are assimilated to traditional cultivars.

Material and methods, for details). We formulate the hypothesis that certified seeds, purchased on the market, are those of improved cultivars while local seeds consist of improved cultivars mixed among traditional cultivars (named traditional cultivars in the following to simplify), reused from one year to another. These production functions consider precipitation conditions, aggregated at administrative 1 level, allowing to represent climatic risks impacts on yields. To simulate yield variability caused by other risks, we add a variability coefficient to yields simulated via production functions. The variability coefficient is measured from expert elicitations yield distributions for several combinations of areas*system (among the same four systems defined above) (see Supplements section 6.4.1.2., for details). Moreover, market risks are integrated to the model under the form of rice selling prices distributions. This variable is exogenous as West Africa is a price taker at world scale because of the large amount of imported rice from major rice producer countries.

If household members earn incomes from other, agricultural or off-farm, activities, we consider it all together and measure it thanks to a relation between the amount of income from non-rice cropping activities and the remaining family labor (i.e., family labor not allocated to the rice activity). The marginal income decreases with the remaining family labor. There is no information on other activities opportunities available in the study area, therefore we use paid opportunities in rice systems in best conditions to capture the local opportunities. To determine this function coefficient, we identify the best paid activity that can be practiced in each area (at administrative level 1), according to the existence of irrigation infrastructures. For rainfed systems (i.e., LLR and ULR), we consider that the most profitable potential activity is the IMP system. For the IMP system, we estimate that it is the most profitable potential activity with an add-on factor of 20% of the potential income. For the IRR system, we consider that the most profitable potential activity is the same system, with an add-on factor of 20%. Function coefficients are measured from the optimization of a simplified model of income maximization, under the hypothesis that the integrality of income is equal to the labor used during a cycle for IMP and IMP+20% and IRR+20% systems, in each area at administrative 1 level (see Supplements section 6.4.1.3). The model is optimized with climatic conditions corresponding to an average year (i.e., no temporal variability) (see Figures S4 2 and S4 3 for optimization results). We also formulate the hypothesis that when 90% of the household workforce capacity is allocated to activities, the 10% remaining has no opportunity income.

We also study the possibility for a household to have credit access to buy fertilizers. The reimbursement of the credit and interests is realized after harvesting, under the condition that incomes are high enough to cover it. If credit and interests cannot be reimbursed because of insufficient incomes, the remaining debt with interests is perpetuated the next year and no new credit can be contracted.

d) Rural household program

At year t , the rice producer has to pay for external costs without delay. At the end of the rice growing cycle, rice is sold and/or self-consumed and other basic requirements have to be supported. The major constraint for households that produce rice is that costs of production have to be estimated by the producer at the beginning of the rice growing cycle and have to be supported by saved money remaining from the previous year.

The difference between remaining incomes after basic consumption and production costs is the household surplus (in cash). This surplus can be used by the household to purchase non-necessary goods or be saved. Nevertheless, it is limited by the cash availability constraint. When the household is not able to invest enough money in the rice activity because of basic needs consumption or very low savings, it cannot improve its incomes from this activity, it is the poverty trap mechanism (Azariadis and Stachurski 2005). We call “income surplus” of the year t the income that remains after satisfying basic needs. It can be expressed, in USD of 2022, as:

$$W_t = R_t - C_t \quad (1)$$

$$W_t = I_t^{other} + I_t^{rice} - q_t \times p^c - c_t \times Q^m - p^F \times q_t^F \times S - p^S \times q^S \times S - p^L \times Q_t^{Lext} \quad (2)$$

With , C_t , production costs of year t , R_t , remaining income after basic consumption for each year, I_t^{other} , the income from activities other than rice for year t , I_t^{rice} , the income from the rice cropping activity (i.e., rice sales) for year t , q_t , the quantity of calories provided by staple crops that have to be purchased on the market to achieve food security for year t , p^c , calories price, c_t , the non-staples food and non-food requirements achieved on year t , Q^m , consumption equivalents in the household, p^F , fertilizer price, q_t^F , achieved fertilizer rate on year t , S , rice plot area, p^S , seeds price, q^S , seeds quantity, p^L , daily wage and Q_t^{Lext} , external workforce needed for year t .

As the objective is to maximize the rice producer household consumption in uncertain environment, we use a CRRA (i.e., Constant Relative Risk Aversion) utility function with an individual relative risk aversion coefficient ρ equal to 0.33 (Le Cotty et al. 2017). We suppose that a household has a rational behavior and chooses optimal cropping practices (i.e., fertilizer quantity and rice plot area) by seeking to maximize its expected utility. Finally, the optimization program is:

$$\max_{q^F, S^*} \{EU(W_1, \dots, W_N, a_1, \dots, a_N, q_1, \dots, q_N, c_1, \dots, c_N)\} \quad (3)$$

$$EU(W_1, \dots, W_N, a_1, \dots, a_N, q_1, \dots, q_N, c_1, \dots, c_N) = \frac{1}{N} \sum_1^N U(W_t + (a_t + q_t) \times p^c + c_t, \\ u. c. \{C_t \leq s \times R_{t-1}\}) \quad (4)$$

With q^F *, optimal quantity of fertilizers supplied per hectare, S *, optimal household rice plot surface, N , the number of years on which the optimization is realized, W_t , the household surplus, a_t , the quantity

of rice self-consumed on year t (expressed in kcal), C_t , production costs for each year, s , annual saving rate, constant from year to year and impacting R_{t-1} , the remaining income after basic consumption from each previous year.

We optimize the expected utility over a 20 years time-period. Production functions considering the effects of production and risk factors on yield are used, allowing to represent yield variability due to production risks for this period of time. Moreover, rice prices are modeled as probability distributions to integrate market risks. An optimization procedure will allow us to estimate optimal fertilizers rate q^{F*} and rice plot area S^* .

4.2.2 Parametrization

All parameters are measured from official data, peer-reviewed or gray literature and vary according to areas (at national or regional level) and/or systems (see Supplements section 6.4.1.4 for details).

To simulate production risks in our model, we use climatic stochastic variables. We rely on CHIRPS reanalysis data, aggregated at the administrative level 1, from 2020 to 2020 at $0.05^\circ \times 0.05^\circ$ resolution. We removed from our dataset all grid cells with below 1% of cultivated areas.

4.2.3 Optimization

We use the *nloptr* package in R studio (Ypma 2022) to run the model and determine optimal cropping strategies for each area*system (i.e., 189*4 combinations). As we seek for a global optimum, with one inequality constraint, repeated for 20 years, we use the algorithm “NLOPT_GN_ISRES” that rely on improved stochastic ranking evolution strategy (Runarsson and Yao 2000). We choose “ftol_abs”=1.0e-6” and “maxeval”=160000” as stop conditions.

We determine optimal practices (i.e., fertilizers supply and rice plot area) for each combination area*system*cultivar type.

4.2.4 Expected utility comparison

Then, by comparing expected utility associated with these optimal practices between systems and cultivar types in each area, we can also identify what system*cultivar type is optimal in each context. The context represents the possibility for a rice producer household to substitute a system*type of cultivar by another. This way, it refers to the environment and to the irrigation infrastructure available for the household. We formulate two assumptions to determine the possibilities of system*cultivar type substitution for a household: (i) the environment is not substitutable (i.e., if lowland area is available for a household, upland area is not, and conversely) and (ii) irrigation perimeters are made available by external funders so that the household is not able to construct it on its own. Thus, we can define three

different contexts: (i) lowland without irrigation infrastructure, (ii) lowland with irrigation infrastructure and (iii) upland without irrigation infrastructure.

To evaluate the impact of several factors such as different saving rates or credit access and comparing systems, we run the model for different combinations of parameters. This allows to study the dynamic of the poverty trap in five areas selected among the 189 West African areas: two areas in the Guinean zone (Kindia in Guinea (GN05) and Nassaram in Nigeria (NG26)), one area in the Sudanian zone (Hauts-Bassins in Burkina Faso (BF53)) and two areas in the Sahelian zone (Mopti in Mali (ML05) and Saint-Louis in Senegal (SN10)) (see Figure S4 1 for precise localization).

4.3 RESULTS

4.3.1 Contrasted results of economic context changes between Sahelian and Sudanian regions and Guinean regions

We perform a sensitivity analysis to analysis the effects of different saving and interest rates values on representative household rice producers in the five West African areas (Figure 4.1).

The orders of magnitude of expected utility are very different between Kindia and Nassarawa regions (i.e., over 100) on one side and Hauts-Bassins, Mopti and Saint-Louis on the other side (i.e., below 100). In essence, household's welfare in the two southern regions is higher than that in the three other regions. As the cumulated precipitation and climate risks constitute major differences between these areas, it might explain the observed difference.

We observe that households in the three northern regions (BF53, ML05, and SN10) have no incentive to produce rice using improved cultivars, even with credit access, resulting in an optimal rice plot area of 0. This may be due to the fact that improved cultivars have lower yield compared to traditional ones during extreme climatic events such as droughts. Moreover, in areas with low precipitation, the yield advantage of improved cultivars is small, and if the additional income from improved rice sales is too low, it is not rational for smallholder rice farmers to purchase certified seeds of improved cultivars. The optimal rice plot area for the IRR system also tends to be equal to 0 for improved cultivars in these areas due to the difficulty of purchasing certified seeds on the market after a bad year, either due to low savings or to credit access with no seed costs covered. This could also be due to the higher average rice selling price in Guinea and Nigeria compared to Burkina Faso, Mali, and Senegal (0.48 USD/kg and 0.39 USD/kg compared to 0.25 USD/kg, 0.31 USD/kg and 0.26 USD/kg respectively).

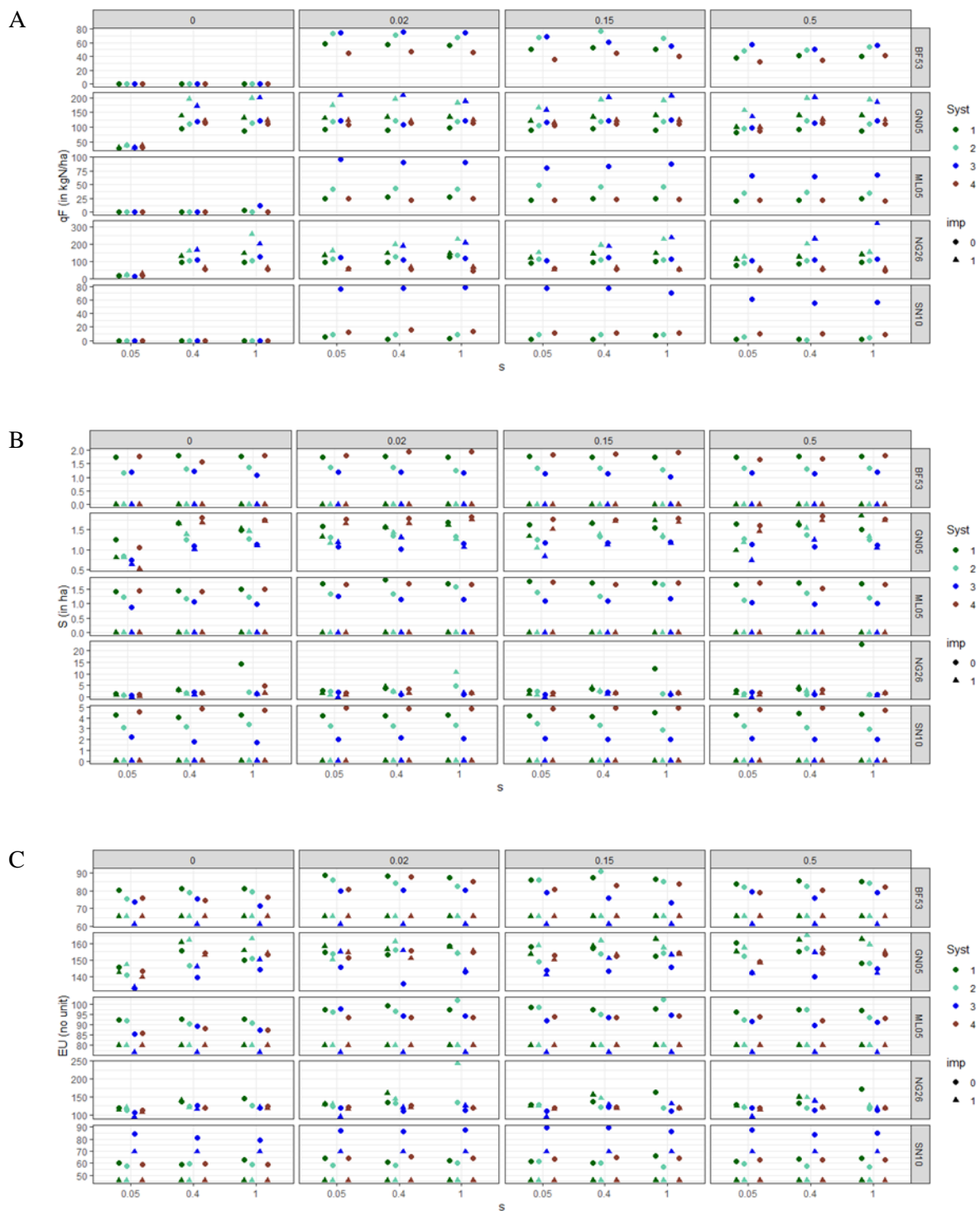


Figure 4.1. Optimal fertilizer supply, expressed in kgN/ha (A), rice plot area, expressed in ha (B) and associated expected utility, with no unit (C) measured with the model in five West African areas: BF53 refers to Hauts-Bassins area in Burkina Faso, GN05 refers to Kindia area in Guinea, ML05 refers to Mopti area in Mali, NG26 refers to Nassarawa area in Nigeria and SN10 refers to Saint-Louis area in Senegal (see Figure S4 1 for precise localization). The horizontal axis of each plot refers to the saving rate values tested (i.e., 0.05, 0.4 and 1). Each grid column refers to the interest rate values tested (0 meaning no access to credit, 0.02, 0.15 and 0.5) and each grid line refers to the area concerned. The dots refer to traditional cultivars use while the triangles refer to improved cultivars use. System 1 (dark green) refers to the LLR system, system 2 (light green) refers to the IMP system, system 3 (blue) refers to the IRR system and system 4 (brown) refers to the ULR system. In the optimal fertilizer quantity grid (i.e., A), points for which the associated optimal area is equal to 0 do not appear. In the

optimal rice plot area and grid (i.e., B), some points do not appear on the graph because they are estimated to 200 ha (i.e., top limit fixed for the optimization). The associated expected utility of these points does not appear either as it is very high (i.e., superior to 1000). The points concerned refer to the NG26 area for saving rate equal to 1.

While an increase in savings rate has no impact on the expected utility of households in the Sahelian and Sudanian regions, credit access improves their expected utility. After the rice growing cycles, incomes are typically low due to low yields, leaving no remaining income to save for the following year. However, with credit access, households can purchase fertilizers even in small quantities to achieve higher average yields. As water availability is limited in these areas, fertilizer rates are kept low. In contrast, in the Kindia and Nassarawa regions, an increased savings rate allows producers to intensify their rice production in areas where water is not limiting. Credit access improves expected utility when the savings rate is too low to purchase optimal fertilizer rates. However, when the savings rate is higher, rice growers have no interest in contracting credit that will have a cost, as their available cash is sufficient to purchase the optimal fertilizer quantity.

4.3.2 The intensification of rice cropping practices is promoted by credit access

The comparison between expected utility associated to optimal cropping practices allow to determine what system*type of cultivar is optimal in each context, at administrative level 1.

Table 4.1. Maximal expected utility and optimal cropping practices associated for each area*context and for two credit access options: without credit access and credit access with interest rate of 0.15. For both, the saving rate is fixed to 0.05. BF53 refers to Hauts-Bassins area in Burkina Faso, GN05 refers to Kindia area in Guinea, ML05 refers to Mopti area in Mali, NG26 refers to Nassarawa area in Nigeria and SN10 refers to Saint-Louis area in Senegal (see Figure S4 1 for precise localization). Dark green text means that, in the context of lowland without irrigation, the LLR system is more optimal compared to the IMP system while light green text means the contrary. Blue text refers to the IRR. Brown text refers to the ULR system. Bold text means that improved cultivars use is optimal when compared with traditional cultivars use. r refers to the interest rate in the case of credit access.

	Context	BF53	GN05	ML05	NG26	SN10
No loan, s = 0,05	Lowland w/o irrigation	EU = 80.4 qF* = 0 S* = 1,74	EU = 147.1 qF* = 39 S* = 0.81	EU = 92.3 qF* = 0 S* = 1.42	EU = 120.8 qF* = 21 S* = 0.75	EU = 60.0 qF* = 0 S* = 4.25
	Lowland w/ irrigation	EU = 73.6 qF* = 0 S* = 1.20	EU = 133.5 qF* = 31 S* = 0.64	EU = 85.3 qF* = 0 S* = 0.89	EU = 107.2 qF* = 12 S* = 0.74	EU = 84.1 qF* = 0 S* = 2.23
	Upland w/o irrigation	EU = 75.9 qF* = 0 S* = 1.77	EU = 143.4 qF* = 32 S* = 1.05	EU = 86.0 qF* = 0 S* = 1.46	EU = 113.3 qF* = 17 S* = 0.88	EU = 58.9 qF* = 0 S* = 4.56
r = 0,15, s = 0,05	Lowland w/o irrigation	EU = 86.2 qF* = 68 S* = 1.33	EU = 158.7 qF* = 166 S* = 1.05	EU = 98.4 qF* = 22 S* = 1.78	EU = 128.1 qF* = 87 S* = 2.76	EU = 61.3 qF* = 9 S* = 3.43
	Lowland w/ irrigation	EU = 79.3 qF* = 69 S* = 1.14	EU = 143.5 qF* = 116 S* = 1.17	EU = 92.2 qF* = 81 S* = 1.10	EU = 110.8 qF* = 103 S* = 1.00	EU = 89.5 qF* = 77 S* = 2.09

Upland w/o irrigation	EU = 80.6 qF* = 36 S* = 1,85	EU = 153.0 qF* = 105 S* = 1.76	EU = 93.8 qF* = 23 S* = 1.73	EU = 119.5 qF* = 59 S* = 1.55	EU = 63.4 qF* = 12 S* = 4.82
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Table 4.1 shows that, with credit access and interest rate equal to 15%, rice producer households tend to have a higher expected utility than without credit access. With credit, they are able to purchase more fertilizers and/or expand their area, especially in Kindia and in Nassawara. The IRR system is associated with lower expected utility except in Saint-Louis region in Senegal. This could be related to the more important needs of workforce in the IRR systems that limit area expansion and, thus, the potential incomes earned from the rice activity. In the Senegal region, as households are bigger, they have more available family workforce (i.e., 4.7 men equivalent compared to 2.6 in BF53, 2.7 in GN05, 2.5 in ML05 and 2.4 in NG26) and they can expand the rice cropping area without being constrained by cash availability. Moreover, optimal fertilizers supply rate and rice plot area tend to be lower in the upland context while they tend to be higher in the lowland with irrigation context. In ULR systems, yields are more prone to be limited by a lack of water so that a high fertilizer supply rate would be useless. Overall, expansion seems to be the option preferred by household rice producers in areas where conditions are not advantageous to intensification (i.e., in the Sudanian and Sahelian zones). This means that the opportunity cost of the family workforce working on the rice activity is higher than working on other farm or off-farm activities.

Improved cultivars use seems to be preferred only in the Guinean regions for lowland systems. This can be explained by the higher average rice selling price in this region in comparison with that in the four other regions. Indeed, it allows higher incomes from rice production sales and thus to cover the production costs induced by certified seeds purchase. Moreover, fertilizers rates measured here are low and do not allow improved cultivars to achieve significant superior yields than traditional cultivars which are more resistant to drought and flooding events. Furthermore, as a loan cannot be used to purchase certified seeds on the market, in the model, credit access does not lead to a bigger use of improved cultivars.

4.3.3 Poverty trap translates into household food insecurity

Households adapt their strategies to risks and constraints they are facing while aiming to at least be food secure, to achieve the poverty threshold and if possible, to release a surplus. However, because of these risks and constraints they can be locked into a poverty situation that cannot be improved. This phenomenon is defined by Azariadis and Stachurski (2004, p.33) as “any self-reinforcing mechanism which causes poverty to persist”.

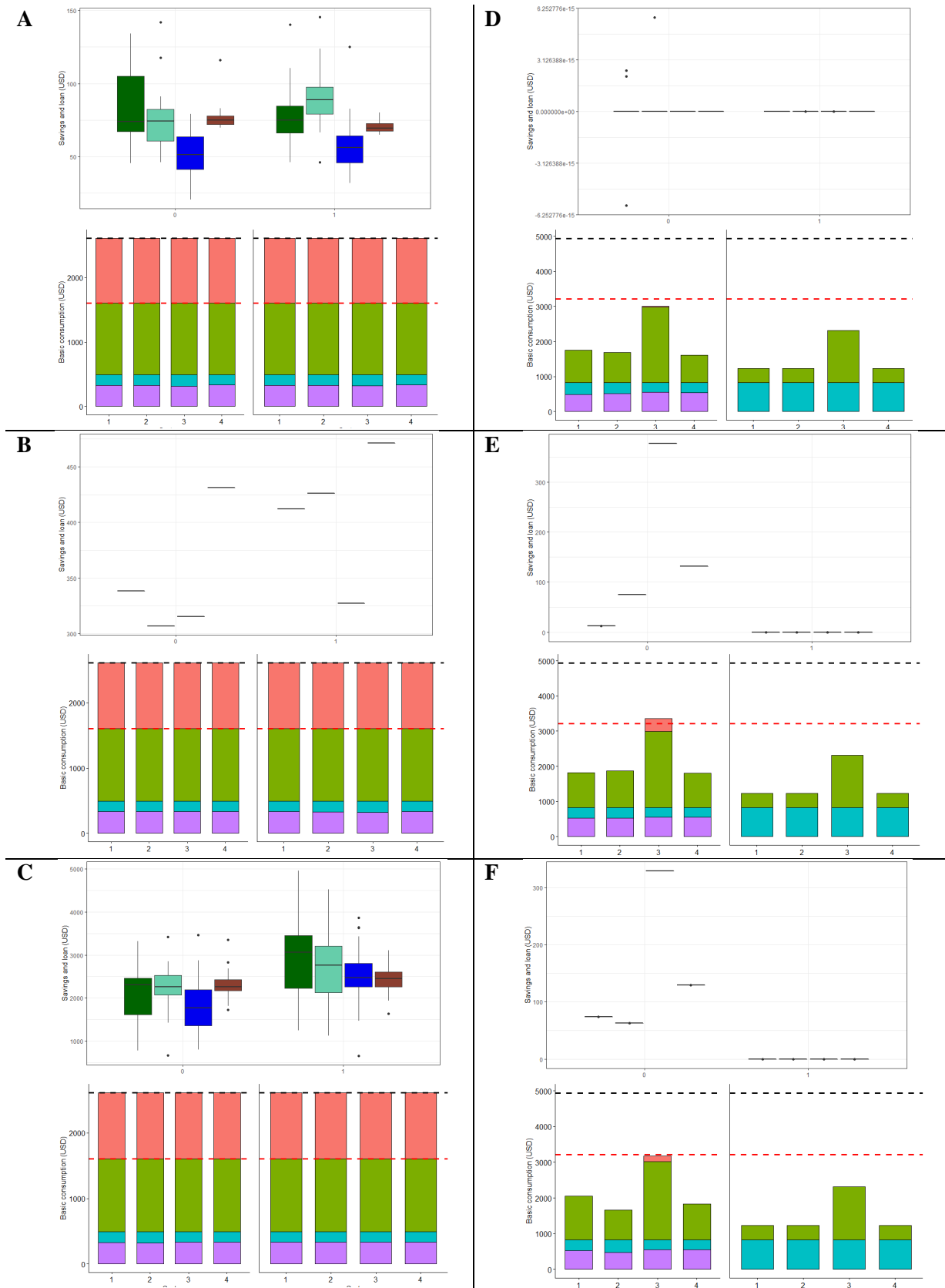


Figure 4.2. 20 years distributions of available cash (i.e., savings and credit) and mean basic consumption composition on the 20 years' time-period for GN05, $s=0.05$, no loan (A), GN05, $s=0.05$, $r=0.15$ (B), GN05, $s=1$, $r=0.15$ (C), SN10, $s=0.05$, no loan (D), SN10, $s=0.05$, $r=0.15$ (E) and SN10, $s=1$, $r=0.15$ (F). Syst 1 refers to the LLR system, Syst 2 refers to the IMP system, Syst 3 refers to the IRR system and Syst 4 refers to the ULR system. The left part of each graph concerns traditional cultivars while the right part refers to improved cultivars. On the

basic consumption graphs, purple area refers to the mean self-consumed rice into the household (valued at staples calories price), blue area refers to the other staple's calories purchased on the market, green area refers to non-staple calories needed to achieve the food security threshold, pink area refers to non-food consumptions needed to achieve the poverty threshold. Dotted red line represents the food security threshold for the whole household and the dotted black line represents the poverty threshold.

On Figure 4.2, we can see that households in the Saint-Louis region cannot achieve food security threshold, on average over years when there is no access to credit as they have no savings. With credit access, they have access to available cash at the beginning of the rice growing cycle to purchase fertilizers on the market. However, here, except for the IRR system, we cannot observe a significant increase of the average food and non-food consumption. The reason is that the credit is used to purchase a low amount of fertilizers (5 kg in total in the LRR system, 32 kg for the IMP system and 24 kg for the ULR system against 162 kg for the IRR system). Indeed, as available water is scarce, the use of higher amounts of fertilizers would not be efficient to improve yields in systems relying on rainfalls. The saving rate, equal to 1, barely changes the average food and non-food consumption in the LLR, IMP and ULR systems as, because of low yields, incomes from rice sales are too low to cover basic requirements and to be saved for the following year. We can notice that households do not seem to have any interest in cultivating improved cultivars in this region, even in the IRR system. Food and non-food consumptions are possible, although in lower quantity than with traditional cultivars cropping, thanks to household other agricultural or off-farm activities' incomes.

On the contrary, in the Kindia region, environmental and economic conditions allow households to achieve the poverty threshold and to be food secure. With no credit access and low saving rate, incomes from rice activity and from other agricultural or off-farm activities allow to answer basic needs and to release a surplus that would be saved for the following year. The high average rice selling price and the favorable precipitation conditions may explain this situation.

Overall, local conditions that impact yields and market flows determine whether representative households are trapped in poverty, despite applying optimal cropping practices. In poverty trap situations, households cultivate rice with no external costs (i.e., no inputs), which hinders the use of improved cultivars that must be purchased on the market. Additionally, due to cash availability constraints, they can only rely on their own workforce. Depending on environmental conditions (e.g., climate, pest and disease occurrences), this low input cropping system might result in very low yields and even crop failure. As a result, smallholders' rice sales are insufficient to cover basic household requirements and do not release a surplus to purchase inputs for the following cropping cycle. From one year to the next, negative feedback prevents households from becoming wealthier. For poor households, the increase of savings rates does not improve their situation as they do not have any income remaining from one year to another. On the other hand, the increase of saving rates allows smallholders who release a surplus to increase their production by using more inputs at fixed areas (i.e., intensification) and/or by

relying on external workforce to increase their rice plot area (i.e., expansion). For households trapped in poverty, the self-consumed calories are insufficient to meet their food needs. Depending on local prices (of fertilizers, seeds, labor, and rice) and climate, representative households can become locked into poverty traps, resulting in food insecurity.

4.4 DISCUSSION AND CONCLUSION

Our results indicate that the poverty trap situation affects the preferences of smallholder rice farmers to either intensify or expand their production (see Table 4.1). When smallholder rice farmers are caught in the poverty trap, they are unable to increase their production through intensification, and they can only expand their rice plot area until the family's workforce capacity is used up. Increasing the saving rates of poor households does not allow them to escape from the poverty trap (see Figure 4.1).

However, with access to credit, they can purchase fertilizers and expect higher yields, which would at least enable them to meet their basic requirements, thus improving their food security (see Figure 4.2). For smallholder rice farmers who are not trapped in poverty, a higher supply rate of fertilizers tends to be preferred (see Table 4.1). Consistent with Donovan et al. (1999), we find that the fertilizer supply rate in the IRR systems in the Sahelian and Sudanian regions, without credit access, is lower than the recommended level of 120 kgN/ha. Credit access leads to higher fertilizer supply rates, as also confirmed by Donovan et al. (1999).

Our model explicitly considers the interactions between agronomic phenomena, whose effects vary according to cropping practices, and economic considerations that limit household choices. By doing so, we are able to analyze how these interactions affect household welfare, and thus understand the adoption of cropping strategies by smallholder rice farmers. Our results capture the behavior of rice farmers with respect to production and market risks. While most economic analyses rely on a one-year time frame to measure profitability (Donovan et al., 1999; Arouna et al., 2017), our model details the impacts of yield and price variability on rice cropping practices chosen by producers.

The reliability of our results depends on the household model construction choices and parameterization methodology. The choices made during these two steps need to be examined. Several mechanisms are not explicitly represented, and assumptions are made to build a model that is generalizable to the entire West African region. For instance, the fallow period, which is a common agricultural practice in West African rice-based systems, particularly in the ULR system (Becker and Johnson, 1998), is not represented in the 20-year time frame used during the model optimization process. However, representing it in the model would have been difficult, as it depends on complex mechanisms such as demographic pressure, trade-offs between potential gains from fallow initiation (i.e., weed biomass

decrease and soil fertility increase with legumes fallow (Akanvou et al. 2000), and revenue shortfall during the fallow period. We also chose to represent only a single rice cropping, as this is the most common in West Africa (Laborte et al. 2017). Although irrigated perimeters (e.g., in the Senegal River Valley in Mauritania and Senegal, in the Office du Niger in Mali) can accommodate double rice cropping due to their independence from precipitation regimes, this is not the case for the largest part of the region (Becker et al. 2003). Furthermore, in our model, we do not account for land pressure as we consider land use to be free and assume no decreasing relationship between area and yields (i.e., best plots are used first). However, the availability of limited family workforce and external workforce costs constrain optimal areas measured. We chose not to explicitly represent the substitution between workforce, animal traction, and mechanization. By doing so, we formulate the hypothesis that if a smallholder rice farm uses animal traction or mechanization, the opportunity cost of this choice is equal to that of family or external workforce. This modeling choice does not allow us to consider the risk of workforce scarcity, which is complex to estimate since we do not have time-series of wages at the administrative level 1. Additionally, for credit access impact analysis on optimal strategy, we assume that the household prioritizes its staple food requirements (i.e., through rice self-consumption and/or rice sales) for the reimbursement of its credit and interests. This hypothesis may limit our model as millers, who are most often the creditors, can seize a part of the harvest to reimburse themselves in practice. However, it allows us to avoid simulating household starvation. Moreover, we simulate the possibility for households to contract credit only to purchase fertilizers. This implies that other inputs, such as external workforce, pesticides, or certified seeds, cannot be purchased with credit.

Parameter estimations rely on peer-reviewed or grey literature, and some methods used can be investigated here. For several parameters (i.e., rice and fertilizer prices, calorie prices, and non-food requirements), due to data scarcity, we have to extrapolate from available data. Furthermore, to simulate yield variability caused by risks other than climatic risks, we use yield distributions collected during an expert's probabilistic elicitation campaign (see Supplements section 6.4.1.2 for details). These distributions simultaneously combine spatial (at administrative 1 level) and temporal yield variability for each area*system. Thus, our model might tend to overestimate yield variability in some cases as it is not possible to separate temporal and spatial variabilities from these yield distributions. However, we are able to use either yield variability due to climate variability or yield variability measured from these distributions and compare results. To measure incomes earned from household's activities other than rice cropping, we chose to simulate a potential best-paid activity in the form of an intensive rice-based cropping system. Other activities could be better paid, but data about wages in West Africa are hard to collect since most of the jobs in agriculture are undeclared. By using only rice growing opportunities, we miss other potential opportunities. The advantage of this choice is that a bias in opportunities, in particular agricultural production opportunities, is avoided, as the opportunities correlate with good cropping conditions, both in terms of climate and availability of water management infrastructures.

Overall, our results show that the local environmental and economic context might impede smallholder rice farmers from increasing their rice production, while it would benefit their food security. Economic incentives, such as credit access, can encourage intensification and/or expansion, depending on the area. This study advocates for the consideration of household's risk perceptions and vulnerability in the implementation of programs to increase West African local rice production.

CHAPTER 5

5 GENERAL CONCLUSION

5.1 GENERAL OBJECTIVE OF THE THESIS

Rural households aim to secure their livelihood and ensure food security by producing enough calories for both self-consumption and market sales. Improving productivity gains in production factors, such as labor, land, and capital, can improve their livelihoods by increasing production (Ken E. Giller et al. 2021). However, rice production is subject to numerous risks, such as climatic variability, pest infestation, and price volatility, leading to reduced harvests and income losses (Hardaker et al. 2004, Lecoq 1998, Serpantié et al. 2020, Sultan et al. 2020). Input use increase can lead to households' income improvement as yields and thus, production is enhanced (Senthilkumar 2022). Nevertheless, constraints such as low selling prices and limited access to credit weigh on rice-growing households, hindering both income increase and risk adaptation strategies (e.g., fertilizer additions, improved cultivars use, perimeter development for better water management) (Wailes et al. 2015, Seydou et al. 2014, Ken E. Giller et al. 2021). While intensive agricultural practices may reduce production risks like droughts, floods, pests, and diseases, they can also lead to dependency on the fertilizer and rice markets (Douxchamps et al. 2016). This is because higher production costs must be covered by selling a portion of the output. Thus, it is important to consider the trade-offs of adopting such practices, as they may have both positive and negative consequences for farmers but also for the environment. Allocating more land to rice cultivation, particularly in lowland areas, can increase local supply (Lançon and Erenstein 2002). This requires less investment in environments where rainfall is sufficient and the risk of drought and flooding is low. However, the development of rice cropping in inland valleys, or the increase in rice areas in the Sahelian zone, may require the implementation of water control measures to reduce the risks of flooding and drought (e.g., dykes, drainage and irrigation canals, upstream water retention basins).

The objective of this thesis is to examine the influence of risks and constraints on rice production and on the strategies adopted by rice farmers. Specifically, my thesis seeks to answer the following research question: To what extent do risks and constraints affecting rice production impact production stability, households' cropping strategies, welfare and food security?

A multidisciplinary approach integrating agronomy and economics was adopted. Firstly, a global agronomy approach was used to carry out a statistical analysis that compared rice yields with those of five staple crops in West Africa, namely cassava, maize, millet, sorghum, and yam. Secondly, rice production functions were developed, based on the agronomic literature and on the results of probabilistic expert elicitation, to quantify the contributions of production factors and risks to yield

levels and variability. Finally, a bioeconomic model was developed to examine the cropping strategies of rice farmers while taking into account the risks and constraints they face.

5.2 MAIN FINDINGS

The primary contribution of this thesis is the connection it establishes between the agronomic mechanisms that affect rice production and the economic context that influence the rice farmers' decisions. By taking into account the risks that impact production, the study provides insight into the strategies employed by households engaged in rice production.

The first part of my dissertation focuses on the challenges associated with increasing rice cultivation areas, which often involves reducing the land and labor allocated to other essential crops. The hypothesis underlying this research is that alternative and traditionally cultivated staple crops such as cassava, maize, millet, sorghum, and yam may have a more stable yield than rice in West Africa. The results of this study demonstrated that, on average, rice yields are significantly less stable than yields of these alternative crops in about 33% of Administrative Level 1 regions in West Africa. Conversely, rice yields are more stable than yields of other crops in 15% of the comparisons. This research also revealed that rice tends to have more variable yields (by approximately 15-30%) than other crops in regions where these are traditionally grown. For instance, in the Guinean zone, tubers such as cassava and yams have more stable yields compared to rice. On the other hand, in the Sahelian and Sudanian zones, sorghum and millet yields tend to be less variable than rice. Furthermore, the study found that interannual and intraseasonal rainfall variability accounts for up to 17% of the variation in yield variability between rice and the other five crops. Rice yields, regardless of the cropping system, are typically more variable than those of other crops in areas with the highest rainfall variability. Therefore, increasing rice cultivation at the expense of other crops poses a risk to both regional food security and the stability of rice-producing households, given the variable nature of rice production. These findings highlight the importance of considering yield stability in scenarios that involve expanding rice cultivation and developing food supply strategies.

My second objective was to investigate the effects of production factors and risks on average yields and yield variability, based on representative rice-growing systems. The underlying hypothesis was that the impact of production factors and climatic risks can vary depending on the rice-growing system and on the location. By examining the contributions of these factors to yields, this hypothesis was partially confirmed. The model's analysis of variance showed that in the Guinean and Sudanian zones, where water scarcity and drought risks are less prevalent, the frequency of weeding has the most significant impact on average yields. However, in the Sahelian zone, rainfall's spatial and temporal variability accounted for approximately 50% of the variance in yield. Additionally, the use of fertilizers and

pesticides, along with controlled water management, increased average yields significantly. Nevertheless, the adoption of these intensive practices did not result in yield stabilization. Furthermore, using improved varieties was associated with increased spatial and temporal variability in yields. However, these results must be approached with caution since rice farmers' adoption of such farming practices is dependent on local factors such as market and production risks and constraints.

In the third part of my dissertation, I investigated the impact of agricultural risks and constraints on the cropping strategies adopted by rice-producing households. The underlying hypothesis was that, due to the risks they face and their limited resources (i.e., land, labor, and capital), rice farmers may not have a strong economic incentive to invest in intensive practices. The results of this analysis partially confirm this hypothesis, as it demonstrates that the economic situation of households influences their decision to invest in rice farming. Specifically, households that are trapped in poverty lack the necessary capital to invest in inputs, unlike those that have been able to generate a surplus and save part of their income. This poverty trap is strongly correlated with the climatic context, as regions with scarce water and a high risk of drought (i.e., the Sahelian and Sudanian zones) have low yields, and water is often the limiting factor, rendering the addition of fertilizer economically insignificant. Moreover, the poverty trap and household food security are closely interconnected, as households unable to achieve high production and to generate sufficient income are also unable to purchase the necessary calories to meet their food security requirements.

In conclusion, the findings from my thesis shed light on the challenges faced by rice-growing households in accessing resources and mitigating risks. The expansion of rice area can destabilize household livelihoods by diverting resources from other staple crops. Intensification practices can make producers vulnerable to market risks, leading to debt and financial instability. However, the use of inputs can be beneficial in areas with abundant rainfall and/or in irrigated systems. The economic situation of rice-farming households is closely tied to the local economic and environmental context. Access to credit and irrigation infrastructure can help households escape the poverty trap and improve their food security through increased production, where there is sufficient rainfall. Encouraging a higher savings rate may also incentivize households to invest in production. Overall, these findings emphasize the need to consider local contexts, risks and constraints when designing agricultural policies and strategies to ensure sustainable food production and secure livelihoods for rice farmers.

5.3 LIMITS AND RESEARCH PERSPECTIVES

I have chosen to discuss three broad topics at the end of this thesis. The first one is related to the analysis framework adopted. The second one pertains to the method selected to address my research question and the third one is related to the type of data used throughout my thesis.

To answer my research question, I chose to work on a large scale (i.e., across West Africa), at a relatively broad level of study (i.e., administrative level 1) in order to be able to compare households' cropping strategies and rice production levels and variability over the whole area while aiming at capturing the diversity of rice production systems, environments and economic contexts in West Africa. While, in the first part of the thesis, I compared rice yield variability with that of the five other major staples of the region, only rice is studied in the two other parts of the thesis. An alternative approach could have consisted in building production functions for other crops and implementing them into the microeconomic model. The first reason for this choice is that data collection to parametrize both models is time consuming because of the fragmented nature of available data on yields and cropping practices. The second reason being that the aim of the households' cropping strategies study was to analyze the factors that determine resources allocation toward rice producing activities and not to quantify the households' resources distribution among the different cropping activities. However, the explicit representation of additional crops could constitute an improvement of the microeconomic model. For instance, it would allow to analyze households' strategies to allocate more resources for one crop instead of another one when considering risks and constraints differently affecting these crops.

Throughout this thesis, I have focused on studying rice production and risks in West Africa through modeling, rather than, for example, conducting interviews with rice growers in a limited number of representative areas. In the first part of my thesis, I relied on statistical modeling to study the impact of rainfall levels and variability on rice yield relative stability. This method allows to determine the localizations where rice yields tend to be more variable than other crops and to quantify the effect of precipitation characteristics on these yield variability differences. The modeling approach selected in the second and third part of my thesis is functional (i.e., use of simplified equations to describe phenomena of interest) and require less input data than crop models (i.e., representation of a larger number of fundamental mechanisms) (Addiscott and Wagenet 1985). The advantage of this approach is that I was able to compare the impacts of the represented mechanisms across different areas based on a relatively small number of equations and parameters. Moreover, with this approach, I was able to integrate the rice production functions built throughout the second part into the microeconomic models and thus consider more precisely how agronomic mechanisms can intervene in rice producing households' decision process. One salient limit is the difficulty to include many factors, missing some that could have a significant impact on production and on household welfare in certain areas (e.g., land pressure, temperature, soils characteristics, local geopolitical context). For instance, I chose to not represent temperature impact on yield whereas it has been found to have a significant effect on yield, at global scale (Zhao et al. 2016). However, rice is tolerant to high temperatures (its optimal range of temperature being 25-35°C (Chaudhari et al. 2003)) so yield loss due to high temperature is rarely an issue in West Africa. It is important to note that due to the large number of hypotheses required to build the agronomic and economic models, the results of this thesis should be interpreted with caution as

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quantitative descriptions meant to understand the processes rather than predictive quantitative facts. Nevertheless, this method consists in a trade-off between complexity (i.e., number of mechanisms represented) and added uncertainty (i.e., imprecision in the representation of complex mechanisms) and, hence, allows for a comprehensive analysis of the problem at hand.

Interesting improvement perhaps lies in the combination of the models built during this thesis with models focusing on the representation of specific mechanisms. For instance, the production functions could be pooled with local hydrology models, parametrized for representative lowlands of West African climatic zones and aquifer types. Indeed, the effect of extreme climatic events is represented in a simple way in the production functions based on simple indicators and parameterizations to take into account the effect of different systems in the entire West African region. Using a more precise modeling of lowlands hydrological functioning would allow to represent more finely the spatial and interannual variability of climatic mechanisms. Another example could be to explicitly integrate other on-farm (e.g., livestock farming) and off-farm activities in the microeconomic model to determine the distribution of resources among all the household activities. However, similarly to the implementation of other cropping practices mentioned above, needed data to parametrize the model could be difficult to find. Moreover, conceptualization effort should be necessary to consider activities generating incomes on different time frames (e.g., livestock on several years versus punctual paid employment for several weeks).

The method presented here and the study scale did constrain the data needed to parametrize the models. Here, I relied on data covering the entire West African area while providing an overview of the diversity of cropping systems, environmental and economic contexts. The availability and the reliability of homogenous data about rice areas and yields according to cropping systems and about cropping practices (e.g., fertilizers use, weeding frequency, type of seeds use) have been a very important concern throughout this thesis. Although various sources can provide this information, it is still fragmented and disparate. Hence, I collected available data among these sources, merged it and cross-referenced it to be able to use it in the models. Here is a brief overview of the diversity of data available, and partially used throughout this thesis:

- Official production, areas and yield data at various levels and precision degree: (i) national (FAOSTAT, USDA), (ii) subnational (FAOCountrySTAT, AgroMAPS), (iii) subnational with cropping system differentiation (e.g., Statistiques de la Production du Riz pluvial et Irrigué au Burkina Faso de 1993 à 2003, Ministère de l'Agriculture, de l'Hydraulique et des Ressources Halieutiques).
- Simulated gridded data from models: (i) irrigated areas (GAEZv3.0, MIRCA2000, SPAM2000), (ii) historical yields simulated through a hybridization of agricultural census

statistics and satellite remote sensing (GHDY), (iii) simulated yields via crop models (ORYZA, CERES-Rice, SARRA-H, EPIC). It should be noticed that this last category of data has not been used during this thesis as the crop models mentioned are not parameterized, yet, and thus not usable either for the whole West African region (CERES-Rice, EPIC), for all cropping systems (SARRA-H) or for various cropping practices (ORYZA).

- Field data published in agronomic articles, allowing to link yields with cropping practices at local scale (e.g., Touré et al. 2009, Becker and Johnson 2001, Saito et al. 2012, Ekeleme et al. 2009)
- Survey data also allowing to study the impact of cropping practices on yields at large scale (LSMS-ISA, World Bank)

To complete existing data, I performed probabilistic expert elicitation that consists of the association of a probability to the range of values that can be taken by a variable of interest by a panel of experts, based on their own knowledge (European Food Safety Authority 2014). This elicitation has allowed to describe the relation between yield distributions, according to cropping systems, at regional level (i.e., administrative level 1) and cropping practices (i.e., fertilizers, pesticides and seeds type use) (see published dataset at <https://doi.org/10.18167/DVN1/44ZJEV>). Moreover, I collected economic and social data (e.g., prices data, households' composition) among various secondary sources. To parameterize the two models developed, I collected data from secondary sources such as reviewed and grey literature, official databases, and expert's probabilistic elicitation, instead of collecting data in the field. This was a necessary compromise, as it was not feasible to collect data for the entire West Africa. This approach allowed me to draw from a variety of data sources and provide a more comprehensive analysis while overcoming the issue of data scarcity. However, it could be possible to realize local surveys to collect data as inputs for both the agronomic and the economic models and, thus, study households' cropping strategies more finely. Moreover, these surveys could allow to evaluate the consistency of the model with declared households' strategies, at local scale.

5.4 POLITICAL IMPLICATIONS

In the current context, rice production enhancement is hampered by risks and constraints faced by rice-producing households. Major risks and constraints affecting rice production are different according to the localization, and in particular to the latitude. In northern areas, where water is scarce, the lack of water tends to be the major constraint to rice cropping in rainfed or improved lowland systems. On the contrary, in the Guinean zone, the insufficient quantity of nutrients is the limiting factor and the available cash, and thus the lack of credit access, to purchase fertilizers is the major constraint. In the intersection zone, risks tend to be more determinant in the rice producing households' decision process as the occurrence probability of bad years, leading to important yield loss, can deter rice producers from

investing in their rice cropping activity. Therefore, initiatives should focus on measures to facilitate rice production, such as subsidies for fertilizers or cultivars, and irrigation projects, set according to the localization.

Moreover, our results show that rice price is a determinant factor for rice producers' expected incomes. Measures to upgrade the rice value chain with the objective of making local rice competitive with imported rice in terms of quality should be implemented so that the producer's price would be higher. This result is supported by studies measuring the interest in enhancing West African food security through rice self-sufficiency and concluding that demand-pull factors (e.g., contract farming development, quality labels implementation) need to be implemented to encourage and support rice producers in enhancing their production (Wailes et al. 2015; Arouna et al. 2021). Wailes et al. (2015) conducted a global rice market analysis to evaluate the impact of Regional and National Rice Development Strategies. The main conclusion of this study is that if local rice is not competitive with imported rice, the enhancement of local production would not be profitable for producers, as prices would be too low.

However, our results show that rice self-sufficiency might not be an efficient way to achieve food security in West Africa, as production can vary greatly according to climatic conditions. Haggblade et al. (2017) found that, in the absence of trade, a decrease of 20% in domestic rainfed cereal production induced by a drought would reduce the calorie consumption of rural poor households by 15% in Sahelian West Africa. In addition to production enhancement, stockpiling and diversification of staple origins would allow for the buffering of local production shocks. Furthermore, changes in diets towards traditional and robust staples, such as tubers, would improve food security in the region (Haggblade et al. 2017).

Moreover, a major concern is the sustainability of production, which must be respectful of the environment and safeguard resources, especially as available water may become a greater concern in the context of climate change, to avoid the impoverishment of households due to resource degradation (Ruijis and Dellink 2007).

SUPPLEMENTS

6 SUPPLEMENTS

6.1 SUPPLEMENTS GENERAL INTRODUCTION

6.1.1 Rice cropping system classification

West African rice cropping systems are very diversified due to the large range of landscapes and available water challenges covered by the region (Lançon and Erenstein 2002). These rice cropping systems are defined according to two indicators:

- Topography (*e.g.*, plateaus, valley bottoms, alluvial plains)
- Water management level (*e.g.*, absent, partial, total)

Topographic sequences can be separated into two major categories, according to altitude and thus, to differentiated soil typologies: lowlands and uplands. Upland areas are characterized by dry soil, well drained, only receiving water from the rain while lowland areas are wet, hydromorphic soils.

Raunet (1985) defines lowland in intertropical region, as flat or concave bottoms of small valleys and flood-prone water flow gutters (Raunet 1985). Their soils are clogged or submerged for a more or less long period of time during the year by a water layer created by the outcrop of groundwater or by run-off. They are different of the large alluvial plains according to several criteria:

- Watershed size (from 10 to 200km²)
- Notable width
- Weak longitudinal slope (< 3%)
- The clogging or submersion for a period of the year (Albergel and Claude 1994)

Due to its important water needs, rice yields are known to be sensitive to water stress (Davis et al. 2019). The average annual precipitation gradient is very wide according to the latitude: from a mean annual precipitation of 200mm at the North, in the Sahelian region, to more than 1200mm per year at the South, in the Guinean region (Sigaud and Eyog-Matig 2001). Furthermore, the characteristics of the West African monsoon is a key determinant of precipitation levels, generating high variability from intra-seasonal to multi-decadal time scales (Sylla et al. 2010; Sultan et al. 2003), with impacts on rainfed crops, including rice (Diagne et al. 2013). To adapt to these different and variable water resource conditions, rice producers use diverse water management systems. Water management equipment's allow to (i) compensate a lack of water by irrigating and/or by retaining a water blade in the paddy fields

or to (ii) eliminate water surplus by drainage. The use of these equipments defines different levels of water management:

- Absent, no water management equipment
- Partial, at least bunds are built around fields, sometimes completed by drain canals
- Total, retention basins and irrigation canals are built upstream to flood fields, when necessary, at the different rice growing steps

The rice cropping system definitions are quite difficult to precise as they can differ according to the region, to the authors and to the language they use.

In South-East Asia, for example, the system called ‘rainfed rice’ (*i.e.*, rice cultivated on terraces) use very similar agricultural practices as in the west African irrigated rice. Rice producers level and built bunds to flood their fields.

For exemple, the expressions ‘riz de coteaux’, ‘riz de plateau’ and ‘riz de montagne’ differ from one to another but they all refer to upland rice in English. Lowland rice in English refers to ‘bas-fonds’ and ‘plaines’ in French whereas the exact translation in French is ‘plaine’.

Table S1 1. Non-exhaustive overview of the panel of rice systems classification as defined by different authors.

Source	Classification based on	Classification
(Windmeijer et al. 1994)	Topography	<ul style="list-style-type: none"> - Rainfed upland rice on plateaus and hydromorphic slopes - Lowland rainfed rice in valley bottoms and floodplains - Irrigated rice in deltas and floodplains - Deep-water floating rice along major rivers - Mangrove swamp rice in lagoons and deltas
(Lançon F. and Erenstein O. 2002)	Topography x water management	<ul style="list-style-type: none"> - Rainfed upland rice on plateaus and slopes of undulated areas - Lowland rainfed rice on valley bottoms and flat plains without water control - Irrigated rice, typically in lowlands with water control - Deep-water, floating rice on flooded river beds or river banks - Mangrove swamp rice in intermittently flooded river deltas and lagoons in coastal areas
(Bezançon 1995)	Water provenance	<ul style="list-style-type: none"> - Water from rain only (i.e., upland rice) - Water from hydromorphic soils (groundwater and run-off) (i.e., lowland rice) - Water from rain, soil and permanent surface water (e.g., rivers): flooded rice cropping (i.e., managed irrigation, non-managed irrigation, mangrove swamp, floated rice)
(Bezançon 1995)	Water management	<ul style="list-style-type: none"> - Water management absent or incomplete for flooding rice (i.e., floating rice, alluvial plain rice, mangrove swamp) - Total water management (i.e., irrigation) - Strictly rainfed (i.e., rainfed upland) - Of flood recession
(Ministère de l'Agriculture, République de Guinée 2012)	Topography x water management	<ul style="list-style-type: none"> - Mangrove swamp - Irrigated lowland - Non-irrigated lowland - Alluvial plain - Irrigated plain - Upland

The problem of the definitions given above is that they do not give enough information about the degree of water management and they do not permit be precise enough. The differentiation between the different water management techniques is not realized for valley bottom and for mangrove swamps.

Mangrove rice systems can be open or closed (i.e., without any water management or with water management);

Valley bottoms can be equipped with bunds, drainage canals and or irrigation canals, which does not represent the same level of water management (Becker and Johnson 2001). In Guinea, the National Office of rural engineering has classified the different levels of water management on valley bottoms following this normative system (Neville et al. 1998):

1. Bunds
2. Bunds + drainage canal
3. Bunds + drainage canal + irrigation canal
4. Bunds + drainage canal + irrigation canal + water stockage basin upstream

Thus, we chose a classification of west African rice cropping systems to facilitate our work and to refer to the same definitions all along the study. This classification is mainly theoretical as, in the reality, the frontiers between each class are diffuse.

Table S1 2. Precise classification constructed based on the literature

Environments		Water management		
		Absent	Partially managed	Totally managed
Lowland*	Alluvial plains /estuaries	Floating rice ¹ , open mangrove swamps ¹ , rice flood recession ²³	Closed mangrove swamp ³	Irrigated ¹
	Valley bottom	Rainfed lowland ²³	Equipped lowland (cat 1, 2, 3) ²³	Irrigated lowland (cat 4) ¹
Upland**	Plateaus, hills	Rainfed upland ³		

Type of soil:

*Hydromorphic soils

**Dry soils, well drained

Water provenance:

¹Surface water (rivers, retention basins)

²Groundwater (water table close to the surface)

³Precipitation

During the expert’s probabilistic elicitation, we merge alluvial plains and valley bottom systems per water management levels as all experts do not make a difference between these two topographic landscapes.

Table S1 3. Classification used during the expert's probabilistic elicitation

Environments		Water management		
		Absent	Partially managed	Totally managed
Lowland*	Alluvial plains /estuaries	Non-irrigated plains Open mangrove swamp Rainfed lowland	Closed mangrove swamp Improved lowland	Irrigated
	Valley bottom			
Upland**	Plateaus, hills	Rainfed upland		

We then chose to construct four different production functions associated with representative systems.

Table S1 4. Production functions associated to the different classes

Environments		Water management		
		Absent	Partially managed	Totally managed
Lowland	Alluvial plains /estuaries	yLLR	yIMP	yIRR
	Valley bottom			
Upland	Plateaus, hills	yULR		

6.2 SUPPLEMENTS CHAPTER 2

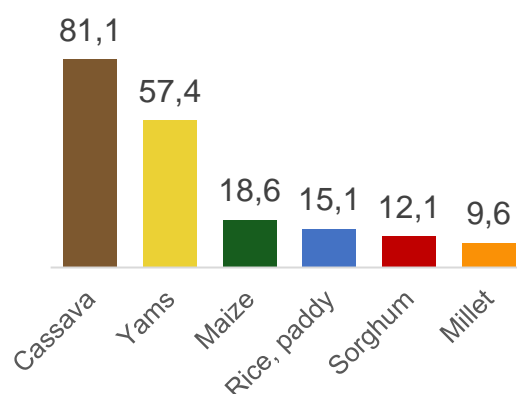


Figure S2 1. Six most important crop species in terms of average production levels for the period 2009-2018 over West Africa. Data extracted from FAOSTAT dataset (in 10⁶ tons fresh weight / year) arranged by descending order.

Table S2 1. Potential yields used in our analysis

Crops	Potential yields	Sources
Rice	18.982 t/ha (Brazil)	Values from the Global Yield Gap Atlas (GYGA) (University of Nebraska and Wageningen University & Research). Note that when possible, we relied on estimates of maximum potential yield for irrigation-based crop systems (i.e., for rice and maize).
Maize	23.44585 t/ha (Iran)	
Millet	9.022093 t/ha (Zambia)	
Sorghum	13.32326 t/ha (Kenya)	
Cassava	80 t/ha (World)	Value based on the grey literature: yield maximum potential according to the FAO (Reddy 2015).
Yams	28,3 t/ha (Colombia)	Value based on the grey literature informing on the most productive yams exploitations in the world: these are located in Colombia (nationwide average annual yield in 2010)

Maximum number of time-series: number of areas (i.e. 201) x number of food items (i.e. 6) = 1206

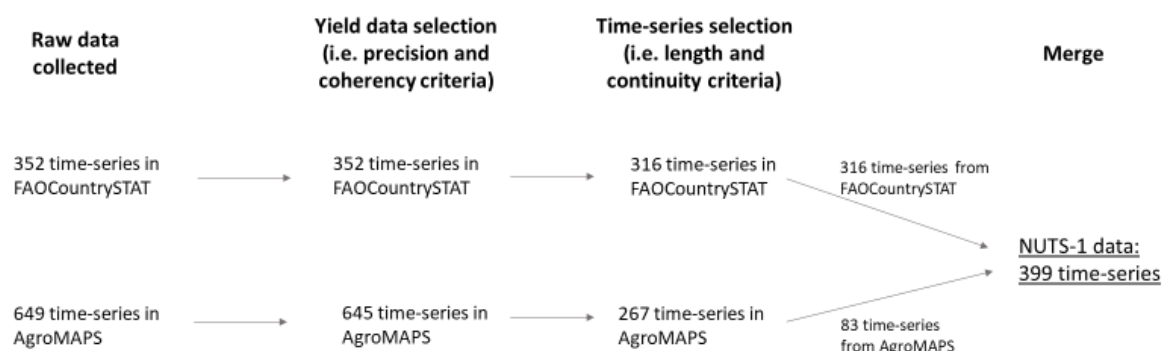


Figure S2 2. Steps from raw data collection to time-series selection

Table S2 2. Selected yield data time-series, years and localization. Name of the region (administrative level 1), crop country, data source and time period (start year, end year and number of years) for each time series included in our study.

Region	Crop	Country	Database	Year_min	Year_max	n_year
Abia	Cassava	Nigeria	FAOCountrySTAT	1995	2012	18
Abia	Maize	Nigeria	FAOCountrySTAT	1995	2012	18
Abia	Rice, paddy	Nigeria	FAOCountrySTAT	1995	2012	18
Abia	Yams	Nigeria	FAOCountrySTAT	1995	2012	17
Adamawa	Cassava	Nigeria	FAOCountrySTAT	1995	2012	18
Adamawa	Maize	Nigeria	FAOCountrySTAT	1995	2012	18
Adamawa	Millet	Nigeria	FAOCountrySTAT	1995	2012	18
Adamawa	Rice, paddy	Nigeria	FAOCountrySTAT	1995	2012	18
Adamawa	Sorghum	Nigeria	FAOCountrySTAT	1995	2012	18
Adamawa	Yams	Nigeria	FAOCountrySTAT	1995	2012	17
Agadez	Maize	Niger	FAOCountrySTAT	2000	2010	11
Agadez	Millet	Niger	FAOCountrySTAT	2000	2011	12
Akwa Ibom	Cassava	Nigeria	FAOCountrySTAT	1995	2012	18
Akwa Ibom	Maize	Nigeria	FAOCountrySTAT	1995	2012	18
Akwa Ibom	Rice, paddy	Nigeria	FAOCountrySTAT	1995	2012	17
Akwa Ibom	Yams	Nigeria	FAOCountrySTAT	1995	2012	18
Anambra	Cassava	Nigeria	FAOCountrySTAT	1995	2012	18
Anambra	Maize	Nigeria	FAOCountrySTAT	1995	2012	18
Anambra	Rice, paddy	Nigeria	FAOCountrySTAT	1995	2012	18
Anambra	Yams	Nigeria	FAOCountrySTAT	1995	2012	18
Ashanti	Cassava	Ghana	FAOCountrySTAT	2000	2011	12
Ashanti	Maize	Ghana	FAOCountrySTAT	2000	2011	12
Ashanti	Rice, paddy	Ghana	FAOCountrySTAT	2000	2011	12
Ashanti	Yams	Ghana	FAOCountrySTAT	2000	2011	12
Bafata	Millet	Guinea-Bissau	FAOCountrySTAT	1988	2010	23
Bafata	Rice, paddy	Guinea-Bissau	AgroMAPS1	1995	2010	13
Bauchi	Cassava	Nigeria	FAOCountrySTAT	1995	2012	18

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Bauchi	Maize	Nigeria	FAOCountrySTAT	1995	2012	18
Bauchi	Millet	Nigeria	FAOCountrySTAT	1995	2012	18
Bauchi	Rice, paddy	Nigeria	FAOCountrySTAT	1995	2012	18
Bauchi	Sorghum	Nigeria	FAOCountrySTAT	1995	2012	18
Bayelsa	Cassava	Nigeria	FAOCountrySTAT	1995	2012	18
Bayelsa	Maize	Nigeria	FAOCountrySTAT	1995	2012	18
Bayelsa	Yams	Nigeria	FAOCountrySTAT	1995	2012	18
Benue	Cassava	Nigeria	FAOCountrySTAT	1995	2012	18
Benue	Maize	Nigeria	FAOCountrySTAT	1995	2012	18
Benue	Millet	Nigeria	FAOCountrySTAT	1995	2012	18
Benue	Rice, paddy	Nigeria	FAOCountrySTAT	1995	2012	18
Benue	Sorghum	Nigeria	FAOCountrySTAT	1995	2012	18
Benue	Yams	Nigeria	FAOCountrySTAT	1995	2012	18
Biombo	Millet	Guinea-Bissau	FAOCountrySTAT	1988	2010	23
Biombo	Rice, paddy	Guinea-Bissau	FAOCountrySTAT	1988	2010	21
Bolama/Bijagos	Rice, paddy	Guinea-Bissau	AgroMAPS1	1995	2010	13
Bolama/Bijagos	Sorghum	Guinea-Bissau	FAOCountrySTAT	1988	2010	23
Bolama/Bijagos	Yams	Guinea-Bissau	FAOCountrySTAT	1988	2010	23
Borno	Maize	Nigeria	FAOCountrySTAT	1995	2012	18
Borno	Millet	Nigeria	FAOCountrySTAT	1995	2012	18
Borno	Rice, paddy	Nigeria	FAOCountrySTAT	1995	2012	18
Borno	Sorghum	Nigeria	FAOCountrySTAT	1995	2012	18
Boucle du Mouhoun	Maize	Burkina Faso	AgroMAPS1	1984	2004	21
Boucle du Mouhoun	Millet	Burkina Faso	AgroMAPS1	1984	2004	21
Boucle du Mouhoun	Rice, paddy	Burkina Faso	AgroMAPS1	1984	2004	21
Boucle du Mouhoun	Sorghum	Burkina Faso	AgroMAPS1	1984	2004	21
Brong Ahafo	Cassava	Ghana	FAOCountrySTAT	2000	2011	12
Brong Ahafo	Maize	Ghana	FAOCountrySTAT	2000	2011	12
Brong Ahafo	Rice, paddy	Ghana	FAOCountrySTAT	2000	2011	12
Brong Ahafo	Yams	Ghana	FAOCountrySTAT	2000	2011	12
Cacheu	Millet	Guinea-Bissau	FAOCountrySTAT	1988	2010	23
Cascades	Maize	Burkina Faso	AgroMAPS1	1984	2004	21
Cascades	Millet	Burkina Faso	AgroMAPS1	1984	2004	21
Cascades	Rice, paddy	Burkina Faso	AgroMAPS1	1984	2004	21
Cascades	Sorghum	Burkina Faso	AgroMAPS1	1984	2004	21
Cascades	Yams	Burkina Faso	AgroMAPS1	1984	2004	19
Central	Cassava	Ghana	FAOCountrySTAT	2000	2011	12
Central	Maize	Ghana	FAOCountrySTAT	2000	2011	12
Central	Rice, paddy	Ghana	FAOCountrySTAT	2002	2011	10
Central	Yams	Ghana	FAOCountrySTAT	2000	2011	12
Centrale	Cassava	Togo	FAOCountrySTAT	2001	2010	10
Centrale	Maize	Togo	FAOCountrySTAT	2001	2010	10
Centrale	Rice, paddy	Togo	FAOCountrySTAT	2001	2010	10

Centrale	Sorghum	Togo	FAOCountrySTAT	2001	2010	10
Centrale	Yams	Togo	FAOCountrySTAT	2001	2010	10
Centre	Maize	Burkina Faso	AgroMAPS1	1984	2004	21
Centre	Millet	Burkina Faso	AgroMAPS1	1984	2004	21
Centre	Sorghum	Burkina Faso	AgroMAPS1	1984	2004	21
Centre-Est	Maize	Burkina Faso	AgroMAPS1	1984	2004	21
Centre-Est	Millet	Burkina Faso	AgroMAPS1	1984	2004	21
Centre-Est	Rice, paddy	Burkina Faso	AgroMAPS1	1984	2004	21
Centre-Est	Sorghum	Burkina Faso	AgroMAPS1	1984	2004	21
Centre-Nord	Maize	Burkina Faso	AgroMAPS1	1984	2004	21
Centre-Nord	Millet	Burkina Faso	AgroMAPS1	1984	2004	21
Centre-Nord	Rice, paddy	Burkina Faso	AgroMAPS1	1984	2004	21
Centre-Nord	Sorghum	Burkina Faso	AgroMAPS1	1984	2004	21
Centre-Ouest	Maize	Burkina Faso	AgroMAPS1	1984	2004	21
Centre-Ouest	Millet	Burkina Faso	AgroMAPS1	1984	2004	21
Centre-Ouest	Rice, paddy	Burkina Faso	AgroMAPS1	1984	2004	21
Centre-Ouest	Sorghum	Burkina Faso	AgroMAPS1	1984	2004	21
Centre-Ouest	Yams	Burkina Faso	AgroMAPS1	1984	2004	19
Centre-Sud	Maize	Burkina Faso	AgroMAPS1	1984	2004	21
Centre-Sud	Millet	Burkina Faso	AgroMAPS1	1984	2004	21
Centre-Sud	Rice, paddy	Burkina Faso	AgroMAPS1	1984	2004	21
Centre-Sud	Sorghum	Burkina Faso	AgroMAPS1	1984	2004	21
Cross River	Cassava	Nigeria	FAOCountrySTAT	1995	2012	18
Cross River	Maize	Nigeria	FAOCountrySTAT	1995	2012	18
Cross River	Rice, paddy	Nigeria	FAOCountrySTAT	1995	2006	12
Cross River	Yams	Nigeria	FAOCountrySTAT	1995	2012	18
Dakar	Millet	Senegal	AgroMAPS1	1990	1999	9
Dakar	Sorghum	Senegal	AgroMAPS1	1991	1999	9
Delta	Cassava	Nigeria	FAOCountrySTAT	1995	2012	18
Delta	Maize	Nigeria	FAOCountrySTAT	1995	2012	18
Delta	Rice, paddy	Nigeria	FAOCountrySTAT	1995	2012	17
Delta	Yams	Nigeria	FAOCountrySTAT	1995	2012	18
Diffa	Millet	Niger	FAOCountrySTAT	2000	2011	12
Diffa	Sorghum	Niger	FAOCountrySTAT	2000	2011	12
Diourbel	Millet	Senegal	AgroMAPS1	1990	1999	9
Diourbel	Sorghum	Senegal	AgroMAPS1	1990	1999	9
Dosso	Maize	Niger	FAOCountrySTAT	2000	2011	12
Dosso	Millet	Niger	FAOCountrySTAT	2000	2011	12
Dosso	Rice, paddy	Niger	FAOCountrySTAT	2000	2011	12
Dosso	Sorghum	Niger	FAOCountrySTAT	2000	2011	12
Eastern	Cassava	Ghana	FAOCountrySTAT	2000	2011	12
Eastern	Maize	Ghana	FAOCountrySTAT	2000	2011	12
Eastern	Rice, paddy	Ghana	FAOCountrySTAT	2000	2011	12
Eastern	Yams	Ghana	FAOCountrySTAT	2000	2011	12
Ebonyi	Cassava	Nigeria	FAOCountrySTAT	1995	2012	18

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Ebonyi	Maize	Nigeria	FAOCountrySTAT	1995	2012	18
Ebonyi	Rice, paddy	Nigeria	FAOCountrySTAT	1995	2012	18
Ebonyi	Yams	Nigeria	FAOCountrySTAT	1995	2012	18
Edo	Cassava	Nigeria	FAOCountrySTAT	1995	2012	18
Edo	Maize	Nigeria	FAOCountrySTAT	1995	2012	18
Edo	Rice, paddy	Nigeria	FAOCountrySTAT	1995	2012	18
Edo	Yams	Nigeria	FAOCountrySTAT	1995	2012	18
Ekiti	Cassava	Nigeria	FAOCountrySTAT	1995	2012	18
Ekiti	Maize	Nigeria	FAOCountrySTAT	1995	2012	18
Ekiti	Rice, paddy	Nigeria	FAOCountrySTAT	1995	2012	17
Ekiti	Yams	Nigeria	FAOCountrySTAT	1995	2012	18
Enugu	Cassava	Nigeria	FAOCountrySTAT	1995	2012	18
Enugu	Maize	Nigeria	FAOCountrySTAT	1995	2012	18
Enugu	Rice, paddy	Nigeria	FAOCountrySTAT	1995	2012	18
Enugu	Yams	Nigeria	FAOCountrySTAT	1995	2012	18
Est	Maize	Burkina Faso	AgroMAPS1	1984	2004	21
Est	Millet	Burkina Faso	AgroMAPS1	1984	2004	21
Est	Rice, paddy	Burkina Faso	AgroMAPS1	1984	2004	21
Est	Sorghum	Burkina Faso	AgroMAPS1	1984	2004	21
Est	Yams	Burkina Faso	AgroMAPS1	1993	2004	9
Fatick	Rice, paddy	Senegal	AgroMAPS1	1990	1999	9
Fatick	Sorghum	Senegal	AgroMAPS1	1990	1999	10
FCT, Abuja	Cassava	Nigeria	FAOCountrySTAT	1995	2012	18
FCT, Abuja	Maize	Nigeria	FAOCountrySTAT	1995	2012	18
FCT, Abuja	Millet	Nigeria	FAOCountrySTAT	1995	2012	18
FCT, Abuja	Rice, paddy	Nigeria	FAOCountrySTAT	1995	2012	18
FCT, Abuja	Sorghum	Nigeria	FAOCountrySTAT	1995	2012	18
FCT, Abuja	Yams	Nigeria	FAOCountrySTAT	1995	2012	18
Gabu	Millet	Guinea-Bissau	FAOCountrySTAT	1988	2010	23
Gabu	Rice, paddy	Guinea-Bissau	FAOCountrySTAT	1991	2010	20
Gao	Millet	Mali	FAOCountrySTAT	2001	2015	13
Gao	Rice, paddy	Mali	FAOCountrySTAT	2001	2015	14
Gao	Sorghum	Mali	FAOCountrySTAT	2001	2015	13
Gombe	Cassava	Nigeria	FAOCountrySTAT	1995	2006	12
Gombe	Maize	Nigeria	FAOCountrySTAT	1995	2012	18
Gombe	Millet	Nigeria	FAOCountrySTAT	1995	2012	18
Gombe	Rice, paddy	Nigeria	FAOCountrySTAT	1995	2012	18
Gombe	Sorghum	Nigeria	FAOCountrySTAT	1995	2012	18
Greater Accra	Cassava	Ghana	FAOCountrySTAT	2000	2011	12
Greater Accra	Maize	Ghana	FAOCountrySTAT	2000	2011	12
Greater Accra	Rice, paddy	Ghana	FAOCountrySTAT	2000	2011	12
Hauts-Bassins	Maize	Burkina Faso	AgroMAPS1	1984	2004	21
Hauts-Bassins	Millet	Burkina Faso	AgroMAPS1	1984	2004	21
Hauts-Bassins	Rice, paddy	Burkina Faso	AgroMAPS1	1984	2004	21
Hauts-Bassins	Sorghum	Burkina Faso	AgroMAPS1	1984	2004	21

Hauts-Bassins	Yams	Burkina Faso	AgroMAPS1	1986	2004	18
Imo	Cassava	Nigeria	FAOCountrySTAT	1995	2012	17
Imo	Maize	Nigeria	FAOCountrySTAT	1995	2012	18
Imo	Rice, paddy	Nigeria	FAOCountrySTAT	1996	2012	14
Imo	Yams	Nigeria	FAOCountrySTAT	1995	2012	18
Jigawa	Maize	Nigeria	FAOCountrySTAT	1995	2012	18
Jigawa	Millet	Nigeria	FAOCountrySTAT	1995	2012	18
Jigawa	Rice, paddy	Nigeria	FAOCountrySTAT	1995	2012	18
Jigawa	Sorghum	Nigeria	FAOCountrySTAT	1995	2012	18
Kaduna	Cassava	Nigeria	FAOCountrySTAT	1995	2012	18
Kaduna	Maize	Nigeria	FAOCountrySTAT	1995	2012	18
Kaduna	Millet	Nigeria	FAOCountrySTAT	1995	2012	18
Kaduna	Rice, paddy	Nigeria	FAOCountrySTAT	1995	2012	18
Kaduna	Sorghum	Nigeria	FAOCountrySTAT	1995	2012	18
Kaduna	Yams	Nigeria	FAOCountrySTAT	1995	2012	18
Kano	Maize	Nigeria	FAOCountrySTAT	1995	2012	18
Kano	Millet	Nigeria	FAOCountrySTAT	1995	2012	18
Kano	Rice, paddy	Nigeria	FAOCountrySTAT	1995	2012	18
Kano	Sorghum	Nigeria	FAOCountrySTAT	1995	2012	18
Kaolack	Millet	Senegal	AgroMAPS1	1990	1999	9
Kaolack	Sorghum	Senegal	AgroMAPS1	1990	1999	10
Kara	Cassava	Togo	FAOCountrySTAT	2001	2010	10
Kara	Maize	Togo	FAOCountrySTAT	2001	2010	10
Kara	Millet	Togo	FAOCountrySTAT	2001	2010	10
Kara	Rice, paddy	Togo	FAOCountrySTAT	2001	2010	10
Kara	Sorghum	Togo	FAOCountrySTAT	2001	2010	10
Kara	Yams	Togo	FAOCountrySTAT	2001	2010	10
Katsina	Maize	Nigeria	FAOCountrySTAT	1995	2012	18
Katsina	Millet	Nigeria	FAOCountrySTAT	1995	2012	18
Katsina	Rice, paddy	Nigeria	FAOCountrySTAT	1995	2012	18
Katsina	Sorghum	Nigeria	FAOCountrySTAT	1995	2012	18
Kayes	Maize	Mali	FAOCountrySTAT	2001	2015	15
Kayes	Millet	Mali	FAOCountrySTAT	2001	2015	15
Kayes	Rice, paddy	Mali	FAOCountrySTAT	2001	2015	15
Kayes	Sorghum	Mali	FAOCountrySTAT	2001	2015	15
Kebbi	Maize	Nigeria	FAOCountrySTAT	1995	2012	18
Kebbi	Millet	Nigeria	FAOCountrySTAT	1995	2012	18
Kebbi	Rice, paddy	Nigeria	FAOCountrySTAT	1995	2012	18
Kebbi	Sorghum	Nigeria	FAOCountrySTAT	1995	2012	18
Kogi	Cassava	Nigeria	FAOCountrySTAT	1995	2012	18
Kogi	Maize	Nigeria	FAOCountrySTAT	1995	2012	18
Kogi	Millet	Nigeria	FAOCountrySTAT	1995	2012	17
Kogi	Rice, paddy	Nigeria	FAOCountrySTAT	1995	2012	18
Kogi	Sorghum	Nigeria	FAOCountrySTAT	1995	2012	18
Kogi	Yams	Nigeria	FAOCountrySTAT	1995	2012	18

SUPPLEMENTS

Kolda	Millet	Senegal	AgroMAPS1	1990	1999	10
Kolda	Rice, paddy	Senegal	AgroMAPS1	1990	1999	10
Kolda	Sorghum	Senegal	AgroMAPS1	1990	1999	10
Kombo Saint Mary	Maize	Gambia	FAOCountrySTAT	1988	2001	14
Kombo Saint Mary	Millet	Gambia	FAOCountrySTAT	1988	2001	14
Kombo Saint Mary	Rice, paddy	Gambia	FAOCountrySTAT	1988	2001	14
Kombo Saint Mary	Sorghum	Gambia	FAOCountrySTAT	1988	2001	14
Koulikoro	Maize	Mali	FAOCountrySTAT	2001	2015	15
Koulikoro	Millet	Mali	FAOCountrySTAT	2001	2015	14
Koulikoro	Rice, paddy	Mali	FAOCountrySTAT	2001	2015	15
Koulikoro	Sorghum	Mali	FAOCountrySTAT	2001	2015	15
Kwara	Cassava	Nigeria	FAOCountrySTAT	1995	2012	18
Kwara	Maize	Nigeria	FAOCountrySTAT	1995	2012	18
Kwara	Millet	Nigeria	FAOCountrySTAT	1995	2012	18
Kwara	Rice, paddy	Nigeria	FAOCountrySTAT	1995	2012	18
Kwara	Sorghum	Nigeria	FAOCountrySTAT	1995	2012	18
Kwara	Yams	Nigeria	FAOCountrySTAT	1995	2012	18
Lagos	Cassava	Nigeria	FAOCountrySTAT	1995	2012	18
Lagos	Maize	Nigeria	FAOCountrySTAT	1995	2012	18
Lagos	Rice, paddy	Nigeria	FAOCountrySTAT	1995	2012	17
Lagos	Yams	Nigeria	FAOCountrySTAT	1995	2012	18
Louga	Millet	Senegal	AgroMAPS1	1990	1999	10
Lower River	Maize	Gambia	FAOCountrySTAT	1988	2001	14
Lower River	Millet	Gambia	FAOCountrySTAT	1988	2001	14
Lower River	Rice, paddy	Gambia	FAOCountrySTAT	1988	2001	14
Lower River	Sorghum	Gambia	FAOCountrySTAT	1988	2001	12
Maradi	Maize	Niger	FAOCountrySTAT	2001	2011	11
Maradi	Millet	Niger	FAOCountrySTAT	2000	2011	12
Maradi	Sorghum	Niger	FAOCountrySTAT	2000	2011	12
Maritime	Cassava	Togo	FAOCountrySTAT	2001	2010	10
Maritime	Maize	Togo	FAOCountrySTAT	2001	2010	10
Maritime	Rice, paddy	Togo	FAOCountrySTAT	2001	2010	10
Maritime	Sorghum	Togo	FAOCountrySTAT	2001	2010	9
Maritime	Yams	Togo	FAOCountrySTAT	2001	2010	10
Mopti	Maize	Mali	FAOCountrySTAT	2001	2015	15
Mopti	Millet	Mali	FAOCountrySTAT	2001	2015	15
Mopti	Rice, paddy	Mali	FAOCountrySTAT	2001	2015	15
Mopti	Sorghum	Mali	FAOCountrySTAT	2001	2015	15
Nassarawa	Cassava	Nigeria	FAOCountrySTAT	1995	2012	17
Nassarawa	Maize	Nigeria	FAOCountrySTAT	1995	2012	18
Nassarawa	Millet	Nigeria	FAOCountrySTAT	1995	2012	18
Nassarawa	Rice, paddy	Nigeria	FAOCountrySTAT	1995	2012	18
Nassarawa	Sorghum	Nigeria	FAOCountrySTAT	1995	2012	18

Nassarawa	Yams	Nigeria	FAOCountrySTAT	1995	2012	17
Niamey	Millet	Niger	FAOCountrySTAT	2000	2011	12
Niamey	Rice, paddy	Niger	FAOCountrySTAT	2001	2011	10
Niamey	Sorghum	Niger	FAOCountrySTAT	2000	2011	12
Niger	Cassava	Nigeria	FAOCountrySTAT	1995	2012	18
Niger	Maize	Nigeria	FAOCountrySTAT	1995	2012	18
Niger	Millet	Nigeria	FAOCountrySTAT	1995	2012	18
Niger	Rice, paddy	Nigeria	FAOCountrySTAT	1995	2012	18
Niger	Sorghum	Nigeria	FAOCountrySTAT	1995	2012	18
Niger	Yams	Nigeria	FAOCountrySTAT	1995	2012	17
Nord	Maize	Burkina Faso	AgroMAPS1	1984	2004	21
Nord	Millet	Burkina Faso	AgroMAPS1	1984	2004	21
Nord	Rice, paddy	Burkina Faso	AgroMAPS1	1984	2004	21
Nord	Sorghum	Burkina Faso	AgroMAPS1	1984	2004	21
North Bank	Maize	Gambia	FAOCountrySTAT	1988	2001	14
North Bank	Millet	Gambia	FAOCountrySTAT	1988	2001	14
North Bank	Rice, paddy	Gambia	FAOCountrySTAT	1988	2001	14
North Bank	Sorghum	Gambia	FAOCountrySTAT	1988	2001	14
Northern	Cassava	Ghana	FAOCountrySTAT	2000	2011	12
Northern	Maize	Ghana	FAOCountrySTAT	2000	2011	12
Northern	Millet	Ghana	FAOCountrySTAT	2000	2011	12
Northern	Rice, paddy	Ghana	FAOCountrySTAT	2000	2011	12
Northern	Sorghum	Ghana	FAOCountrySTAT	2000	2011	12
Northern	Yams	Ghana	FAOCountrySTAT	2000	2011	12
Ogun	Cassava	Nigeria	FAOCountrySTAT	1995	2012	18
Ogun	Maize	Nigeria	FAOCountrySTAT	1995	2012	18
Ogun	Rice, paddy	Nigeria	FAOCountrySTAT	1995	2012	17
Ogun	Yams	Nigeria	FAOCountrySTAT	1995	2012	18
Oio	Millet	Guinea-Bissau	FAOCountrySTAT	1988	2010	23
Oio	Rice, paddy	Guinea-Bissau	AgroMAPS1	1995	2010	13
Ondo	Cassava	Nigeria	FAOCountrySTAT	1995	2012	18
Ondo	Maize	Nigeria	FAOCountrySTAT	1995	2012	18
Ondo	Rice, paddy	Nigeria	FAOCountrySTAT	1995	2012	17
Ondo	Yams	Nigeria	FAOCountrySTAT	1995	2012	18
Osun	Cassava	Nigeria	FAOCountrySTAT	1995	2012	18
Osun	Maize	Nigeria	FAOCountrySTAT	1995	2012	18
Osun	Yams	Nigeria	FAOCountrySTAT	1995	2012	18
Oyo	Cassava	Nigeria	FAOCountrySTAT	1995	2012	18
Oyo	Maize	Nigeria	FAOCountrySTAT	1995	2012	18
Oyo	Sorghum	Nigeria	FAOCountrySTAT	1995	2012	18
Oyo	Yams	Nigeria	FAOCountrySTAT	1995	2012	17
Plateau	Cassava	Nigeria	FAOCountrySTAT	1995	2012	18
Plateau	Maize	Nigeria	FAOCountrySTAT	1995	2012	18
Plateau	Millet	Nigeria	FAOCountrySTAT	1995	2012	18
Plateau	Rice, paddy	Nigeria	FAOCountrySTAT	1995	2012	18

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Plateau	Sorghum	Nigeria	FAOCountrySTAT	1995	2012	18
Plateau	Yams	Nigeria	FAOCountrySTAT	1995	2012	18
Plateau Central	Maize	Burkina Faso	AgroMAPS1	1984	2004	21
Plateau Central	Millet	Burkina Faso	AgroMAPS1	1984	2004	21
Plateau Central	Rice, paddy	Burkina Faso	AgroMAPS1	1984	2004	21
Plateau Central	Sorghum	Burkina Faso	AgroMAPS1	1984	2004	21
Plateaux	Cassava	Togo	FAOCountrySTAT	2001	2010	10
Plateaux	Maize	Togo	FAOCountrySTAT	2001	2010	10
Plateaux	Rice, paddy	Togo	FAOCountrySTAT	2001	2010	10
Plateaux	Sorghum	Togo	FAOCountrySTAT	2001	2010	10
Plateaux	Yams	Togo	FAOCountrySTAT	2001	2010	10
Quinara	Sorghum	Guinea-Bissau	FAOCountrySTAT	1988	2010	23
Rivers	Cassava	Nigeria	FAOCountrySTAT	1995	2012	18
Rivers	Maize	Nigeria	FAOCountrySTAT	1995	2012	18
Rivers	Yams	Nigeria	FAOCountrySTAT	1995	2012	18
Sahel	Maize	Burkina Faso	AgroMAPS1	1984	2004	20
Sahel	Millet	Burkina Faso	AgroMAPS1	1984	2004	21
Sahel	Rice, paddy	Burkina Faso	AgroMAPS1	1993	2004	11
Sahel	Sorghum	Burkina Faso	AgroMAPS1	1984	2004	21
Saint Louis	Millet	Senegal	AgroMAPS1	1990	1999	10
Saint Louis	Rice, paddy	Senegal	AgroMAPS1	1990	1999	10
Saint Louis	Sorghum	Senegal	AgroMAPS1	1990	1999	10
Savanes	Maize	Togo	FAOCountrySTAT	2001	2010	10
Savanes	Millet	Togo	FAOCountrySTAT	2001	2010	10
Savanes	Rice, paddy	Togo	FAOCountrySTAT	2001	2010	10
Savanes	Sorghum	Togo	FAOCountrySTAT	2001	2010	10
Savanes	Yams	Togo	FAOCountrySTAT	2001	2010	10
Segou	Maize	Mali	FAOCountrySTAT	2001	2015	15
Segou	Millet	Mali	FAOCountrySTAT	2001	2015	15
Segou	Rice, paddy	Mali	FAOCountrySTAT	2001	2015	15
Segou	Sorghum	Mali	FAOCountrySTAT	2001	2015	15
Sikasso	Maize	Mali	FAOCountrySTAT	2001	2015	15
Sikasso	Millet	Mali	FAOCountrySTAT	2001	2015	15
Sikasso	Rice, paddy	Mali	FAOCountrySTAT	2001	2015	15
Sikasso	Sorghum	Mali	FAOCountrySTAT	2001	2015	15
Sikasso	Yams	Mali	AgroMAPS1	1985	1994	9
Sokoto	Cassava	Nigeria	FAOCountrySTAT	1995	2012	17
Sokoto	Maize	Nigeria	FAOCountrySTAT	1995	2012	18
Sokoto	Millet	Nigeria	FAOCountrySTAT	1995	2012	18
Sokoto	Rice, paddy	Nigeria	FAOCountrySTAT	1995	2012	18
Sokoto	Sorghum	Nigeria	FAOCountrySTAT	1995	2012	18
Sud-Ouest	Maize	Burkina Faso	AgroMAPS1	1984	2004	21
Sud-Ouest	Millet	Burkina Faso	AgroMAPS1	1984	2004	21
Sud-Ouest	Rice, paddy	Burkina Faso	AgroMAPS1	1984	2004	21
Sud-Ouest	Sorghum	Burkina Faso	AgroMAPS1	1984	2004	21

Sud-Ouest	Yams	Burkina Faso	AgroMAPS1	1984	2004	21
Tahoua	Millet	Niger	FAOCountrySTAT	2000	2011	12
Tahoua	Sorghum	Niger	FAOCountrySTAT	2000	2011	12
Tambacounda	Millet	Senegal	AgroMAPS1	1990	1999	9
Tambacounda	Rice, paddy	Senegal	AgroMAPS1	1990	1999	10
Tambacounda	Sorghum	Senegal	AgroMAPS1	1990	1999	10
Taraba	Cassava	Nigeria	FAOCountrySTAT	1995	2012	18
Taraba	Maize	Nigeria	FAOCountrySTAT	1995	2012	18
Taraba	Millet	Nigeria	FAOCountrySTAT	1995	2012	18
Taraba	Rice, paddy	Nigeria	FAOCountrySTAT	1995	2012	18
Taraba	Sorghum	Nigeria	FAOCountrySTAT	1995	2012	18
Taraba	Yams	Nigeria	FAOCountrySTAT	1995	2012	18
Thies	Millet	Senegal	AgroMAPS1	1990	1999	10
Thies	Sorghum	Senegal	AgroMAPS1	1990	1998	9
Tillaberi	Maize	Niger	FAOCountrySTAT	2001	2011	10
Tillaberi	Millet	Niger	FAOCountrySTAT	2000	2011	12
Tillaberi	Rice, paddy	Niger	FAOCountrySTAT	2000	2011	12
Tillaberi	Sorghum	Niger	FAOCountrySTAT	2000	2011	12
Tombali	Rice, paddy	Guinea-Bissau	AgroMAPS1	1995	2007	11
Tombali	Sorghum	Guinea-Bissau	FAOCountrySTAT	1988	2010	23
Tombouctou	Millet	Mali	FAOCountrySTAT	2001	2015	14
Tombouctou	Rice, paddy	Mali	FAOCountrySTAT	2001	2015	14
Tombouctou	Sorghum	Mali	FAOCountrySTAT	2001	2015	14
Upper East	Maize	Ghana	FAOCountrySTAT	2000	2011	12
Upper East	Millet	Ghana	FAOCountrySTAT	2000	2011	12
Upper East	Rice, paddy	Ghana	FAOCountrySTAT	2000	2011	12
Upper East	Sorghum	Ghana	FAOCountrySTAT	2000	2011	12
Upper River	Maize	Gambia	FAOCountrySTAT	1988	2001	14
Upper River	Millet	Gambia	FAOCountrySTAT	1988	2001	14
Upper River	Rice, paddy	Gambia	FAOCountrySTAT	1988	2001	14
Upper River	Sorghum	Gambia	FAOCountrySTAT	1988	2001	14
Upper West	Maize	Ghana	FAOCountrySTAT	2000	2011	12
Upper West	Millet	Ghana	FAOCountrySTAT	2000	2011	12
Upper West	Rice, paddy	Ghana	FAOCountrySTAT	2000	2011	11
Upper West	Sorghum	Ghana	FAOCountrySTAT	2000	2011	12
Volta	Cassava	Ghana	FAOCountrySTAT	2000	2011	12
Volta	Maize	Ghana	FAOCountrySTAT	2000	2011	12
Volta	Rice, paddy	Ghana	FAOCountrySTAT	2000	2011	12
Volta	Sorghum	Ghana	FAOCountrySTAT	2000	2011	12
Volta	Yams	Ghana	FAOCountrySTAT	2000	2011	12
West Coast	Maize	Gambia	FAOCountrySTAT	1988	2001	14
West Coast	Millet	Gambia	FAOCountrySTAT	1988	2001	14
West Coast	Rice, paddy	Gambia	FAOCountrySTAT	1988	2001	14
West Coast	Sorghum	Gambia	FAOCountrySTAT	1988	2001	14
Western	Cassava	Ghana	FAOCountrySTAT	2000	2011	12

Western	Maize	Ghana	FAOCountrySTAT	2000	2011	12
Western	Rice, paddy	Ghana	FAOCountrySTAT	2000	2011	12
Western	Yams	Ghana	FAOCountrySTAT	2000	2011	12
Yobe	Cassava	Nigeria	FAOCountrySTAT	1995	2012	17
Yobe	Maize	Nigeria	FAOCountrySTAT	1995	2012	18
Yobe	Millet	Nigeria	FAOCountrySTAT	1995	2012	18
Yobe	Rice, paddy	Nigeria	FAOCountrySTAT	1995	2012	18
Yobe	Sorghum	Nigeria	FAOCountrySTAT	1995	2012	18
Zamfara	Maize	Nigeria	FAOCountrySTAT	1995	2012	18
Zamfara	Millet	Nigeria	FAOCountrySTAT	1995	2012	18
Zamfara	Rice, paddy	Nigeria	FAOCountrySTAT	1995	2012	18
Zamfara	Sorghum	Nigeria	FAOCountrySTAT	1995	2012	18
Ziguinchor	Rice, paddy	Senegal	AgroMAPS1	1990	1999	9
Ziguinchor	Sorghum	Senegal	AgroMAPS1	1990	1999	9
Zinder	Millet	Niger	FAOCountrySTAT	2000	2011	12
Zinder	Sorghum	Niger	FAOCountrySTAT	2000	2011	12

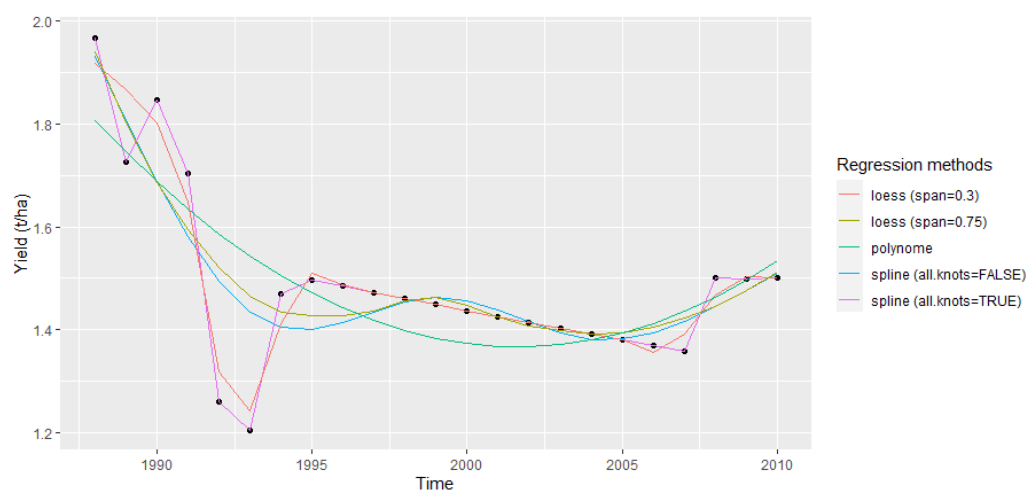


Figure S2 3. Illustration of the three detrending methods used in our study, here for sorghum yields in Quinara (Togo). Yields are expressed in ton per hectare, time in year. Black points represent observed yield for each year. Colored lines represent each regression method tested (pink and olive: loess, green: polynomial, blue and purple: spline). For local regressions two tuning parameters (span and all.knots) are tested as illustration.

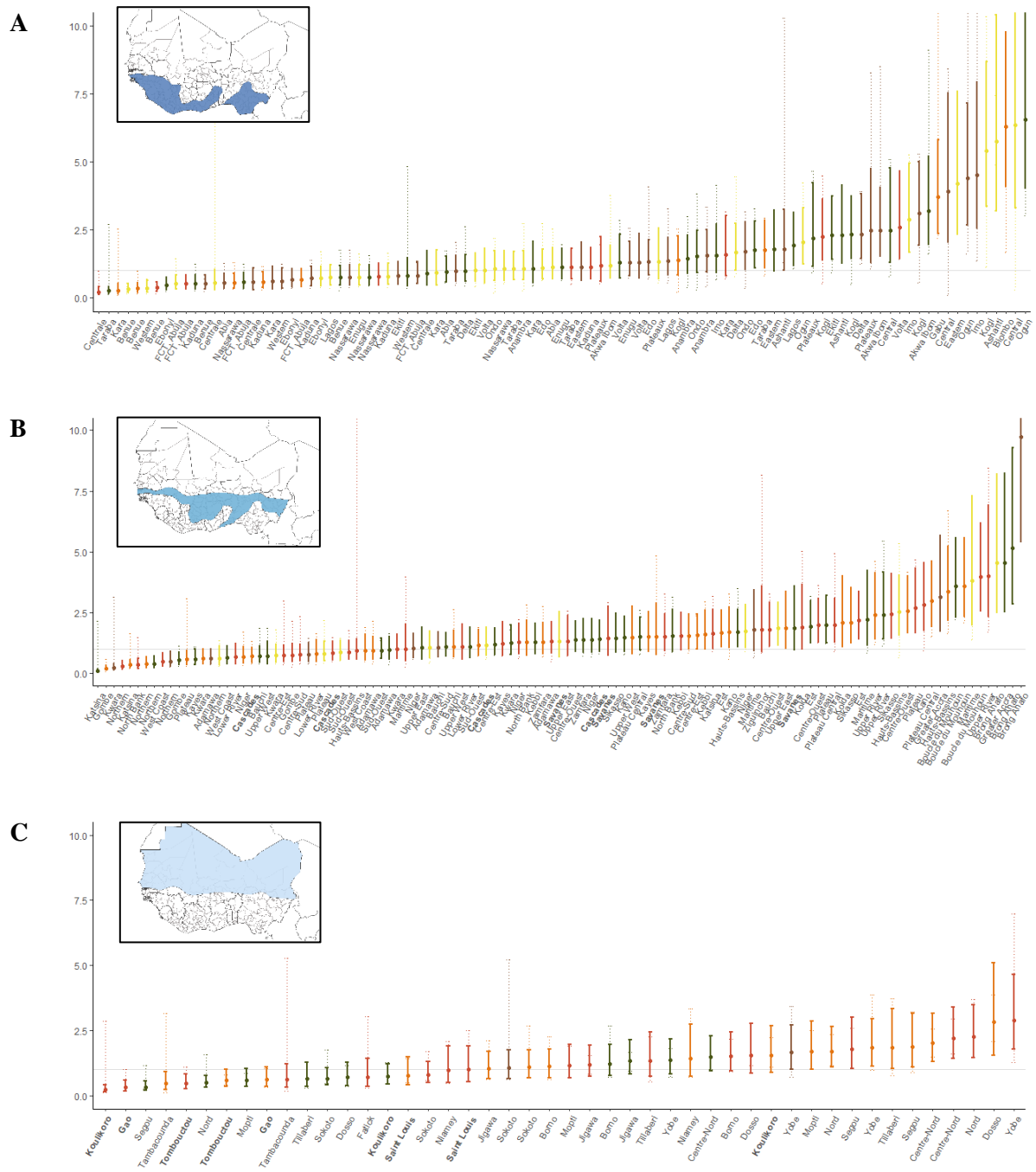


Figure S2.4. Yield variability ratio in the Guinean (A), Sudanian (B) and Sahelian (C) regions of West Africa. Yield variability differences are estimated from yield variance ratios for rice (numerator) to alternative food crops (denominator). Yield variance are, here, measured on observed yield data normalized by the average yield on the time-series length, without detrending. A ratio is estimated in each subnational level 1 area where rice and any of the five alternative food crops yields are informed for at least 9 (non-consecutive) years. Results are presented per crop region combination for cassava (brown), maize (dark green), millet (orange), sorghum (orange) and yams (yellow). Note that one area where several crops of interest are cultivated is represented several times. Confidence intervals estimated via bootstrapping (dotted lines) and based on Nakagawa et al (2015) (Nakagawa et al. 2015) analytical approximations (bold lines). The areas written in bold refer to the predominantly irrigated areas (i.e., >80% of the total area is irrigated), identified from SPAM2000. The points are organized by ascending order for each of the three broad climatic regions with the Guinean region delineated by cumulative annual rainfall superior to 1200 mm, the Sudanian region with cumulative rainfall between 700 and 1200 mm and the Sahelian below 700mm (see Figure S13). Grey horizontal bar delineates SD ratio equal to 1 (rice yield variability is equal to that of the other crop species). A ratio superior to 1 indicates that rice yield variability is higher than that of the

other crop (i.e., rice is less stable than its alternative). A confidence interval including 1 indicates non-significant results.

6.2.1 Climate data treatment

We remove regions with below threshold cropped area. We rely on the Global Croplands data set built by Ramankutty et al. (2008) (Ramankutty et al. 2008). This data set gives the cropping area gridded at a resolution of $5^\circ \times 5^\circ$ for the year 2000, all crops considered and all around the world. Based on this data set, we removed the grid cells where the land crop ratio (i.e., area of crop land over grid cell area) is below 1%. This help avoiding the inclusion of crop-free grid cells (e.g., deserts) in the computation of climate indices. 1% threshold is selected after several tests as a good balance between the inclusion of crop-free areas and the removal of potentially marginally cropped areas (e.g., the Senegal river basin) but which tend to include rice cropping (see Figures S2 5 and S2 6).

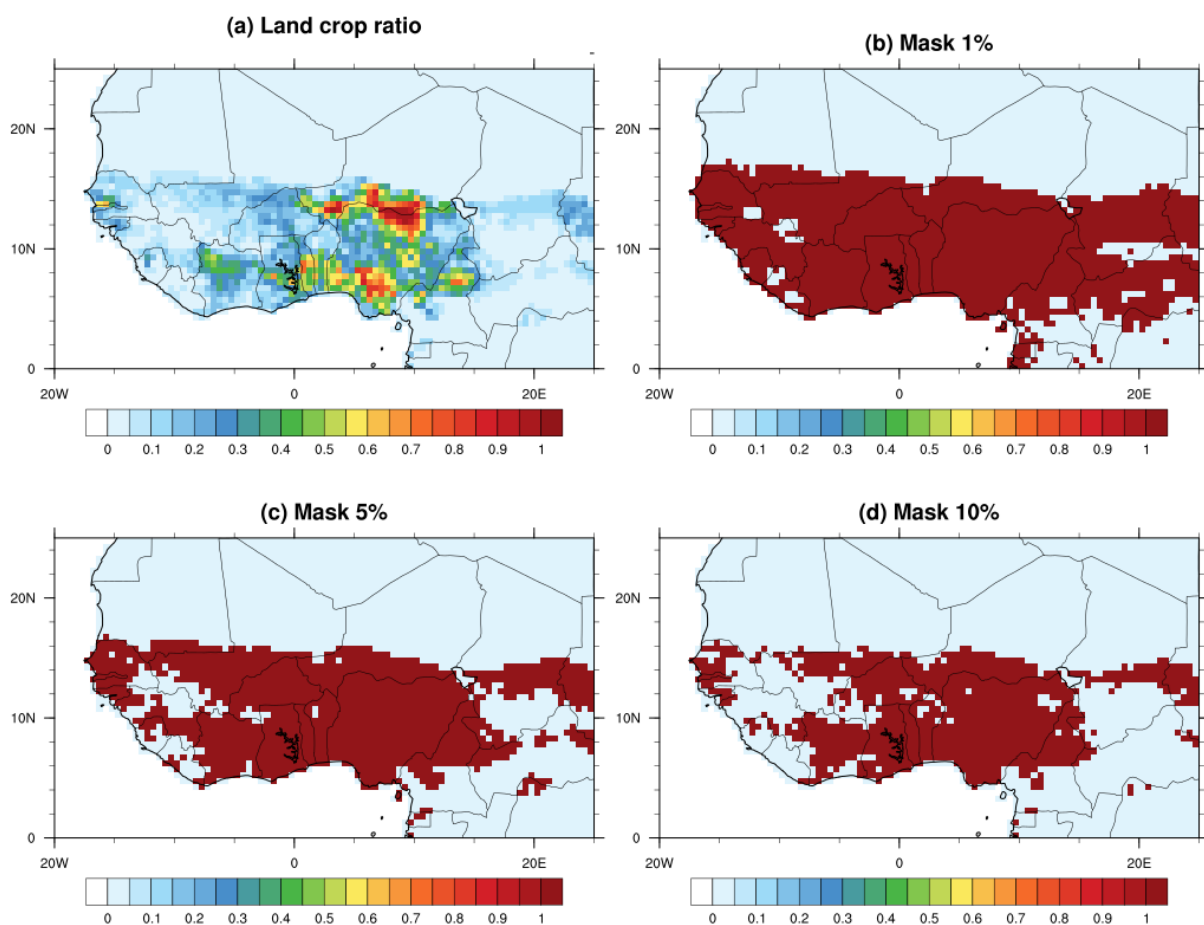


Figure S2 5. Land crop ratio circa year 2000 on a $0.5^\circ \times 0.5^\circ$ grid, with a focus on West Africa. The map in (a) shows the land crop ratios from 0 to 1. The maps in (b), (c) and (d) show the grid cells kept (red grid cells) after the exclusion of areas with below 1%, 5% and 10% cropped areas respectively.

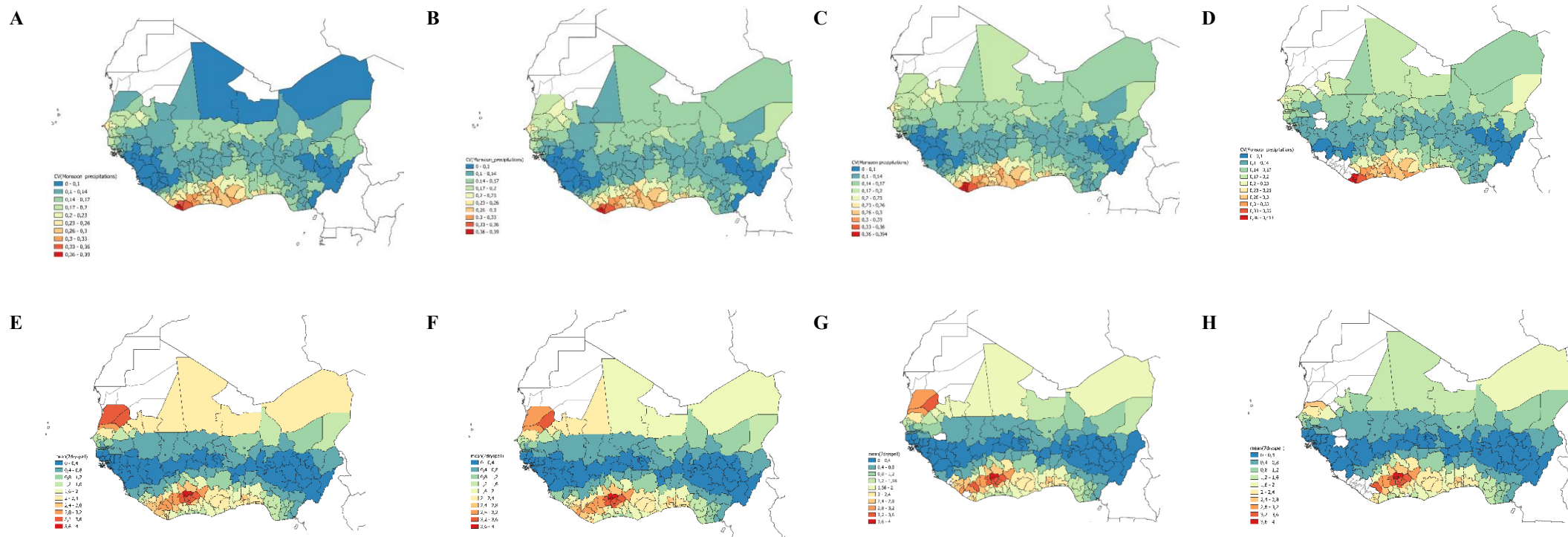


Figure S2.6. Comparison of the statistic climate indicators before and after removing below threshold cropped areas for the coefficient of variation of monsoon precipitations (A - D) and average dry spell occurrence (E - H) for all areas included (A, E), with a 1% threshold (B, F), with a 5% threshold (C, G) and a 10% threshold (D, H).

Table S2 3. Model (4) summary for each of the 12 climate indicators independently. The results presented here are computed for climate indices computed over the totality of the grid cells.

'M_SDMP_des_irri' refers to model (4) run with sd(monsoon precipitations) as explicative variable, 'M_CVMP_des_irri' refers to model (4) run with CV(monsoon precipitations) as explicative variable, 'M_mMP_des_irri' refers to model (4) run with mean(monsoon precipitations) as explicative variable, 'M_SDAP_des_irri' refers to model (4) run with sd(annual precipitations) as explicative variable, 'M_CVAP_des_irri' refers to model (4) run with CV(annual precipitations) as explicative variable, 'M_mAP_des_irri' refers to model (4) run with mean(annual precipitations) as explicative variable, 'M_SDML_des_irri' refers to model (4) run with sd(monsoon length) as explicative variable, 'M_CVML_des_irri' refers to model (4) run with CV(monsoon length) as explicative variable, 'M_mML_des_irri' refers to model (4) run with mean(monsoon length) as explicative variable, 'M_SD7DS_des_irri' refers to model (4) run with sd(7 days dryspell) as explicative variable, 'M_CV7DS_des_irri' refers to model (4) run with CV(7 days dryspell) as explicative variable, 'M_m7DS_des_irri' refers to model (4) run with mean(7 days dryspell) as explicative variable. R² represents the variance explained by the whole model (fixed and random effects)

Model	(Intercept)	Inter_p-value	Slope	Slope_p-value	AIC	R2
M_SDMP_des_irri	-0.241	0.0913	0.0032	0.0012	566.7175	0.5295
M_CVMP_des_irri	-0.4209	0.0182	4.4857	4,00E-04	550.5401	0.5191
M_mMP_des_irri	0.0777	0.6508	1,00E-04	0.511	580.8506	0.5286
M_SDAP_des_irri	-0.2296	0.1634	0.0036	0.0074	569.6325	0.5286
M_CVAP_des_irri	-0.148	0.5051	3.0251	0.1226	560.0175	0.5198
M_mAP_des_irri	0.0407	0.8001	1,00E-04	0.3358	580.7384	0.5291
M_SDML_des_irri	-0.19	0.1159	0.0205	5,00E-04	561.7096	0.5189
M_CVML_des_irri	-0.2023	0.1178	3.2267	9,00E-04	552.7202	0.5187
M_mML_des_irri	-0.0416	0.912	0.0014	0.5515	569.5645	0.5371
M_SD7DS_des_irri	-0.0086	0.9441	0.3653	0.0676	563.5961	0.5249
M_CV7DS_des_irri	0.2194	0.1973	-0.0415	0.8037	567.2769	0.5255
M_m7DS_des_irri	0.0772	0.4445	0.1401	0.1688	566.4273	0.5221

Table S2 4 Model (4) summary for each of the 12 climate indicators independently. The results presented here are computed for climate indices computed over grid cells with above 1% cropped areas.

'M_SDMP_des_irri' refers to model (4) run with sd(monsoon precipitations) as explicative variable, 'M_CVMP_des_irri' refers to model (4) run with CV(monsoon precipitations) as explicative variable, 'M_mMP_des_irri' refers to model (4) run with mean(monsoon precipitations) as explicative variable, 'M_SDAP_des_irri' refers to model (4) run with sd(annual precipitations) as explicative variable, 'M_CVAP_des_irri' refers to model (4) run with CV(annual precipitations) as explicative variable, 'M_mAP_des_irri' refers to model (4) run with mean(annual precipitations) as explicative variable, 'M_SDML_des_irri' refers to model (4) run with sd(monsoon length) as explicative variable, 'M_CVML_des_irri' refers to model (4) run with CV(monsoon length) as explicative variable, 'M_mML_des_irri' refers to model (4) run with mean(monsoon length) as explicative variable, 'M_SD7DS_des_irri' refers to model (4) run with sd(7 days dryspell) as explicative variable, 'M_CV7DS_des_irri' refers to model (4) run with CV(7 days dryspell) as explicative variable, 'M_m7DS_des_irri' refers to model (4) run with mean(7 days dryspell) as explicative variable. R² represents the variance explained by the whole model (fixed and random effects).

Model	(Intercept)	Inter_p-value	Slope	Slope_p-value	AIC	R2
M_SDMP_irri	-0.2382	0.0986	0.0032	0.0014	567.1056	0.5293
M_CVMP_irri	-0.3714	0.0423	4.0758	0.0015	553.0786	0.5191
M_mMP_irri	0.08	0.6417	1,00E-04	0.5215	580.8675	0.5285
M_SDAP_irri	-0.2221	0.1872	0.0035	0.0103	570.2038	0.5284
M_CVAP_irri	-0.0844	0.7032	2.426	0.211	560.8596	0.521
M_mAP_irri	0.0502	0.7572	1,00E-04	0.3755	580.8614	0.5289
M_SDML_irri	-0.171	0.1622	0.0193	0.001	563.2067	0.519

M_CVML_irri	-0.1642	0.2112	2.8704	0.0031	555.0648	0.519
M_mML_irri	-0.1217	0.7435	0.002	0.4117	569.2585	0.5369
M_SD7DS_irri	0.0043	0.972	0.3386	0.0904	564.0762	0.5248
M_CV7DS_irri	0.2417	0.1611	-0.0653	0.6987	567.1649	0.5248
M_m7DS_irri	0.0532	0.5983	0.1752	0.0932	565.4533	0.5212

We can observe that the results with both climate indicators datasets are quite similar. This can be explained by the fact that only 14 regions over 79 are impacted by this removal (i.e. 38 couple region*product2 over 258).

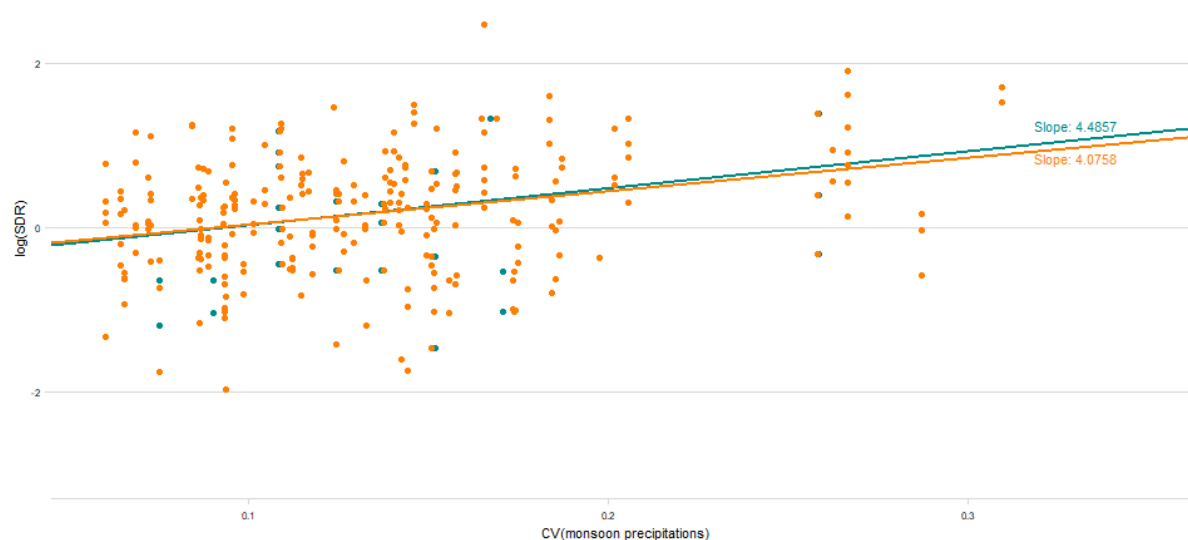


Figure S2 7. Differences of model (4) results for CV(Monsoon precipitations) relying on climate indices computed over the totality of grid cells (orange) or the ones with at least 1% cropped areas (blue). The dots represent the log(SDR) values for each values of CV(monsoon precipitations), the lines represent the regression line of model (4) for both climate datasets.

Table S2 5. Model (5) results: coefficients, p-values and R2 for the best model selected based on the AIC criteria. R2 is the r.squared given by the summary function in R. It represents the percent of the variance explained by the model, after subtraction the error. Models are here presented based on climate indices computed over the totality of grid cells.

Product2	Best_model	Intercept	pvalue_int	Slope	pvalue_slo	AIC	R2
Cassava	CVMP	-0.6638	0.0626	6.0236	0.0159	104.146	0.155
Maize	m7DS	-0.2188	0.0859	0.5276	4,00E-04	150.2784	0.1694
Millet	CVML	-0.5614	0.0274	7.1194	0.002	116.904	0.1668
Sorghum	m7DS	0.3362	0.0081	-0.3642	0.0348	127.5024	0.0758
Yams	sdML	-0.1434	0.4733	0.0177	0.0483	80.5276	0.104

Table S2 6. Model (5) results: coefficients, p-values and R2 for the best model selected based on the AIC criteria. R2 is the r.squared given by the summary function in R. It represents the percent of the variance explained

by the model, after subtraction the error. Models are here presented based on climate indices computed only for grid cells with at least 1% cropped areas.

Product2	Best_model	Intercept	pvalue_int	Slope	pvalue_slo	AIC	R2
Cassava	CVMP	-0.6638	0.0626	6.0242	0.0159	104.147	0.155
Maize	m7DS	-0.2193	0.0853	0.5284	4,00E-04	150.2538	0.1697
Millet	sdAP	-0.4601	0.0659	0.0069	0.0061	119.0454	0.1337
Sorghum	sd7DS	0.5398	0.0058	-1.0458	0.0233	126.786	0.087
Yams	sdML	-0.1433	0.4736	0.0177	0.0484	80.5301	0.1039

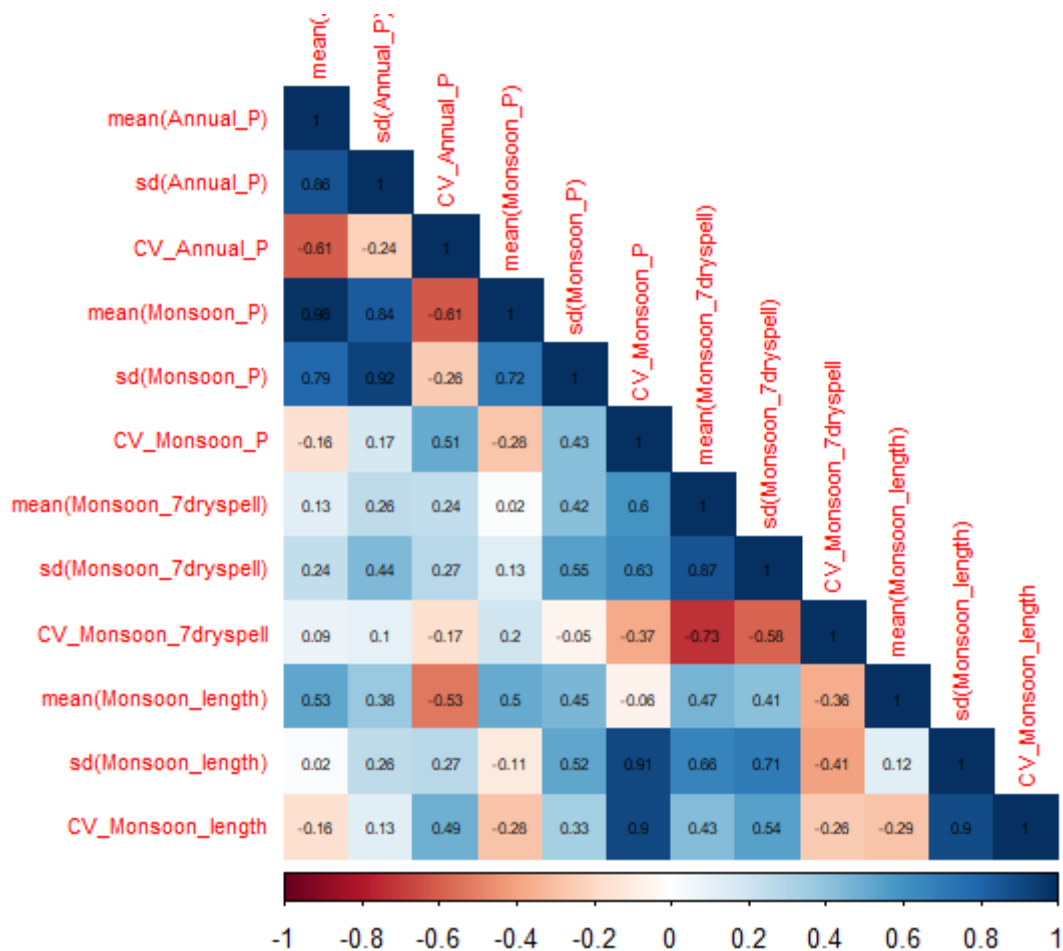


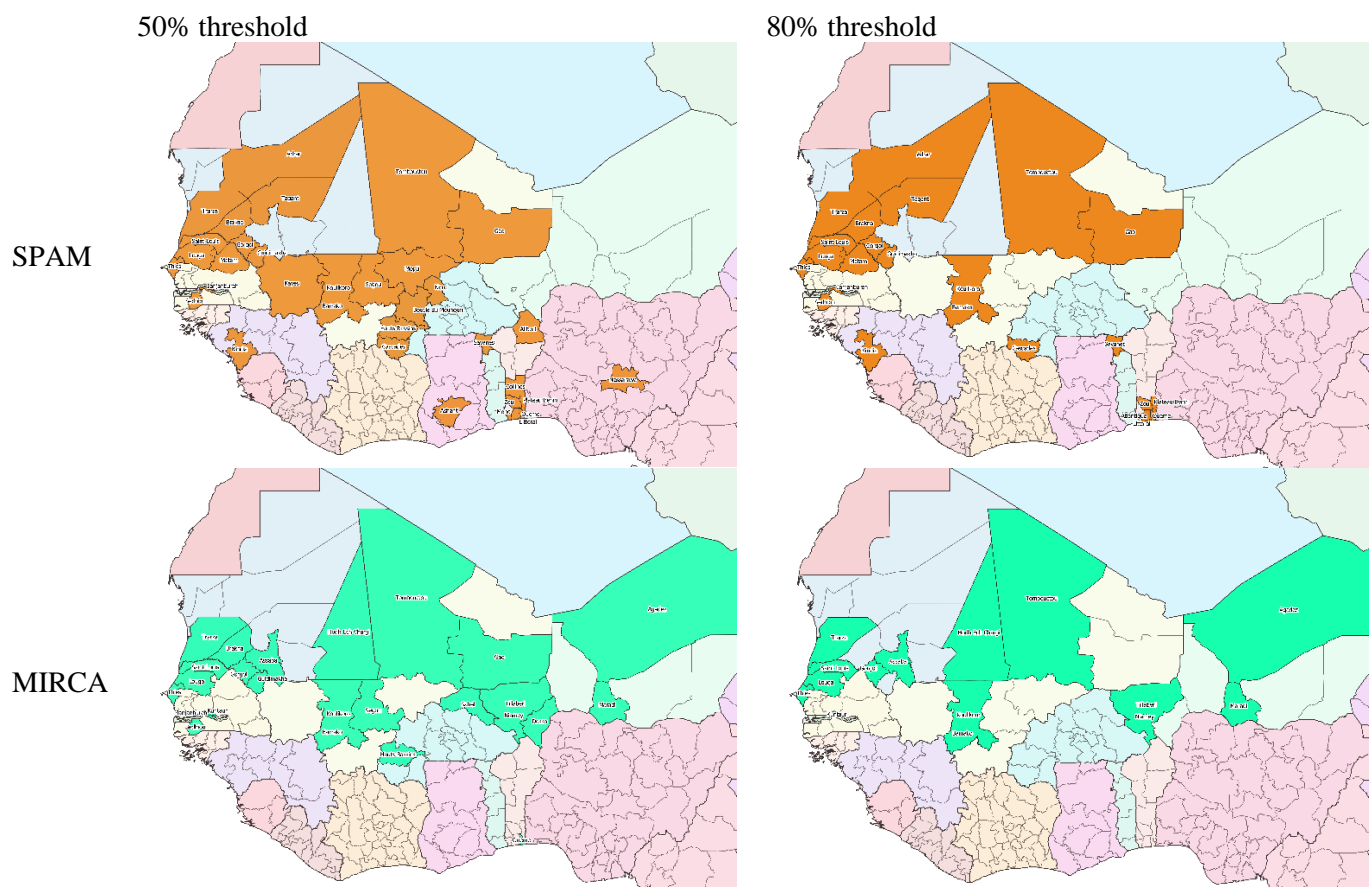
Figure S2 8. Correlation matrix of the 12 climate indicators selected in our analysis. We relied on time series computed from gridded data at administrative level 1 in West Africa for the time period 1981-2019. Mean (Annual_P) is the average annual cumulated rainfall, sd (Annual_P) is the standard deviation of annual cumulated rainfall, CV_Annual_P is the coefficient of variation of annual cumulated rainfall. Mean (Monsoon_P) is the average cumulated monsoon rainfall, sd (Annual_P) is the standard deviation of cumulated monsoon rainfall, CV_Annual_P is the coefficient of variation of cumulated monsoon rainfall. Mean (Monsoon_7dryspell) is the average of the occurrence of 7-days dryspells, sd (Monsoon_7dryspell) is the standard deviation of the occurrence of 7-days dryspells, CV_Monsoon_7dryspell) is the coefficient of variation of the occurrence of 7-days dryspells. Mean (Monsoon_length) is the average length of the monsoon (difference between Onset and Retreat), sd (Monsoon_length) is the standard deviation of monsoon length, CV_Monsoon_length is the coefficient of variation of monsoon length. Red squares indicate a negative correlation and a blue square, positive correlation.

6.2.2 Identification of the predominantly irrigated areas

We assessed the sensitivity of relative rice yield variability (i.e., the SDR) to the predominance of rice irrigation. To do so, we use the three maps that give estimations of rainfed and irrigated areas per crops in a 5'x5' grid. We rely on three irrigation databases for year circa 2000.

- SPAM2000 (You and Wood 2006), data for rice
- MIRCA2000 (Portmann et al. 2010), data for rice
- GAEZv3 (FAO and IIASA 2012), data for rice

We sum irrigated versus rainfed rice cropped areas at administrative level 1 and identify the regions where the ratio irrigated rice area / total rice area is superior to alternatively 50% and 80% (i.e. the regions where the irrigated system is predominant). According to the crop studied, the results of the different crop systems models (i.e., SPAM, MIRCA and GAEZ) vary substantially as they do not rely on the same inputs (Anderson et al. 2015).



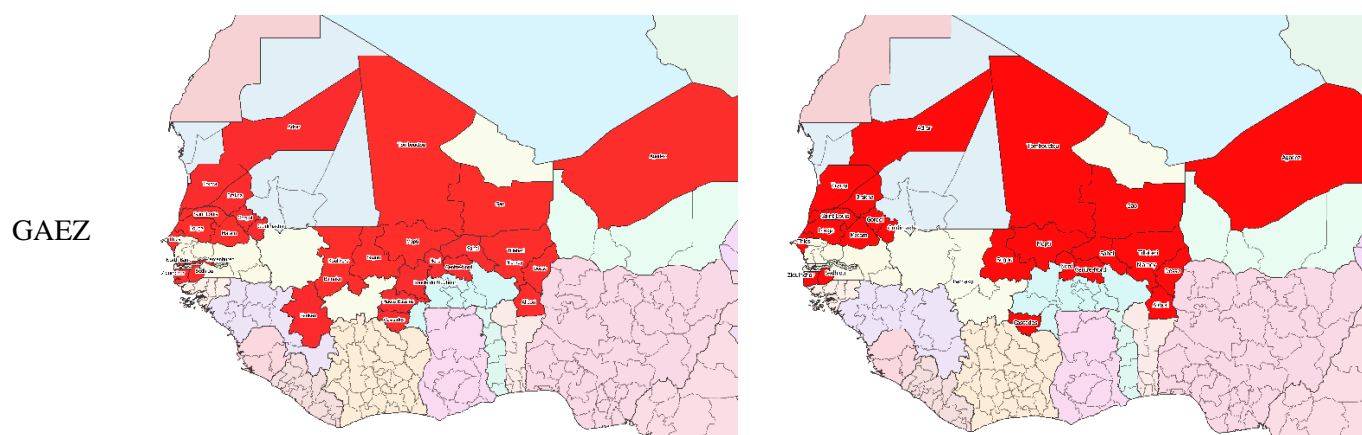


Figure S2 9. Predominant irrigated system regions identified with SPAM2000 (or here SPAM) areas in orange, MIRCA2000 (or here MIRCA) areas in green and GAEZv3 (or here GAEZ) areas in red for a threshold of 50% (left column) or 80% irrigation for rice (right column).

Table S2 7. Model (3) results when removing the intercept for all areas (rows called "Cassava", "Maize", "Millet", "Sorghum" and "Yams"), when removing the irrigated areas identified (areas where irrigated rice areas are superior to 80% of the rice area) from SPAM2000 (rows beginning by "SPAM"), from MIRCA2000 (rows beginning by "MIRCA") and from GAEZ (rows beginning by "GAEZ"). The "mean_effect" column is calculated as $\exp(\text{Estimate})$, which is easier to interpret when comparing to 1. The colored rows mean a p-value <5% for the estimate of the mean effect of the product.

	Estimate	Std. Error	df	t value	Pr(> t)	mean_effect
Cassava	0.1383	0.1196	243.8754	1.1566	0.2486	1.1483
Maize	0.1277	0.0915	182.0459	1.3963	0.1643	1.1362
Millet	0.226	0.0992	207.4964	2.2785	0.0237	1.2536
Sorghum	0.2075	0.098	207.1955	2.1176	0.0354	1.2306
Yams	0.2077	0.1177	242.3335	1.7643	0.0789	1.2308
SPAM_Cassava	0.1625	0.1207	224.7239	1.3465	0.1795	1.1764
SPAM_Maize	0.1534	0.094	168.4827	1.6316	0.1046	1.1658
SPAM_Millet	0.2579	0.1043	196.866	2.473	0.0142	1.2942
SPAM_Sorghum	0.283	0.1029	196.8445	2.7492	0.0065	1.3271
SPAM_Yams	0.24	0.1214	225.5399	1.9761	0.0494	1.2712
MIRCA_Cassava	0.1619	0.1217	202.4673	1.3307	0.1848	1.1757
MIRCA_Maize	0.2181	0.0984	148.3219	2.216	0.0282	1.2437
MIRCA_Millet	0.2044	0.1104	179.977	1.8516	0.0657	1.2268
MIRCA_Sorghum	0.1984	0.1093	180.098	1.8144	0.0713	1.2195
MIRCA_Yams	0.2303	0.1215	202.3855	1.896	0.0594	1.259
GAEZ_Cassava	0.1502	0.1205	184.9296	1.2469	0.214	1.1621
GAEZ_Maize	0.2018	0.1003	138.2983	2.0121	0.0461	1.2236
GAEZ_Millet	0.1408	0.1137	170.8305	1.2384	0.2173	1.1512
GAEZ_Sorghum	0.2474	0.1125	171.1959	2.1991	0.0292	1.2807
GAEZ_Yams	0.1993	0.1218	187.1401	1.6357	0.1036	1.2205

Table S2 8. Model (4) results when testing each of the 12 climate indicators, after removing the identified areas where the irrigated system predominates (>80% of the total area) from SPAM2000.

'M_SDMP_des_irri' refers to model (4) run with sd(monsoon precipitations) as explicative variable, 'M_CVMP_des_irri' refers to model (4) run with CV(monsoon precipitations) as explicative variable, 'M_mMP_des_irri' refers to model (4) run with mean(monsoon precipitations) as explicative variable, 'M_SDAP_des_irri' refers to model (4) run with sd(annual precipitations) as explicative variable, 'M_CVAP_des_irri' refers to model (4) run with CV(annual precipitations) as explicative variable, 'M_mAP_des_irri' refers to model (4) run with mean(annual precipitations) as explicative variable, 'M_SDML_des_irri' refers to model (4) run with sd(monsoon length) as explicative variable, 'M_CVML_des_irri' refers to model (4) run with CV(monsoon length) as explicative variable, 'M_mML_des_irri' refers to model (4) run with mean(monsoon length) as explicative variable, 'M_SD7DS_des_irri' refers to model (4) run with sd(7 days dryspell) as explicative variable, 'M_CV7DS_des_irri' refers to model (4) run with CV(7 days dryspell) as explicative variable, 'M_m7DS_des_irri' refers to model (4) run with mean(7 days dryspell) as explicative variable. . R² represents the variance explained by the whole model (fixed and random effects). The colored row refers to the model which has the lowest AIC. The bold numbers refer to the model coefficient estimates that have a p-value < 5%.

Model	(Intercept)	Inter_p-value	Slope	Slope_p-value	AIC	R2
M_SDMP_SPAM	-0.1614	0.2946	0.0028	0.0072	534.132	0.5237
M_CVMP_SPAM	-0.3693	0.0434	4.3316	8,00E-04	515.911	0.5135
M_mMP_SPAM	0.2353	0.2061	0	0.9209	545.2239	0.5224
M_SDAP_SPAM	-0.1228	0.4919	0.0029	0.0411	536.6854	0.523
M_CVAP_SPAM	-0.2524	0.2803	4.3846	0.0378	521.9731	0.5135
M_mAP_SPAM	0.1891	0.2814	0	0.8544	545.5805	0.5231
M_SDML_SPAM	-0.1394	0.2622	0.0194	0.001	527.3063	0.5151
M_CVML_SPAM	-0.1504	0.2568	3.0494	0.0018	518.1422	0.5145
M_mML_SPAM	0.0617	0.8714	0.001	0.6742	534.5784	0.5324
M_SD7DS_SPAM	0.0401	0.7509	0.3387	0.0938	528.1681	0.5209
M_CV7DS_SPAM	0.3971	0.0299	-0.1881	0.28	530.139	0.518
M_m7DS_SPAM	0.0225	0.8283	0.2787	0.0152	526.2064	0.517

Table S2 9. Model (4) results when testing each of the 12 climate indicators, after removing the identified areas where the irrigated system predominates (>80% of the total area) from MIRCA2000.

'M_SDMP_des_irri' refers to model (4) run with sd(monsoon precipitations) as explicative variable, 'M_CVMP_des_irri' refers to model (4) run with CV(monsoon precipitations) as explicative variable, 'M_mMP_des_irri' refers to model (4) run with mean(monsoon precipitations) as explicative variable, 'M_SDAP_des_irri' refers to model (4) run with sd(annual precipitations) as explicative variable, 'M_CVAP_des_irri' refers to model (4) run with CV(annual precipitations) as explicative variable, 'M_mAP_des_irri' refers to model (4) run with mean(annual precipitations) as explicative variable, 'M_SDML_des_irri' refers to model (4) run with sd(monsoon length) as explicative variable, 'M_CVML_des_irri' refers to model (4) run with CV(monsoon length) as explicative variable, 'M_mML_des_irri' refers to model (4) run with mean(monsoon length) as explicative variable, 'M_SD7DS_des_irri' refers to model (4) run with sd(7 days dryspell) as explicative variable, 'M_CV7DS_des_irri' refers to model (4) run with CV(7 days dryspell) as explicative variable, 'M_m7DS_des_irri' refers to model (4) run with mean(7 days dryspell) as explicative variable. . R² represents the variance explained by the whole model (fixed and random effects). The colored row refers to the model which has the lowest AIC. The bold numbers refer to the model coefficient estimates that have a p-value < 5%.

Model	(Intercept)	Inter_p-value	Slope	Slope_p-value	AIC	R2
M_SDMP_MIRCA	-0.2087	0.1756	0.0031	0.0036	540.5519	0.5361
M_CVMP_MIRCA	-0.3768	0.0398	4.3084	9,00E-04	523.8996	0.5258
M_mMP_MIRCA	0.1685	0.3709	0	0.8391	552.9261	0.5348
M_SDAP_MIRCA	-0.1823	0.3118	0.0033	0.0223	543.3344	0.5352

M_CVAP_MIRCA	-0.2251	0.3403	4.0043	0.0603	530.5057	0.5263
M_mAP_MIRCA	0.127	0.4746	1,00E-04	0.6361	553.1222	0.5354
M_SDML_MIRCA	-0.143	0.2538	0.0188	0.0016	535.7987	0.5266
M_CVML_MIRCA	-0.1409	0.2923	2.8683	0.0037	527.1739	0.5265
M_mML_MIRCA	-0.019	0.9615	0.0014	0.5653	542.4506	0.546
M_SD7DS_MIRCA	0.026	0.8364	0.3407	0.0939	535.9192	0.5325
M_CV7DS_MIRCA	0.3386	0.064	-0.1425	0.4166	538.3915	0.5307
M_m7DS_MIRCA	0.0251	0.8103	0.2547	0.0265	534.9525	0.5287

Table S2 10. Model (4) results when testing each of the 12 climate indicators, after removing the identified areas where the irrigated system predominates (>80% of the total area) from GAEZv3.

‘M_SDMP_des_irri’ refers to model (4) run with sd(monsoon precipitations) as explicative variable, ‘M_CVMP_des_irri’ refers to model (4) run with CV(monsoon precipitations) as explicative variable, ‘M_mMP_des_irri’ refers to model (4) run with mean(monsoon precipitations) as explicative variable, ‘M_SDAP_des_irri’ refers to model (4) run with sd(annual precipitations) as explicative variable, ‘M_CVAP_des_irri’ refers to model (4) run with CV(annual precipitations) as explicative variable, ‘M_mAP_des_irri’ refers to model (4) run with mean(annual precipitations) as explicative variable, ‘M_SDML_des_irri’ refers to model (4) run with sd(monsoon length) as explicative variable, ‘M_CVML_des_irri’ refers to model (4) run with CV(monsoon length) as explicative variable, ‘M_mML_des_irri’ refers to model (4) run with mean(monsoon length) as explicative variable, ‘M_SD7DS_des_irri’ refers to model (4) run with sd(7 days dryspell) as explicative variable, ‘M_CV7DS_des_irri’ refers to model (4) run with CV(7 days dryspell) as explicative variable, ‘M_m7DS_des_irri’ refers to model (4) run with mean(7 days dryspell) as explicative variable. . R² represents the variance explained by the whole model (fixed and random effects). The colored row refers to the model which has the lowest AIC. The bold numbers refer to the model coefficient estimates that have a p-value < 5%.

Model	(Intercept)	Inter_p-value	Slope	Slope_p-value	AIC	R2
M_SDMP_GAEZ	-0.2186	0.2012	0.003	0.0074	500.2372	0.5575
M_CVMP_GAEZ	-0.3729	0.0503	4.2967	0.0014	483.1395	0.5494
M_mMP_GAEZ	0.2186	0.31	0	0.9457	511.2159	0.5574
M_SDAP_GAEZ	-0.1626	0.4156	0.003	0.0503	503.078	0.5568
M_CVAP_GAEZ	-0.2588	0.3074	4.4268	0.0587	488.7323	0.549
M_mAP_GAEZ	0.1595	0.4302	0	0.8076	511.5516	0.5579
M_SDML_GAEZ	-0.1586	0.2245	0.0197	0.0013	493.8767	0.552
M_CVML_GAEZ	-0.1614	0.242	3.099	0.0026	484.8513	0.5508
M_mML_GAEZ	-0.0653	0.8813	0.0017	0.5339	499.1234	0.5648
M_SD7DS_GAEZ	0.0107	0.9356	0.3673	0.0785	494.0226	0.5564
M_CV7DS_GAEZ	0.3858	0.0441	-0.19	0.2956	496.3393	0.5544
M_m7DS_GAEZ	-0.007	0.949	0.2967	0.0125	491.982	0.5534

Table S2 11. Model (5) results: coefficients, p-values and R2 for the best model selected based on the AIC criteria, without removing predominantly irrigated areas. R2 is the r.squared given by the summary function in R. It represents the percent of the variance explained by the model, after subtraction the error. Models are here presented based on climate indices computed only for grid cells with at least 1% cropped areas.

Product2	Best_model	Intercept	pvalue_int	Slope	pvalue_slo	AIC	R2
Cassava	CVMP	-0.6638	0.0626	6.0242	0.0159	104.147	0.155
Maize	m7DS	-0.2193	0.0853	0.5284	4,00E-04	150.2538	0.1697

Millet	sdAP	-0.4601	0.0659	0.0069	0.0061	119.0454	0.1337
Sorghum	sd7DS	0.5398	0.0058	-1.0458	0.0233	126.786	0.087
Yams	sdML	-0.1433	0.4736	0.0177	0.0484	80.5301	0.1039

Table S2 12. Model (5) results: coefficients, p-values and R2 for the best model selected based on the AIC criteria, after removing predominantly irrigated areas (i.e., >80% of the rice cropping area), identified from SPAM2000. R2 is the r.squared given by the summary function in R. It represents the percent of the variance explained by the model, after subtraction the error. Models are here presented based on climate indices computed only for grid cells with at least 1% cropped areas.

Product2	Best_model	Intercept	pvalue_int	Slope	pvalue_slo	AIC	R2
Cassava	CVMP	-0.6638	0.0626	6.0242	0.0159	104.147	0.155
Maize	m7DS	-0.2192	0.098	0.5264	6,00E-04	146.0384	0.1688
Millet	CVML	-0.5493	0.0406	7.1931	0.0027	105.9055	0.1756
Sorghum	sd7DS	0.5871	0.0024	-1.0178	0.028	107.5509	0.0911
Yams	CVMP	-0.2695	0.3137	3.7823	0.0546	77.5032	0.1044

Table S2 13. Model (5) results: coefficients, p-values and R2 for the best model selected based on the AIC criteria, after removing predominantly irrigated areas (i.e., >80% of the rice cropping area), identified from MIRCA2000. R2 is the r.squared given by the summary function in R. It represents the percent of the variance explained by the model, after subtraction the error. Models are here presented based on climate indices computed only for grid cells with at least 1% cropped areas.

Product2	Best_model	Intercept	pvalue_int	Slope	pvalue_slo	AIC	R2
Cassava	CVMP	-0.6638	0.0626	6.0242	0.0159	104.147	0.155
Maize	m7DS	-0.2074	0.1091	0.5271	5,00E-04	146.584	0.1704
Millet	CVAP	-0.6457	0.0365	7.841	0.0048	108.8647	0.1544
Sorghum	sd7DS	0.6092	0.002	-1.1412	0.0164	110.9067	0.1057
Yams	sdML	-0.1433	0.4736	0.0177	0.0484	80.5301	0.1039

Table S2 14. Model (5) results: coefficients, p-values and R2 for the best model selected based on the AIC criteria, after removing predominantly irrigated areas (i.e., >80% of the rice cropping area), identified from GAEZv3.0. R2 is the r.squared given by the summary function in R. It represents the percent of the variance explained by the model, after subtraction the error. Models are here presented based on climate indices computed only for grid cells with at least 1% cropped areas.

Product2	Best_model	Intercept	pvalue_int	Slope	pvalue_slo	AIC	R2
Cassava	CVMP	-0.6638	0.0626	6.0242	0.0159	104.147	0.155
Maize	m7DS	-0.1369	0.2823	0.4953	7,00E-04	130.7933	0.1759
Millet	CVML	-0.6288	0.0383	7.9243	0.0058	99.1774	0.1678
Sorghum	sd7DS	0.4987	0.0157	-1.0705	0.0384	101.991	0.0918
Yams	sdML	-0.1519	0.4576	0.0178	0.0501	79.6917	0.1053

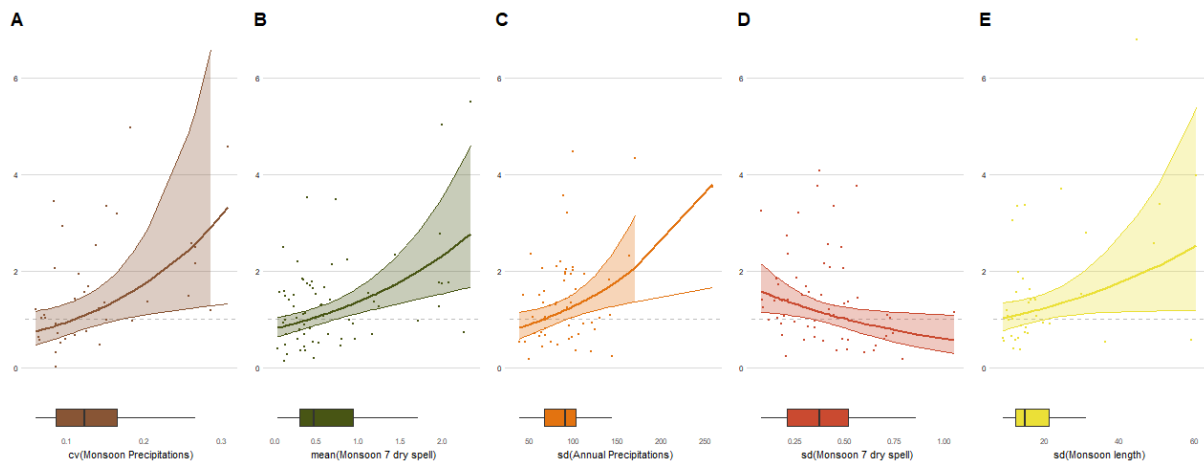


Figure S2 10. Relationship between the climate indicator associated to the best model (i.e., lowest AIC), and the relative variability of rice yields compared to cassava (A), maize (B), millet (C), sorghum (D), and yams yields variability (E), without removing areas where irrigated rice predominates. Median relationship (bold lines) and 95% confidence intervals are modeled based on a fixed-effects model (see method section). Boxplot represents the distribution of the coefficient of variation of precipitation during the monsoon season or of the average dry spell occurrences in the areas where yield data are available. Note that the time-periods on which these relationships are computed vary between crops because of data availability. Grey horizontal dotted bar delineates SD ratio equal to 1 (rice yield variability is equal to that of another crop species) with values above one indicating higher variability in rice (or lower stability) in comparison to the other crop species considered.

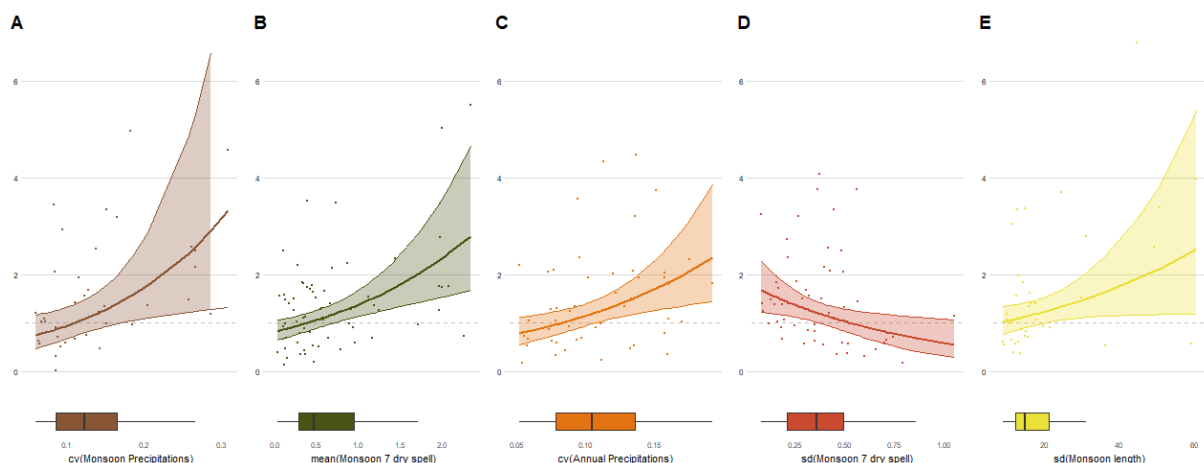


Figure S2 11. Relationship between the climate indicator associated to the best model (i.e., lowest AIC), and the relative variability of rice yields compared to cassava (A), maize (B), millet (C), sorghum (D), and yams yields variability (E), after removal of the areas where irrigated rice predominates (i.e., >80% of the total rice area), identified from MIRCA. Median relationship (bold lines) and 95% confidence intervals are modeled based on a fixed-effects model (see method section). Boxplot represents the distribution of the coefficient of variation of precipitation during the monsoon season or of the average dry spell occurrences in the areas where yield data are available. Note that the time-periods on which these relationships are computed vary between crops because of data availability. Grey horizontal dotted bar delineates SD ratio equal to 1 (rice yield variability is equal to that of another crop species) with values above one indicating higher variability in rice (or lower stability) in comparison to the other crop species considered.

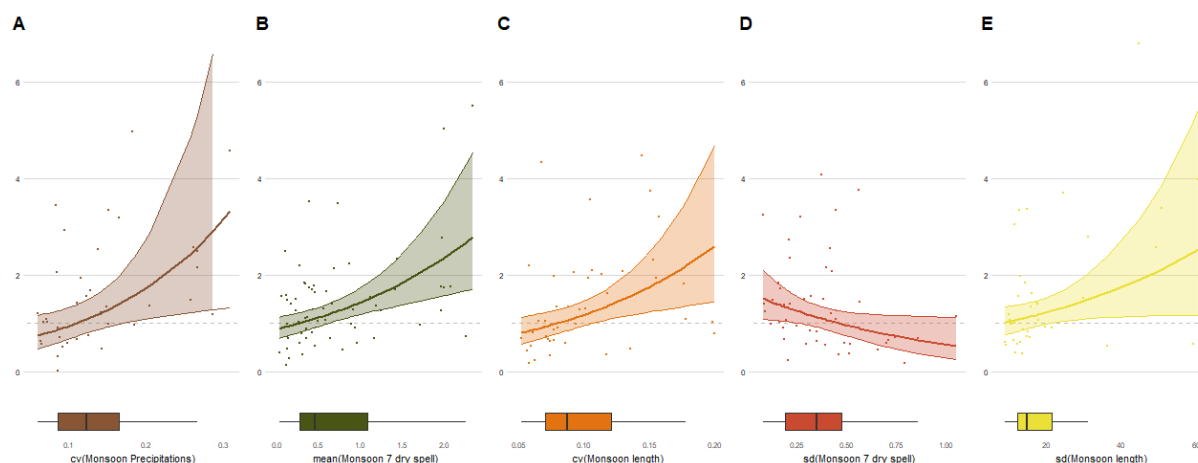


Figure S2 12. Relationship between the climate indicator associated to the best model (i.e., lowest AIC), and the relative variability of rice yields compared to cassava (A), maize (B), millet (C), sorghum (D), and yams yields variability (E), after removal of the areas where irrigated rice predominates (i.e., >80% of the total rice area), identified from GAEZ. Median relationship (bold lines) and 95% confidence intervals are modeled based on a fixed-effects model (see method section). Boxplot represents the distribution of the coefficient of variation of precipitation during the monsoon season or of the average dry spell occurrences in the areas where yield data are available. Note that the time-periods on which these relationships are computed vary between crops because of data availability. Grey horizontal dotted bar delineates SD ratio equal to 1 (rice yield variability is equal to that of another crop species) with values above one indicating higher variability in rice (or lower stability) in comparison to the other crop species considered.

Table S2 15. Detailed results obtained with model (5). for each climate indicator and for each alternative crop. MP is the cumulated monsoon precipitations. AP is the cumulated annual precipitations. ML is the monsoon length and 7DS is the 7-days dry spell occurrence. (.)= p-value <0.1, (*)=p-value <0.05, (**)=p-value<0.01, (***)=p-value<0.001). R² is the marginal coefficient of determination for Generalized mixed-effect models, measured with the function `r.squaredGLMM()` in R studio. It represents the variance explained by the fixed effect only.

	Model	Intercept	Slope	AIC	R2
Cassava	CVMP	-0.6638	6.0242	104.147	0.155
	sdMP	-0.5986	0.0044	104.147	0.1051
	mMP	0.4502	-2,00E-04	104.147	0.0116
	CVAP	-1.1924	14.1718	104.147	0.1294
	sdAP	-0.3802	0.0036	104.147	0.0386
	mAP	0.298	-1,00E-04	104.147	0.0037
	CVML	-0.2464	3.2101	104.147	0.0758
	sdML	-0.2782	0.0199	104.147	0.083
	mML	-0.3796	0.0028	104.147	0.0037
	CV7DS	0.8403	-0.8061	104.147	0.1124
	sd7DS	-0.2244	0.5267	104.147	0.0475
	m7DS	-0.3988	0.5527	104.147	0.1517
Maize	CVMP	-0.4381	4.356	146.0384	0.0873
	sdMP	-0.3895	0.004	146.0384	0.1198
	mMP	-0.0731	2,00E-04	146.0384	0.0137
	CVAP	-0.2099	3.2931	146.0384	0.0193

	sdAP	-0.4419	0.005	146.0384	0.104
	mAP	-0.1263	2,00E-04	146.0384	0.025
	CVML	-0.2858	3.5961	146.0384	0.1022
	sdML	-0.3446	0.0267	146.0384	0.1539
	mML	-0.9735	0.0072	146.0384	0.074
	CV7DS	0.7113	-0.6102	146.0384	0.0866
	sd7DS	-0.2568	0.7656	146.0384	0.1259
	m7DS	-0.2192	0.5264	146.0384	0.1688
Millet	CVMP	-0.7519	7.9639	105.9055	0.1598
	sdMP	-0.3385	0.0055	105.9055	0.0841
	mMP	0.4224	-2,00E-04	105.9055	0.0094
	CVAP	-0.6706	8.2424	105.9055	0.1728
	sdAP	-0.3922	0.0064	105.9055	0.1111
	mAP	0.4269	-2,00E-04	105.9055	0.0097
	CVML	-0.5493	7.1931	105.9055	0.1756
	sdML	-0.6549	0.0603	105.9055	0.1566
	mML	1.7221	-0.0107	105.9055	0.1056
	CV7DS	0.1632	0.0499	105.9055	9,00E-04
	sd7DS	0.0275	0.5634	105.9055	0.0162
	m7DS	0.227	-0.0273	105.9055	1,00E-04
Sorghum	CVMP	0.179	0.3301	107.5509	4,00E-04
	sdMP	0.495	-0.0028	107.5509	0.02
	mMP	0.5894	-4,00E-04	107.5509	0.0317
	CVAP	0.1746	0.4213	107.5509	6,00E-04
	sdAP	0.5868	-0.0039	107.5509	0.0315
	mAP	0.5845	-4,00E-04	107.5509	0.032
	CVML	0.1287	0.833	107.5509	0.0037
	sdML	0.1505	0.0046	107.5509	0.002
	mML	0.8568	-0.0045	107.5509	0.0273
	CV7DS	0.1292	0.0906	107.5509	0.0027
	sd7DS	0.5871	-1.0178	107.5509	0.0911
	m7DS	0.3736	-0.3562	107.5509	0.0367
Yams	CVMP	-0.2695	3.7823	77.5032	0.1044
	sdMP	-0.0874	0.0018	77.5032	0.0344
	mMP	0.5135	-2,00E-04	77.5032	0.0172
	CVAP	-0.2785	5.3088	77.5032	0.0304
	sdAP	0.161	3,00E-04	77.5032	6,00E-04
	mAP	0.3801	-1,00E-04	77.5032	0.0062
	CVML	-0.0991	2.7878	77.5032	0.0861
	sdML	-0.1314	0.0173	77.5032	0.1012
	mML	0.0035	0.0011	77.5032	7,00E-04
	CV7DS	0.5624	-0.4027	77.5032	0.057
	sd7DS	-8,00E-04	0.3238	77.5032	0.0276
	m7DS	-0.046	0.2736	77.5032	0.0682

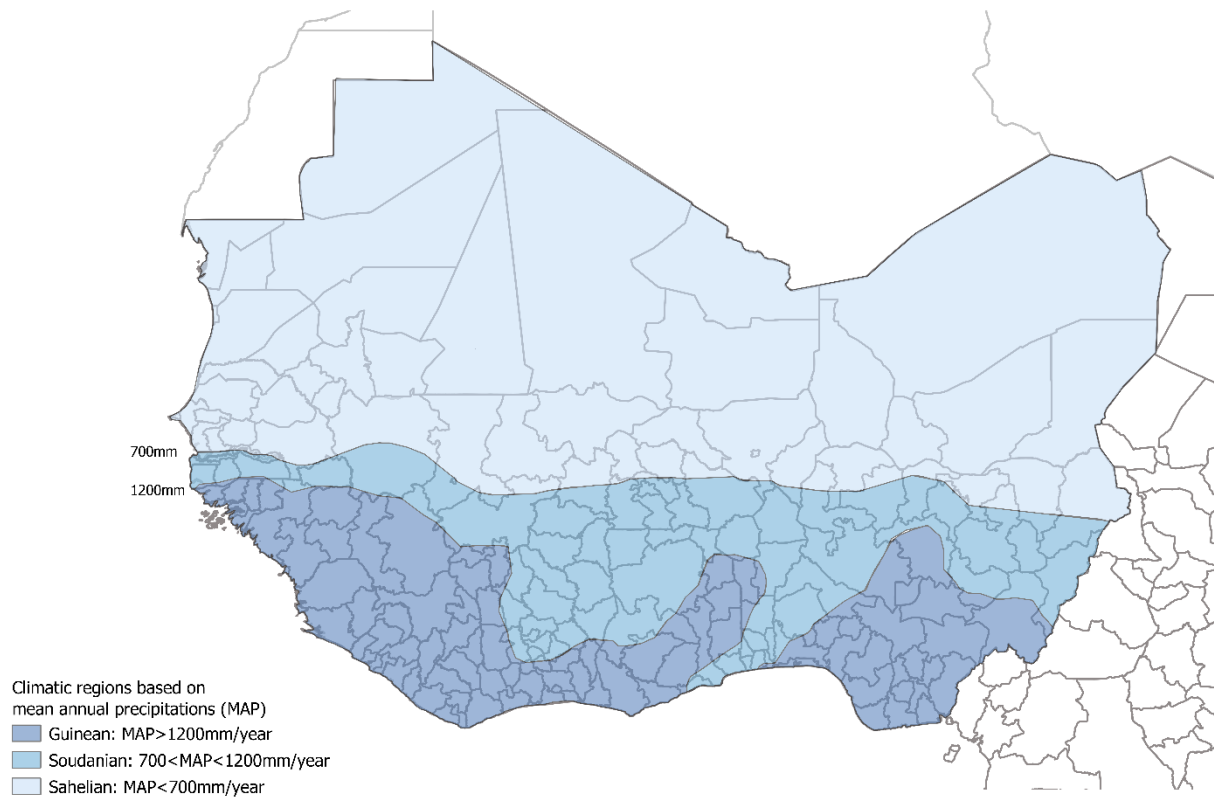
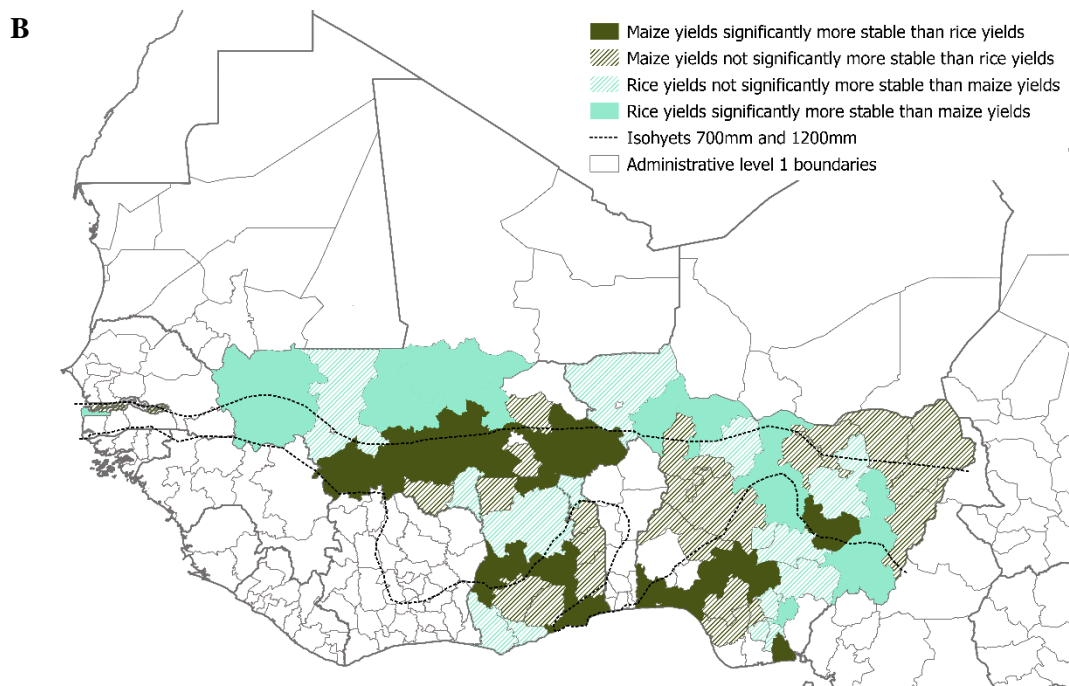
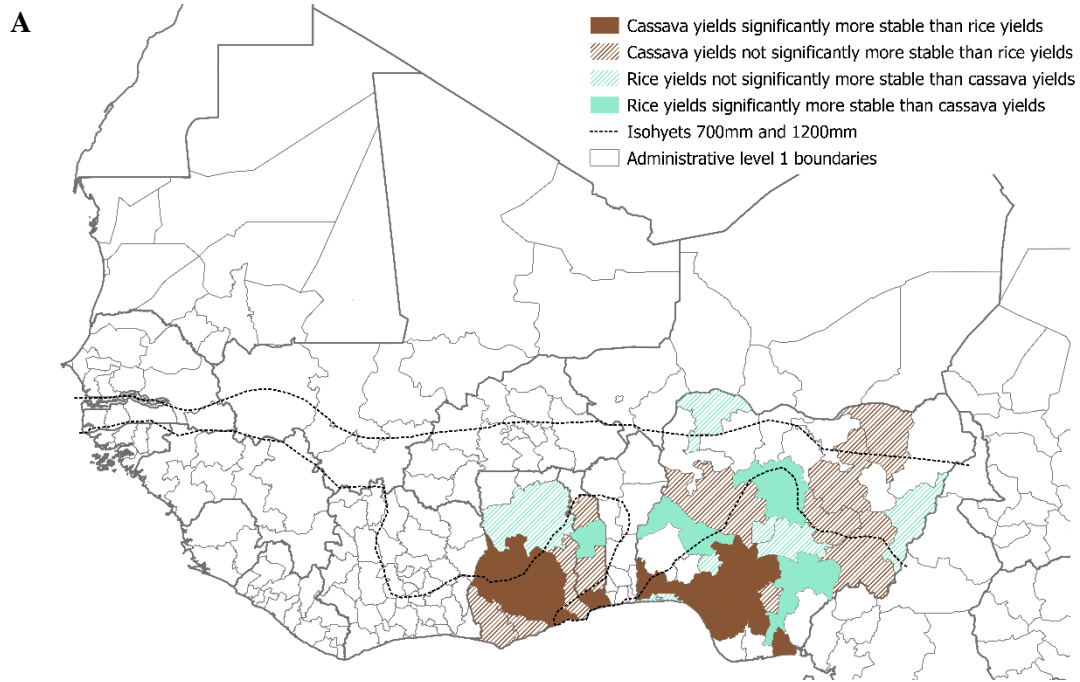
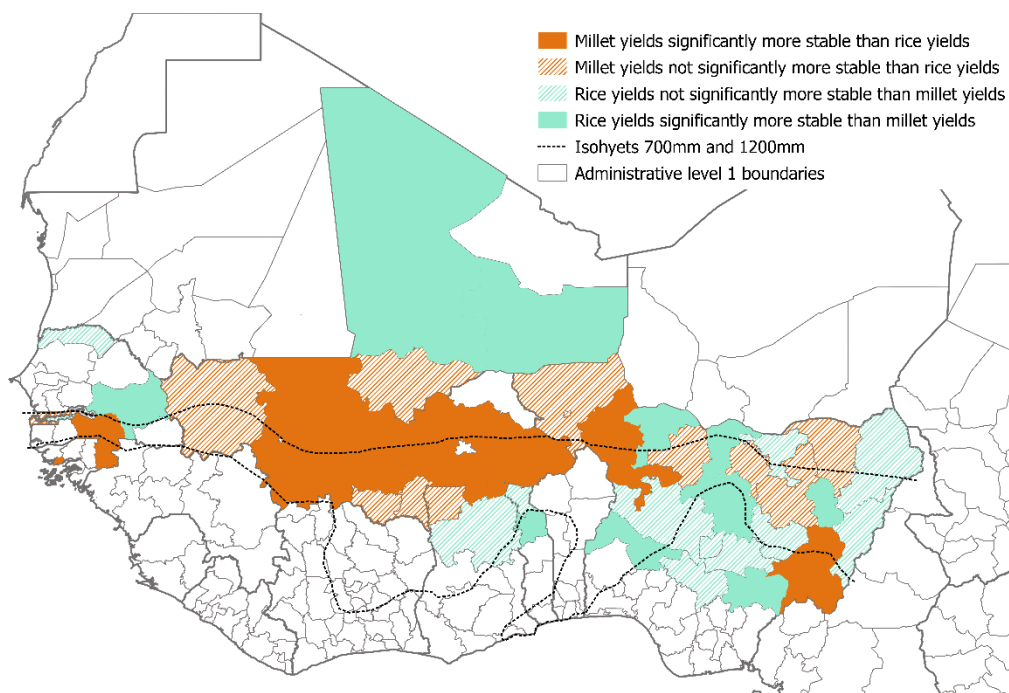


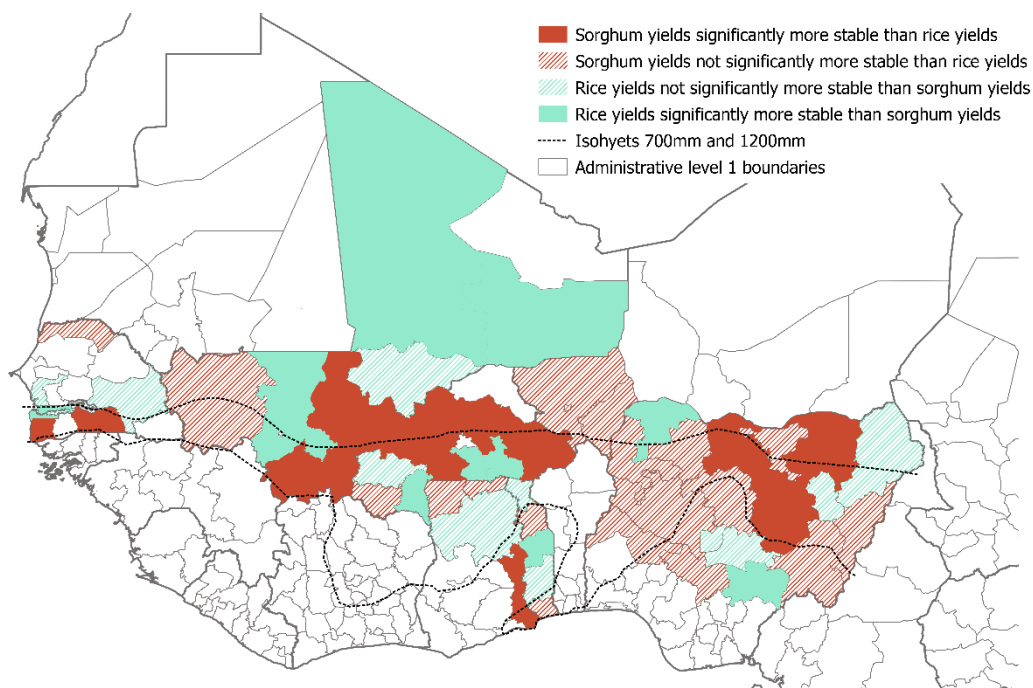
Figure S2 13. West African climatic regions defined from mean annual precipitation (MAP) measured in each administrative level 1 region between 1981 and 2019. Guinean region (dark blue) corresponds to the area where MAP is superior to 1200mm/year, Soudanian region (medium blue) corresponds to the area where MAP is inferior to 1200mm/year and superior to 700mm/year and Sahelian region (light blue) corresponds to the area where MAP is inferior to 700mm/year. The definitions of west African climatic regions area based on a simplified definition of the Food and Agriculture Organization (Pierre Sigaud 2001).



C



D



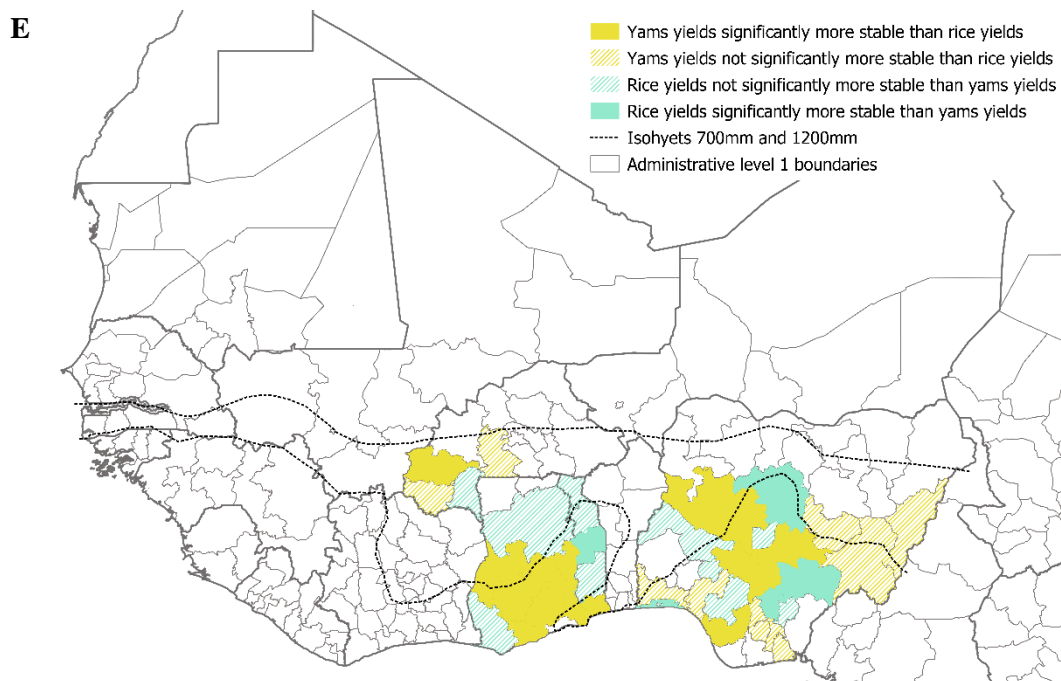


Figure S2 14. Details of the comparison of rice yields variability and that of cassava (A), maize (B), millet (C), sorghum (D) and yams (E). Full green areas delineate the areas where rice yields are significantly more stable than that of alternative crops (i.e., $SDR < 1$). Plain areas of other colors (brown for cassava, green for maize, orange for millet, red for sorghum and yellow for yams) are the areas where rice yields are significantly less stable than that of the alternative food crop (i.e., $SDR > 1$). Light green dashed areas are the areas where rice yields are more stable than that of the compared crop yields but not significantly. Dashed areas of other colors (brown for cassava, green for maize, orange for millet, red for sorghum and yellow for yams) are the areas where the alternative food crops yields are more stable than that of rice but not significantly.

Table S2 16. Detailed results obtained for complex models with at least two climate variables, after removing free crop grid cells and the predominantly irrigated areas (i.e., where irrigated rice area is superior to 80% of the total rice area), identified from SPAM000. R^2 represents the variance explained by the whole model (fixed and random effects).

Coefficients	Estimate	p-value	R^2	AIC
M1 <- lmer(log(SD_ratio)~Product2+sd.Monsoon_P.+(1 Area))				
(Intercept)	-0.34	0.089	0.5240	548.50
Table\$Product2Maize	0.05	0.718		
Table\$Product2Millet	0.19	0.177		
Table\$Product2Sorghum	0.22	0.123		
Table\$Product2Yams	0.08	0.582		
Table\$sd.Monsoon_P.	0.00	0.002		
M2 <- lmer(log(SD_ratio)~Product2*sd.Monsoon_P.+(1 Area))				
(Intercept)	-0.44	0.097	0.5478	588.86
Table\$Product2Maize	0.03	0.919		
Table\$Product2Millet	0.17	0.651		
Table\$Product2Sorghum	0.98	0.009		
Table\$Product2Yams	0.47	0.185		
Table\$sd.Monsoon_P.	0.00	0.012		
Table\$Product2Maize:Table\$sd.Monsoon_P.	0.00	0.860		
Table\$Product2Millet:Table\$sd.Monsoon_P.	0.00	0.802		

Table\$Product2Sorghum:Table\$sd.Monsoon_P.	-0.00	0.0127				
Table\$Product2Yams:Table\$sd.Monsoon_P.	-0.00	0.227				
M3 <- lmer(log(SD_ratio)~Product2+sd.Monsoon_7dryspell.+(1 Area))						
(Intercept)	-0.09	0.611	0.5227	543.48		
Table\$Product2Maize	0.02	0.863				
Table\$Product2Millet	0.16	0.273				
Table\$Product2Sorghum	0.18	0.213				
Table\$Product2Yams	0.08	0.565				
Table\$sd.Monsoon_7dryspell.	0.41	0.050				
M4 <- lmer(log(SD_ratio)~Product2*sd.Monsoon_7dryspell.+(1 Area))						
(Intercept)	-0.06	0.771	0.5676	536.63		
Table\$Product2Maize	-0.17	0.463				
Table\$Product2Millet	0.12	0.670				
Table\$Product2Sorghum	0.70	0.009				
Table\$Product2Yams	0.15	0.590				
Table\$sd.Monsoon_7dryspell.	0.41	0.163				
Table\$Product2Maize:Table\$sd.Monsoon_7dryspell.	0.35	0.273				
Table\$Product2Millet:Table\$sd.Monsoon_7dryspell.	0.04	0.945				
Table\$Product2Sorghum:Table\$sd.Monsoon_7dryspell.	-1.54	0.004				
Table\$Product2Yams:Table\$sd.Monsoon_7dryspell.	-0.12	0.758				
M5 <- lmer(log(SD_ratio)~sd.Monsoon_P.+sd.Monsoon_7dryspell.+(1 Area))						
(Intercept)	-0.17	0.283	0.5255	536.17		
Table\$sd.Monsoon_P.	0.00	0.027				
Table\$sd.Monsoon_7dryspell.	-0.21	0.504				
M6 <- lmer(log(SD_ratio)~sd.Monsoon_P.*Product2+sd.Monsoon_7dryspell.*Product2+(1 Area))						
(Intercept)	-0.48	0.095	0.5716	588.38		
Table\$sd.Monsoon_P.	0.01	0.028				
Table\$Product2Maize	0.08	0.800				
Table\$Product2Millet	0.19	0.613				
Table\$Product2Sorghum	1.02	0.007				
Table\$Product2Yams	0.51	0.144				
Table\$sd.Monsoon_7dryspell.	-0.47	0.342				
Table\$sd.Monsoon_P.:Table\$Product2Maize	-0.00	0.293				
Table\$sd.Monsoon_P.:Table\$Product2Millet	-0.00	0.751				
Table\$sd.Monsoon_P.:Table\$Product2Sorghum	-0.00	0.251				
Table\$sd.Monsoon_P.:Table\$Product2Yams	-0.01	0.121				
Table\$Product2Maize:Table\$sd.Monsoon_7dryspell.	0.80	0.148				
Table\$Product2Millet:Table\$sd.Monsoon_7dryspell.	0.44	0.565				
Table\$Product2Sorghum:Table\$sd.Monsoon_7dryspell.	-0.81	0.274				
Table\$Product2Yams:Table\$sd.Monsoon_7dryspell.	0.72	0.296				
M7 <- lmer(log(SD_ratio)~Product2+CV_Monsoon_P+(1 Area))						
(Intercept)	-0.45	0.032			0.5169	531.92
Table\$Product2Maize	-0.48	0.997				
Table\$Product2Millet	0.12	0.384				

Table\$Product2Sorghum	0.14	0.323		
Table\$Product2Yams	0.9	0.542		
Table\$CV_Monsoon_P	4.43	0.001		
M8 <- lmer(log(SD_ratio)~Product2*CV_Monsoon_P+(1 Area))				
(Intercept)	-0.63	0.020	0.5357	518.42
Table\$Product2Maize	0.21	0.489		
Table\$Product2Millet	-0.17	0.659		
Table\$Product2Sorghum	0.80	0.028		
Table\$Product2Yams	0.37	0.254		
Table\$CV_Monsoon_P	5.82	0.002		
Table\$Product2Maize:Table\$CV_Monsoon_P	-1.58	0.452		
Table\$Product2Millet:Table\$CV_Monsoon_P	2.54	0.393		
Table\$Product2Sorghum:Table\$CV_Monsoon_P	-5.20	0.054		
Table\$Product2Yams:Table\$CV_Monsoon_P	-2.24	0.334		
M9 <- lmer(log(SD_ratio)~CV_Monsoon_P+CV_Monsoon_7dryspell+(1 Area))				
(Intercept)	-0.42	0.172	0.5161	519.49
Table\$CV_Monsoon_P	4.44	0.002		
Table\$CV_Monsoon_7dryspell	0.04	0.842		
M10 <- lmer(log(SD_ratio)~CV_Monsoon_P*Product2+CV_Monsoon_7dryspell*Product2+(1 Area))				
(Intercept)	-0.25	0.633	0.5375	528.78
Table\$CV_Monsoon_P	4.85	0.027		
Table\$Product2Maize	0.21	0.725		
Table\$Product2Millet	-0.68	0.285		
Table\$Product2Sorghum	0.11	0.867		
Table\$Product2Yams	-0.02	0.972		
Table\$CV_Monsoon_7dryspell	-0.28	0.410		
Table\$CV_Monsoon_P:Table\$Product2Maize	-1.52	0.540		
Table\$CV_Monsoon_P:Table\$Product2Millet	3.75	0.247		
Table\$CV_Monsoon_P:Table\$Product2Sorghum	-3.48	0.256		
Table\$CV_Monsoon_P:Table\$Product2Yams	-1.15	0.685		
Table\$Product2Maize:Table\$CV_Monsoon_7dryspell	0.01	0.990		
Table\$Product2Millet:Table\$CV_Monsoon_7dryspell	0.38	0.316		
Table\$Product2Sorghum:Table\$CV_Monsoon_7dryspell	0.49	0.215		
Table\$Product2Yams:Table\$CV_Monsoon_7dryspell	0.29	0.492		
M11 <- lmer(log(SD_ratio)~CV_Monsoon_P*Product2+mean.Monsoon_7dryspell.*Product2+(1 Area))				
(Intercept)	-0.60	0.030	0.5561	518.61
Table\$CV_Monsoon_P	4.98	0.121		
Table\$Product2Maize	0.36	0.249		
Table\$Product2Millet	-0.15	0.694		
Table\$Product2Sorghum	0.68	0.067		
Table\$Product2Yams	0.32	0.346		
Table\$mean.Monsoon_7dryspell.	0.11	0.716		
Table\$CV_Monsoon_P:Table\$Product2Maize	-4.57	0.190		

Table\$CV_Monsoon_P:Table\$Product2Millet	4.70	0.254		
Table\$CV_Monsoon_P:Table\$Product2Sorghum	-2.03	0.614		
Table\$CV_Monsoon_P:Table\$Product2Yams	-0.27	0.948		
Table\$Product2Maize:Table\$mean.Monsoon_7dryspell.	0.37	0.230		
Table\$Product2Millet:Table\$mean.Monsoon_7dryspell.	-0.75	0.183		
Table\$Product2Sorghum:Table\$mean.Monsoon_7dryspell.	-0.64	0.122		
Table\$Product2Yams:Table\$mean.Monsoon_7dryspell.	-0.21	0.58		
M12 <- lmer(log(SD_ratio)~Product2+CV_Monsoon_P+mean.Monsoon_7dryspell.+(1 Area))				
Intercept)	-0.43	0.043		
Table\$Product2Maize	0.01	0.928	0.5171	535.41
Table\$Product2Millet	0.14	0.321		
Table\$Product2Sorghum	0.16	0.272		
Table\$Product2Yams	0.09	0.544		
Table\$CV_Monsoon_P	3.73	0.038		
Table\$mean.Monsoon_7dryspell.	0.09	0.577		

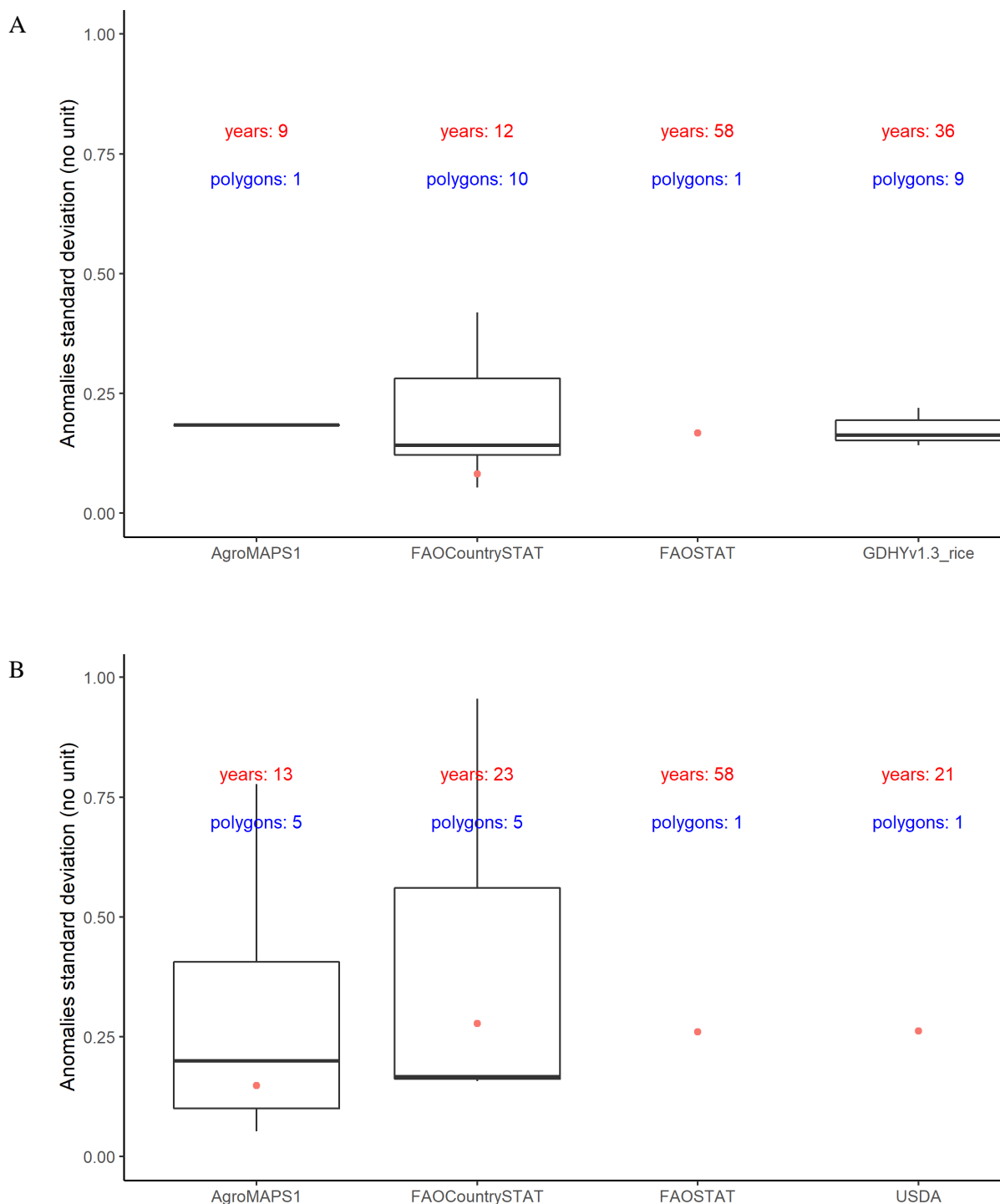


Figure S2 15. Illustration of the yield standard deviation distribution across 4 databases for (A) rice in Ghana and (B) millet in Guinea-Bissau. Each boxplot represent the distribution of crop yield standard deviations estimated at administrative level 1 for AgroMAPS1 and FAOCountrySTAT data and in each square of a grid of dimension 0.5°x0.5° for GDHYv1.3_rice (Iizumi and Sakai 2020). FAOSTAT and USDA only inform data at the national scale. The red point associated with AgroMAPS1 and FAOCountrySTAT data is the standard deviation measured when aggregating observed regional yields at the national level. The number of years indicated on the top of each database results is the average length of the time-series used to measure the standard deviations. The number of administrative level 1 polygons are indicated at the top of each boxplot and correspond to the number of time-series used to represent the standard deviation distribution (e.g., polygons=1 when the database gives

national data, polygons=5 significates that the standard deviations are measured in 5 areas for the crop and in the corresponding country).

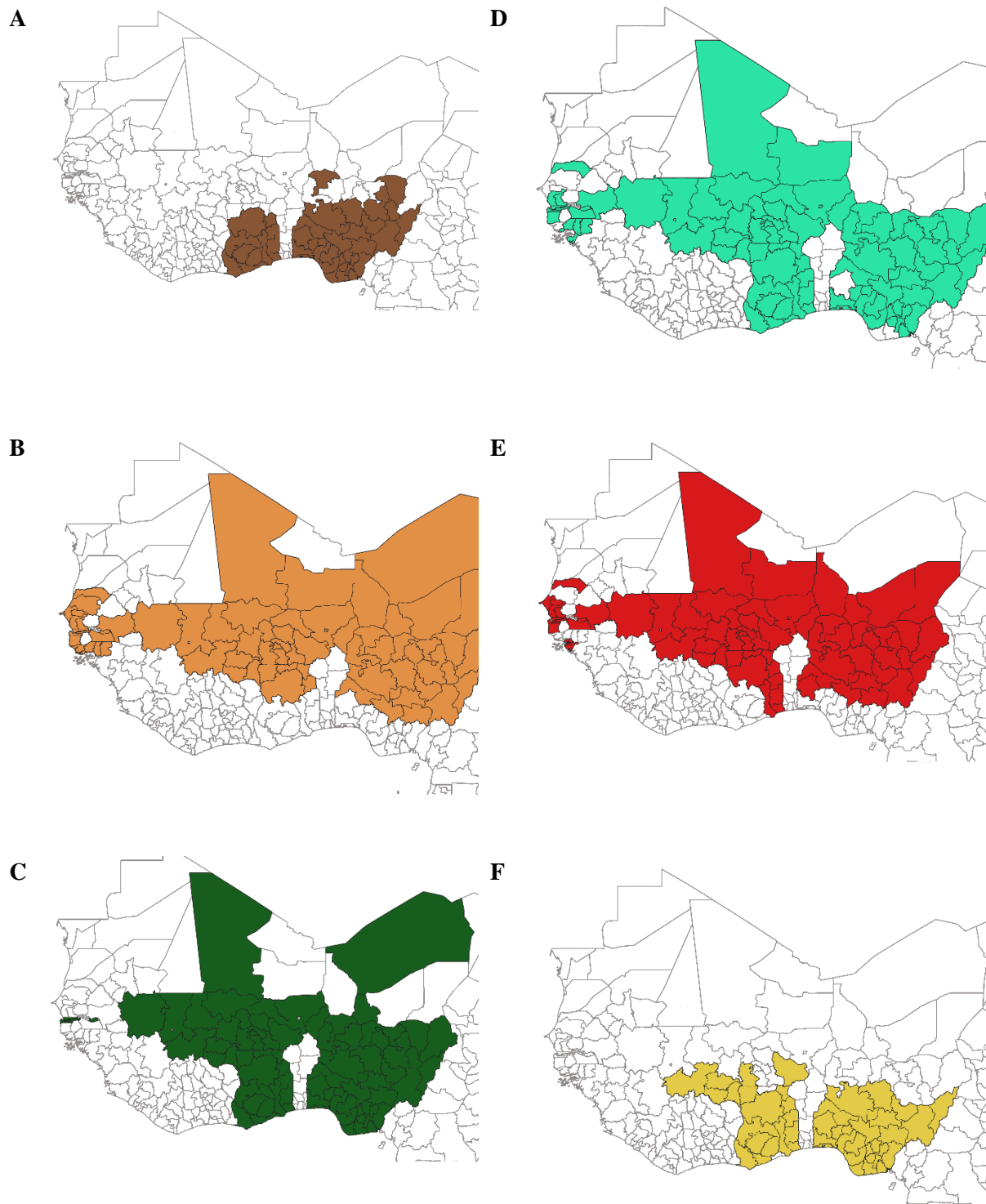


Figure S2 16. Localization of included yield time series for cassava (A), maize (B), millet (C), rice (D), sorghum (E), yams (F).

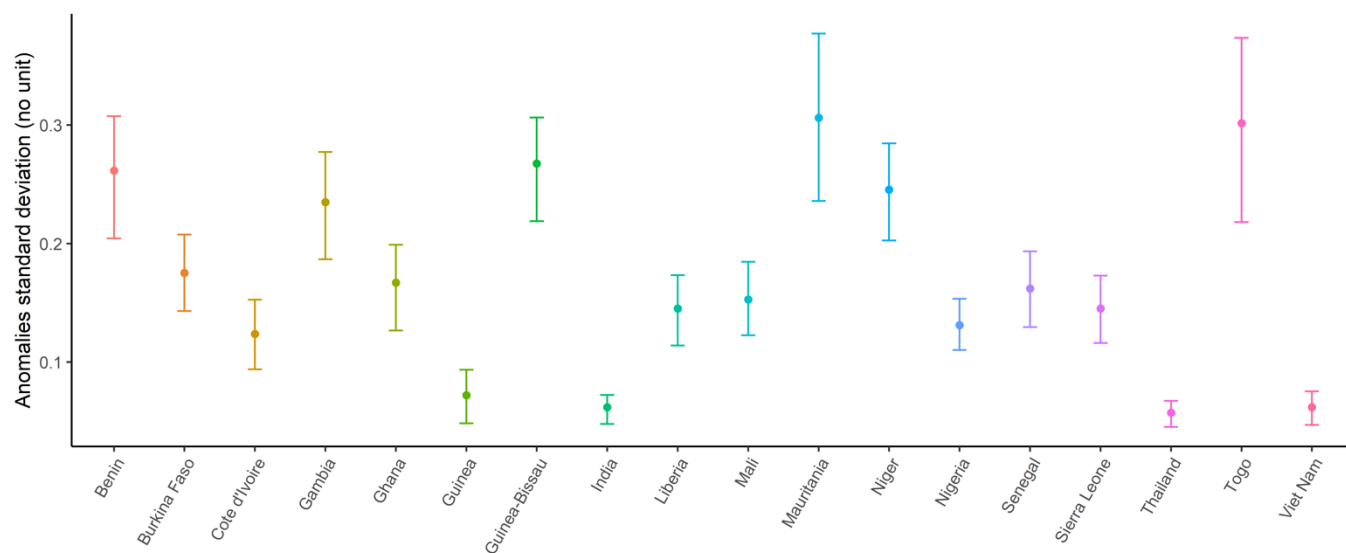


Figure S2 17. Normalized rice yield residuals standard deviation, measured at national level, for the period 1961-2018. Observed yield time-series are collected from FAOSTAT dataset. Confidence intervals are estimated via bootstrapping.

6.3 SUPPLEMENTS CHAPTER 3

6.3.1 Supplementary data & method

6.3.1.1 Rice production systems

Table S3 1. Classification of rice cropping systems in West Africa used during expert probabilistic elicitation and the construction of production functions

Environments		Water management		
		Absent	Partially managed	Totally managed
Lowland	Alluvial plains /estuaries	Non-irrigated plains	Closed mangrove swamp Improved lowland	Irrigated
	Valley bottom	Open mangrove swamp Rainfed lowland		
Upland	Plateaus, hills	Rainfed upland	/	/

6.3.1.2 Elicitation

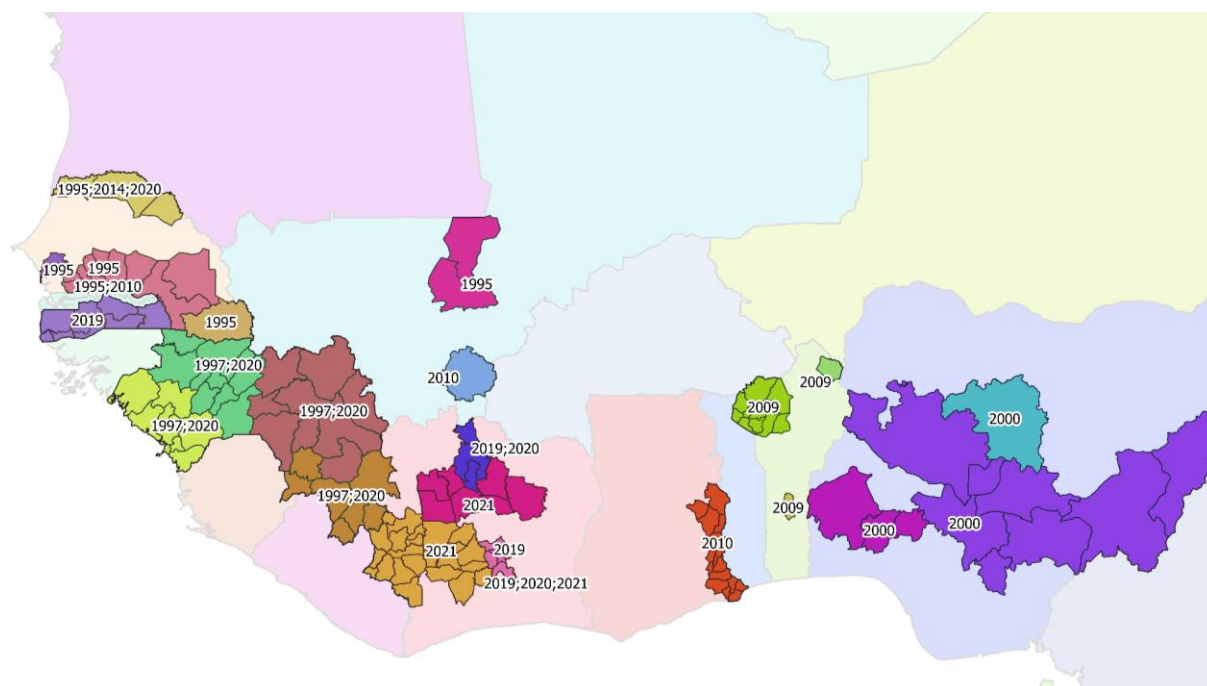


Figure S3 1. Localization and end year of each area where yields were elicited. Each color represents a given region considered as relatively homogeneous in terms of landscape and climate by the experts. Because of space issues, we hereby present the end year of the time period elicited. If several years are indicated, it shows that more than one expert was elicited in the same region.

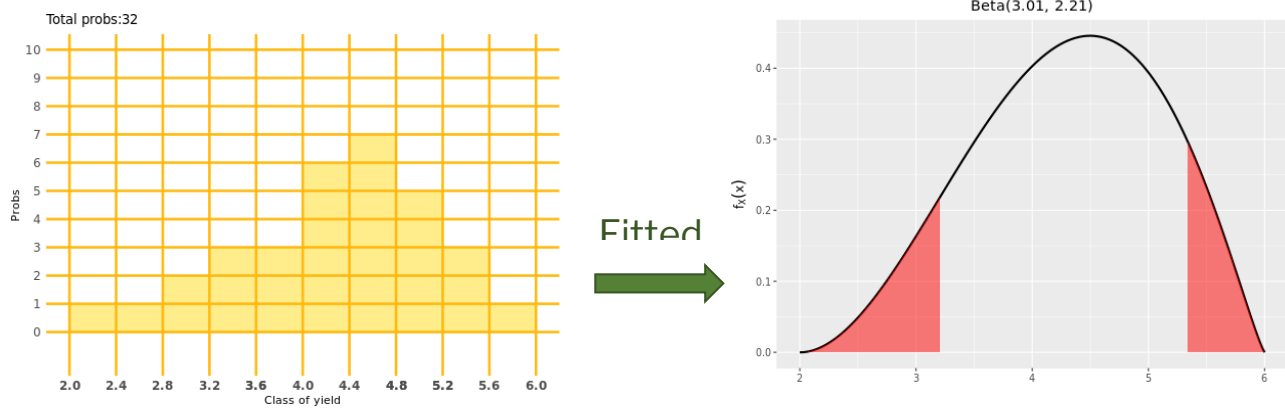


Figure S3 2. (left) representation of the probabilistic expert elicitation interface and (right) corresponding probability density function. Example of irrigated rice yield elicitation in the Segou region (Mali).

6.3.1.3 *Production functions*

Table S3 2. Summary of non-calibrated parameters and their corresponding methods. LLR refers to the rainfed lowland system, IMP refers to the improved lowland system, IRR refers to the irrigated system and ULR refers to the rainfed upland system.

SYSTEM	CULTIVAR	PARAMETER VALUE	UNITE	METHOD	SOURCES
CYCLE LENGTH					
ULR	All cultivars	100	days	To determine the length of the different stages of the growing cycle (i.e., vegetative stage, reproductive stage and maturity stage), we found that the reproductive stage lasts about 35 days and the maturity stage lasts about 30 days whatever the length of the growing cycle. Thus, for ULR, the vegetative stage lasts 35 days, for LLR it lasts 65 days and for IMP and IRR it lasts 75 days.	Expert knowledge. (Vergara 1984) (CEDEAO et al. 2016)
LLR	All cultivars	130	days		
IMP	All cultivars	140	days		
IRR	All cultivars	140	days		
POTENTIAL YIELD					
ULR	Improved	4.32	t/ha	Measurement of the mean yield potential for all traditional cultivars (i.e., <i>oryza glaberrima</i> species) and for all imported and improved cultivars (i.e., <i>oryza sativa</i> and <i>oryza japonica</i> species and hybrids) for each system (we consider that IMP and IRR are similar)	(CEDEAO et al. 2016; FAO 2008; Ministère de l'Agriculture et du Développement Rural, République de Côte d'Ivoire 2002)
	Local	4	t/ha		
LLR	Improved	5.8	t/ha		
	Local	4.2	t/ha		
IMP	Improved	7.96	t/ha		
	Local	5	t/ha		
IRR	Improved	7.96	t/ha		
	Local	5	t/ha		
RELATION BETWEEN CUMULATED RAINFALL AND YIELD EFFECT COEFFICIENT					
ULR	All cultivars	0.0010	mm-1	According to Djaman et al. 2019, the total ETPa of rice in an irrigated system, with 120kgN/ha, is about 800mm. We formulate the hypothesis that about 20% of cumulated rainfall during the growing period is lost in runoff and infiltration. So 1000mm of rainfall is needed to achieve an ETPa of 800mm without irrigation. $a=1/1000=0.0010$ mm-1	(Djaman et al. 2019; Mayer and Bonnefond 1973)

LLR	All cultivars	0.0013	mm-1	In LLR, we consider that crops benefit from the upstream runoff. We assume that this upstream runoff is similar to the rainfall proportion lost in runoff and infiltration. So, the precipitation is equal to the actual evapotranspiration: 800mm of cumulated rainfall is needed to achieve an ETPa of 800mm. $a=1/800=0.0013$ mm-1	
IMP	All cultivars	0.0014	mm-1	As in the IMP system, bunds are built to reduce runoff. We assume that only 10% of cumulated rainfall is lost downstream, while crops benefit from 20% additional runoff from upstream. So, the precipitation is 10% lower than the ETPa of 800mm ($Q^{plim} = ETP_{lim}/1.1=727$ mm). $a=1/727=0.0014$ mm-1	
CRITIC DROUGHT PERIOD					
ULR	All cultivars	10	days	According to Mayer and Bonnefond, 1973, a 10 days period of dry spell would negatively affect yields for upland rice. We estimate that lowland topography allows water to stay longer on the fields thanks to a buffer effect. We also made the hypothesis that in the IMP system, bunding enables water to remain longer.	(Mayer and Bonnefond 1973)
LLR	All cultivars	12	days		
IMP	All cultivars	15	days		
DROUGHT DAILY LOSSES COEFFICIENT DURING REPRODUCTIVE STAGE					
All systems	Improved	0.018	days-1	Measurement from Serpantie et al data. Reproductive stage is the most critical stage of rice cycle as a drought period during this stage impacts yield a lot because it increases the spikelets infertility rate.	(Serpantié et al. 2020)
All systems	Local	0.0108	days-1	We estimate that traditional cultivars are more robust to drought than improved cultivars so their daily loss coefficient is 40% lower.	
CRITIC FLOOD PERIOD					
LLR	All cultivars	7	days	We made the hypothesis that drainage canals allow to evacuate water more easily than in LLR.	Expert discussion
IMP	All cultivars	8	days		
FLOODING EVENT IDENTIFICATION					

All systems, all cultivars		80	%	We compare the slope of cumulated rainfall with the average slope on 1980-2019 on a running window of 7 days during the growing cycle. We identify a flood event when the slope is 80% superior to the average slope.	Authors estimation
FLOOD DAILY LOSSES COEFFICIENT DURING VEGETATIVE STAGE					
All systems	Improved	0.03	days-1	Vegetative stage is the most critical stage of the rice cycle as a flooding period during this stage impacts yield a lot because it reduces the tillering.	(Serpantié et al. 2020)
All systems	Local	0.018	days-1	We estimate that local cultivars are more robust to flood than improved cultivars so their daily loss coefficient is 40% lower	Discussions with experts
YIELD WITH NO NITROGEN SUPPLY					
Upland	All cultivars	0.5	t/ha	Nitrogen balance following the FAO methodology. See table S3 3 and S3 4 for calculation details.	(FAO)
Lowland	All cultivars	1	t/ha		
NITROGEN USE EFFICIENCY WITH VERY LOW NITROGEN SUPPLY (I.E., SLOPE AT THE ORIGIN)					
Upland	All cultivars	55	kg/kgN	Nitrogen balance following the FAO methodology. See table S3 3 and S3 4 for calculation details.	(FAO)
Lowland	All cultivars	55	kg/kgN		
WEEDING EFFECT ON YIELD (I.E., SLOPE)					
All systems, all cultivars		0.3	weeding-1	We did a review of agronomic papers that study weeding impact on yields according to cropping systems and/or to the type of seeds or cultivars in West Africa. We were not able to find a clear pattern on the effect of weeding according to the cropping system and type of seed. For this reason, we make the hypothesis that the weeding relative effect is similar whatever the system and the cultivar are, and that the threshold is reached for 2 weedings. When potential yields are different, the net effect of weeding is different.	(Touré et al. 2009; Ekeleme et al. 2009; Niang et al. 2017; Worou et al. 2017; Saito et al. 2010)
EFFECT OF NO WEEDING (I.E., INTERCEPT)					

All systems, all cultivars	0.4	SU	We determine a mean ratio between yield achieved with no weeding over max yield achieved in weed free conditions.	(Ekeleme et al. 2009)
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Table S3 3. Nitrogen balance for upland rice, based on the FAO method (FAO). The method is modified when the values are not relevant for low nitrogen input systems.

		No fertilization	10kg N
EX1	Harvested product	$0,016 \times y(0)$	$0,016 \times y(10)$
EX2	Cropping residue	0	0
EX3	Run-off	5	$5+0,1*IN1$
EX4	Gas losses	0	0
EX5	Erosion	0	0
IN1	Synthetic fertilizer	0	10
IN2	Manure	0	0
IN3	Deposition	8,06	8,06
IN4	Biological nitrogen fixation	5	5
IN5	Sedimentation	0	0

Table S3 4. Nitrogen balance for lowland rice, based on the FAO method (FAO). The method is modified when the values are not relevant for low nitrogen input systems.

		No fertilization	10kg N
EX1	Harvested product	$0,016 \times y(0)$	$0,016 \times y(10)$
EX2	Cropping residue	0	0
EX3	Run-off	3	$3+0,3*IN1$
EX4	Gas losses	$12 + 2,5 - PN \times 0,1$	$12 + 2,5 - PN \times 0,1$
EX5	Erosion	2,5	2,5
IN1	Synthetic fertilizer	0	10
IN2	Manure	0	0
IN3	Deposition	8,06	8,06
IN4	Biological nitrogen fixation	30	30
IN5	Sedimentation	$0,1 \times IN1$	$0,1 \times IN1$

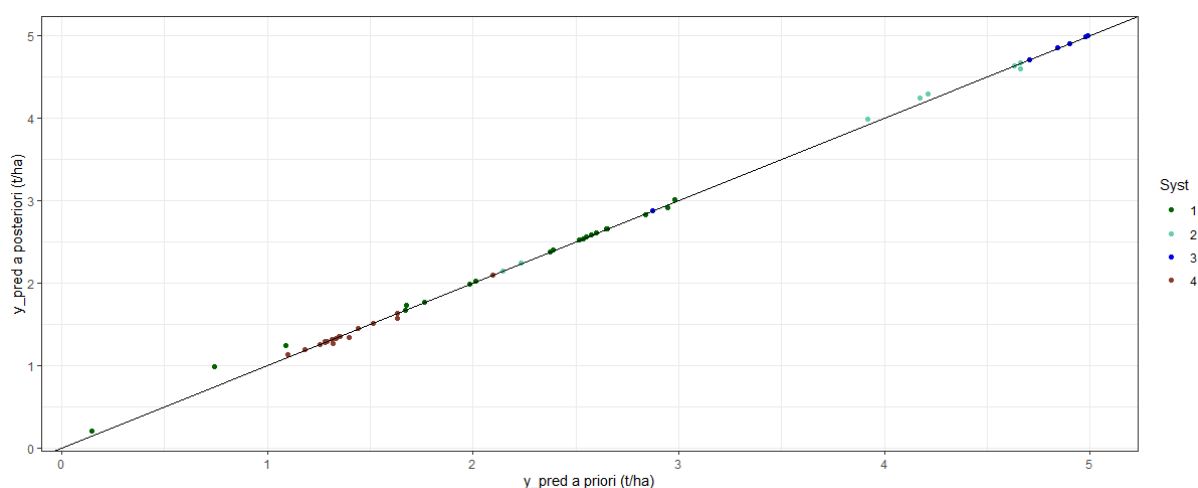


Figure S3 3. Comparisons between the two methods that can be used to consider average climatic conditions. The x-axis refers to the yield predicted a priori: average climatic variables on a ten years period are measured before simulating yields. The y-axis refers to the yield predicted a posteriori: 10 yields are simulated with our model using 10 years of climatic data (i.e., 10 different values for climatic variables) and are averaged. Syst 1 refers to the LLR system, Syst 2 refers to the IMP system, Syst 3 refers to the IRR system and Syst 4 refers to the ULR system. Yields are all expressed in t/ha.

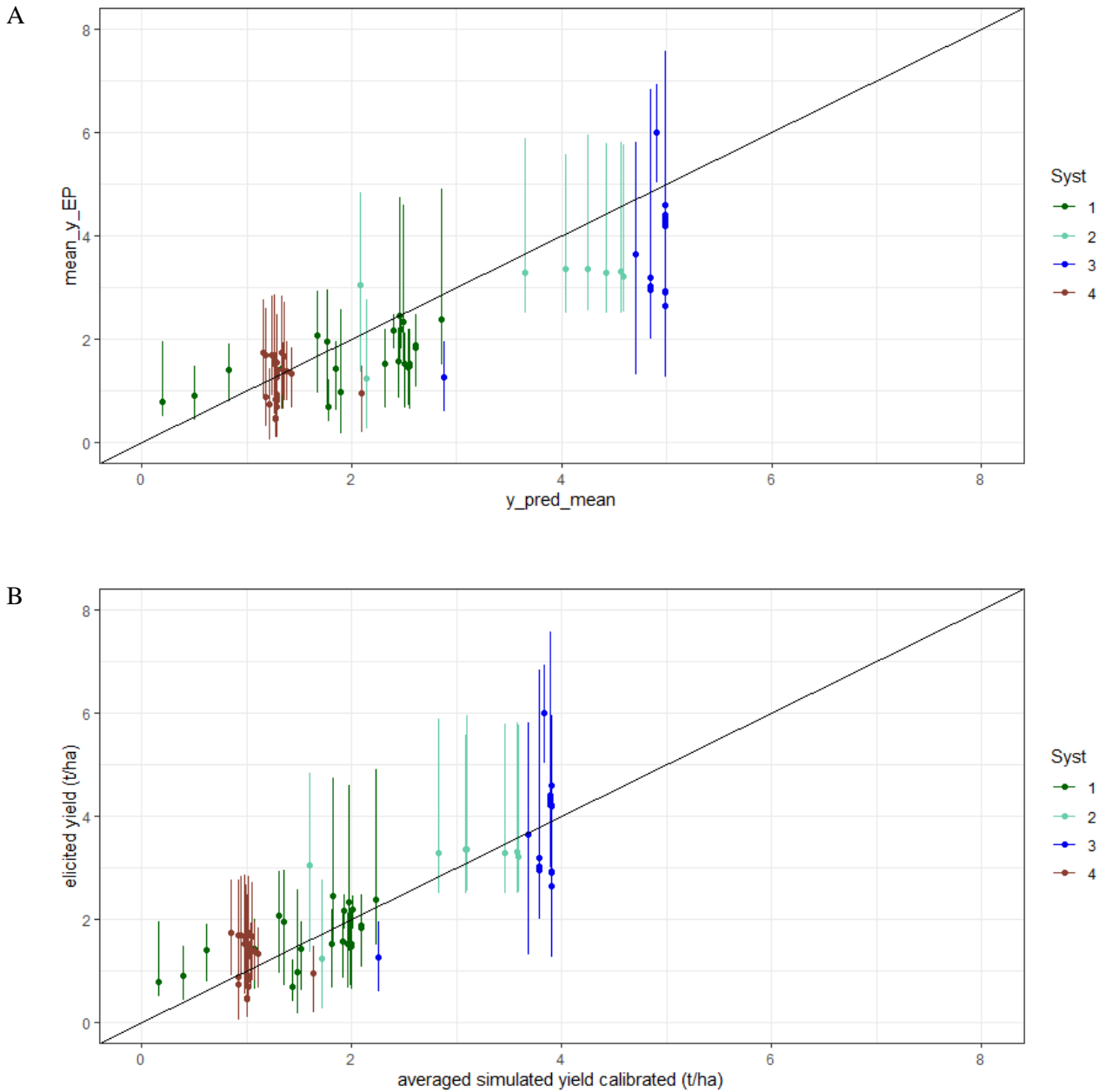


Figure S3.4. Comparisons of simulated yield before (A) and after (B) adjustment with averaged elicited yield by the experts. Syst 1 refers to rainfed lowland, Syst 2 to improved lowland, Syst 3 to irrigated and Syst 4 refers to rainfed upland. The error bars represent the range between the maximal and the minimum yield that can be achieved in a region, according to the expert.

6.3.2 Supplementary results

6.3.2.1 Elicitation analysis

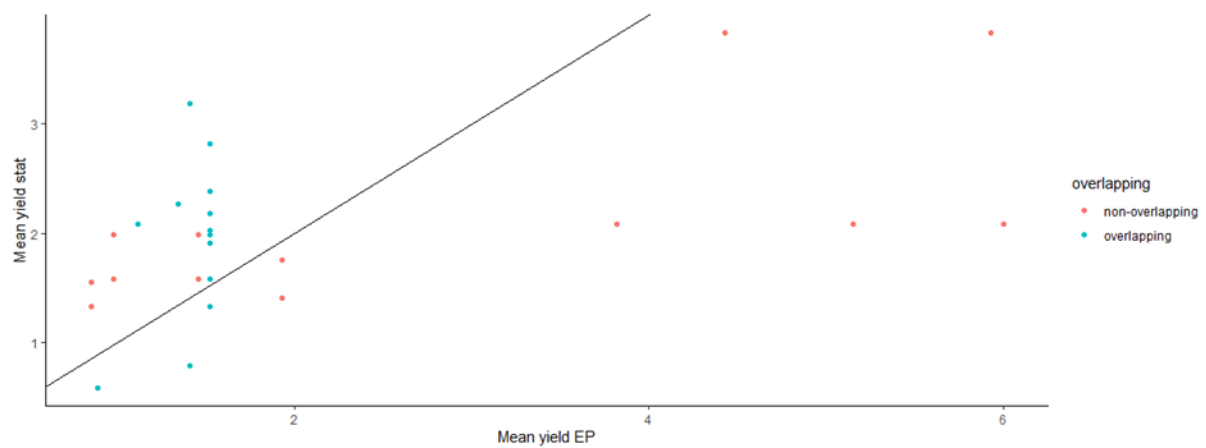


Figure S3 5. Comparison of mean yield measured from the expert elicitation distributions and to the mean yield measured from the statistical databases FAOCountrySTAT and AgroMAPS at the administrative level 1. The blue points represent the mean measurement period of time corresponding between the two sources of data. The red points represent mean measurement periods of time that do not correspond. The dark line represents the relation 1:1.

6.3.2.2 Simulated yields

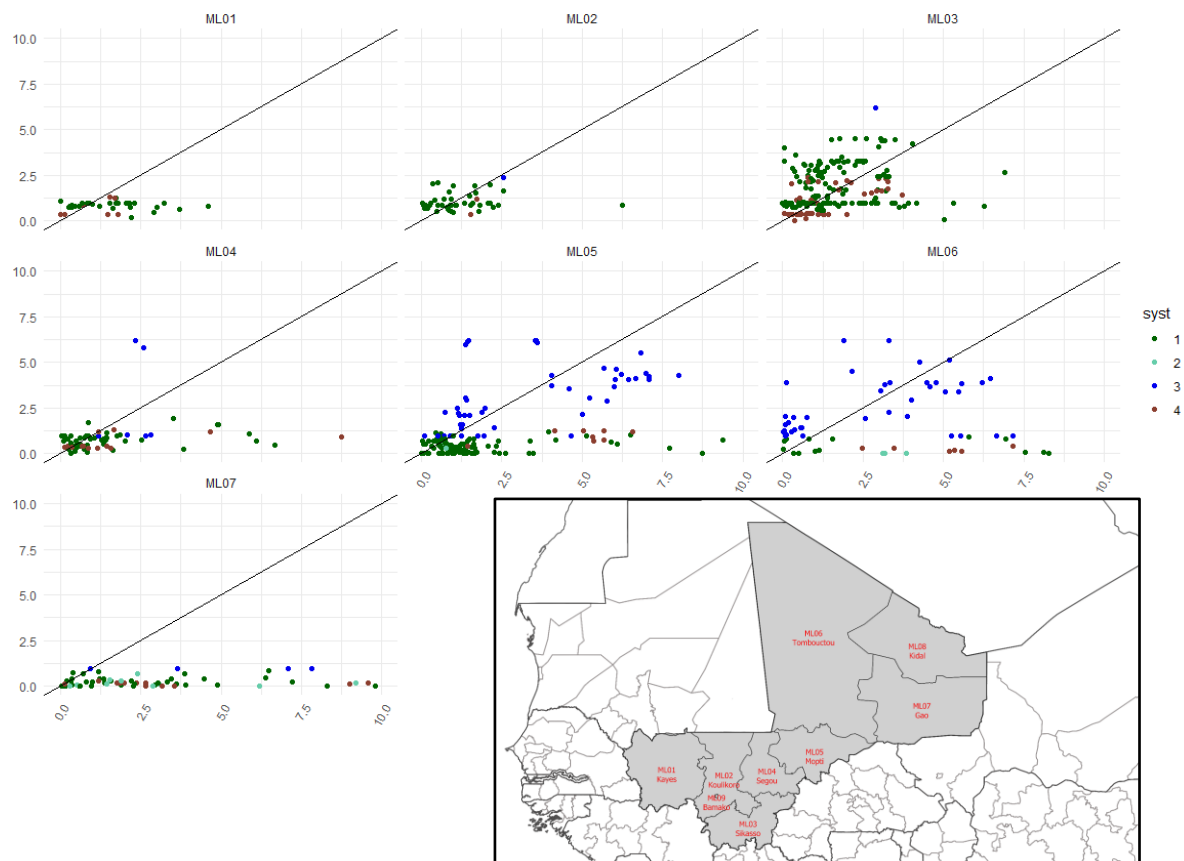


Figure S3 6. Comparison of simulated yield and yields obtained from the LSMS-ISA survey, in Mali in 2014-2015 (Cellule de Planification et de Statistiques et al. 2014-2015). Each graph refers to an administrative region (NUTS 1). The x-axis gives the yield (in t/ha) as estimated by rice producers and the y-axis gives the yield measured with the corrected production functions. System 1 refers to LLR, system 2 refers to IMP, system 3 refers to IRR and system 4 refers to ULR. Relatively high yields often reported for System 1 and 4 are also implausible, but it is not certain that all are erroneous.

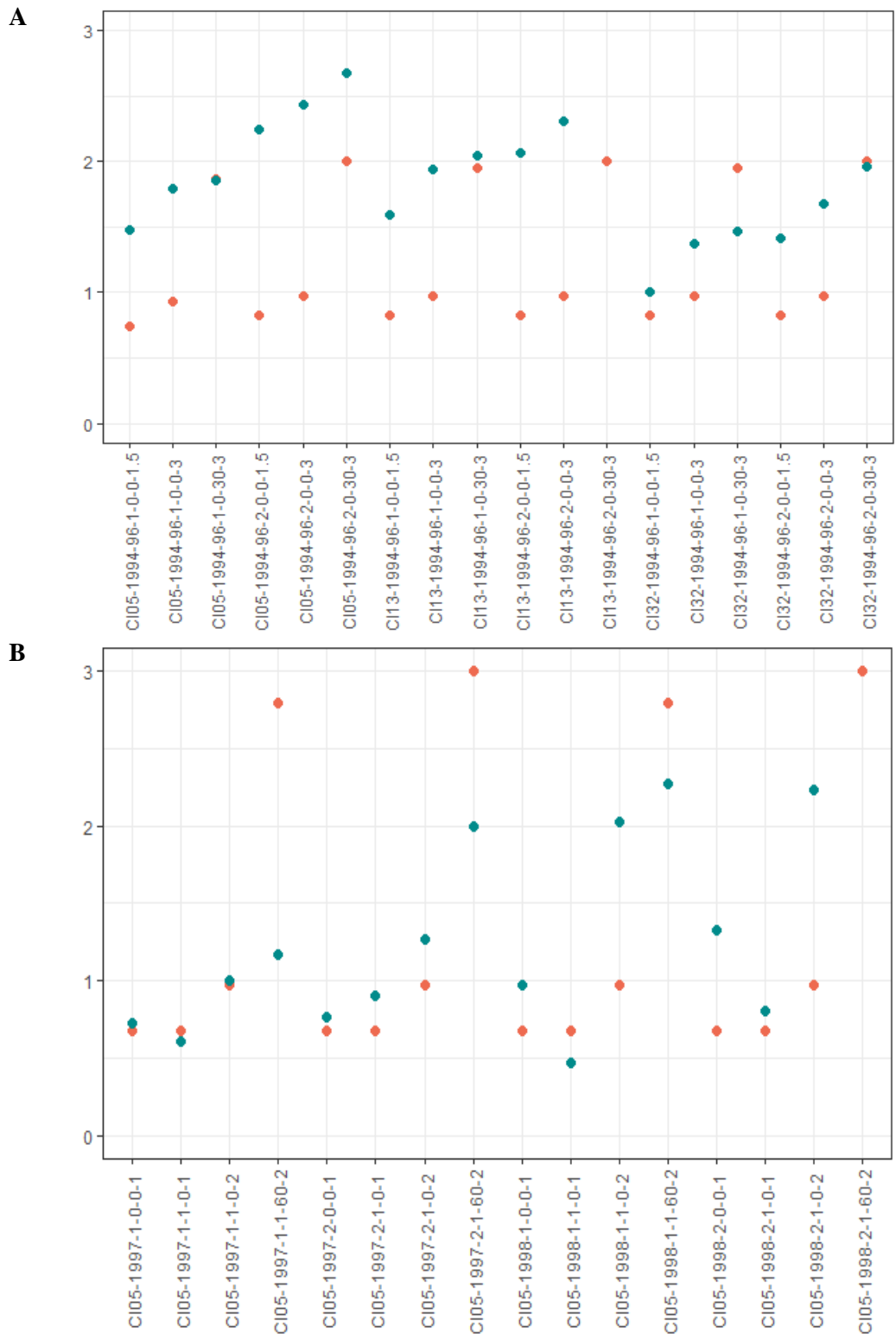


Figure S37. Comparison of simulated yield and yields obtained from two agronomic trials, in Côte d'Ivoire : (Becker and Johnson 2001) (A) and (Touré et al. 2009) (B). Orange points refer to simulated yields and blue points refer to trial's yields. X-axis labels are written following the pattern: "adminIPcod"- "Trials years"- "System"- "Seeds origin"- "Fertilizers quantity"- "Number of weedings". System 1 refers to LLR and system 2 refers to IMP. For seeds origine, 0 means that local seeds are used and 1 means that certified seeds are used. Fertilizer quantity is expressed in kgN/ha. The Y-axis represents yield values expressed in t/ha. CI32 region (Tonkpi region) is a monomodal forest, CI13 region (Goh region) is a bimodal forest and CI05 region (Bagoué region) is a Guinea savanna. In (B), for the point CI05-1998-2-1-60-2, yield trial is superior to 3 (3.07) so it is outside the graph.

6.4 SUPPLEMENTS CHAPTER 4

6.4.1 Supplementary material & method

6.4.1.1 Model conceptualization and formulation

- Total household consumption (in man equivalent):

$$Q^m = (m + w + o) * 1 + (t + c) * 0.5 \quad (1)$$

With,

m , the number of men able to work in the household

w , the number of women able to work in the household

o , the number of adults (both male and female) too old to work in the household

t , the number of teenagers (both male and female) in the household

c , the number of children (both male and female) in the household

- Family labor capacity (in man equivalent):

$$q^f = m * 1 + w * 0.75 + t * 0.5 + (o + c) * 0 \quad (2)$$

- Total household workforce capacity (in man.day-1):

$$Q^f = q^f \times w \quad (3)$$

With,

w , number of days that can be worked by a man each year (in man.day-1)

- Total needed workforce for household rice activity (in man.day-1):

$$Q^L = q^L \times S = (q^{Lh}(y) + q^{L\setminus h}) \times S \quad (4) \quad \& \quad Q^L = \beta Q^f + Q^{Lext} \quad (3)$$

With,

q^L , the workforce needed for one hectare of rice (in man.day-1/ha), it depends on the type of cropping system

S , the rice plot area (in ha)

$q^{Lh}(y)$, workforce needed during the harvest (in man.day-1/ha)

$q^{L\setminus h}$ is the workforce needed for other steps (in man.day-1/ha)

β , the proportion of the family labor capacity working on the rice plot (without unit)

Q^{Lext} , the external labor needed to work on rice plots (in man.day-1)

$$Q^{Lext} > 0 \text{ only if } \beta = 1 \quad (4)$$

- Workforce needed during the harvest (in man.day-1/ha):

$$q^{Lh}(y) = a^{Lh} \times y \quad (5)$$

With,

a^{Lh} , the harvest labor needs coefficient

- External workforce needed without considering harvest (in man.day-1):

$$Q^{L\backslash hext} = \min \{S \times q^L - \beta \times Q^f - S \times q^{Lh}(y), 0\} \quad (6)$$

- Staple's crops calorie's requirement for the whole household, for one year (in kcal):

$$\bar{Q} = \bar{q}^{staples} \times Q^m \quad (7)$$

With,

$\bar{q}^{staples}$, calories provided by staples crops (e.g., cassava, maize, millet, rice, sorghum, yam) to achieve food security threshold (in kcal/man equivalent)

- Rice self-consumption quantity (in tons):

$$a = \min\{y \times S; \bar{a}\} \quad (8)$$

With,

\bar{a} , the average rice consumption of a representative household (in tons), if local seeds are reused from one year to another, the quantity needed is included in \bar{a}

- Remaining staples requirements to be purchased (in kcal):

$$q = \bar{Q} - a \times k \quad (9)$$

With,

k , the conversion coefficient used to express a in kcal (in kcal/ton).

- Other basic requirements for one adult, for one year (in USD/adult/year):

$$c = c^{food} + c^{non-food} \quad (10)$$

With,

c^{food} , non-staples calories need (in USD/adult/year)

$c^{non-food}$, non-food requirement to achieve poverty threshold (in USD/adult/year)

- Achieved yield with type of cultivar c and in system s (in tons/ha) (production functions built in Chapter 3, see Material and Methods):

$$y_{c,s}(q^F) = Y_{c,s} \times A_{c,s} \times \min\{\theta^F(q^F); \theta^P\} \times \alpha \times (1 + \varepsilon_s) \quad (11)$$

With,

q^F , the quantity of fertilizers (in kg/ha)

$Y_{c,s}$, potential yield (in tons/ha)

$A_{c,s}$, the effects of weeding numbers, of dry spells and of flood events (no unit)

$\theta^F(q^F)$, the effect of fertilizers (no unit)

θ^P , the effect of cumulative rainfall (no unit)

α , the calibration coefficient, measured based on average elicited yields, estimated to 0.777 (see Chapter 3, section 3.2.4 Production function post-processing for details)

ε_i , added variability variable (no unit) (see section 6.4.1.2 for details)

- Fertilizers costs (in USD):

$$C^F = p^F \times q^F \times S \quad (12)$$

With,

p^F , the price of fertilizers (in USD/kgN)

- Seeds costs (in USD):

$$C^S = p^S \times q^S \times S \quad (13)$$

With,

p^S , the price of seeds (in USD/kg), that depends of the seeds type (i.e., local or certified)

- External workforce costs (in USD):

$$C^L = p^L \times Q^{L/hext} \quad (14)$$

With,

p^L , the salary for one working day (in USD/man.day-1)

- Reimbursement of existing loans, with interests (in USD):

$$L = (1 + r) \times e \quad (15)$$

With,

r , the loan interest rate (no unit)

e , the annual amount that must be reimbursed (in USD)

- Incomes provided by rice sales (in USD):

$$I^{rice} = (y \times S - a) \times p^r \quad (16)$$

With,

p^r , rice paddy price paid to producer (in USD/ton)

- Incomes from other activities of the household (in USD):

$$I^{other} = (A \times (1 - \beta) \times Q^f + B) \times (1 - \beta) \times Q^f \quad (17)$$

$$A = -\frac{p^{Lmax}}{2 \times 0.9 \times Q^f} \quad (18)$$

$$B = \frac{p^{Lmax}}{0.9} \quad (19)$$

With,

p^{Lmax} , the maximal opportunity incomes in the area (in USD/man.day-1)
 A and B , the coefficients of the relation between remaining family workforce and opportunity incomes (A in USD/man.day-1² and B in man.day-1)

- Sum of external costs, for year t (in USD):

$$C_t = p^F \times q_t^F \times S_t + p^S \times q_t^S \times S_t + p^L \times Q^{L\backslash hex t} \quad (20)$$

- Net income of year t-1 (in USD):

$$R_{t-1} = I_{t-1}^{other} + I_{t-1}^{rice} - q_{t-1} \times p^c - c_{t-1} \times Q^m \quad (21)$$

With,

p^c , average price for calories expressed (in USD/kcal)

- Cash availability constraint:

$$C_t \leq s \times R_{t-1} \quad (22)$$

With,

s , the saving rate (no unit)

- Household surplus (in USD):

$$W_t = R_t - C_t \quad (23)$$

- Credit access and loan amount (in USD):

$$e_t = (q^{F*} - q_t^F) \times S^* \times p^F \quad (24)$$

With,

q^{F*} , optimal fertilizer rate (in kgN/ha)

q_t^F , realized fertilizer rate at year t (in kgN/ha)

S^* , optimal rice plot area (in ha)

p^F , fertilizer price (in USD/kgN)

- Household utility of year t:

$$U(W, a, q, c) = \frac{1}{1-\rho} \times \left(\frac{(W+(a \times k+q) \times p^c+c \times Q^m)}{Q^m} \right)^{(1-\rho)} \quad (25)$$

With,

ρ , individual coefficient of risk aversion

- Household optimization program:

$$\max_{q^F, S^*} \{EU(W_1, \dots, W_N, a_1, \dots, a_N, q_1, \dots, q_N, c_1, \dots, c_N)\} \quad (26)$$

$$EU(W_1, \dots, W_N, a_1, \dots, a_N, q_1, \dots, q_N, c_1, \dots, c_N) = \frac{1}{N} \sum_{t=1}^N U(W_t + (a_t + q_t) \times p^c + c_t, \\ u. c. \{C_t \leq s \times R_{t-1}\}) \quad (27)$$

6.4.1.2 Yield variability simulation

6.4.1.2.1 Yield variability due to climatic variability

To simulate climatic variability impact on yield, we randomly draw 20 years with release in the period from 2000 to 2019. Three variables impact yield in production functions used in the bioeconomic model: (i) cumulated rainfall over the rice growing cycle, (ii) dry spells occurrence and range and (iii) flooding events occurrence (see Chapter 3, section Materials & methods for more details). Rice yield simulated in irrigated systems is not impacted by climatic conditions in the model as we formulate the hypothesis that water is totally managed and no dry spells nor floods can occur in this system. Upland rainfed rice systems are only impacted by dry spells but never by floods and lowland rainfed and improved systems can be impacted by dry spells and by flooding events with variable relative effects. The results of the modeled impacts of climatic variability on yield can be found in Chapter 3, section Results).

6.4.1.2.2 Added yield variability

As we do not explicitly represent other risks than climatic risks in the production functions, we added a variable to yield to illustrate this variability due to other risks (e.g., pests and diseases, human mistake). This variable follows a centered Normal probability law whose coefficients vary according to cropping systems and areas. The following equation represent the addition of variability to simulated yield:

$$y_{i,s,c} = \hat{y}_{i,s,c} \times (1 + \varepsilon_{i,s}) \quad (28)$$

With,

$y_{i,s,c}$, simulated yield with added variability in area i, for system s and for cultivar type c (i.e., improved or traditional) (in ton/ha)

$\hat{y}_{i,s,c}$, simulated yield with only climatic variability (or no variability at all in the case of the irrigated system) in area i, for system s and for cultivar type c, simulated with production functions built in Chapter 3 (in ton/ha)

$\varepsilon_{i,s}$, added variability variable, whose coefficients are written μ , mean fixed to 0, $\sigma_{i,s}$, standard deviation and which is truncated between -1 and 1 (no unit), in area i, for system s

The method we used to estimate standard deviation coefficients differs according to systems.

We formulated the hypothesis that in the irrigated and improved lowland systems, the whole variability determined by experts during the expert probabilistic elicitation (see Chapter 3, section Materials & Methods) is represented by the expert elicited variability. This hypothesis is detailed in the PhD thesis Duvallet M.

methods) represent temporal variability. We estimate that as environmental parameters and risks are very controlled in this type of systems and, thus, yield variability factors are temporal more than spatial (e.g., bad water management, damaged irrigation devices, pump breakdown). Hence, we estimate variability coefficient in this system by averaging all standard deviations of yield distributions elicited in this system by experts (experts elicitation database can be found at: <https://doi.org/10.18167/DVN1/44ZJEV>). To calculate average standard deviation for each system, we weighted the standard deviation elicited in each different area*system by the cropped area concerned by either the irrigated system or by the improved lowland system. To do so, we use the weight elicited by experts to represent the proportion of surface concerned by each system over the rice surface in each area (rice surfaces at administrative level 1 were collected on FAOCountrySTAT and AgromAPS datasets). For rainfed lowland and upland systems, a significant part of yield variability estimated by the experts might be originated from spatial variability. However, in the yield distributions elicited, interannual and spatial variability are confounded so that we are not able to only consider temporal variability. We chose to consider the whole variability elicited by experts, but this must entangle cautionary results interpretation.

As no yield variability due to climatic condition is simulated with the model for the irrigated system, we kept the average standard deviation measured as an estimation of the standard deviation of the variable used to add variability (i.e., $\sigma_{i,IRR} = 0.64$).

For improved lowland, lowland and upland rainfed systems, as yield variability is modeled, we first had to remove this variability due to climatic variability. To do so, we simulated 10 years of yields with the model for each area*system. Then, for each area*system we randomly sampled 1000 times with release in this simulated distribution (i.e., which variability is only due to rainfall precipitation) and in the elicited yield distribution. The next step was to determine a distribution for $\varepsilon_{i,s}$ from these 1000 yields values. We centered ε distribution to 0 and we delimited it between -1 and 1 as for some combinations, ε values were very high. It should be noticed that, for the improved lowland system, standard deviation, system weight in the area and surface data were available only for one point so that we only kept the yield distributions associated to this point. We obtained $\sigma_{i,IMP} = 0.54$. Finally, for lowland and upland rainfed systems, to attribute an added variability variable to each area - as elicited data was not covering all west African areas at administrative level 1 - we extrapolate values measured for $\varepsilon_{i,s}$ to areas not covered by elicited data, we rely on the geographical proximity.

6.4.1.3 Maximum opportunity income measurement

Simplified model used to measure maximum opportunity income:

$$\max_{q^{F*}} \{y \times p^r = p^F \times q^F + p^S \times q^S\} \quad (29)$$

$$p^{Lmax} = \frac{y(q^{F*})}{q^L(y(q^{F*}))} \quad (30)$$

6.4.1.4 *Model parametrization*

Table S4 1. Microeconomic model parametrization.

Parameter	Unit	Geographic level	Hypothesis and method	Sources
HOUSEHOLD COMPOSITION				
Consumption equivalent, Q^m	Without unit	Country	<p>We take most recent data for each country (between 2012 and 2018, according to the country). We take a number of members a little bit superior to the national average number of members in household as rural households tend to be larger than the urban ones. We separate members according to their age, under the following hypothesis:</p> <ul style="list-style-type: none"> - Young child (not able to work) → from 0 to 10 years old - Teenager (able to work) → from 10 to 15 years old - Adult (able to work) → from 16 to 64 years old - Old adult (not able to work) → over 65 years old <p>We suppose that women represent half of the adult's number (rounding at superior integer)</p> <p>By default, we fix the number of old adults to 1</p> <p>To measure the consumption equivalent of the whole household we weight the number of each members category:</p> <ul style="list-style-type: none"> - Adults (men, women, old people) are weighted by 1 - Teenagers and children are weighted by 0.5 	(Department of Economic and Social Affairs, Population Division, UN 2019)
Workforce capacity, Q^f	man.day-1	Country	<p>We consider that a man can work 300 days per year (with about one day-off per week). Similarly, to consumption equivalent measurement, we weight the number of each members category according to its ability to work:</p> <ul style="list-style-type: none"> - Men are weighted by 1 - Women are weighted by 0.75 as they also take care of domestic duties - Teenagers are weighted by 0.5 - Old adults and young children are weighted by 0 	(Department of Economic and Social Affairs, Population Division, UN 2019; Aboudou et al. 2021)
Maximal familial workforce allocation to rice, β^{max}	Without unit	Same everywhere	<p>We formulate the hypothesis that one rice growing cycle lasts about 200 days, when considering land preparation before seeding. Each man equivalent can work 171 days on a 200 days duration, if we estimate that he has one day free per week. As we estimate that rice growing cycle lasts 171 days and that a whole year lasts 300 days, when removing days off, β cannot be superior to 0.57.</p>	See chapter 3 for rice growing cycle length.

HOUSEHOLD BASIC REQUIREMENTS				
Maximal rice self-consumption, \bar{a}	kg/adult/year	Country	We set the maximal rice self-consumed to 100 kg/adult/year. When local seeds are reused from one year to the other, seeds quantity needed is added to the maximal rice self-consumed value.	
Annual calories need, from staples crops, \bar{q}	kcal/adult/year	Same everywhere	2300 kcal are needed daily per adult. We estimate that in West Africa, about 65% of these calories are provided by staples. Thus, the daily calories need, from staples crops, for an adult is: $2300 \times 0.65 = 1500$ kcal and the annual calories need from staples crops is 547 500 kcal/adult/year. Staples refer to cereals and tubers.	(Staple foods: What do people eat? 1995)
Non-staple food requirement, c^{food}	USD/adult/year	Country	We calculate food security threshold in each country, from the 2019 food security threshold in Mali and using conversion factors, then converting it in 2019 USD and finally considering inflation to express it in 2022 USD. We, then, subtract the annual staple food requirement per adult, expressed in 2022 USD (i.e., $\bar{q} \times p^c$) to each country food security threshold to measure non-staple food security requirement.	Mali food security threshold: (Institut National de la Statistique Octobre 2020)_p.23 Conversion factors: (World Bank Group 2023)
Non-food requirement, $c^{non-food}$	USD/adult/year	Country	We calculate non-food threshold in each country, from the 2019 non-food security threshold in Mali and using conversion factors, then converting it in 2019 USD and finally considering inflation to express it in 2022 USD.	Mali non-food security threshold : (Institut National de la Statistique Ocotbre 2020)_p.23 Conversion factors: (World Bank Group 2023)
CROPPING PRACTICES				
Harvest labor needs coefficient, a^{Lh}	man.day-1/ton	Same everywhere	As harvest labor needs depend on yield we determine a relation between these two variables: $q^{Lh} = a^{Lh} \times y$ with q^{Lh} the total labor needs to harvest one hectare (in man.day-1/ha) and y the realized yield (in t/ha). We used yield and labor needs data collected in Komatsu et al. 2022 to measure this coefficient: for $y=1.97$, $q^{Lh}=43.7$, for $y=2.56$, $q^{Lh}=66.1$ and fixe the origin at (0,0). Thus, we obtain the relation $q^{Lh} = 24.467 \times y$ with $R^2=0.9857$. The coefficient a^{Lh} value is the same for all systems in all areas.	(Komatsu et al. 2022)
Labor needs without harvest, $q^{L\backslash h}$	man.day-1/ha	System	We formulate the hypothesis that labor need for all cycles steps does not depend on yield but on system as some practices such as transplanting, sowing methods (i.e., broadcasting, dibbling) are more usually used in certain systems. Irrigation and drainage devices maintenance is also considered in	(Ministère de l'Agricultur de l'Hydraulique et des Ressources Halieutiques 2004; Komatsu et al. 2022; Levasseur 1981;

			<p>this variable, as land work (e.g., levelling, bunding). We cross several sources to determine the value of this parameter for each system.</p> $q_{LLR}^{L\backslash h} = 151 \text{ man.day-1/ha}$ $q_{IMP}^{L\backslash h} = 180 \text{ man.day-1/ha}$ $q_{IRR}^{L\backslash h} = 215 \text{ man.day-1/ha}$ $q_{ULR}^{L\backslash h} = 134 \text{ man.day-1/ha}$	Njoku and Karr 1973; Dossouhoui et al. 2017)
Seeds quantity, q^S	kg/ha	System	<p>As the seeds quantity mostly relies on the seeding method, we formulate the hypothesis that in rainfed systems (i.e., LRR and ULR) direct seeding was more usually used while in IMP and IRR transplanting was more usual, based on Niang et al. rice producer practices statistic analysis. We cross different sources to determine the value of this parameter for each system.</p> $q_{LLR}^S = 39 \text{ kg/ha}$ $q_{IMP}^S = 28 \text{ kg/ha}$ $q_{IRR}^S = 28 \text{ kg/ha}$ $q_{ULR}^S = 60 \text{ kg/ha}$	(Ministère de l'Agricultur de l'Hydraulique et des Ressources Halieutiques 2004; Niang et al. 2017; Agence Japonaise des Ressources Vertes 2007; APRAO; SPID Juillet 2011)
PRICES				
Fertilizer prices, p^F	USD/kg	Country	To simplify we do not consider any interannual variability neither subnational variability in fertilizer prices. We collect national urea (most used fertilizer in quantity in West African countries) for June 2022 when available. When data is not available, we extrapolate through geographical proximity. We then convert urea prices into nitrogen prices using nitrogen proportion in urea (i.e., 46%).	Fertilizer prices: (AfricaFertilizer 2022)
Seeds prices, p^S	USD/kg	Area NUTS1	We fixed a ratio between seeds prices and average producer rice price of 1.5. For local seeds, the price is fixed to 0.	(Dossouhoui et al. 2017; Sylla 2019)
Labor price, p^L	USD/man.d ay-1	Country	We collect average monthly earnings of employees all sexes confounded, for most recent available year and for “Skilled agricultural, forestry and fishery workers”. When data is not available, we extrapolate through geographical proximity.	(ILOSTAT 2023)
Rice prices, p^r	USD/ton	Area NUTS1, year	We collect rice prices data (i.e., average price, price standard deviation, min price and max price during the time period) in major market centers from the FAO Food Price Monitoring and Analysis (FPMA) Tool. Data time period vary according to markets (from 2006 to 2022). When possible, we select local rice prices but, in some cases, only imported rice prices were available.	Rice prices: (FAO 2022) Prices conversion: Tondel et al. 2020 table 7, page 43

			<p>As these prices concerned retail or wholesome milled rice, we have to convert it in producer prices for paddy rice:</p> <ol style="list-style-type: none"> 1. Conversion of imported rice prices to local rice prices: we consider imported rice being 30% more expensive than local rice. 2. Conversion of retail rice prices to wholesome rice prices: we estimate that retail rice is about 9% more expensive than wholesome rice because of retailer gross margin of 5% plus transport costs. 3. Conversion of wholesome rice prices to producer prices (for milled rice): to simplify we consider a similar ratio of 20% between these two prices for all countries. 4. Conversion of milled rice prices to paddy rice prices: milling yield varies between 0.55 to 0.65. To simplify, we consider a milling yield of 0.60 for all countries. <p>We formulate the hypothesis that prices distributions are normal.</p>	
Calories from staples prices, p^c	USD/kcal	Same everywhere	<p>Headey et al. estimated a price for 1000 kcal of 0.36 USD in 2019 (0.41 USD/1000kcal, after inflation correction, in 2022) for staples. As our model focus on subsistence farmers, we estimate that they have access to these calories at half price. To simplify, we set a price of calories provided by staples to 0.0002 USD/kcal for all countries.</p>	(Headey and Alderman 2019)

6.4.1.5 Sensitivity analysis

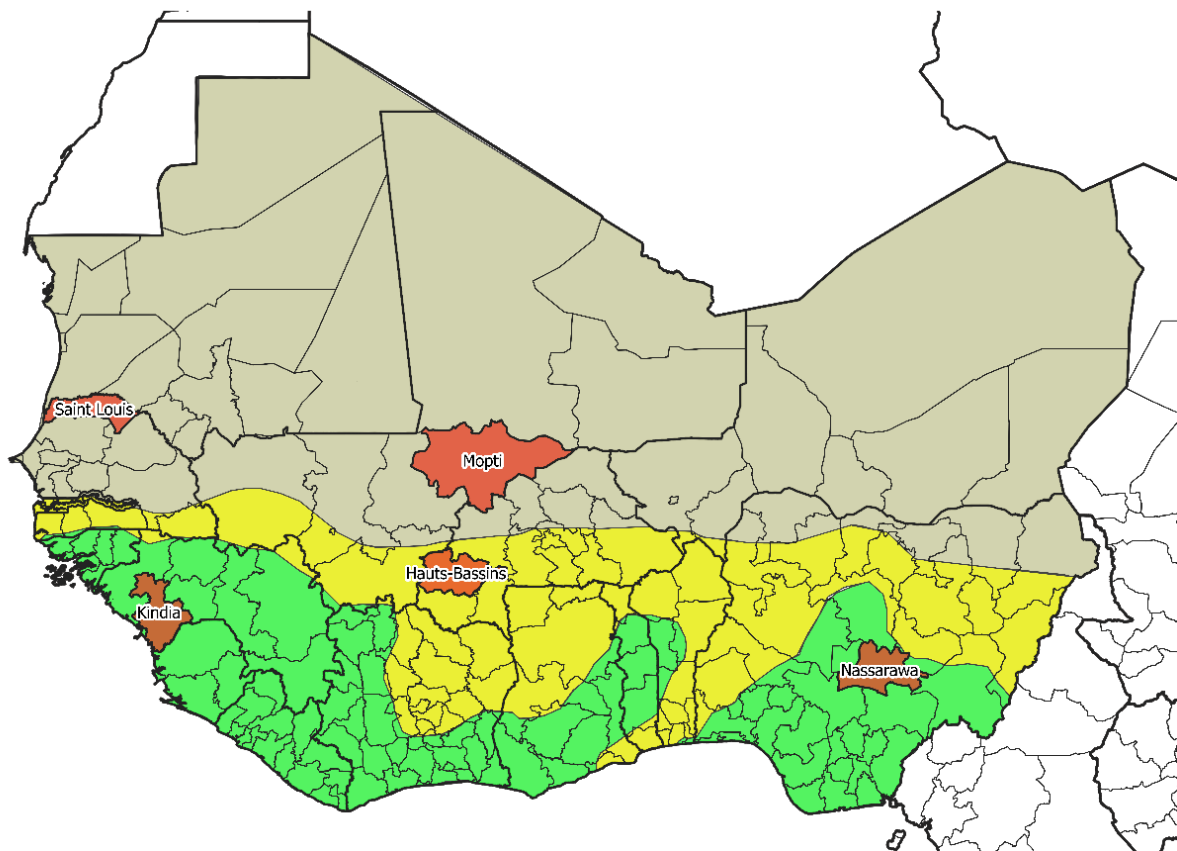


Figure S4 1. Localization of the five areas studied during the sensitivity analysis. Hauts-Bassins is localized in Burkina Faso, Kindia is localized in Guinea, Mopti is localized in Mali, Nassarawa is localized in Nigeria and Saint-Louis is localized in Senegal. The green area refers to the Guinean climatic region (i.e., mean annual precipitation superior to 1200 mm/year), yellow area refers to the Sudanian climatic region (i.e., mean annual precipitation superior to 700 mm/year and inferior to 1200 mm/year) and grey area refers to the Sahelian climatic region (i.e., mean annual precipitation inferior to 700 mm/year).

6.4.2 Supplementary results

6.4.2.1 Maximum opportunity income results

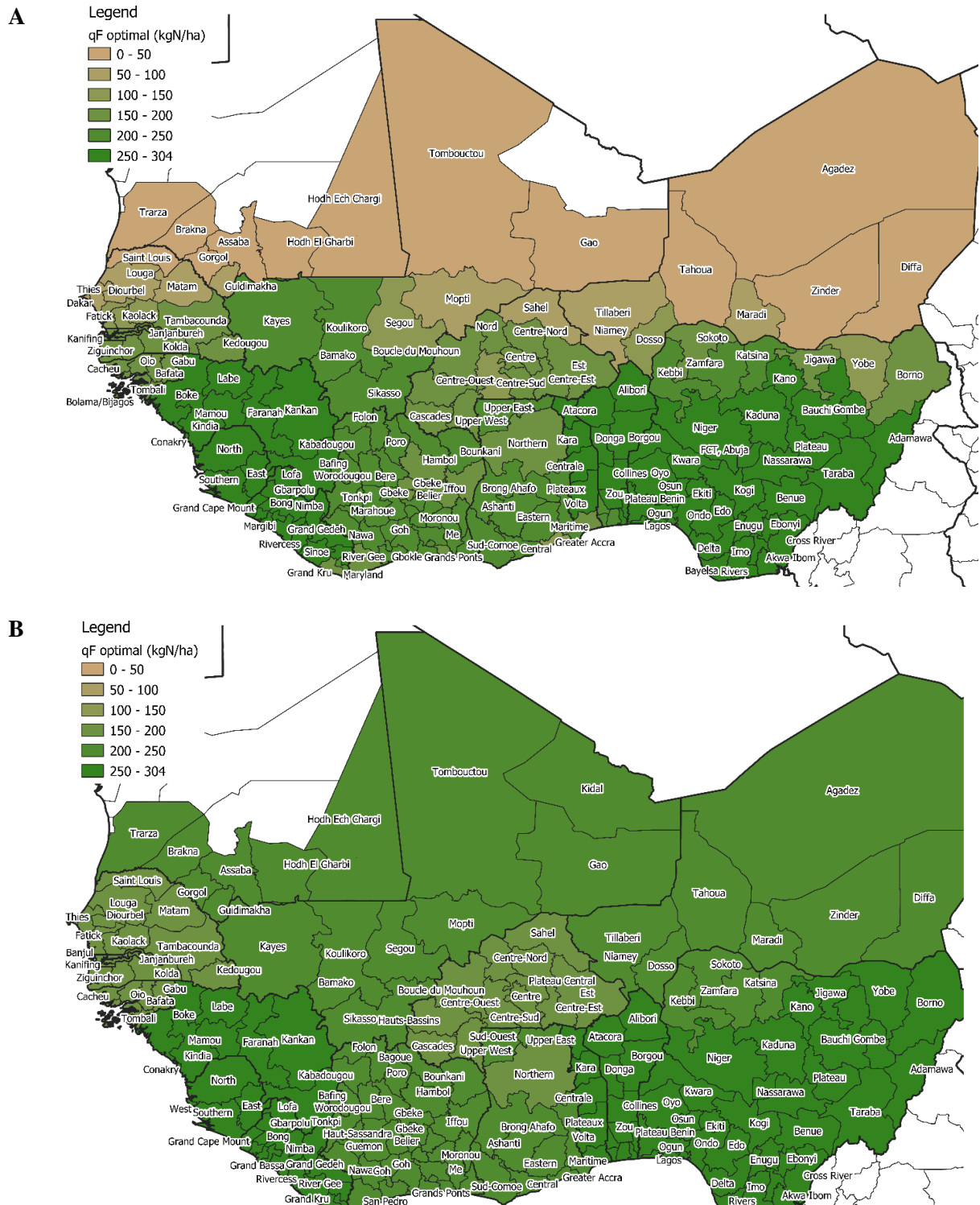


Figure S4 2. Optimal qF^* measured with simplified model for IMP systems (A) and for IRR systems (B) at administrative level 1.

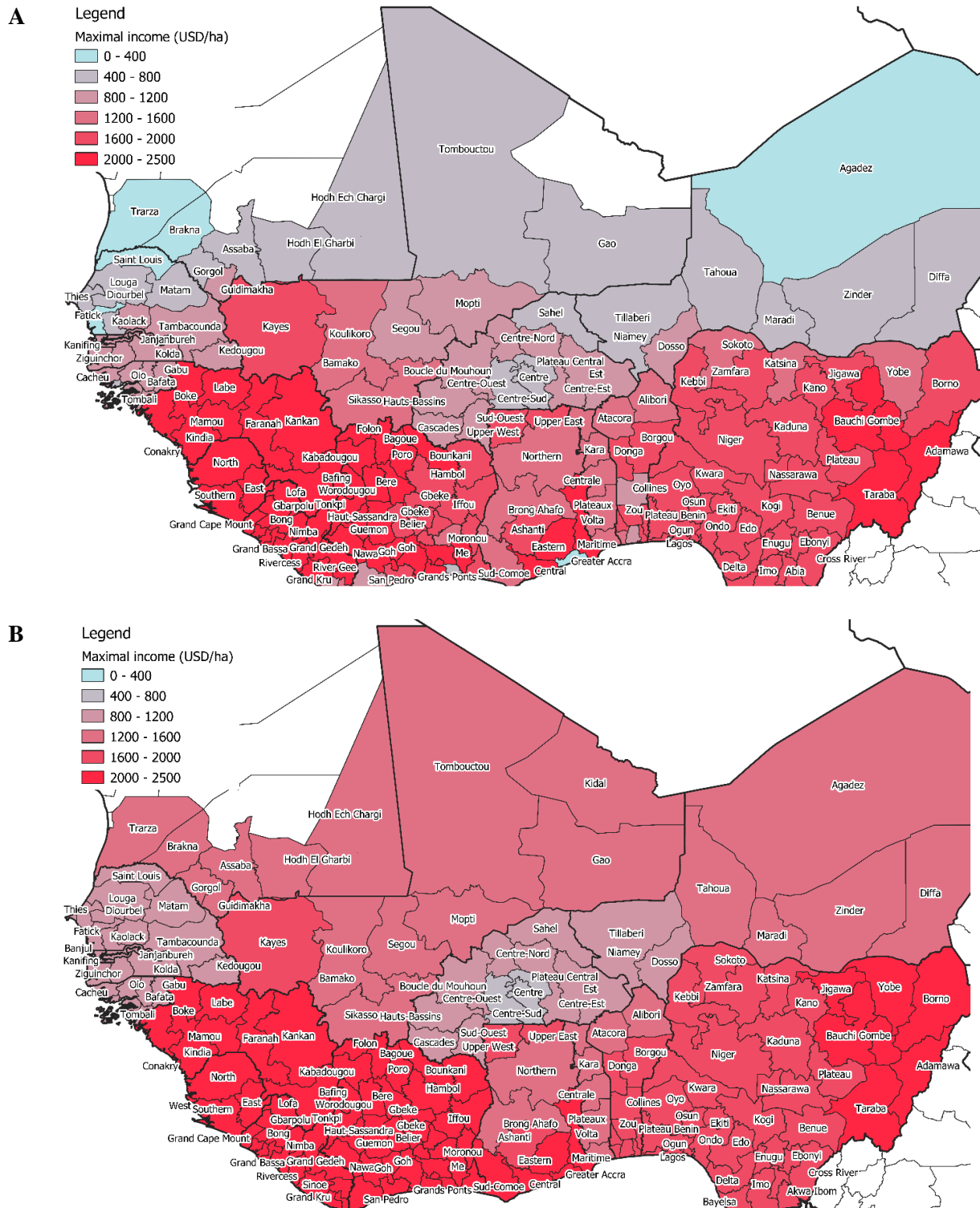


Figure S4 3. Maximal income measured with simplified model for IMP systems (A) and for IRR systems (B) at administrative level 1.

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