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SOCIO-ECONOMIC IMPACTS OF CLIMATE CHANGE IN DEVELOPING COUNTRIES

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A mon père et ma mère !

"Act now to avoid bad future "

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RÉSUMÉ

Il est un fait avéré que les conséquences du changement climatique font peser une menace considérable sur le bien-être de l'humanité tout entière. Depuis de nombreuses années maintenant, les conséquences du changement climatique, parmi lesquelles les sécheresses, les inondations et l'accroissement de la fréquence et de l'intensité des phénomènes météorologiques graves, se font sentir partout sur la planète. Par ailleurs, les coûts économiques de ces phénomènes climatiques sont plus importants dans les pays en développement qu'ailleurs. En effet, la variabilité de la température ou de la pluviométrie réduit fortement la productivité agricole qui est le secteur prédominant dans ces pays. Aussi, leurs défaillances institutionnelles sont un obstacle à leur adaptation ou à faire face aux effets pervers du changement climatique. Ainsi, cette thèse contribue à la littérature existante en proposant quatre chapitres sur les impacts socioéconomiques du changement climatique en Asie du Sud-Est et en Afrique. Plus précisément, nous analysons les impacts des tendances et chocs climatiques sur l'activité agricole, la sécurité alimentaire, le bien-être des ménages, et les conflits sociaux. Les deux premiers chapitres s'intéressent au cas du Vietnam et les deux derniers chapitres se concentrent sur l'Afrique. Dans le premier chapitre, les résultats indiquent que les chocs climatiques ont deux effets (direct et indirect) sur la productivité agricole. L'effet direct est appréhendé par l'impact non linéaire de la moyenne de la température et de la précipitation sur le rendement agricole. Ensuite, l'effet indirect est capté par la relation négative et significative entre les chocs climatiques et l'efficience technique des producteurs agricoles. Aussi, les résultats des simulations sont pessimistes quant à l'évolution de l'efficience technique dans un contexte où le réchauffement climatique sera plus important. Par la suite, dans le second chapitre, nous menons une réflexion sur la relation entre les facteurs de risques environnementaux et la sécurité alimentaire à travers une analyse multidimensionnelle. Les résultats de ce chapitre indiquent que les facteurs de risques environnementaux qui incluent la variabilité du climat empêchent les ménages ruraux d'atteindre un statut nutritionnel adéquat. Le chapitre 3 s'intéresse à l'analyse de la relation entre bien-être et conditions climatiques au Mali. Il ressort de ce chapitre que le bien-être des ménages au Mali est sensible aux conditions climatiques. Plus intéressant, nos résultats montrent que l'élasticité de la consommation à la variation de la pluviométrie varie selon les types de consommation et les groupes socio-économiques. Premièrement, nous trouvons que la valeur de l'élasticité consommation-pluviométrie est plus élevée pour la consommation non alimentaire et beaucoup plus faible pour la consommation alimentaire. Deuxièmement, nous trouvons que les ménages pauvres qui sont le plus souvent situés loin de la capitale (Bamako) et dépendants fortement des revenus agricoles sont les plus touchés par la variabilité et l'instabilité du climat. La pauvreté étant un déterminant clé des conflits en Afrique, le chapitre 4 analyse l'impact des chocs climatiques sur l'incidence des conflits domestiques. Nous trouvons que les chocs climatiques, tels que capturés par l'indice d'aridité augmentent la probabilité des conflits domestiques jusqu'à 38 %. Cet effet est amplifié dans les pays où la répartition des revenus est plus inégale et où la proportion de jeunes hommes est plus importante. Les résultats de ce chapitre mettent aussi en évidence des facteurs clés de résilience, notamment l'amélioration constante de la mobilisation des recettes intérieures, le renforcement de la protection sociale et l'augmentation des investissements publics dans le secteur agricole.

Mots clés : Changement climatique, chocs climatiques, agriculture, sécurité alimentaire, bien-être, pauvreté, conflits, pays en développement, Asie du Sud-Est, Vietnam, Mali, Afrique, économétrie appliquée.

Classifications JEL: D12, D24, D74, J11, I30, O12, O13, Q12, Q54

SUMMARY

It is a fact that the consequences of climate change pose a considerable threat to the well-being of all humanity. For many years now, the consequences of climate change, including droughts, floods, and increases in the frequency and intensity of severe weather events, have been felt around the world. Moreover, the economic costs of these climatic phenomena are greater in developing countries than elsewhere. Indeed, the variability of temperature or rainfall strongly reduces agricultural productivity, which is the predominant sector in these countries. Also, their institutional failures are an obstacle to their adaptation or to face the perverse effects of climate change. Thus, this thesis contributes to the existing literature by proposing four chapters on the socio-economic impacts of climate change in Southeast Asia and Africa. Specifically, we analyze the impacts of climate trends and shocks on agricultural activity, food security, household welfare, and social conflict. The first two chapters focus on the case of Vietnam and the last two chapters focus on Africa. In the first chapter, the results indicate that climate shocks have two effects (direct and indirect) on agricultural productivity. The direct effect is captured by the non-linear impact of average temperature and precipitation on agricultural yield. Then, the indirect effect is captured by the negative and significant relationship between climate shocks and the technical efficiency of agricultural producers. Also, the results of the simulations are pessimistic about the evolution of technical efficiency in a context where global warming will be more important. Subsequently, in the second chapter, we reflect on the relationship between environmental risk factors and food security through a multidimensional analysis. The results of this chapter indicate that environmental risk factors that include climate variability prevent rural households from achieving adequate nutritional status. Chapter 3 focuses on the analysis of the relationship between well-being and climatic conditions in Mali. This chapter shows that household well-being in Mali is sensitive to climatic conditions. More interestingly, our results show that the elasticity of consumption to changes in rainfall varies across consumption types and socio-economic groups. First, we find that the value of consumption-rainfall elasticity is higher for non-food consumption and much lower for food consumption. Second, we find that poor households that are most often located far from the capital (Bamako) and heavily dependent on agricultural income are the most affected by climate variability and instability. Since poverty is a key determinant of conflict in Africa, Chapter 4 analyzes the impact of climate shocks on the incidence of domestic conflict. We find that climate shocks, as captured by the aridity index, increase the likelihood of domestic conflict by up to 38 percent. This effect is amplified in countries with more unequal income distribution and a higher proportion of young men. The results in this chapter also highlight key resilience factors, including continued improvements in domestic revenue mobilization, enhanced social protection, and increased public investment in the agricultural sector.

Keywords: Climate change, weather shocks, agriculture, food security, welfare, poverty, conflict, developing countries, Southeast Asia, Vietnam, Mali, Africa, and applied econometrics.

JEL Classifications: D12, D24, D74, J11, I30, O12, O13, Q12, Q54

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LISTE DES ACRONYMES ET DES ABRÉVIATIONS

ACLED	Armed Conflict Location Events Datasets
CAPC	Centre Africain des Politiques en matière de Climat
CC	Climate Change
CCKP	Climate Change Knowledge Portal
CF	Control Function
CHIRPS	The Climate Hazards Group InfraRed Precipitation with Station
COP	Conférence des Parties
CPC	Climate Prediction Center
CRE	Correlated Random Effect
CRU	Climate Research Unit
DEA	Data Enveloppe Analysis
ECMWF	European Centre for Medium-Range Weather Forecasts
EKC	Environmental Kuznets Curve
EM-DAT	Emergency Events Database
EMOP	Enquête Modulaire auprès des Ménages
FAO	Organisation des Nations unies pour l'alimentation et l'agriculture
FSI	Food Security Index
GDD	Growing Degree Days
GES	Gaz à Effet de Serre
GHI	Global Hunger Index
GIEC	Groupe d'Experts Intergouvernemental dur l'Evolution du Climat
IMF	International Monetary Fund
IPCC	International Panel on Climate Change
KGDD	Killing Growing Degree Days

MODIS	Moderate-Resolution Imaging Spectroradiometer
NASA	National Aeronautics and Space Administration
NOAA	National Oceanic and Atmospheric Administration
OCDE	Organisation de coopération et de développement économiques
OMM	Organisation Météorologique Mondiale
ONG	Organisation Non Gouvernementale
ONU	Organisation des Nations Unies
PCA	Principal Component Analysis
PCCI	Per Capita Calories Intakes
RCP	Representative Concentration Pathway
SDGs	Sustainable Development Goals
SFA	Stochastic Frntier Analysis
SPEI	Standardized Precipitation Evapotranspiration Index
SWIID	Standardized World Income Inequality Database
UCDP GED	Uppsala Conflict Data Program's Georeferenced Event Dataset
UN	The United Nations
UNHCRE	Haut Commissariat des Nations Unies pour les réfugiés
VHLSS	Vietnamese Households Living Standard Surveys
VND	Vietnamese Dong

INTRODUCTION GENERALE

I. Contexte et Justification

Le changement climatique en cours est l'un des plus grands enjeux du 21ème siècle pour l'humanité. Le concept de changement climatique fait référence à une augmentation durable de la température moyenne de la terre. C'est un fait réel dont les conséquences sur le bien-être des individus sont devenues une menace pour l'humanité. Ce constat est basé sur l'observation d'une augmentation des températures moyennes de l'air et des océans à travers le monde, de la fonte généralisée des neiges et de la glace ainsi que d'une élévation du niveau moyen de la mer **(IPCC 2007)**. Depuis de nombreuses années maintenant, les conséquences du changement climatique, notamment les sécheresses, les inondations et la fréquence et l'intensité croissante des phénomènes météorologiques violents se font sentir partout dans le monde. Le réchauffement climatique risque d'atteindre le seuil critique de 1,5°C entre 2030 et 2052 si la température continue de croître à son rythme actuel. La crise climatique devient donc réelle, profonde et durable. Elle est qualifiée de réelle car les faits actuels corroborent les alertes déclarées et réitérées par le GIEC depuis leur premier rapport d'évaluation en 1990. Aussi, la crise climatique devient profonde car son impact devient très important et affecte tous les secteurs économiques qui engendre des coûts très important aussi bien au niveau humain, économique et social. Enfin, il est difficile avec les moyens actuels, à court ou moyen terme, de s'adapter ou contenir les coûts engendrés par les dérèglements climatiques ce qui rend le phénomène durable.

Depuis 20 ans, la gouvernance du climat s'est hissée au cœur du débat international. L'objet climat relevant d'abord des sciences physiques et atmosphériques est devenu un objet politique à la fin du XX e siècle. En effet, la réalité de la diffusion des émissions du gaz à effet de serre (GES) au niveau mondial, la principale cause du CC, appelle à une coopération internationale afin de lutter contre ce phénomène. Ainsi, plusieurs conférences internationales ont contribué à la prise de conscience de la réalité et des conséquences du réchauffement climatique. Ces conférences ont contribué de manières significatives à la dynamique des politiques et des acteurs autour du climat. **L'Organisation Météorologique Mondiale (OMM)** fût la première instance mondiale fondée en 1947 pour discuter de la question de l'émission du GES de nature anthropique. C'est sous son égide que plusieurs assemblées internationales ont vu le jour et qu'un comité scientifique de réflexion sur le climat (World Climate Research program) est lancé et qui devient le **Groupe d'experts intergouvernemental sur l'évolution du climat** (**GIEC** ou *Intergovernmental Panel on Climate Change* (IPCC) en anglais) en 1988. Le GIEC a pour mission principale d'évaluer les informations d'ordre économiques, sociales et politiques qui permettront de mieux comprendre le risque lié au changement climatique d'origine anthropique. Son rôle secondaire est de passer en revue les possibilités d'atténuation et d'adaptation au changement climatique. A l'état actuel, la GIEC a publié 5 grands rapports[1]. Dès la première publication du FAR en 1990 qui a fait la distinction entre le réchauffement climatique naturel et anthropique, la conférence sur l'environnement et le développement de l'ONU est tenue à Rio de Janeiro en 1992. Cette conférence a vu signer la Convention-cadre des Nations unies sur les changements climatiques par 168 pays qui constitue le socle de la coopération internationale sur le climat et a permis de structurer l'arène climatique. En effet, la convention de Rio n'inclut pas d'objectifs spécifiques mais a permis d'accélérer les négociations futures sur le régime climatique. En 1997, le protocole de Kyoto est signé par 184 pays et a pour objectif principal de réduire d'au moins 5% les émissions de GES entre 2008 et 2012 par rapport à son niveau de 1990. Cependant, le refus des Etats-Unis de ratifier le protocole engendre un changement dans la dynamique des négociations internationales. Désormais, deux assemblées se réunissent lors des conférences autour du climat : l'une formée par la conférence des parties (COP) et l'autre par les signataires du protocole de Kyoto. Aujourd'hui, nous comptons 26 conférences des parties, dont la COP 26 prévue en 2021 à Glasgow. La COP 21 de 2015 à Paris est la plus emblématique car elle a permis d'une part de fixer la limitation du réchauffement climatique entre 1.5°C et 2°C d'ici 2100 et, d'autre part, elle a contribué à discuter de l'engagement des pays riches à financer les actions climatiques dans les pays du Sud. L'ensemble de ces conférences ont permis d'alimenter le débat sur la question climatique en favorisant la croissance et la dynamique des acteurs (Etats, ONG, Société Civile…) et celles des questions autour du climat (impacts, atténuation et adaptation).

Cependant, le bilan de la gouvernance du climat reste marginale même si elle a contribué à une prise de conscience au niveau mondiale **(Aykut et Dahan 2015)**. Selon le rapport du GIEC de

[1] : FAR (***First Assessment Report***) en 1990, SAR (***Second Assessment Report***) en 1995, TAR (***Third Assessment Report***) en 2001 ; AR4 (***4th Assessment Report***) en 2007 ; AR5 (***5th Assessment Report***) en 2014 et le dernier rapport en cours AR6 (***6th Assessment Report***) prévu pour 2022.

2018[2] « Le réchauffement climatique devrait atteindre le seuil critique de 1,5°C entre 2030 et 2052 si la température continue de croître à son rythme actuel. » Ainsi, la recherche autour du climat est toujours nécessaire pour comprendre ses impacts potentiels et identifier les stratégies d'adaptation. Dans cette thèse, nous nous intéressons à l'analyse des impacts socio-économiques des dérèglements climatiques dans les pays en développement. Les résultats et contributions des chapitres de cette thèse contribuent ainsi à la réflexion sur les conséquences du CC et proposent des actions politiques concrètes qui pourront faciliter l'adaptation et la résilience des acteurs économiques face à ce phénomène. La section suivante fait un état des lieux des études empiriques sur l'impact du changement climatique dans différents contextes.

II. Analyses empiriques sur le changement climatique : La nouvelle littérature climato-économique

Ce qui rend intéressant l'étude de l'évaluation de l'impact du climat sur des variables économiques est sa nature exogène. Ainsi, il existe une littérature croissante sur les effets des variables climatiques sur les variables économiques. Toute cette littérature a montré que la variabilité de la température et la précipitation, et l'occurrence des évènements extrêmes ont un impact multidimensionnel significatif et économique. Ces études mettent en évidence les canaux par lesquels le changement climatique affecte l'activité économique globale, le secteur agricole, l'activité industrielle, la productivité du travail, la santé, la croissance économique, les conflits, etc. A partir de diverses méthodologies, les auteurs arrivent à montrer les résultats suivants : (i) le climat a changé ; (ii) le changement climatique a des coûts économiques énormes ; (iii) ces impacts peuvent varier selon le secteur et le contexte géographique considéré ; (iii) la nécessité de mettre en place des mécanismes d'adaptation afin de réduire la vulnérabilité des agents économiques face au changement climatique.

1. Mesure du changement climatique

Avant de faire une évaluation de l'impact du changement climatique sur les variables économiques, il est important de comprendre la notion de climat. Il existe généralement deux concepts pour définir les conditions climatiques dans les études empiriques : **le changement climatique et les chocs climatiques**. Selon le GIEC, le changement climatique est défini comme tout changement

[2] A consulter ici: https://www.ipcc.ch/sr15/chapter/spm/

persistant du climat au fil du temps causé par des activités humaines ou des événements naturels tandis que les chocs climatiques sont considérés comme des variabilités climatiques à court terme mesurées par un écart climatique par rapport à sa tendance de long terme.[3] Cette définition est similaire à celle de **Auffhammer et al. (2013)** qui définissent la météo comme les conditions de l'atmosphère sur un horizon temporel court et le climat comme la variabilité des conditions de l'atmosphère sur une période relativement longue. Ainsi, l'interprétation des coefficients associés au climat diffère selon que l'on s'intéresse aux chocs climatiques ou au changement climatique.

Bien qu'il existe plusieurs variables climatiques, **la température et les précipitations** sont les standards qui sont les plus utilisées. **Burke et Emerick (2016)** utilisent une approche de différence de long terme pour mesurer le changement climatique. Dans leur analyse, le changement climatique est mesuré comme une différence de la moyenne de la température et de la précipitation entre deux longues périodes. Par ailleurs, **Schlenker et Roberts (2009)** utilisent les données sur les précipitations et températures quotidiennes pour mesurer les anomalies climatiques sur la période de croissance de chaque culture agricole. Cette mesure climatique appelée **Growing Degree Days** consiste à calculer la température optimale et la précipitation optimale quotidienne nécessaire à la croissance de chaque culture. Ainsi, la variabilité du climat est captée par une déviation de la température ou des précipitations par rapport à ces seuils optimaux. **Eastin (2018)** mesure les chocs climatiques à partir des Z-scores qui sont calculés à partir de la formule suivante :

$$Z_{it} = \frac{(X_{it} - X_i)}{\sigma_i}$$

Où X_{it} répresente la valeur de la temperature ou la précipitation à un moment donné t; X_i la moyenne de la température ou la précipitation sur les cinq dernières années ; et σ_i l'écart-type de la température ou de la précipitation. Cet indicateur permet de capter la déviation normalisée de court terme de la température ou de la précipitation.

En plus de la température et les précipitations, plusieurs autres variables sont utilisées pour mesurer les conditions climatiques. L'indice de sécheresse SPEI (Standard Precipitation Evapotranspiration Index) développé par **Vicente-Serrano, Beguería, et López-Moreno (2010)** permet de mesurer le degré d'humidité (sècheresse) d'une zone. Il est défini comme la différence entre la précipitation

[3] Dans cette thèse nous utiliserons ces deux expressions : « Changement climatique » et « Chocs climatiques ».

et l'évapotranspiration des plantes ; qui elle-même est fonction du niveau de température. Selon les auteurs, cet indicateur est plus avantageux relativement aux autres mesures de chocs climatiques. D'une part, il prend en compte l'interaction entre les températures et précipitations. Ainsi, l'indicateur est calculé de sorte qu'il combine à la fois les chocs de température et de précipitation. D'autre part, il permet la comparaison entre les régions caractérisées par des saisonnalités climatiques différentes. Par ailleurs, les évènements extrêmes climatiques tels que l'occurrence des catastrophes naturelles (sècheresse, inondation, cyclone…) sont aussi utilisées. Le Tableau 0. 1 ci-dessous résume quelques sources de données climatiques qui sont facilement accessibles.

2. Littérature existante sur les impacts socioéconomiques du changement climatique

(i) Coût économique du changement climatique

L'impact économique du CC est global et multisectoriel. Plusieurs études montrent que le réchauffement climatique a un effet très significatif et négatif sur la richesse des nations. **Gallup, Sachs, et Mellinger (1999)** montrent que relativement aux régions tempérées, les régions tropicales sont caractérisées par des niveau de développement plus faible. Les résultats de leur analyse mettent en évidence que le revenu des pays tropicaux était 50 pourcent plus faible en 1950 avec une faible croissance annuelle moyenne de 0,9 point de pourcentage entre 1965 et 1990. En utilisant des données à faible résolution (1°lat x 1°long), **Nordhaus (2006)** trouve que les variables géographiques qui incluent la température et la précipitation expliquent environ 20 pourcent de différence entre le niveau de revenu des pays de l'Afrique Subsaharienne et les pays industrialisés de l'Europe. L'impact du CC sur le revenu est aussi détecté lorsqu'on s'intéresse à une analyse plus désagrégée entre les localités d'un même pays. **Dell, Jones, et Olken (2009)** analysent la relation entre la température et le revenu au sein de plusieurs municipalités dans 12 pays en Amérique. Ils arrivent à montrer que l'augmentation du niveau moyen de la température affecte la différence de revenu entre les pays et entre les municipalités au sein de chaque pays. Par exemple, une augmentation de la température de 1°C diminue le revenu de 1 à 2 % (intra-pays) et de 8,5% (inter-pays). Cette relation négative entre réchauffement climatique et revenu est corroborée par plusieurs autres analyses empiriques dans différents contextes **(Hsiang 2010; Barrios, Bertinelli, et Strobl 2010; Dell, Jones, et Olken 2012)**.

Tableau 0. 1:Source de données climatiques

Variables	Nom de la base	Type of data	Unité géographique	Horizon temporelle	Sources
Précipitations	CRU (Climate Research Unit)	Mensuelle	0.5x0.5°	1901-2019	CRU TS version 4.04 –University of East Anglia): https://crudata.uea.ac.uk/cru/data/hrg/
	CHIRPS (Climate Hazards Group InfraRed Precipitation with Station data)	Journalière; Mensuelle	0.05x0.05°	1981-2020	http://chg.geog.ucsb.edu/data/chirps/
	CPC (Climate Prediction Center)	Journalière	0.5x0.5°	1979-2021	https://psl.noaa.gov/data/gridded/data.cpc.globaltemp.html
Température	CRU (Climate Research Unit)	Mensuelle	0.5x0.5°	1901-2019	CRU TS version 4.04 –University of East Anglia): https://crudata.uea.ac.uk/cru/data/hrg/
	MODIS (Moderate Resolution Imaging Spectroradiometer)	Mensuelle	0.05x0.05°	2000-2020	https://modis.gsfc.nasa.gov/data/
	CPC (Climate Prediction Center)	Journalière	0.5x0.5°	1979-2021	https://psl.noaa.gov/data/gridded/data.cpc.globaltemp.html
SPEI: Standard Precipitation Evapotranspiration Index	Vicente et al (2010)	Mensuelle	0.5x0.5°	1901-2018	Climate Research Unit (CRU): https://spei.csic.es/database.html
Catastrophes naturelles	EM-DAT: The international Disaster Database	Annuelle	Pays	1900-2021	Centre for Research on the Epidemiology of Disasters-CRED: https://public.emdat.be/data

Par ailleurs, d'autres auteurs analysent les coûts économiques engendrés par les évènements extrêmes climatiques tels que les périodes de sécheresse, l'occurrence des cyclones, les inondations et autres évènements similaires. En effet, ces évènements extrêmes sont une conséquence majeure du changement climatique (Knutson et al. 2020). Les résultats de ces études sont ambigus. Certaines analyses trouvent un effet positif des catastrophes naturelles sur la croissance tandis que d'autres trouvent que les catastrophes naturelles ont un effet négatif sur la croissance du PIB. Par exemple **Caballero et Hammour (1994)** montrent que les chocs climatiques extrêmes pourraient être considérés comme un facteur exogène et catalytique de l'incitation à réinvestir et donc à augmenter la productivité du capital. Le même résultat a été trouvé par **Skidmore et Toya (2002)**. Ils montrent que pendant la période post-désastres naturels, le stock de capital est mis à jour et l'adoption de nouvelle technologie est encouragée. Ces derniers étant considérés comme des facteurs qui permettent d'améliorer les performances de croissance de l'activité économique. Aussi, les pays qui ont l'habitude d'expérimenter les catastrophes naturelles deviennent de moins en moins impacter économiquement car ils apprennent à mieux se préparer aux prochaines catastrophes **(Anbarci, Escaleras, et Register 2005; Cavallo, Powell, et Becerra 2010; Escaleras, Anbarci, et Register 2007)**. Cependant, selon **Raddatz (2009)**, ces évènements extrêmes ont engendré des coûts macroéconomiques très important durant les décennies récentes. L'auteur montre que le PIB par tête est au moins réduit de 0,6% à cause de l'occurrence des catastrophes climatiques. **Cavallo et al. (2013)** montrent que les catastrophes de très grande ampleur ont un effet négatif sur la croissance économique des pays, tant à court terme qu'à long terme. **Nakamura et al. (2013)** estiment le coût économique des catastrophes dans 24 pays sur plus de 100 ans. Les auteurs constatent que les catastrophes augmentent la volatilité de la croissance de la consommation, plus précisément la consommation chute de 30% à court terme avant que la moitié de cette baisse soit récupérée à long terme.

(ii) Impact multisectoriel du changement climatique

Les conséquences du changement climatique sont aussi multisectorielles. De tous les secteurs économiques, l'agriculture est le secteur le plus touché par le changement climatique. En effet, le processus biologique de croissance de la plante est très sensible à la variabilité des niveaux de températures et de précipitation. Ainsi l'impact de la variabilité du climat sur un le rendement des cultures agricoles est considéré comme un lien direct et naturel **(Dell, Jones, et Olken 2014)**. Aussi, la sécurité alimentaire est menacée par le changement climatique car il conduit à une instabilité de la production, des prix et par conséquent toute la chaîne de la production agricole se voit affectée par le changement climatique **(Sanchez 2000; Siwar, Ahmed, et Begum 2013)**. **Il existe plusieurs approches méthodologiques pour estimer l'effet du climat sur la productivité agricole**. La première approche est l'estimation de la relation entre le climat et le rendement agricole à partir des méthodes de simulations basées sur une fonction de production. Pour simuler l'effet du changement climatique sur le rendement agricole, la fonction de production est calibrée avec des données issues de l'expérimentation **(Adams 1989; Kaiser et al. 1993; Adams et al. 1995)**. Cependant, cette approche a été beaucoup critiquée car elle est jugée non réaliste du vrai comportement des agriculteurs. Par exemple, les comportements d'adaptation ou encore le changement des prix des facteurs de production ne sont pas pris en compte dans ces modèles, ce qui tend à biaiser les vrais effets du changement climatique sur le rendement agricole **(Schlenker, Hanemann, et Fisher 2006)**. L'approche du modèle Ricardien permet de prendre en compte ces limites. Le principe de cette méthode est d'évaluer la valeur présente et future de la terre agricole en tenant compte de l'influence des facteurs climatiques et économiques. Ainsi, l'objectif principal des agriculteurs est de trouver une combinaison optimale d'intrants (qui prennent en compte les possibilités d'adaptation telle que l'irrigation) et de rendement qui permet de maximiser le revenu net agricole, étant donné les variations exogènes climatiques. En utilisant le modèle Ricardien sur 3000 comtés aux USA, **Mendelsohn, Nordhaus, et Shaw (1994)** montrent que l'effet des variabilités climatiques sur la production agricole est moins important que l'effet estimé avec la fonction de production agricole standard. Cependant, cette analyse effectuée en coupe transversale est beaucoup critiquée dans la littérature. **Schlenker et Roberts (2009)** pensent que l'analyse en coupe transversale ne permet pas non seulement de capter l'hétérogénéité spatiale et temporelle, mais ne tient pas compte des vagues d'adaptations historiques des agriculteurs. L'analyse en coupe transversale est donc soumise aux problèmes de variables omises. Ainsi, la nouvelle littérature sur l'impact du changement climatique sur le secteur agricole utilise principalement la méthodologie des données de panel **(Deschênes et Greenstone 2007; A. C. Fisher et al. 2012; Deryugina et Hsiang 2017)**.

Le changement climatique a également des conséquences négatives sur la production du secteur industriel et celui des services. Cette relation s'explique par le canal de l'impact des conditions climatiques sur la productivité du travail des ouvriers ou employés. Le géographe américain, **Huntington (1924)**, dans une des premières études sur le sujet, trouve que la productivité des ouvriers dans les industries de coton est importante durant la saison du printemps, où la température est généralement modérée et baisse considérablement durant l'été et l'hiver qui sont marquées par des températures extrêmes. **Hsiang (2010)** mesure l'effet de la température et les catastrophes naturelles sur la production de 28 pays Caribéens sur la période 1970-2006. Il trouve que la production du secteur non agricole baissait de 2,4 % lorsque la température augmentait de 1°C. Par ailleurs, **Dell, Jones, et Olken (2012)** montrent que la valeur ajouté du secteur industriel, dans les pays pauvres, diminuait de 2% avec une augmentation marginale de la température de 1°C.

(iii) Coût social du changement climatique

En plus des coûts économiques causés par le changement climatique, certains auteurs mesurent les coûts sociaux du changement climatique. Ces effets sociaux du changement climatiques sont observés sur l'incidence de la pauvreté **(Hope Sr 2009; Hertel et Rosch 2010; Skoufias, Rabassa, et Olivieri 2011; Leichenko et Silva 2014; Fankhauser et Stern 2016; Hallegatte, Fay, et Barbier 2018)**, l'incidence des crimes **(Jacob, Lefgren, et Moretti 2007; Ranson 2014)** et conflits **(Miguel, Satyanath, et Sergenti 2004; M. B. Burke et al. 2009; Hidalgo et al. 2010; Hsiang, Burke, et Miguel 2013).** Ces études montrent que le changement climatique augmente la pauvreté et les inégalités. L'une des explications est que le changement climatique participe à l'augmentation de la vulnérabilité des ménages dont le revenu dépend fortement du secteur agricole. Aussi, les conflits domestiques ont tendance à augmenter dans les zones où les ressources naturelles (ex : gestion de l'eau ou terre arable) se font rare à cause du changement climatique. Ceci est souvent accompagné par des manques d'opportunités pour les jeunes ce qui favorise leur recrutement dans des mouvements de rebellions.

(iv) Adaptation au changement climatique

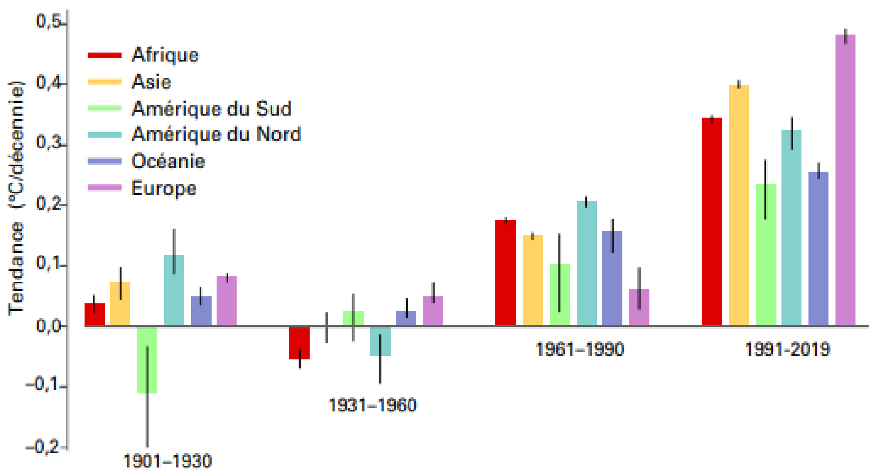
L'intensité de l'ampleur des impacts du changement climatique est fonction de la capacité d'adaptation des entités économiques (ménages, entreprises, pays, régions, etc.). Le GIEC définit l'adaptation comme le processus d'ajustement au climat actuel et attendu ainsi qu'à ces conséquences. Ainsi, la capacité d'adaptation rassemble les moyens potentiels (actuels ou futures) dont disposent les agents économiques pour faire face aux évènements climatiques extrêmes afin de réduire leurs conséquences. On distingue deux types d'adaptation : **l'adaptation incrémentale et l'adaptation transformationnelle**. L'adaptation incrémentale désigne l'ensemble des actions qui sont mise en place dans un horizon de court terme pour atténuer les dommages des chocs climatiques sans toutefois modifier le système de production actuel. L'adaptation transformationnelle est plutôt basée sur les stratégies qui sont mise en place sur une période assez longue et qui consiste à modifier le processus de production afin qu'il réponde mieux au contexte climatique actuel. Même si ces deux typologies d'adaptations semblent différentes, elles sont complémentaires **(Loorbach, Frantzeskaki, et Huffenreuter 2015)**. Par exemple, au niveau des ménages ou firmes, l'investissement dans de nouvelles technologies (ex : les variétés d'engrais plus résistant aux chocs climatiques, investissement dans l'agriculture ou la modification du système de production) permet de diminuer les conséquences des chocs climatiques sur le revenu des individus **(Mendelsohn et Seo 2007; Bryan et al. 2009; Kurukulasuriya, Kala, et Mendelsohn 2011; Eichberger et Guerdjikova 2012; Tambo et Abdoulaye 2012)**. Aussi, les ménages peuvent décider de migrer et se relocaliser dans les lieux où le climat est propice à leur activité de production **(Ellis 2000; Laczko et Aghazarm 2009; Blaikie et al. 2014; Marchiori, Maystadt, et Schumacher 2017)**. La diversification des sources de revenu à travers l'entreprenariat dans les activités moins dépendantes des conditions climatiques facilite l'absorption des chocs climatiques **(Ma et Maystadt 2017; Marchiori, Maystadt, et Schumacher 2017; Wuepper, Yesigat Ayenew, et Sauer 2018; Chuang 2019)**. Cependant, il existe plusieurs contraintes qui empêchent les agents économiques de mieux s'adapter au changement climatique. **Castells-Quintana, Lopez-Uribe et McDermott (2018)** montrent que l'accès aux ressources financières (crédit, assurance…), la fourniture d'infrastructures (énergie, transport, assainissement…) et la disponibilité d'informations climatiques (système de prévisions météo) sont les contraintes majeures liées à l'adaptation au changement climatique. Ces limites rendent certaines entités (ménages, entreprises, pays et régions) plus vulnérables par rapport à d'autres.

Pour résumer, la littérature existante révèle que le changement climatique est un fait réel et global dont les conséquences sur le bien-être des individus sont énormes. Cependant, la distribution de l'impact du changement climatique n'est pas uniforme entre les pays développés et les pays en développement ; d'où l'importance des analyses qui s'appuient sur des données géolocalisées précises. En effet, les pays en développement sont les plus vulnérables au changement climatique ; en particuliers les régions d'Afrique et d'Asie du Sud-Est qui englobent la majorité des pays en développement. D'où l'intérêt de s'intéresser à ces zones d'études dans cette thèse.

III. Motivation de l'étude : changement climatique en Asie du Sud-Est et en Afrique

Notre travail couvre deux grandes régions : l'Asie du Sud-Est et l'Afrique. Le choix de ces deux régions comme champs d'études n'a pas été aléatoire. Ces deux régions sont identifiées comme les zones où les impacts du changement climatique sont les plus prononcés à cause de leur **dépendance à l'agriculture et le manque de mobilisation des ressources pour s'adapter aux dommages climatiques. Aussi, la tendance et les projections du climat sont pessimistes dans ces deux régions.** La **figure 0. 1** montre que l'Afrique et l'Asie ont connu une augmentation de la température à un taux comparable aux autres continent mais un peu plus rapidement depuis le début du 20ème siècle.

Figure 0. 1: Trend of temperature per region



Source : Organisation Météorologique Mondiale, 2019

(i) Quelques faits stylisés sur l'Afrique

L'agriculture est le secteur clé de l'économie de la plupart des pays d'Afrique. L'agriculture contribue à environ 32% du PIB du continent Africain et plus des deux tiers de la population dépendent des activités agricoles pour leurs subsistances **(Tongwane and Moeletsi, 2018)**. L'agriculture en Afrique est majoritairement pluviale ce qui rend ce secteur encore plus vulnérable aux variations climatiques. **Knox et al. (2012)** trouvent que la production agricole diminuera de 8% en 2050 en Afrique à cause du changement climatique. Ils montrent qu'en Afrique, les rendements agricoles baisseront de -17% (blé), -5% (maïs), -15% (sorgho) et -10% (mil). Aussi, le réchauffement climatique amplifie l'invasion des insectes dévastateurs et la propagation des maladies comme le paludisme. Les dommages causés par le changement climatique dans cette zone ne font que s'accroître car les actions politiques autours du climat sont marginales. Les résultats de **Mendelsohn, Dinar, et Dalfelt (2000)** montrent que les rendements agricoles en Afrique pourraient chuter de manière assez spectaculaire en l'absence de mesures d'adaptation. En effet, la technologie agricole actuelle est basique, et les revenus sont faibles, ce qui suggère que les agriculteurs auront peu de possibilités de s'adapter. Aussi, les infrastructures publiques telles que les routes, les systèmes de prévisions météorologiques saisonnières, la recherche et la vulgarisation agricoles sont actuellement insuffisantes pour garantir une adaptation appropriée.

L'agriculture est le canal principal par lequel le changement climatique affecte la sécurité alimentaire **(Ringler et al. 2010; Tumushabe 2018)**, l'incidence de la pauvreté **(Thornton et al. 2006; 2008; Hope Sr 2009)**, les inégalités et les conflits **(Brown, Hammill, et McLeman 2007; Mwiturubani et Van Wyk 2010; Hendrix et Salehyan 2012)**. Selon l'Organisation des Nations Unies pour l'alimentation et l'agriculture (FAO), le nombre de personne malnutries a augmenté de 45,6% depuis 2012 dans les pays d'Afrique sujets à la sécheresse.

La recherche autour du climat en Afrique est une nécessité car les projections des conditions climatiques sont assez pessimistes. Selon le GIEC, une grande partie de l'Afrique s'est déjà réchauffée de plus de 1°C depuis 1901, avec une augmentation des jours de canicule et des vagues de chaleur. Aussi, une majeure partie de l'Afrique du Nord et de l'Afrique du Sud-Ouest connaitra une réduction des précipitations. Le Centre Africain pour la Politique en matière de Climat (CAPC) prévoit que le PIB subirait une baisse importante à la suite d'une augmentation de la température mondiale, dans les cinq sous-régions africaines[4]. Selon cette étude, le PIB global du continent connaitra une diminution de 2,25% à 12,12% respectivement sous les scénarios où la température mondiale augmenterait de 1°C et 4°C par rapport aux niveaux préindustriels. L'impact est beaucoup plus important en Afrique Subsaharienne qu'en Afrique du Nord. Par ailleurs, la région du Sahel qui inclut le Mali connaît de plus en plus des périodes de sècheresses et plus de dix millions d'habitants sont impactés[5].

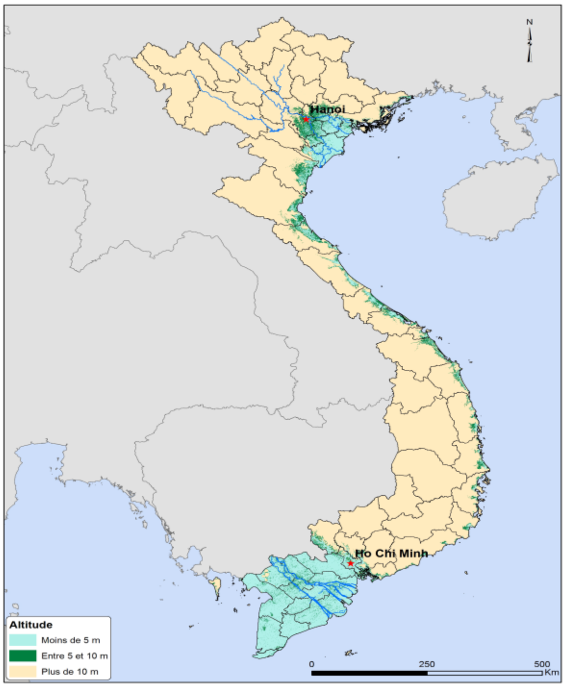
[4] https://repository.uneca.org/bitstream/handle/10855/24206/b11882840.pdf?sequence=1&isAllowed=y

[5] Sécurité alimentaire et implications humanitaires en Afrique de l'Ouest et au Sahel - Note conjointe FAO/PAM, Avril 2017 - Mai 2017.

(ii) Asie du Sud-Est : Vietnam

En ce qui concerne l'Asie du Sud Est, les faits stylisés sur la vulnérabilité climatique sont similaires aux caractéristiques de l'Afrique **(World Bank 2013)**. Nous focalisons notre étude sur le Vietnam qui constitue le grenier de la production agricole dans cette sous-région. Le Vietnam est un pays long et étroit composé de deux grandes fleuves (le Mékong au sud et le fleuve Rouge au nord), des zones montagneuses à l'Est et au Nord Est de ses frontières et deux grands deltas qui sont en même temps les greniers à riz du continent. Cette géographie fait du Vietnam un pays exposé aux risques climatiques tels que les sécheresses, les inondations, les tempêtes tropicales et à la montée des eaux entraînant la salinisation et la perte des surfaces terrestres (cf. figure 2).

Figure 0. 2: Géographie du Vietnam



Source : Olivier Santoni, 2018

Le Vietnam figure parmi les cinq pays les plus vulnérables selon le portail de connaissances sur le changement climatique (CCKP) de la Banque mondiale[6], en raison de la fréquence des catastrophes naturelles (inondations, typhons et sécheresse) et de l'augmentation des températures moyennes, qui ont déjà atteint près de deux degrés dans certaines provinces. Selon l'indice INFORM, le Vietnam est classé respectivement en 1ère et 8ème position sur 191 pays en matière de vulnérabilité au inondation et aux cyclones[7]. Par ailleurs, les projections climatiques du Vietnam sont plutôt pessimistes quant à ses dommages futurs. **Yu et al. (2013)** prévoient une augmentation de la température moyenne de 2,5°C en 2070 et du niveau de la mer de 33 cm en 2050. Cette exposition au risque climatique est plus évidente dans les régions du delta du Mékong au sud du pays et dans les zones côtières.

Par ailleurs, le secteur agricole joue un rôle important dans le processus de développement et de la réduction de la pauvreté au Vietnam. Malgré sa faible contribution au PIB (environ 15%), le secteur agricole emploie la majorité de la main-d'œuvre active du pays (43%), principalement localisée dans les zones rurales. Le riz est la principale culture de production et emploie les deux tiers de la main d'œuvre totale dans le milieu rural. Selon la FAO, le Vietnam est le cinquième producteur de riz au monde avec une production totale de 42,76 millions de tonnes par an et un rendement de 5,55 tonnes par hectare en 2017. Cependant, l'agriculture vietnamienne est menacée par la persistance des conséquences du changement climatique. **Yu et al. (2010)** analyse l'impact du changement climatique sur la production de riz au Vietnam. Ils trouvent que le changement climatique entraînera en moyenne une baisse de la production du riz de 2,7 millions de tonnes en 2050. Cet impact négatif du changement climatique est non uniforme dans les différentes régions du Vietnam. Leur modèle de simulation prédit une baisse des rendements de riz de 4,3 à 8,3 % en 2050 dans la région du delta du Mékong, tandis que l'impact est encore plus prononcé pour la région du delta du fleuve Rouge (7,5 à 19,1 %). La production du riz dans la région du delta du fleuve Rouge aurait diminué de 15% comparée à la production de 2008 de la région du Mékong. Ainsi, l'agriculture vietnamienne a besoin d'être développée afin de la rendre plus résiliente aux variabilités climatiques. Les agriculteurs doivent être assistés et éduqués sur l'utilisation des stratégies d'adaptations à leur

[6] Portail accessible ici : https://climateknowledgeportal.worldbank.org/country/vietnam/vulnerability
[7] Données accessibles ici : Inform risk index from World Bank Group Climate Change Knowledge Portal

disposition comme l'irrigation **(Trinh 2018)**. La baisse de la productivité agricole est une contrainte majeure pour la sécurité alimentaire dans le pays.

Outre l'impact du changement climatique sur le secteur agricole, des études ont mis l'accent sur le lien entre changement climatique et pauvreté au Vietnam. **Arouri, Nguyen, et Youssef (2015)** montrent que l'occurrence des évènements extrêmes climatiques est associée négativement avec le revenu des ménages. Dans le même temps, **Narloch et Bangalore (2018)** trouvent les résultats suivants au Vietnam : (i) la pauvreté est plus élevée dans les districts qui sont sujets à un risque climatique important, (ii) au niveau ménage, les ménages pauvres sont ceux qui sont les plus exposés au risque climatique, (iii) le lien entre risque climatique et pauvreté varie selon le milieu de résidence (urbain/rural). En effet, la variabilité de la précipitation et les périodes de sécheresse sévère ont un impact plus prononcé dans le milieu rural que le milieu urbain.

Au regard de ces faits stylisés sur l'Afrique et l'Asie du Sud-Est, il apparait pertinent et nécessaire de s'intéresser à la problématique du climat dans ces régions. Plus précisément, nous discutons des questions suivantes dans les différents chapitres de notre thèse :

- **Comment mesurer les impacts socioéconomiques du changement climatique en Afrique et en Asie du Sud-Est ?**
- **Quelles actions politiques doivent être mise en place pour réduire la vulnérabilité des individus et la vulnérabilité de la structure économique de ces pays au changement climatique ?**

IV. Méthodologie, contributions et organisation de la thèse

La présente thèse propose une contribution à l'analyse empirique et au débat politique sur la question des impacts du changement climatique dans les pays en développement. Plus précisément, notre travail consiste à analyser les impacts socioéconomiques des dérèglements climatiques en Asie du Sud-Est et en Afrique et ainsi à contribuer à la littérature déjà existante sur cette question.

Notre thèse est structurée en quatre chapitres complémentaires. Les deux premiers chapitres analysent la relation entre le changement climatique et l'agriculture au Vietnam. Les résultats de ces chapitres fournissent des preuves empiriques qui pourront être prise en compte dans la politique agricole vietnamienne « **National Nutrition Strategy for 2011-2020, with a vision toward 2030** » qui a pour but global d'augmenter la production agricole et réduire l'insécurité alimentaire. La prise en compte des recommandations de politiques économiques pourraient faciliter le processus de développement du secteur agricole au Vietnam. Les chapitres 3 et 4 se focalisent sur l'Afrique. Dans le troisième chapitre, nous avons mesuré l'élasticité de la consommation à la variation de la pluviométrie au Mali, pays de la région du Sahel qui fait face à plusieurs défis comme le changement climatique et les crises conflictuelles. Cette étude a permis de cibler les groupes de populations les plus vulnérables aux variations de la pluviométrie. Aussi, nous montrons que l'augmentation de la pauvreté est en partie expliquée par la diminution de la pluviométrie. La pauvreté étant un déterminant clé des conflits, ce chapitre donne ouverture au quatrième chapitre qui analyse l'impact des chocs climatiques sur l'incidence des conflits domestiques en Afrique. A notre connaissance, ce chapitre est le premier qui analyse à la fois l'impact des chocs climatiques sur l'incidence des conflits tout en identifiant les facteurs macroéconomiques catalyseurs ou atténuateurs des conflits internes en Afrique. Dans chacun de ces quatre chapitres, nous discutons aussi les actions politiques qui pourraient faciliter l'adaptation des populations locales au CC. Dans les lignes qui suivent, nous présentons le résumé de chaque chapitre qui inclut la méthodologie, la contribution, les résultats ainsi que les recommandations de politiques économiques qui en découlent.

Le premier chapitre intitulé « Impacts of Extreme Climate Events on Technical Efficiency in Vietnamese Rice Farming» analyse l'impact des évènements extrêmes climatiques sur l'efficience technique de la production du riz au Vietnam. Le Vietnam est exposé à plusieurs chocs climatiques réguliers et son économie est fortement dépendante de la production du Riz. Notre stratégie d'identification est basée sur une estimation en deux étapes. La première étape consiste à estimer l'efficience technique à partir du modèle de frontière stochastique et la seconde étape permet d'analyser les chocs climatiques comme déterminant de l'inefficience technique agricole. L'efficience est définie comme étant la capacité des producteurs à utiliser de manière optimale les ressources à leur disposition afin de maximiser leur production. Elle est calculée comme étant la différence entre la production potentielle et la production effective de l'agriculteur. Cette analyse quantitative a été possible grâce à la combinaison des données socio-économiques (VHLSS) et climatiques (CPC) qui existent pour le Vietnam. Nous rappelons que jusque-là, le lien de causalité entre les chocs climatiques et la productivité du secteur du riz mesuré en termes d'efficience n'avait pas encore été exploré dans la littérature. Les résultats de cette étude permettent de distinguer deux effets des conditions climatiques sur le secteur du riz au Vietnam. D'abord un effet direct qui met en relation le climat et le potentiel de la production du riz. Ensuite, un effet indirect qui met en évidence l'effet des chocs climatiques sur la performance des producteurs:

- **Effet direct** : la production du riz mesurée en volume est conditionnée par l'existence d'un bon climat. En effet, nous trouvons qu'au-delà de 28°C, la température a un effet négatif sur la production potentielle du riz vietnamien.
- **Effet indirect** : Nous constatons que les chocs météorologiques mesurés par les occurrences d'inondations, les typhons et les sécheresses ont un impact négatif sur l'efficience technique. En outre, des jours supplémentaires avec une température supérieure à 31°C, réduisent l'efficacité technique et l'effet négatif augmente avec la température. L'impact marginal est compris entre 3 et 9 points de pourcentage. Aussi, les jours très chauds ont relativement plus d'impact sur l'efficience des agriculteurs durant la saison sèche que la saison humide. En effet, la saison humide est caractérisée par des niveaux de précipitation assez importantes, en moyenne 238,20 mm par mois, qui atténueraient l'effet négatif des températures élevées sur la performance des riziculteurs.

L'impact négatif de ces chocs s'explique principalement par le manque d'adaptation des riziculteurs. En effet, l'occurrence des chocs climatiques crée des biais dans les anticipations des agents, qui conditionne leurs décisions agricoles. Il est donc difficile pour ces derniers, particulièrement les ménages pauvres, de s'ajuster automatiquement aux chocs de court terme. Ainsi, ils utilisent de manière sous-optimale les intrants et ressources nécessaires pour la gestion de leurs activités agricoles. Par ailleurs, en utilisant les scenarios RCP 4.5 et 8.5 du GIEC, les simulations affichent une tendance baissière de l'efficience respectivement d'environ 10% et 40%, si aucune adaptation n'est entreprise d'ici 2050. En outre, la riziculture vietnamienne doit maintenant faire face à des problèmes importants aux niveaux national et international. Au niveau national, l'agriculture vietnamienne doit faire face au triple défis : **la réduction de la pauvreté dans les zones rurales**, à **la sécurité alimentaire** (alimentation avec des produits de bonne qualité) et à **la préservation de l'environnement**. Ces défis nationaux ont des implications au niveau international. La compétitivité de l'agriculture vietnamienne dépend de **la performance des agriculteurs** et des entreprises à fournir des produits fiables en ce qui concerne la qualité, la sécurité et la durabilité des produits fournis. Ainsi, la fragilité du secteur du riz face au changement climatique devient une urgence politique pour le gouvernement Vietnamien.

Plusieurs solutions sont envisageables pour réduire la vulnérabilité des producteurs de riz face au chocs climatiques :

- La mise en place des systèmes de prévisions météo dans les zones défavorisées pourrait faciliter l'anticipation des événements extrêmes climatiques et donc de s'y adapter.
- Aussi, les aides techniques qui consisteraient à faciliter l'implémentation et l'usage des systèmes d'irrigation et de drainage sont utiles pour atténuer l'effet négatif de la sécheresse et des inondations sur l'efficience technique des riziculteurs.
- Enfin, encourager la diversité productive en passant d'une spécialisation dans la production du riz à la mise en culture des produits qui sont plus résilients au réchauffement climatique à l'image de ce qui a déjà été initié dans certaines régions du Vietnam notamment le delta du Mékong.

Le second chapitre a pour but d'analyser l'association entre dégradation environnementale et sécurité alimentaire dans le milieu rural au Vietnam. Dans ce chapitre, nous faisons une analyse multidimensionnelle de la relation entre environnement et la sécurité alimentaire. D'une part, la dégradation de l'environnement est mesurée à travers plusieurs indicateurs comme la variabilité de la température et précipitation, les catastrophes naturelles, la pollution de l'air et la déforestation. D'autre part, la sécurité alimentaire est analysée à travers ses quatre dimensions : disponibilité, accessibilité, diversité et stabilité. Ces dimensions découlent de la définition de la sécurité alimentaire donnée par le Sommet mondial de l'alimentation en 1996 : "La sécurité alimentaire existe lorsque tous les êtres humains ont, à tout moment, un accès physique et économique à une nourriture suffisante, saine et nutritive qui répond à leurs besoins et préférences alimentaires pour mener une vie saine et active." Ainsi, nous construisons un indicateur composite qui prend en compte ces dimensions. Aussi, l'analyse de la relation entre environnement et sécurité alimentaire est complexe car certaines variables environnementales peuvent être endogènes aux dimensions de la sécurité alimentaire. Par exemple, la déforestation peut impacter positivement le bien-être des ménages en lissant leur consommation ou revenu à travers l'activité forestière **(Fisher 2004)**. Ainsi, la déforestation peut être considérée comme source de revenu et faciliter l'accès des ménages aux aliments de qualité. Cependant, l'activité agricole elle-même peut contribuer à la perte du couvert forestier à travers les activités d'extension agricole. Ce lien de simultanéité est aussi valable pour la variable pollution de l'air par le canal de l'intensité des cultures sur brûlis. Ainsi, nous proposons une analyse multidimensionnelle basée sur la méthode « control function » de **Wooldridge (2015)** pour corriger l'endogénéité de ces variables environnementales. Nos résultats révèlent que la dégradation environnementale à travers les dérèglements climatiques, la déforestation et la pollution a un effet négatif et significatif sur la sécurité alimentaire. L'ampleur et la significativité de l'impact dépend de la nature du risque d'une part et de la dimension de la sécurité alimentaire d'autre part. Parmi les trois catastrophes naturelles considérées, seules les inondations ont un impact négatif sur l'indice global de sécurité alimentaire. Les trois catastrophes naturelles considérées dans l'étude (sècheresse, inondation et cyclone) ont un effet négatif sur la dimension de la diversité ; les inondations et les typhons ont un effet négatif sur la valeur de la production agricole alors qu'aucune de ces catastrophes n'a d'effet sur l'accessibilité. En ce qui concerne les écarts de température et de précipitations, ces deux variables ont un effet négatif sur la sécurité alimentaire et chacune de ses composantes, à l'exception de la dimension diversité qui n'est affectée que par l'écart de température. Nous constatons que la déforestation affecte négativement les dimensions d'accessibilité et de diversité mais n'a aucun effet sur la valeur de production. La pollution atmosphérique explique de manière significative et négative toutes les composantes de la sécurité alimentaire. Ces résultats sont la preuve de la nécessité d'une intervention du gouvernement vietnamien afin de faciliter la résilience des ménages aux conséquences de la dégradation de l'environnement. Une politique de ciblage devrait être axée sur les populations qui sont localisées dans les zones géographiques défavorisées.

Le troisième chapitre nous a permis de mesurer la sensibilité de la consommation des ménages maliens à la variation de la pluviométrie. Le Mali est l'un des pays les plus secs du monde avec une superficie de 1 242 248 km2 dont les deux tiers sont des zones désertiques. En raison de sa caractéristique géographique, il est aussi sévèrement affecté par le changement climatique et, en particulier, par la sécheresse. Selon le scénario A2 du GIEC, le Mali est classé parmi les pays les plus à risque avec un indice de gravité de la sécheresse de -5 (calculé avec l'indice de gravité de Palmer). Pour examiner l'impact des conditions climatiques sur la consommation, nous utilisons les données d'enquêtes modulaires auprès des ménages (EMOP de 2010 à 2018) que nous combinons avec des bases de données climatiques satellitaires. Ces bases de données d'enquêtes sont représentatives au niveau régional et national qui offre un instrument très précieux dans la mesure des conditions socioéconomiques des ménages maliens. Ce chapitre vise à élargir les connaissances sur l'impact du changement climatique sur les économies et les moyens de subsistance dans les pays africains. Nous trouvons les résultats suivants :

- L'élasticité de la consommation des ménages à la variation des précipitations est, en moyenne, égale à 0,38.
- Cependant, l'élasticité est différente pour les différents types de consommation. L'élasticité est plus élevée pour la consommation non alimentaire (1,9) et beaucoup plus faible pour la consommation alimentaire (0,1).
- Nous trouvons aussi que la baisse des précipitations augmente la probabilité qu'un ménage soit classé comme pauvre.
- Enfin, l'élasticité moyenne de la consommation des ménages à la variation des précipitations est déterminée par des groupes spécifiques de ménages de notre échantillon. Nos résultats empiriques indiquent que le niveau de revenu de la famille et sa localisation influencent la manière dont sa consommation est affectée par la variation des précipitations. En effet, la consommation des ménages qui vivent dans la capitale Bamako n'est pas sensible à la variation de la pluviométrie. Par ailleurs, si l'on considère les agriculteurs, c'est-à-dire les ménages dont le revenu principal provient du secteur agricole, l'élasticité est importante (0,57) et statistiquement significative tandis que les non-agriculteurs ne sont pas affectés par la variation des précipitations.

Dans **le quatrième chapitre**, nous analysons les liens entre les chocs climatiques et l'incidence des conflits internes en Afrique tout en discutant le rôle des décideurs politiques pour atténuer ce lien. Cet article complète la littérature sur le changement climatique en se concentrant sur le lien entre chocs climatiques et conflits domestiques. Les conflits domestiques sont souvent désignés comme l'une des conséquences sociales les plus graves du changement climatique, étant donné l'occurrence de plus en plus fréquente de conflits domestiques en raison de la concurrence pour l'accès aux ressources naturelles **(Reuveny 2007; Kniveton et al. 2008; Scheffran et al. 2012)**. Cependant, comme le soulignent **Von Uexkull et al. (2016)**, « *à ce jour, la communauté des chercheurs n'a pas réussi à atteindre un consensus sur la nature et l'importance de la relation entre la variabilité climatique et les conflits armés* ». Le présent article vise à combler cette lacune en examinant si et dans quelle mesure les chocs climatiques affectent l'incidence des conflits nationaux, et comment les décideurs politiques peuvent développer des stratégies de résilience pour briser ce lien vicieux. Nous nous appuyons sur un large panel de 51 pays africains sur la période 1990-2018. À notre connaissance, il s'agit du premier article qui évalue empiriquement les liens entre les chocs climatiques, les conflits intérieurs et la résilience des politiques en Afrique. L'accent mis sur l'Afrique s'explique par le fait qu'elle est l'un des continents les plus durement touchés, non seulement par les chocs climatiques, mais aussi par les conflits internes des dernières décennies. D'une part, le nombre annuel de personnes touchées par les catastrophes naturelles (sécheresse, inondations et cyclones) est plus élevé en Afrique que dans les autres pays en développement, mais avec une intensité variable selon la nature du choc climatique. Les épisodes de sécheresse semblent peser plus lourdement sur le patrimoine des populations, ce qui fait des chocs climatiques, tels qu'ils sont saisis par l'indice d'aridité, un indicateur pertinent tout au long de cette étude. Nous trouvons des résultats clés avec des implications politiques de grande portée. Premièrement, nous trouvons qu'une hausse de l'aridité, augmente la probabilité de conflits intercommunautaires jusqu'à 38 %. Deuxièmement, l'effet est amplifié dans les pays où la répartition des revenus est plus inégale et où la proportion de jeunes hommes est plus importante, et la protection sociale et la mobilisation des recettes fiscales sont considérées comme des facteurs de résilience aux chocs climatiques. Troisièmement, ces résultats sont robustes et mettent en évidence les principaux facteurs de résilience des politiques, notamment l'amélioration constante de la mobilisation des recettes intérieures, le renforcement de la protection sociale et l'augmentation des investissements dans le secteur agricole.

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Chapter 1: IMPACTS OF EXTREME CLIMATE EVENTS ON TECHNICAL EFFICIENCY IN VIETNAMESE RICE FARMING

Abstract

The aim of this study is to examine farm household-level impacts of weather extreme events on Vietnamese rice technical efficiency. Vietnam is considered among the most vulnerable countries to climate change, and the Vietnamese economy is highly dependent on rice production that is strongly affected by climate change. A stochastic frontier analysis is applied with census panel data and weather data from 2010 to 2014 to estimate these impacts while controlling for both adaptation strategy and household characteristics. We find that weather shocks measured by the occurrence of floods, typhoons and droughts negatively affect technical efficiency. Also, additional days with a temperature above 31°C dampen technical efficiency and the negative effect is increasing with temperature. Also, this study combines estimated marginal effects of extreme temperature on technical efficiency with future climate scenarios (RCP 4.5 and 8.5) to project the potential impact of hot temperatures till the end of century on rice technical efficiency.

Keywords*:* Weather Shocks, Technical Efficiency, Rice Farming, Vietnam

JEL Classification: D24, O13, Q12, Q54[8]

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I. Introduction

Given the increasing awareness about climate change and the growing concern about its downside consequences, the question of a quantitative assessment of the economic consequences of climate change is of great importance. This issue is particularly topical in countries heavily exposed to the risks of weather variability and climate change like Vietnam, which is among the countries most vulnerable to climate change according to the Climate Change Knowledge Portal (CCKP) of the World Bank[9]. Since the country lies in the tropical cyclone belt, it is heavily exposed to climatic-related risks like extreme temperature, droughts, floods, tropical storms (typhoons), rising sea level and saltwater intrusion (**Bank, 2010**). This vulnerability is also increased by the topography of the country. Vietnam is a long narrow country consisting of an extensive coastline of more than 3,000 km long subjected to accelerated erosion and rising sea level. It contains two major river deltas (the Mekong delta in the South and the Red River delta in the North) highly exposed to floods and rising sea level (**Dasgupta et al., 2007**), which concentrate a high proportion of the country's population and economic assets such as rice farming, and mountainous areas on its eastern and northeastern borders.

In Vietnam, rice farming has played a central role in economic development since 1980 and the beginning of market and land reforms[10]. Paddy rice is by far the main crop produced in Vietnam and employs two thirds of total rural labor force. However, it is also one of the most climate-change affected sectors due to its direct exposure to, and dependence on, weather and other natural conditions (**Bank, 2010**). The ongoing climate change and its related effects have and will have significant impacts on rice production and farmer livelihoods. From census data (the Vietnam Household Living Standard Survey (VHLSS)) between 2010 and 2014, and weather data on temperature and precipitation, this study examines farm household-level impacts of weather

[9] Source: the CCKP website.

[10] These last years, while the contribution of Vietnamese farming to national GDP has become less important (from about 40% in 1990 to about 16% in 2017), rural areas still generate employment and income for a significant part of the population (**Bank, 2010**). In 2016, 66% of the population live in rural areas where 43% of the country's active workforce is employed.

shocks, defined as extreme temperatures and three natural hazards (floods, droughts and typhoons) on agricultural productivity in the Vietnamese rice farming[11].

This study contributes to the growing literature that uses farm-level panel data (here the VHLSS) coupled with finely-scaled climate data to estimate the weather change impacts, here on Vietnamese rice farming (**Yu et al., 2010; Trinh, 2017**). The use of a panel structure allows to control for time-invariant omitted variables correlated with weather extreme events that may confound the climatic effect in pure cross-sectional studies (**Blanc and Schlenker, 2017**). Also, we study two weather effects on rice farming from a Stochastic Frontier Analysis (SFA). We first estimate the effect of weather trend, defined as the mean daily temperature and the mean daily precipitation, on rice farming output. Then, we assess the effect of weather extreme events, measured by the occurrence of floods, typhoons, droughts and extreme temperatures, on rice farming productivity defined as technical efficiency[12]. Also, this study combines estimated marginal effects of extreme temperature on technical efficiency with future climate scenarios (RCP 4.5 and 8.5) to project the potential impact of hot temperatures till the end of century on rice technical efficiency. As a result, we find that weather shocks measured by the occurrence of floods, typhoons and droughts have a strong and negative effect on technical efficiency. Also, daily temperatures above 31°C dampen technical efficiency in the dry season, an effect which is increasing with temperature. For instance, a one day increase in the bin [33°C34°C] lowers technical efficiency between 6.84 and 8.05 percentage points. Simulation results show dramatic drops in technical efficiency after 2040. In the case of the RCP8.5 scenario, technical efficiency collapses from 40 percent points, while it stabilizes in the RCP4.5 scenario around 10 percent points below the reference period[13].

The remaining of the chapter is organized as follows. Section 2 presents the literature related to the climate-agriculture nexus. Section 3 details the rice sector and climate conditions in Vietnam.

[11] This study investigates weather impacts rather than climate impacts (**Auffhammer et al., 2013**). More precisely, the former is defined as the conditions of the atmosphere over a short time horizon while the latter is the variability of the conditions of the atmosphere over a relatively long period. Thus, the interpretation of the coefficients associated with climatic variables have to be interpreted as weather shocks in the short run and climate change in the long run.

[12] To our knowledge, only **Key and Sneeringer (2014)** use a SFA methodology to study heat stress on technical efficiency on dairy production in United States.

[13] We only used one CORDEX-SEA model for climate projections in this version of the chapter, which limits the level of confidence we can have for these projections. We will use all the existing simulations as soon as they are available, so that we can discuss the uncertainty issue about future climates.

Sections 4, 5 and 6 present respectively the empirical methodology, data and descriptive statistics, and econometric results. Section 7 gives the results from simulations and Section 8 concludes.

II. Literature reviews

This section reviews the theoretical and empirical studies that estimate the economic impact of climate change on agriculture. The literature can be divided between the longrun climate effect approach using the Ricardian hedonic model with cross-sectional data (see **Mendelsohn and Massetti (2017)** for a discussion of main advantages and weaknesses of this approach), and the weather-shock approach using Ricardian hedonic model with panel data (see **Blanc and Schlenker (2017)** for a discussion of main advantages and weaknesses of this approach).

The first approach consists in examining how the long-run climate (the distribution of weather over 30 years) affects the net revenue or land value of farms across space using the Ricardian method (also called the hedonic approach). The principle of this method is to estimate the impact of climate on agricultural productivity by regressing net revenue or farmland value (use as a proxy for the expected present value of future net revenue) on climate in different spatial areas. The model assumes that competitive farmers are profit-maximizing agents. Farmers choose an optimal combination of inputs and output to maximize net agricultural income, subject to the exogenous variable such as climatic conditions that are beyond the farmer's control. Put differently, if climate is different, the farmer has to adapt his production and choose a different output (crop switching) and different inputs (new pesticides for instance). This is probably the main advantage of the Ricardian approach that allows to capture long-run adaptation to climate. So the goal is to regress net revenue on different arrays of climates to estimate the impact of climate. According to **Mendelsohn and Massetti (2017)**, this approach has been used in 41 studies over 46 countries. The first attempt is **Mendelsohn et al. (1994)** who estimate the impact of temperatures on land prices in 3,000 counties in the United States. They found from simulation based to the econometrically estimated impacts of temperature that global warming may have economic benefits for the U.S. agriculture.

This initial approach has been then improved in different ways to take into account many empirical issues. One of them concerns the measure of climate. Most studies used seasonal climate variables but the type of variable changes from one study to another. Some studies include mean seasonal temperature and rainfall (**Mendelsohn et al., 1994; Schlenker et al., 2005**) while other use the degree days over the growing season that are the sum of temperatures above a floor (**Schlenker et al., 2006; Deschênes and Greenstone, 2007**)[14].

Another important empirical issue is related to the cross-sectional nature of the method. In fact, many existing studies estimate a Ricardian model using data for a single year or two. However, a main disadvantage of cross-sectional data is potential omitted variables that might bias the results since average climate over a long period is not random across space. For instance, **Dell et al. (2009)** find that poorer countries tend to be hotter. But this relationship can be considered as spurious correlation if there are some omitted variables correlated with climate that can explain income (institutions for instance). The model has to control for these potential omitted variables. Two solutions have been developed in the literature to avoid omitted variable bias. The first solution is to account for all factors that are both correlated with climate and the impacted farmland values. One first example is irrigation that is correlated with temperature. For instance, **Schlenker et al. (2005)** show that access to subsidized irrigation water is both capitalized into farmland values and correlated with hotter temperatures. This means that the impacts of irrigation has to be control while estimating the impact of temperature on land value.

If not, the regression estimates not only the direct effect of temperature, but also the beneficial effect of access to irrigation water (which is positively correlated with higher temperatures). To resolve this issue, **Schlenker et al. (2005)** separate irrigated and rainfed farms and estimate models for each sample. Another solution is the one implemented by **Kurukulasuriya et al. (2011)**. The authors first estimate the probability of making the irrigation choice and then estimate the conditional Ricardian model given the choice of making irrigation. However, this solution can never completely eliminate the possibility of omitted variables. In fact, there might always be an additional control variable (e.g. soil quality) that is correlated with climate (e.g. temperature) but unfortunately not correlated with the other control variables (e.g. irrigation) included in the specification.

The second solution may address this concern and consists in using panel data into the Ricardian model (i.e., estimate long-run climate impact) (**Deschênes and Greenstone, 2007**). Panel data allow for the use of fixed effects, which control for any time-invariant confounding variation. However, in a model with fixed effects, it is impossible to estimate the effect of the long-run climate averages because climate has no temporal variation. However, while **Deschênes and Greenstone (2007)** show that the Ricardian results are not robust when estimated as a series of repeated cross

[14] See **Massetti et al. (2016)** for a discussion of these two approaches and the pitfalls of the degree days approach with the Ricardian method. Note that this issue concerns also the weather approach discussed infra.

sections, **Schlenker et al. (2006)**; **Massetti and Mendelsohn (2011**) provide evidences that the Ricardian model is stable when estimated with panel methods. **Massetti and Mendelsohn (2011)** for instance provide two robust methods to estimate Ricardian functions with panel data: (1) a two-stage model based on **Hsiao (2014)** where agricultural outcome is regressed on time varying variables using the covariance method with fixed effects and then, in the second stage, the time-mean residuals from stage 1 are regressed on non-varying time variables such as climate variables (also used by **Trinh (2017)**); (2) a single stage "pooled" panel model. While the Hsiao model is less vulnerable to the omitted variable bias than the pooled panel model, it is less efficient than the pooled panel model estimated in one step. The main result of **Massetti and Mendelsohn (2011)** is that the overall effect of climate change is likely to be beneficial to U.S. farms over the next century.

The second main approach is the weather-shock approach using Ricardian hedonic model with panel data (**Schlenker and Roberts, 2009; Schlenker et al., 2013; Deryugina and Hsiang, 2017**). The starting point of this approach is to take advantage of fine-scaled weather data in both time and space to detect for instance nonlinearity through the large degree of freedoms that give panel data. For instance, **Schlenker and Roberts (2009)** find a non-linear relationship between temperature and U.S. crop production. Beyond the respective thresholds of 29°, 30° and 32°, the temperature generates major damage on wheat, soybean and cotton yields respectively. Also, this approach allows to avoid the omitted variable bias by controlling for fixed effects. Another advantage of this approach is to account for short-term adaptation. Although panel analysis allows for spatial and temporal heterogeneity, it is not free of limits (**Blanc and Schlenker, 2017**). One of them is the consideration of spatial autocorrelation in crop yields and climatic variables which is necessary in order to limit the estimation bias. **Chen et al. (2016)** take this criticism into account in their analysis of the link between climate change and agricultural sector in China. They find that Chinese agricultural productivity is affected by the trend in climate and the existence of a non-linear and U-inversed shape between crop yields and climate variability.

Our study uses the weather-shock approach with panel data. However, instead of using a Ricardian hedonic model, we follow **Key and Sneeringer (2014)** and estimate the relationship between weather and rice farming productivity defined as technical efficiency using a stochastic production frontier model.

III. Rice production and climate condition in Vietnam

3.1. Rice production in Vietnam

Since the beginning of the Vietnam's Đổi Mới (renovation) process launched in 1986, Vietnam has witnessed unprecedented transitions from planned and collectivized agriculture to market and household-based farming.

The market reform periods of Vietnamese rice farming began with the output contracts period (1981–87) which launched the move to de-collectivize agriculture (**Kompas et al., 2002, 2012**). It was the first attempt towards private property rights. Farmers were allowed to organize production activities privately but the most part of rice production had still to be sold in state markets at low state prices. However, private domestic markets emerged for some portion of output sold (approximately 20%). This period was thus characterized by a "dual price" system (a low state price and a competitive market price) with strict state controls.

From 1988, the period of trade and land liberalization began with the aim to establish effective private property rights over both land (initially 10–15 year leases) and capital equipment while restrictions on farm size and prohibitions against the removal of land from rice production were maintained. In 1990 the central government abolished the dual price system and rice was authorized to be sold on competitive domestic markets. However, while those reforms were intended to incite farmers to invest, in practice, farmers were reluctant to undertake long-term investments because the land-use rights were not seen as secure as they were not tradable. Consequently, the government passed a new Land Law in 1993. This law extended the lease period to twenty years for land used to produce rice (increased to 30 years in 1998 revisions) and allowed farmers to transfer, trade, rent, mortgage and inherit their land-use rights (**Scott, 2008**). Also, from 1993, farmers could now sell rice freely in international markets.

From the mi-1990s, land and market reforms implemented from 1981 allowed the decentralization of production decisions at the farmer's level and guaranteed that all farm income (after tax) was retained by the farmer. Individual efforts were rewarded in order to push farmers to invest and produce more. More recently, beyond these market and land reforms, government implemented a rice policy helping to increase yield through the development of rice varieties, large investment in irrigation (roughly 85% of rice area are applied with active irrigation drainage system), the support in case of emergency cases, the ease of credit access, input support (reducing valued-added tax for key inputs as fertilizers), etc.

As a consequence, Vietnam has become the fifth rice producer in the world with a total production of 42.76 millions of tons per year and a yield of 5.55 tons per hectare in 2017, a lot more than annual 12.4 millions of tons produced and the yield of 2.19 tons per hectare in 1980, and a leading world exporter (about 7 millions tons)[15].

Regarding the geographical distribution of rice production, rice area covers roughly 7,8 millions hectares (23% of total land area and 82% of arable land) owned by 9 millions of households (accounting for more than 70% of rural households) so that the average farm size is below one hectare. Rice area is located mostly in the Mekong River Delta (about 55% of total rice production (23 millions of tons produced in 2017) and 90% of rice exports) followed by the Red River Delta in the northeast (about 15% of total rice production) and the north-central coast[16].

Despite the increase of the yield in rice production these last decades, some important pitfalls remain. For instance, rural inputs and land markets or access to agricultural extension services and farm credit remain still far less developed in some provinces, trapping farmers into poverty **(Kompas et al., 2012)**. Also, the expansion of rice production for the last thirty years was reached by focusing on quantity increases. The abuse of chemical inputs **(Berg and Tam, 2012)** produce important environmental damages in terms of soil fertility or depletion of fishery resources for instance. Besides, past international successes of Vietnamese rice production was based mainly on high production of low quality rice sold at very low price on international markets, a strategy that the recent increase in input prices (fertilizer, fuel, and labor) could well jeopardize (**Demont and Rutsaert, 2017**). Vietnamese rice farming now has to deal with significant issues both at national and international levels. At the national level, Vietnamese farming has to deal both with poverty alleviation of rice households (by encouraging crop diversification on rice), food security (feeding both Vietnamese with good quality rice products) and environmental preservation (by promotion organic rice farming, soil preservation, etc.) (**Tran and Nguyen, 2015**). These national challenges have also implications at the international level. The competitiveness of Vietnamese farming depends on the performance of farmers and companies to deliver rice products with reliability regarding the quality (i.e. switching to high value rice to follow change in world demand), safety and sustainability of the products supplied (**Demont and Rutsaert, 2017**). Beyond these national

[15] Data come from FAOSTAT.

[16] Data come from GSO, the general statistics office of Vietnam.

and international issues, the ongoing climate change is also an imperious issue that Vietnamese have to face in order to preserve their rice production and the livelihood of millions of farmers.

3.2. Climate condition

3.2.1. Seasonal variability of temperature and precipitation

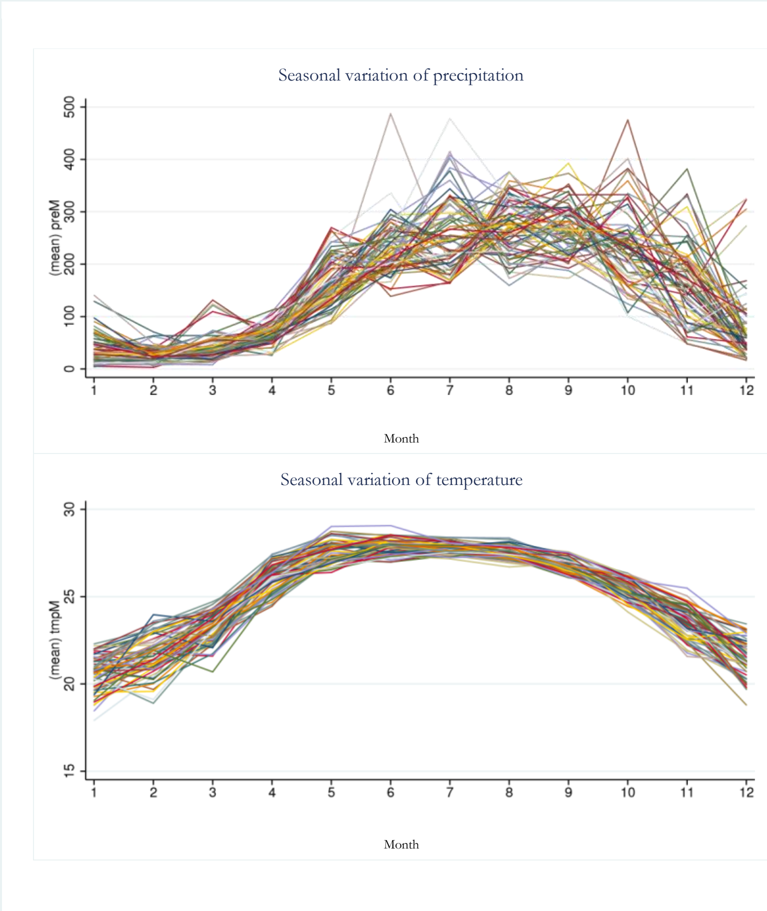
Due to the diversity in topography, it is likely that the impacts of climate change will be different depending both on the place and the months of the year. The curves in Figure 1.1 transcribe the seasonal variations of the temperatures and precipitations according to the months of the year. High temperatures are observed from May to October (the average is 27.12°C) and lower temperatures from November to April (the average temperature is 22.73°C). In addition, a greater instability of temperatures appears in the middle of the year (an average amplitude of 2°C). Similarly precipitations are higher during the period from May to October (an average rainfall of 238.20 mm) and relatively low from November to April (an average rainfall of 68.93 mm). These observations allow us to distinguish two major climatic seasons in Vietnam: a dry season (November to April) and a wet season (May to October).

As in **Hsiang (2010)** and **Trinh (2017)**, we use these seasonal temperature and precipitation variables to measure the impact of seasonal variability to test the dependence of technical efficiency on the periodic occurrence of weather shocks. However, we are aware that these time intervals can vary weakly from one region to another throughout the country.

3.2.2. Temperature and precipitation trends by Vietnamese regions (1950-2015)

Figure 1.2 and 1.3 represent the average trends in temperatures and precipitations over the period 1950-2015 at sub-national levels. There is a strong spatial heterogeneity in the variability of climatic conditions. The Mekong region in the south has experienced a more pronounced global warming which is manifested by a mean annual temperature trend increase of 0.02°C corresponding to an increase of 1.3°C over the period 1950-2015. However, the temperature in the Red Delta region in the north-east remains pretty stable.

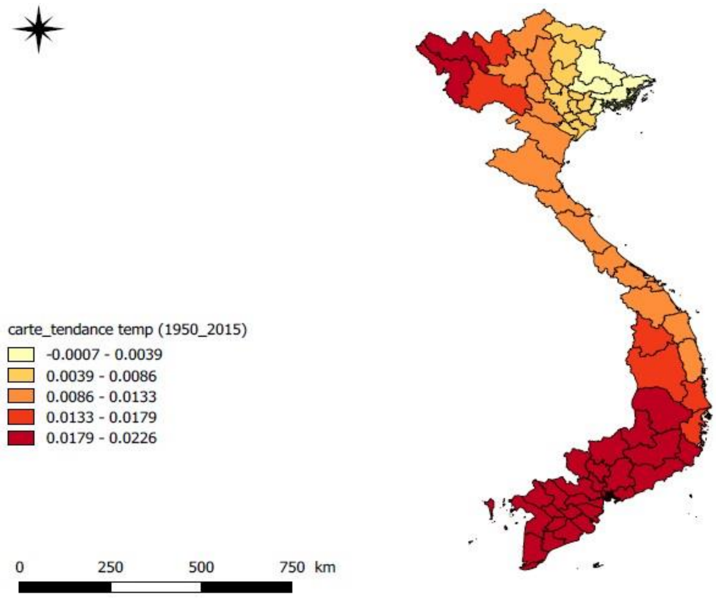
Figure 1. 1: Seasonal variation of precipitation and temperature (1950-2015)



Source: authors from CHIRPS and MODIS data

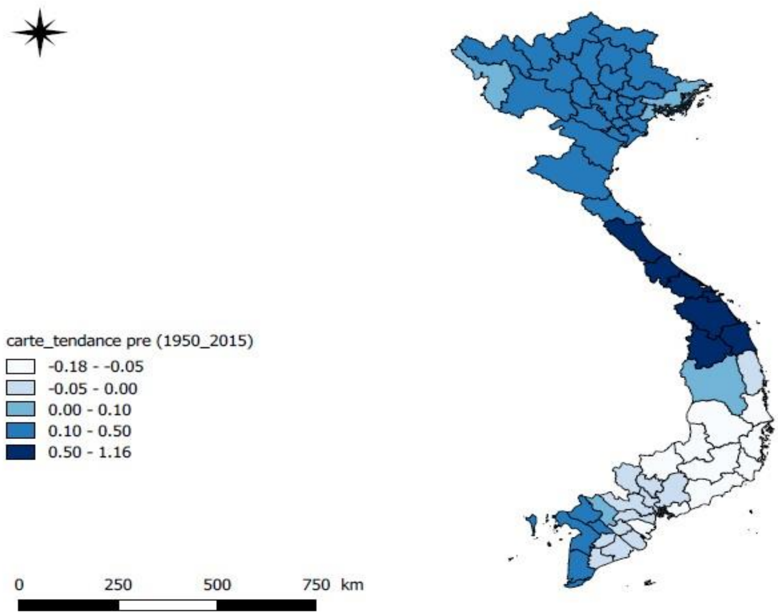
On the other hand, there is an average decrease in precipitations in the south, unlike in the north and center where there has been a relative increase in monthly precipitations. In addition, Figures A1.1 and A1.2 in Appendix respectively show the evolution of the level of temperatures and precipitations according to the month of the year. In these figures, we are able to perceive the occurrence of short-term climatic shocks by month and by year.

Figure 1. 2: Average annual temperature trend increase over the period 1950-2015



Source: authors from MODIS data

Figure 1. 3: Average annual rainfall trend increase over the period 1950-2015



Source: authors from CHIRPS data

IV. Empirical methodology

The link between agricultural productivity in rice farming and weather (trends and shocks) is analyzed through a two-step approach. Agricultural productivity is first defined in terms of technical efficiency calculated from a stochastic production frontier model in which weather trend is also used to explain agricultural production. In the second step, the estimated technical efficiency is explained by weather extreme events. Before presenting the econometric model, we present the conceptual framework on which the econometric analysis relies.

4.1. Conceptual framework

4.1.1. Definition of efficiency

Farrell (1957) defines agricultural productivity as productive efficiency, which is the ability of producers to efficiently use the available resources, called inputs hereafter, in order to produce maximum output at the minimum cost. It differs from effectiveness that refers to the degree of achievement of a desired goal. In addition, productive efficiency is the combination of allocative efficiency (AE hereafter) and technical efficiency (TE hereafter).

AE is based on the optimal combination of inputs given their market prices, production technology and the market prices of the output. It necessarily leads to the maximization of profit or even the minimization of production costs. TE refers to the performance of the producer to avoid waste of inputs to produce. This waste can be avoided in two ways: either by reducing the quantity of inputs for the same level of production (the input-oriented measure of TE), or by increasing the production for the same given level of inputs (the output-oriented measure of TE). While AE is estimated from a profit function or a cost function, TE is estimated from a production function. In this study, we work on TE because we do not have price information on inputs and output.

4.1.2. Estimation of technical efficiency

Technical efficiency is estimated under three auxiliary hypotheses regarding the choice of the estimation method, the choice of the production function and the choice of the functional form of TE over time.

Firstly, the estimation of TE relies on either the non-parametric method or the parametric method. The principle of the non-parametric method also called data envelopment analysis (DEA) is to impose no restriction on the distribution of inefficiency, no behavioral assumptions (goal of profit maximization) unlike the parametric method which is based on the methods and techniques of econometric estimation. However, DEA imposes to consider that all shocks to the value of output have to be considered as technical inefficiency whereas some factors (ex. climatic conditions) are not related to producer behavior and can directly affect the production frontier. This explains why parametric method is often preferred in the literature, by using stochastic production functions called stochastic frontier analysis (SFA)(**Aigner et al., 1977; Meeusen and van Den Broeck, 1977)**. This method allows the error term to have two components: a negative component that measures inefficiency and an idiosyncratic error that represents all other idiosyncratic shocks. However, imposing on the inefficiency component to be negative requires strong assumptions about its distribution law. The most used distributions are the half-sided normal law, the exponential law and the normal truncated law (**Stevenson, 1980**). The use of the half-sided normal law and the exponential law assumes that the majority of the observation units are efficient relative to the truncated normal law[17].

Secondly, the form of the production function has to be chosen in a SFA technique. In microeconomics, the production function expresses the relationship between outputs and inputs. Its functional representation has to respect certain properties[18], taking into account the presence or not of economies scale and the nature of the substitutability between inputs. The production function is often modelled using a Cobb-Douglas form (**Cobb and Douglas, 1928**) or a transcendental logarithmic ("translog") specification (**Christensen et al., 1971**) in the literature. The Cobb-Douglas form is often preferred because it gives convex and smoothed isoquantes. However, it is based on strong assumptions such as the constancy of the elasticities and the hypothesis that all the elasticities of substitutions are supposed to be equal to -1. More flexible forms of production such as the translog form have emerged by not imposing restrictions on the production technology, especially with regard to the substitution between inputs. In our analysis, we estimate the production function by considering the translog form[19].

Thirdly, the estimation of TE in panel model implies to model the functional form of TE over time. The first models are those of **Pitt and Lee (1981)** and **Schmidt and Sickles (1984)** where inefficiency is supposed not to vary over time. This type of model is comparable to a fixed effect

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[17] The mode of the semi-normal law and the exponential law is equal to 0.

[18] The production frontier requires monotonicity (first derivatives, i.e., elasticities between 0 and 1 with respect to all inputs) and concavity (negative second derivatives). These assumptions should be checked *a posteriori* by using the estimated parameters for each data point.

[19] And the Wald test applied to interactive terms confirm the using of this model.

in panel model. However, these models are based on very strong assumptions. On the one hand, the model is valid under the assumption that the inefficiency is uncorrelated with the inputs used to estimate the production function. On the other hand, inefficiency has not to vary over time. Thus, other models emerged to allow temporal variation of TE. However, the problem that has arisen concerns the functional form of the temporal variation of inefficiency. **Cornwell et al. (1990)** proposes the CSS model in which inefficiency varies with time according to a quadratic form. While the temporal variation of TE is not necessarily quadratic, this hypothesis is very restrictive. **Battese and Coelli (1992)** and **Kumbhakar et al. (2000)** develop a model in which the temporal variation of the inefficiency term takes an exponential form. **Lee and Schmidt (1993)** provide more flexibility in the form of temporal variation in inefficiency. Their time-varying fixed-effects model does not impose restrictions on the functional form of inefficiency. In other words, inefficiency is supposed to vary over time without imposing a particular functional form on this variation. This model is particularly advantageous for studies with a fairly large number of observation units and a relatively short time dimension. This advantage also makes possible to circumvent the concern of incident parameters (**Chamberlain, 1979**) potentially present with panel models[20].

In this study, we implement the stochastic frontier analysis by using both the CobbDouglas and the translog production functions following the literature as well as the model developed by **Lee and Schmidt (1993)** given that the time dimension of our base is quite short (three years), while the number of farms is large (2,592 households).

4.2. Econometric strategy

We now apply the conceptual framework explained above to an econometric model in agricultural production to firstly estimate TE and secondly to estimate the effects of weather shocks on TE.

[20] Other models such as **Greene (2005)** make it possible to dissociate the individual fixed or random effect from TE. However, the large number of parameters to be estimated in these models is still subject to the incidental parameter concern.

4.2.1. First step: Estimation of Technical Efficiency

Consider a farmer i at time t who uses x inputs (defined later) to produce rice defined by y. The production function can be written as follows:

$$y_{i,t} = f(x_{i,t}), \tag{1}$$

where f is a function that defines the production technology. The rational producer aims at maximizing his total production of rice while minimizing the total use of his inputs. On the frontier, the farmer produces the maximum output for a given set of inputs or uses the minimum set of inputs to produce a given level of output. Thus, the definition of the production frontier and the estimation of technical efficiency depend on the type of orientation: input-oriented or output-oriented. We use the output-oriented measure of technical efficiency (more output with the same set of inputs) that gives the technical efficiency of a farmer i as follows:

$$TE_{i,t}(x,y) = [max\phi : \phi y \leq f(x_{i,t})]^{-1}, \tag{2}$$

where ϕ is the maximum output expansion with the set of inputs $x_{i,t}$.

The output-oriented measure of technical efficiency defined by Eq. 2 is estimated under three auxiliary hypotheses.

Firstly, Eq.1 is applied to an econometric model as follows:

$$y_{i,t} = f(x_{i,t},\beta).e^{-U_{i,t}} \tag{3}$$

where y_i is a scalar of output, x_i is a vector of inputs used by farmers i=1,…,N; $f(x_i;\beta)$ is the production frontier and β is a vector of technology parameters to be estimated. U_i are non-negative unobservables random variables associated with technical inefficiency that follow an arbitrary half-sided distribution law.

Secondly, we use a stochastic frontier analysis in which we assume that the difference between the observed production and maximum production is not entirely attributed to TE and can also be explained by idiosyncratic shocks such as weather. Eq.3 becomes:

$$y_{i,t} = f(x_{i,t},\beta).e^{-U_{i,t}}.e^{V_{i,t}}, \tag{4}$$

where $V_{i,t}$ represent random shocks which are assumed to be independent and identically distributed random errors with a normal distribution of zero mean and unknown variance. Under that hypothesis, a farmer beneath the frontier is not totally inefficient because inefficiencies can also be the result of random shocks (such as climatic shocks). Since $TE_{i,t}$ is an output-oriented measure of technical efficiency, a measure of $TE_{i,t}$ is:

$$TE_{i,t} = \frac{y_{i,t}^{obs}}{y_{i,t}^{max}} = \frac{f(x_{i,t},\beta).e^{-U_{i,t}}.e^{V_{i,t}}}{f(x_{i,t},\beta).e^{V_{i,t}}} \tag{5}$$

Thirdly, the production function is modeled by a translog specification. The general form of the translog is as follows:

$$ln(y_{i,t}) = \beta_0 + \sum_{j=1}^{4} \beta_j ln(X_{ij,t}) + 0.5 \sum_{j=1}^{4}\sum_{k=1}^{4} \beta_{jk} ln(X_{ij,t}) ln(X_{ik,t}) - U_{i,t} + V_{i,t}, \tag{6}$$

where $i = 1,N$ are the farmer unit observations; $j,k = 1,...,4$ are the four applied inputs explained later; $ln(y_{i,t})$ is the logarithm of the production of rice of farmer i at time t; $ln(X_{ij})$ is the logarithm of the jth input applied of the ith individual; and β_j,β_{jk} are parameters to be estimated.

The final empirical model estimated in the translog case is twofold. It does first not take into account the weather variables as follows:

$$ln(Rice_{i,t}) = \beta_0 + \beta_1 ln(famlabor_{i,t}) + \beta_2 ln(hirlabor_{i,t}) + \beta_3 ln(capital_{i,t})$$

$$+\beta_4 ln(runningcosts_{i,t}) + \beta_5 ln(famlabor_{i,t})^2 \quad (7) \; + ... + \beta_9 ln(famlabor_{i,t}).ln(hirlabor_{i,t}) + ... + a_t - U_{i,t} + V_{i,t},$$

Rice is the output defined as the total rice production over the past 12 months. *farmlabor* and *hirlabor* define respectively family labor (in hours) and hired labor (in wages). *capital* is the total value of investment in machinery and *runningcosts* is the value of running costs (e.g. fertilizers and irrigation). Both output and inputs are normalized by farm land area devoted to rice farming. More information can be found in Table A1.1 in the Appendix. t refers to the year of the last three surveys used in this study (2010-20122014)[21]. Each household i has been surveyed two or three times. a_t measures

[21] The year 2016 will be added in a future version.

temporal fixed effects which represent the unobserved characteristics common to each region and which vary over time and which affect agricultural yields (e.g. inflation, macroeconomic policy, price shock of commodities ...). In addition, this variable takes into account the possibility of neutral technical progress in the sense of Hicks.
Then, the empirical model integrates both irrigation and the weather variables as follows:

$$ln(Rice_{i,t}) = \beta_0 + \beta_1 ln(famlabor_{i,t}) + ... + \beta_{15} irrig_{i,t} + \beta_{16} clim_{m,t} + a_t - U_{i,t} + V_{i,t}, \quad (8)$$

where *irrig* is a dummy variable (1 = irrigation) and *clim* represents both the average daily temperature over the production period and the total precipitation over the production period in the municipality *m*[22].

Fourthly, the functional form of TE over time is defined following **Lee and Schmidt (1993)** as follow:

$$U_{i,t} = \delta_t * \gamma_i \geqslant 0, \quad (9)$$

where δ_t encompasses the parameters that capture the variability of technical inefficiency. In this model both the components of δ_t and γ_i are deterministic. Although **Lee and Schmidt (1993)** estimated this model without any distributional assumptions on γ_i. This specification makes the temporal variability of inefficiency quite flexible. γ_i is the measure of the technical efficiency of producer *i*.
Finally, efficiency scores are computed from the estimation of $U_{i,t}$ in Eqs. 8 and 9 as follows:

$$TE_{i,t} = e^{-U_{i,t}} \quad (10)$$

[22] The production period is defined as the twelve last months before the household is surveyed. Climatic variables are available at municipality level so that all household living in the same municipality share the same climatic variables.

The maximum likelihood estimator is used to estimate the technical efficiency under a half-sided normal law.

4.2.2. The second step: the effects of weather shocks on TE

Once TE is estimated from the first stage, it is used as dependent variable in the second stage as follows:

$$TE_{i,t} = a_0 + a_1.Z_{i,t} + a_2.W_{i,t} + \epsilon_{i,t}, \tag{11}$$

Equation 11 is estimated with the fixed effects model. W includes control variables (household size and gender, education level and age of the household head) and Z represents weather shocks[23]. Weather shocks are considered as short-term extreme climatic events measured by the occurrence of extreme temperatures and natural disasters (flood, typhoon and drought).

We define a weather shock in terms of temperature in two ways. Firstly, we follow **Schlenker and Roberts (2009)** who use data on daily precipitations and temperatures to calculate the Growing Degree Days (GDD) index. This measure consists in calculating the optimal daily temperature and the optimal daily precipitation required for the growth of each crop. Thus, climate variability is captured by a deviation of temperature or precipitation from these optimal thresholds[24]. GDD can be computed as follows:

$$GDD_{base,opt} = \sum_{i=1}^{N} DD_i \quad , \tag{12}$$

$$DD_i = \begin{cases} 0 & \text{if } T_i < T_{low} \text{ or } T_i > T_{up} \\ T_i - Tbase & \text{if } T_{low} \leq T_i \leq T_{up} \end{cases} \tag{13}$$

Where i represents day, and T_i is the average of the minimal (T_{min}) and maximal (T_{max}) temperature during this time-span. T_{low} and T_{up} are respectively the lower and upper thresholds of a given temperature range. DD represents the degree day of each day during the growing stage. N is the

[23] More information in Table 1. A1 in Appendix.

[24] There also exist several works **(McMaster and Wilhelm (1997), Lobell et al. (2011) and Butler and Huybers (2013)**) which propose a different way to compute GDD

number of days within a growing season. However, this way to compute GDD has some limitations. Indeed, through these equations, we note that below the minimum threshold or beyond the maximum threshold, the temperature makes no contribution to the development of the plant. Thus, we do not capture the negative effect of extreme temperatures on the plant's development process. To tackle this issue, our strategy is close to that of **Schlenker and Roberts (2009)** and **Chen et al. (2016)**. Here, the GDD is calculated in terms of days where the temperature is in an interval considered optimal for the growth of the plant. The days when the temperature is outside this range are considered harmful to the plant. It will be called Killing Growing Degree Days (KGDD). We follow **Sánchez et al. (2014)** to define the optimal temperature thresholds for rice in Vietnam. The authors make a meta-analysis on the different temperature thresholds (T_{min}, T_{opt} and T_{max}) that rice needs according to the phase of the cycle of its growth. Thus, we have identified the temperature levels of 10°C and 30°C respectively as the minimum and maximum temperature levels necessary for the development of rice culture throughout its growing cycle. In our climatic base, the average of the numbers of days where temperature is below 10°C during the growing season for rice is equal to one day. Its range of temperature is not considered. Then, two measures of weather shocks are considered: KGDD heat dry and KGDD heat wet which are respectively the number of days when the temperature is above 30°C during either dry season or wet season.

In our regression, we decompose the KGDD by 1°C bin interval ([30-31[, [31-32[, [3233[, [33-34[, [34-35[and [35-plus[) for both dry and wet seasons[25]. Then, for each interval, we compute the following variable:

$$IT_{[a-b[} = \sum_{i=1}^{N} DD_i \quad , \tag{14}$$

$$DD_i = \begin{cases} 0 & \text{if } T_i < a \text{ or } T_i \geq b \\ 1 & \text{if } a \leq T_i < b \end{cases} \tag{15}$$

Secondly, we define other weather shocks by using the occurrence of floods, typhoons and droughts over the production period.

[25] Variables $[34-35]_{Dry}$ and $[35-plus[_{Dry}$ do not exist because there are no days where average daily temperature is above 34°C during the dry season.

4.3. Data and descriptive statistics

The data used in this study are derived from both socio-economic and climate data.

4.3.1. Socio-economic data

The socio-economic data come from the Vietnam Household Living Standard Survey (VHLSS) provided by the GSO (General Statistics Office of Vietnam). The main objective of VHLSS is to collect data at the household and commune level to define and evaluate national policies or programs that include assessing the state of poverty and inequality of individuals. The survey questionnaire is administered at two levels.

On the one hand, a questionnaire is administered at the household level. It collects data on agricultural production (outputs and inputs), income (farming and off-farming) and socio-demographic characteristics of individuals within a household (gender, age, level of education ...). In this study, variables in monetary values (i.e. output and some inputs) are calculated based on the 2010 consumer price index. Table 1.1 gives descriptive statistics of variables used in this study. Inputs and output variables are normalized by the area allocated to rice production. The average rice production is 2,420 VND per squared meter with a very strong heterogeneity (minimum = 190 VND/m2 – households called "small producer" ; maximum = 25,540 VND/m2 – households called "large producers"). Regarding socio-demographic variables, we note from Table 1 that women are very poorly represented in rice farming (only 16% of all household heads are women). Also, only 1% of the household heads reached the university level, compared to 27% at no level, 26% at the primary level and 46% at the secondary level. Also the average age of the household head is 48 years with a high degree of dispersion (a standard deviation of about 13 years).

The average household size is about four persons with a standard deviation of 1.54.

Table 1. 1: Descriptive statistics for variables used for econometric analysis

Variables	Obs	Mean	Std. Dev.	Min	Max
Rice yield (1,000 VND/m^2)	5,894	2.42	.75	.19	25.54
Capital (1,000 VND/m^2)	5,894	.22	.16	0	2.25
Hired labor (1,000 VND/m^2)	5,894	.09	.14	0	1.26
Family labor (number of hours/m^2)	5,894	.32	.35	0	4.92
Running costs (1,000 VND/m^2)	5,894	.75	.32	0	10.02
Irrigation (0 = rain-fed farms, 1 = irrigated farms)	5,894	0.41	0.49	0	1
Temperature (°C)	5,894	24.82	1.92	19.13	28.83
Precipitation (mm)	5,894	8.35	2.40	1.23	20.77
IT_30_31 (number of days)	5,894	20.69	13.45	0	61
IT_31_32 (number of days)	5,894	9.57	8.36	0	37
IT_32_33 (number of days)	5,894	3.92	5.06	0	24
IT_33_34 (number of days)	5,894	1.26	2.58	0	23
IT_34_35 (number of days)	5,894	.19	.87	0	7
IT_35_plus (number of days)	5,894	.01	.08	0	3
Flood (0= non occurred, 1= occurred)	5,894	0.16	0.37	0	1
Typhoon (0= non occurred, 1= occurred)	5,894	0.14	0.34	0	1
Drought (0= non occurred, 1= occurred)	5,894	0.10	0.30	0	1
Age (years)	5,894	48	13	16	99
Gender (2=female)	5,894	1.15	.35	1	2
Education (1= no education to 9= univ. level)	5,461	1.49	1.23	0	9
Household size (number of persons)	5,894	4.21	1.54	1	15

On the other hand, there is a questionnaire at the municipal level. It is administered to the local authorities of each municipality. It collects information on infrastructure (schools, roads, markets...) and economic conditions (work opportunities, agricultural production...) of each municipality. Through this questionnaire, we get information on the occurrence of extreme events by category (typhoons, floods, cyclones ...).

All of these questionnaires collect data from 9,000 representative households each year. This allows us to build our database from the last three VHLSS surveys (2010-20122014)[26]. In our analysis, we retain only households that produced rice and are followed at least twice over the three years of surveys. In total, there are 2,592 households and 5,894 observations in the database.

4.3.2. Climate data

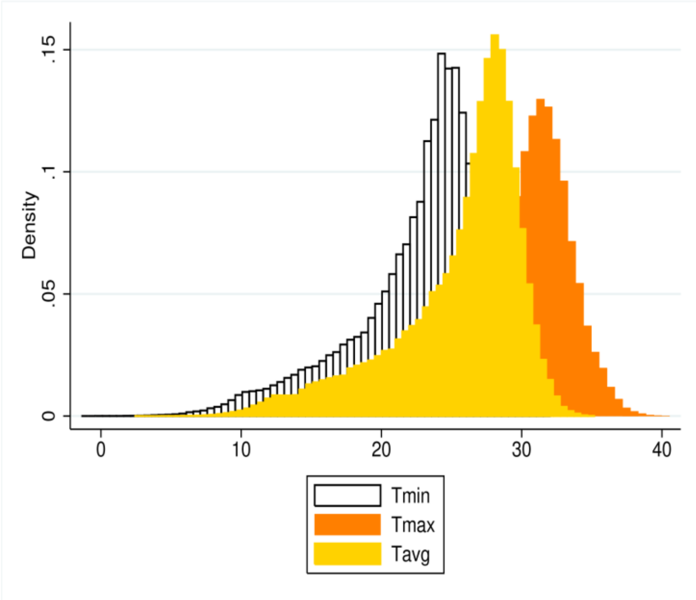
The climate data used in this study are daily temperatures and precipitations. These data come from the Climate Prediction Center (CPC) database developed by the National Oceanic and Atmospheric Administration (NOAA). It provides historical data on maximum and minimum temperature and precipitation levels for a grid of 0.5 degree by 0.5 degree of latitude and longitude. The daily average temperature (precipitation) can be generated from these T_{max} and T_{min}. Thus, at each geographic coordinate (longitude and latitude), a mean precipitation value is associated with an average temperature value per day, month and year.

However the geographical coordinates of this base did not correspond exactly to those which we had for the municipalities of Vietnam. To overcome this problem, we use the STATA *geonear* command. For each given municipality, we compute the average daily precipitation and temperature of the four nearest localities weighted by the inverse of the squared distance.

The Figure 1.4 gives the distribution of minimum, maximum and average daily temperatures over the period 2010-2014. There is a strong dispersion of the daily temperature levels in Vietnam. The minimum daily temperature is between -1.4°C and 32°C while the maximum temperature is up to 41°C. The averages of the minimum and maximum daily temperatures are respectively 22.3°C and 28.8°C. T_{avg} is the average of the daily minimum and maximum temperature levels. It is worth noting that extreme temperatures (above 30°C) is not negligible in Vietnam.

[26] There are data for surveys before 2010. However, these data are not usable because the sampling method and questionnaire content changed in 2004 and 2010.

Figure 1. 4: Distribution of tmin, tmax and tavg



Source: authors from CPC data

Finally, from Table 1.1, we note an average daily precipitation of 8.35 mm and an average daily temperature of 24.82°C over the period (2010-2014).

V. Econometric results

5.1. Estimation of the SFA model

The first step is to estimate TE scores from a translog production function within a SFA.

Table **1.2** presents the estimation results[27].

In the first column, we use only inputs (hired and family labor, capital and running costs) as well as their quadratic and interactive terms as explanatory variables. However, the results of this estimation are potentially subject to the problems of omitted variables. First, the production technology may be different depending on whether irrigation is used or not. In column 2, we thus

[27] Note that all variables are expressed in logarithm. We transform the variable X into $\ln(1 + X)$ to account for the null values in variables. The interaction terms are reported in Table A1.5 of Appendix. Note that the Wald test in column 1 of Table 2 suggests that quadratic and interactive terms of the translog production have to be included. This test confirms the relevance of the translog production function compared to the Cobb-Douglass production function.

include a dummy variable to control for irrigation practices. Moreover, temperature and precipitation levels have direct effect on agricultural yields.

To limit this bias, we include the temperature and precipitation levels in column 3 by hypothesizing that temperature and precipitation levels impact agricultural yields while weather shocks influence technical efficiency (second step). To test the consistency of this model, we apply the Wald test to the coefficients of the climatic variables. The test concludes that the inclusion of climatic variables in the first step is more relevant than their exclusion. Thus, we will continue with this model to estimate the technical efficiency scores and proceed to estimate the second stage equation.

Also, we check the theoretical consistency of our estimated efficiency model by verifying that the marginal productivity of inputs is positive. If this theoretical criterion is met, then the obtained efficiency estimates can be considered as consistent with production theory. As the parameter estimates of the translog production function reported in Table 1.2 do not allow for direct interpretation of the magnitude and significance of any inputs, we compute the output elasticities for all inputs at the sample mean, minimum, maximum and median, and report them in Table A1.3 in Appendix. We find that rice farming in Vietnam depends more strongly on running costs (0.64), Hired labor (0.34) and capital (0.29) at the sample mean. These results capture the important role of mechanization and intensification in rice farming in Vietnam. However, the marginal productivity of family labor appears very low (0,13) at the sample mean. This result seems to be relevant within the context of Vietnamese agriculture where surplus labor may exist. The over-use of labor inputs implies that the marginal productivity of labor must be very low, even negative in some cases.

Regarding the effect of climatic variables, our results are consistent with those found in the literature. Indeed, we find that the impact of temperature and precipitation on agricultural production is non-linear.

5.2. Impact of extreme weather events on TE

Table 1.3 summarizes the distribution of technical efficiency (TE) scores obtained from the column 3 of Table 1.2 and the formula of **Jondrow et al. (1982)**[28]. TE scores range from 0.29 to 1 with an

[28] In **Jondrow et al. (1982)**, technical efficiency is calculated as the mean of individual efficiency conditional to the global error terms which encompasses idiosyncratic error term and efficiency term.

average of 0.67. There are 55% of households with efficiency scores below this value. The results show that on average, Vietnamese rice farmers could save about one third (1-0.67) of their inputs. Form these TE scores, we assess the impact of extreme weather events (extreme temperatures, typhoons, droughts and floods) on TE with both a fixed effects model (Table 1.4) and a Tobit model (Table 1.5).

As a result, we find that the occurrence of temperature shocks and extreme events relative to what is expected prevents agents to efficiently use their potential technological resources. Thus, this expectation bias creates inefficiency in the decision making of their agricultural activities.

Table 1. 2: Estimation of production frontier

Variables	(1)	(2)	(3)
Hired labor	1.606***	1.605***	0.559
	(0.483)	(0.483)	(0.518)
Family labor	1.277***	1.280***	0.264
	(0.215)	(0.215)	(0.269)
Running costs	2.205***	2.189***	0.863***
	(0.224)	(0.227)	(0.317)
Capital	0.223	0.217	0.186
	(0.432)	(0.432)	(0.432)
Irrigation		0.0164	0.0168
		(0.0351)	(0.0350)
Temperature			0.065***
			(0.017)
Temperature squared			-0.00163***
			(0.0005)
Precipitation			4.08e-05
			(0.0001)
Precipitation squared			-1.22e-08
			(3.55e-08)
Interactions factors	x	x	x
Observations	5,894	5,894	5,894
Number of HH	2,592	2,592	2,592
Wald test	126.69	-	39.53

Estimation method: Maximum likelihood estimator with time-variant TE. The dependent variable is the rice yield per square meter. *** statistical significance at 1%, ** statistical significance at 5%, * statistical significance at 10%.

Table 1. 3:Distribution of efficiency score

Efficiency score	Nbr	Percent	Cum.
0-0.5	436	7.40	7.40
0.5-0.6	1,592	27.01	34.41
0.6-0.7	1,711	29.03	63.44
0.7-0.8	1,094	18.56	82.00
0.8-0.9	969	16.44	98.44
0.9-1	92	1.56	100.00
Average	0.67		
Min	0.29		
Max	1		

Table 1. 4: Impact of weather shocks on TE: fixed effects model

Variables	(1)	(2)	(3)	(4)
IT_30_31_Dry	0.376***	0.424***	0.410***	0.239*
	(0.144)	(0.142)	(0.140)	(0.132)
IT_31_32_Dry	-0.491**	-0.573***	-0.571***	-0.145
	(0.212)	(0.207)	(0.204)	(0.457)
IT_32_33_Dry	-4.342***	-4.528***	-4.355***	-2.928***
	(1.093)	(1.077)	(1.008)	(.939)
IT_33_34_Dry	-7.940***	-8.053**	-6.849**	-7.001**
	(3.050)	(3.148)	(2.782)	(3.474)
IT_30_31_Wet	-0.386***	-0.388***	-0.383***	-0.386***
	(0.0582)	(0.0579)	(0.0578)	(0.058)
IT_31_32_Wet	0.165*	0.141	0.152*	-0.106
	(0.0881)	(0.0881)	(0.0859)	(0.082)
IT_32_33_Wet	0.134	0.189**	0.236***	0.251***
	(0.0890)	(0.0897)	(0.0870)	(0.083)
IT_33_34_Wet	0.112	0.167	0.263**	0.126
	(0.138)	(0.135)	(0.134)	(0.134)
IT_34_35_Wet	0.430*	0.342	0.492**	0.745***
	(0.248)	(0.237)	(0.238)	(0.238)
IT_plus_35_Wet	-3.000	-2.808	-3.425*	-2.823*
	(1.850)	(1.740)	(1.770)	(1.728)
Flood		-4.060**	-3.540**	-3.154**
		(1.629)	(1.629)	(1.655)
Typhoon		-7.748***	-7.367***	-7.676***
		(1.389)	(1.444)	(1.419)
Drought		-2.614**	-2.522**	-3.663***
		(1.132)	(1.105)	(1.124)
Age			0.652***	0.573***
			(0.0974)	(0.092)
Educ			1.254***	1.151***
			(0.408)	(0.366)
HH size			-0.659**	-0.676**
			(0.283)	(0.269)
Gender			-2.901	-2.767
			(2.154)	(2.049)
Constant	70.97***	71.64***	44.30***	82.41***
	(0.949)	(0.955)	(5.844)	(21.307)
Observations	5,894	5,894	5,461	5,461
Number of HH	2,592	2,592	2,457	2,457
R-squared	0.060	0.084	0.130	0.296

Estimation method: within fixed effects estimator. The dependent variable is the score of technical efficiency estimated from col. 3 of Table 1. 2. In col. 4, daily precipitation are controlled for. Robust standard errors in parentheses. *** statistical significance at 1%, ** statistical significance at 5%, * statistical significance at 10%.

In the first column of Table 1.4, we assess only the effect of extreme temperatures on TE according to the dry and wet seasons. We find that the effect of extreme temperatures on TE is differential according to the seasons. During the dry season, extreme temperatures above 31°C lessen TE and the effect is increasing with temperature. Indeed, an increase of one day corresponds to a reduction in TE of 0.49 percentage points in the bin [31°C32°c], 4.34 percentage points in the bin [32°C-33°C] and 7.94 percentage points in the bin [33°C-34°C]. During the wet season, only the bin [30-31[has a significant and negative effect on TE but this effect is relatively small. The insignificant effects for wet season above 31°C can be explained by the mechanisms of adaptation. Farmers are used to very high frequencies during this season and they adapt to that. Thus, the level of temperature must be very extreme to have a detrimental effect on TE. For instance, even if the effect is not significant, it is worth noting that above 35°C, a one day increase above this degree decreases efficiency by 3 percentage points.

In column 2, the occurrence of natural disasters such as floods, typhoons and droughts is introduced. These events are found to be significantly detrimental for TE. More precisely, the efficiency diminishes respectively by 4.06, 7.74 and 2.61 percentage points after the occurrence of a flood, a typhoon and a drought, respectively. The previous results found in column 1 for the extreme temperatures remain the same.

In column 3, we test the robustness of the effect of climate variables to the inclusion of several control variables related to the household (gender, age, education and household size)[29]. The effects of extreme temperatures in the dry season and natural disasters remain unchanged. However, a one day increase in the bin [35°C[during the wet season becomes significant (a reduction of 3.42 percentage points of TE). Regarding household variables, age and education are found to positively affect TE. These results suggest that older and more educated rice farmers are more efficient than others. In addition, it appears that men are more efficient than women. This result should be interpreted with caution because women represent only 18% of our sample. Also, women have less access to credit or insurance systems for lack of collateral, while the literature shows the important role of these factors on efficiency (**Helfand and Levine (2004), Fontan (2008)**). Finally,

[29] It is useful to note that there are several standard household variables that we do not take into account (for instance, the access to credit, land tenure, ...). However, the purpose of this analysis is not to list exhaustively the determinants of TE but to investigate whether climate shocks affect TE. Since climate shocks are exogenous to household characteristics, we limit the problem of omitted variables.

household negatively size affects TE. This result can reflect a problem of misallocation of inputs mainly in term of family labor.

In column 4, average daily precipitations are introduced (**Zhang et al., 2014**). Previous results concerning extreme temperatures and natural disasters remain the same except for the coefficient of the bin [31°C, 32°C[during the dry season that becomes non-significant.

However, since TE scores are truncated to 1, the Tobit estimator is used to estimate the impact of weather shocks on TE. Results are presented in Table 1.5. It is worth noting that the effects of climate variables remain the same.

Table 1. 5: Impact of weather shocks on TE: Tobit model

Variables	(1)	(2)	(3)	(4)
IT_30_31_Dry	0.168***	0.174***	0.165***	0.0934**
	(0.0440)	(0.0437)	(0.0450)	(0.0460)
IT_31_32_Dry	-0.652***	-0.691***	-0.678***	-0.536***
	(0.126)	(0.125)	(0.128)	(0.127)
IT_32_33_Dry	-5.023***	-4.913***	-4.892***	-4.930***
	(0.551)	(0.548)	(0.545)	(0.538)
IT_33_34_Dry	-5.931	-7.133**	-6.939*	-6.270*
	(3.612)	(3.586)	(3.557)	(3.509)
IT_30_31_Wet	-0.0133	-0.0312	-0.0666***	-0.0212
	(0.0207)	(0.0207)	(0.0215)	(0.0216)
IT_31_32_Wet	0.144***	0.139***	0.136***	0.113***
	(0.0402)	(0.0399)	(0.0404)	(0.0400)
IT_32_33_Wet	0.0271	0.0782	0.0655	0.106*
	(0.0631)	(0.0628)	(0.0632)	(0.0627)
IT_33_34_Wet	0.169	0.199*	0.152	0.0683
	(0.103)	(0.103)	(0.103)	(0.102)
IT_34_35_Wet	-0.0518	0.0208	0.171	0.192
	(0.250)	(0.248)	(0.251)	(0.251)
IT_35_+_Wet	-3.563*	-4.054**	-3.961*	-3.867*
	(2.079)	(2.064)	(2.054)	(2.026)
Flood		-1.873**	-1.950**	-1.787**
		(0.757)	(0.776)	(0.768)
Typhon		-4.214***	-4.121***	-4.069***
		(0.687)	(0.712)	(0.703)
Drought		-4.742***	-4.725***	-4.912***
		(0.685)	(0.708)	(0.702)
Age			0.0585***	0.0581***
			(0.0133)	(0.0132)
Educ			0.397***	0.387***
			(0.134)	(0.132)
HH size			-0.220**	-0.230**
			(0.109)	(0.108)
Gender			-0.469	-0.354
			(0.480)	(0.474)
Constant	65.48***	66.20***	65.19***	36.43***
	(0.292)	(0.299)	(1.037)	(8.789)
Observations	5,894	5,894	5,461	5,461
Number of HH	2,592	2,592	2,457	2,457

Estimation method: Tobit estimator. The dependent variable is the score of technical efficiency estimated from col. 3 of Table 1. 2. In col. 4, daily precipitation are controlled

During the dry season, the more temperature increases above 31°C, the lower TE is. More precisely, over the four estimations (col. 1 to col. 4), the effects range between -0.69 and -0.64 percentage point for the bin [31 32]), -5.02 and -4.80 percentage point for the bin [32 33], -7.13 and - 5.93 percentage point for the bin [33 34]. However, we now find that the impact of one more day in the bin [35 and more] during the wet season significantly reduces TE from -3.56 to -4.20 percentage points for the four estimations. In addition, floods, typhoons and droughts have still detrimental effects on TE. However, the magnitude of the coefficients change. While typhoons are found to have the highest detrimental impact in Table 1.4, droughts have now the highest negative effect. More precisely, over the four estimations (col. 1 to col. 4), the effects range between -1.95 and - 1.83 percentage points for flood, -4.21 and -3.97 percentage points for typhoon, and -5.03 and - 4.73 percentage points for drought.

5.3. Heterogeneity effects

5.3.1. Farm size and weather shocks

In this section, we investigate whether the effect of climate shocks on TE is different according to the area devoted to rice farming. The sample is thus split into two categories. One the one hand, there are the small farms defined as farms with a rice area less than the median area of the total sample (0.40 hectare). These farms have an average size of 0.23 hectares while larger farms (i.e., farms with an area above 0.40 hectare) have an average size of 1.27 hectares.

For each of these two categories, we redo the estimation of column 4 in Table 1.4. Results are presented in Table A1.5 in Appendix.

It is noted that climate shocks tend to be more harmful for small farms. In general, the occurrence of extreme temperatures is rather detrimental for small farmers in the dry season. For the wet season, there are no significant effects for large farms. Also, it is observed that the occurrence of typhoons and droughts negatively affects the efficiency of smallholders whereas only the occurrence of typhoons is harmful for large farms.

5.3.2. Liquidity constraint and weather shocks

The literature shows that the relaxation of liquidity constraints plays an important role in improving agricultural productivity. Good farm management requires access to resources (**Carter and Wiebe, 1990**) both *ex ante* and *ex post*. Firstly, access to resources will enable the farmer to buy the inputs necessary for his production (hired labour, investment, and access to land ...). Secondly, resource use may be needed after production by allowing farmers to smooth their income when a shock hits their production. Thus, access to resources allows the farmer to adopt better technology for her production and to smooth her farm income. More specifically, access to new resources can enable poor farmers to optimize the use of inputs that conditions final production.

In order to measure the liquidity constraint faced by each farmer during the growing rice production, we sum three different sources of income obtained off the rice farming. More precisely, we sum total value of remittances received by households (both internal and external), total non-farm income of households and total government aid received by households after the occurrence of disasters. We analyze the impact of this variable on efficiency and test the conditional effect of extreme climate events on efficiency through it.

Table A1.6 in Appendix presents the results of liquidity constraint relaxation effects on efficiency. We find a non linear effect of liquidity on TE. More precisely, there is a minimum of liquidity available to households which can be used to improve their TE. From column 2, the threshold is 270.43 (1000 VND) from which total off-farm income positively affects TE. This threshold is not trivial because 34% of the rice farmers in the sample have an off-farm income below this threshold. In other words, these farmers can face a liquidity constraint.

In Table A1.7, we interact climate shocks variables with the liquidity variable to test the conditional effect of climate shocks on technical efficiency through liquidity availability. The interactive terms allow to test whether farmers with more off-farm income can be more resilient to weather shocks. Our results do not confirm this assumption. Two explanations are possible for these results.

Firstly, the utility of these amounts as resilience factors to climate shocks may be a function of the phase of the crop's life cycle (land preparation, planting, cultivation and harvesting) during which the shocks occur. Liquidity can play an important role during the first phase by allowing an optimal adjustment of the inputs needed for production (Ex: purchases of seeds, fertilizers, pesticides, hired labor, access to capital ...). However, the effect of climate shocks on efficiency is not only due to a lack of adaptation to these shocks but also to forecast and expectation errors in these shocks that affect the optimality of farmers' production decisions. Hence, liquidity may not be a mitigating factor of the effect of shocks on efficiency even if it is true that these resources can be considered as a resilience factor to climate shocks by allowing individuals to smooth their consumption (**Arouri et al., 2015**). Secondly, as we have pointed out above, the amount of these resources is not large enough to deal with climate shocks more precisely to natural disasters whose magnitude of effects on efficiency is very high. Thus these additional resources are used to smooth household consumption rather than to invest in the agricultural sector.

VI. 6. Simulation

We can use the previous estimations of the impact of weather shocks on technical efficiency in rice production to derive the potential impacts of future global warming on that sector. This is done under several important and strong hypotheses that will be detailed below. The idea of this kind of estimation is not to predict with certainty the future impact of global warming in terms of technical efficiency losses, but rather to have a picture of possible futures depending on the future climate change in Viet Nam[30].

The future climate projections are obtained from the Regional Climate Model version 4.3 (RegCM) (**Giorgi et al., 2012**). RegCM is a hydrostatic, limited-area model with a sigma vertical coordinate. In this study, the model was implemented with 18 vertical -levels with the top level set at 5 mb and with a horizontal resolution of 25 km. The physical options used for the RegCM4.3 experiment in this study are the radiative transfer scheme of the NCAR Community Climate Model (CCM3) (**Kiehl et al., 1996**), the subgrid explicit moisture (SUBEX) scheme for large-scale precipitation (**Pal et al., 2007**), the planetary boundary layer scheme of (**Holtslag and Moeng, 1991**), the MIT-Emanuel convective scheme (**Nilsson and Emanuel, 1999**), the BATS1e ocean flux scheme (**Dickinson et al., 1993**). This setting is based on the sensitivity experiments conducted previously by the Coordinated Regional Climate Downscaling Experiment -Southeast Asia (CORDEXSEA) community (**Cruz et al., 2017; Juneng et al., 2016; Ngo-Duc et al., 2017**). Boundary and initial conditions of RegCM are provided by the outputs of the CNRM5 GCM model (**Voldoire et al., 2013**).

In order to compute the estimated yearly impacts of climate change on rice technical efficiency, we compute for each year and for each temperature bin the difference between the new conditions induced by warming (as a moving average on twenty years every year), on the two Representative Concentration Pathways (RCPs) 8.5 and 4.5, and a reference average of the years 1986−2005. These differences are then multiplied by the coefficients estimated in Table 1.4 and 1.5. We thus get the relative impact on technical efficiency of the change in climate in each pixel of the Viet Nam map

[30] This is all the more true that we use in this version the outcomes of only one regional climate model. A future version will include all available simulations from the CORDEX-SEA program, which are not yet available.

for the different estimation strategies. We will just show here the results in the case of the fixed effects model, when taking floods, typhoons and droughts into account, but looking only at the effects of temperature. This corresponds to the temperature coefficients in the second column of Table 1.4.

The results appear on Figure 1.6 and 1.7. They show that in all cases, losses in technical efficiency reach the highest levels in the Red River Delta and in Northern mountains. Rice producers in these regions see their technical efficiency shrink sharply in 2050. After 2050, the full effect of the RCP8.5 appears, and the two scenarios really diverge, as shown in Figure 1.6. Technical efficiency losses diffuse through the Mekong delta in both scenarios.

Looking at the differentiated effect of the dry and the wet seasons (see Figure 1.7) in the RCP 8.5 scenario is particularly striking. It appears that the negative effect of the dry season is much more pronounced than the one of the wet season. However, the effect of the wet season is much more concentrated in specific geographical areas, such as the Red River delta, and later on the coastal areas and the Mekong delta. On the contrary, the effect of the dry season seems much more homogeneous around the country, the Mekong delta emerging as a threatened area only at the end of the century

It must be recalled that only temperature increases have been taken into account in these projections, all other factors (economic or climate) remaining constant. So the good news on the Mekong region should not be a matter of optimism if we recall that the area is prone to other kinds of climate threats such as storm surges, typhoons, and sea-level rise in the longer run.

On aggregate, we can also calculate the average loss in technical efficiency for Viet Nam as a whole, by simply aggregating with equal weights the losses evaluated for each cell. This exercise shows that RCP4.5 and RCP8.5 scenarios start diverging soon after 2040. Technical efficiency losses reach 40 percentage points before the end of the century in the case of the RCP8.5 scenario, while the RCP4.5 scenario seems to stabilize technical efficiency losses around 8 percentage points losses. Here again, we must recall the very simplified assumptions made around these projections. In particular, no technical progress or adaptation strategy is taken into account here, which could make the situation better. On the other side, no macroeconomic retrofitting of climate damages to other sectors are taken into account, which could make matters worse.

VII. Conclusion

In this study, we investigate the impact of extreme weather events on rice farming TE using a SFA model. These weather events are defined as extreme temperatures in both dry and wet season, and the occurrence of typhoons, floods and droughts during the rice production period.

We first find that extreme temperatures in the dry season are detrimental for TE. More precisely, temperatures above 31°C dampen TE and the effect is increasing with temperature. An increase of one day corresponds to a reduction in TE between 0.49 and 0.57 percentage points in the bin [31°C-32°c[, 2.92 and 4.52 percentage points in the bin [32°C-33°C[, and 6.84 and 8.05 percentage points in the bin [33°C-34°C[. Secondly, during the wet season, only the bin [30°C-31°C[and [35°C and more[have a significant and negative effect on TE. For instance, a one day increase in the bin [35°C and more[dampens TE between 2.82 and 3.42 percentage points. Thirdly, we find that floods, typhoons and droughts reduce TE. The magnitude is the highest for typhoons that lessen TE from 7.37 to 7.75 percentage points.

Small farms are more vulnerable to climate shocks than larger farms. In addition, farmers' liquidity has a non-linear effect on their efficiency. In other words, households with more liquidity are technically more efficient than others. However, the negative effect of climate extremes on efficiency is not conditioned to the liquidity owned by households. Hence, liquidity may not be a mitigating factor of the effect of climate shocks on efficiency even if it is true that these resources can be considered as a factor of resilience to climate shocks by allowing individuals to smooth their consumption.

From these results, some economic policy recommendations can be suggested. First, the establishment of weather forecasting systems in less favored areas can be advocated. A meteorological system that provides real-time data will reduce biases in individuals' expectations. Indeed, it is difficult for households, specifically poor households, to automatically adjust to exogenous shocks in the short term. Secondly, policies aimed at helping people affected by extreme temperatures and natural disasters should be discriminating by favoring households with small farms. Regarding natural disasters, our results confirm those of **Arouri et al. (2015)**. In other words, natural disasters have negative effects on the welfare of households. The implementation of irrigation and drainage systems would mitigate the negative effects of drought and flood on the farmers' efficiency, although the impact of climate change on the water cycle should be taken into account as well.

Figure 1. 5: Aggregate damage on technical efficiency (% points lost)

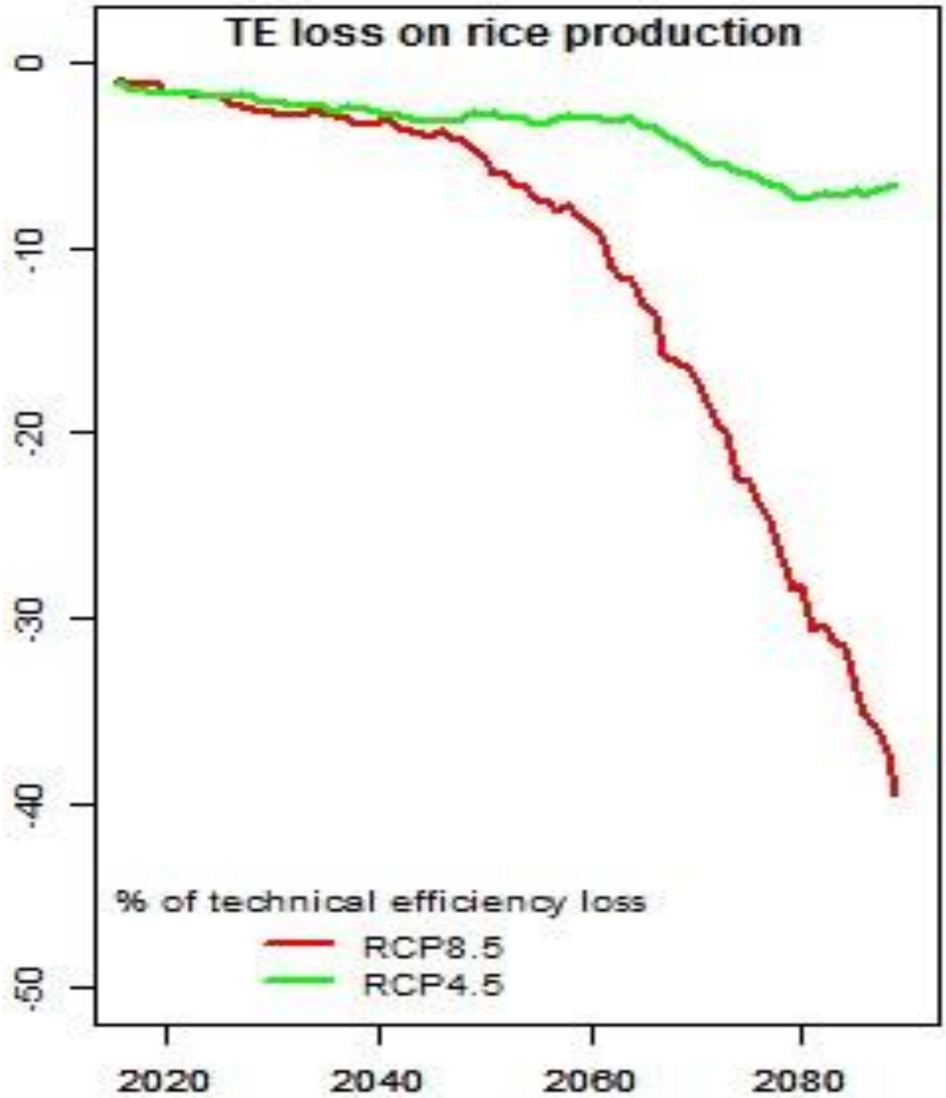
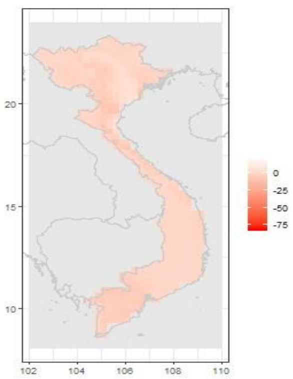
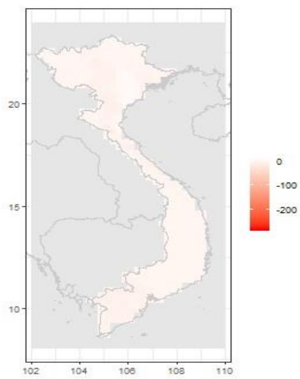


Figure 1. 6: Technical efficiency losses in 2030, 2050 and 2090 compared to the reference period 1986 – 2005, for dry and wet seasons combined, RCP4.5 and RCP8.5.

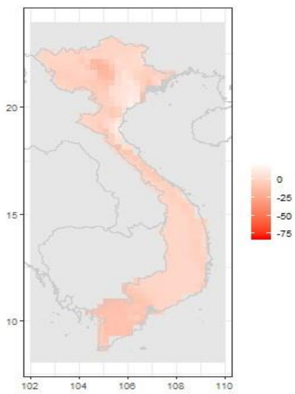
(a) RCP4.5 - 2030



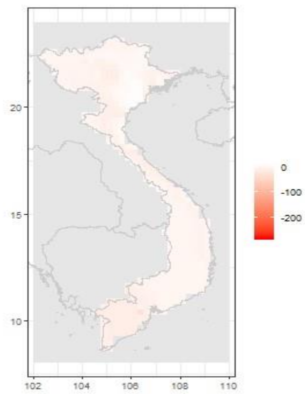
(b) RCP8.5 - 2030



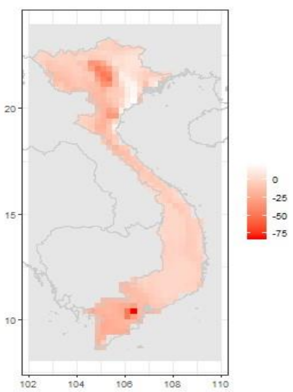
(c) RCP4.5 - 2050



(d) RCP8.5 - 2050



(e) RCP4.5 – 2090



(f) RCP8.5 - 2090

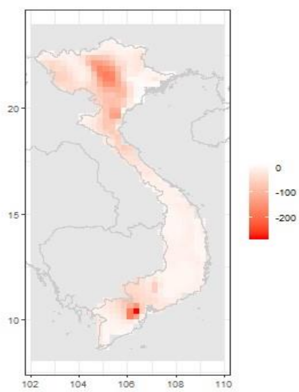
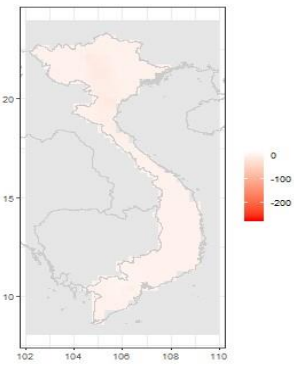
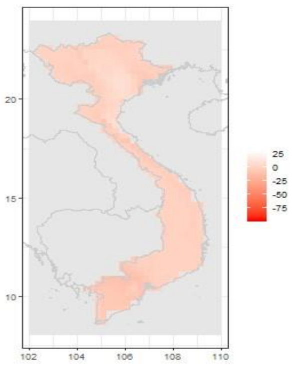


Figure 1. 7: Technical efficiency losses in 2030, 2050 and 2090 compared to the reference period 1986 − 2005, for dry and wet seasons separated, RCP8.5 only.

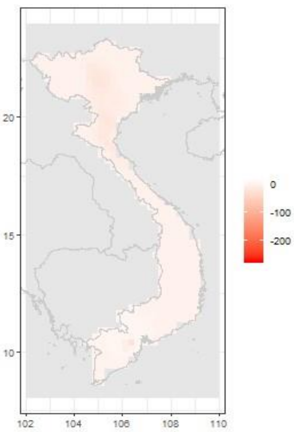
(a) Dry season - 2030



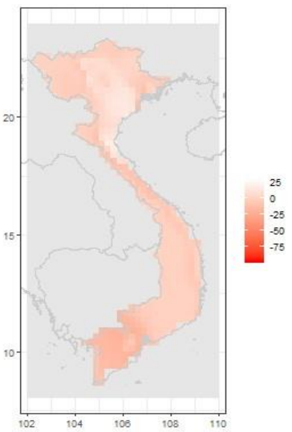
(b) Wet season - 2030



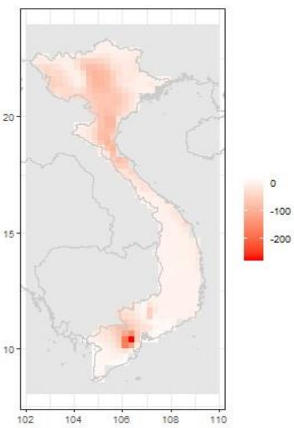
(c) Dry season - 2050



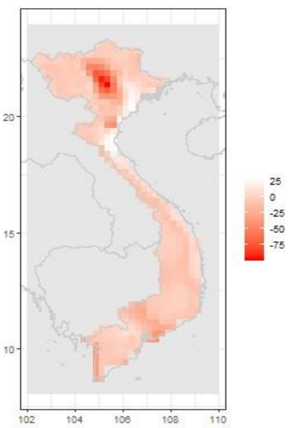
(d) Wet season - 2050



(e) Dry season - 2090



(f) Wet season - 2090



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Appendix

Figure A1. 1: Evolution of temperature level by month (1950-2015)

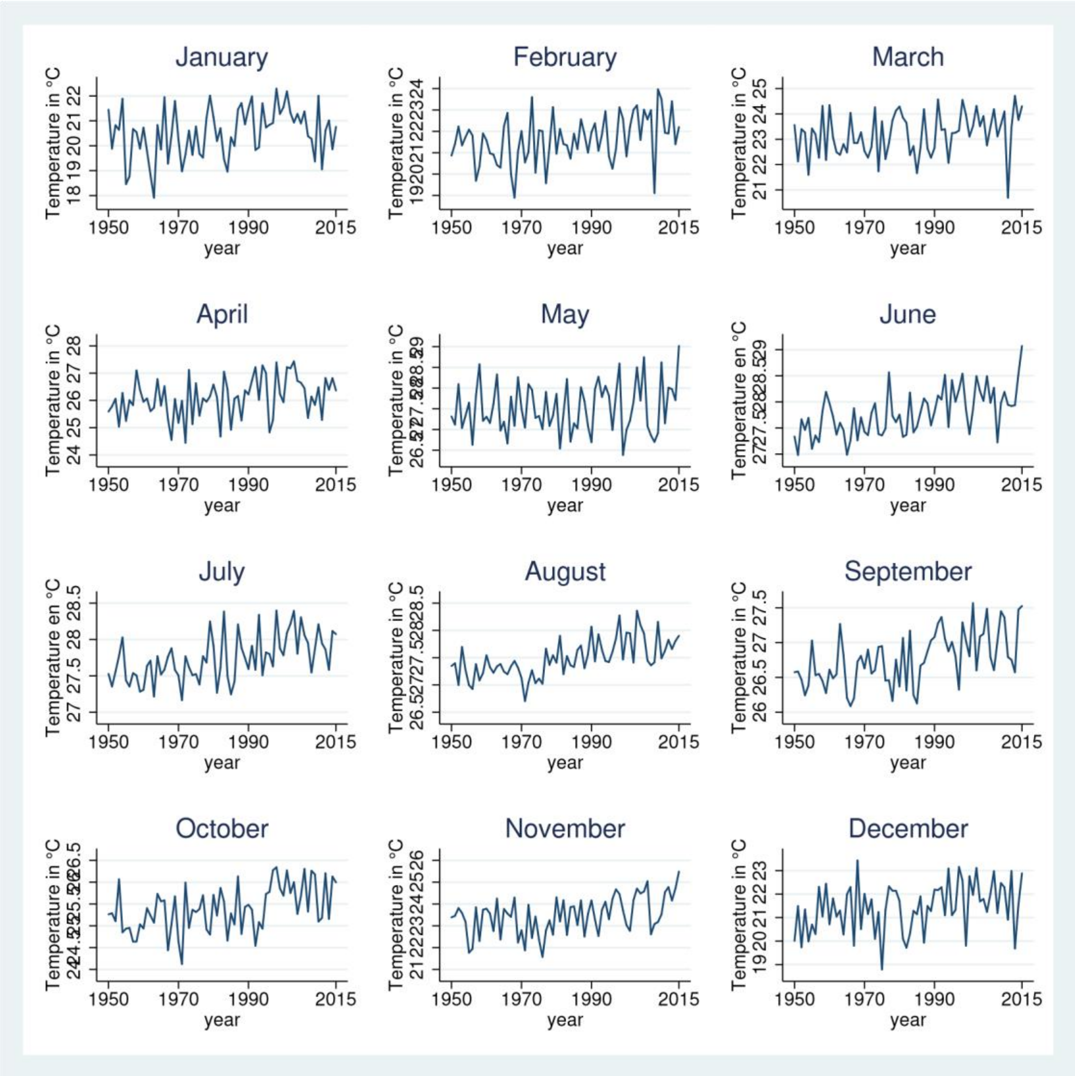
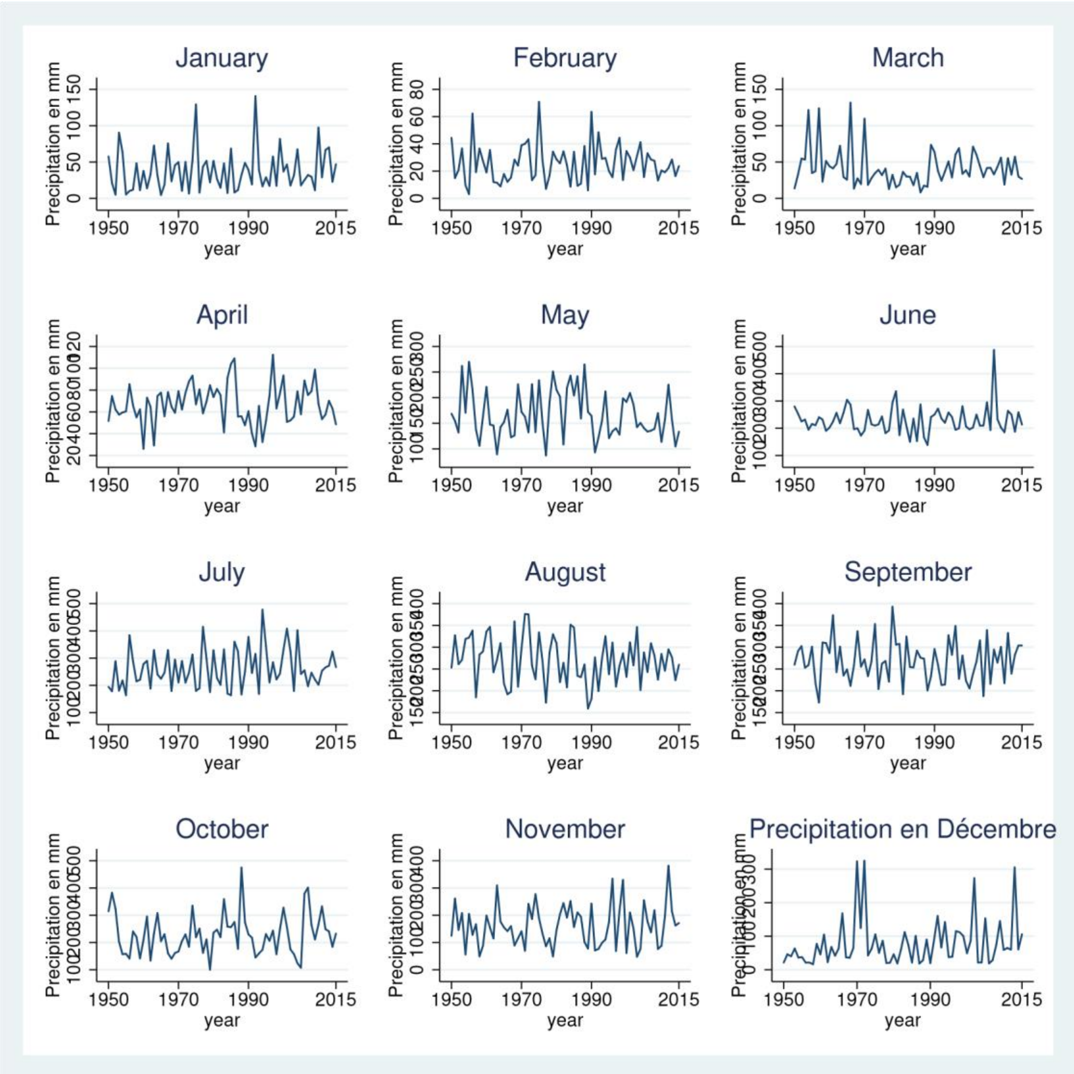


Figure A1. 2: Evolution of precipitation level by month (1950-2015)



Variables	Definition and description
Rice income	Total rice production during past 12 years: Thousand VND per squared meter.
Capital	Total value of investment in machinery: Thousand VND per squared meter.
Hired labor	Payment of hired labor for rice production: Thousand VND per squared meter.
Family labor	Number of hours for family labours. Hours per squared meter.
Running costs	Other costs (fertilizer, seeds, irrigation ...): Thousand VND per squared meter.
Irrigation	= 1 if farm is irrigated.
Temperature	Daily temperature average over the production period: °C.
Precipitation	Daily precipitation over the production period: mm.
IT_[a b]	Number of days when average daily temperature is between a and b.
Flood	=1 if there is flood during rice the production period.
Typhoon	=1 if there is Typhoon during rice the production period.
Drought	=1 if there is drought during rice the production period.
Gender	Gender of household head (1=male, 2=Female).
Age	Age of household head.
Educ	Education level of household head (0 (no qualification) to 9 (university level)).
Household size	Number of persons living together in one house.

Table A1. 1: Test technology difference across regions

Variables	Sud	North+Center	Diff	P-value
Capital	0.2238	0.2186	-0.0052	0.1748
Family labor	0.1132	0.3737	0.2606	0.00
Hired labor	0.1225	0.0864	-0.0361	0.00
Running costs	0.8210	0.7357	-0.0854	0.00
Area	22167.97	4001.851	-18166.12	0.00
Irrigation	0.2234	0.4500	0.2266	0.00

Table A1. 2: Inputs elasticities

Inputs variables	Mean	Min	Max	Median
Hired labor	0.34	0.56	-0.85	0.37
Family labor	0.13	0.26	-0.60	0.14
Running costs	0.64	0.86	-0.20	0.65
Capital	0.29	0.19	0.60	0.33
Total	1.40	1.87	-1.04	1.49

Calculation method: coefficient estimates from the results of column 3 in Table 1. 2. Elasticities calculated at sample mean, sample median, minimum and maximum of inputs.

Table A1. 3: Estimation of stochastic production frontier model.

Variables	(1)	(2)	(3)
Hired labor	1.606***	1.605***	0.559
	(0.483)	(0.483)	(0.518)
Family labor	1.277***	1.280***	0.264
	(0.215)	(0.215)	(0.269)
Running costs	2.205***	2.189***	0.863***
	(0.224)	(0.227)	(0.317)
Capital	0.223	0.217	0.186
	(0.432)	(0.432)	(0.432)
Capital*Capital	1.733	1.761	0.871
	(1.341)	(1.342)	(1.350)
Capital*Hired labor	-1.810	-1.811	-0.528
	(1.692)	(1.692)	(1.698)
Capital*Family labor	-1.793**	-1.786**	-0.660
	(0.890)	(0.890)	(0.906)
Capital*Running costs	0.513	0.482	0.159
	(1.148)	(1.150)	(1.151)
Hired labor*Hired labor	-0.653	-0.657	-0.389
	(1.273)	(1.272)	(1.277)
Hired labor*Family labor	-1.985*	-1.981*	-0.493
	(1.189)	(1.189)	(1.212)
Hired labor*Running costs	-2.598*	-2.605*	-0.288
	(1.365)	(1.365)	(1.417)
Family labor*Family labor	-0.472	-0.471	-0.0417
	(0.303)	(0.303)	(0.313)
Family labor*Running costs	-2.178***	-2.184***	-0.154
	(0.670)	(0.670)	(0.749)
Running costs*Running costs	-1.770***	-1.746***	-0.378
	(0.561)	(0.563)	(0.606)
Irrigation		0.0164	0.0168
		(0.0351)	(0.0350)
Temperature			0.0654***
			(0.0171)
Temperature squared			-0.00163***
			(0.000544)
Precipitation			4.08e-05
			(0.000119)
Precipitation squared			-1.22e-08
			(3.55e-08)
Interactions factors	x	x	x
Observations	5,894	5,894	5,894
Number of HH	2,592	2,592	2,592
Wald test	126.69		39.53

Estimation method: Maximum likelihood estimator with time-variant TE. The dependent variable is the rice yield per square meter. *** statistical significance at 1%, ** statistical significance at 5%, * statistical significance at 10%.

Table A1. 4: Farm size, weather shocks and TE

VARIABLES	(1) Small farm Efficiency	(2) Large farm Efficiency
IT_30_31_Dry	-1.517**	0.554***
	(0.635)	(0.119)
IT_31_32_Dry	-1.790***	0.323
	(0.654)	(0.214)
IT_32_33_Dry	-2.009	-3.094*
	(1.285)	(1.810)
IT_33_34_Dry	-4.309	-2.854
	(4.184)	(4.056)
IT_30_31_Wet	-0.785***	-0.291***
	(0.0643)	(0.0607)
IT_31_32_Wet	0.113	-0.490***
	(0.101)	(0.113)
IT_32_33_Wet	0.172	0.0198
	(0.122)	(0.108)
IT_33_34_Wet	-0.652***	0.0816
	(0.179)	(0.190)
IT_34_35_Wet	0.759**	-0.345
	(0.352)	(0.341)
IT_35_+_Wet	-4.634	-3.603
	(3.970)	(3.732)
Flood	0.941	-0.768
	(1.754)	(2.069)
Typhoon	-4.328*	-6.543***
	(2.330)	(1.530)
Drought	-2.750**	0.346
	(1.287)	(1.482)
Age	0.466***	0.633***
	(0.122)	(0.131)
Educ	1.026***	0.988*
	(0.358)	(0.516)
HH_size	-0.671*	-0.546
	(0.378)	(0.363)
Gender	-1.980	0.302
	(2.174)	(2.956)
Constant	104.8***	99.32***
	(22.79)	(19.38)
Observations	2,787	2,674
R-squared	0.370	0.399
Number of hid	1,477	1,4

Estimation method: within fixed effects estimator. The dependent variable is the score of technical efficiency estimated from col. 3 of Table 1. 2. Robust standard errors in parentheses. *** statistical significance at 1%, ** statistical significance at 5%, * statistical significance at 10%.

Table A1. 5: Liquidity constraint, weather shocks and TE

VARIABLES	(1) Efficiency	(2) Efficiency	(3) Efficiency
IT_30_31_Dry	0.410***	0.412***	0.411***
	(0.140)	(0.141)	(0.140)
IT_31_32_Dry	-0.571***	-0.571***	-0.582***
	(0.204)	(0.205)	(0.204)
IT_32_33_Dry	-4.355***	-4.336***	-4.376***
	(1.008)	(1.016)	(1.022)
IT_33_34_Dry	-6.849**	-7.022**	-6.963**
	(2.782)	(2.787)	(2.822)
IT_30_31_Wet	-0.383***	-0.382***	-0.376***
	(0.0578)	(0.0578)	(0.0577)
IT_31_32_Wet	0.152*	0.152*	0.151*
	(0.0859)	(0.0858)	(0.0857)
IT_32_33_Wet	0.236***	0.228***	0.238***
	(0.0870)	(0.0874)	(0.0872)
IT_33_34_Wet	0.263**	0.264**	0.265**
	(0.134)	(0.134)	(0.135)
IT_34_35_Wet	0.492**	0.501**	0.498**
	(0.238)	(0.239)	(0.239)
IT_plus_35_Wet	-3.425*	-3.365*	-3.509*
	(1.770)	(1.767)	(1.797)
Flood	-3.540**	-3.589**	-3.538**
	(1.629)	(1.631)	(1.644)
Typhon	-7.367***	-7.311***	-7.267***
	(1.444)	(1.442)	(1.441)
Drought	-2.522**	-2.503**	-2.415**
	(1.105)	(1.107)	(1.120)
Age	0.652***	0.653***	0.649***
	(0.0974)	(0.0976)	(0.0972)
Educ	1.254***	1.259***	1.261***
	(0.408)	(0.406)	(0.404)
HH size	-0.659**	-0.679**	-0.672**
	(0.283)	(0.283)	(0.283)
Gender	-2.901	-2.938	-2.907
	(2.154)	(2.153)	(2.138)
ln (liquidity)		**-0.0995**	**-0.653*** **
		(0.0728)	(0.240)
ln (liquidity) squared			**0.0582**** (0.0233)
Constant	44.30***	44.89***	44.96***
	(5.844)	(5.846)	(5.835)
Observations	5,461	5,461	5,461
R-squared	0.130	0.131	0.133
Number of hid	2,457	2,457	2,457

Table A1. 6: Liquidity constraint, weather shocks and TE - interactions terms

VARIABLES	(1) Efficiency
Liquidity	-0.256
	(0.260)
Liquidity squared	0.0699***
	(0.0270)
IT_30_31_Dry	0.374**
	(0.149)
IT_31_32_Dry	-0.383*
	(0.233)
IT_32_33_Dry	-4.492***
	(1.452)
IT_33_34_Dry	-8.935*
	(4.997)
IT_30_31_Wet	-0.161**
	(0.0760)
IT_31_32_Wet	-0.0206
	(0.105)
IT_32_33_Wet	0.245*
	(0.129)
IT_33_34_Wet	0.330*
	(0.198)
IT_34_35_Wet	0.0832
	(0.464)
IT_plus_35_Wet	-0.826
	(2.218)
Flood	-3.415
	(2.268)
Typhon	-3.699
	(2.280)
Drought	-1.853
	(1.855)
Liquidity*IT_30_31_Dry	0.00381
	(0.0151)
Liquidity*IT_31_32_Dry	-0.0331
	(0.0316)
Liquidity*IT_32_33_Dry	0.0246
	(0.165)
Liquidity*IT_33_34_Dry	0.221
	(0.397)
Liquidity*IT_30_31_Wet	-0.0371***
	(0.00850)
Liquidity*IT_31_32_Wet	0.0282**
	(0.0134)
Liquidity*IT_32_33_Wet	-0.00281
	(0.0173)

Liquidity*IT_33_34_Wet	-0.00891
	(0.0274)
	(0.0274)
Liquidity*IT_34_35_Wet	0.0616
	(0.0504)
Liquidity*IT_35_+_Wet	-0.461
	(0.470)
Liquidity*Flood	0.0435
	(0.264)
Liquidity*Typhon	-0.739***
	(0.242)
	(0.242)
Liquidity*Drought	-0.0916
	(0.227)
Age	0.646***
	(0.0899)
Educ	1.224***
	(0.447)
HH size	-0.678**
	(0.298)
Gender	-3.292*
	(1.947)
Constant	43.02***
	(4.849)
Observations	5,461
Number of hid	2,457
R-squared	**0.145**

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Chapter 2: ENVIRONMENTAL DEGRADATION EFFECTS ON FOOD SECURITY IN VIETNAMESE RURAL AREAS: MULTIDIMENSIONAL ANALYSIS AND ENDOGENEITY ISSUES.

Abstract

Vietnam is a country with a high environmental risk and has experienced many climate shocks and agriculture remains the key sector that employs rural households. In this study, we analyze the association between environmental degradation and food security of rural households. Food security is assessed in all its four dimensions (availability, accessibility, diversity and stability) through composite index. In addition, we deal with endogeneity concern of some risk variables (deforestation and pollution), which could hinder these links, using control function method by **Wooldridge (2015)**. Our identification strategy is implemented with data from the three latter VHLSS waves (2010-2012-2014) and high resolution georeferenced data for risks variables. Results show that environmental risks are among the main factors that slowed down Vietnamese rural households' ability to achieve a better nutritional status and the magnitude and significance of this link depends on the nature of the risk on the one hand and the dimension of food security considered on the other. Then, political intervention is needed to make rural households more resilient to these risks factors.

Keywords: Climate change, Environment, Risk, Food security, Vietnam

JEL classifications: D24, O12, Q12, Q54

I. Introduction

Development debate is used to mention the link between food security and environment but the complex association is seldom explored. First, the degree of vulnerability of people could depend to the type of environment risk factor. Second, the dimensions of food security are not related to environment risk factors in the same way. This study aims to evaluate the effect of environment degradation on food security status by taking food security concept in all of its four dimensions: availability, accessibility, diversity and stability. We define environment risk as the actual or potential threat of adverse effects of environment component degradation on the the living standard of people. Environment components are divided into climate, soil conditions, biodiversity and air quality (**Reardon and Vosti, 1995**). These environment factors could have different effect on food safety depend to the dimension considered. In addition, the inter-dependence between each factor can amplify the vulnerability of people to environment degradation and the intensity of these effects will depend to the resilience or adaptation capacity of people. For example, deforestation, air pollution and slope can reinforce people exposure to climate shocks like natural disasters, temperature and precipitation variability.

Moreover, the current climate context is still alarming and according to the latest IPCC report, 2018 "Global warming is likely to reach the critical threshold of 1.5◦C between 2030 and 2052 if the temperature continues to grow at its current rate." Thus environmental degradation could fuel the negative effects of climate change on income (**Adger, 1999**), inequalities (**Bui et al., 2014**), poverty (**Gentle and Maraseni, 2012**) (viceversa). The projections by **Parry et al. (1999)** showed that the number of people at risk of starvation due to climate change would reach 80 million by 2080. This damage is most evident in developing countries which lack the means to cope with it or mitigate its effects. Like climate change, environmental risk factors are also considered as a source of vulnerability for certain categories of people and geographical areas. Assessing its damages is therefore an emergency for policy makers.

Vietnam is one of the best examples for assessing the causal link between these risks factors and food security. This country ranks among the top five most vulnerable countries according to Climate Change Knowledge Portal (CCKP) of World Bank[31] with frequent occurrence of natural

[31] Source: http://sdwebx.worldbank.org/climateportal/countryprofile/home.cfm?page=country$_{p}$*rofileCCode* = *V NMThisTab* = *Dashboard*

disasters (floods, typhoons and drought) and an increase in average temperatures that have already reached nearly two degrees in some regions. Vietnam climate projections are rather pessimistic about its future damage. **Yu et al. (2013)** predicted an increase in the average temperature of 2.5◦C in 2070 and sea level of 33 cm in 2050.

This exposure to climate risk is most evident in the Mekong regions Delta and coastal areas (**Dasgupta et al., 2007**). Also, Vietnam is emblematic for its potential exposure to climate variability: more than 3000 km of coastline are subject to an accelerated erosion. This country has been subject to a wide spectrum of natural disasters and ranked respectively as the 4th, 5th and 6th in terms of number of people exposed to the occurrence of floods, drought and other similar climatic events (UNISDR[32], 2009). The agricultural sector is the first sector identified as being most affected by global warming and environmental degradation.

In Vietnam, agricultural sector has undergone a major change and constitutes the main source of income for rural households which are generally victims of climatic hazards. In 1986, the Vietnamese government has committed itself to a goal of poverty reduction with the implementation of the "DOI Moi" reform. It has facilitated the country's economic transition from a planned economy to a market economy. The reform has been very successful in reducing poverty (from 60% in 1990 to 13.5% in 2014 (World Bank Data, 2016)), improving the living conditions of households and social stability in the country. Despite its small contribution to GDP, agricultural sector employ the majority of the country's active workforce (43%) mainly located in rural areas. The vulnerability of this group is directly linked to any shock which affect agricultural sector. In addition, there are still gaps to be filled because the country's current poverty rate of 13.5% remains significant and inequalities still exist between social groups (rural vs urban, ethnic groups (Kinh and others), poor and rich). The poverty situation of these groups limits their access to certain quality of food items (**Thang and Popkin, 2004**). Also, the nutritional status of Vietnamese remains critical. The GHI (Global Hunger Index) is still high: out of 119 countries, Vietnam ranks 62th among countries which suffers from malnutrition and starvation in 2019. In Southeast Asia, specifically in China and Vietnam, the nutrition transition from 2005 to 2015 resulted in energy-dense food consumption on the one hand, in urban quality on the other hand and had little benefited for households living in rural areas (**Nguyen et al., 2018**). Thus, improving food security in all its dimensions in rural area is crucial for Vietnamese policies (National Nutrition Strategy for 2011-2020, with a vision toward 2030). The establishment of such policy should not neglect the

[32] United Nations Office for Disaster Risk Reduction.

climate and environmental risk that are a reality in the country and increasingly threatens agricultural sector productivity (**Diallo et al., 2019**) which is the key driver of food security.

In this study, we highlight the causal effect of environmental risk factors on people well-being. Well-being is approached differently than income, more precisely, well-being is apprehended by the status of food security of households from a multidimensional approach. By answering this problematic, this study is in line with the literature on the assessment of environment degradation effects and the determinants of food security. Our chapter aims to contribute to existing literature in different ways. First, our approach is multidimensional. Since food security is a multidimensional concept (**Schmidhuber and Tubiello, 2007**), we take into account all the dimensions of food security proposed by FAO (availability, accessibility, diversity and stability). The simultaneous and individual analysis of each dimension makes it possible to understand the global effect of environment risk on food security and these effects on each component and thus allows us to identify the components most affected by climatic hazards and environmental risk. However, most studies are limited to analyzing the effect of climate change on food production or productivity, which is only one dimension among many (**Yu et al., 2010; Trinh, 2018**). These studies are only partial analysis of the relationship between food security and environmental conditions. We take advantage of the wealth of our database to take into account all dimensions of food security. Secondly, we use multiple indicators about environment risks data as food security determinants. All the literature on food security analysis in Vietnam has focused more on the income-nutrition relationship (**Dien et al. (2004), Molini (2006), Mishra and Ray (2009)** and **Thi et al. (2018**)), without taking into account the environmental aspect. To our knowledge, there is no study exists on the analysis of the causal relationship between environmental risks and food safety in Vietnam. Finally, we also contribute methodologically by addressing endogeneity issue between some of our environmental risk variables and food security. The innovative control function (CF) method proposed by **Wooldridge (2015)** is advantageous for dealing with this concern. The CF estimator tackles the endogeneity by adding an additional variable to the regression, generating a more precise and efficient estimator than the instrument variable (IV) estimator.

Our results show that the fact of living in risk areas affects negatively nutritional status of rural households. The magnitude and significance of this link depend on the nature of the risk on the one hand and the dimension of food security considered on the other. These results can serve as political instruments to the Vietnamese government in the implementation of its National Nutrition Strategies for 2011-2020. To make rural households more resilient environmental risks, their dependence on the agricultural sector should be reduced by creating new income-generating opportunities. Moreover, relaxing liquidity constraints may be possible through the development of microfinance activities in rural areas or social protection through weather index insurance for agriculture (**Barnett and Mahul, 2007**). Government must boost mechanisms to combat climate change by setting up more modern irrigation and drainage systems or seasonal weather services to anticipate temperature and precipitation shocks. Also, policies against deforestation and pollution can also be encouraged.

The remaining of the chapter is organized as follows: Section 2 presents the literature related to the link between environmental, climate, people well-being and food security. Section 3 details data used. Sections 4, 5 and 6 present respectively the conceptual framework, econometric model and main results. We conclude and make some policies recommendation in section 7.

II. Literature review

In this section, we first review the literature on the link between environmental risks and well-being. This will allow to understand the different channels by which the components of environment degradation could impact the welfare of households. Secondly, the multidimensional concept and determinants of food security are analyzed. Finally, the link between environment risk variables and each dimension of food security is highlighted in figure 1.

2.1 What do we know about the link between environment and people's well-being?

The relationship between environment and development economics is not new in the literature. This link was first highlighted by **Grossman and Krueger (1991)** and was followed by several other chapters (**Grossman and Krueger (1996), Shafik and Bandyopadhyay (1992), Selden and Song (1994), Panayotou et al. (1993)** and **Cropper and Griffiths (1994)**). The common point of most of these studies is the u-inverted relationship between environmental degradation and the level of development of countries, commonly referred to Environmental Kuznets Curve (EKC). Indeed, in the early stages of development or economic growth of a country, environment quality is deteriorated because of industrialization process that facilitates pollutants emission or deforestation from factories installation. Awareness of this degradation is neglected at this stage as people are motivated to search for jobs and accumulate wealth rather than to a healthy environment (**Dasgupta et al., 2002**). Once the minimum income is reached, environment becomes more and more considered useful asset in the preference basket of people and policy makers.

Environmental degradation manifests in several ways: air pollution through the emission of pollutants, water pollution, deforestation, soil erosion, etc. In developing countries where environmental regulation is not a priority anyway and the important role of the agricultural sector in household income portfolio, environmental degradation could lead to adverse effects on people well-being and lead to poverty trap situation. Environmental risk is unequally distributed around the world and even households within a country are not vulnerable in the same way. Over the last decade, activists, academics, and policy makers have paid close attention to ”environmental equity” or the notion that potential sources associated to environment risk may be concentrated among minorities, some ethnic groups and poor. At the global level, poor countries are most exposed to environmental risks (**Barbier (2010)** and **Sloan and Sayer (2015)**). Indeed, the impact of extreme environmental events differs between countries, regions and individuals; the damage they suffer depends on their degree of exposure and their ability to adapt with it (**Clark et al., 1998**). In developing countries, the literature shows a positive relationship between environmental risks and poverty (**Narloch and Bangalore, 2018**). In addition, case studies within country show that most provinces and districts experiencing environmental degradation are areas with relatively high rates of poverty (**Winsemius et al., 2015**). At household level, rich households are less exposed to climate and environment risk than poor households (**Wodon et al., 2014**). In fact, by the principle of ”vote by feet” from **Tiebout (1956)**, rich households settle in areas which are least exposed to environment degradation and correspond to their preferences. Houses prices in these areas increase due to environment quality and this increase limits access of them to poor people. Thus, poor households are settle in localities exposed to more climate and environment risks and poor amenities.

However, there is a considerable number of studies done by other researchers who find different results. The impact of climate risk on people well-being would depend on the nature of the risk considered. **Arouri et al. (2015)** find that the occurrence of cyclones, floods and droughts negatively impact household income with different magnitudes. For example, the effect of cyclones was relatively small compared to the effect of floods and drought. Also, poor households are more exposed to drought and temperature variability because their income is generally based on the agricultural sector whose production is linked to these types of climate hazards contrary to rich households that are more affected by floods because their physical assets are more at risk **(Hallegatte et al., 2016). Pasanen et al. (2017)** find a strong link between poverty and domestic pollution and air quality while the connection between non-domestic pollution, soil erosion and poverty is quite weak.

2.2 Food security link to environmental risks factors

According to World Food Summit, 1996 "Food security exists when all people, at all times, have physical and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life". This definition shows the multidimensional nature of food security concept. FAO identifies four main dimensions to understanding food security. The first dimension is availability which means sufficient and quality food production available to households. This dimension refers to an adequate supply of a healthy diet except that it does not take into account the ability **(Sen, 1981)** of people to appropriate it. So, the second dimension, which is accessibility, is on the demand side. In addition to the first dimension, it takes into account households' access to sufficient food that is linked to the resources or opportunities they have. The third component is the diversity in the basket of food consumption and the use of these goods. Indeed, a balanced diet is necessary to have an adequate nutritional state. Moreover, the use of these food products, which would reflect its effectiveness, depends on the quality of the environment around the household (water quality, air quality ...). The last component reflects the stability of the three components mentioned. To ensure food security, households must have access to sufficient, healthy and diversified food at all times.

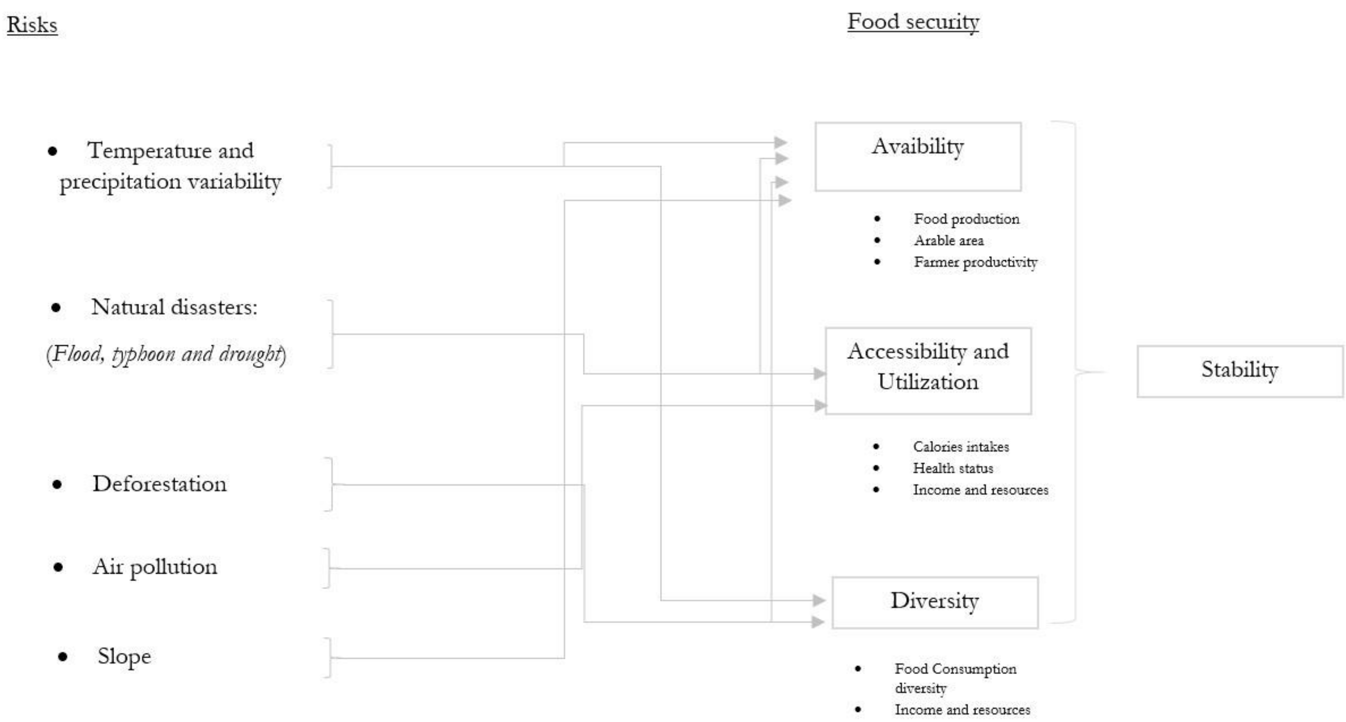
The Sustainable Livelihood Framework approach divides food security (FSI) determinants into five broad categories (**Ashley et al., 1999**): human capital (HC), social capital (SC), physical capital (PC), financial capital (FC) and natural capital (NC).

$$FSI = f(HC,SC,CP,FC,NC) \tag{1}$$

Human capital are skills that together enable people to have different means of livelihoods. At the household level, it can be understood by the household size, health status, education level, etc. Social capital is defined as social resources (social network, membership to an association, level of trust ...) which facilitates cooperation, access to certain goods and services and therefore reduces transaction costs. Physical capital includes public goods or the basic infrastructure available to people who make their subsistence activities easy by improving their productivity (road traffic, adequate supply of water and electricity, access to information, etc.). Financial capital refers to the financial means that allow individuals to smooth their income and consumption. These financial resources can be stocks (savings) or flows (cash transfer, remittances, subsidies ...). Natural capital is the term used to refer to natural resource stocks from which resource flows and services for livelihoods are derived. The resources constituting natural capital vary considerably, ranging from intangible public goods such as the atmosphere (temperature, precipitation ...) and biodiversity to divisible assets directly used for production (trees, land, etc.). Our analysis is essentially based on the last category (natural capital) controlling for some variables of other. Environmental risk variables are used to define natural capital.

We distinguish eight risk variables related to environment degradation[33]. These risk variables can affect food security in many ways. Figure 2.1 below summarizes the channels through which environmental risks factors could impact each dimension of food security:

Figure2. 1: Food security and environmental degradation association



- **Temperature and precipitation variability:**

There is no doubt that agricultural output is strongly linked to climatic conditions. **Mendelsohn et al. (1994)** found a nonlinear effect of temperature and precipitation on agricultural production in USA. **Schlenker and Roberts (2009)** found that beyond the respective thresholds of 29°, 30° and 32°, the temperature generates major damage on wheat, soybean and cotton yields respectively.

[33] These variables are close to those used by **Narloch and Bangalore (2018)** with different sources. See section about data for more details

Climate Shocks also can affect the technical efficiency of farmers and then reduce agriculture productivity (**Diallo et al., 2019**).

- **Natural disasters**

The occurrence of natural disasters aggravates the poverty situation of rural households (**Arouri et al., 2015**). Typhoons lead to the destruction of assets; Floods and drought negatively impact farm income which is the main component in the household income portfolio in rural areas. Moreover, since income is the key determinant of diversity and accessibility, variability in temperature, precipitation and natural disasters have an indirect impact on the accessibility dimension and the diversity dimension. Also the quite important periods of drought increase the duration of agricultural production season and thus acts on the supply and the price of food goods.

- **Air pollution**

About air pollution, chronic exposure to it is associated with adverse health effects like metabolic dysfunction and increase morbidity and mortality (**McMichael et al. (2008)** and **Pope III et al. (2009)**). Thus, utilization dimension is affected. Otherwise, bad health due to air pollution affect negatively workers productivity and diminish their income while income is a main determinant of accessing to good quality food.

- **Deforestation**

The effect of deforestation on food security is ambiguous. On the one hand, deforestation leads to a decline in ecological services and thus to the nutritional possibilities of rural and poor households. On the other hand, deforestation is a substitution for an income shock for poor households. Therefore, it can be considered as additional resources and thus facilitates access to food. In addition, deforestation reflects the extensification of agricultural sector by increasing the total area of arable land.
So it could favor the local offer and thus have a positive effect on food availability.

- **Slope**

High slope can put agricultural yield at risk. Areas with steep slopes are much more exposed to surface runoff and soil erosion - especially areas affected by heavy rainfall and loss of forest cover (**Sidle and Ochiai (2006); Vezina et al. (2006)**). Therefore, farming in these areas requires a significant investment in terms of labor, capital.
Hence, agricultural productivity is threatened in these areas.

Stability dimension resulting from the other three dimensions is necessarily linked to all climate and environmental risk variables. The transmission channels explained above are not exhaustive. There may be other more complex channels that link climate and environmental risk to food security. Through figure 1, we highlight the dependence of each dimension of food security with the degree of exposure to climatic hazards and environmental risk. The separate analysis of the impact of risk variables considered is complex because they are strongly correlated. We include these variables simultaneously in econometric estimation.

III. Data

We combine two categories of data in this analysis: socioeconomic data and environmental risk data. Environmental risks data are close to those used by **Narloch and Bangalore (2018)** from different sources.

3.1 Socioeconomic data

The socio-economic data are from Vietnam Household Living Standard Survey (VHLSS) lead by General Statistics Office of Vietnam (GSO) with the support of World Bank. Initiated since 2002, VHLSS's main objective is to collect data at household and commune levels in order to define and evaluate national policies or programs that include poverty analysis and inequalities between gender, socio-groups and regions in Vietnam. The survey questionnaire is administered every two years at two levels. On the one hand, we have a questionnaire administered at household level. It collects data on sociodemographic characteristics of individuals within a household (sex, age, level of education...). Moreover, for each household, we have information on different sources of income (agricultural, non-agricultural, services...) and their use (consumption, health, education ...). The calculation of our measure of food security is deduced from agriculture section and the use of household income section specifically their consumption expenditure[34]. On the other hand, the questionnaire at municipal level is administered to local authorities of each municipality. It collects information on infrastructure (schools, roads, markets ...) and economic conditions (work opportunities, agricultural production...) within municipality. Through this questionnaire, we also have information on the occurrence of extreme events by category (typhoons, floods, cyclones ...)

All of these questionnaires collect data from 9000 representative households each year. This allows us to build our database from the last three VHLSS surveys (2010-2012-2014). In this study, we are

[34] All monetary values are deflated by 2010 Consumer Price Index.

interested in households living in rural areas. They are vulnerable to climatic shocks and environmental risk because their resources depend heavily on them and they lack of adaptation strategies. In total we have 10113 households that are selected over the three study periods. We recall that our database is not balanced, so that a household can be or not be followed more than once during the analysis period.

3.2 Risks data

We distinguish eight risk variables that concern the degradation of environment components. All of these variables are well suited to study households' exposure to environmental risk. Table 2.1 below describes these variables and their sources.

It is difficult to merge the socio-economic database (VHLSS at household level) with the database of risk variables because the geographical coordinates of households are not known. In addition, all risk data are not observed with the same resolution. With the exception of natural disaster variables, the other risk variables are not initially observed at the commune level but rather at smaller resolutions. Thus, in order to have the information for each risk variable in given commune, we calculate the average of all the observations, for that variable, where the resolution belongs to that commune. Then we merge socioeconomic database with the risk databases at commune level.

IV. Conceptual framework

4.1 PCA to compute Food Security Index

The measure of food security is complex because of its multidimensional nature. This complexity usually leads researchers to limit its analysis to a single dimension among the four dimensions identified above. To take account four dimensions together, Principal Component Analysis (PCA) approach can be used. PCA is a statistical tool that summarizes the inertia contained in several correlated variables in a smaller number of indicators called principal components of composite indicators (**Dunteman, 1994**). This method was used by **Abafita and Kim (2014)** to analyze the impact of rainfall shocks on food security in Ethiopia.

Table 2. 1: Risks data description and sources

Variables	**Description**	**Source**
Temperature variability	For one year, we compute temperature variability as deviation of average temperature for this year to their five last year average, in a given commune.	Moderate-Resolution Imaging Spectroradiometer (MODIS): **6km grids**
Precipitation variability	For one year, we compute precipitation variability as difference of average precipitation for this year to their five last year average, in a given commune	Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS): **Resolution of 0.05°**
Natural disasters (*Flood, drought and typhoon*) **Environnemental risk**	binary variable (=1 if this type of Natural disaster occured during the past two year)	VHLSS (**Commune level**)
Air pollution	Annual concentration of PM2.5 particles (g / m3).	NASA's Moderate Resolution Imaging Spectroradiometer (MODIS), Multi-angle Imaging SpectroRadiometer (MISR), and the Sea-Viewing Wide Field-of-View Sensor (SeaWiFS).
Deforestation	For a given year, deforestation is defined as a minimum loss of 20% or more of the vegetation cover compared to deforestation in 2000. Using Landstat data, the authors have spatialised the dynamics of the vegetation cover in terms of gain, expansion and loss at a spatial resolution of 30 km.	Hansen et al (2013): **30km grids**
Slope	The average slope of a second arc about 30 m to Ecuador. It is measured in%	NASA Shuttle Radar Topography Mission Global 1 arc second V003

We use the same approach to construct a Food Security Index (*FSI*) that encompasses the first three dimensions (availability, accessibility and diversity):

$$PC_m = a_{m1}.X_1 + a_{m2} + ... + a_{mp}.X_p; \quad (2)$$

Where a_{mp} represents the weight associated with the component *m* and dimension *p* of food security. Table 2.2 shows variables used to represent each dimension. To construct food security index, we only include the first three dimensions (availability, accessibility and diversity). Stability dimension is analyzed differently. To understand stability dimension, we make a longitudinal analysis by study the persistence and transition of FSI and their tercile dimension. Table 2.3 present the descriptive statistics and component loading of PCA results. Initially, the number of components was four and we use the Kaiser[35] criterion to choose the best components. Then, we select two component with eigenvalue more than one. FSI corresponds to first component (*PC*1) because this component got the maximum information (41% of total inertia) of correlated variables more than the second component.

Table 2. 2: PCA variables description

Dimensions	Variables
Avaibility	Value of agricultural production by type of crop (rice, vegetables, vegetables, fruits, livestock and aquaculture) and agriculture surface.
Accessibility	Per capita calories intakes per day (PCCI)
Diversity	Dietary diversity index

Note: Some variables such as agricultural area, agriculture production value and PCCI were normalized with a logarithmic transformation. See the appendix for PCCI calculation method. To compute the production dietary diversity index, we use the Simpson and Shanon indices. The indicators are also more detailed in Appendix.

[35] Criterion of **Kaiser (1960)** allows to select only component with eigenvalue superior to 1.

(3)

About first component, all variables used are positively associated with it witch correspond to our expectation. *Production value* and *agriculture surface* are strongly correlated with FSI which correspond respectively to 0.69 and 0.67 as weights. Otherwise, having large agriculture surface and agriculture production value are positively associated with per capita calories intake, production and dietary diversity. However, the contribution of consumption diversities is quite low. This means that FSI is less dependent on this variable. Still, there is a positive correlation between FSI and diversity indicator. FSI is recalculated using the min-max method[36] and follows a normal distribution.

Table 2. 3: Summary statistics and component loadings of food security index

Variable	Mean	Std. Dev.	Component loading (PC1)	Component loading (PC2)
Agriculture surface	8.0953	1.1109	0.6706	-0.2632
Production value	9.9901	1.1772	0.6914	0.0004
PCCI	8.6301	0.3838	0.2644	0.5162
Dietary diversity	1.2024	0.2632	0.0488	0.8150
Eigenvalue			**1.64**	**1.07**
Variance explained (%)			**0.41**	**0.27**

The second component is different from the first one. In this component, we observe a clear representation of households who low production and consume several goods at a time. And the agricultural production value has a negative contribution to the loading of this component. Also, this axis shows that high size of agriculture land is opposed to production value. Also, a significant consumption of calories is followed by a diversification in the consumption basket. As can be seen, this component does not reflect the structure of a food security indicator. Our analysis focuses on the first component because not only does it capture the largest information but also all the variables used for PCA are associated with the right sign.

Despite its advantages, PCA has some limitations. First of all the share of information retained in our food security index is only 41%, which means that 59% of the information is lost and will not be exploited. Also, the low weight associated with diversity dimension is not justified. Normally,

[36] This method consist to range variable between 0 and 1 by transform it as: $FSI_{norm} = \frac{FSI - \min(FSI)}{\max(FSI) - \min(FSI)}$.

the weight associated with each dimension should be expected to be positive and important as all four dimensions contribute to food security (**Abafita and Kim, 2014**). To circumvent these concerns, we conduct robustness analyzes by assessing the effect of climate and environmental risks on each dimension of food security in addition to the effect on the overall FSI.

4.2 Stability dimension

For FSI and each of its dimensions, we break down our sample into three groups according to the tercile to which household belongs. Thus, for a given year, households are classified from the most vulnerable (first tercile) to the least vulnerable (last tercile) according to their food security status. The stability is measured by the ability of household to be in same tercile over time. This way to analyse stability dimension is similar to the approach used by **Bigsten et al. (2003), Qureshi (2007)** and **Demeke et al. (2011)**. Also, the decomposition into tercile allows to take into account the inequalities between different groups of households in terms of nutrition. This inequality could be explained by chronic exposure to climate hazards and living in a risky environment.

Table 2.4 is transition matrix that gives the evolution of each tercile of FSI indicator and each of its dimensions over the 2010-2014 period. There is a high degree of instability in the nutritional status of households in our sample. This instability is manifested by the movement of households from one tercile to another over the three years (2010 2012 2014) period of this analysis. For example, about the global indicator FSI, we observe around 73% of individuals who initially belonged to the first tercile who remained stable in their group. 23% of them went to the second tercile and only 4% saw their nutritional status improved (last tercile). In addition, 26% of households in third tercile in 2010 have moved to a lower status. Otherwise, we remark that small producer stay always small and big producer remain big in term of agriculture production value over 2010-2014. Thus, there is exist a trap in agriculture production among small and big producers in Vietnam. About PCCI, more than 50 percent of each quintile sample transit to other quintile: 36% of second tercile (T2) in 2010 move to inferior tercile (T1) and 27% move to superior tercile (T3) and only 37% stay to initial status (T2). Also, diversity in consumption behaviour is non stable. For each tercile, the probability to move in another tercile in 2012 or 2014 is very important: From T1 group, 53.15% stay in less secure status; from T2 group, 27% move back to less secure status and 34% move forward.

Table 2. 4: Food security factor score evolution between 2010 and 2014

FSI		T1	T2	T3	Total
	T1	**72.61**	22.91	4.48	100.00
	T2	24.22	**56.07**	19.70	100.00
	T3	4.71	21.77	**73.52**	100.00
Food production					
	T1	**67.21**	25.61	7.18	100.00
	T2	23.16	**52.60**	24.23	100.00
	T3	4.37	20.08	**75.56**	100.00
PCCI					
	T1	**57.86**	28.21	13.93	100.00
	T2	35.83	**36.99**	27.18	100.00
	T3	18.97	30.05	**50.98**	100.00
Diversity					
	T1	**53.15**	30.97	15.88	100.00
	T2	27.11	**38.75**	34.14	100.00
	T3	14.63	32.96	**52.41**	100.00

Notes: T1: Food insecure people, T2: Vulnerable people and T3: Food secure people. In rows we have the nutritional status of households in 2010 and in column we have the measure of the nutritional stability of these same households in 2012 and 2014.

V. Econometric model

5.1 Endogeneity issues

Causal analysis of environment risks and food security is very complex because of endogeneity issues. There are two potential sources of endogeneity in this analysis. The first one is the inverse causality between food security and environmental risk since the pressure of people on environment services especially in rural areas is not negligible. **Fisher (2004)** shows that forests prevent poverty by smoothing income, and may also help to improve the living standards of households. So deforestation itself explains household income and therefore their access to good food. Also, extensive agriculture practice, which is the main determinant of food availability, contributes to environment degradation through deforestation. Moreover, by the principle of vote by feet of **Tiebout (1956)**, the choice of people's location is a function of their income and therefore of the importance they attach to environment quality. This choice creates a distortion in the price of housing. The poor, who generally suffer from food insecurity, tend to settle in polluted areas because they are cheaper relative to the rich. Thus, there is self-selection between food-insecure people and their environmental vulnerability because residing in a polluted area is a function of the individual's level of well-being. In Vietnam, farmers could also contribute to air pollution by rice straw burning. To prepare farm land for next season, producers burn rice straw according two methods: i) piling the residues after hand harvesting; ii) burning the residues without piling, after machine harvesting. **Lasko and Vadrevu (2018)** findings suggest that pile burning method and non-pile burning method contribute respectively to 180 Gg and 130 Gg of PM2.5 emissions in Vietnam for year 2015. The second cause of endogeneity is the omitted variable bias. However, taking into account several climatic and environmental risks indicators in the analysis reduces this bias. Also, it should also be remembered that our risk variables are at commune level and socioeconomic variables are at household level. This difference in unit level reduce endogeneity concern.

To tackle endogeneity concern, we use control function approach from **Wooldridge (2015)**. CF approach is two steps estimation strategy used to solve endogeneity issues in linear and non-linear models. First step consists to regress each endogenous variables on instruments variables and other exogenous variables (reduced form). In the second step, residuals from reduced form are integrate in final equation (structural form) as additional explanatory variables. By doing this, orthogonality condition for endogeneity variables and error term is respected. Consider the model:

$$y_1 = \sigma_1.z_1 + a_1.y_2 + \epsilon_1; \tag{4}$$

where z_1 is a subvector of exogenous variables z that also includes a constant, and σ_1 and a_1 are parameters to be estimated. The exogeneity of z is given by the orthogonality restriction:

$$E(z'\epsilon_1) = 0 \tag{5}$$

The first step in the CF approach consist to estimate a reduced-form equation of endogenous explanatory variable y_2:

$$y_2 = \pi_2.z + v_2 \quad (6)$$

$$E(z'v_2) = 0 \quad (7)$$

where π_2 are parameters to be estimated. Endogeneity of y_2 arises if there is correlation between ϵ_1 and v_2. The linear projection of ϵ_1 on v_2 in error form is:

$$\epsilon_1 = \phi_1.v_2 + e_1 \quad (8)$$

By definition, $E(v_2 e_1) = 0$ and $E(z e_1) = 0$ because ϵ_1 and v_2 are both uncorrelated with z. In the second step, the residuals obtained from the reduced form estimation are used as an additional explanatory variable in the structural model regression:

$$y_1 = \sigma_1.z_1 + a_1.y_2 + \phi_1.v_2 + e_1 \quad (9)$$

However, v_2 is not observable. We can rewrite $v_2 = y_2 - \pi_2.z$ and consistently estimate π_2 by OLS and replace v_2 with $\hat{v}_2$ the OLS residuals from the first-stage regression of y_2 on z_2. Simple substitution gives:

$$y_1 = \sigma_1.z_1 + a_1.y_2 + c.\hat{v}_2 + e_1 \quad (10)$$

Equation (10) is CF estimates, because the inclusion of the residuals $\hat{v}_2$ "**controls**" for the endogeneity of y_2 in the original equation. If the coefficient of $\hat{v}_2$ on the generalized residual is significantly different from zero in the structural model, the explanatory variable of interest, y_2, is endogenous.

This method is similar to 2LS standard method because both have the same kinds of identification conditions and lead to the same results when endogenous variables appear linear. However, CF approach is better than 2LS when there is a non-linearity in endogenous variables[37].

We used several variables to instrument deforestation and air pollution. For deforestation, we use three instruments: These instruments relate to the deforestation history in each commune, which captures household dependency on forest resources. Thus, the greater this dependency in a given commune, the greater the effect it will have on the forest cover of that commune. For each commune and year *t* (2010-2012-2014), we approximate this deforestation history by the value of

[37] These advantages are at the asymptotic level and the respect of the conditions of a good instrument i.e exogenous and rank condition

forest cover loss in $t-1$, $t-2$ and $t-3$. The level of air pollution of each municipality is instrumented by the pollution history (t-1, t-2 and t-3) and the wind speed in that municipality. Wind speed has been identified in the literature as an important determinant of the concentration of particulates matter (**Lu and Fang, 2002; Chaloulakou et al., 2003; Zhao et al., 2009**). There is a strong negative correlation between wind speed and PM concentrations which means that high winds speed flush pollutants out of the system, and low wind speed limits the dispersion of pollutants and therefore increase pollution level. Wind speed data from ECMWF (European Centre for Medium-Range Weather Forecasts) database[38] and have a resolution of 0.5° (about 50km). For a given commune, we calculate the average of pixels data belonging to this commune.

5.2 Food security change between households and over time

We use two types of models to estimate the impact of environmental and climate risk on food security. The first is the **"pooled cross section"** to analyze the effect of each risk considered on the difference in nutritional status between households. And "**panel model**" to assess the effect of each risk on the change in nutritional status of households over the three survey periods. The econometric equations are summary as follow:

- Reduced forms:

$$def_{j,t} = b_0 + \sum_{j,p=1}^{3} b_p.def_{j,t-p} + \sum_{i,j,k,t} d_{k0}.Z_{i,j,t} + u1_{jt} \tag{11}$$

$$poll_{j,t} = a_0 + \sum_{j,p=1}^{3} a_p.poll_{j,t-p} + a_4.WS_{j,t} + \sum_{i,j,k,t} d_{k1}.Z_{i,j,t} + u2_{jt} \tag{12}$$

- Structural form:

$$Y_{i,j,t} = a_0 + \sum_{r,j,t} a_{1,r}.NC_{r,j,t} + \sum_{i,j,k,t} a_{2,k}.Z_{i,j,k,t} + year_t + \phi_1.u1_{jt} + \phi_2.u2_{jt} + \epsilon_{ijt} \tag{13}$$

[38] https://www.ecmwf.int/.

Reduced forms includes the instrumentation equations 11 and 12 of *deforestation* and *pollution* variables. Where deforestation of a commune j is explained by its three lags values: def_{t-1}, def_{t-2} and def_{t-3}. Pollution of commune j at year t is explained by its three lags value: $poll_{t-1}$, $poll_{t-2}$ and $poll_{t-3}$ and wind speed (WS) at year t of this commune. In structural equation 13, $Y_{i,j,t}$ represents the global indicator FSI and its three components (Food production, PCCI and consumption diversity) for household i live in commune j at time t. NC is the natural capital that represents all eight climate and environmental variables at commune level j: *Temperature*, *Precipitation*[39], *Flood*, *Typhoon*, *Drought*, *Airpollution*, *Deforestation* and *Slope*. *year* is a dummy for each period (2010 2012 2014) of our panel data . These temporal dummies catch here the common shocks (e.g. price shocks, macroeconomic policy) to our entire sample. This reduces the possibility that some unobserved variant variables could be correlated with our risk variables. And $u1_{jt}$ and $u2_{jt}$ are residuals from reduced form and non-correlated with error term $\epsilon_{i,j,t}$.

5.3 Food security stability: difference between households and evolution over time

As we have shown in the section above, the global indicator of food security FSI and each of its components are unstable over the study period. This instability results in the movement of an individual from one group of terciles to another. For each component, we identify three groups of individuals according to the tercile of belonging: T1: less food secure, T2: Medium food secure and T3: High food secure. This classification being ordered, we use an ordered probit model. The principle of ordered probit is to identify factors that are associated with the probability that a household belongs to a better tercile (from less food secure (1) to high food secure (3) status) according to the FSI indicator and each of its dimensions. The reduced form is that defined by equations 11 and 12. Consider $Q*$, the latent variable that classifies individuals according to their nutritional status. So we have terciles ($q1$, $q2$ and $q3$) for FSI global index and each of its dimensions (Food production, PCCI and consumption diversity) and explained by same explanatory variables used in previous models.

$$Q*_{it} = a_0 + \sum \beta_{1,r}.NC_{r,j,t} + \sum \beta_{3,k}.Z_{i,j,k,t} + year_t + u1_{jt} + u2_{jt} + \epsilon_{ijt}, \tag{14}$$

[39] For one year, temperature and precipitation measure respectively annual temperature and precipitation deviation to their five last year average.

The structural form is defined as:

$$Prob(Q_{it} = q) = \Phi(NC_{r,j,t}, Z_{i,j,k,t}, year_t, u1_{jt}, u2_{jt}) \tag{15}$$

with q=1, 2, 3.

In this model, the dependent variable is the probability that household belongs to tercile q. ϕ is the distribution function of residual term ϵ_{ijt} from equation 15; ϵ_{ijt} is assumed to follow a reduced centered normal distribution. With pooled cross section, this estimation makes it possible to understand the difference in nutritional status between the different groups of quintile. The panel estimation allows identifying the factors that facilitate or hinder the transition from one group to another over time.

VI. Results

Table 2.5 presents descriptive statistic about environment and household characteristics variables. We observe that the occurrence of natural disasters is regular phenomenon in Vietnam. About 15%, 16% and 11% of Vietnam commune are respectively affected by *flood*, *typhoon* and *drought*. Descriptive statistics show an increasing pathway of temperature (0.08°C) and diminishing in precipitation level (-3.79mm). Otherwise deforestation, pollution and geographic structure are very heterogeneous.

Table 2. 5: Descriptive statistics of explanatory variables

Variable	Mean	Std. Dev.	Min	Max
flood	0.15	0.36	0	1
typhoon	0.16	0.37	0	1
drought	0.11	0.31	0	1
temperature deviation	0.08	1.34	-7.39	4.16
precipitation deviation	-3.79	285.83	-1414.432	2007.14
deforestation	0.21	0.74	0	14.62
PM2.5	24.20	11.99	4.15	44.34
slope	14.44	14.21	1.71	57.98
wind speed	2.39	0.42	1.75	5.54
gender	1.17	.37	1	2
age	48.67	13.52	16	99
education	1.49	1.28	0	12
HH size	4.10	1.57	1	15

Notes: Temperature and precipitation are measured as deviation to last five years average level.

Area deforested varies from 0 to 14.62 ha. The level of minimal value of PM2.5 concentration is 4.15 $\mu g/m3$ while maximal value is 44.34 $\mu g/m3$ which correspond to 40 $\mu g/m3$ as extend. Also the standard deviation of area slope is very high (15%) with %1.71 and 57.98% as minimum and maximum value. These figures allow to understand the potential climate and environmental risk that faced Vietnamese households. As we showed in section 1.2, these risks could affect people well-being by many ways.

Table 2.6, results from pooled cross section estimation, help to identify the ways that live in a risk area could affect household nutritional status. In column 1, the dependent variable is food security indicator from the PCA analysis. Among three natural disaster variables, only the occurrence of floods negatively affects food security. Indeed, an occurrence of flood would lead to a decrease of food security indicator by 0.02 unit. This result is statistically significant at a threshold of 1%. Even if the marginal impact of the typhon and drought is not significant, the negative sign of the coefficients corresponds to our expectation. This link is more highlighted by the columns (2), (3), (4) and (5).). In column (2), the occurrence of floods has a negative and significant impact on the value of agricultural production while the effects of typhoon and drought are still not significant. This non-significance of drought can be explained by the importance of irrigation (more than 40%) used as a strategy for adapting to climate change in agricultural production in Vietnam. However, mitigation systems for other types of disasters such as drainage for flood and dike systems for typhoons are not sufficiently developed. In column (3), none of natural disasters have a significant effect on the number of calorie per capita consumed. This result is not surprising, as there are surely substituability mechanisms in household consumption patterns. They also choose to consume foods that are cheaper compared to foods that are priced higher because of climate shocks. This assertion is confirmed by columns (4) and (5). Diversity indicators in consumption are negatively affected by the occurrence of the three types of natural disasters considered: Flood (-0.03), Typhoon (-0.02) and Drought (-0.03). Therefore, we can say that to cope with the occurrence of natural disasters, households tend to less diversify their consumption basket.

Table 2. 6: Food security, weather shocks and environment risk: Pooled cross section estimation

	(1)	(2)	(3)	(4)	(5)
VARIABLES	FSI	Production value	PCCI	Simpson index	Shanon index
Flood	-0.0186***	-0.175***	-0.00979	-0.0136***	-0.0341***
	(0.00245)	(0.0227)	(0.0116)	(0.00311)	(0.00608)
Typhoon	-0.00266	-0.0261	-0.0101	-0.00871**	-0.0181**
	(0.00206)	(0.0217)	(0.0101)	(0.00348)	(0.00716)
Drought	-0.00395	-0.0376	0.00999	-0.0145***	-0.0302***
	(0.00383)	(0.0463)	(0.0135)	(0.00400)	(0.00853)
Temperature	-0.00365***	-0.0487***	-0.00682*	-0.00179**	-0.00533***
	(0.000681)	(0.00832)	(0.00358)	(0.000799)	(0.00153)
Precipitation	-8.90e-06***	-0.000121***	-2.35e-05*	3.93e-06	8.25e-07
	(2.99e-06)	(3.14e-05)	(1.35e-05)	(3.23e-06)	(7.12e-06)
Deforestation	-0.000445	-0.0342*	-0.0205***	-0.00385**	-0.00887***
	(0.00194)	(0.0193)	(0.00571)	(0.00166)	(0.00284)
PM2.5	-0.00259***	-0.0174***	-0.00117***	-0.000937***	-0.00272***
	(0.000101)	(0.00106)	(0.000340)	(0.000113)	(0.000233)
Slope	-0.000222	-0.00597***	-0.00110**	-0.00167***	-0.00365***
	(0.000144)	(0.00130)	(0.000482)	(0.000141)	(0.000293)
gender	-0.0156***	-0.398***	0.273***	0.00197	0.0102
	(0.00343)	(0.0375)	(0.00937)	(0.00323)	(0.00648)
age	-0.000623***	-0.00425***	-0.00660***	-0.000140	-0.000433**
	(0.000120)	(0.00122)	(0.000405)	(0.000102)	(0.000200)
education	0.00182*	0.0166	0.0237***	0.00987***	0.0186***
	(0.000987)	(0.0108)	(0.00428)	(0.00126)	(0.00261)
HH_size	0.0164***	0.175***	0.0290***	-0.00845***	-0.0169***
	(0.000698)	(0.00856)	(0.00327)	(0.000765)	(0.00166)
ethnicity	-0.0108***	0.0116	0.0539***	0.0493***	0.0985***
	(0.00395)	(0.0384)	(0.0160)	(0.00443)	(0.00910)
2012.year	-0.00857**	-0.0484	-0.0456***	-0.00181	-0.0147**
	(0.00328)	(0.0365)	(0.00840)	(0.00354)	(0.00665)
2014.year	-0.00749**	0.0303	-0.0663***	0.0201***	0.0374***
	(0.00311)	(0.0361)	(0.0101)	(0.00427)	(0.00811)
Constant	0.482***	10.48***	8.528***	0.602***	1.313***
	(0.00976)	(0.103)	(0.0290)	(0.00828)	(0.0177)
Observations	11,984	11,984	11,984	11,984	11,984
R-squared	0.176	0.119	0.115	0.173	0.179

Notes: this table indicates coefficients estimated from 'Pooled' Cross-section model using Ordinary Least Squares. *0.10, **0.05, ***0.01 significance level. Values in parentheses indicate standard errors corrected for cluster correlation at the commune level.

Moreover, a temperature or precipitation shock causes a decrease in the global indicator. A deviation of 1 °C (1000mm) from the temperature (precipitation) compared to its trend of the last five years corresponds to a decrease of the FSI by 0.004 (0.009), for a significance threshold of 1 %. Analysis for each dimension of food security does not say the opposite. Temperature shocks have negative effects on each of the dimensions: Production value (-5 %), PCCI (-0.7 %), Simpson index (-0.002) and Shanon index (-0.005). Similarly, for the deviation of precipitation levels except that the effect on the diversity dimension is not significant.

As shown in the section above, the effect of deforestation on food security is ambiguous because its function is to smooth income (consumption) on the one hand and to reduce ecological services on the other. The results from Table 2.6 show that it impacts each dimension but the effect on the overall indicator not being significant. Pollution has negative effects on the overall FSI indicator and all of these dimensions. These effects are statistically significant at the 1% level. We will provide a thorough interpretation of the results of these two variables after taking into account the endogeneity problem they present.

The average slope of agricultural land plays a very important role in the development of agricultural practices which are the main key factors of food security. There is a negative effect of high slope agricultural areas on the overall indicator of food security and on each of its dimensions. A high slope necessarily requires additional efforts to increase the agricultural yield which conditions the value of agricultural production. In addition, self-consumption plays an important role in the consumption basket of rural households. So, a shock on the agricultural yield would lead to a decrease in terms of the number of calories consumed. As the household income is affected because of the value of agricultural production, the latter is restricted to having access to several foodstuffs, so the diversity dimension is also negatively affected.

Regarding sociodemographic characteristics, we observe that households with chief woman are relatively less food secure than men. However, there is no significant difference in terms of dietary diversification between men and women. If the difference existed, it would be positive, which would indicate that women tend to diversify their food basket more than men. Also household with woman as household head tend to access more to dietary than other. Education of head household plays a positive role in food security index and each of its dimension, specifically the diversification of consumption and the number of calories consumed by the household. The effect of household size on food security is heterogeneous. First of all, size can be considered as a labor factor for an agricultural household and thus contribute to the improvement of agricultural production. This is observed in column (2) where one more individual in the household has a positive effect on the value of agricultural production (16%). However, household size is not favorable to diversity dimensions. This result is consistent with both diversity indicator we use: Simpson and Shanon index. Indeed, the larger the household size, the lower the food intake of an individual in this household is diversified. It would be more expensive for a large household to diversify their diet because it will require a significant amount of each food for it to be sufficiently consumed by each member of the household. Column (2) and (3) shows that the positive effect of size on the value of agricultural production and per capita calories intakes outweigh its negative effects on diversity dimensions. This translates into a positive total effect on the food security indicator.Kinh group have more access to food and diversify their consumption basket relatively to minority ethnic groups.

6.1 Endogeneity issues

Deforestation and air pollution are subject to endogeneity issues for many reasons explained above. Tables 2.7 and 2.8 show the results from control function approach to take into account this concern. Reduced forms estimation are summarized in table 2.7. Results from estimation of reduced forms (11) and (12) are shown respectively in column 1 and 2. Our instruments are very relevant and statistically significant at 1%. The deforestation and pollution of previous years have a significant and positive impact on current levels of deforestation and pollution. The marginal effect is non-linear depending on the lag considered. The amplitude is greater when the lag is close to the year under consideration. An increase of one km2 in deforestation observed in the years t-1, t-2 and t-3, increases respectively the current deforestation by 0.54, 0.27 and 0.30. For deforestation, the non-linearity is explained by the decrease in the forest stock as it is depleted and thus reduces the potential of forest that could be deforested in nexts years. Also, An increase of one $\mu g/m3$ in PM2.5 concentration observed in the years t-1, t-2 and t-3, increases respectively the current PM2.5 concentration by 0.47, 06. and 0.23 $\mu g/m3$. On the other hand, wind speed reduces the concentration of fine particles. Indeed, an increase of $1 m.s{-}1$ in the wind speed of a commune leads to a reduction in the concentration of fine particles by 0.52 $\mu g/m3$. Table 2.8 shows the results after taking into account for endogeneity issues about deforestation and air pollution variables. For deforestation, this correction allows to extract income effect in its global effect observed in table 2.6.[40]

[40] The exclusivity condition of deforestation instruments is confirm only for accessibility dimension (column (3) because of the significance of $u1$ and not for other dimensions. At the same time, instruments for pollution respect exclusivity condition for each dimensions except for accessibility. We’re not sure about this result. Indeed, our pollution and deforestation variables are not measured at the same level of disaggregation with our dependent

Table 2. 7: Estimation of reduced forms equations

VARIABLES	(1) deforestation	(2) PM2.5	(3) PM2.5
deforest(t-1)	**0.537*** **		
	(0.110)		
deforest(t-2)	**0.271*** **		
	(0.0958)		
deforest(t-3)	**0.296***		
	(0.155)		
pollution(t-1)		**0.468*** **	**0.462*** **
		(0.0112)	(0.0115)
pollution(t-2)		**0.357*** **	**0.338*** **
		(0.0171)	(0.0178)
pollution(t-3)		**0.233*** **	**0.254*** **
		(0.0109)	(0.0114)
wind Speed			**-0.518*** **
			(0.0493)
Controls	**yes**	**yes**	**yes**
Constant	-0.0946**	-0.0433	1.369***
	(0.0431)	(0.0655)	(0.144)
Observations	12,085	12,102	11,939
R-squared	0.529	0.990	0.990

Notes: this table indicates coefficients estimated from reduced equations by 'Pooled' Cross-section model using control function approach. *0.10, **0.05, ***0.01 significance level. Values in parentheses indicate standard errors corrected for cluster correlation at the commune level. Controls include all risks variables excepted deforestation and pollution, education, age head, female head, household size ethnicity, year 2012, and year 2014.

Marginal impact of deforestation in PCCI has been multiplied by 2. The diminishing of vegetation cover from 1 km2 decreases per capita calories intakes by 4%. Similarly, the marginal impact of deforestation on diversity in consumption is significant and the magnitude has increased (from -0.0037 in table 2.6 to 0.0051 in table 2.8). Regarding air pollution, the effects on food security index and each of its dimension do not really change after correcting for endogenous.

variables (food security). The risk variables are measured at the commune level while the dimensions of food security are calculated at the household level. Thus, the endogeneity bias is partially mitigated.

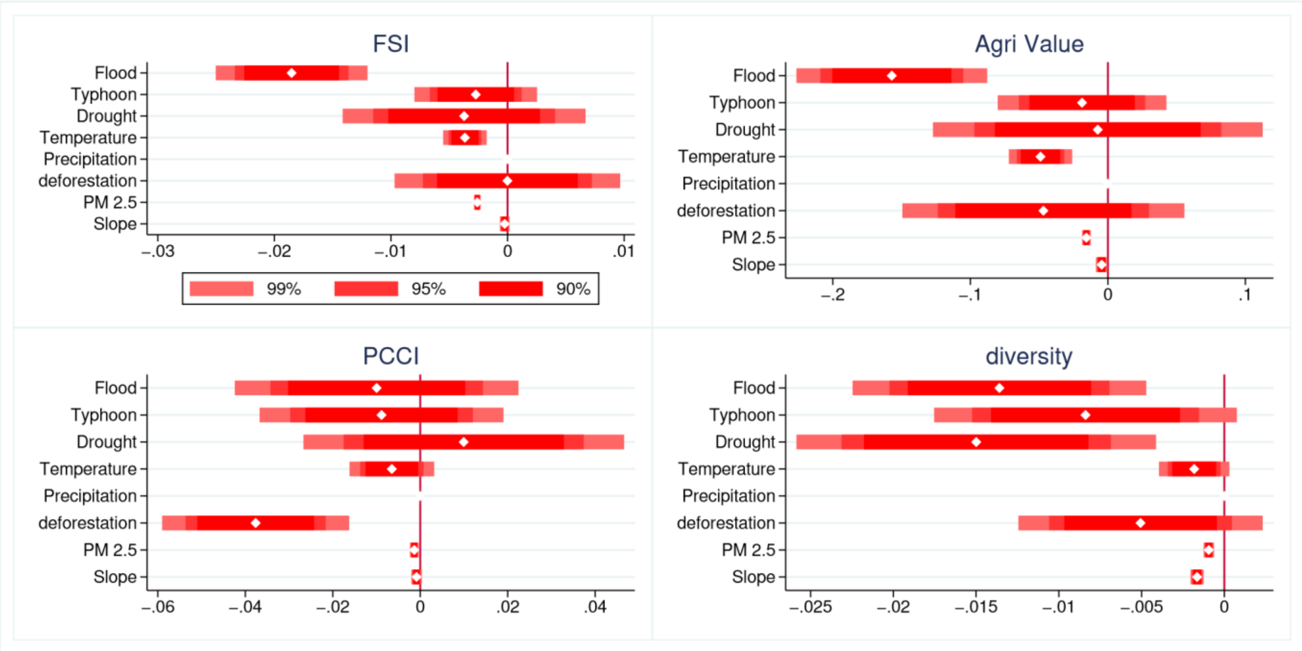
Table 2. 8: Food security, weather shocks and environment risk: IV+ Pooled cross section estimation

	(1)	(2)	(3)	(4)	(5)
VARIABLES	FSI	Production value	PCCI	Simpson index	Shanon index
Flood	-0.0202***	-0.201***	-0.0137	-0.0131***	-0.0329***
	(0.00290)	(0.0288)	(0.0130)	(0.00305)	(0.00599)
Typhoon	-0.00329	-0.0424*	-0.0111	-0.00932**	-0.0192**
	(0.00200)	(0.0216)	(0.0104)	(0.00365)	(0.00748)
Drought	-0.00311	-0.0228	0.000429	-0.0148***	-0.0314***
	(0.00431)	(0.0445)	(0.0127)	(0.00400)	(0.00835)
Temperature	-0.00355***	-0.0419***	-0.00602*	-0.00146*	-0.00467***
	(0.000759)	(0.00784)	(0.00318)	(0.000830)	(0.00154)
Precipitation	-8.09e-06**	-8.92e-05**	-2.74e-05**	3.35e-06	-3.04e-07
	(3.20e-06)	(3.46e-05)	(1.29e-05)	(3.43e-06)	(7.43e-06)
deforestation	0.0102	0.0237	-0.0665***	-0.0245**	-0.0552***
	(0.00780)	(0.0845)	(0.0240)	(0.00979)	(0.0187)
PM2.5	-0.00291***	-0.0235***	-0.00110***	-0.000928***	-0.00268***
	(0.000104)	(0.00122)	(0.000329)	(0.000114)	(0.000242)
slope	-0.000392**	-0.00910***	-0.000705	-0.00148***	-0.00325***
	(0.000147)	(0.00132)	(0.000464)	(0.000186)	(0.000376)
gender	-0.0308***	-0.304***	-0.0725***	0.00221	0.0108
	(0.00376)	(0.0381)	(0.00934)	(0.00341)	(0.00691)
age	-0.000430***	-0.00365***	-0.00421***	-0.000151	-0.000472**
	(0.000125)	(0.00121)	(0.000380)	(0.000104)	(0.000195)
education	0.00122	-0.000923	0.0280***	0.00949***	0.0176***
	(0.00118)	(0.0132)	(0.00417)	(0.00129)	(0.00268)
HH size	0.0139***	0.158***	-0.0141***	-0.00836***	-0.0168***
	(0.000725)	(0.00881)	(0.00219)	(0.000834)	(0.00182)
ethnicity	-0.0210***	-0.134***	0.0509***	0.0511***	0.102***
	(0.00398)	(0.0420)	(0.0145)	(0.00447)	(0.00932)
u1	-0.0131	-0.0556	0.0540**	0.0247**	0.0543***
	(0.00802)	(0.0888)	(0.0258)	(0.00970)	(0.0190)
u2	0.00786**	0.0546	0.0135*	-0.00461	-0.0129
	(0.00349)	(0.0367)	(0.00721)	(0.00407)	(0.00885)
2012.year	-0.0112***	-0.0760*	-0.0595***	-0.00229	-0.0155**
	(0.00374)	(0.0389)	(0.00921)	(0.00352)	(0.00667)
2014.year	-0.0104***	-0.00680	-0.0792***	0.0193***	0.0360***
	(0.00314)	(0.0333)	(0.0111)	(0.00393)	(0.00751)
Constant	0.557***	10.29***	8.827***	0.601***	1.312***
	(0.00933)	(0.0999)	(0.0245)	(0.00877)	(0.0186)
Observations	11952	11952	11952	11952	11952
R-squared	0.18	0.13	0.064	0.175	0.181

Notes: this table indicates coefficients estimated from structural forms by 'Pooled' Cross-section model using control function approach. *0.10, **0.05, ***0.01 significance level. Values in parentheses indicate standard errors corrected for cluster correlation at the commune level.

We summarize our results on figure 2.2 by plotting the marginal effects of risks variables on food security index and each of its dimensions. Overall, the significance and the marginal effect of environmental or climatic risk on household food security depends not only on the risk under consideration but also on the food security dimension. Diversity dimension tends to be most affected by risks variable than other dimensions of food security.

Figure2. 2: Food security, environmental and climates risks association



To assess the change of FSI and its dimensions over time, we use panel random effect estimation. Among our explanatory variables, there are variables that do not vary a lot (deforestation) and even non-variant (slope). Thus, the estimation with the fixed-effect model will not make it possible to know the effect of these variables. Results from table A2.4 confirm that risk variables explain the difference in food security status between households and its changing over the three periods considered (2010, 2012 and 2014). There is no important difference with pooling cross section analysis (cf. table 2.8) in terms of sign and magnitudes of risk variables.

6.2 Food security stability change between households and over time

Table 2.9 presents the result of the estimation of equation 15 with the ordered probit model. Remember that the dependent variable is the probability to belong to a given tercile group. For each dimension, T1 is defined as the group of the least secure, T2 moderately secure and T 3 most secure. In the table 2.9, we do not have the marginal impacts directly. However, the sign of the coefficient is the same as that of the marginal impacts. Thus, we will interpret the impact of the risk variables in terms of sign and their statistical significance. Among our risk variables, it is noted that the occurrence of floods, temperature deviations, air pollution, and large slopes reduce the probability of an individual to have a better state of food security (cf. column 1). These variables are significant at the 1% level. Nutritional inequalities are deep in areas with high climatic and environmental risks. The other risk variables are not significant. The analysis of the different dimensions does not say the opposite. In Column 2, the dependent variable is the probability that a household belongs to a tercile group according to the value of its agricultural production. In addition to the factors that were significant for the first column, significant rainfall deviations impact negatively the likelihood that a household will be in a better and stable nutritional status. In column 3, we are interested in the accessibility dimension that is reflected in this model by the inequality in households' consumption. The results show that our risk variables, apart from the occurrence of typhoons and droughts, reduce the probability of a household being in the group of households that have more access to sufficient food in terms of per capita calories intakes. Finally, in columns 4 and 5, we see the same results for stability in the diversification of consumption. Here, all natural disaster variables are statistically significant at the 1% level with negative effects on the likelihood that an individual will further diversify his consumption basket. Only the deviation of the average temperature level is not significant even if its sign corresponds to our expectation.

In panel analysis, the objective is to take into account the temporal dimension of our data, which will allow us not only to compare the groups of households with each other but also to monitor the evolution of the nutritional status of each household over time. Table A2.5 confirms the results found in cross section. It can therefore be said that climatic and environmental risks increase nutritional inequalities among individuals and affect the stability of the nutritional status of rural households over time.

All these results are in phase with our expectations, i.e. living in a risky area increases the instability of the nutritional status of households. This result is true for all dimensions of food security. In fact, households with better nutritional status in any year are very vulnerable to climate and environmental risks in the following years. The last tercile group (T3) may see their nutritional status deteriorated at the occurrence of climatic shocks or because they live in an area that presents a high risk in terms of deforestation, pollution or even unfavorable to agricultural practice (high slope of land). Similarly, for households with poor nutritional status, there is a risk of trapping this situation.

VII. Conclusion and policies recommendations

Vietnam is a country with a high environmental risk and agriculture remains the key sector that employs rural households. In this study, we analyze the association between environment risks factors and food security of rural households. Food security is understood in all four dimensions (availability, accessibility, diversity and stability) through composite index. In addition, we deal with endogeneity concern of some risk variables (deforestation and pollution), which could hinder this link, using control function method by **Wooldridge (2015)**.

Our results show that living in risky areas affects negatively nutritional status of rural households. The magnitude and significance of this link depends on the nature of the risk on the one hand and the dimension of food security considered on the other. Among three natural disasters considered, only flood impact negatively global food security index (FSI). While, Flood and typhoon have negative effect on agriculture production value; three natural disasters are detrimental for diversity dimension and none of these disasters have an effect on accessibility dimension. About temperature and precipitation deviations, both of these variables have negative effect on FSI and each of its components except for diversity dimension, which is only affected by temperature deviation. Also, availability dimension is most affected than other by these two weather shocks. The effect of deforestation must be interpreted with caution because deforestation could increase food production by extensification process but also diminished ecological services and limit their access to households. Our findings confirm this ambiguity. We find that deforestation affects negatively accessibility and diversity dimensions but have no effect on production value. Air pollution significantly explains all components of food security. The main channel that would explain this link would potentially be the health status of people living in a polluted area that would necessarily affect their productivity (availability dimension) and their ability to consume (accessibility).

Table 2. 9: Stability of food security, weather shocks and environment risk: IV+ ordered probit estimation

	(1)	(2)	(3)	(4)	(5)
VARIABLES	FSI	Production Value	PCCI	Simpson index	Shanon index
Flood	-0.215***	-0.169***	-0.0289	-0.126***	-0.174***
	(0.0294)	(0.0271)	(0.0335)	(0.0396)	(0.0330)
Typhoon	-0.0277	-0.00676	-0.0356	-0.0949***	-0.0916***
	(0.0275)	(0.0268)	(0.0289)	(0.0339)	(0.0325)
Drought	-0.0301	-0.0235	0.0221	-0.118***	-0.128***
	(0.0500)	(0.0457)	(0.0441)	(0.0318)	(0.0378)
Temperature	-0.0432***	-0.0538***	-0.0238**	-0.0152	-0.0194*
	(0.00863)	(0.00764)	(0.0120)	(0.00998)	(0.0104)
Precipitation	-7.66e-05**	-0.000126***	-7.77e-05*	8.63e-05***	5.01e-05*
	(3.36e-05)	(3.68e-05)	(4.01e-05)	(3.04e-05)	(2.82e-05)
Deforestation	-0.00485	-0.0709**	-0.116***	-0.0515**	-0.0531***
	(0.0345)	(0.0337)	(0.0274)	(0.0257)	(0.0206)
PM2.5	-0.0279***	-0.0165***	-0.00369***	-0.00873***	-0.0123***
	(0.00145)	(0.00136)	(0.00103)	(0.00114)	(0.00102)
Slope	-0.00242	-0.00723***	-0.00315**	-0.0150***	-0.0159***
	(0.00175)	(0.00170)	(0.00150)	(0.00171)	(0.00147)
Gender	-0.161***	-0.391***	0.841***	0.0171	0.0353
	(0.0301)	(0.0326)	(0.0350)	(0.0305)	(0.0294)
Age	-0.00502***	-0.00183	-0.0202***	-0.00202**	-0.00194**
	(0.00158)	(0.00127)	(0.00111)	(0.000996)	(0.000976)
education	0.0176*	0.0205*	0.0592***	0.0936***	0.0805***
	(0.0103)	(0.0111)	(0.0100)	(0.0128)	(0.0122)
HH size	0.174***	0.163***	0.0857***	-0.0624***	-0.0701***
	(0.0102)	(0.0102)	(0.00797)	(0.00787)	(0.00700)
Ethnicity	-0.221***	-0.0372	0.156***	0.410***	0.400***
	(0.0448)	(0.0532)	(0.0466)	(0.0499)	(0.0432)
u1	-0.0341	0.0393	0.0572*	0.00423	-0.00761
	(0.0501)	(0.0475)	(0.0334)	(0.0326)	(0.0301)
u2	0.0330***	0.0325***	0.0216*	0.0234***	0.0272***
	(0.00862)	(0.00765)	(0.0127)	(0.00848)	(0.00796)
2012.year	-0.114***	-0.0538	-0.195***	-0.00831	-0.0763**
	(0.0352)	(0.0336)	(0.0309)	(0.0365)	(0.0386)
2014.year	-0.136***	-0.000839	-0.231***	0.186***	0.158***
	(0.0348)	(0.0337)	(0.0295)	(0.0436)	(0.0471)
/cut1	-1.148***	-0.897***	-0.226***	-0.825***	-1.001***
	(0.133)	(0.126)	(0.0850)	(0.0761)	(0.0736)
/cut2	-0.174	0.0138	0.706***	0.150*	-0.0143
	(0.133)	(0.129)	(0.0796)	(0.0785)	(0.0724)
Observations	11859	11859	11859	11859	11859
Pseudo R-squared	0.0708	0.0484	0.0520	0.0622	0.0667
Wald Chi2(17)	2577	3555	8476	4044	3069
Prob Chi2	0	0	0	0	0

Notes: this table indicates coefficients estimated from structural forms by 'Pooled' Cross-section model using control function approach. ∗0.10, ∗∗0.05, ∗∗∗0.01 significance level. Values in parentheses indicate standard errors corrected for cluster correlation at the commune level.

Unfortunately, the accessibility dimension is not perfectly measured because we do not have information on the amount of calories actually consumed per household but rather on the amount of food purchased in the household. We therefore make the assumption that all the quantity purchased is actually consumed. Higher slope tends also to deteriorate household food security status. This is true for all component of food security but the magnitude effect is more important for availability dimension. Finally, these risks variables have negative effects on the stability of global food security index and all of its components (availability, accessibility and diversity). We can note the PM2.5 concentration and higher slope effects are persistent on all food security components considered.

Environmental risk factors are among the main factors that slow down Vietnamese rural households' ability to achieve a better nutritional status in all its dimensions (availability, accessibility, diversity and stability). Then, political intervention is needed to make rural households more resilient to these risk factors. First, think about the diversification of the income portfolio of rural households with the aim of reducing their dependence on the income of agriculture, which is conditioned by weather shocks. To facilitate access to foods, it will be necessary to create opportunities for them to relax their liquidity constraint which limits their access to various quality foods. Relaxation of liquidity constraints may be possible through the development of microfinance activities in rural areas or social protection through Weather index insurance for agriculture (**Barnett and Mahul, 2007**). And government must boost mechanisms to fight climate change by setting up more modern irrigation and drainage systems. Or seasonal weather services to anticipate temperature and precipitation shocks. The fight against deforestation and pollution are also to be encouraged. Moreover, in the implementation of policies to improve agricultural yield, a favor is given to farmers whose farms are in areas with unfavorable geographical characteristics (a fairly high average slope). Indeed, households residing in areas where the average slope of farmland is quite high, must make more effort than others to have better productivity. Also, Access to modern inputs remains a necessity for rural households.

However, our analysis has some limitations. The data we use are not purely nutritional and therefore limit the measurement of the different dimensions of food security. Also, due to a lack of data, we do not test the above-mentioned mechanisms that can mitigate the effect of the risks on the nutritional status of rural Vietnamese households. Future studies could use nutritional survey data and test the effectiveness of the set of policy recommendations to identify the best intervention policies.

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APPENDIX

PCCI calculation

TCI

In our analysis accessibility dimension of food security is measured with Total Calories Intakes (TCI) by household. TCI measures total nutritional intake for each food item consumed by household. For each household, VHLSS provides information about all of food items consumed during the last twelve months. Otherwise one section is dedicated to consumption expenditure during festive periods which are high food consumption period. We are information about quantity and expenditure value by items consumed. Thus we use conversion table from Vietnamese National Institute of Nutrition in 2007 (Table A1) to convert quantity consumed to TCI for each item.

Limits of VHLSS data

VHLSS isn't nutritional survey then there is not easy to make nutritional analysis because of data limit. Some foods items have not information about quantity consumed. Only expenditure value is available. For these last ones, we follow method elaborated by **Hoang et al. (2009)** and **Thi et al. (2018)**:

- First, we compute the median of one calorie price[41] of food items for which both quantity (and thus the corresponding TCI value) and expenditure value are available.
- Second, for each food item with only expenditure value, TCI is approximate by dividing expenditure value by the median calorie price from group of this item.

Another limit of nutritional data from VHLSS is the fact that information about quantity and expenditure of food items are those purchased and not directly consumed by household. The last information is the best to understand accessibility dimension of food security. However, expenditure or quantity purchased for one food item is strongly correlated with the actual consumption of that food. So our approach can be acceptable.

[41] Price of one calorie correspond to the ratio between expenditure value and total calorie intake for this item. This calculation is desegregated by geographic unit and consumption period (festive or non-festive)

Equivalence scales (ES)

It is difficult to make nutritional status comparison across individuals in our sample since TCI is computed household level while households differ in size and composition (age structure). Thus, for best quantitative analysis is necessary to take into account these elements in TCI calculation. Common practice use equivalence scale to make households comparable by normalizing TCI value at household level by equivalence scales. This method allows to switch from TCI by household to its corresponding value at a person's level called Per Capita Calorie Intake (PCCI).

Table A2. 1: Conversion table from National Institute of Nutrition (2007).

item	groupe	item code	Food type	gram	kcal
1	Cereal and other starches	101	Ordinary rice	1000	353
1	Cereal and other starches	102	Glutinous rice	1000	355
1	Cereal and other starches	103	Corn/maize	1000	364
1	Cereal and other starches	104	Cassava	1000	156
1	Cereal and other starches	105	Potatoes	1000	108,8
1	Cereal and other starches	106	Bread, wheat, flour	1000	301,5
1	Cereal and other starches	107	Noodle, pho noodle,instant rice soup	1000	358
1	Cereal and other starches	108	Rice noodle	1000	340
1	Cereal and other starches	109	Vermicelli	1000	128,5
2	Meat Fish tofu rich protein	110	Pork	1000	395,6
2	Meat Fish tofu rich protein	111	Beef	1000	123,3
2	Meat Fish tofu rich protein	112	Buffalo's meat	1000	123,3
2	Meat Fish tofu rich protein	113	Chicken	1000	175,9
2	Meat Fish tofu rich protein	114	Duck and other poultry meat	1000	126
2	Meat Fish tofu rich protein	115	Other meat	1000	x
2	Meat Fish tofu rich protein	116	Processed meat	1000	325,9
3	Fats and oils	117	Fat and oil	1000	927
2	Meat Fish tofu rich protein	118	Fresh fish, shrimp	1000	90
2	Meat Fish tofu rich protein	119	Dried and processed fish and shrimp	1000	240,9
2	Meat Fish tofu rich protein	120	Other seafood (crab, snails etc.)	1000	x
2	Meat Fish tofu rich protein	121	Chicken or duck eggs (per one)	50	7,8
2	Meat Fish tofu rich protein	122	Tofu	1000	98
4	Vegetables	123	Peanuts, sesame seeds	1000	544,5
4	Vegetables	124	Beans	1000	314,2
4	Vegetables	125	Fresh peas	1000	73,5
4	Vegetables	126	Water morning glory	1000	21
4	Vegetables	127	Kohlrabi	1000	30
4	Vegetables	128	Cabbage	1000	37
4	Vegetables	129	Tomatoes	1000	37
4	Vegetables	130	Other vegetables	1000	x
5	Fruits	131	Oranges	1000	43

5	Fruits	132	Bananas	1000	83
5	Fruits	133	Mangoes	1000	29
5	Fruits	134	Other fruits	1000	x
8	Food Away From Home	135	Fish sauce and dipping sauce	1000	33,2
8	Food Away From Home	136	Salt	1000	0
8	Food Away From Home	137	Spices,powdered soup	1000	0
8	Food Away From Home	138	Food seasoning	1000	0
6	Sugar and drink	139	Sugar, molasses	1000	390
8	Food Away From Home	140	Cakes, jams, sweets	1000	402,6
7	Milk and other dairy product	141	Condensed milk,powdered milk	1000	354,4
7	Milk and other dairy product	142	Ice creams,yoghurtsa	1000	50
7	Milk and other dairy product	143	Fresh milk	1000	86,8
6	Sugar and drink	144	Liquor	1000	47
6	Sugar and drink	145	Beer	1000	47
6	Sugar and drink	146	Bottled & canned refreshment	1000	47
6	Sugar and drink	147	Instant coffeea	1000	0
6	Sugar and drink	148	Powdered coffee	1000	129
6	Sugar and drink	149	Powdered tea/instant tea	1000	0
6	Sugar and drink	150	Dried tea	1000	0
8	Food Away From Home	153	Outdoor meals	1000	x
8	Food Away From Home	154	Others	1000	x

The idea of PCCI is to get comparable numbers among households. Sometimes, PCCI is refered as adult equivalent calorie intake.

There are several methods to compute equivalence scale:

(i) **Household size**: This method consist to normalized consumption or welfare variable collected at household level by household size. It's generally used because of its simplicity.

(ii) **OECD** equivalent scales: The first method limit household demographic characteristics to household size only. While households could differs from gender and age composition. To deal it, OECDE integrate age in ES calculation:

$$ES_{OECDE} = 1+0.7* \textit{adult} +0.5* \textit{child} \qquad (16)$$

adult correspond to the number of adults other than the household head (age above to 18) and *child* is the number of children (below to 18) in the household whatever member gender. There is also modified OECDE equivalence scales which differs from the first one by the weight associated to *adult* (0.5) and *child* (0.3).

(iii) Method by **Aguiar and Hurst (2013)**: to compute ES, the authors purpose to take into account gender, age and household localisation (urban vs rural). This method consist to estimate separately ES according to geographical localisation and VHLSS wave: First, the following regression model is estimated separately by area of residence (urban vs rural):

$$log(TCI_i) = \gamma_0 + \gamma_1 gender_i + \gamma_2 Adult_i + \gamma_3 Child_{a,g,i} + \epsilon_i \quad (17)$$

where TCI_i is total household i calorie intake, $gender_i$ is the gender of the head of the household (*gender* equal to 0 ih HH is male and 1 otherwise), $adult_i$ is the number adult other than household head in the household other than the head, and $child_{a,g,i}$ counts the numbers of children by gender (*g*) and age categories (*a*: 0-2; 3-5; 6-13; and 14-17) in household *i*.

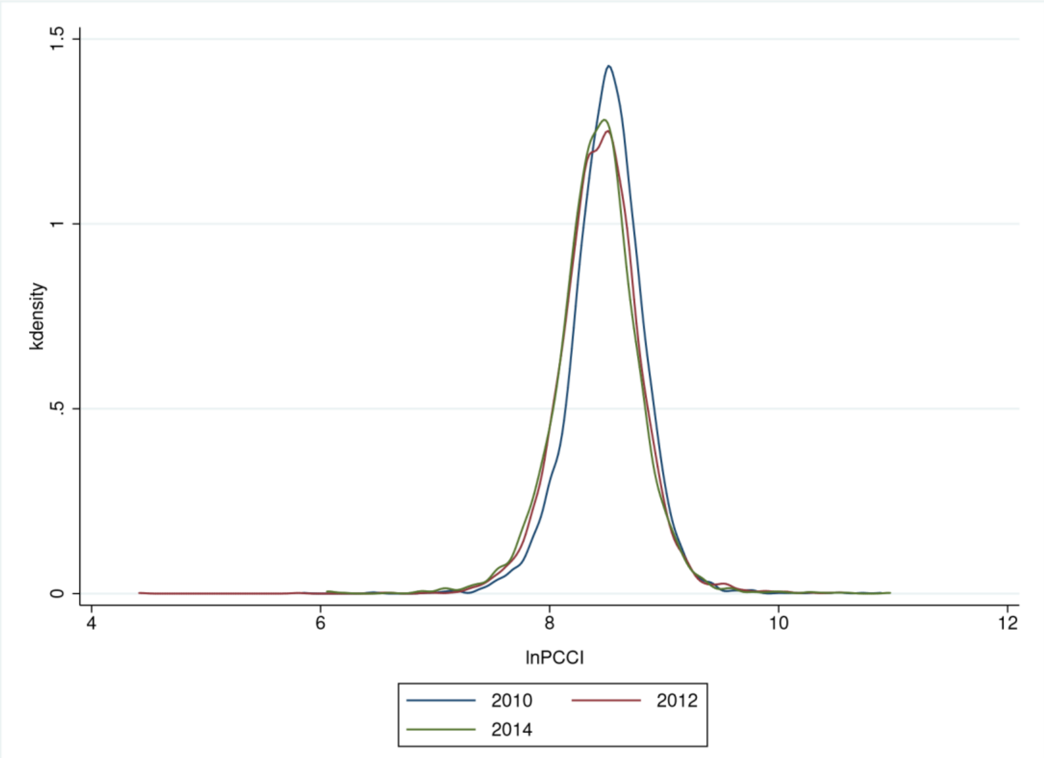
Second, TCI_i for singleton households (i.e. Household Head only which correspond to adult equivalent.) is predicted and correspond to ES_i:

$$ES_i = \begin{cases} e^{\gamma_0} & \text{if } HH \text{ gender is male} \\ e^{\gamma_0+\gamma_1} & \text{if } HH \text{ gender is female} \end{cases} \quad (18)$$

In this study, we use the last method from **Aguiar and Hurst (2013)** to generate household equivalence scale because of its complete relatively to others. This way to compute households *ES* is the same used by **Santaeulàlia-Llopis and Zheng (2017**) and **Thi et al. (2018)**.

Per capita calorie intake (PCCI) or adult equivalent calorie intake, is then computed as the ratio of household total calorie intake and household equivalence scale. We find that, on average, a rural Vietnamese household consumes about 4985 kcal per day over 2010-2014 period. This value is consistent and similar to other studies: **Thi et al. (2018)** (3631 kcal); FAO, 2015 (2713 kcal) and **Nguyen and Winters (2011)** (3212 kcal). The difference is marginal and can be explained by PCCI calculation method used in each study.

Figure A2. 1: Kernel distribution of PCCI logarithm



Diversity index

In literature, diversity dimension of food security is assessed using diversity index. Diversity index must allow to catch the variety of food items consumed by household. Generally, the number of food items or food groups in the household is used to compute diversity index. However, this way to compute diversity index doesn't capture the degree of concentration in household's food basket. Since, nutrient levels vary between food items and food groups, the weight of each food groups in total calories intake by household must be considered. To take into account this aspect, we follow **Nguyen and Winters (2011)** by using two type of dietary and production diversity index:

$$Simpson.index = 1 - \sum_i w_i^2 \tag{19}$$

where i identifies the food groups. We distinguish eight food groups[42]: *(i) Cereal and other starches, (ii) Meat, fish, tofu, rich protein, (iii) Fats and oils, (iv) Vegetables, (v) Fruits, (vi) Milk and other dairy products, (vii) Sugar and beverages, and (viii) Food away from home*. w_i is calorie share of food group i. Simpson's index

[42] For production diversity index, we identify 4 cultures: (i) Rice, (ii) Staple nonfood, (iii) Industrial crops and (iv) Fruits crops.

ranges from zero (no diversified) to one (more diversified). Otherwise, Shannon' index measures the concentration degree of food groups, and is measured as:

$$Shannon.index = -\sum_i w_i log(w_i) \tag{20}$$

It takes on values from zero to the value of log of the highest number of food groups.

Figure A2. 2: Simpson index distribution from VHLSS (2010-2014))

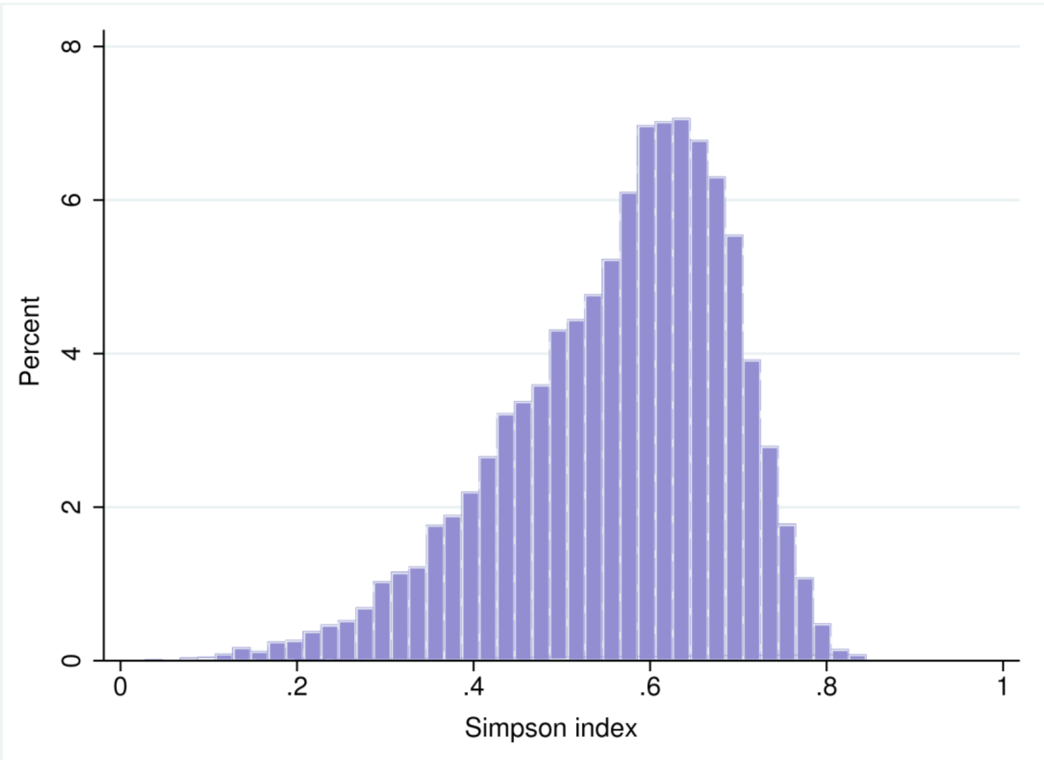
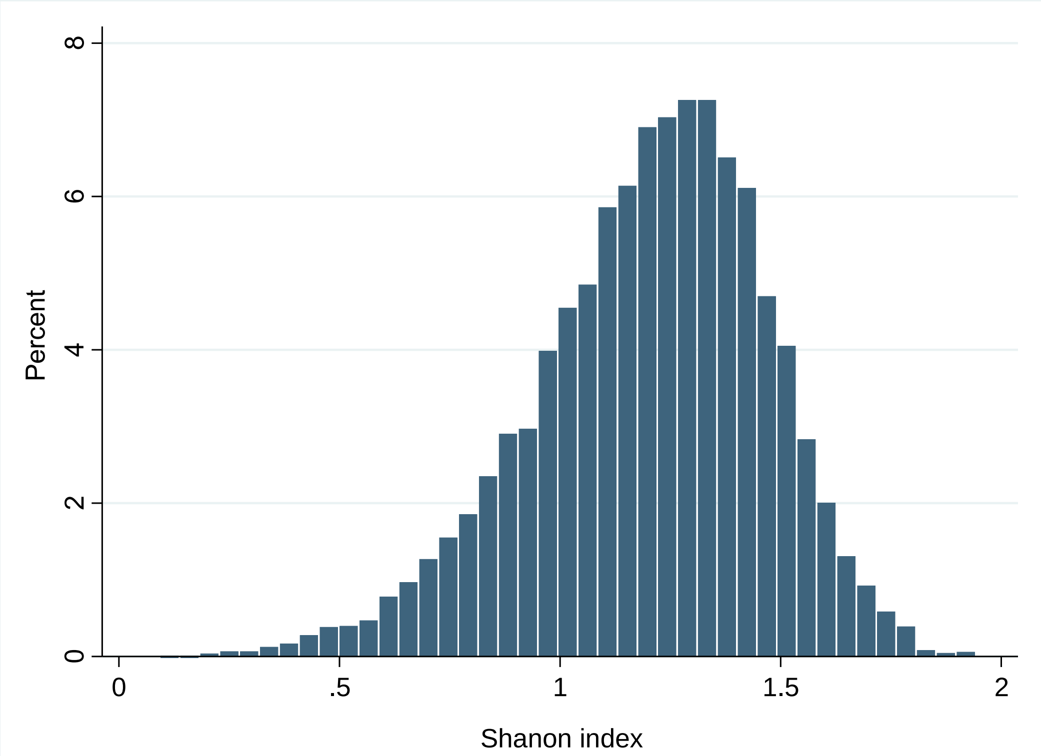


Figure A2. 3: Shanon index distribution from VHLSS (2010-2014)



PCA method

Table A2. 2: Correlation matrix of PCA variables

	Agriculture Area	Agriculture value	PCCI	Diversity
Agriculture Area	1.0000			
Agriculture value	0.5905	1.0000		
PCCI	0.0884	0.1529	1.0000	
Diversity	-0.0973	0.0860	0.1055	1.0000

Table A2. 3: Inertie of each PCA component

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	1.63784	0.56461	0.4095	0.4095
Comp2	1.07323	0.167653	0.2683	0.6778
Comp3	0.905574	0.522211	0.2264	0.9042
Comp4	0.383363		0.0958	1.0000

Estimation results

Table A2. 4: Food security, weather shocks and environment risk: IV+ Panel with random

	(1)	(2)	(3)	(4)	(5)
VARIABLES	FSI	Production value	PCCI	Simpson index	Shanon index
Flood	-0.0126***	-0.106***	-0.0146	-0.0104***	-0.0265***
	(0.00230)	(0.0178)	(0.0114)	(0.00302)	(0.00582)
Typhoon	-0.00286*	-0.0299*	-0.00983	-0.00766**	-0.0146**
	(0.00155)	(0.0158)	(0.00980)	(0.00325)	(0.00684)
Drought	-0.00401	-0.0415	0.00855	-0.0130***	-0.0268***
	(0.00271)	(0.0352)	(0.0139)	(0.00345)	(0.00737)
Temperature	-0.00154***	-0.0261***	-0.00459	-0.00115*	-0.00377***
	(0.000531)	(0.00543)	(0.00352)	(0.000687)	(0.00126)
Precipitation	-4.92e-06**	-7.37e-05***	-1.73e-05	1.97e-06	-2.47e-06
	(1.95e-06)	(2.16e-05)	(1.15e-05)	(3.73e-06)	(7.77e-06)
Deforestation	0.00175	-0.0337	-0.0331***	-0.00567**	-0.0123***
	(0.00257)	(0.0326)	(0.00824)	(0.00230)	(0.00426)
PM2.5	-0.00252***	-0.0173***	-0.00137***	-0.000905***	-0.00263***
	(0.000100)	(0.00117)	(0.000342)	(0.000118)	(0.000253)
Slope_mean	-0.000214	-0.00655***	-0.000817*	-0.00171***	-0.00378***
	(0.000153)	(0.00126)	(0.000474)	(0.000136)	(0.000289)
Gender	-0.0141***	-0.385***	0.273***	0.000863	0.00733
	(0.00358)	(0.0390)	(0.0100)	(0.00318)	(0.00653)
Age	-0.000612***	-0.00444***	-0.00665***	-0.000118	-0.000387**
	(0.000129)	(0.00146)	(0.000386)	(9.60e-05)	(0.000186)
education	0.00154*	0.0151	0.0234***	0.00973***	0.0185***
	(0.000876)	(0.0105)	(0.00410)	(0.00126)	(0.00260)
HH_size	0.0143***	0.157***	0.0282***	-0.00861***	-0.0173***
	(0.000612)	(0.00821)	(0.00351)	(0.000756)	(0.00165)
Ethnicity	-0.0122***	-0.0222	0.0537***	0.0470***	0.0931***
	(0.00381)	(0.0360)	(0.0155)	(0.00413)	(0.00871)
u1_re	-0.00246	0.0328	0.0301**	0.00566	0.0119
	(0.00281)	(0.0432)	(0.0144)	(0.00445)	(0.00879)
u2_re	0.00236***	0.0240***	0.00421	0.00265***	0.00592***
	(0.000574)	(0.00706)	(0.00405)	(0.000649)	(0.00151)
2012.year	-0.00317	0.0121	-0.0419***	-0.000645	-0.0116**
	(0.00199)	(0.0182)	(0.00837)	(0.00319)	(0.00584)
2014.year	-0.00420**	0.0686***	-0.0632***	0.0200***	0.0369***
	(0.00193)	(0.0256)	(0.00930)	(0.00392)	(0.00734)
Constant	0.482***	10.52***	8.536***	0.605***	1.319***
	(0.0100)	(0.107)	(0.0261)	(0.00865)	(0.0187)
Observations	11,859	11,859	11,859	11,859	11,859
Number of hid	8,588	8,588	8,588	8,588	8,588
R-squared	0.173	0.103	0.115	0.170	0.175

Notes: this table indicates coefficients estimated from structural forms of control function approach using panel with random effects model. *0.10, **0.05, ***0.01 significance level. u1_re and u2_re are residuals from reduced forms estimated with random effects model. Values in parentheses indicate standard errors corrected for cluster correlation at the commune level.

Table A2. 5: Stability of food security, weather shocks and environment risk: IV+ panel ordered probit with random effect.

VARIABLES	(1) FSI	(2) Production value	(3) PPCI	(4) Simpson index	(5) Shanon index
Flood	-0.346***	-0.250***	-0.0551	-0.180***	-0.122***
	(0.0558)	(0.0378)	(0.0418)	(0.0370)	(0.0457)
Typhoon	-0.0592	-0.0163	-0.0461	-0.100**	-0.110***
	(0.0423)	(0.0352)	(0.0352)	(0.0400)	(0.0417)
Drought	-0.0567	-0.0406	0.0358	-0.143***	-0.121***
	(0.0693)	(0.0706)	(0.0575)	(0.0422)	(0.0334)
Temperature	-0.0514***	-0.0735***	-0.0256*	-0.0156	-0.0130
	(0.0158)	(0.0101)	(0.0146)	(0.0123)	(0.0118)
Precipitation	-8.31e-05	-0.000140***	-8.50e-05*	6.04e-05*	9.53e-05**
	(6.05e-05)	(5.29e-05)	(4.52e-05)	(3.43e-05)	(3.95e-05)
Deforestation	-0.00184	-0.124***	-0.141***	-0.0597**	-0.0557**
	(0.0447)	(0.0394)	(0.0344)	(0.0240)	(0.0244)
PM2.5	-0.0538***	-0.0326***	-0.00471***	-0.0145***	-0.0100***
	(0.00282)	(0.00260)	(0.00119)	(0.00122)	(0.00136)
Slope	-0.00384	-0.0135***	-0.00382*	-0.0200***	-0.0188***
	(0.00325)	(0.00280)	(0.00195)	(0.00179)	(0.00187)
Gender	-0.337***	-0.761***	1.052***	0.0324	0.0144
	(0.0616)	(0.0718)	(0.0429)	(0.0338)	(0.0357)
Age	-0.00953***	-0.00398	-0.0252***	-0.00175	-0.00168
	(0.00317)	(0.00251)	(0.00127)	(0.00113)	(0.00114)
Education	0.0260	0.0347**	0.0742***	0.0995***	0.113***
	(0.0166)	(0.0172)	(0.0125)	(0.0138)	(0.0140)
HH size	0.297***	0.284***	0.104***	-0.0876***	-0.0773***
	(0.0197)	(0.0212)	(0.0104)	(0.00875)	(0.00887)
Ethnicity	-0.431***	-0.0790	0.179***	0.477***	0.486***
	(0.0872)	(0.0942)	(0.0556)	(0.0490)	(0.0576)
u1_re	-0.0464	0.148***	0.111*	-0.00907	0.00623
	(0.0568)	(0.0533)	(0.0633)	(0.0492)	(0.0380)
u2_re	0.0568***	0.0624***	0.0283*	0.0400***	0.0365***
	(0.0153)	(0.0120)	(0.0162)	(0.00921)	(0.00989)
2012.year	-0.136***	-0.0298	-0.237***	-0.0720	0.00676
	(0.0522)	(0.0503)	(0.0353)	(0.0450)	(0.0416)
2014.year	-0.199***	0.0762	-0.287***	0.201***	0.232***
	(0.0558)	(0.0583)	(0.0325)	(0.0540)	(0.0495)
Observations	11,859	11,859	11,859	11,859	11,859
Number of hid	8,588	8,588	8,588	8,588	8,588
Log-likelihood	-11341	-11663	-12194	-12022	-12084
Wald Chi2(17)	2262	1649	7355	4292	9360

Notes: this table indicates coefficients estimated from structural forms by panel ordered probit with random effect model using control function approach. *0.10, **0.05, ***0.01 significance level. Values in parentheses indicate standard errors corrected for cluster correlation at the commune level.

Chapter 3: MEASUREMENT AND ANALYSIS OF THE EFFECTS OF WEATHER CONDITIONS ON THE WELFARE OF THE HOUSEHOLDS IN MALI

Abstract

The chapter aims to assess the effects of weather conditions on the welfare of households. We focus our analysis on the case of Mali that faces major challenges in recent years like climate change and security. In Mali, most of household's income is more related to agriculture sector, which make them vulnerable to bad weather conditions. We take advantage of a unique dataset, a nationally representative household survey, from 2010 to 2018 that offers a very valuable instrument and source of household level data including at the regional level. This database is combined with georeferenced data about climate variables to lead our assessment. Our results show that the sensibility of consumption level to rainfall varies among the types of consumption and socioeconomic groups. First, our results show that the elasticity is higher for non-food consumption and much lower for food consumption. Second, we find suggestive evidence that poor households who are more located far from the capital (Bamako) and depend strongly on agriculture revenue are the most impacted by weather variability. From a policy standpoint, the results suggest that additional efforts should be done to reduce inequality and poverty among socioeconomic groups.

Keywords: Rainfall, Climate Change, Welfare, Poverty.

JEL classifications: Q54, D12, I30

I. Introduction

The purpose of the study is to estimate the effects of weather conditions on the welfare of the households in Mali. Mali is one of the driest countries in the world with a surface of 1,242,248 sq.km, two-thirds of which is a desert[43]. Due to its geographic characteristic, it is also severely affected by climate change and, in particular, by drought. According to the IPCC A2 scenario[44], Mali is ranked among the most at-risk countries with a drought severity index of -5, (calculated with the Palmer severity index). To examine the impact of climatic conditions on economic outcomes, we take advantage of a unique dataset, a nationally representative household survey that offers a very valuable instrument and source of household-level data, including at the regional level. This study seeks to expand the knowledge on how climate change affects economies and livelihoods in African countries.

The World Bank estimates that a hundred million people globally are at risk of falling back into poverty due to climate change. The most affected are concentrated in Sub-Saharan Africa and South Asia. Sub-Saharan Africa is indeed home to households most exposed to climatic shocks, given the highest incidence of extreme poverty. The projected demographic trends in this region, that is high fertility rates and population growth, may also add to challenges in alleviating extreme poverty soon.

Climate change has important implications for economic growth. Besides affecting the physical environment, climate change has considerable implications for economic growth. This is through various channels, including impact on economic sectors, such as agriculture, natural resources, tourism among others. Climate change affects human health through, for example, environmental pollution. Air pollution is already among the top ten causes of death in the advanced economies, while extreme weather leads to injury and loss of life. Human health affects productivity and thus economic output. Climate change leads to a higher probability of extreme weather events, like floods and droughts. Estimates suggest that a 1 percent increase in the area affected by drought can slow a country's growth by 2.7 percent per year and a 1 percent increase in the area experiencing extreme rainfall can reduce economic growth by 1.8 percent.[45] Such effects cause severe damages to livelihoods perpetuating poverty and inequality.

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[43] National Institute of Statistics

[44] The A2 scenario family is one of the IPCC's forecasting models in which it predicts a much more heterogeneous world: economic growth and the development of energy-efficient technologies vary greatly from region to region, and the population will reach 15 billion by the end of the century and continue to grow.

[45] https://ec.europa.eu/environment/integration/research/newsalert/pdf/359na1_en.pdf

Climate change could slow or even set back progress in poverty reduction in low-income countries. Mali is a country among those with the lowest social indicators in the world.[46] Climatic conditions, including lack of rainfall and frequent droughts, are among the factors that affect most people's lives and livelihoods in the country. 80 percent of the population are employed in agriculture and therefore are heavily dependent on climatic conditions. Furthermore, climate change will affect both those engaged in farming, but also urban or other vulnerable population through food prices and food insecurity. Agricultural production and farming lands are already affected by ongoing insecurity. The COVID pandemic has exacerbated the situation as the economic contraction has considerably reversed the progress in poverty reduction achieved in recent years. Moreover, lack of financial and technical capacities to manage climate risks also makes Malian population extremely vulnerable to weather conditions.

Difference channels and factors can play a role in increasing vulnerability of households to climatic shocks. Geographical location affecting the degree of exposure to extreme weather conditions plays an important role: regional location, living in rural or urban areas are likely factors defining the potential impact. It can also affect access to infrastructure and markets. Other factors such as education level, professional activity, access to assets and savings, income sources, expenditure structure can play a part in determining the impact of the weather on the welfare of a household. There is also evidence that women or female headed households are more vulnerable to poverty and thus to climate change. Increases in food prices due to drop in agricultural production because of climatic events will affect not only rural population employed in agriculture, but also those working in different sectors or urban population, especially, the poor ones. The poor are generally less protected against the impact of the climate change if compared to the rich.

The extent to which weather and climate change impact incomes and poverty depends on the extent of adaptation by households to emerging circumstances and available adaptive policies. Such policies can include building well-targeted and effective safety nets, improving access to credit and insurance markets, especially, for the poor, investing in irrigation and improved water management, measures to smooth the impact on food prices of climate shocks and others.

Our contribution is three-fold. First, our study contributes to understanding of the impact of the climate shocks and weather conditions on livelihoods of households in Sahel region. Second, we take advantage of a unique dataset, a nationally representative household survey that offers a very valuable instrument and source of household level data, including at the regional level. Indeed, in Mali, very few studies have considered in detail the relationships between welfare and rainfall

[46] https://www.wfp.org/countries/mali

variability. Third, we establish factors that are likely to make households more vulnerable to climatic risks.

This study suggests that climate change affects negatively the welfare of people by decreasing consumption levels and increasing poverty. We highlight the following key results. The average elasticity of household's consumption to rainfall is equal to 0.38% that means where rainfall is increasing by 1%; the level of consumption will increase by 0.38%. Interestingly, the sensibility of consumption level to rainfall varies among the types of consumption and socioeconomic groups. First, our results show that the elasticity is higher for non-food consumption (e.g. energy, transport, communication...) and much lower for food consumption. Second, we find suggestive evidence that poor households who are more located far from the capital (Bamako) and depend strongly on agriculture revenue are the most impacted by weather variability.

The government needs to put in place policies that improve resilience of agricultural production and households to declining rainfall, for instance by improvidng access to finance for poor households in rural areas. The government should also prepare to possible internal movement of population by improving urban planning, especially in the capital Bamako. These movements triggered by worsening economic conditions due to climate change could increase the risk of poverty in urban areas. Fast population growth will increase the challenge of building an economic and social infrastructure resilient to climate change. Adaptation strategies in sub-saharian Africal play a bigger role than migitation strategies (IMF Regional Economic Outlook, April 2020). This is because the Malian economy (as well as other sub-saharian countries) are dependent on climate-sensitive sectors – like agriculture and tourism.

The chapter proceeds as follows. Section II sets the stage by discussing the growing literature in the area of climate change and its impact on economic growth and poverty. Section III presents data and stylized facts. Section IV describes the methodology and presents results. Section V discusses policy options available for low-income countries in mitigating climate change and weather conditions. Section VI concludes.

II. Literature review

Existing studies showed that climate change is a major obstacle to the development process in developing countries specifically in Sub-Saharan Africa **(Slingo et al. 2005; Azzarri et Signorelli 2020).** Indeed, climate change will not only affect the income of people; it will also fuel the dynamic of people to fall into a poverty trap. Two main factors could explain Africa's greater vulnerability to climate shocks compared to other regions. First, their economies remain mostly undiversified, with most countries largely dependent on the agricultural sector – which remains highly subject to the variation of the weather **(Mendelsohn, Dinar, et Dalfelt 2000; IMF 2017)**. With a large segment of the active labor force still employed in the agriculture sector, this makes climate shocks a pivotal driver of changes in poverty and income inequality in Africa. Second, low resilience to climate shocks or a lack of adaptation strategies, as reflected in the large infrastructure gaps and limited access to financial services, makes it more arduous for populations to recover from damages caused by climate shocks **(IPCC 2007; McIntyre 2009; Müller et al 2011)**. This low resilience magnifies the economic and social consequences of climate shocks **(IMF, 2020)**.

Many channels could explain the vulnerability of households to climate variation: productivity, consumption, and opportunity channels **(Hallegatte et al. 2014).** Climate change may affect food systems in several ways ranging from direct effects on crop production to changes in food price levels and its volatility. There is no doubt that agriculture yields are strongly linked with climate conditions especially when coping strategies are lacking. Through a Ricardian model, **Mendelsohn, Nordhaus, et Shaw (1994)** found a nonlinear effect of temperature and precipitation on agriculture production. In their meta-analysis of 52 studies, **Knox et al. 2012** estimated the mean change in yield of all crops in Africa to be -8% by 2050. The projected impact differs by culture: -5% (maize), − 10% (millet), -15% (sorghum) and -17% (wheat). The negative impact of climate conditions on agriculture productivity are reflected in food prices. The projection by **(Porter et al. 2014)** suggests an increase in food prices by 3 to 84% due to climate change by 2050.

Moreover, changes and variation in energy and asset prices are also affected by weather shocks. Water stress reduces the availability of hydro energy generation and increases energy pricing. Besides, climate change effects through a disaster like a flood contribute to asset losses. **Lybbert and all 2004** find a low level of annual rainfall induce 25 to 35% of livestock mortality in Ethiopia. The same result is found by **(Clarke, Daniel J et Hill, Ruth Vargas 2013)** in Kenya context. In addition, during a crises, vulnerable population tend to liquidate productive assets to smooth the impact of a shock on their income and consumption **(Hoddinott, John 2006)**.

The impact of climate shocks on prices of food, energy, and assets lead to increase in the poverty incidence **(Ürge-Vorsatz et Tirado Herrero 2012).** Indeed, the poor spend a significantly of their income on food and energy than the non-poor. **Hallegatte et al. 2014** show that poor households in Sub-Saharan Africa spend 64% of their budget on food consumption while the non-poor spend 48%.

There are a number of studies on the relationship between climate shocks and households' welfare in Mali. Most of these studies are focused on the direct impact of climate change on agricultural production **(Butt et al. 2005; Morand et al. 2012; Traore et al. 2013; Toure, Diekkrüger, et Mariko 2016; Bakhtsiyarava, Grace, et Nawrotzki 2017; Traore et al. 2017)**. This analysis is original in this sense by estimating the elasticity of household consumption to rainfall variation. Also, we test the substitution effect in the consumption basket of households (food consumption and non-food consumption). Finally, we identify vulnerable groups who are most affected by weather conditions.

III. Data and stylized facts

3.1. Climate data

- **Climate variables include Temperature, Precipitation,** and **SPEI (**Standardized Precipitation-Evapotranspiration Index**).** These variables are from the Climate Research Unit (CRU TS version 4.04 – University of East Anglia). This database is one of the most widely used, particularly for work on climate change and its economic consequences **(Dell et al., 2014).** The raw geolocalized data from CRU TS refer to a grid of 0.5° latitude and longitude (approximately 50X50 km at the Equator). Each grid cell has one climate data for each month over the period **1901-2019** generated by interpolation[47].

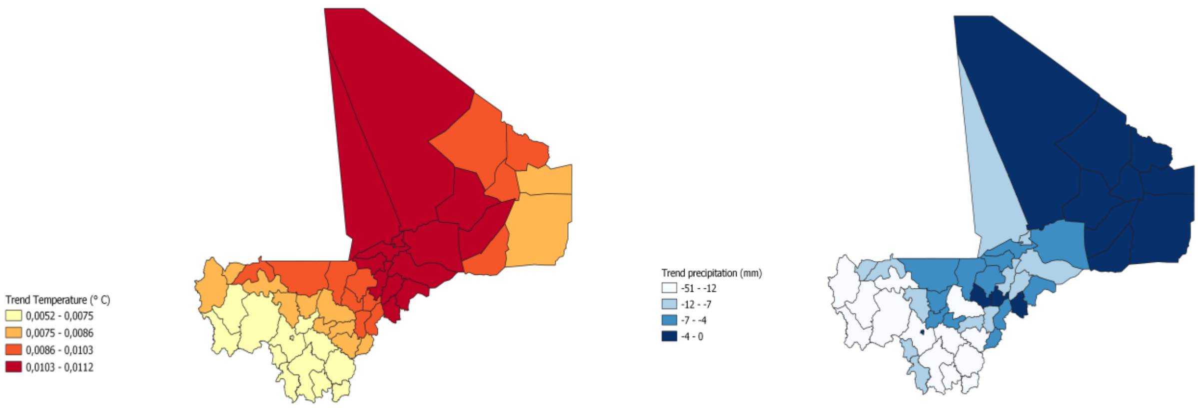
- **Temperature is increasing across all regions of Mali, while precipitation levels tend to decline.** In Figure 3.1, we show temperature and precipitation trends from 1901 to 2019 (**119 years**). For each region and both climate variables, the trend is obtained from estimating the following equation:

$$\boldsymbol{Y_t = \alpha + \beta . t + \varepsilon_t}$$

[47] The interpolation method is the same used by Olivier Santoni (2015). For each Mali county, we computed the average weighted of gridded data for all station belong tis county.

With Y_t climate variables (average annual temperature and annual cumulative precipitation), t year variable (1901, 1902,.., 2019); ε_t residual term. Parameter $\boldsymbol{\beta}$ is the measurement of trend, which measure the annual variation of temperature (precipitation) over the period 1901-2019.

Figure 3. 1: Temperature and Precipitation trends over 1901-2019



Source: Author calculation with CRU data

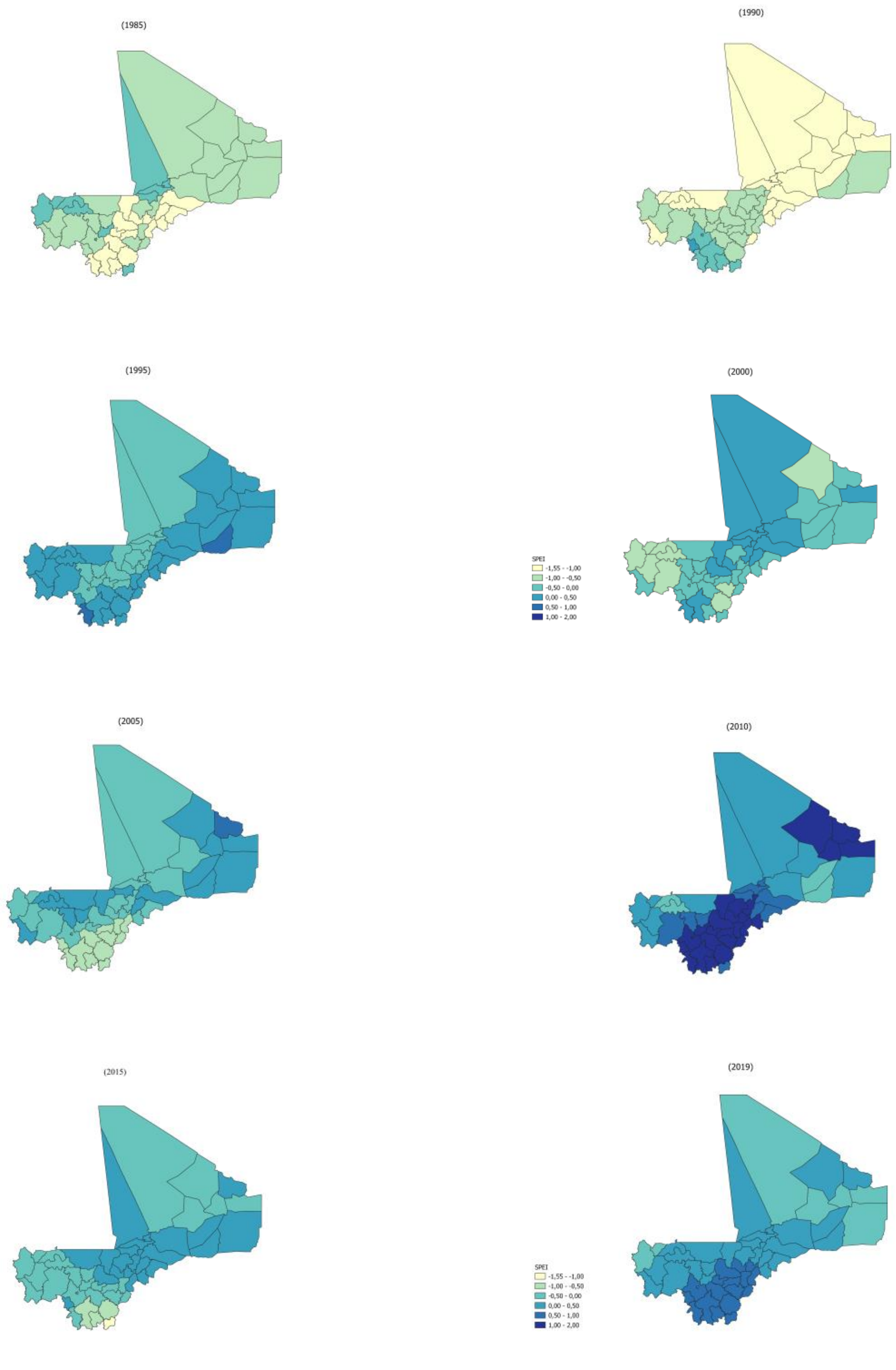
We found that all regions have seen their level of temperature (precipitation) increasing (decreasing) over the period. On average, the annual temperature increased by **1.07 °C** while the annual cumulative precipitation decreased by **-1191.19 mm.** However, the degree of climate change differs by region: Northern regions experience more global warming than southern regions. For example, the maximum temperature increase (0.0112°C which corresponds to a total increasing of **1.33°C=119*0.0112** over **1901-2019**) is seen in the region of Timbuktu while the minimum change (**0.6°C=119*0.005**) is observed in the southern region of **Sikasso**. Data on precipitation levels suggests that southern regions where the agriculture sector is developed have also experienced the most significant reduction in rainfall. Thus, climate change poses a serious risk to the agricultural sector development and food security.

- **Drought occurrence in Mali is regular and its intensity varies across regions and time**.

Drought is among the consequences of climate change in Mali. Drought is measured by Standardized Precipitation Evapotranspiration Index (SPEI) from CRU dataset that was developed by **Vicente-Serrano et al (2010).** This indicator measures the degree of humidity (dryness) of an area. It is defined as the difference between precipitation and evapotranspiration, which itself is a function of the level of temperature. According to **Vicente-Serrano et al (2010)**, this indicator has certain advantages relative to other existing measures. First, it is computed using both temperature and precipitation data. Second, it allows the comparison between regions characterized by different climatic seasonality. The negative level of SPEI index means a drought situation in the given locality.

Figure 3.2 shows the evolution of drought index across Mali regions from 1985 to 2019. Most of dry episodes are observed in **1985** and **1990** for all regions. From **1995 to 2019**, there is variation across regions and time. Indeed, most of the south region localities move from dry episodes to wet episodes from 2000 to 2010 while the same localities become dry in 2015. In table 3.1, we represent the distribution of SPEI across regions over 1901-2019. We can observe that most of Mali regions recorded the minimum value of SPEI, which correspond to severe drought episode, at the years 1983 and 1987 except Sikasso (2002) and Segou (2002). In addition, the SPEI index is very volatile for each region with a standard error of around 0.6.

Figure 3. 2: SPEI distribution across Mali regions over 1985-2019



Source: author's calculation with CRU data

Table 3. 1: SPEI value descriptive statistics across region and time over 1901-2019

Regions	SPEI min		SPEI max		Instability
	Value	Year	Value	Year	Standards deviation
Bamako	-1,66	1983	1,62	1967	0,65
Gao	-1,69	1987	1,37	1953	0,56
Kayes	-1,31	1980	2,05	1906	0,61
Kidal	-1,53	1983	1,59	2010	0,55
Koulikro	-1,53	1983	1,28	1928	0,60
Mopti	-1,51	1984	1,27	1953	0,59
Sikasso	-1,69	2002	1,24	1928	0,62
Segou	-1,65	2002	1,33	2010	0,60
Timbuktu	-1,29	1987	1,55	1918	0,57

3.2. Socio-economic data

In this study, we use households' data from EMOP (*Enquête Modulaire et Permanante auprès des Menages*) survey from 2011 to 2018[48]. The main objective of EMOP is to produce, on a regular and permanent basis, relevant indicators on the socio-economic situation of households to implement various sectoral policies. The results of the surveys are representative at the national and regional levels but also at the level of each area (Urban and Rural) with an acceptable level of accuracy[49]. All regions of Mali are included in the study except for Kidal because conflict limits the access to this region after the year 2012. This dataset is not a panel because households are not interviewed more than one time. Our analysis will be a "pooled cross-section" at the household level.

Table 3. 2: Survey samples

Years	Sample size	Urban	Rural	Poverty threshold (1000 FCFA)
2011	7095	2806	3727	172000
2013	5215	2225	2990	174000
2014	6057	2700	3357	175000
2015	5881	2717	3164	177000
2016	5915	2712	3203	175000
2017	5921	2709	3212	178343
2018	5674	2759	2915	181201

48 There is no survey in 2012 because of political crisis across the regions of Mali.
49. The EMOP's sample methodology proposes an allowable relative margin of error at the threshold of 10% and 15% for the national and regional indicators, respectively.

Nine sections are included in the questionnaire to understand the situation of each households: **(i)** ***Households' characteristics*** provides information on the age and gender of household member and their link with household head; matrimonial status; (ii) ***Education*** section provides information on the education of household members, level of schooling achieved, degrees and literacy; (iii) **Health** section provides information on the morbidity of certain diseases and the use of health facilities; (iv) a section on ***Employment*** provides information on employment indicators such as the duration of time worked in the last 12 months, the unemployment rate...; (v) ***Housing and Assets*** provides information on the characteristics of the dwelling such as type of housing, number of rooms, type of roof, type of amenities and household possessions; (vi) ***Migration and Remittances*** section gives migration flow within the household and the value of remittances received or sent by the household; (vii) ***Food Security*** section mentions the difficulties faced by household to feed themselves; (viii) ***Poverty*** section catches the perception of people about their economic situation and (ix) ***Consumption*** section identifies the living standard or well-being of households through their consumption expenditure. In addition to those bases section, other sections may be included at the request of other sectoral structures.

Table 3.3 shows the descriptive statistics about households 'poverty statute, total expenditure per capita according to region and milieu of residence. Total expenditure per capita is a good proxy of well-being because of its stability contrary to income. Indeed, the higher the consumption expenditure per capita of household, the more the household is supposed to satisfy its livelihoods. On average, the annual total consumption expenditure in Mali is estimated to 283 657 FCFA (526.9 dollars). The average value of annual consumption pc is higher in urban areas than rural areas due to the importance of non-food goods and services in the consumption baskets of households in urban areas. Moreover, the expenditure per capita is very heterogeneous across Mali regions with a high value for Bamako and minimum value recorded in Mopti and Sikasso. The total per capita expenditure includes food and non-food expenditure. The proportion of food expenditure represents more than 60% in households consumption basket excepted Bamako where access to new services is easy. Also, we note that food part expenditure is always high in rural than urban areas.

Table 3. 3: Expenditure per capita and poverty incidence per region over 2011-2018

Regions	Zone	Poor (%)	Total expenditure pc (1000 FCFA)	Food expenditure (%)
Kayes	*All*	23,44	312,499	75,20
	Urban	33,89	361,638	70,64
	Rural	66,11	287,404	77,54
Koulikoro	*All*	38,06	226,719	74,06
	Urban	30,17	290,631	69,38
	Rural	68,83	199,089	76,08
Sikasso	*All*	52,51	221,279	64,91
	Urban	36,76	306,611	61,12
	Rural	63,24	171,398	67,13
Ségou	*All*	39,57	231,797	70,82
	Urban	31,8	293,73	65,87
	Rural	68,2	203,288	73,10
Mopti	*All*	48,92	218,826	75,69
	Urban	36,23	294,064	71,22
	Rural	63,77	176,434	78,21
Tombouctou	*All*	17,39	352,419	74,00
	Urban	44,01	420,499	67,69
	Rural	55,99	298,513	78,99
Gao	*All*	36,22	241,898	75,89
	Urban	59,84	263,515	74,16
	Rural	40,16	211,307	78,33
Bamako	*All*	5,72	459,696	52,50
	Urban	100	459,696	52,50
	Rural	x	x	x
All Mali	*All*	33,72	283,657	69,63
	Urban	45,22	364,349	63,32
	Rural	54,78	217,171	74,81

In the column 3, we compute the poverty incidence based on the total annual per capita expenditure of households and the poverty line. The poverty incidence rate is measured by the proportion of household whom total expenditure per capita is under the poverty line (see the table 3.2 for poverty line for each year of the study). Poverty is more widespread in rural areas; more than 50% of poor people are living in rural areas. Across regions, the poverty rate is different with fewer poor in Bamako (5.72%) and many poor in Sikasso (52.51%). In **Figures 3.3 & 3.4**, we can observe that the poverty line in all Mali and rural is stable over the given period while the poverty trend seems to decrease since 2015 in urban areas included Bamako. Thus, the effort to reduce poverty should be more accentuated to improve people living standards with more focus in rural areas.

Figure 3. 3: Evolution of poverty incidence by area

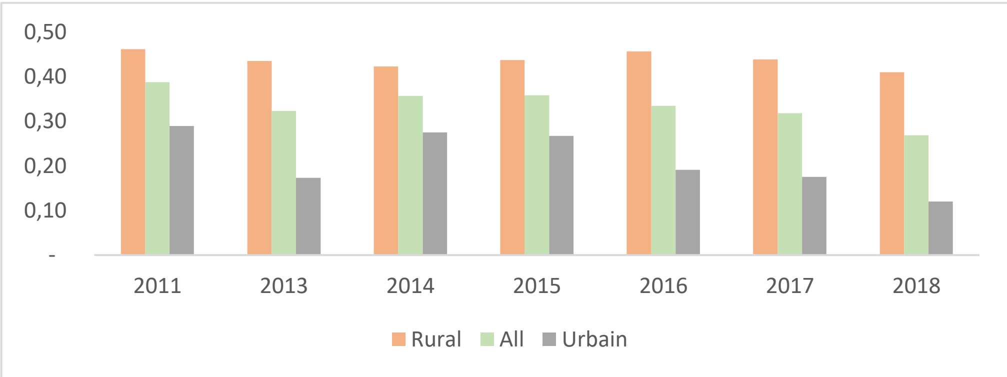


Figure 3. 4: Evolution of poverty rate per area (+ Bamako)

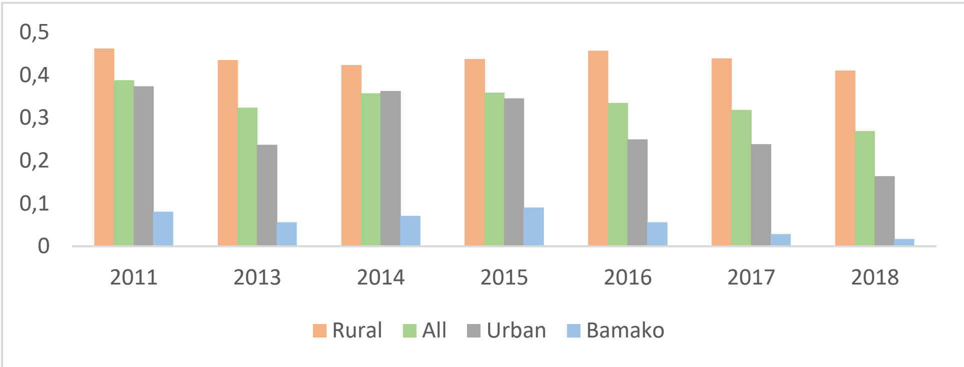
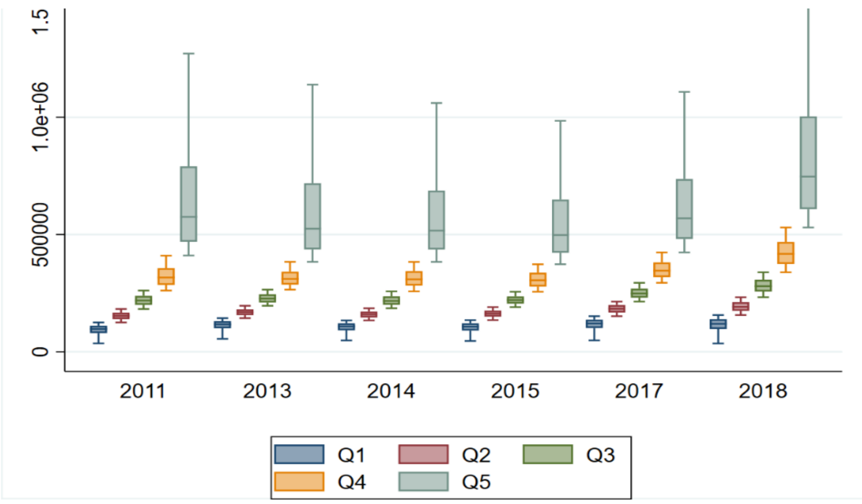


Figure 3. 5: Evolution of annual expenditure per capita distribution per quintile group



IV. Empirical analysis

4.1. Methodology and data

The aim of this study is to estimate the sensibility of household welfare to climate variability. The former is captured by households' consumption patterns. Household characteristics are from the household survey conducted on the population in several years since 2011. Households however are not necessarily the same over time, so the relationship between household welfare and climate is estimated by **pooled cross section.** The empirical analysis is based on the following econometric model:

$$\ln(Y_{ijt}) = \alpha + \beta_1.\ln(Rain)_{jt} + \beta_2.X_{ijt} + \beta_3.Rur_{ijt} + R_j + \varepsilon_{ijt}$$

Where $\ln(Y_{ijt})$ represents the logarithm of the welfare of household i in region j at time t; the welfare is captured by the total annual household expenditure per capita. The natural logarithm of per capita consumption is used in the regression to normalize the distribution of consumption and this transformation improves the explanatory power of the various models and brings ease in interpreting the coefficients as a percentage change of the outcome variable. $\ln(Rain)_{jt}$ is the logarithm of average cumulative rainfall of localities of region j. For each year, this variable is computed at regional units and its values are same of households in the same regions; the coefficient β_1 is the measurement of the elasticity of households' welfare to rainfall variability. We expect the positive sign of β_1 which means that household welfare increases with the positive variation of rainfall; X_{ijt} is the set of households' characteristics which may affect consumption, including household head's **age, gender and education level**; Rur_{ijt} is a dummy variable equal to 1 if household live in rural area and 0 otherwise and we control for regional fixed effect by introducing a dummy which accounts for the region where the household live. Finally, ε_{ijt} is the residual term.

We consider several versions of this econometric model, with dependent variables being different specifications of total consumptions (food and non-food consumption). These models are estimated using an OLS method with the inclusion of regional fixed effect (the region within Mali where the household lives) and clustering the standard errors to sub-regional level in order to account for spatial correlation.

Finally, we also consider a probit specification of the model to test the impact of rainfall on the probability of a household being poor. Consider *P**, the latent variable that classifies individuals according to their poverty status and depend to explanatory variables according to the following equation:

$$\mathrm{P}^* = \alpha + \beta_1.\ln(Rain)_{jt} + \beta_2.X_{ijt} + \beta_3.Rur_{ijt} + R_j + \varepsilon_{ijt}$$

The probit model will estimate the next specification where the dependent variable is the probability that household being poor. F is the distribution function of residual term ε_{ijt} assumed to follow a reduced centered normal distribution.

$$\mathrm{Prob(Poor = 1)} = F(\alpha + \beta_1.\ln(Rain)_{jt} + \beta_2.X_{ijt} + \beta_3.Rur_{ijt} + R_j + \varepsilon_{ijt})$$

4.2. Results

4.2.1. Baseline result

The estimation of the econometric model provides evidence of a statistically significant effect of rainfall on household consumption. The elasticity of households' consumption to rainfall is, on average, 0.38. A rainfall reduction of 1 percent would result in 0.38 percent reduction in consumption. Even when controlling for regional fixed effects and household characteristics (Table 3.4 column 3), rainfall has a positive and statistically significant effect on household consumption – the estimated coefficient indicates an elasticity of 0.34. As expected, the elasticity is different for different types of consumption. The elasticity is higher for non-food consumption (1.9) and much lower for food consumption (0.1). The control variables have the expected signs. Living in a rural area significantly lowers consumption (of both food and non-food products), while consumption increases with the level of education (Table 3.4 columns 2-5). This result is robust to geographical differences within Mali, which we accounted for by controlling for the region where the household lives (Table 3.4). Interestingly, consumption tends to be higher when the "head" of the household is a female.

Poverty is also affected by rainfall. Declining rainfall increases the probability of a household to be classified as poor (Table 3.4, column 6). The estimated coefficient is statistically significant and indicates that a lower rainfall would increase the probability of the household being poor. This result is confirmed when other co-variates are included, such as living in rural areas (which increases the probability of being poor) and the level of education of the household head (which reduces the probability of being poor).

Table 3. 4: Average elasticity of consumption to rainfall variation

VARIABLES	(1) Ln(exppc)	(2) Ln(exppc)	(3) Ln(exppc)	(4) Ln(food pc)	(5) Ln(non-food pc)	(6) poor
ln(rain)	0.376***	0.331***	0.344***	0.100**	1.903***	-0.707***
	(0.0581)	(0.0569)	(0.0514)	(0.0478)	(0.0768)	(0.116)
Rural		-0.356***	-0.238***	-0.192***	-0.458***	0.263***
		(0.0152)	(0.0135)	(0.0126)	(0.0192)	(0.0302)
Age HH			-0.00351***	-0.00394***	-0.00413***	0.00664***
			(0.000221)	(0.000212)	(0.000315)	(0.000530)
Gender HH			0.278***	0.221***	0.253***	-0.474***
			(0.0122)	(0.0117)	(0.0168)	(0.0305)
Education HH			0.0511***	0.0342***	0.0776***	-0.0848***
			(0.00109)	(0.000961)	(0.00149)	(0.00269)
Constant	9.534***	10.12***	9.728***	11.35***	-3.930***	4.962***
	(0.457)	(0.448)	(0.405)	(0.379)	(0.605)	(0.918)
Regions dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	41,575	41,575	41,445	41,445	41,445	41,445
R-squared	0.177	0.235	0.328	0.245	0.412	

Robust standard errors in parentheses. *, **, and *** indicate the significance level of 10%, 5%, and 1%, respectively.

4.2.2. Identification of vulnerable groups

To compare the coefficient between groups (Bamako vs Non-Bamako; Poor vs Non-Poor and Farmers vs Non-Farmers), we run the Z-test $Z = \frac{\mu_1 - \mu_2}{\sqrt{\frac{\sigma_1}{n_1} + \frac{\sigma_2}{n_2}}}$ of difference of coefficients between each subgroups. For all coefficients comparisons, the test is significant, allowing to reject the null hypothesis that the elasticity of consumption to rainfall between comparison groups is the same. **The effect of rainfall on household welfare depends therefore on socio-economic groups.**

The average elasticity of household consumption to rainfall may be driven by specific groups of households in the sample. In this section, we specify the econometric model to account for different groups of households and their geographical location. The latter seems to be quite important, as households living in the capital (Bamako) do not display any statistically significant elasticity, indicating that their consumption – and presumably their income – is not affected by variations in rainfall. By contrast, the average elasticity for households outside of the capital is larger (0.4) and statistically significant (Table 3.5 column 2 and 3).

Besides geographical location, consumption pattern and sensitivity to rainfall may also depend on savings a household can use in dire times. Indeed, the consumption of poor households is more affected by rainfall than consumption of non-poor households. Interestingly also non-poor households are affected as long as they do not live in the capital Bamako. Still, the consumption pattern of households in the highest quintile of the income distribution is not affected by rainfall This result is driven by households in Q5 mainly living in Bamako (65% of the total sample).

These empirical findings suggest that systematic changes in rainfall exacerbate income inequalities as richer households are less affected, and geographical differences as rural areas are more affected than urban ones.

These empirical results indicate that the level of income of the family and their location influence the way in which consumption is affected by rainfall, suggesting a link between the way in which the family income is generated and the impact of rainfall. Looking at farmers (i.e., household with primary income from the agricultural sector, the elasticity is large (0.57) and statistically significant (Table 3.6 column 4), while non-farmers are not affected by rainfall (i.e., household with primary income not from agriculture. This result indicates that variation in rainfall affects income in the agricultural sector and thus consumption.

Table 3. 5: Average elasticity of consumption to rainfall variation by sub-groups

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	Bamako	Non Bamako	Non poor	Poor	Q1	Q5
VARIABLES	lnexppc	lnexppc	lnexppc	lnexppc	lnexppc	lnexppc	lnexppc
ln(rain)	0.344***	-0.0636	0.405***	0.127***	0.218***	0.181***	0.0904
	(0.0514)	(0.119)	(0.0555)	(0.0476)	(0.0377)	(0.0383)	(0.0659)
Rural	-0.238***		-0.235***	-0.164***	-0.149***	-0.0329***	0.0149
	(0.0135)		(0.0136)	(0.00859)	(0.00889)	(0.00797)	(0.0129)
age_HH	-0.00351***	-0.00348***	-0.00346***	-0.00189***	-0.00137***	-0.00110***	-0.000855**
	(0.000221)	(0.000579)	(0.000239)	(0.000209)	(0.000185)	(0.000201)	(0.000358)
gender_HH	0.278***	0.253***	0.284***	0.203***	0.0313***	0.0134	0.111***
	(0.0122)	(0.0261)	(0.0137)	(0.0115)	(0.0117)	(0.0123)	(0.0144)
education_HH	0.0511***	0.0473***	0.0523***	0.0368***	0.0104***	0.00685***	0.0162***
	(0.00109)	(0.00206)	(0.00128)	(0.000988)	(0.00110)	(0.00128)	(0.00118)
Constant	9.728***	13.17***	9.234***	11.62***	10.20***	10.22***	12.47***
	(0.405)	(1.025)	(0.438)	(0.376)	(0.298)	(0.303)	(0.522)
Regions Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	41,445	5,685	35,760	27,580	13,865	8,296	8,282
R-squared	0.328	0.160	0.255	0.234	0.115	0.048	0.048

Robust standard errors in parentheses. *, **, and *** indicate the significance level of 10%, 5%, and 1%, respectively.

Table 3. 6: Average elasticity of consumption to rainfall variation according to household's main activity (Farming vs Non-Farming)

	(1)	(2)	(3)	(4)
	All	**All**	**Non Farmers sample**	**Farmers sample**
VARIABLES	lnexppc	lnexppc	lnexppc	lnexppc
ln(rain)	**0.344*** **	**0.260*** **	**-0.0363**	**0.572*** **
	(0.0514)	(0.0509)	(0.0699)	(0.0666)
Farmer		-0.264***		
		(0.0101)		
Rural	-0.238***	-0.140***	-0.161***	-0.107***
	(0.0135)	(0.0132)	(0.0148)	(0.0185)
Age HH	-0.00351***	-0.00421***	-0.00661***	-0.00196***
	(0.000221)	(0.000272)	(0.000391)	(0.000368)
Gender HH	0.278***	0.190***	0.185***	0.247***
	(0.0122)	(0.0153)	(0.0166)	(0.0335)
Education HH	0.0511***	0.0426***	0.0456***	0.0189***
	(0.00109)	(0.00110)	(0.00118)	(0.00241)
Constant	9.728***	10.60***	13.00***	7.740***
	(0.405)	(0.402)	(0.550)	(0.528)
Regions Dummies	Yes	Yes	Yes	Yes
Observations	41,445	33,9	17,536	16,364
R-squared	0.328	0.357	0.250	0.143

Robust standard errors in parentheses. *, **, and *** indicate the significance level of 10%, 5%, and 1%, respectively.

4.2.3. Weather instability and welfare

To test the sensitivity of our results, we estimate the effect of instability of weather conditions on household welfare. We use several weather variables: precipitation, temperature, and standard precipitation evapotranspiration index (SPEI). Instability is captured by the long-term standard deviation of each variable during the last 50 years (1969-2018). Table 3.7 shows that the instability in weather conditions (precipitation, temperature, and SPEI) impact negatively household' consumption and increase their probability to being poor. The magnitude of temperature and SPEI instability seems to be more important than precipitation instability.

Table 3. 7: Impact of instability in climate conditions on consumption level and poverty.

VARIABLES	(1) lnexppc	(2) poor	(3) lnexppc	(4) poor	(5) lnexppc	(6) poor
Rainfall instability	-0.00537***	0.0102***				
	(0.000705)	(0.00164)				
Temperature instability			-2.934***	5.406***		
			(0.649)	(1.522)		
SPEI instability					-1.026***	1.675***
					(0.185)	(0.429)
Rural	-0.251***	0.290***	-0.243***	0.271***	-0.248***	0.283***
	(0.0133)	(0.0302)	(0.0133)	(0.0301)	(0.0130)	(0.0300)
Age HH	-0.00350***	0.00665***	-0.00349***	0.00661***	-0.00351***	0.00664***
	(0.000222)	(0.000534)	(0.000224)	(0.000536)	(0.000222)	(0.000537)
Gender HH	0.277***	-0.470***	0.280***	-0.476***	0.276***	-0.467***
	(0.0123)	(0.0308)	(0.0123)	(0.0307)	(0.0123)	(0.0307)
Education HH	0.0509***	-0.0847***	0.0509***	-0.0842***	0.0506***	-0.0841***
	(0.00110)	(0.00271)	(0.00110)	(0.00271)	(0.00110)	(0.00272)
Constant	12.60***	-0.954***	13.36***	-2.349**	12.95***	-1.471***
	(0.0553)	(0.125)	(0.416)	(0.964)	(0.0952)	(0.222)
Regions Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	40,659	40,659	40,659	40,659	40,659	40,659
R-squared	0.332		0.329		0.332	

Robust standard errors in parentheses. We conrol for average level of each climate variable: Precipitation, Temperature and SPEI. *** p<0.01, ** p<0.05, * p<0.1

V. Conclusion

This chapter provides empirical evidence on the climate change impact on welfare in Mali, a key missing link in the existing literature. We build on broad household survey data over the 2010-2018 period. We highlight the following key results. The average elasticity of household's consumption to rainfall is equal to 0.38% that means where rainfall is increasing by 1%; the level of consumption will increase by 0.38%. Interestingly, the sensibility of consumption level to rainfall varies among the types of consumption and socioeconomic groups. Our results show that the elasticity is higher for non-food consumption (e.g.: energy, transport, communication...) and much lower for food consumption. Also, we find suggestive evidence that poor households that are most often located far from the capital (Bamako) and depend strongly on agriculture revenue are the most impacted by weather variability and instability.

Mali is a part of Sahel faces many issues like climate change and security. From these results, many actions should be taken to reduce the vulnerability of households to climate change. The government needs to put in place policies that improve resilience of agricultural production and households to declining rainfall, for instance by improvidng access to finance for poor households in rural areas. The government should also prepare to possible internal movement of population by improving urban planning, especially in the capital Bamako. These movements triggered by worsening economic conditions due to climate change could increase the risk of poverty in urban areas. Fast population growth will increase the challenge of building an economic and social infrastructure resilient to climate change. Adaptation strategies in sub-saharian Africal play a bigger role than migitation strategies (IMF Regional Economic Outlook, April 2020). This is because the Malian economy (as well as other sub-saharian countries) are dependent on climate-sensitive sectors – like agriculture and tourism.

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Chapter 4: CLIMATE SHOCKS AND DOMESTIC CONFLICTS IN AFRICA

Abstract

This chapter analyzes the interlinkages between climate shocks and domestic conflicts in Africa. It builds on a Correlated Random Effect model to assess these interrelationships on a broad sample of 51 African countries over the 1990-2018 period. We find suggestive evidence that climate shocks, as captured through weather shocks, increase the likelihood of intercommunal conflicts, by as high as up to 38 percent. The effect is magnified in countries with more unequal income distribution and a stronger share of young male demographics. The results, robust to a wide set of sensitivity checks, point to key policy resilience factors, including steadily improving domestic revenue mobilization, strengthening social protection, and scaling up public investment in the agriculture sector.

JEL Classification Numbers: Q54, D74, J11,

Keywords: Weather shocks, Domestic conflicts, Demographics, Resilience

I. INTRODUCTION

The economic and social damages of climate change (CC) have taken center stage in the public and academic debates. The adverse consequences of climate shocks (droughts, floods, severe weather events) are increasingly felt with greater frequency and intensity around the world (**Masson-Delmotte and others, 2018**). Developing countries, and more particularly rural areas across Africa, appear among the hardest hit by the adverse consequences of CC **(Helgeson and others, 2013; IMF 2019; 2020a**). According to the International Monetary Fund, sub-Saharan African economies are reduced by one percent when average temperature rises 0.5 above its long-term trend, or a 60 percent greater impact compared to other developing countries. In a similar vein, the International Panel on Climate Change (IPCC) documented that the CC-driven locust invasion worsened food insecurity in East African countries in 2019 (IPCC, 2020).

It goes without saying that tackling more decisively CC and its adverse consequences rose to the forefront of the global policy agenda. The United Nations (UN) adopted the mitigation of CC-driven natural disasters as one of its main Sustainable Development Goals (SDGs), calling for greater resource mobilization worldwide to support developing countries' endeavors to achieve this goal (13^{th} SDG). The ratification of the Paris Agreement by 195 countries in 2015, which aims to reduce greenhouse gas emissions, further rekindled this renewed international momentum towards tackling more decisively CC and its dire social and economic consequences.

This chapter adds to the literature and policy debate by focusing on the CC-domestic conflicts nexus, a missing link in the existing literature. Domestic conflicts are often referred to as one of the most serious social consequences of CC, given the increasingly frequent occurrence of domestic conflicts on account of competition for access to natural resources **(Reuveny, 2007; Kniveton and others, 2008; and Scheffran and others, 2012**).[50] However, as pointed out by von Uexkull and others (2016), "*to date, the research community has failed to reach a consensus on the nature and significance of the relationship between climate variability and armed conflicts*".[51] The present

[50] Migration is also referred to as another serious consequence of these conflicts for access to natural resources.
[51] The existing literature on the determinants of conflicts focused on the role of institutional, demographic and political factors, with ethnic diversity found as the main historical causes of civil conflicts incidence and duration

chapter aims to fill this gap by examining whether and to what extent climate shocks affect domestic conflicts incidence, and how policymakers can develop resilience strategies to break this vicious link. We build on a broad panel of 51 Africa countries over the 1990-2018 period. To the best of our knowledge, this is the first chapter that assesses empirically the interlinkages between climate shocks, domestic conflicts, and policy resilience in Africa.

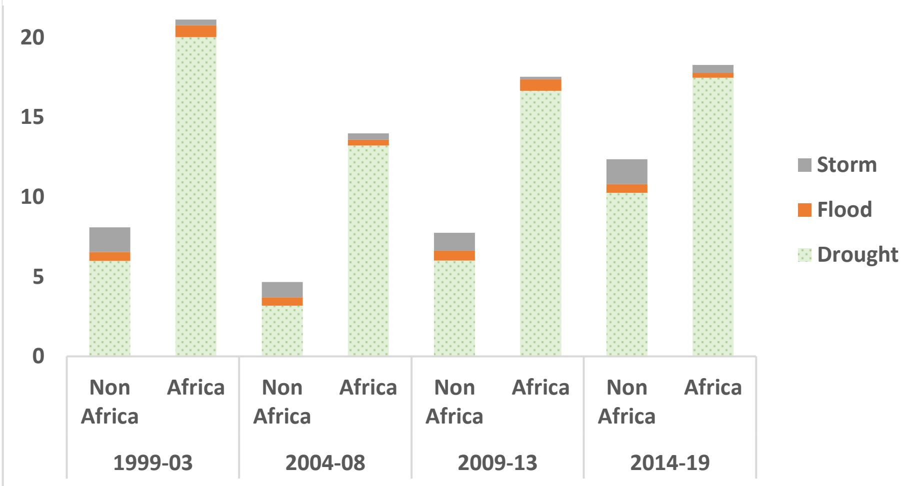
We focus on Africa as it stands out as one of the hardest-hit continents by both climate shocks and domestic conflicts over the past decade. On the one hand, the annual number of people afflicted by natural disasters (drought, floods, and cyclones) is higher in Africa compared to other developing countries, although to varying intensity depending on the nature of the weather shock (Figure 4.1). Drought episodes appear to be weighing more severely on population's assets (Von Uexkull et al. 2016), thus making weather shocks, as captured through the *aridity index*, a relevant proxy for CC throughout this study. On the other hand, a good number of African countries experienced at least one conflict[52] per year over the 2010-18 period (Figure 4.2), encompassing terrorism incidents and intercommunal clashes, including because of competition to access scarce natural resources **(OECD 2013; Africa report 2020)**[53].

(Horowitz, 1989; Esteban and Ray, 1999; Collier and Hoeffler, 2001). Other recent studies point to poverty, inequality, institutional weaknesses and dependence on natural resources as primary causes of civil war **(Elbadawi 2000)**.

[52] *Type 1 (State-based armed conflict)* refers to "the use of armed force between two armed parties, of which at least one is the government of a state, results in at least 25 battle-related deaths in a calendar year."; *Type 2 (non-state* conflict) refers to "the use of armed force between two organized armed groups, neither of which is the government of a state, which results in at least 25 battle-related deaths in a year."; and *Type 3 (One-sided violence)* refers to "the use of armed force by the government of a state or by a formally organized group against civilians, which results in at least 25 deaths". More details in section 3.1 below.

[53] In figure 2, conflict type 1, type 2 and type 3 refer respectively to *state, non-state* and *one-sided* conflict according to UCDP/PRIO classification. Terrorism incidents and intercommunal clashes are increasingly threatening the fabric of social cohesion in several Western and Central African countries (Burkina Faso, Cameroon, Central African Republic, Chad, Mali, Niger, Nigeria, etc.).

Figure 4. 1: Annual natural disasters-afflicted populations (%) in Africa over 1995-2019



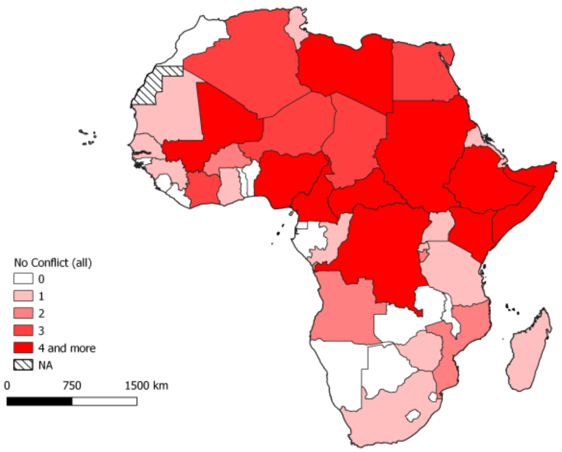
Source: EMDAT, WDI, and authors calculations

We find key results with far-reaching policy implications. First, we find suggestive evidence that climate shocks, as captured through weather shocks, increase the likelihood of intercommunal conflicts, by as high as up to [38 percent]. Second, the effect is magnified in countries with more unequal income distribution and a stronger share of young male demographics, while higher quality social protection, stronger tax revenue mobilization and scaled up investment in the agricultural sector appear as relevant resilience factors to climate shocks. The results are robust to a wide set of robustness checks

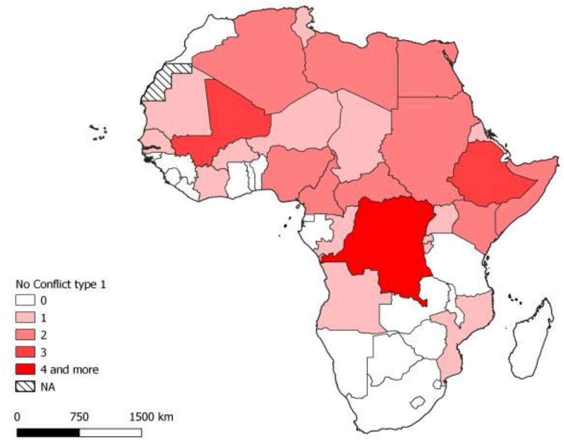
The remainder of the chapter is organized as follows. Section II briefly reviews the literature on the determinants of domestic conflicts. Section III introduces the dataset, while section IV presents the methodological approach used to assess the interlinkages between weather shocks, domestic conflicts, and resilience factors. Section V discusses the main results and some robustness checks, while section VI briefly concludes and draws some policy recommendations.

Figure 4. 2: Annual average number of conflicts over the period 2010-18

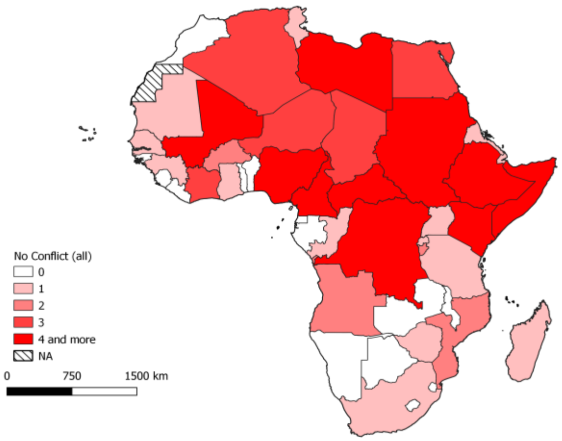
(a) All conflicts



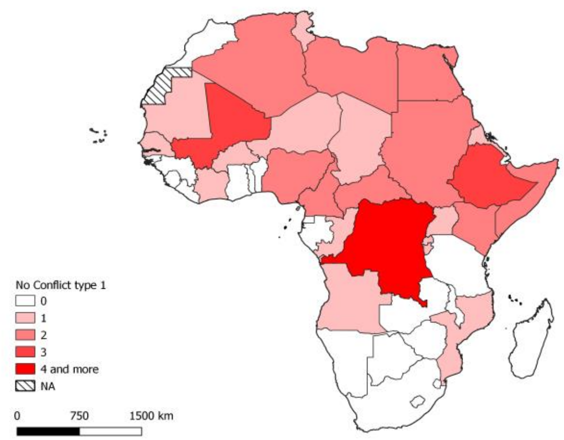
(b) Conflict *type 1*



(c) Conflict *type 2*



(d) Conflict *type 3*



Source: UCDP/PRIO and authors' calculations

II. Literature Review

The existing literature points to both institutional and economic determinants of domestic conflicts. A common finding in the literature is that countries with weak institutions and low level of economic development face a higher risk of experiencing civil and military conflicts **(Fearon et Laitin 2003; Collier et Hoeffler 2004; 2005; Håvard Hegre et Sambanis 2006)**.

- **Regarding economic factors**, high level of economic development and strong economic growth are found to be associated with greater government's ability to upgrade human capital and reduce domestic (income and social) inequalities through a more adequate delivery of basic social services such as education and health **(Cammeraat 2020)**. Relatedly, stronger economic growth, along with its induced greater employment opportunities, increases the opportunity cost for young people to be recruited into rebellions, thereby reducing the incidence of domestic conflicts **(Collier et Hoeffler 2004)**.

- **As regards institutional factors**, a commonly found result is that weaker institutions are more conducive to inefficient resource allocation, which leads to economic exclusion of segments of the population, and in turn, to revolts. Fearon (2004) finds that stronger democratic institutions help reduce the risk of domestic conflicts through facilitating effective negotiation and credible engagement in conflict resolution. In a similar vein, **(Håvard Hegre et Sambanis 2006; Colaresi et Carey 2008)** show that States with stronger democratic institutions rely less on violence and repression against civilians. However, several chapters pointed to some heterogeneity in this relationship, in the form a U-inverted relationship between the level of democracy and the probability of domestic conflict. Particularly, a semi-democratic regime, that is a regime that combines both autarchy and democracy, faces a higher risk of domestic conflict compared to a purely autarchic or democratic regime **(Havard Hegre 2014)**.

Beyond the economic and institutional factors, climate variability is also increasingly pointed out as a key source of domestic conflicts in poorer countries. Most empirical studies point to a converging finding that climate shocks pose a significant threat to domestic stability in developing countries **(Hendrix et Glaser 2007; Gleick 2014; Von Uexkull et al. 2016)**. A key channel behind this empirical regularity lies in these countries' large dependence on the agricultural sector, which is also one of the most affected sectors by climate variability. In rural Africa for example, agricultural-based income remains the norm and occupies about 52% of rural populations, thus rendering economic and social stability highly vulnerable to climate shocks. In addition, CC also drives domestic conflicts through accelerating the competition to access scarce natural resources such as fresh water, arable land, forest, and water for irrigation (Homer-Dixon, 1994). According to the International Panel on Climate Change, the reduced water availability in the semi-arid savanna ecosystems across tropical Africa is likely to exacerbate conflicts between herdsmen and farmers (IPCC, 2001)

- Some non-linearity is also present in the relationship between climate shocks and domestic conflicts. Country-specific social and economic characteristics, including the demographics structure, the strength of the social protection system and policy resilience, affect the relationship between climate shocks and domestic conflicts. **(Urdal, 2011)** documents that the population growth rate as well as its density contribute a great deal to the growing pressure on renewable natural resources such as arable land, fresh water, forests, and fisheries.

- Moreover, countries' ability to reap the demographic dividend depends on the implementation of well-anticipated policies allowing to improve human capital and create appropriate employment opportunities **(T. Homer-Dixon 1999; Zakaria 2001; Urdal 2005)**. Failing to implement such policies reduces the opportunity cost for young people to be enlisted in rebellion **(Collier 2000)**.

- The persistence of domestic inequalities and poverty along with the availability of policies to tackle them also stand as major catalysts of social tensions **(Ostby 2008; Ostby, Nordas, et Rod 2009; Ikejiaku 2012)**. Indeed, climate shocks negatively affect households' well-being through their adverse effects on income, food security, and human capital. This negative impact does not necessarily lead to conflicts, as it depends on the availability of adequate social protection to cope with the adverse consequences of climate shocks. Particularly, domestic conflicts are more likely to arise when some population groups are excluded from government social programs **(Von Uexkull et al. 2016)**.

- The intensity of conflicts is also a function of domestic factors that can accelerate the formation of conflicting groups, which in turn fuels the conflicts. A factor found in the literature to drive the formation of conflicts and political groups in developing countries is ethnic fragmentation **(Stewart 2016; Schleussner et al. 2016; Fearon 2006)**. Furthermore, in some African countries, decisions on specialization in economic sectors are made on an intercommunal basis, thus adding to the complexity of the relationship between competition for access to natural resources and domestic conflicts. In Mali for example, conflicts often arise between the *Peuhls* (who are predominantly herders) and the *Dogons* (who are predominantly farmers), on the ground of competition for access to scarce natural resources **(Sangaré et McSparren 2018)**.

III. DATA

Our study covers 51 African countries over the period 1990-2018, based on data availability. We relied on the following variables.

3.1. Dependent variable: *Intercommunal conflict*

Our dependent variable is the incidence of *intercommunal conflicts*, defined as the conflict between two social groups (Example: ethnicity, religious), which occur within the borders of a state.

- We use data from Uppsala Conflict Data Program's Georeferenced Event Dataset (UCDP GED Version 19.1), which records information on fatal violence at event level around the world over the 1989-2018 period **(Sundberg et Melander 2013; Pettersson, Högbladh, et Öberg 2019)**. Recorded fatal violence refer to conflict events that result in at least 25 battle-related deaths in a calendar year. For each event, the dataset provides information about the actors, the dyad, the type of conflict, the geographical location and coordinates, and the specific occurrence dates of the violence. UCDP classifies conflict events into three categories: *state-based conflict, non-state conflict and one-sided violence*. These three categories of events are mutually exclusive and differentiated based on the identity of participating actors in the conflict.

(i) ***State-based armed conflict*** refers to the use of armed force between two armed parties, of which at least one is the government of a state.

(ii) ***Non-state conflict*** refers to "the use of armed force between two organized armed groups, neither of which is the government of a state".

(iii) ***One-sided violence*** refers to the use of armed force by the government of a state or by a formally organized group against unarmed civilians.

- Our dependent variable is circumscribed to *non-state conflicts (point (ii) above)*, covering conflicts between communal groups within a country, or so-called *intercommunal clashes* **(Yilmaz 2005)**. We are focusing on this type of conflicts because it is the most associated with the consequences of climate change like resources scarcity or water and land management.

- For robustness purpose, we also rely on alternative variables. On the one hand, we carried out a *placebo*[54] test using the other two types of conflicts ((i) and (iii) above to explore whether the effect of climate shocks on domestic conflicts holds only for intercommunal clashes or holds for all types of conflicts. On the other hand, for the sake of further robustness check, we also rely on conflict data from *Armed Conflict Location Events Dataset (ACLED)*, which compiles real time data on the locations, dates, actors, fatalities, and types of all conflicts events across all regions of the world (Eck, 2012). Two main reasons explain the reliance on UCDP GED as primary database in this study compared to ACLED. First, unlike UCDP GED, ACLED does not provide a distinction between the intensity and the nature of violence, nor does it clarify whether the involved actor reports to the state As such, to

[54] Placebo tests are intended to ensure that the relationship between climate variability and conflict is true only for internal conflicts and not for other types.

conduct this robustness check, we filter the "INTERACTION"[55] variable from ACLED to obtain data on intercommunal conflicts, through selecting only conflicts between communal militia groups[56] **(Raleigh et Dowd, 2015)**.. Second, ACLED covers a shorter period, starting only in 1997, compared to 1989 for UCDP.

3.2. Interest variable: ***Weather shocks***

Weather shocks can materialize through several forms, including drought, floods, extreme temperatures, storms, etc.. As such, differentiated effects may arise from conflicts incidence, depending on the very nature of the weather shocks **(Buhaug et al. 2014; Selby 2014)**. As shown in Figure 1 above, droughts appear as the most frequent climate shock in Africa, hence the greater reliance on drought-related variable in the literature when it comes to assessing the influence of climate shocks on conflicts on that continent. We rely on the *aridity index* from **(Santoni Olivier 2017)** as proxy for weather shock.

- Aridity is viewed as a climatic phenomenon reflected mostly through low rainfall, with rainfall in arid or dry regions standing out below potential evapotranspiration – Evapotranspiration is the amount of water that evaporates through the soil, groundwater and plant transpiration.

- Santoni (2017) calculates the aridity index as the ratio between precipitation and evapotranspiration, using data from the Climate Research Unit (CRU). To allow for a more direct interpretation, we use the inverse of the initial aridity index. As such, the higher the value of the aridity index used in our study, the greater the degree of aridity in this region. In addition, we normalized the index using a min-max transformation, allowing for a less dispersed distribution, with the index now ranging between 0 to 1[57].

[55] "INTERACTION" variable allows identifying the parties (Civils, Armed-State, Armed-Social group) who are in conflicts.
[56] In ACLED codebook, for variable interaction, we select code 44 "- COMMUNAL MILITIA VERSUS COMMUNAL MILITIA" and 47 "COMMUNAL MILITIA VERSUS CIVILIANS" which correspond to inter communal conflicts.
[57] Min-Max transformation for X consists of transforming it into an index Z through the following formula: $Z = \frac{X - \min(X)}{Max(X) - Min(X)}$

For robustness purposes, we also use two alternatives proxies to capturing drought. First, we use the *drought intensity* indicator from EM-DAT, measured as the number of people affected by drought. The underlying idea is that droughts may lead to conflicts between groups if and only if the impact on people's property is substantial. Second, we rely on *extreme dry episodes* (during calendar year), calculated as the number of months, for a given country during a given calendar year, over which the Standard Evapotranspiration Index (SEPI, from CRU) reaches a level meeting Ye and others (2015)'s criteria for an extreme dry episode.[58]

3.3. Control variables

We account for potential drivers of intercommunal conflicts, in line with the literature review above. First, we control for country's level of economic development, captured through per capita GDP and access to electricity, based on data availability.[59] As well as for real GDP growth rate. . Second, we account for variables related to the demographic structure, namely the population size, population growth rate, population density and ethnic fractionalization.[60] Third, we control for income distribution, captured through Gini index on disposable income, using the Standardized World Income Inequality Database (SWIID), version 8. Fourth, we take account of factors measuring the quality of institutions and political stability in a country. Finally, control for a time trend and the lagged value of the dependent conflict variables, with a view to catch the dynamic in conflict occurrence, in line with **Von Uexkull et al. 2016**). Table (A1) provides a more detailed description of variables definition along with their summary statistics.

IV. METHODOLOGY

We build on a Logit binary outcome model given that the dependent variable equals to 1 for all observations in the data for which a domestic conflict is happen , and 0 for the remaining ones (non-occurrence of conflict). Specifically, we consider the following equation:

[58] A period is considered as an extreme dry episode when the SPEI value is inferior to -2.
[59] Access to electricity proxies not only for poverty (along the lines of access to basic public services) but also for access to quality infrastructure. Data paucity prevented us from accounting for more direct poverty indicators such as poverty rates. Data on access to electricity come from the World Development Indicators (WDI).
[60] Data on the size, growth and density of population are taken from WDI dataset. Data on ethnic fractionalization, viewed as the degree of ethnic diversity within a country, come **(Drazanova 2019)**

$$Pr(Y_{it}|X_{it}, Z_{it-1}) = G(\alpha + \beta_0 . X_{it} + \sum_{k=1}^{n} \beta_k . Z_{ikt-1}) = \alpha + \beta_0 . X_{it} + \sum_{k=1}^{n} \beta_k . Z_{ikt-1} + year + \mu_i + \varepsilon_{it}, \qquad (1)$$

Where $\boldsymbol{Y_{it}}$ is a binary variable taking the value 1 if an intercommunal conflict occurs in a country i at year t. X_{it} stands for a weather shock measurement, including the aridity index, drought intensity and extreme dry episode, respectively (as discussed above). Z_{it} represents the set of control variables. We use the one-year lagged value of some of our control variables mitigate endogeneity concerns. $Year$ stands for the time trend, while β captures the estimated parameters, μ_i an unobserved time-invariant country specificity and ε_{it} the residual term.

We rely on the Correlated Random Effect (CRE) to estimate Equation (1), to overcome estimation challenges posed by standard Fixed effect (FE) and Random effect (RE) models. The CRE proceeds from an attempt to combine properties from both the FE and RE models, through estimating within effects in random effects **(Mundlak 1978; Allison 2009; Wooldridge 2010)**. This hybrid model, consists adding to the right-hand side of equation (1), the mean value of each covariates variables ($\overline{X_\iota}$ and $\overline{Z_\iota}$) at the country level *i*. We briefly discuss below the points behind the preference for the CRE over both the FE and RE models.

- Under RE, μ_i is assumed not to be correlated with the covariates, namely $Cov(\mu_i, X) = 0$. However, this independence assumption between country's unmeasured features and covariates is rather strong, as unobserved country specificity may well be correlated with covariates (Wooldridge 2019a). For instance, a country's unmeasured historical feature such as colonization might explain its contemporaneous level of economic development and institutional quality **(Acemoglu, Johnson, et Robinson 2001)**, so might its geographical structure for when it comes to its degree of vulnerability to climate shocks.

- Although FE allows for a correlation between individual specific effects and the covariates, namely Cov(μ_i, X)≠0, it also carries some drawbacks that limit its use. First, FE is not fit for variables that do not vary over time such as our binary dependent variable. Relatedly, FE may lead to selection bias, as countries having experienced zero intercommunal conflict throughout the study period (43% of our sample) will be excluded from the analysis **(Caballero 2016)**, while one cannot rule out the possibility of a correlation between the factors explaining the lack of time-variation in the dependent binary variable for these observations and the factors driving weather shocks. Second, FE suffers from the incidental parameter problem, in reference to the point that individual heterogeneities are considered as parameters to be estimated **(Chamberlain 1979; Wooldridge 2019)**. Thus, the total number of parameters to be estimated (constant, control variables and individual heterogeneities) will be very large and will bias the results.

With the CRE, Equation (1) above is transformed into Equation (2) below.

$$Pr(Y_{it}|X_{it}, Z_{it-1}) = \alpha + \beta_0 . X_{it} + \sum_{k=1}^{n} \beta_k . Z_{ikt-1} + \overline{X_\iota} + \overline{Z_\iota} + year + \mu_i + \varepsilon_{it} \qquad (2)$$

$\overline{X_\iota}$ and $\overline{Z_\iota}$ stand for respectively the mean average of X_{it} and Z_{it} over time for country i.

Including mean values of independent variables allows controlling for unobserved country specificity, which could be correlated with the interest and/or control variables. As such, the independence assumption between country's unmeasured features and covariates (Cov(μ_i, X)=0) can now prevail The added variables (mean values of all time-varying covariates in the regression) are constant for a given country over the study period but vary across countries. While for the vector of time-averaged variables, we still control for time-constant unobserved heterogeneity, as with fixed effects, thus avoiding the problem of incidental parameters in nonlinear models because the individual heterogeneities parameters are not included. Another appealing feature of the CRE is that it allows estimating the effects of time-constant independent variables, just as in a traditional random effects model **(Wooldridge 2019)**. It follows that by accounting for country-specific and time-invariant features affecting the likelihood of domestic conflicts as well as weather shocks occurrence, or both, the CRE allows for differences within and between-country, through (Caballero 2016). Last but not the least, unlike the FE, the CRE allows avoiding the likely selection bias in the face of time-invariant binary dependent variable.

V. ECONOMETRIC RESULTS

5.1. Baseline results

Table 4.1 below reports the baseline results on the relationship between weather shocks and domestic conflicts incidence. Weather shocks, as captured through the drought index, are positively associated with domestic conflicts occurrence (columns 1-6), with a statistical significance of one percent, suggesting that weather shocks increase the likelihood of intercommunal conflicts. This effect does not hold only for contemporaneous drought episode, but for past drought episodes (one-year lag of the aridity index), as captured through the significantly positive coefficients associated with both variables (columns 7-8).[61] The bottom panel of the table reports on statistics capturing the area under the ROC curve (AUROC) (along with their associated standard errors), meant to gauge the predictive power of the CRE estimations.[62] The reported AUROC statistics stand above 0.88 in all columns – except column 1 (where only the aridity index is included as regressor), pointing to a rather good fit of the model.

We rely on the odds ratio to provide a quantitative interpretation of the estimated coefficients, the latter not standing directly for marginal effects in logit models[63]. One minus the odds ratio provides the percent change in odds for each unit increase in the drought index. The estimated odds ratio ranges between 1.26 and 1.65, which suggests that countries in our study face between 26 percent and 65 percent higher chance of experiencing an intercommunal conflict for each one-unit increase in the drought index.

Besides the influence of weather shocks, additional interesting results stand out as regards drivers of domestic conflict occurrence, in line with the existing literature (columns 2-8).

- First, intercommunal conflicts tend to persist over time, as reflected in the significantly

[61] Controlling jointly for past aridity and current aridity (column 8) particularly allows disentangling the effect of a conflict starting at the beginning of a given calendar year from the effect of a conflict that carried from the end of the previous calendar year.
[62] ROC stands for Receiver operating characteristic. AUROC statistics range between zero and one, with higher values reflecting greater predictive power of the model.
[63] In a logit model, the odds ratio refers to the exponential value of estimated coefficients.

positive coefficient associated with the one-year lag of the dependent variable.

- Second, the higher a country's economic development level, the lower its probability of experiencing an intercommunal conflict,, as reflected in the negative and significant coefficient associated with per capita GDP. This finding holds when using access to electricity as proxy for access to quality infrastructure (hence for economic development) or for poverty (through the lens of access to basic public services) (column 3). Relatedly, economic buoyancy (captured through real GDP growth) is associated with lower likelihood of domestic conflict occurrence, though the statistical significance of the estimated coefficient is rather weak (the coefficient is significant in three out of eight columns).

- Third, political stability mitigates the incidence of domestic conflict. Indeed, the coefficient associated with political stability is significantly negative. .

- Fourth, social and demographic factors also matter for intercommunal conflict incidence. On the one hand, ethnic fractionalization stands out as a catalyst for domestic conflicts, as evident from its associated positive and statistically significant coefficient. On the other hand, larger population size is associated with higher probability of experiencing intercommunal conflicts. .

- Sahel countries do not behave differently compared to other African countries when it comes to the influence of drought episodes on intercommunal conflicts occurrence. The coefficient associated with the Sahel dummy variable is significant only in one (column 1) out of 8 cases. It is however worth noting that when focusing on government-involved domestic conflicts, Sahel countries do experience higher occurrence probability compared to their African peers (see Placebo test-based robustness check in Table 4.5)

Table 4. 1: Baseline results

VARIABLES	(1) Conflict	(2) Conflict	(3) Conflict	(4) Conflict	(5) Conflict	(6) Conflict	(7) Conflict	(8) Conflict
Drought index	**0.339*** **	**0.394*** **	**0.360*** **	**0.374*** **	**0.292** **	**0.294*** **		**0.222** **
	(0.077)	(0.144)	(0.130)	(0.138)	(0.144)	(0.096)		(0.103)
Drought index(t-1)							**0.196*** **	**0.227** **
							(0.050)	(0.098)
lnGDP (t-1)		-1.010*		-0.672	-0.982**	-1.927***	-1.944***	-1.940***
		(0.569)		(0.460)	(0.403)	(0.675)	(0.680)	(0.671)
Electricity (t-1)			-0.020**					
			(0.009)					
Growth(t-1)		-2.222**	-1.288	-1.484*	-1.932	-1.248	-1.235	-1.222
		(1.063)	(0.884)	(0.842)	(2.507)	(0.924)	(0.984)	(0.977)
EF index		4.581*	3.323	4.259*	4.717**	6.020**	7.126*	6.799**
		(2.447)	(2.224)	(2.227)	(2.272)	(2.371)	(3.650)	(2.782)
lnPop (t-1)		2.453***	1.848***	1.967***	2.318***	2.449***	2.506**	2.492***
		(0.618)	(0.429)	(0.461)	(0.536)	(0.928)	(0.989)	(0.945)
Conflict(t-1)			1.967***	1.896***	1.273	1.851***	1.851***	1.860***
			(0.485)	(0.426)	(0.779)	(0.430)	(0.436)	(0.433)
PVE(t-1)					-1.451***			
					(0.444)			
Sahel	2.236**	0.313	0.243	-0.0398	0.185	0.202	0.142	0.159
	(0.984)	(0.847)	(0.763)	(0.698)	(0.791)	(0.813)	(0.792)	(0.802)
year	0.008	-0.047	-0.008	-0.025	-0.137***	-0.021	-0.022	-0.022
	(0.028)	(0.037)	(0.029)	(0.029)	(0.052)	(0.039)	(0.041)	(0.040)
Constant	-20.32	65.69	-12.88	22.97	245.6**	14.73	16.09	16.19
	(56.87)	(69.16)	(56.03)	(56.28)	(100.9)	(68.97)	(70.79)	(69.66)
Observations	1,377	1,098	839	1,098	575	1,098	1,098	1,098
Number of id	51	45	46	45	43	45	45	45
Log likelihood	-415.9	-290.7	-215.5	-274.1	-120.9	-269.7	-269.5	-269.2
Wald Chi2	23.17	52.41	59	57.85	52.70	95.24	66.79	81.40
Rho(LR)	0.753	0.599	0.441	0.470	0.244	0.419	0.425	0.421
P-value	3.72e-05	4.84e-09	7.33e-10	1.23e-09	8.45e-08	0	1.27e-09	0
AUROC	0.603	0.884	0.914	0.914	0.943	0.916	0.916	0.917
seAUROC	0.019	0.012	0.011	0.010	0.012	0.009	0.009	0.009

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

5.2. Conditional effects

We now turn on to exploring factors that could exacerbate or mitigate the influence of weather shocks on intercommunal conflicts occurrence. We explore the following heterogeneity factors, which are likely to alter the climate shocks-conflicts incidence nexus, using the set up below.

$$Pr(Y_{it} = 1|X_{it}, Z_{it-1}) = \alpha + \beta_0.X_{it} + \beta_1.C_{it} + \varphi.X_{it} * C_{it}\sum_{k=1}^{n}\beta_k.Z_{ikt-1} + year + \mu_i + \varepsilon_{it},$$

Where C_{it} represents the vector of conditional factor and φ the coefficient of interaction terms between drought index and conditional factor. If $\varphi > 0$ that means the conditional factor amplifies the effect of drought on conflict incidence; while $\varphi < 0$ means the conditional factor is considered as a resilience factor to conflict occurrence.

Table 2 below reports results on the weather shocks-domestic conflicts nexus, conditional on the influence of factors related to the demographic structure. We focus on the role youth share (aged 15 to 24) in the population, which is ambiguous à priori. On the one hand, a larger youth share can turns out a blessing, through the lens of the so-called, as a larger youth share can turn out to be a powerful growth engine through labor supply and hence contribute to reducing intercommunal conflict occurrence ("peace dividend" channel), should it benefit from appropriate education and professional training. On the other hand, large youth cohorts could give rise to greater probability of domestic conflict occurrence, should governments fail to provide them with opportunities to participate in education, labor market, and in governance , rendering cheaper the recruitment cost of unemployed young people into armed conflict groups (Urdal, 2012; and Collier and others, 2000).

- We divided our sample into two groups around the median size of youth share. In Table

4.2 (columns 1 and 2), Group 1(2) refers to countries with a youth share below (above) 20 percent of the population. It stands out that the coefficient associated with the drought index is significantly positive under Group 2, while it is positive but not statistically significantly under Group 1. This finding suggests that the catalyst effect of weather variability on intercommunal conflicts is magnified in countries with a large share of youth.

- When tweaking the result further, it turns out within the subsample of youthly populated countries (Group 2), that catalyst role of weather shocks on domestic conflicts occurrence is stronger when male youth outweighs female youth (columns 3 and 4).

Table 4. 2: Role of Demographic structure factors on the weather shocks-conflicts nexus

	(1)	(2)	(3)	(4)
	Youth Share		Youth Gender	
Dependent variable :	Group 1	Group 2		
Intercommunal conflict	(<20%)	(≥20%)	Female	Male
L.drought_index	0.023	0.654***	-0.698	0.343**
	(0.155)	(0.208)	(1.222)	(0.141)
Controls variables included	Yes	Yes	Yes	Yes
Number of observations	527	614	599	542
Number of countries	39	42	32	32
Log likelihood	-140.1	-135.1	-111.3	-161.3
Wald Chi2	140	42.95	73.58	125.1
Rho(LR)	0.310	0.521	0.553	0.284
P-value	0	5.08e-06	0	0
AUROC	0.918	0.903	0.883	0.914
AUROC (standard error)	0.009	0.009	0.013	0.010

Notes. Robust standard errors in parentheses. *, **, and *** indicate the significance level of 10%, 5%, and 1%, respectively.

Table 4.3 below presents results on the likely role of macroeconomic factors on the weather shocks-domestic conflicts nexus. We particularly explore the influence of tax revenue mobilization, remittances, social spending, income inequality, social protection, investment in agriculture sector, and forest coverage.

- **Tax revenue mobilization**

The coefficient associated with the interactive term between the drought index and tax revenue is negative and statistically significant, suggesting that greater tax revenue mobilization mitigates the catalyst role of weather shocks for inter-communal conflicts occurrence. Indeed, tax revenue mobilization is critical for creating necessary fiscal space to expand social safety nets, and upgrade public infrastructure, which in turn help respectively preserve social cohesion and speed up recovery from damages caused by natural disasters and climate change (IPCC, 2007; McIntyre, 2009; and Cabezon and others, 2015). More broadly, enhanced tax revenue mobilization stands as a resilience-strengthening factor, in that it allows building fiscal buffers critical for smoothening out effects of adverse shocks to the economy, including weather shocks. Improved tax revenue collection also helps ease financial constraints, especially in developing countries, given their limited access to international market and the shallowness of their domestic financial markets (Catalano and others, 2020).

- **Remittances**

Financial constraints faced by people to adapt to climate change can be relaxed through remittances. Remittances might help households smoothen out consumption, thus coping with adverse shocks, through easing financial constraints. (Le De and others, 2013; and Bendandi and Pauw, 2016). As such, remittances might mitigate the conflict catalyst role of weather shocks. As expected, the interactive term between the drought index and remittances is negative. However, the estimated coefficient is not statistically significant (columns 3 and 4).

- **Social spending, income inequality, and social cohesion**

Government spending in priority social sectors such as health can improve households' access to quality health care services, thus reducing their exposure to poverty and vulnerability to shocks (Celikay and Gumus, 2017). It is thus expected that enhanced priority social spending helps lessen the catalyst effect of weather shocks on domestic conflicts occurrence. The estimated coefficient associated with the interactive term between health spending and the drought index is significantly negative, in line expectations (columns 5 and 6). This finding holds when relying on an alternative proxy for access to health care services, namely the number of hospital beds per 1000 people (columns 7 and 8). Relatedly, stronger social protection systems are found to subdue the influence of weather shocks on domestic conflicts occurrence, as reflected in the significantly negative effect of the coefficient associated with the interactive term between the drought index and social protection (columns 11 and 12). These findings suggest that improved public basic services such as expanded social safety nets and upgraded health care services contribute to strengthening social cohesion and softening by the same token the catalyst effect of weather shocks on domestic conflicts occurrence through rendering it less likely that segments of the population feel marginalized to the point of getting themselves recruited into armed groups. The same applies to income redistribution, which stands out as a key factor towards preserving the very fabric of the society, essential for holding back the materialization of the weather shocks-domestic conflicts nexus. Indeed, the coefficient associated with the interactive term between the drought index and the GINI-based inequality index is significantly positive, highlighting that the more unequal income is distributed the higher the likelihood of weather shocks igniting intercommunal conflicts (columns 9 and 10).

- **Investment in agricultural sector**

Most developing countries remain largely dependent on the agricultural sector, which also remains highly subject to the vagaries of the weather (Mendelsohn and others, 2000; and IMF, 2017). With a large segment of active labor force still employed in the agriculture sector, this makes weather shocks a pivotal driver of changes in poverty and income inequality in Africa. Moreover, several studies documented that climate change reduces the productivity in the agriculture sector, increases malnutrition and heightens food insecurity **(Mendelsohn, Dinar, et Dalfelt 2000; Ringler et al. 2010; Tumushabe 2018)**. Enhanced public investment in the agricultural sector, in the forms of larger subsidies to facilitate access to inputs access (irrigation system, tractors, seeds, fertilizers, etc.), technical capacity building, or cash transfer to farming group in the aftermath of an adverse shock, thus stands as essential for strengthening the sector's resilience or adaptability to weather shocks, through improving farmers' ability to recover more quickly from damages caused by climate shocks (IPCC, 2007; and McIntyre, 2009, IMF, 2020). As expected, the estimated coefficient associated with the interactive term between the drought index and agricultural sector investment is negative and statistically significant (columns 13 and 14), confirming that scaled up public investment in agriculture sector decreases the probability of experiencing a domestic conflict following weather shocks.

- **Forest coverage**

Forests are identified as powerful instruments towards strengthening adaptability and resilience to climate change, through its pivotal roles as carbon sequestrator as well as vehicle of economic and sociocultural opportunities (Canadell and Raupach, 2008). As such, expanded forest coverage is expected to mitigate the materialization of the weather shocks-domestic conflicts nexus. Our results confirm this expectation, with the estimated coefficient associated with the interactive term between the drought index and forest coverage turning out negative and statistically significant (columns 15 and 16). This finding thus underscores the prominence of reforestation initiatives for slowing down desertification along with its catalyst role on domestic conflicts occurrence.

5.3. Robustness checks

In this section, we test our baseline results robustness to alternative specifications.

5.3.1. Using alternative conflict variables

First, we check the results robustness to the reliance on alternative proxies for domestic conflicts.

(iv) We start by using the number of domestic conflicts experienced during a calendar year as dependent variable, with a view to going beyond the simple occurrence of conflicts and rather capturing the intensity of conflicts. In the sample at hand, countries experience on average 11 domestic conflicts per calendar year. We re-arranged this variable into five categories based on the number of recorded domestic conflict.

Table 4. 3: Conditional effects and resilience factors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	X=Tax revenue		X=Remitances		X=Health expenditure		X=Hospital beds per 1000 people		X=Gini		X=Social protection		X=Agriculture Investment		X=Forest coverage	
VARIABLES	Conflict	Conflict	Conflict	Conflict	Conflict	Conflict	Conflict	Conflict	Conflict	Conflict	Conflict	Conflict	Conflict	Conflict	Conflict	Conflict
Drought index(t-1)	0.278***	1.396***	0.169	0.195	0.136	1.336**	0.181**	1.513***	0.214***	-4.474**	0.262***	1.817***	0.215**	0.789**	0.0928	0.164**
	(0.105)	(0.480)	(0.116)	(0.163)	(0.115)	(0.644)	(0.0837)	(0.564)	(0.0379)	(1.913)	(0.0471)	(0.436)	(0.0871)	(0.307)	(0.0621)	(0.0641)
X(t-1)	-0.0457	0.0278	-0.0156	0.00844	-0.0391	0.00672	-0.269	0.681	15.75	-4.882	-0.465*	0.0691	-0.650*	-0.471	0.0289	0.0652
	(0.0870)	(0.0909)	(0.103)	(0.146)	(0.0884)	(0.0953)	(0.346)	(0.769)	(16.37)	(20.44)	(0.250)	(0.0433)	(0.337)	(0.322)	(0.120)	(0.132)
Drought index(t-1)*X(t-1)		-0.0737**		-0.0111		-0.201*		-0.567***		12.58**		-0.116***		-0.425*		-0.456*
		(0.0339)		(0.0256)		(0.118)		(0.198)		(5.136)		(0.0327)		(0.248)		(0.262)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Modele	CRE	CRE	CRE	CRE	CRE	CRE	CRE	CRE	CRE	CRE	CRE	CRE	CRE	CRE	CRE	CRE
Observations	935	935	904	904	643	643	216	216	837	837	818	818	741	741	1,070	1,070
Number of id	43	43	45	45	44	44	44	44	44	44	43	43	38	38	44	44
Log likelihood	-232.1	-229.9	-213.2	-213.1	-144.9	-142.7	-61.84	-58.10	-202.3	-199.1	-197.8	-198.4	-196.7	-195.5	-275.3	-272.2
Wald Chi2	79.52	176	62.74	72.60	104.9	103.9	154.3	985.8	136.1	138.5	190.8	185.4	50.94	341.3	94.02	122.6
Rho(LR)	0.647	0.685	0.475	0.472	0.236	0.222	1.55e-06	1.11e-06	0.249	0.250	0.142	0.143	0.780	0.775	0.332	0.260
P-value	0	0	1.69e-08	1.53e-09	0	0	0	0	0	0	0	0	9.56e-07	0	0	0
AUROC	0.874	0.865	0.921	0.921	0.936	0.935	0.895	0.898	0.936	0.938	0.931	0.929	0.769	0.773	0.897	0.911
seAUROC	0.0135	0.0144	0.00988	0.00992	0.0122	0.0121	0.0269	0.0264	0.00950	0.00915	0.0108	0.0110	0.0179	0.0177	0.0112	0.0101

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables are included

Specifically, we set "Number of Conflicts" equal to 0 when no domestic conflict occurs in a country on a given year; 1 when the number of conflicts per year ranges between one and three; 2 when the number of conflicts per year ranges between four and five; 3 when the number of conflicts per year ranges between six and eight; and 4 when the number of conflicts per year exceeds 9. We build on an ordered *probit* model to estimate the relationship between the drought index and the re-arranged "Number of Conflicts" variable. Table 4.5 below reports the corresponding results, which confirm that the larger the drought index, the greater the probability of experiencing more intense intercommunal conflicts.

(v) We then explore whether the catalyst role of weather shocks on domestic conflicts occurrence holds only for intercommunal conflicts or applies to all types of domestic conflicts. To this end, we run ***placebo*** tests, where the dependent variable in the baseline model remains intercommunal conflicts. This choice is predicated on the most commonly-held assumption, namely that climate variability is more likely to drive conflicts among various groups because of competition to access natural resources (Reuveny, 2007; Kniveton and others, 2008; and Scheffran and others, 2012). The validity of this assumption can be confirmed through the UCDP/PRIO database that allows classifying conflicts into three categories, namely *State-based armed conflict, non-state conflict and One-sided violence*, in line with the discussion from section 3.1 above. Table 4.4 below report the corresponding estimations results. In column 1, the dependent variable is as in the baseline ("*non-state conflict*"). In column 2, the dependent variable refers to all conflicts, irrespective of the type of domestic conflicts, while columns 3 and 4 feature results respectively for "*State-based armed conflict*" and *"One-sided violence"*. The results point to significant heterogeneity: the catalyst role of weather shocks on domestic conflicts occurrence holds true only for intercommunal conflicts (column 1), not for other types of domestic conflicts or violence. Indeed, the coefficient associated with the drought index is significantly positive when focusing on intercommunal conflicts (column 1), it is no longer statistically significant when considering other types of conflicts (columns 2 to 4). This result is particularly important, given the heavy human toll of intercommunal clashes: in the Sahel for example, intercommunal conflicts are costing thousands lives and causing millions of population displacements[64]. Also, it is worth noting that while the Sahel dummy is not statistically significant under the baseline, it turns out significantly positive when focusing on state-based armed conflicts (column 3), suggesting that compared to their African peers, Sahel countries face higher probability of experiencing government-involved domestic conflicts.

Table 4. 4: Placebo test

VARIABLES	(1) Conflict type 2 (Non-State conflict)	(2) All types of conflict	(3) Conflict type 1(*State-based armed conflict)*	(4) Conflict type 3(*One-sided violence)*
Drought index(t-1)	**0.196***	0.0618	-0.236	0.0873
	(0.0500)	(0.162)	(0.174)	(0.190)
	(0.436)	(0.283)	(0.356)	(0.346)
Sahel	0.142	**1.150***	**2.623***	0.607
	(0.792)	(0.667)	(0.927)	(0.640)
Control Variables	Yes	Yes	Yes	Yes
Modele	CRE	CRE	CRE	CRE
Observations	1,098	1,098	1,098	1,098
Number of id	45	45	45	45
Log likelihood	-269.5	-388	-342.3	-419.4
Wald Chi2	66.79	112	82.33	71.32
Rho(LR)	0.425	0.391	0.536	0.369
P-value	1.27e-09	0	0	1.81e-10
AUROC	0.916	0.894	0.829	0.883
seAUROC	0.00965	0.0110	0.0127	0.0117

Notes. Robust standard errors in parentheses. *, **, and *** indicate the significance level of 10%, 5%, and 1%, respectively. Controls variables are included.

(vi) For the sake of further robustness check, we also rerun the baseline regression, using this time ALCED-based conflicts data instead of UCDP GED data used so far (see discussion in section 3.1. above). The results are qualitatively similar to the benchmark estimate, confirming that drought-led weather shock increases the likelihood of experiencing intercommunal conflicts

[64] According to UNHCR (2020): "*The Central Sahel countries of Burkina Faso, Mali, and Niger are the epicentre of the forced displacement crisis. More than 1.5 million internally displaced people (IDPs) and 365,000 refugees have fled violence in the Central Sahel, including over 600,000 this year alone*".

(Table 4.6, column 3).

Table 4. 5: Using "Number of conflicts per year" as dependent variable

VARIABLES	(1) Number of conflict	(2) Number of conflict	(3) Number of conflict	(4) Number of conflict	(5) Number of conflict	(6) Number of conflict	(7) Number of conflict
Drought index	**0.408****	**0.366****	**0.306****	**0.340****	**0.214*****		**0.225*****
	(0.169)	(0.167)	(0.154)	(0.156)	(0.0788)		(0.0817)
Drought index (t-1)						**0.248*****	**0.257*****
						(0.0926)	(0.0905)
lnGDP (t-1)		-0.691	-1.099***	-0.458	-1.357*	-1.359*	-1.358*
		(0.471)	(0.343)	(0.429)	(0.741)	(0.741)	(0.742)
Growth (t-1)		-0.834**	-1.107	-0.571*	-0.334	-0.286	-0.323
		(0.354)	(2.245)	(0.329)	(0.458)	(0.452)	(0.460)
EF index		4.697**	5.666**	4.547**	5.995**	5.974**	5.980**
		(2.174)	(2.271)	(2.200)	(2.999)	(2.998)	(2.997)
lnPop (t-1)		2.275***	2.471***	1.910***	1.820***	1.816***	1.820***
		(0.422)	(0.419)	(0.355)	(0.572)	(0.573)	(0.573)
Conflict (t-1)			1.363*	2.108***	2.089***	2.115***	2.118***
			(0.767)	(0.467)	(0.475)	(0.484)	(0.482)
Sahel	2.198**	0.367	-0.0729	0.0344	0.0739	0.0650	0.0713
	(0.938)	(0.688)	(0.689)	(0.576)	(0.647)	(0.646)	(0.647)
year	0.0307	-0.0165	-0.102***	0.00480	0.0195	0.0196	0.0198
	(0.0269)	(0.0310)	(0.0363)	(0.0247)	(0.0324)	(0.0325)	(0.0325)
L.pve			-1.517***				
			(0.319)				
Observations	1,377	1,098	575	1,098	1,098	1,098	1,098
Number of id	51	45	43	45	45	45	45
Log likelihood	-678	-486.3	-210.7	-464.7	-461.8	-461.7	-461.3
Wald Chi2	11.14	52.25	138.7	65.53	175.3	172.8	177.5
P-value	0.0110	5.21e-09	0	0	0	0	0

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables are included

5.3.2. Using alternative weather shock variables

Second, we check the results robustness to the use of alternative weather shock indicators namely the "Drought intensity" index, the "Extreme drought episode" index, and ACLED-based in line with the discussion from section 3.2 above. Table 4.6 below (columns 1 and 2) reports the corresponding estimation results. The coefficients associated with the drought intensity index (column 1) and the extreme drought episode (column 2) are qualitatively similar to the baseline estimates – positive and statistically significant, upholding the catalyst role of weather shocks on intercommunal conflicts occurrence.

Table 4. 6: Using alternative weather shock indicators (Drought intensity, Extreme Drought episodes, and ACLED-based weather shock)

Dependent variables	(1) Non-state Conflict	(2) All Conflicts	(3) Conflict (ACLED)
Drought index			**0.511*** **
			(0.153)
Drought_intensity	**0.087** **		
	(0.035)		
L.Drought_intensity	**0.062***		
	(0.037)		
Extreme_dry		**0.563*** **	
		(0.123)	
L.Extreme_dry		**0.553*** **	
		(0.132)	
Constant	654.7	110.3	-329.8***
	(437.6)	(75.66)	(69.41)
Control Variables	Yes	Yes	Yes
Model	CRE	CRE	CRE
Number of Observations	655	1,116	847
Number of countries	33	44	43
Log likelihood	-185	-270.8	-321.9
Wald Chi2	66.93	166.9	103.5
Rho(LR)	0.636	0.280	0.350
P-value	3.42e-08	0	0
AUROC	0.880	0.922	0.851
AUROC (standard errors)	0.015	0.009	0.013

Notes. Robust standard errors in parentheses. *, **, and *** indicate the significance level of 10%, 5%, and 1%, respectively.

5.3.3. Controlling for further covariates

Finally, we check the results robustness by controlling to the extent possible for variables that are likely to matter simultaneously for both weather shocks and domestic conflicts. Controlling for such covariables help mitigate concerns of likely omitted variables bias. We account for three groups of covariates: those reflecting macroeconomic resilience factors (capital stock and paved roads), resources scarcity (share of agriculture and arable lands), and the socio-economic factors (youth unemployment, male youth versus female unemployment, share of rural population), respectively. Accounting for these additional covariates left the estimate of the influence of the drought index qualitatively unchanged, upholding the weather shocks-intercommunal conflicts nexus from the baseline results.

Table 4. 7: Robustness Check: Controlling for further Covariates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	X=Capital stock	X=Paved road length	X=Youth Unemployment rate	X=MaleYouth Unemployment rate	X=FemaleYouth Unemployment rate	X=Agriculture land	X=Arable land	X=Rural population
VARIABLES	Conflict	Conflict	Conflict	Conflict	Conflict	Conflict	Conflict	Conflict
L.drought_index	0.208***	0.335***	0.167***	0.168***	0.171***	0.182***	0.189***	0.146***
	(0.054)	(0.072)	(0.058)	(0.059)	(0.045)	(0.055)	(0.054)	(0.054)
X(t-1)	**-0.888****	**-0.0001*****	**0.044***	**0.046****	**0.020**	**-0.116***	**-0.155***	**0.213****
	(0.393)	(3.31e-05)	(0.024)	(0.020)	(0.030)	(0.063)	(0.082)	(0.083)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Model	CRE	CRE	CRE	CRE	CRE	CRE	CRE	CRE
Number of observations	990	357	1,056	1,056	1,056	1,070	1,070	1,098
Number of countries	41	41	45	45	45	44	44	45
Log likelihood	-243.3	-77.49	-252.9	-252.6	-253.5	-261.1	-261.8	-264.1
Wald Chi2	106	1449	75.79	77.66	73.07	148.2	131.9	75.99
Rho(LR)	0.310	0.522	0.419	0.420	0.416	0.289	0.316	0.457
P-value	0	0	6.78e-11	0	2.17e-10	0	0	6.24e-11
AUROC	0.933	0.899	0.923	0.923	0.923	0.919	0.917	0.917
AUROC (standard errors)	0.009	0.019	0.009	0.009	0.009	0.009	0.009	0.009

Notes. Robust standard errors in parentheses. *, **, and *** indicate the significance level of 10%, 5%, and 1%, respectively.

VI. CONCLUDING REMARKS

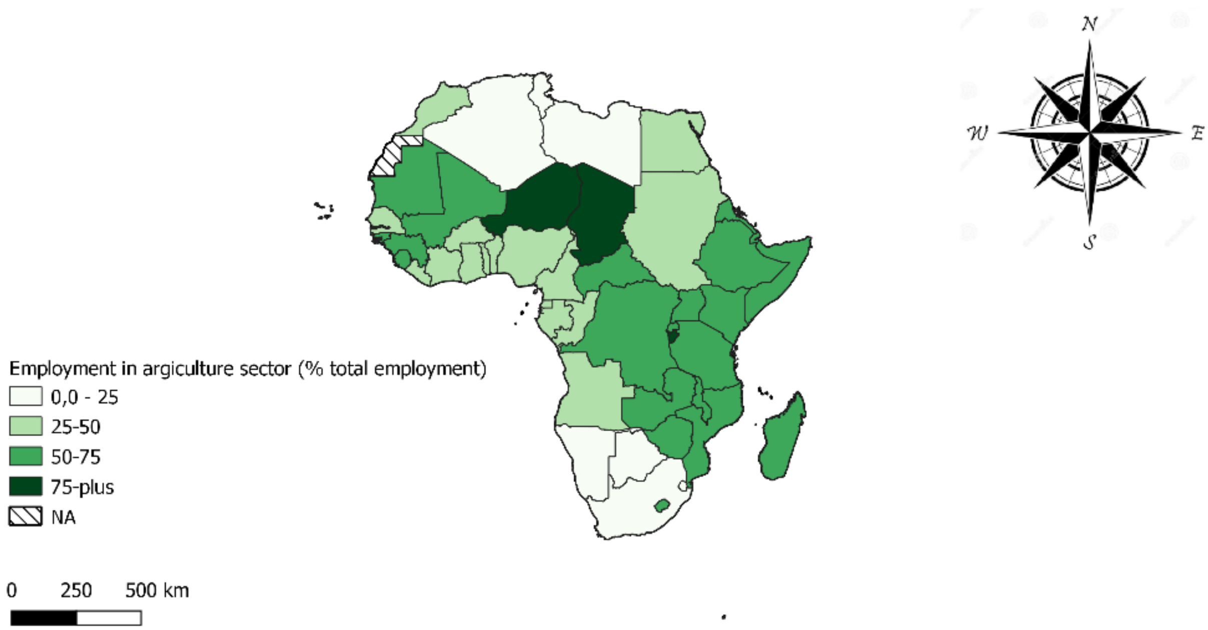
This chapter adds to the policy debate by providing the first empirical evidence on the climate change-domestic conflicts nexus in Africa, a key missing link in the existing literature. We build on a broad panel of 51 Africa countries over the 1990-2018 period. **We unveil key results with far-reaching policy implications.**

First, we find suggestive evidence that climate shocks, as captured through weather shocks, increase the likelihood of domestic conflicts, by as high as up to 38 percent. Second, the effect holds only for intercommunal conflicts, not for government-involved conflicts or other types of domestic conflicts. Third, the effect is magnified in countries with more unequal income distribution and a stronger share of young male demographics, while higher quality social protection and access to basic health care services, stronger tax revenue mobilization, scaled up public investment in the agricultural sector, and stepped up reforestation efforts appear as relevant resilience factors to climate shocks. Fourth, the results are robust to a wide set of robustness checks.

From a policy standpoint, these findings call for holistic reforms geared towards strengthening African countries' adaptability and resilience to climate shocks and macroeconomic shocks more broadly, including notably steadily improving tax revenue mobilization, unleashing job creation opportunities for the youth, stepped up reforestation efforts, and tackling the root causes of social inequalities. The latter, which requires bolds steps towards expanding social safety nets, improving access to quality health care services, and scaling up public investment in the agricultural sector, are critical for preserving the very fabric of the society, developing a greater sense of belonging to a "Nation", thereby helping to ward off the catalyst role of climate shocks on intercommunal conflicts.

ANNEX

Figure A4. 1: Employment in agriculture sector (% total employment) in 2015



Source: WDI and author's calculation

Table A4. 1: List of countries

Algeria	Eswatini	Mozambique
Angola	Ethiopia	Namibia
Benin	Gabon	Niger
Botswana	Gambia	Nigeria
Burkina Faso	Ghana	Rwanda
Burundi	Guinea	Senegal
Cabo Verde	Guinea-Bisseau	Sierra Leone
Cameroon	Kenya	Somalia
Central African Republic	Lesotho	South Africa
Chad	Liberia	South Sudan
Congo, Dem. Rep.	Libya	Sudan
Congo, Rep.	Madagascar	Tanzania
Cote d'Ivoire	Malawi	Togo
Djibouti	Mali	Tunisia
Egypt, Arab Rep.	Mauritania	Uganda
Equatorial Guinea	Mauritius	Zambia
Eritrea	Morocco	Zimbabwe

Table A4. 2: Data description and sources

Variables	Description	Sources
Control variables		
GDP per capita	Gross Domestic Product constant 2010	World Economic Outlook (IMF)
GDP growth	Annual growth of Gross Domestic Product	World Economic Outlook (IMF)
EF index	EF index measures the ethnicity fragmentation within a country	Drazanova (2019)
Population	Total population	World Development Indicator (WDI-World Bank)
Pve	Political stability score	World Bank Governance Indicator (WGI)
Conditional variables		
Tax revenue (%GDP)	Total Tax revenue as percentage of GDP	World Economic Outlook (IMF)
Remittances (%GDP)	Total personal remittances received (current US$)	World Development Indicator (WDI-World Bank)
Health Expenditure (%GDP)	Level of current health expenditure expressed as a percentage of GDP	World Development Indicator (WDI-World Bank)
Hospital beds per 1000 people	Total Hospital beds per 1000 people. Hospital beds include inpatient beds available in public, private, general, and specialized hospitals and rehabilitation centers.	World Development Indicator (WDI-World Bank)
Gini disposable	Estimation of Gini based on household disposable income (post-transfer, post-tax)	Standardized World Income Inequality Database (SWIID)
Investment in agriculture (%GDP)	Percentage of agriculture expenditure in total GDP	International Food Policy Research Institute (IFPRI)
Forest coverage (%)	Share of total land under forest cover	World Development Indicator (WDI-World Bank)
Covariates variables		
Capital stock	Total capital stock (private and public), in billions of constant 2011 international dollars.	IMF
Length of paved road	Length of total paved roads in kilometers	International Road Federation; World Bank
Youth Unemployment	Youth unemployment refers to the share of the labor force ages 15-24 without work but available for and seeking employment.	World Development Indicator (WDI-World Bank)
Youth Unemployment Male	Unemployment rate in Male youth cohort	World Development Indicator (WDI-World Bank)
Youth Unemployment Female	Unemployment rate in Female youth cohort	World Development Indicator (WDI-World Bank)
Agriculture Land (%)	Agricultural land refers to the share of land area that is arable, under permanent crops, and under permanent pastures	World Development Indicator (WDI-World Bank)
Arable Land (%)	The share of land area that is arable	World Development Indicator (WDI-World Bank)
Rural population (%)	Rural population refers to people living in rural areas as a percentage of total population	World Development Indicator (WDI-World Bank)

Table A4. 3: Statistics descriptive of variables

Variables	Observations	Mean	Std. Dev.	Min	Max
Dependent variables					
Conflict type 1	1,479	.3089926	.4622344	0	1
Conflict type 2	1,479	.2129817	.4095533	0	1
Conflict type 3	1,479	.3536173	.4782539	0	1
Drought index	1,377	.5050179	1.16678	0	10
Extreme Dry Months	1,479	.0628803	.5681869	0	11
Drought intensity	1,479	1.462908	4.236494	0	16.951
GDP per capita	1,37	4474.611	5447.501	438.6431	40368.08
GDP growth	1,374	4.192457	8.200983	-62.07592	149.973
EF index	1,219	.6187605	.2463901	.014	.89
Total population	1,472	1.80e+07	2.53e+07	337950	1.96e+08
Pve	988	-.5823957	.8948663	-3.314937	1.219244
Conditional variables					
Tax revenue (%GDP)	1,206	15.46551	8.42928	.5855501	53.32792
Remittances	1,156	4.193562	11.77208	0	167.4317
Health Expenditure	820	7.250061	3.843578	0	23.24532
Hospital beds per 1000 people	270	1.476799	1.05411	.1	6.3
Gini disposable	919	.4358797	.0686048	.3183966	.6234737
Relative redistribution	919	10.04701	3.804742	-7.778729	15.77442
Investment in agriculture	804	1.295056	1.207912	.0015456	9.464178
Forest coverage (%)	1,32	27.84946	23.10903	.0442011	90.03765
Covariates variables					
Capital stock	1,118	130.9442	238.2048	1.448561	1353.867
Length of paved road	436	740.8006	1722.486	.126	14840.23
Youth Unemployment	1,428	16.54519	14.32871	.4	60.83
Youth Unemployment Male	1,428	15.61686	12.85227	.59	55.89
Youth Unemployment Female	1,428	18.24705	17.15754	.16	69.52
Agriculture Land (%)	1,317	46.0377	21.48512	2.655081	82.67134
Arable Land (%)	1,317	12.56063	12.39098	.0431406	48.72219
Rural population (%)	1,472	60.78488	17.67953	10.63	94.584

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CONCLUSION GENERALE ET PERSPECTIVES

L'objectif général de cette thèse était d'évaluer les dommages socioéconomiques des dérèglements climatiques en Asie du Sud Est et en Afrique. Ces deux régions englobent la majorité des ménages pauvres qui dépendent fortement de l'agriculture. Cependant, le changement climatique demeure un obstacle majeur au développement du secteur agricole. Dans notre quête d'estimer les dommages du changement climatique, nous nous sommes intéressés à plusieurs variables de résultats: **la productivité agricole, la sécurité alimentaire, la pauvreté** et **l'incidence des conflits**.

Nous avons utilisé plusieurs outils méthodologiques tels que la révision de la littérature, la mise en évidence des faits stylisés à partir des statistiques descriptives et l'analyse économétrique pour montrer la réalité des dommages des chocs climatiques et proposer des mesures d'adaptations qui pourront aider à lutter contre le réchauffement climatique. Nos analyses ont été effectuées avec la combinaison des données microéconomiques, macroéconomiques et des bases de données satellitaires concernant la mesure des variables climatiques. Ainsi, nous pensons avoir contribué à la littérature existante à travers les quatre chapitres de cette thèse. Les deux premiers chapitres s'intéressent respectivement à évaluer l'impact des chocs climatiques sur l'efficience technique agricole et la sécurité alimentaire au Vietnam. Les deux derniers chapitres sont des études sur l'Afrique. Le chapitre 3 a permis d'analyser le lien entre pluviométrie et bien-être (au Mali) qui est mesuré à travers les dépenses de consommation et le statut de pauvreté des ménages. Ensuite, le dernier chapitre a abordé avec un angle macroéconomique la relation entre choc climatique et incidence des conflits domestiques. Ces quatre chapitres font ressortir plusieurs résultats intéressant qui pourront aider les décideurs politiques.

Résultats principaux des chapitres

Dans le premier chapitre nous avons montré qu'il existe un lien indirect entre choc climatique et la productivité agricole à l'aide d'une estimation avec le modèle SFA (Stochastic Frontier Analysis). En effet, le modèle SFA nous a permis d'estimer la valeur de l'efficience technique de chaque producteur de riz et ensuite d'évaluer les déterminants de ces scores d'efficiences. Nos résultats montrent qu'en plus des caractéristiques sociodémographiques des ménages agricoles, les variables climatiques sont aussi déterminantes de leur productivité. Nous avons également révélé que les jours chauds et l'occurrence des catastrophes naturelles sont néfastes pour la productivité agricole car ils réduisent la performance des agriculteurs. Par ailleurs, nous faisons ressortir des effets hétérogènes selon certaines caractéristiques des exploitants agricoles. Premièrement, nous montrons que les petits exploitants sont plus impactés par rapport aux grands exploitants. Aussi, les ménages qui font face à des contraintes de liquidités financières étaient limitées dans l'adoption de nouvelles technologies pour améliorer leur performance.

Le secteur agricole étant un facteur important de la sécurité alimentaire, nous nous sommes intéressés à évaluer la relation entre les facteurs de risques environnementaux et la sécurité alimentaire dans le second chapitre. Cette analyse est multidimensionnelle car elle traite de l'impact de plusieurs facteurs de risques environnementaux sur chacune des composantes de la sécurité alimentaire : la disponibilité, l'accessibilité, la diversité et la stabilité. Ainsi, nous avons construire un indicateur global de sécurité alimentaire à partir d'une analyse en composante principale (ACP). Les résultats de ce chapitre montrent que les facteurs de risques environnementaux tels que la variabilité de la température et précipitation, l'occurrence régulière des catastrophes naturelles, la pollution de l'air et la déforestation sont comptés parmi les facteurs qui empêchent les ménages d'avoir un bon état nutritionnel. Toutefois l'ampleur de l'impact dépend selon le facteur de risque considéré et de la dimension de la sécurité alimentaire.

Le chapitre 3 a évalué les effets des conditions climatiques sur le bien-être des ménages. Nous concentrons notre analyse sur le cas du Mali qui fait face à des défis majeurs ces dernières années comme le changement climatique et la sécurité. Au Mali, la plupart des ménages dépendent de l'agriculture pluviale, ce qui les rend vulnérables aux mauvaises conditions météorologiques. Nous profitons d'un ensemble de données unique, une enquête des ménages représentative au niveau national, de 2010 à 2018 combinée avec des données géo-référencées sur les variables climatiques pour mener notre évaluation. Nos résultats montrent que l'élasticité de la consommation à la variation de la pluviométrie varie selon les types de consommation et les groupes socio-économiques. Premièrement, nos résultats montrent que l'élasticité est plus élevée pour la consommation non alimentaire et beaucoup plus faible pour la consommation alimentaire. Deuxièmement, nous trouvons que les ménages pauvres qui sont le plus souvent situés loin de la capitale (Bamako) et dépendant fortement des revenus agricoles sont les plus touchés par la variabilité et l'instabilité du climat. D'un point de vue politique, les résultats suggèrent que des efforts supplémentaires devraient être faits pour réduire l'inégalité et la pauvreté parmi les groupes socio-économiques.

La pauvreté étant l'une des causes majeures des conflits domestiques en Afrique, le chapitre 3 est complémentaire au chapitre 4 qui analyse l'impact des chocs climatiques sur les conflits internes. Ce chapitre s'appuie sur un modèle à effets aléatoires corrélés pour évaluer cette relation sur un large échantillon de 51 pays africains sur la période 1990-2018. Nous trouvons que les chocs climatiques, tels que capturés par l'indice d'aridité augmentent la probabilité des conflits domestiques, jusqu'à 38 %. Cet effet est amplifié dans les pays où la répartition des revenus est plus inégale et où la proportion de jeunes hommes est plus importante. Les résultats mettent en évidence des facteurs clés de résilience, notamment l'amélioration constante de la mobilisation des recettes intérieures, le renforcement de la protection sociale et l'augmentation des investissements publics dans le secteur agricole.

Recommandations de politiques économiques

Plusieurs recommandations politiques émergent de ces quatre chapitres dont les plus importants sont :

- Tout d'abord, on peut préconiser la mise en place de systèmes de prévision météorologique saisonnières dans les zones moins favorisées. Un système météorologique qui fournit des données en temps réel réduira les biais dans les attentes des individus. En effet, il est difficile pour les ménages, notamment les ménages pauvres, de s'ajuster automatiquement aux chocs exogènes à court terme. Ainsi, les dommages climatiques sont d'autant plus amplifiés que le biais d'anticipation est important.

- Ensuite, le changement climatique étant un obstacle pour le développement du secteur agricole, les autorités locales doivent faire encore plus d'effort en investissant massivement dans ce secteur. Par exemple, les ménages agricoles doivent avoir facilement accès aux intrants (fertilisants, engrais…) et technologies (les systèmes d'irrigation, la mécanisation…) qui sont plus résilients à la variabilité du climat (l'agriculture de précision, l'agriculture écologique, la rotation des cultures, etc.).

- Par ailleurs, la diversification des sources de revenu des ménages devrait être encouragée afin de réduire la dépendance de ces derniers au secteur agricole. Pour ce faire, la mise en place d'un système de protection sociale solide à travers l'accès au crédit, les cash transferts ou les subventions, en relâchant les contraintes de liquidité, pourraient aider les individus à beaucoup investir dans l'entreprenariat.

- Au niveau macroéconomique, les gouvernements dans les pays en développement doivent axés leur politique sur la mobilisation des ressources internes dans les périodes sans chocs afin de financer la résilience ou l'adaptation en période de chocs climatiques.

- Enfin, le changement climatique est un phénomène global qui engendre des externalités. Malheureusement, ces dommages sont plus importants dans les pays où la pauvreté et les inégalités sont déjà élevées. Ainsi, la réduction de son impact nécessite une prise de conscience au niveau mondial. Même si des initiatives sont en cours comme le fonds vert pour le climat de l'ONU et la décision du président américain Joe Biden de doubler l'aide des USA[65], il demeure important de mentionner que des efforts additionnels peuvent être fournis pour faire face à l'urgence climatique.

Limites de nos recherches et perspectives

Les différentes analyses que nous avons effectuées dans cette thèse peuvent être améliorer au niveau méthodologique.

Dans le chapitre 1, nous utilisons un modèle de frontière très ancien (**Lee and Schmidt (1993)**). Ce modèle ne permet pas de faire une estimation simultanée des deux étapes de notre stratégie d'identification, ce qui pourrait impacter la qualité de nos estimations. Toutefois, parmi tous les modèles SFA à notre porté, celui-ci était le seul qui convergeait. Nous proposons une amélioration de ce chapitre en utilisant un modèle de frontière plus robuste et qui permettrait de lever les limites du modèle de **Lee and Schmidt (1993)**.

Dans le chapitre 2, nous avons traité la question de la sécurité alimentaire. La mesure des différentes composantes de la sécurité alimentaire (disponibilité, accessibilité, diversité et stabilité) est très complexe car elle nécessite la prise en compte de plusieurs facteurs structurels comme les prix des biens alimentaires, l'accès aux marchés, la disponibilité des infrastructures…L'accès à ces variables étant limité, nous avons utilisé autant que possible des variables « proxies » disponibles dans la base de donnée de l'enquête VHLSS pour prendre en compte ces dimensions. Par ailleurs, il est bien de noter que la base VHLSS n'est pas une base nutritionnelle. Ainsi, le calcul de la quantité de calories consommée par le ménage a été basée sur les dépenses alimentaires. Cette manière de calculer la consommation énergétique du ménage pourrait sous-estimer ou surestimer la valeur

[65] https://www.lemonde.fr/planete/article/2021/04/22/le-sommet-sur-le-climat-organise-par-joe-biden-un-test-de-credibilite-pour-les-etats-unis_6077605_3244.html

réelle de la quantité de calorie consommée. Nous conseillons donc l'utilisation des données d'enquêtes nutritionnelles, si disponible, pour affiner nos analyses.

Enfin, pour une grande efficacité de nos recommandations de politiques économiques, il est nécessaire de faire des analyses plus approfondies de la question autour de l'adaptation au changement climatique. Par exemple, une méta-analyse qui permettrait de hiérarchiser les différentes possibilités d'adaptation selon leur efficacité et le contexte géographique, est fortement recommandée. Aussi, il serait nécessaire de faire une étude plus approfondie sur l'identification du rôle de chaque acteur (ménage, entreprises, Gouvernements, ONG, institutions internationales …) dans l'implémentation des politiques de résilience ou dans l'adoption des comportements d'adaptations au changement climatique.

CONTRIBUTION POUR LES CO-ECRITURES

Mes travaux de thèse m'ont permis de collaborer avec d'autres chercheurs. Certains chapitres ont été coécrits avec la collaboration d'autres chercheurs. De façon plus détaillée, mes contributions sont les suivantes :

- Chapitre 1 : Ce chapitre a été coécrit avec Sébastien Marchand[66] et Etienne Espagne[67]. Ma contribution se situe à plusieurs niveaux :

    - ✓ La revue de littérature
    - ✓ Apurement de la base de donnée
    - ✓ Régression économétrique
    - ✓ Rédaction

- Les Chapitres 2 et 3 sont des œuvres individuelles.

- Chapitre 4 : Ce chapitre a été coécrit avec René Tapsoba[68] pendant mon stage au bureau représentatif du FMI au Mali. Ma contribution se situe à plusieurs niveaux :

    - ✓ La revue de littérature
    - ✓ Apurement de la base de donnée
    - ✓ Régression économétrique
    - ✓ Rédaction

- Enfin, j'ai collaboré avec Olivier Santoni (géomaticien au CERDI) pour l'extraction et la préparation des bases de données climatiques qui ont été utilisées dans les différents chapitres.

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RÉSUMÉ

Il est un fait avéré que les conséquences du changement climatique font peser une menace considérable sur le bien-être de l'humanité tout entière. Depuis de nombreuses années maintenant, les conséquences du changement climatique, parmi lesquelles les sécheresses, les inondations et l'accroissement de la fréquence et de l'intensité des phénomènes météorologiques graves, se font sentir partout sur la planète. Par ailleurs, les coûts économiques de ces phénomènes climatiques sont plus importants dans les pays en développement qu'ailleurs. En effet, la variabilité de la température ou de la pluviométrie réduit fortement la productivité agricole qui est le secteur prédominant dans ces pays. Aussi, leurs défaillances institutionnelles sont un obstacle à leur adaptation ou à faire face aux effets pervers du changement climatique. Ainsi, cette thèse contribue à la littérature existante en proposant quatre chapitres sur les impacts socioéconomiques du changement climatique en Asie du Sud-Est et en Afrique. Plus précisément, nous analysons les impacts des tendances et chocs climatiques sur l'activité agricole, la sécurité alimentaire, le bien-être des ménages, et les conflits sociaux. Les deux premiers chapitres s'intéressent au cas du Vietnam et les deux derniers chapitres se concentrent sur l'Afrique. Dans le premier chapitre, les résultats indiquent que les chocs climatiques ont deux effets (direct et indirect) sur la productivité agricole. L'effet direct est appréhendé par l'impact non linéaire de la moyenne de la température et de la précipitation sur le rendement agricole. Ensuite, l'effet indirect est capté par la relation négative et significative entre les chocs climatiques et l'efficience technique des producteurs agricoles. Aussi, les résultats des simulations sont pessimistes quant à l'évolution de l'efficience technique dans un contexte où le réchauffement climatique sera plus important. Par la suite, dans le second chapitre, nous menons une réflexion sur la relation entre les facteurs de risques environnementaux et la sécurité alimentaire à travers une analyse multidimensionnelle. Les résultats de ce chapitre indiquent que les facteurs de risques environnementaux qui incluent la variabilité du climat empêchent les ménages ruraux d'atteindre un statut nutritionnel adéquat. Le chapitre 3 s'intéresse à l'analyse de la relation entre bien-être et conditions climatiques au Mali. Il ressort de ce chapitre que le bien-être des ménages au Mali est sensible aux conditions climatiques. Plus intéressant, nos résultats montrent que l'élasticité de la consommation à la variation de la pluviométrie varie selon les types de consommation et les groupes socio-économiques. Premièrement, nous trouvons que la valeur de l'élasticité consommation-pluviométrie est plus élevée pour la consommation non alimentaire et beaucoup plus faible pour la consommation alimentaire. Deuxièmement, nous trouvons que les ménages pauvres qui sont le plus souvent situés loin de la capitale (Bamako) et dépendants fortement des revenus agricoles sont les plus touchés par la variabilité et l'instabilité du climat. La pauvreté étant un déterminant clé des conflits en Afrique, le chapitre 4 analyse l'impact des chocs climatiques sur l'incidence des conflits domestiques. Nous trouvons que les chocs climatiques, tels que capturés par l'indice d'aridité augmentent la probabilité des conflits domestiques jusqu'à 38 %. Cet effet est amplifié dans les pays où la répartition des revenus est plus inégale et où la proportion de jeunes hommes est plus importante. Les résultats de ce chapitre mettent aussi en évidence des facteurs clés de résilience, notamment l'amélioration constante de la mobilisation des recettes intérieures, le renforcement de la protection sociale et l'augmentation des investissements publics dans le secteur agricole.

Mots clés : Changement climatique, chocs climatiques, agriculture, sécurité alimentaire, bien-être, pauvreté, conflits, pays en développement, Asie du Sud-Est, Vietnam, Mali, Afrique, économétrie appliquée.

Classifications JEL: D12, D24, D74, J11, I30, O12, O13, Q12, Q54

SUMMARY

It is a fact that the consequences of climate change pose a considerable threat to the well-being of all humanity. For many years now, the consequences of climate change, including droughts, floods, and increases in the frequency and intensity of severe weather events, have been felt around the world. Moreover, the economic costs of these climatic phenomena are greater in developing countries than elsewhere. Indeed, the variability of temperature or rainfall strongly reduces agricultural productivity, which is the predominant sector in these countries. Also, their institutional failures are an obstacle to their adaptation or to face the perverse effects of climate change. Thus, this thesis contributes to the existing literature by proposing four chapters on the socio-economic impacts of climate change in Southeast Asia and Africa. Specifically, we analyze the impacts of climate trends and shocks on agricultural activity, food security, household welfare, and social conflict. The first two chapters focus on the case of Vietnam and the last two chapters focus on Africa. In the first chapter, the results indicate that climate shocks have two effects (direct and indirect) on agricultural productivity. The direct effect is captured by the non-linear impact of average temperature and precipitation on agricultural yield. Then, the indirect effect is captured by the negative and significant relationship between climate shocks and the technical efficiency of agricultural producers. Also, the results of the simulations are pessimistic about the evolution of technical efficiency in a context where global warming will be more important. Subsequently, in the second chapter, we reflect on the relationship between environmental risk factors and food security through a multidimensional analysis. The results of this chapter indicate that environmental risk factors that include climate variability prevent rural households from achieving adequate nutritional status. Chapter 3 focuses on the analysis of the relationship between well-being and climatic conditions in Mali. This chapter shows that household well-being in Mali is sensitive to climatic conditions. More interestingly, our results show that the elasticity of consumption to changes in rainfall varies across consumption types and socio-economic groups. First, we find that the value of consumption-rainfall elasticity is higher for non-food consumption and much lower for food consumption. Second, we find that poor households that are most often located far from the capital (Bamako) and heavily dependent on agricultural income are the most affected by climate variability and instability. Since poverty is a key determinant of conflict in Africa, Chapter 4 analyzes the impact of climate shocks on the incidence of domestic conflict. We find that climate shocks, as captured by the aridity index, increase the likelihood of domestic conflict by up to 38 percent. This effect is amplified in countries with more unequal income distribution and a higher proportion of young men. The results in this chapter also highlight key resilience factors, including continued improvements in domestic revenue mobilization, enhanced social protection, and increased public investment in the agricultural sector.

Keywords: Climate change, weather shocks, agriculture, food security, welfare, poverty, conflict, developing countries, Southeast Asia, Vietnam, Mali, Africa, and applied econometrics.

JEL Classifications: D12, D24, D74, J11, I30, O12, O13, Q12, Q54