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Impacts of extreme climate events on technical efficiency in Vietnamese agriculture

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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. Also, this study combines these estimated marginal effects with future climate scenarios (Representative Concentration Pathways 4.5 and 8.5) to project the potential impact of hot temperatures in 2050 on rice technical efficiency. 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. For instance, a one day increase in the bin [33°C-34°C] ([35°C and more]) lessen technical efficiency between 6.84 (2.82) and 8.05 (3.42) percentage points during the dry (wet) season.

Keywords

Weather shocks, Technical efficiency, Rice farming, Vietnam.

JEL Codes

D24, O12, Q12, Q54.

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1 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[1]. Since the country lies in the tropical cyclone belt, it is heavily exposed to climatic-related risks like 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[2]. 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 between 2010 and 2014, and weather data on temperature and precipitation, this study examines farm household-level impacts of weather shocks, defined as extreme events such as extreme temperatures, floods, droughts and typhoons, on agricultural productivity in the Vietnamese rice farming[3].

This study contributes to the growing literature that uses farm-level panel data (here the Vietnam Household Living Standard Survey (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

[1] Source: the CCKP website.

[2] These last years, while the contribution of Vietnamese farming to national GDP has become less important (from about 40% in 1990 to about 18% in 2016), 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.

[3] 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.

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[4]. As a result, we find that weather shocks measured by the occurrence of floods, typhoons and droughts negatively affect 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°C-34°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%, while it stabilizes in the RCP4.5 scenario around 10% below the reference period[5].

The remaining of the paper 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. 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.

2 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 long-run 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

[4]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.

[5]We only used one CORDEX-SEA model for climate projections in this version of the paper, 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.

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)[6].

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

[6]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.

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 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.

3 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 on, 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)[7].

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[8].

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 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.

[7]Data come from FAOSTAT.

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

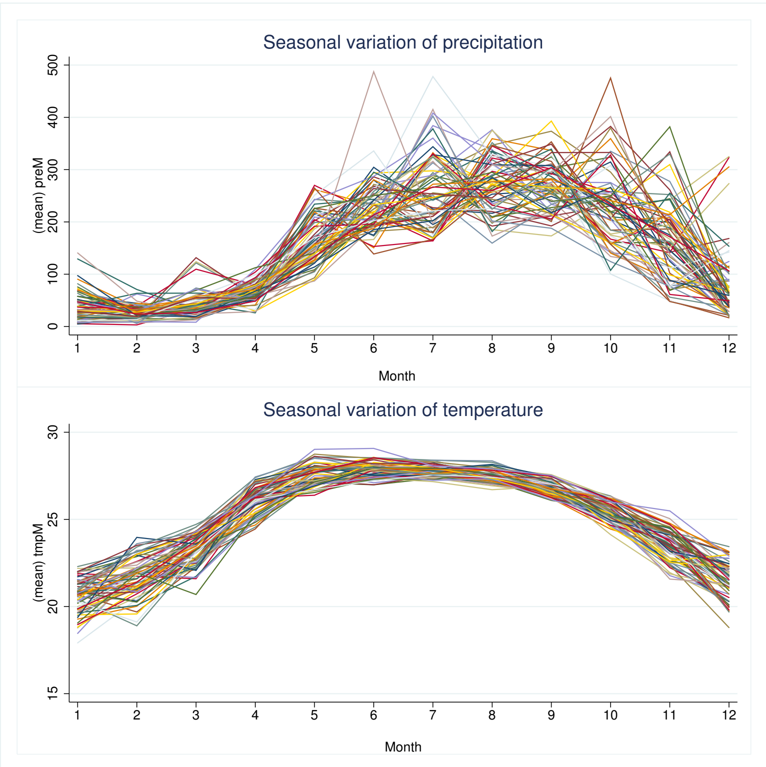
3.2 Climate condition

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 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 from one region to another throughout the country.

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



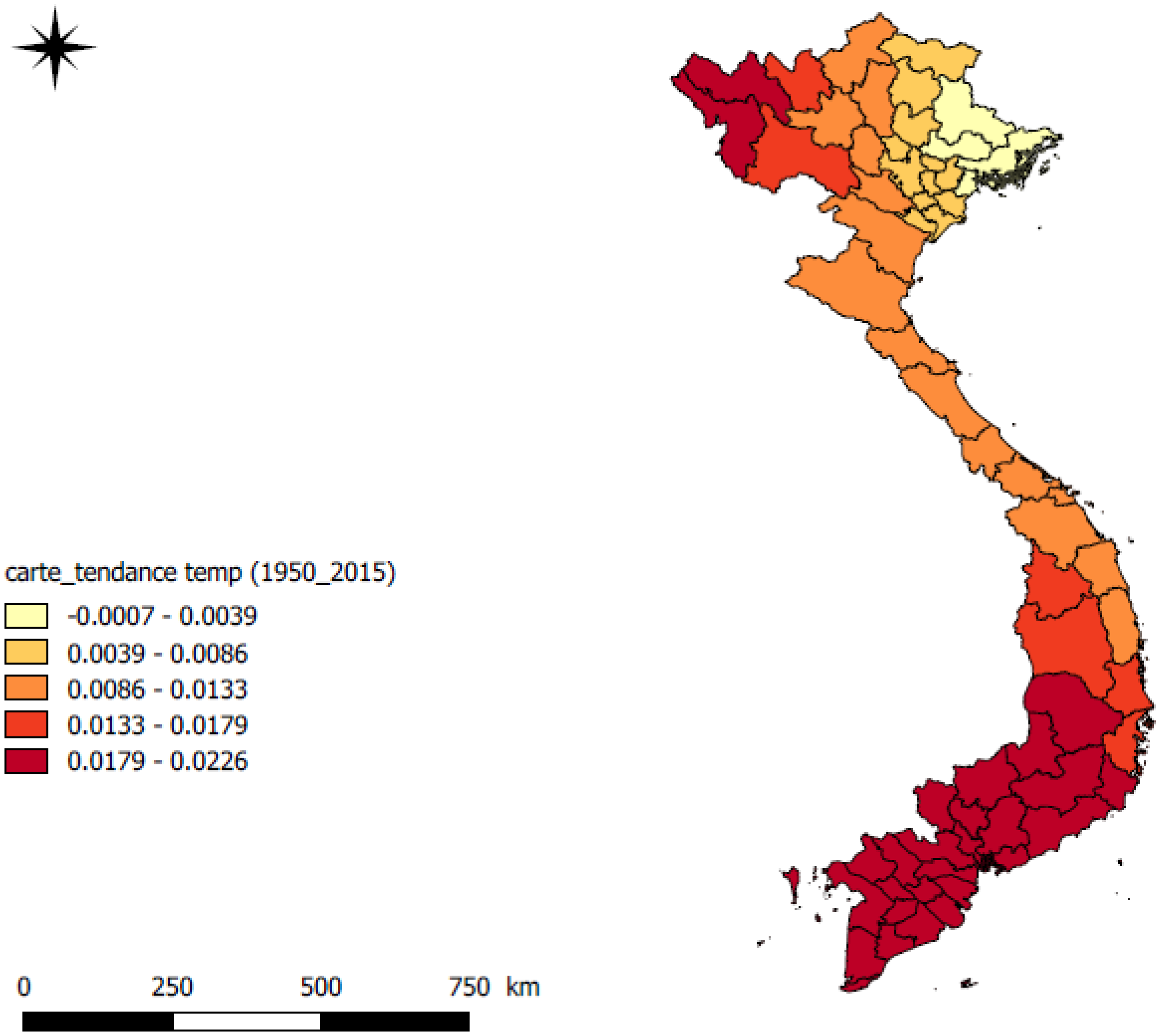
Source: authors from CHIRPS and MODIS data

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

Figures 2 and 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.

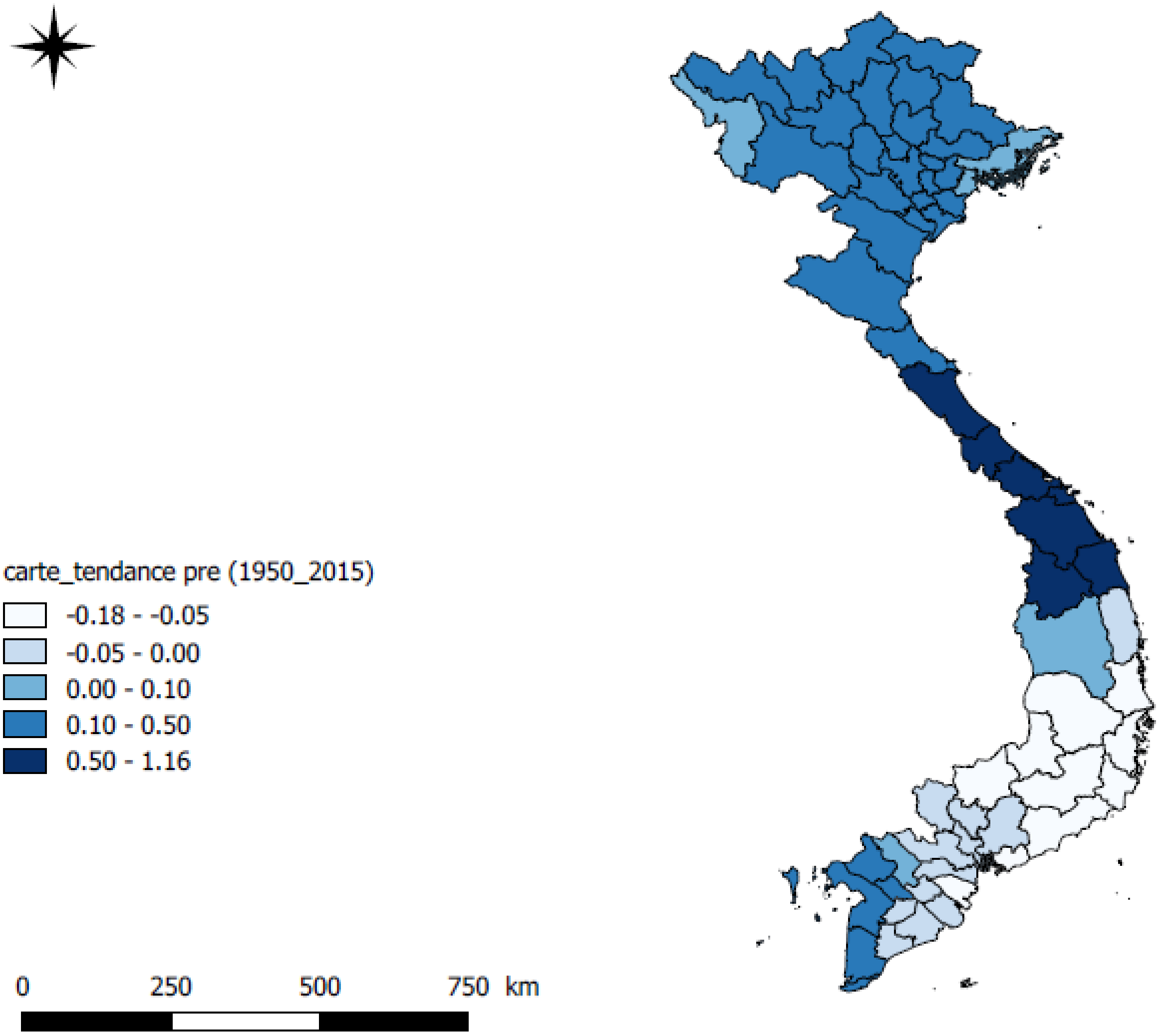
On the other hand, there is an average decrease in precipitations in the south, unlike in the north and center where there has been a relative increase in monthly precipitations. In addition, Figures A1 and A2 in Appendix respectively show the evolution of the level of temperatures and precipitations 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 2: Average annual temperature trend increase over the period 1950-2015



Source: authors from MODIS data

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



Source: authors from CHIRPS data

4 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 informations 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[9].

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[10], 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[11].

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 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[12].

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

[10] 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.

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

[12] 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

In this study, we implement the stochastic frontier analysis by using both the Cobb-Douglas 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.

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.

to the incidental parameter concern.

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:

$$\begin{aligned} ln(Rice_{i,t}) = \beta_0 + \beta_1 ln(famlabor_{i,t}) + \beta 2 ln(hirlabor_{i,t}) + \beta 3 ln(capital_{i,t}) \\ + \beta 4 ln(runningcosts_{i,t}) + \beta 5 ln(famlabor_{i,t})^2 \\ + ... + \beta 9 ln(famlabor_{i,t}) ln(hirlabor_{i,t}) + ... + \alpha_t - U_{i,t} + V_{i,t}, \end{aligned} \tag{7}$$

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 in the Appendix. t refers to the year of the last three surveys used in this study (2010-2012-2014)[13]. Each household i has been surveyed two or three times. α_t measures temporal

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

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:

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

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[14].

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

$$U_{i,t} = \delta_t * \gamma_i \geqslant 0, \tag{9}$$

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:

$$TE_{i,t} = e^{-U_{i,t}} \tag{10}$$

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 computed from the first stage, it is used as dependent variable in the second stage as follows:

$$TE_{i,t} = \alpha_0 + \alpha_1.Z_{i,t} + \alpha_2.W_{i,t} + \epsilon_{i,t}, \tag{11}$$

Equation 11 is estimated with the fixed effects model. W includes control variables

[14] 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.

(household size and gender, education level and age of the household head) and Z represents weather shocks[15]

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[16]. GDD can be computed as follows:

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

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

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 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

[15]More information in Table A1 in Appendix.

[16]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

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[, [32-33[, [33-34[, [34-35[and [35-plus[) for both dry and wet seasons[17]. Then, for each interval, we compute the following variable:

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

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

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

5 Data and descriptive statistics

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

5.1 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 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%

[17] 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.

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.

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 (2010-2012-2014)[18]. 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.

5.2 Climate data

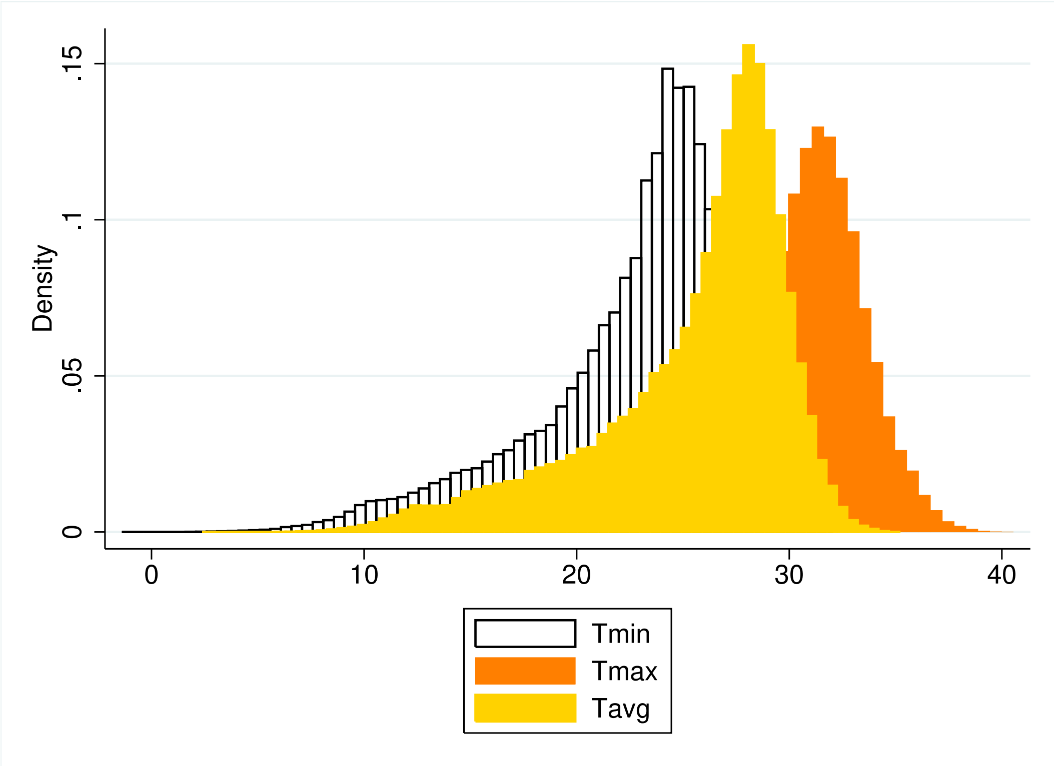
The climate data used in this study are daily temperatures and precipitations. These data come from the Climate Prediction Center (CPC) database developed by the National Oceanic and Atmospheric Administration (NOAA). It provides historical data on maximum and minimum temperature and precipitation levels 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 precipitation and daily temperature of the four nearest localities weighted by the inverse of the squared distance.

The Figure 5 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.

[18]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 4: Distribution of tmin, tmax and tavg



Source: authors from CPC data

Finally, from Table 1, we note an average cumulative precipitation of 1,475.24 mm and an average daily temperature of 24.82°C over the period (2010-2014).

Table 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)	5,894	.32	.35	0	4.92
Running costs (1,000 VND/m^2)	5,894	.75	.32	0	10.02
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
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

6 Econometric results

6.1 Estimation of the SFA model

The first step is to estimate TE scores from a translog production function within a SFA. Table 2 presents the estimation results[19].

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 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 microeconomics theory. As the parameter estimates of the translog production function reported in Table 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 A2 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.

[19] 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 A4 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.

Table 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%.

6.2 Impact of extreme weather events on TE

Table 3 summarizes the distribution of technical efficiency (TE) scores obtained from the column 3 of Table 2 and the formula of Jondrow et al. (1982)[20]. TE scores range from 0.29 to 1 with an 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.

Table 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		

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 4) and a Tobit model (Table 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.

In the first column of Table 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°C-32°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

[20]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.

Table 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 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%.

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)[21]. 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, 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 5. It is worth noting that the effects of climate variables remain the same. 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 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,

[21]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.

Table 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 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%.

-4.21 and -3.97 percentage points for typhoon, and -5.03 and - 4.73 percentage points for drought.

6.3 Heterogeneity effects

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 4. Results are presented in Table A4 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.

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 A5 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 A6, 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.

7 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[22].

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

[22] 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.

-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 sub-grid 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 (CORDEX-SEA) 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 tables 4 and 5. We thus get the relative impact on technical efficiency of the change in climate in each pixel of the Viet Nam map 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 4.

The results appear on figure 6 and 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 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 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.

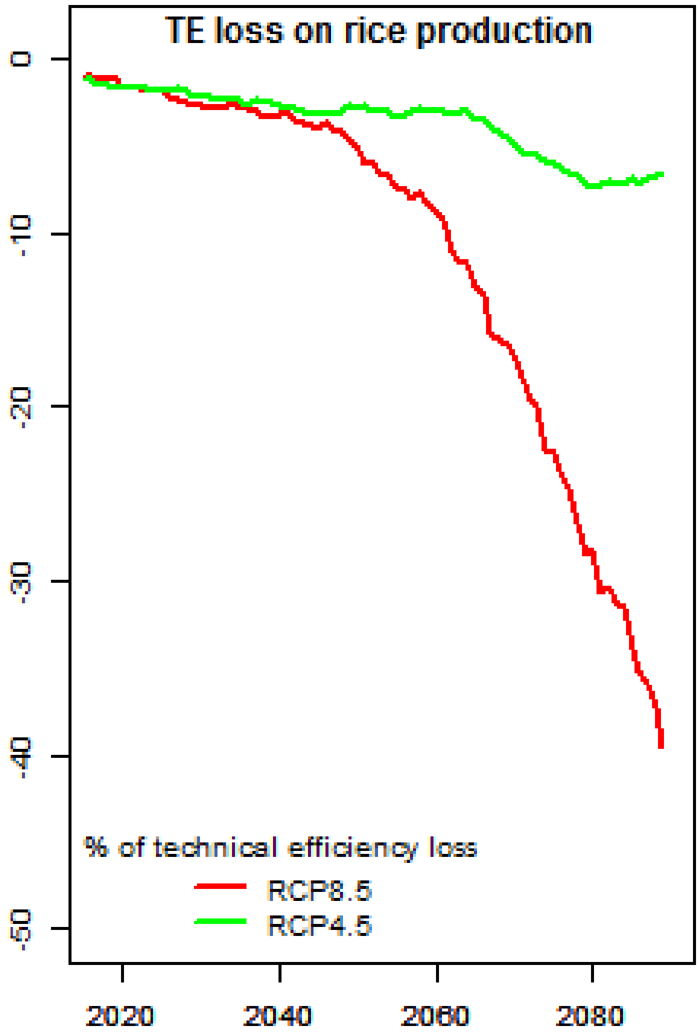
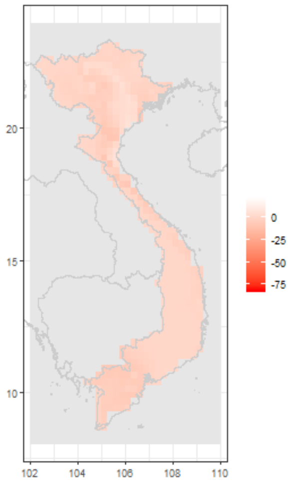


Figure 5: Aggregate damage on technical efficiency (% points lost)

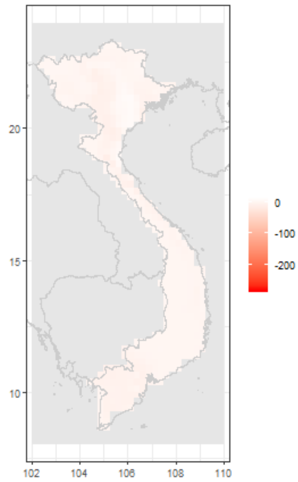
On aggregate, we can also calculate the average loss in technical efficiency for Viet Nam as a whole, by simply aggregating with equal weights the losses evaluated for each cell. This exercize shows that RCP4.5 and RCP8.5 scenarios start diverging soon after 2040. Technical efficiency losses reach 40 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.

Figure 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.

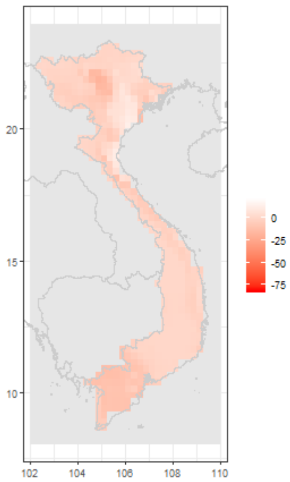
(a) RCP4.5 - 2030



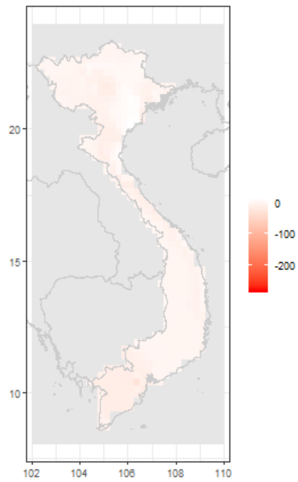
(b) RCP8.5 - 2030



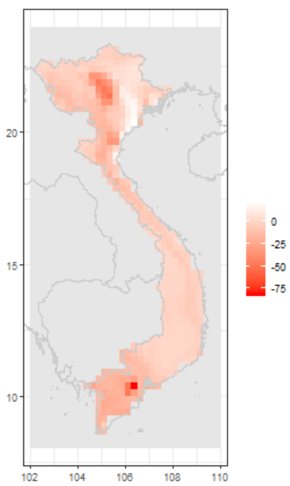
(c) RCP4.5 - 2050



(d) RCP8.5 - 2050



(e) RCP4.5 - 2090



(f) RCP8.5 - 2090

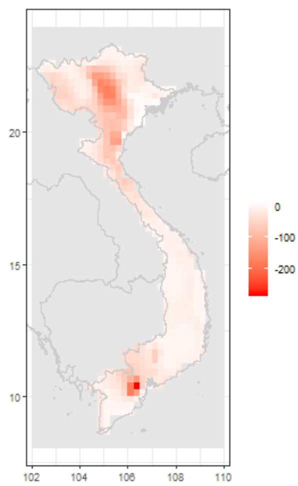
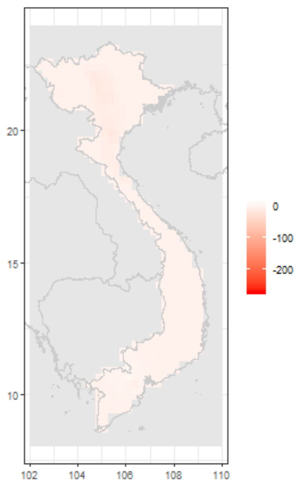
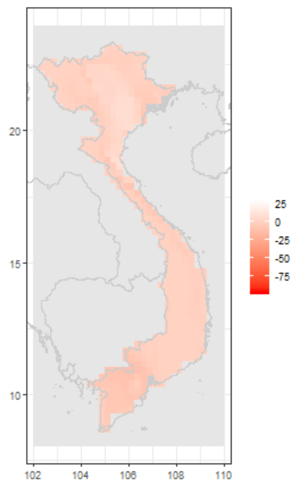


Figure 7: Technical efficiency losses in 2030, 2050 and 2090 compared to the reference period 1986 – 2005, for dry and wet seasons separated, RCP8.5 only.

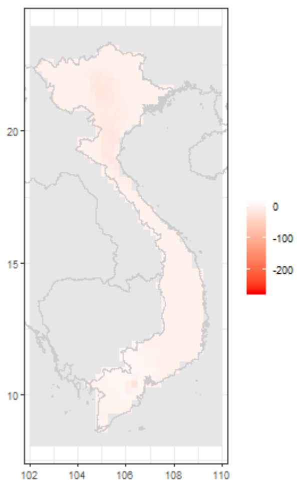
(a) Dry season - 2030



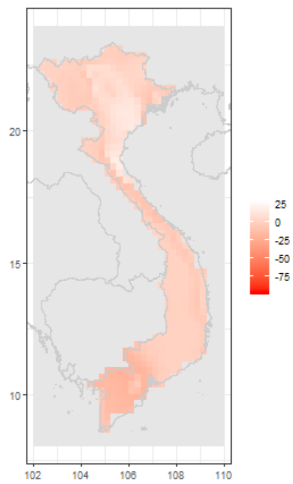
(b) Wet season - 2030



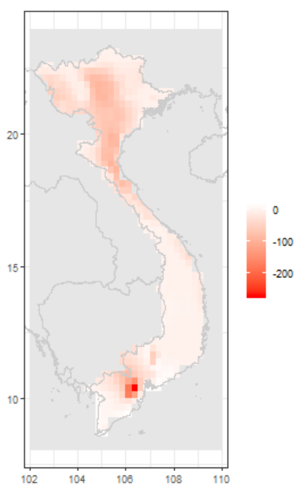
(c) Dry season - 2050



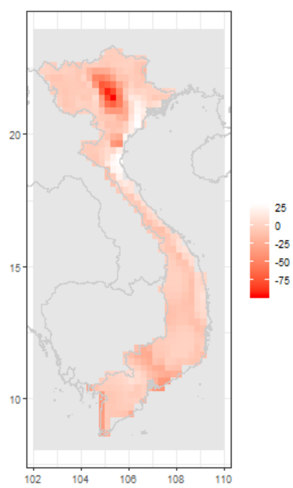
(d) Wet season - 2050



(e) Dry season - 2090



(f) Wet season - 2090



8 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 wed 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[have a significant and negative effect on TE. For instance, a one day increase in the bin [35°C[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.

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A Appendix

Table A1: List of variables

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 A2: 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 2. Elasticities calculated at sample mean, sample median, minimum and maximum of inputs.

Table A3: 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 A4: 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)
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)
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)
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	1,400

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

Table A5: 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)
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)

Table A5 continued

VARIABLES	(1) Efficiency	(2) Efficiency	(3) Efficiency
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)
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

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

Table A6: Liquidity constraint, weather shocks and TE - interactions terms

VARIABLES	(1) Efficience
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)
Age	0.646***
	(0.0899)
Educ	1.224***
	(0.447)
HH size	-0.678**
	(0.298)
Gender	-3.292*
	(1.947)
Flood	-3.415
	(2.268)
Typhon	-3.699
	(2.280)
Drought	-1.853
	(1.855)

Table A6 continued

VARIABLES	(1) Efficience
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)
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)
Liquidity*Drought	-0.0916
	(0.227)
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

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

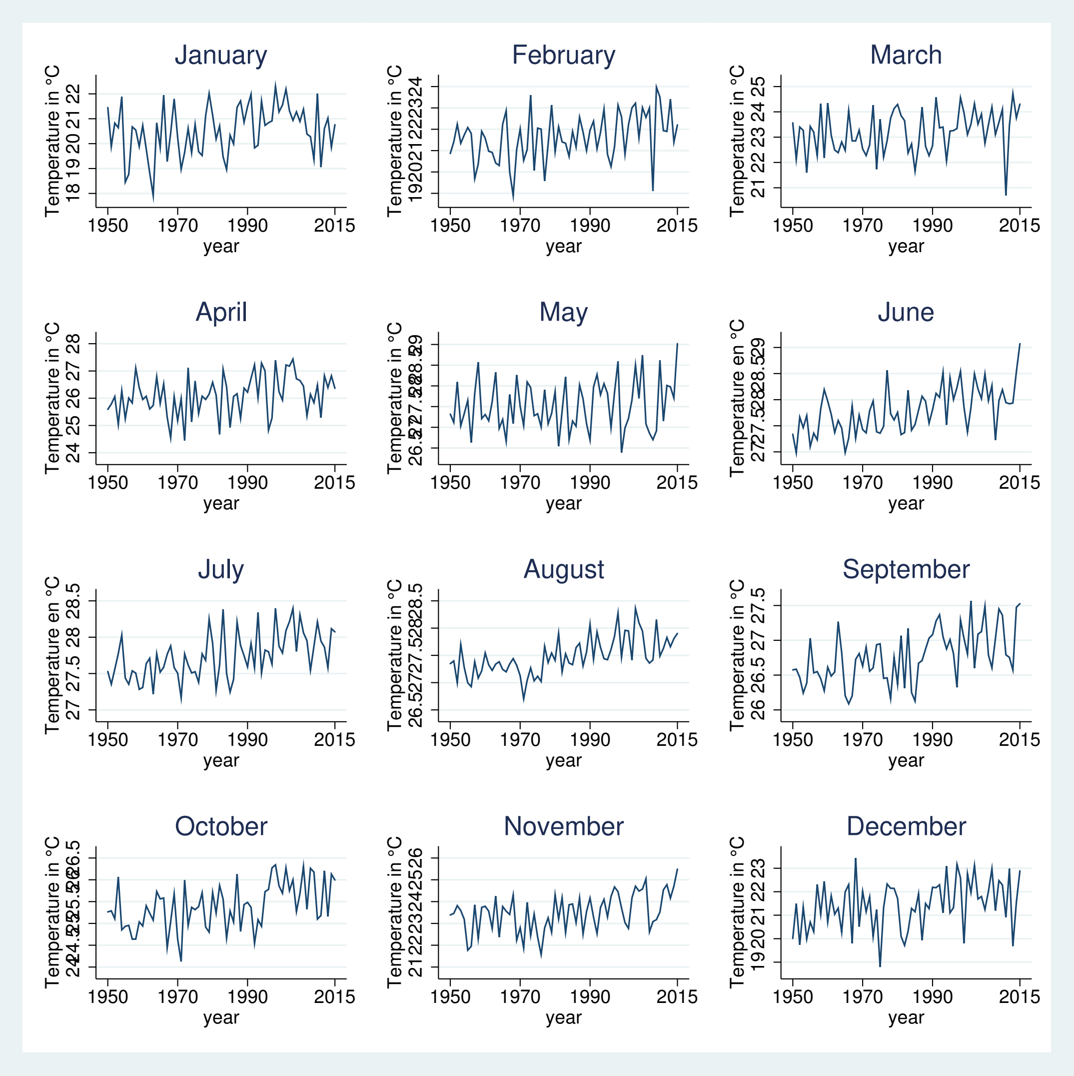

Figure A2: Evolution of precipitation level by month (1950-2015)