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Effect of climate change vulnerability on farm technical efficiency in central Africa: the case of rural Cameroun

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Received 14 January 2024
Revised 23 October 2024
Accepted 30 October 2024

Abstract

Purpose – A major topical issue in the 21st century is climate change, and its impact on humanity cannot be quantified, as it affects agriculture, water levels, settlements and more. This study aims to evaluate the effect of climate change on farm technical efficiency in rural Cameroon and suggest ways for improvement.

Design/methodology/approach – We employ a two-step approach to assess whether the efficiency of these farms is vulnerable to climate change. In the first step, we calculate efficiency using the stochastic frontier approach with a Cobb–Douglas specification. In the second step, we investigate the effect of climate change on efficiency by applying a Tobit model. The data used come from a questionnaire survey of 419 randomly selected farmers.

Findings – The findings reveal that the average level of technical efficiency is 62.9%. This implies that there are existing opportunities to increase technical efficiency if resources are used optimally. The results also show that increases in the climate change vulnerability index have statistically significant negative effects on the technical efficiency of farms. This negative relationship is attributable to the adverse influence of the exposure and sensitivity components of the climate change vulnerability index.

Originality/value – We provide an understanding of the effect of climate change vulnerability on the technical efficiency of farms in rural Cameroon and suggest means of improving it. Additionally, we examine whether the influence of climate change varies across agro-ecological zones.

Keywords Climate change, Cameroon, Rural, Technical efficiency, Vulnerability

Paper type Research paper

1. Introduction

Climate change is one of the major challenges for humanity in the 21st century (IPCC, 2021; Masson and Fritsche, 2021). The work of the Intergovernmental Panel on Climate Change (IPCC) and the World Bank has concluded that climate change caused by the accumulation of anthropogenic greenhouse gases (GHGs) in the atmosphere has an unprecedented impact on global economic activity (IPCC, 2007, 2014, 2021; World Bank Group, 2021). Climate forecasts for the African continent indicate an increase in average temperatures of between 0.2 and 0.8 °C, with a projected average increase of between 3 and 4 °C by 2,100 (IPCC, 2021). Moreover, the continent suffers nearly 80% of the effects of climate change, even though it is the world's smallest emitter of GHGs. In Cameroon specifically, meteorological data show that the average annual temperature has risen by 0.7 °C since 1960, or at an average rate of 0.15 °C per decade (Amougou, 2018). The average rainfall for the period 1981–2000 is 20–40%, which is lower than for the period 1961–1980. There has been a decline in rainfall since 1960 of about −2.2% per decade or −2.9 mm per month (PNACC, 2015). Furthermore, climate predictions for the country predict an increase in average annual temperatures of between 1.5 and 4.5 °C, including an increase of 1.6 and 3.3 °C in the coastal zone and 2.1 and 4.5 °C in the Sudano-Sahelian zone (SSZ) by 2,100 (Amougou, 2018).

We acknowledge everyone who have and will still contribute to the great success of this research work. We acknowledge Owolabi Kayode's assistance towards this research paper.

Funding details: The authors received no direct funding for this research work.

Declaration of interest statement: The authors declare no conflict of interest.

Agricultural Finance Review
Vol. 85 No. 1, 2025
pp. 1-18

e-ISSN: 2041-6326
p-ISSN: 0002-1466
DOI 10.1108/AFR-01-2024-0005

The analysis of the effects of climate change on agriculture is one of the issues that has received the most attention from the scientific community (Malhi *et al.*, 2021; Mendelshon *et al.*, 1994; Soviadan *et al.*, 2019; World Bank, 2021). Agriculture provides a livelihood for more than 3 billion of the world's 6 billion people and employs nearly 1.34 billion people or about 43% of the global workforce (FAO *et al.*, 2020). More than 80% of African agriculture is small-scale family farming and generates about 15–20% of the gross domestic product (GDP), employing 26.75–60% of the continent's labour force (Njongan, 2012; WDI, 2021). This is also true in Cameroon, where 97% of agriculture is practiced by small family farms, contributing 15.27% of the GDP and employing nearly 60% of the active population (INS, 2014; WDI, 2021). Moreover, 80% of farmers live in rural areas and suffer from poverty (INS, 2014). As a result, farm households' welfare relies heavily on improving agricultural efficiency (Alim and Abega, 2021).

Several studies have analysed the determinants of the technical efficiency of farms in Cameroon (Akamin *et al.*, 2017; Alim and Abega, 2021; Mengui *et al.*, 2019; Mukete, 2018; Nchare, 2008; Nchinda *et al.*, 2016; Njikam and Alhadji, 2017; Tabe-Ojong and Molua, 2017). The most commonly analysed determinants, which show a significant relationship, include gender (Akamin *et al.*, 2017; Alim and Abega, 2021; Mengui *et al.*, 2019), level of education (Akamin *et al.*, 2017; Alim and Abega, 2021; Nchare, 2008), access to credit (Mengui *et al.*, 2019; Nchinda *et al.*, 2016; Tabe-Ojong and Molua, 2017), number of crops grown in the farm (Nchinda *et al.*, 2016), the distance of the farm from the nearest market and the nearest agricultural post (Mukete, 2018; Nchinda *et al.*, 2016; Njikam and Alhadji, 2017; Tabe-Ojong and Molua, 2017), the number of years of experience (Alim and Abega, 2021; Mengui *et al.*, 2019) and agricultural education (Nchinda *et al.*, 2016) and climate change (Dontsi *et al.*, 2023).

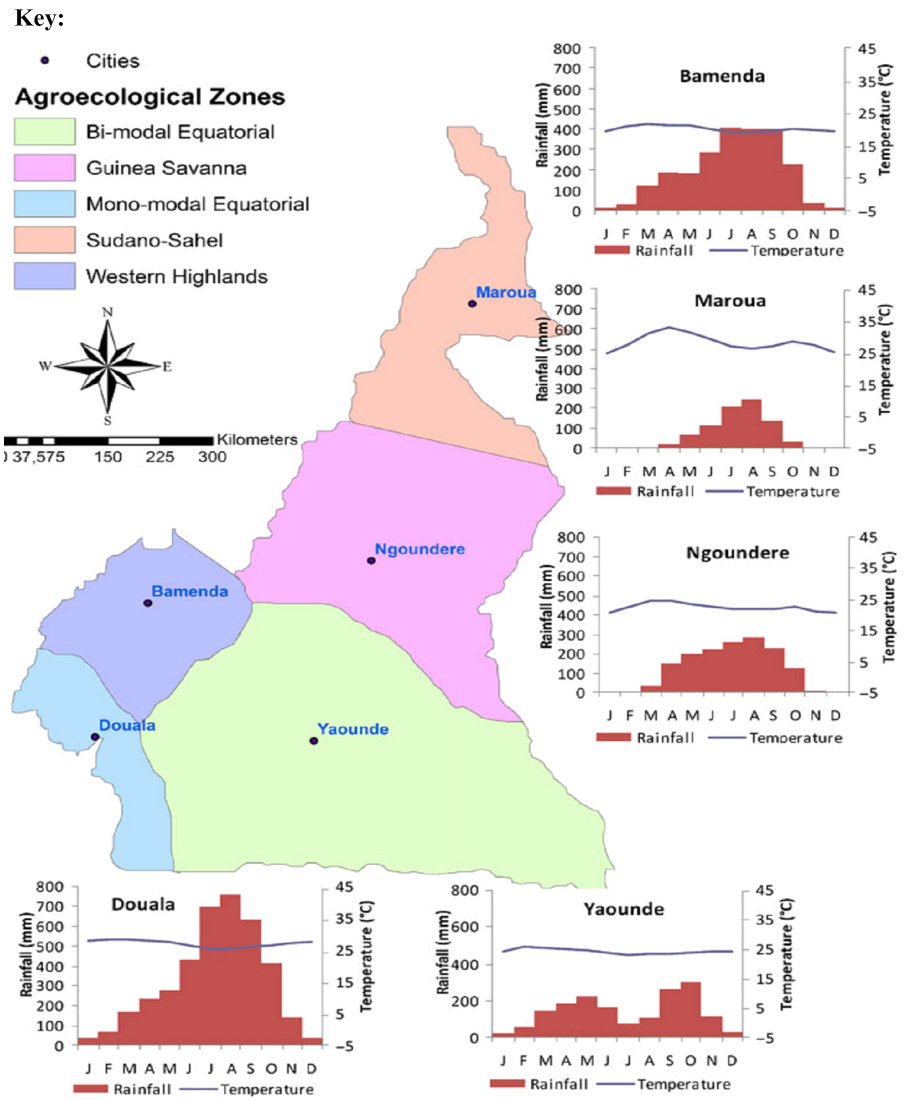
Thus, concerning these works, there are very few studies analysing the effect of climate change on the technical efficiency of farms in Cameroon. The pioneering work of Molua (2008) shows that an increase in average annual temperatures of 2.5 and 5 °C will reduce farm income by about US$0.79 and US$1.94bn, respectively. A 7% decrease in precipitation will reduce net farm income by about US$2.86bn. Given this, it is concluded that analysing the effects of vulnerability to climate change on the technical efficiency of Cameroonian farms is very important, given that the country's agricultural production remains highly dependent on climatic conditions.

This study aims to evaluate the effect of climate change vulnerability on farm technical efficiency in rural Cameroon. We contribute to the literature in two ways. Firstly, we provide an understanding of the effect of climate change vulnerability on the technical efficiency of farms and suggest interventions for improvement. Secondly, we examine whether the influence of climate change vulnerability on farmers' technical efficiency differs across agro-ecological zones. Thus, we provide policymakers with information on the nature of the problems farmers face to design programmes that improve their resilience to climate change through improved production efficiency. The rest of this paper is organised as follows: Section 2 presents the review of past literature, Section 3 discusses the methodology, Section 4 discusses the results and Section 5 concludes.

2. Materials and methods

2.1 Study area and data collection

This study covered three agro-ecological zones of Cameroon: SSZ, Monomodal High Forest Zone (MFZ) and Bi-modal High Forest Zone (BFZ) (Figure 1, Yengoh and Ardo, 2013). These agro-ecological zones were purposively selected due to the significant climatic differences between them and because more than 80% of Cameroon's agricultural production comes from these areas (Amougou, 2018; MINADER, 2021). The sampling technique used was multi-stage sampling. In the first stage, we purposely sampled three areas where smallholder farming households predominantly produce cereal crops in each of the selected agro-ecological zones.



Source(s): Yengoh and Ardo (2013)

Figure 1. Major agro-ecological zones of Cameroon

Cereal crops were selected because they are cultivated in nearly all agro-ecological zones and form the staple diet of households in Cameroon (MINADER, 2021). In the second stage, we randomly sampled two communities in each of the three selected regions.

Furthermore, in the third stage, a farmer was randomly selected as a respondent in each community using proportional random sampling. The entire sample consisted of 419 farmers, which is distributed as follows: 100 for the SSZ, 135 for the BFZ and 184 for the MFZ. The climate data were collected from the National Observatory of Climate Change (ONACC, 2020) and covered the period 1999–2019.

2.2 Methodology

2.2.1 Methodology to assess climate change vulnerability. Several approaches to assessing climate change vulnerability are identified in scientific literature. These include the biophysical approach (Kurukulasuriya and Mendelsohn, 2007), the economic approach (Chaudhuri *et al.*, 2002; Hoddinott and Quisumbing, 2003) and the integrated approach (Adu *et al.*, 2018; Cutter *et al.*, 2000; Füssel, 2007; Hahn *et al.*, 2009). The integrated approach is the most widely used one in the literature, as it combines the other two and presents advantages to the understanding and decision-making of policymakers and planners (Panthi *et al.*, 2016). In this study, we use the integrated approach to construct the Livelihood Vulnerability Index (LVI) of IPCC (LVI_IPCC), which groups the eight components of the LVI (socio-demographic profile, livelihood strategies, social networks, food, health, water, finance and natural disasters and climate variability) into three components, namely exposition, sensitivity and adaptive capacity (Adu *et al.*, 2018; Etwire *et al.*, 2013; Gerlitz *et al.*, 2017; Hahn *et al.*, 2009; Senapati, 2020).

2.3 Measure of LVI_IPCC

The eight LVI components are composed of a different number of sub-components (see Table 1). For each sub-component, we use normalisation to bring them to the same scale, as they are measured in different units. To do this, the balanced weighted average approach is used for normalisation. The equation used for this conversion is the one used by Gerlitz *et al.* (2017) and Ludena and Yoon (2015). This applies the ratio of the difference between the actual values and a preselected minimum and the difference between the predetermined maximum and minimum and is calculated as follows:

$$Indice_{Xd} = \frac{X_d - X_{min}}{X_{max} - X_{min}} \tag{1}$$

Where X_d is the initial sub-component for a household d and X_{min} and X_{max} are the minimum and maximum values, respectively, for each sub-component determined using the farm household characteristics data. For variables that measure frequencies, the maximum value is 100, while the minimum value is set at 0. For variables measured by a ratio, they are created by taking the inverse of the raw indicator, as an increase in the raw indicator is assumed to decrease vulnerability in this case. The maximum and minimum values are also transformed according to this logic, and Equation (1) is used to normalise these sub-components.

After normalising each of the components, the sub-components were averaged using Equation (2) to determine the value of each principal component of the LVI. These components reflect the IPCC (2007) concept of vulnerability in terms of exposure, sensitivity and adaptive capacity. The aggregation formula follows the work of Etwire *et al.* (2013), Hahn *et al.* (2009), Adu *et al.* (2018) and Senapati (2020) and is presented as follows:

$$CF_d = \frac{\sum_{i=1}^{3} wm_i M_{di}}{\sum_{i=1}^{3} wm_i} \tag{2}$$

Where CF_d is a contributing factor defined by the IPCC (exposure, sensitivity or adaptive capacity) for a household d, M_{di} are the principal components (see Table 1) of household d indexed by i, wm_i is the weight of each principal component and 3 is the number of principal components of each contributing factor. After calculating each of the components – sensitivity, exposure and adaptive capacity – Equation (3) combines them to calculate the IPCC climate change vulnerability index scores as follows:

Table 1. Main components and sub-components of the livelihood vulnerability index

Variables	Values	LVI	LVI-IPCC
% of female heads of household	0.284	Socio-economic profile *(0.365)*	Adaptive capacity *(0.417)*
% of household heads educated	0.789		
Dependency ratio (number of people with income/ Size of household)	0.103		
% of households with orphans	0.284		
% of households in an association	0.715	Social Network *(0.357)*	
% of households that received credit	0.181		
% of households that did not receive government assistance in the last 12 months	0.174		
% of households living solely from agriculture	0.758	Livelihood Strategies *(0.367)*	
% of households diversifying their income sources	0.241		
% of households with an emigrant	0.102		
Income from the marketing of the production	0.078	Finance *(0.598)*	
% of households that did not borrow money from a bank	0.980		
% of households not receiving transfers and compensation	0.735		
average distance to a health centre	0.053	Health *(0.179)*	Sensitivity *(0.330)*
% of households with a member with a chronic disease	0.100		
% of households where a member did not come to work on the farm due to illness (last two weeks)	0.384		
Crop diversification index	0.680	Food *(0.410)*	
Share of own consumption in total production	0.035		
% of households that do not preserve crops	0.284		
% of households not saving seed	0.755		
% of households that eat less than two meals a day	0.298		
% of households without access to water for irrigation	0.379	Water *(0.362)*	
% of households without sufficient water	0.328		
% of households using natural water resources	0.738		
% of households reporting water conflicts	0.326		
% of households affected by flooding	0.424	Natural disasters and climate variability *(0.538)*	Exposition *(0.538)*
% of households not receiving climate information	0.653		
% of households experiencing drought severity	0.658		
% of households experiencing erratic rainfall	0.463		
Average monthly maximum temperatures over the last 20 years	0.301		
Average monthly minimum temperature for the last 20 years	0.338		
Average number of rainy days	0.7268		
Average monthly precipitation over the last 20 years	0.7437		
LVI-IPCC			*0.3626*

Source(s): Authors, based on the work of Hahn *et al.* (2009), Adu *et al.* (2018) and Senapati (2020)

$$LVI\_IPCC_d = (E_d + S_d) - A_d \tag{3}$$

where *LVI_IPCCd is* the *LVI* for household *d* expressed using the IPCC vulnerability framework. A_d, E_d and S_d are the scores of adaptive capacity, exposure and sensibility calculated for household *d*, respectively. The household with the lowest LVI_IPCC score is considered the least vulnerable and vice versa.

2.3.1 Methodology to assess farm efficiency. The stochastic frontier analysis (SFA) was independently suggested by Aigner *et al.* (1977) and Meeusen and Van Den Broeck (1977) and improved by Jondrow *et al.* (1982) to allow the estimation of unit-specific technical efficiency indices. This method decomposes the error of the function under study into two independent terms. The first term represents random effects and measurement errors and is distributed across the production frontier. The second term represents the degree of technical efficiency and is distributed on one side of the production frontier only. By assumption, the random error term follows an asymmetric distribution defined positively for a cost function and negatively for a production or profit function. The advantage of this type of production frontier is that this model makes it possible to explain the deviations observed between the random production frontier and the production observed by, on the one hand, the technical inefficiency of the unit and, on the other hand, random factors such as institutional and socio-economic factors and the omission of certain explanatory variables.

The basic model is as follows: if we consider a production function whose maximum output is achievable from the vector of inputs x and y is the observed output, the technology is defined by the production function $f(.)$ verifying the properties of strict concavity, continuity and monotonicity. It is written:

$$y = f(x, \beta) - u \text{ with } u \geq 0 \tag{4}$$

The function $f(.)$ is linearised. β is an unknown vector of parameters to be estimated; u measures the difference between the observed output y and the maximum output achievable by the efficient technology. It represents technical inefficiency and is zero for technically efficient firms or decision units. Furthermore, if u represents only one effect, that of technical inefficiency, then it is a deterministic model. And in this type of model, Farrell's efficiency measures are simply estimated by the quotient: $\frac{y_i}{f(x_i,\widehat{\beta})}$, where $\widehat{\beta}$ is an unbiased estimator of β.

If we add a random term to the deterministic specification v, we obtain a stochastic model, and the frontier is said to be parametrically stochastic. $\frac{y_i}{f(x_i,\widehat{\beta})+v_i}$

By adding the random error term v in relation (4), we obtain a compound error model:

$$y = f(x, \beta) + (v - u), u \geq 0; -\infty \leq v \leq +\infty \tag{5}$$

In addition, v and u are independent of each other and of x. The relation (5) can be written as follows:

$$y_i = \beta_0 + \sum \beta_j x_{ij} + \varepsilon_i \text{ with } \varepsilon_i = v_i - u_i \tag{6}$$

u_i represents the technical inefficiency of the production unit and is written:

$$u_i = \delta_0 + \sum_{j=1}^{J} \delta_{ij} Z_{ij} + W_i \tag{7}$$

with $\delta_0 et\, \delta_i$ unknown parameters, Z_i the vector of characteristics explaining the technical inefficiency of the units and W_i the usual error term.

According to Aigner *et al.* (1997), v and u follow a normal distribution: $v \rightarrow N(0{,}\sigma_v^2)$ and $u \rightarrow N(0{,}\sigma_u^2)$

The technical efficiency of unit i is then defined by:

$$TE_i^* = \frac{Y_i}{Y_i^*} \tag{8}$$

Where $Y_i^* = f(X_i, \beta)$ is the highest or predicted value of y_i and $TE_i^* = e^{-u_i}$. Technical inefficiency is therefore defined as 1-TE_i^*.

Bravo-Ureta and Pinheiro (1993) suggested that the stochastic production frontier function can be estimated in two ways: the least squares method and by the maximum likelihood (ML) method.

The first method is used in the absence of a specification of the efficiency structure. In this case, Equation (6) is reformulated to give the following equation:

$$y_i = \beta_0' - \sum \beta_j x_{ij} + \varepsilon_i' \tag{9}$$

With $\beta_0' = (\beta_0 - u)$ and $\varepsilon_i' = v - (u_i - E(u)) = v_i - (u_i - \mu) = \varepsilon_i - \mu$. The estimation of Equation (9) is done in two steps:

As a first step, since the distribution of ε_i' is symmetric, we can estimate (9) by the ordinary least square method; all β_j will be unbiased; in the second step, the frontier is completely identified by estimating β_0 and thus μ. To do this, one must specify a particular distribution for each of the error terms. We can then estimate μ by the method of moments and, subsequently, β_0 (Aigner *et al.*, 1997).

From the residual vector of $\widehat{\varepsilon'}$, we obtain an estimate of the second and third-order moments $\widehat{\mu_2}$ and $\widehat{\mu_3}$ and thus of $\widehat{\sigma_u^2}$ and $\widehat{\sigma_v^2}$. The variances $\widehat{\sigma_u^2}$ and $\widehat{\sigma_v^2}$ are then convergently estimated by:

$$\widehat{\sigma_u^2} = \left| \widehat{\mu_3} \frac{\sqrt{\pi}}{\sqrt{2}} \cdot \frac{\pi}{\pi - 4} \right|^2 \tag{10}$$

and

$$\widehat{\sigma_v^2} = \widehat{\mu_2} - \left(\frac{\pi - 2}{\pi} \right) \widehat{\sigma_u^2} \tag{11}$$

A convergent estimator of β_0 is in these conditions given by:

$$\widehat{\beta_0} = \widehat{\beta_0'} + \frac{\sqrt{2}}{\sqrt{\pi}} \widehat{\sigma_u^2} \tag{12}$$

The problem with this estimation method is that the estimator obtained by the method of moments may or may not exist (Olson *et al.*, 1980). This will be the case if $\widehat{\mu_3}$ is positive or when the value of $\widehat{\sigma_u^2}$ is negative, which is absurd. The same will be true when it is possible from certain values $\widehat{\mu_2}$ and $\widehat{\mu_3}$ to find negative values $\widehat{\sigma_v^2}$. According to Greene (1980), the ML method, which assumes a specific distribution of the efficiency structure, appears to be more efficient because it allows the estimation of both the unknown parameters and the stochastic production frontier.

The likelihood function is defined in terms of the variance of the parameters as follows:

$$\sigma^2 = \sigma_u^2 + \sigma_v^2 \; (13) \text{ and } \gamma = \frac{\sigma_u}{\sigma_v} \tag{14}$$

γ is the share of the variance of u in the total variance and measures the relative variability of two sources of inefficiency. $\gamma^2 \to 0$ implies that $\sigma_v^2 \to +\infty$ and/or $\sigma_u^2 \to 0$ and implies that random shocks dominate the explanation of inefficiency. σ^2 is the variance of the dependent variable that expresses technical inefficiency. Thus, when $\sigma_v^2 \to 0$, the deviations from the frontier are essentially due to technical inefficiency. The parameters β, γ and σ^2 are given by the log likelihood estimate of Equation (6).

The variables used in the evaluation of the technical efficiency are the following. Output is the quantity of cereal production in kilograms. Labour is the number of hours used and includes family and external labour. Capital is the sum of raw materials and equipment and is measured in CFAF. Fertiliser includes all sorts of organic and inorganic fertilisers used by the farm household and is measured by purchasing expenditure in CFA Franc (CFAF). Phytosanitary products and seed are measured as purchasing expenditures in CFAF, respectively. The land is the cultivated area in hectares. The farmers' socio-economic characteristics include: gender is coded as 1 for male-headed households and 0 otherwise; education level is coded as 1 for the household head educated and 0 otherwise; access to credit is measured as a binary variable, coded 1 if the farmer has access to credit and 0 otherwise; number of crops cultivated in the farm; distance of the farm from the village measured in Km and farmers' experience measured by the number of years spent in producing cereal. Agricultural training is coded 1 if the farmer received any agricultural training and 0 otherwise. Climate change is measured by the climate change vulnerability index (LVI_IPCC) and its components' exposure, sensitivity and adaptive capacity. Descriptive statistics are in Table 3.

3. Results and discussion

3.1 Results of climate change vulnerability index of farmers

The eight main components of the LVI are grouped into three vulnerability components according to the IPCC, namely, exposition, sensitivity and adaptive capacity (Table 1). The results generally show that, on average, agricultural households are weakly vulnerable to climate change, with an LVI_IPCC equal to 0.3626. Analysis of the main components of this index shows that the adaptive capacity component is equal to 0.417 on average. It is noted that the finance sub-component (0.598) is the main contributor to this component. The sensitivity component has an average value of 0.330, and the food sub-component (0.410) is the main contributor. Finally, we note that the exposure component consisting of a single sub-component (natural disaster and climate variability) has an average value of 0.538.

Table 2 presents the distribution of the LVI_IPCC and its components at the agro-ecological zone level. The results show that agricultural households in the SSZ are the most exposed and sensitive to climate (0.693 and 0.3923, respectively). In addition, households in this zone have the lowest adaptive capacity (0.4155). The overall analysis of the LVI_IPCC shows that farms in the SSZ (0.4510) are more vulnerable than those in the BFZ (0.3589) and the MFZ (0.3188). These results are in line with the predictions made by Amougou (2018), who shows that the SSZ is the agro-ecological zone that suffers the most from the adverse effects of climate change in Cameroon.

Figure 2 graphically presents the triangle of the LVI_IPCC constructed from the three main components. It can be seen that households' exposure to natural disasters and climate variability and their sensitivity to their internal situation outweigh their adaptive capacity.

3.2 Results of farm efficiency in rural Cameroon

Input-output data and characteristics of farmers are presented in Table 3. On average, each farm produces 1,029 kg of cereal, ranging from 594 to 1,386 kg in the SSZ and MFZ, respectively. Farmers spend an average of 514×10^3 CFAF, of which 134.57×10^3 CFAF in SSZ and 741.53×10^3 CFAF in BFZ. Similarly, farms spend an average of 88.13×10^3 and 201.97×10^3 CFAF on the purchase of raw materials and equipment. Regarding fertilisers and plant protection products, we note that all farms spend an average of 185.431×10^3 and 216.59×10^3 CFAF, respectively. On the one hand, expenditure on fertilisers is high in the SSZ (451×10^3 CFAF), and on the other hand, expenditure on plant protection products is high in the BFZ (376.39×10^3). On average, farms cultivate 7,742 ha of land, ranging from 2.96 to 12.694 ha in the SSZ and MFZ, respectively. The average expenditure on seeds for all farms is equal to 216.59×10^3 CFAF or 53.21×10^3 and 280.29×10^3 CFAF for the SSZ and BFZ, respectively.

About 71.60% of the heads of farm households are men, 79% are educated and 50.84% have received training in agriculture, while only 18.14% have access to credit. The distance of the farm from the village is on average 6.49 km, ranging from 4.79 to 9.03 km in MFZ and

BFZ. Their experience in rice farming is quite high (about 17 years on average) and varies from 12 to 24 years in the BFZ and SSZ, respectively. Finally, it is noted that all the farms cultivate , on average, 2 cereals on the same plot.

3.2.1 Production frontier estimates. Table 4 shows ML estimates obtained from the Cobb–Douglas stochastic frontier for cereal production in Cameroon. The study revealed that labour, equipment, quantity of phytosanitary, quantity of seed and the area of cereal cultivation are important determinants of cereal production. The estimated coefficient for land area (0.009) was found to be positive and significant at 5%. Land has been shown to have a positive and significant effect on agricultural crop production, as is the case in our findings. Nchinda *et al.* (2016), Alim and Abega (2021) and Tabe-Ojong and Molua (2017) all found that an increase in farm size significantly improved agricultural crop output. The estimated coefficient of labour

Table 2. IPCC vulnerability index results (LVI-IPCC)

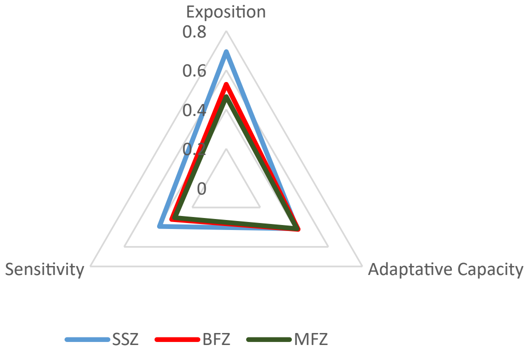
Factors contributing to vulnerability IPCC	SSZ	BFZ	MFZ	*p*-values
Exposition	0.6936	0.5275	0.4648	0.0001
Adaptative capacity	0.4155	0.4220	0.4158	0.3808
Sensitivity	0.3923	0.3208	0.3030	0.0001
LVI-IPCC	*0.4510*	*0.3589*	*0.3188*	0.0001

Note(s): The *p*-values are for the Kruskal–Wallis *H*-test
Source(s): Authors, based on survey data

Table 3. Descriptive statistics

			Agro-ecological zones					
	All sample		SSZ		BFZ		MFZ	
Variables	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Dependent variable								
Log (production in Kg)	8.919	0.694	8.689	0.321	8.727	0.605	9.185	0.841
Production function variable								
Log (labour in hours)	5.667	1.188	4.754	0.576	6.245	1.012	5.740	1.260
Log (raw material in CFAF)	3.688	1.284	3.622	0.546	4.553	1.090	3.089	1.348
Log (equipment in CFAF)	4.747	1.176	5.045	0.527	5.349	1.117	4.144	1.190
Log (fertilizes in CFAF)	4.655	1.118	5.975	0.559	4.068	0.578	4.370	1.074
Log (phytosanitary in CFAF)	5.105	1.091	4.028	0.557	5.704	0.781	5.250	1.088
Log (seed in CFAF)	4.945	1.080	3.843	0.544	5.398	0.777	5.211	1.084
Log (land area in ha)	1.483	1.029	0.965	0.524	1.263	0.766	1.926	1.208
Inefficiency variables								
Vulnerability index (LVI-IPCC)	0.363	0.114	0.451	0.118	0.358	0.093	0.318	0.097
LVI-IPCC component sensitivity	0.330	0.099	0.392	0.087	0.321	0.086	0.303	0.100
LVI-IPCC component exposition	0.539	0.145	0.694	0.125	0.528	0.109	0.463	0.109
LVI-IPCC component adaptation	0.418	0.094	0.416	0.090	0.422	0.088	0.416	0.100
Gender (1 = female; 0 = male)	0.716	0.451	0.450	0.500	0.867	0.341	0.750	0.434
Education level (1 = educated; 0 = no)	0.864	0.362	0.080	0.929	0.067	0.300	0.141	0.445
Access to credit (1 = yes; 0 = no)	0.181	0.386	0.240	0.429	0.119	0.324	0.196	0.398
Number of crops cultivated	1.867	1.309	1.120	0.327	2.681	1.519	1.670	1.150
Distance farm to agricultural post	6.495	4.759	6.140	3.579	9.037	5.693	4.796	3.638
Experience in years	16.834	11.920	24.690	17.881	12.089	6.977	16.046	8.062
Agricultural training (1 = yes; 0 = no)	0.508	0.501	0.320	0.469	0.630	0.485	0.522	0.501
Sample size	419		100		135		184	

Source(s): Authors' computation



Source(s): Authors' computation

Figure 2. Distribution of the LVI-IPCC according to agro-ecological zones

(0.105) was positive and significant at 1%. This result shows that the increase in labour has a positive impact on agricultural production and is in line with the conclusions of Akamin *et al.* (2017) and Mengui *et al.* (2019), who find the same results in Cameroon. About the coefficient of seed quantity (0.132), it is noted that it is positive and significant at 1%. This result would mean that an increase in the quantity of seed increases agricultural production. This result is similar to that of Tabe-Ojong and Molua (2017), who find that the increase in the quantity of seed increases the production of tomato producers in Cameroon.

The estimated coefficients for equipment and phytosanitary were negative and significant at 1%. This implies that a percent increase in the quantity of equipment and phytosanitary will decrease the cereal output by 14.1 and 15%, respectively. This is not very expected and corresponds with the results of Alim and Abega (2021) and Mukete (2018) for equipment and phytosanitary, respectively.

Finally, it should be noted that the parameters γ are significantly different from zero (0) for both equations, which proves the existence of the stochastic frontier and leads to the rejection of the hypothesis that the variance of the efficiency σ_u^2 is zero. The existence of non-zero gamma values (γ) informs us about the existence of productive inefficiency of the production units in the three equations. These results indicate that the discrepancies between the observed and potential output of farms are partly due to the inefficiency of their production process and partly to the presence of random effects and measurement errors.

3.2.2 Technical efficiency estimates. Figure 3 presents the distribution of farmers according to the technical efficiency score, while the descriptive statistics and frequency distribution of farmers' technical efficiency are presented in Table 5, Panels A–B. The average technical efficiency of the population is estimated to be 0.629. Therefore, on average, farmers are able to obtain 62.9% of their potential output from a given combination of inputs. This result also indicates that about 37.1% of production, on average, is lost due to technical inefficiency. This average level of efficiency is lower than the average level of 71.2% of rice farmers in Cameroon (Njikam and Alhadji, 2017), but higher than the average level of 55% of cocoa farmers in the Mbam and Kim department in Cameroon (Nso Ngang *et al.*, 2020). However, our result is in line with that of Mengui *et al.* (2019), who found an average technical efficiency roughly equal to 62% for the sweet potato sector in Santa Department, Cameroon. The distribution at the level of agro-ecological zones shows that BFZ farmers are the most efficient, with an average technical efficiency equal to 72%, indicating that 28% of their technical potential is not realised. In contrast, farmers in SSZ and MFZ have a relatively lower average technical efficiency (60.7 and 57.4%, respectively), indicating that 39.3 and 42.6% of their technical potential are not realised, respectively. Overall, it can be concluded that through the

Table 4. Stochastic production frontier estimates

Variables	(1) Frontier	(2) Inefficiency effect model
Log labour	0.105***	
	(0.032)	
Log raw materials	0.023	
	(0.040)	
Log equipment	−0.141***	
	(0.040)	
Log fertilizer	−0.001	
	(0.032)	
Log phytosanitary	−0.150***	
	(0.038)	
Log seed	0.132***	
	(0.035)	
Log land area	0.009**	
	(0.003)	
Vulnerability index		−0.978***
		(0.331)
Gender of household head		−0.140*
		(0.074)
Education of household head		0.001
		(0.024)
Access to credit		0.120
		(0.073)
Log number of crops cultivated		−0.088***
		(0.027)
Log distance farm to agricultural post		−0.012*
		(0.006)
Log experience in years		0.002
		(0.002)
Agricultural training		0.024
		(0.058)
Constant	10.51***	1.067***
	(0.322)	(0.264)
$\sigma^2(\text{sigma}^2) = \sigma_u^2 + \sigma_v^2$	0.1779***	
$\gamma\,(\text{gamma}) = \sigma_u^2/(\sigma_u^2 + \sigma_v^2)$	0.44***	
Prob > χ^2	0.0000	
Number of observations	419	
Likelihood-ratio test	3.13	

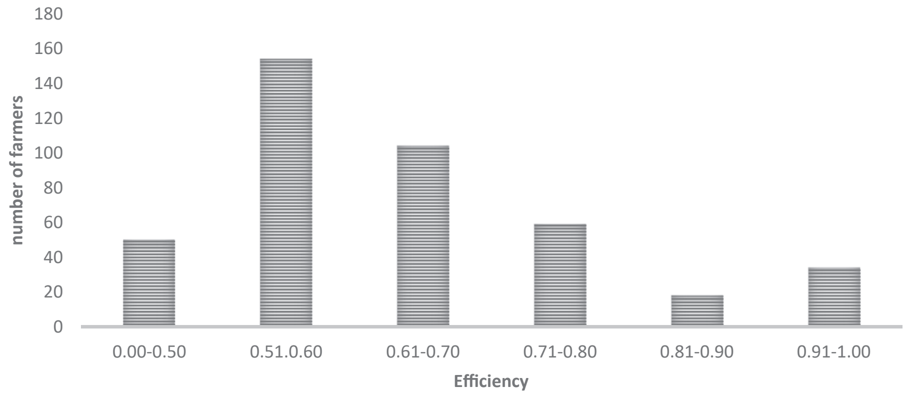
Note(s): Data in parentheses are standard errors; *, ** and *** significant at 10, 5 and 1%, respectively
Source(s): Authors' computation

efficient use of existing inputs, cereal production in these areas can be increased. Therefore, by effectively using existing inputs, production in BFZ, SSZ and MFZ can be increased by about 28, 39.3 and 42.6%, respectively, without any additional cost to the farmers.

In Panel B, farmers are classified as low efficiency (Technical Efficiency [TE]<50%), medium efficiency (50% < TE<90%) and high efficiency (ET>90%). Overall, the results show that only 6.52% of farmers are highly efficient in the MFZ compared to 16.30% in the BFZ. In addition, none of the 100 farms in the SSZ are considered highly efficient.

3.3 Relationship between climate change vulnerability and farm technical efficiency

Tables 6 and 7 present, respectively, the marginal effects of the regressions of the vulnerability index to climate change, on the one hand, and of its main components on the other hand, on the technical efficiency of farms in Cameroon. To do this, in each of these tables, an estimate was



Source(s): Authors' computation

Figure 3. Distribution of farmers according to efficiency score

Table 5. Summary statistics and frequency distribution of farmer's technical efficiency

Variables	Total sample	Agro-ecological zones SSZ	BFZ	MFZ
Panel A: descriptive statistics of technical efficiency				
Mean	0.629	0.607	0.720	0.574
Standard dev	0.130	0.071	0.141	0.110
Min	0.246	0.462	0.296	0.247
Max	1	0.830	1	1
Panel B: frequency distribution of technical efficiency				
	<50%	*50%<te<90%*	*>90%*	*Total*
SSZ	4 (4.00)	96 (96.00)	–	100
BFZ	3 (2.22)	110 (81.48)	22 (16.30)	135
MFZ	43 (23.37)	129 (70.11)	12 (6.52)	184
Total sample	50 (11.93)	335 (79.95)	34 (8.11)	419

Note(s): Numbers in the parentheses are the percentages
Source(s): Authors' computation

made for the whole sample numbered (1) and an estimate for each of the three agro-ecological zones of the study numbered (2), (3) and (4). The estimates per agro-ecological zone allow us to observe the existence of differences that may exist between these zones (Upadhyay *et al.*, 2015).

In general, we note that the χ^2 tests are statistically significant and indicate that the models are globally significant. The analysis of the climate change vulnerability index shows that it has a negative and significant effect at the 1% level on the technical efficiency of farms. This effect implies that an increase in vulnerability to climate change reduces the probability of farms being technically efficient. This result is the same observed for all agro-ecological zones. Furthermore, it is noted that the BFZ has the highest probability. This result is in line with that found by Than and Koji (2021), which show that vulnerability to Climate Change negatively affects the economic performance of 352 rice farmers in Vietnam.

As regards the control variables, we note that the gender of the head of the household, access to credit, the number of crops cultivated and the distance between the farm and the agricultural post exert positive and significant influences on the technical efficiency of farms.

Table 6. Marginal effect of climate change vulnerability on technical efficiency

Variables	(1) All sample	(2) SSZ	(3) BFZ	(4) MFZ
Vulnerability index (LVI-IPCC)	−0.634***	−0.602***	−0.722***	−0.585***
	(0.018)	(0.009)	(0.037)	(0.041)
Gender of household head	0.085***	0.0851***	0.100***	0.080***
	(0.004)	(0.001)	(0.009)	(0.008)
Education of household head	−0.002**	−0.001	−0.004*	−0.001
	(0.001)	(0.001)	(0.002)	(0.002)
Access to credit	0.088***	0.070***	0.110***	0.087***
	(0.004)	(0.002)	(0.008)	(0.009)
Log number of crops cultivated	0.062***	0.053***	0.067***	0.058***
	(0.001)	(0.002)	(0.001)	(0.003)
Log distance farm to agricultural post	0.007***	0.007***	0.008***	0.006***
	(0.000)	(0.000)	(0.000)	(0.001)
Log experience in years	−0.001***	−0.001***	−0.001***	−0.001**
	(0.000)	(5.3e-05)	(0.000)	(0.000)
Agricultural training	−0.016***	−0.013***	−0.022***	−0.015**
	(0.003)	(0.002)	(0.005)	(0.007)
Observations	411	100	134	177

Note(s): Data in parentheses are standard errors; *, ** and*** significant at 10, 5 and 1%, respectively
Source(s): Authors' computation

Table 7. Marginal effect of climate change vulnerability components on technical efficiency

Variables	(1) All sample	(2) SSZ	(3) BFZ	(4) MFZ
Sensibility	−0.273***	−0.240***	−0.308***	−0.253***
	(0.020)	(0.013)	(0.034)	(0.036)
Exposition	−0.262***	−0.235***	−0.320***	−0.215***
	(0.014)	(0.009)	(0.024)	(0.033)
Adaptive capacity	0.530***	0.663***	0.566***	0.469***
	(0.025)	(0.016)	(0.042)	(0.046)
Gender of household head	0.083***	0.086***	0.090***	0.083**
	(0.005)	(0.002)	(0.010)	(0.009)
Education of household head	−0.002*	−0.001	−0.003	−0.001
	(0.001)	(0.001)	(0.002)	(0.002)
Access to credit	0.086***	0.067***	0.109***	0.091**
	(0.005)	(0.002)	(0.009)	(0.010)
Log number of crops cultivated	0.0629***	0.054***	0.067***	0.059***
	(0.001)	(0.003)	(0.001)	(0.003)
Log distance farm to agricultural post	0.007***	0.007***	0.008***	0.006***
	(0.000)	(0.000)	(0.000)	(0.001)
Log experience in years	−0.001***	−0.001***	−0.001***	−0.001**
	(0.000)	(6.9e-05)	(0.000)	(0.000)
Agricultural training	−0.016***	−0.014***	−0.020***	−0.016**
	(0.003)	(0.002)	(0.005)	(0.007)

Note(s): Data in parentheses are standard errors; *, ** and*** significant at 10, 5 and 1%, respectively
Source(s): Authors' computation

On the other hand, we note that the education of the head of household, the number of years of experience and the agricultural training exert negative and significant influences on the technical efficiency of farms.

Regarding the gender of the head of the household, it is noted that female farmers are more technically efficient than male farmers. This is because women are more concerned with the production of cereals directly related to household food security. This result is similar to those of Akamin *et al.* (2017) and Alim and Abega (2021) who find that gender positively influences agricultural technical efficiency in Cameroon. Regarding access to credit, the results show that farmers with access to credit are technically more efficient than those without access. This result is in line with Mengui *et al.* (2019) and Castro *et al.* (2023) who show that sweet potato farmers with access to credit are more efficient than those without access to credit in Santa Department, Cameroon and Ecuador, respectively. In terms of the number of crops grown, it is noted that farms that diversify crops are technically more efficient than those that do not diversify. This would mean that production efficiency increases in mixed cropping systems than in monoculture systems. This result is in line with Nchinda *et al.* (2016) who find that growing yam in combination with other crops such as cereals (maize and beans) and other tubers (cassava and potato) increases the technical efficiency of farms in Cameroon. Similarly, Yengoh and Ardo (2013) show that crop association creates excellent biophysical conditions for agricultural production and therefore increases yield and technical efficiency. The results also show that the distance from the farm to the nearest agricultural station exerts a positive influence on farmers' technical efficiency. This result is in line with that found by Mukete *et al.* (2016) and contrary to those of Nchinda *et al.* (2016), Tabe-Ojong and Molua (2017) and Njikam and Alhadji (2017) who find that reducing the distance of the farm to the nearest agricultural station positively influences technical efficiency, as farmers have quick access to advice and control from agricultural technicians. In terms of household head education, we find that households with educated heads are less technically efficient than households with uneducated heads. This result is consistent with that of Alim and Abega (2021) and contrary to that of Teh *et al.* (2017) who find that being educated increases the capacity and propensity of farmers to adopt new ideas and production techniques and thus increases their output. Regarding the relationship between technical efficiency and the number of years of experience of the household head, a negative relationship was found, showing that increasing the number of years of experience reduces the probability of farmers being technically efficient. This result is similar to that found by Alim and Abega (2021) in Cameroon. Finally, the results show that agricultural training has a negative and significant influence on the technical efficiency of farms. This would mean that the training provided to farmers does not give them an adequate understanding of technology, which significantly contributes to the improvement of their technical efficiency. This result is in line with the findings of Nchinda *et al.* (2016) who found that agricultural training contributes negatively and significantly to yam production in Cameroon.

Given the negative relationship between vulnerability to climate change and technical efficiency found in Table 6, Table 7 shows which component of vulnerability contributes to this negative relationship. The results show that sensitivity and exposure to climate change exert negative influences on the technical efficiency of farms. This result is in line with the findings of Vigh *et al.* (2018), Auci and Vignani (2020) and Rahman and Anik (2020) who show that climate change negatively impacts the technical efficiency of farms in Hungary, Italy, and Bangladesh, respectively. Regarding the adaptive capacity component, it is noted that it has a positive and significant influence on the technical efficiency of farms. This would imply that farmers with high adaptive capacity are technically more efficient than those without adaptive capacity. This result is in line with Adzawla and Alhassan (2021) who find that the adoption of one or more climate change adaptation strategies increases the technical efficiency of maize farmers in northern Ghana.

4. Conclusion

This study aims to investigate and evaluate the effect of climate change vulnerability on farm technical efficiency in rural Cameroon. A Cobb–Douglas production function and an inefficiency model were specified. ML estimates for the parameters of the stochastic production function showed that estimated coefficients of land area, seed and labour were positive and significant. Theoretically, we expand knowledge on the SFA and LVI models by applying them to the three zones considered in this paper.

Evidence suggested that farmers in the study area had a mean technical efficiency of 62.9%, implying there are some existing opportunities to increase the technical efficiency if resources are optimally used and agronomic practices are well respected. We also note that the BFZ is the most technically efficient agro-ecological zone, with an average score of 72%. In terms of the distribution of vulnerability to climate change, the results indicate that the SSZ is more vulnerable to climate change than the BFZ and MFZ. Concerning the analysis of technical inefficiency model determinants, the findings reveal that climate change vulnerability index has a significant negative relationship with technical efficiency.

Analysis of the influence of the main components of the climate change vulnerability index on technical efficiency shows that sensitivity and exposure have a negative influence on technical efficiency while adaptive capacity has a positive influence. The farmers should be encouraged to respect agronomic technique and adopt novel innovations and farm technologies to target adaptation to the impacts of climate change. Regarding the control variables, we note that the gender of the head of household, access to credit, the number of crops cultivated and the distance between the farm and the agricultural post have positive and significant influences on the technical efficiency of farms.

Empirically, this study shows results are in line with the predictions made by Amougou (2018) who shows that the SSZ is the agro-ecological zone that suffers most from the adverse effects of climate change in Cameroon. Farmers in the MFZ zone are more experienced in rice farming than any other zones (about 17 years on average) and vary from 12 to 24 years in the BFZ and SSZ, respectively. Furthermore, it is noted that all the farms cultivate, on average, two cereals on the same plot, which improve land use and contribute slightly to the technical efficiency. In addition, the study proved that an increase in labour has a positive impact on agricultural production.

4.1 Recommendations

Since the SSZ is the agro-ecological zone that suffers most from the adverse effects of climate change in Cameroon and expenditure on fertilisers is high in the zone, we suggest that the government can assist farmers in the zone as well as other zone, with less polluting organic and biological fertilisers, stimulate sustainable investment to combat climate change in agriculture and develop microcredit programmes specifically designed for famers, with a focus on smallholders. It is important to note that this study only considered the rural part of Cameroon due to the nature of the objective stated for this work, and future researchers can consider every part of Cameroon and some parts of central Africa to largely determine the impacts of climate change on farm technical efficiency. Also, future study can focus on ways to improve technical efficiency since it contributes significantly to agricultural output of the regions. In addition, access to credit is important in managing climate change vulnerability; hence, future study can focus on the role played by access to credit in the relationship between climate change vulnerability and technical efficiency of agricultural production.

References

Adu, D.T., Kuwornu, J.K.M., Anim-Somuah, H. and Sasaki, N. (2018), "Application of livelihood vulnerability index in assessing smallholder maize farming households' vulnerability to climate change in Brong-Ahafo region of Ghana", *Kasetsart Journal of Social Sciences*, Vol. 39 No. 1, pp. 22-32, doi: 10.1016/j.kjss.2017.06.009.

Adzawla, W. and Alhassan, H. (2021), "Effects of climate adaptation on technical efficiency of maize production in Northern Ghana", *Agricultural and Food Economics*, Vol. 9 No. 1, p. 14, doi: 10.1186/s40100-021-00183-7.

Aigner, D., Lovell, C.A.L. and Schmidt, P. (1997), "Formulation and estimation of stochastic Frontier production function models", *Journal of Econometrics*, Vol. 6 No. 1, pp. 21-37, doi: 10.1016/0304-4076(77)90052-5.

Akamin, A., Bidogeza, J.C., Minkoua, N.J.R. and Afari-Sefa, V. (2017), "Efficiency and productivity analysis of vegetable farming within root and tuber-based systems in the humid tropics of Cameroon", *Journal of Integrative Agriculture*, Vol. 16 No. 8, pp. 1865-1873, doi: 10.1016/S2095-3119(17)61662-9.

Alim, B. and Abega, N. (2021), "The impact of microfinance services on the efficiency of family farms in Sub-Saharan Africa: the case of Cameroon", *Agricultural Finance Review*, Vol. 81 No. 1, pp. 21-38, doi: 10.1108/AFR-02-2019-0021.

Amougou, J.A. (2018), "Situation des changements climatiques au Cameroun-Les éléments scientifiques, incidences, adaptation et vulnérabilité", in *Environmental Law and Policy in Cameroon (Nomos Verlagsgesellschaft mbH, P. 687-712)*.

Auci, S. and Vignani, D. (2020), "Climate variability and agriculture in Italy: a stochastic Frontier analysis at the regional level", *Economia Politica*, Vol. 37 No. 2, pp. 381-409, doi: 10.1007/s40888-020-00172-x.

Bravo-Ureta and Pinheiro (1993), "Efficiency analysis of developing country agriculture: a review of the function literature, agriculture research", *Economic Review*, Vol. 22 No. 1, pp. 88-101, doi: 10.1017/s1068280500000320.

Castro, M., Reyes, D.A., Villegas, A. and Chanci, L. (2023), "The effect of crop insurance in Ecuadorian rice farming: a technical efficiency approach", *Agriculture Finance Review*, Vol. 83 No. 3, pp. 478-497, doi: 10.1108/AFR-10-2022-0122.

Chaudhuri, S., Jalan, J. and Suryahadi, A. (2002), "Assessing household vulnerability to poverty: a methodology and estimates for Indonesia", Department of Economics Discussion Paper No. 0102-52. New York: Columbia University.

Cutter, S., Mitchell, J. and Scott, M. (2000), "Revealing the vulnerability of people and places: a case study of Georgetown County South Carolina", *Annals of the Association of American Geographers*, Vol. 90 No. 4, pp. 713-737-737, doi: 10.1111/0004-5608.00219.

Dontsi, Embolo, A.B.X. and Nankap, S.A. (2023), "Climate change and technical efficiency of farms in Cameroon", *Agricultural Economics Review*, Vol. 24 No. 1, pp. 24-44.

Etwire, P.M., Al-Hassan, R.M., Kuwornu, J.K.M. and Osei-Owusu, Y. (2013), *Application of Livelihood Vulnerability Index in Assessing Vulnerability to Climate Change and Variability in Northern Ghana*, Vol. 3, p. 15.

FAO, IFAD, UNICEF, WFP and WHO (2020), *The State of Food Security and Nutrition in the World 2020. Transforming Food Systems for Affordable Healthy Diets*, FAO.

Füssel, H.M. (2007), "Vulnerability: a generally applicable conceptual framework for climate change research", *Global Environmental Change*, Vol. 17 No. 2, pp. 155-167, doi: 10.1016/j.gloenvcha.2006.05.002.

Gerlitz, J.-Y., Macchi, M., Brooks, N., Pandey, R., Banerjee, S. and Jha, S.K. (2017), "The multidimensional livelihood vulnerability index – an instrument to measure livelihood vulnerability to change in the Hindu Kush himalayas", *Climate and Development*, Vol. 9 No. 2, pp. 124-140, doi: 10.1080/17565529.2016.1145099.

Greene, W.H. (1980), "Maximum likelihood estimation of econometric Frontier", *Journal of Econometrics*, Vol. 13 No. 1, pp. 27-56, doi: 10.1016/0304-4076(80)90041-x.

Hahn, M.B., Riederer, A.M. and Foster, S.O. (2009), "The livelihhod vulnerability index : a pragmatic approach to assessing risks from climate variability and change: a case study in Mozambique", *Global Environmental Change*, Vol. 19 No. 1, pp. 74-88, doi: 10.1016/j.gloenvcha.2008.11.002.

Hoddinott, J. and Quisumbing, J. (2003), "Methods for microeconometric risk and vulnerability assessments", Social Protection Discussion Paper Series No. 0324. Social Protection Unit, Human Development Network. Washington D.C.: World Bank.

INS (2014), *Tendance, profil et déterminants de la pauvreté au Cameroun entre 2001-2014*, Instut National de la Statistique du Cameroun.

IPCC (2007), *Climate Change 2007: Impacts, Adaptation and Vulnerability*, Intergovernmental Panel on Climate Change (IPCC).

IPCC (2014), *Climate Change 2014: Synthesis Report*, Intergovernmental Panel on Climate Change (IPCC).

IPCC (2021), *Climate Change 2021:The Physical Science Basis*, Intergovernmental Panel on Climate Change (IPCC).

Jondrow, J., Lovell, C.A.L., Maesterov, I.S. and Schmidt, P. (1982), "On the estimation of technical inefficiency in the stochastic frontier production function model", *Journal of Econometrics*, Vol. 19 No. 2, 233-238.

Kurukulasuriya, P. and Mendelsohn, R. (2007), "Endogenous irrigation: the impact of climate change on farmers in Africa", World Bank Policy Research Working Paper, 4278, pp. 1-25.

Ludena, C. and Yoon, S.W. (2015), "Local vulnerability indicators and adaptation to climate change: a survey", *Environmental Sciences*, Vol. 3, pp. 1-51.

Malhi, G.S., Kaur, M. and Kaushik, P. (2021), "Impact of climate change on agriculture and it's mitigation stratégies: a review", *Sustainability*, Vol. 13 No. 3, pp. 13-18, doi: 10.3390/su13031318.

Masson, T. and Fritsche, I. (2021), "We need climate change mitigation and climate change mitigation needs the 'we': a state-of-the-art review of social indentity effects motivating climate change action", *Current Opinion in Behavioral Sciences*, Vol. 42, pp. 89-96, doi: 10.1016/j.cobeha.2021.04.006.

Mendelshon, R., Nordhaus, W. and Shaw, D. (1994), "The impact of global warming on agriculture: a Ricardian analysis", *The American Economic Review*, Vol. 4 No. 84, pp. 753-771.

Mengui, K.C., Oh, S. and Lee, S.H. (2019), "The technical efficiency of smallholder Irish potato producers in Santa subdivision, Cameroon", *Agriculture*, Vol. 9 No. 12, p. 259, doi: 10.3390/agriculture9120259.

Meeusen, W. and Van Den Broeck, J. (1977), "Efficiency estimation from cobb-douglas production functions with composed errors", *International Economic Review*, Vol. 18 No. 2, pp. 435-444, doi: 10.2307/2525757.

MINADER (2021), *Enquête nationale sur la sécurité alimentaire et Nutritionnelle : République du Cameroun*, Ministère de l'Agriculture et du développement Rural: Programme National de Veille et de Renforcement de la Sécurité alimentaire.

Molua, E. (2008), "Turning up the heat on African agriculture: the impact of climate change on Cameroon's agriculture", *African Journal of Agricultural Research*, Vol. 2 No. 1, 45-64.

Mukete, N. (2018), "Cocoa production in Cameroon : a socioeconomic and technical efficiency perspective", *International Journal of Agricultural Economics*, Vol. 3 No. 1, p. 1, doi: 10.11648/j.ijae.20180301.11.

Mukete, N., Zhu, J., Beckline, M., Gilbert, T., Jude, K. and Dominic, A. (2016), "Analysis of the technical efficiency of smallholder cocoa farmers in South west Cameroon", *American Journal of Rural Development*, Vol. 4 No. 6, pp. 129-133.

Nchare, A. (2008), "Analysis of factors affecting the technical efficiency of arabica coffee producers in Cameroon", *AERC Research Papers*, Vol. 163, pp. 1-63.

Nchinda, V.P., Villano, R.A., Hadley, D. and Morales, E.L. (2016), "Performance of smallholder minisett seed yam farm enterprises in Cameroon", *African Journal of Agricultural and Resource Economics*, Vol. 11 No. 4, pp. 1-15.

Njikam, O. and Alhadji, H.A. (2017), "Technical efficiency among smallholder rice farmers: a comparative analysis of three agro-ecological zones in Cameroon: technical efficiency among smallholder rice farmers", *African Development Review*, Vol. 29 No. 1, pp. 28-43, doi: 10.1111/1467-8268.12236.

Njongan, B. (2012), "Services d'appui aux initiatives locales de développement", *La voix du Paysan*.

Nso Ngang, A., Kamdem, C.B., Kaldjob, M.C.B., Pedelahore, P., Onana, D. and Etoa, A.M.J. (2020), "Contrat de travail et performance des exploitations cacaoyères dans le Mbam et Kim au Cameroun", *African Journal of Agricultural and Resource Economics*, Vol. 15 No. 2, pp. 111-126, doi: 10.53936/afjare.2020.15(2).08.

Olson, J.A., Schmidt, P. and Waldman, D.M. (1980), "A monte carlo study of estimators of stochastic Frontier production functions", *Journal of Econometrics*, Vol. 13 No. 1, pp. 67-82.

ONACC (2020), "Evaluation économique de l'impact des changements climatiques sur les rencdements des cultures vivrières dans les régions du Centre, de l'Est, de l'Extrême-Nord et du Sud-Ouest Cameroun", Observatoire National des Changements climatiques, p. 77.

Panthi, J., Aryal, S., Dahal, P., Bhandari, P., Krakauer, N.Y. and Pandey, V.P. (2016), "Livelihood vulnerability approach to assessing climate change impacts on mixed agro-livestock smallholders around the Gandaki River Basin in Nepal", *Regional Environmental Change*, Vol. 16 No. 4, pp. 1121-1132, doi: 10.1007/s10113-015-0833-y.

PNACC (2015), "Plan National d'Adaptation aux Changements Climatiques du Cameroun", *Ministère de l'Environnement, de la Protection de la Nature et du Développement Durable*.

Rahman, S. and Anik, A.R. (2020), "Productivity and efficiency impact of climate change and agroecology on Bangladesh agriculture", *Land Use Policy*, Vol. 94 No. 4, 104507, doi: 10.1016/j.landusepol.2020.104507.

Senapati, A.K. (2020), "An indicator-based approach to assess farm households' vulnerability to climate change: evidence from Odisha, India", *Spatial Information Research*, Vol. 28 No. 2, pp. 139-157, doi: 10.1007/s41324-019-00277-x.

Soviadan, M.K., Koffi-Tessio, E., Enete, A.A. and Nweze, N.J. (2019), "Impact of climate change on cotton production: case of savannah region, Northern Togo", *Agriculture Sciences*, Vol. 10 No. 07, pp. 927-947, doi: 10.4236/as.2019.107071.

Tabe-Ojong, M.P. and Molua, E.L. (2017), "Technical efficiency of smallholder tomato production in semi-Urban farms in Cameroon: a stochastic frontier production approach", *Journal of Management and Sustainability*, Vol. 7 No. 4, p. 27, doi: 10.5539/jms.v7n4p27.

Teh, N.J., Fon, D.E. and Bidogeza, J.C. (2017), "Technical efficiency of diversification versus specialization of vegetable-based farms in the west region of Cameroon", *American Journal of Agriculture and Forestry*, Vol. 5 No. 4, pp. 112-120, doi: 10.11648/j.ajaf.20170504.15.

Than, T.H. and Koji, S. (2021), "The effects of multiple climate change responses on economic performance of rice farms: evidence from the Mekong Delta of Vietnam", *Journal of Cleaner Production*, Vol. 315, pp. 1-15.

Vigh, E., Fertő, I. and Fogarasi, J. (2018), "Impacts of climate on technical efficiency in the Hungarian arable sector", *Studies in Agricultural Economics*, Vol. 120 No. 1, pp. 41-46, doi: 10.7896/j.1729.

WDI (2021), *World Develpment Indicators 2021*, World Bank Group.

World Bank Group (2021), *World Bank Climate Change Action Plan 2021-2025: Supporting Green, Resilient, and Inclusive Development*, Washington, DC.

Yengoh, G.T. and Ardo, J. (2013), "Crops yield gaps in Cameroon", *Royal Swedish Academy of Sciences*, Vol. 4 No. 1, pp. 175-190.

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