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Explanatory Factors of Carbon Dioxide Emissions in the European Union

The European Union (EU) is committed to decarbonising its economy by 2050. To that end, significant reductions in greenhouse gases from the energy and agricultural sectors are of critical importance. However, while the EU member states each pursue a different climate strategy, all member states' emissions are regulated by EU climate law. This paper investigates the factors explaining carbon dioxide (CO_2) emissions in the 27 member countries, using fully modified least squares (FMOLS) and quantile regression models. Before estimations, panel unit root and cointegration tests have been used for the period 1990-2018. The applied model examines the impact of economic growth, energy intensity, renewable energy consumption and agricultural trade on carbon dioxide emissions. Estimates have shown that the intensification of energy stimulates carbon emissions. Economic growth indicates an increase in carbon emissions. The results reveal that agricultural trade decreases carbon dioxide emissions in the EU, highlighting that intra EU trade is more environmentally friendly. Finally, the impact of renewable energy is limited to contributing to climate mitigation goals by reducing emissions.

Keywords: carbon dioxide emissions, economic growth, energy intensity, renewable energy, agricultural trade, European Union

JEL classifications: Q15, Q32

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Introduction

The Paris agreement aimed to persuade nations to significantly decrease their greenhouse gas emissions and limit global temperature increases. As a result, the European Union (EU) has committed to decarbonising its economy and becoming carbon neutral by 2050. To realise this target, a significant reduction in carbon dioxide (CO_2) emissions is needed. The EU has implemented climate acts, the European Green Deal, renewed the EU emissions trading system (ETS), and developed Fit for 55 incentives to achieve its goals. Economic development is closely associated with changes in CO_2 emissions. Higher economic development is regularly accompanied by higher energy consumption, which can lead to additional greenhouse gas emissions (GHG). A substantial part of the environmental economics literature focuses on the relationship between environmental pollution and income (Gross Domestic Product, GDP).

In recent years, several studies have been applied to explore the association between GHG and the energy industry, agricultural and forestry sectors (Burakov, 2019; Balsalobre-Lorente *et al.,* 2019) but only a limited number of studies (Mert *et al.,* 2019; Balsalobre-Lorente and Leitão, 2020) have investigated environmental pollution in the EU member states.

This paper aims to consider the determinants of CO_2 emissions in the Member States of the European Union using various panel regression models for 1990-2018. The research enriches the existing empirical literature in several ways. First, it examines economic growth, renewable energy, and energy intensity in the EU in the short and long run. Second, it explores the role of EU agricultural trade played in GHG emissions. Finally, it suggests policy recommendations for European decision makers to improve mitigation policies at the sectoral level. The paper is structured as follows. The literature review emerges in Section 2; Section 3 refers to the methodology and description of the variables used in this study. Results and discussion are to be found in Section 4. Finally, the article ends with the conclusion.

Review of the relevant literature

A wide range of literature addresses the nexus of economic growth, energy consumption, trade, and carbon emissions. However, most recent empirical studies have focused principally on country-specific, cross-country perspectives or European Union-related issues examining the Environmental Kuznets Curve (EKC). Where methodology is concerned, the authors have used panel data applied to a set of countries, a sector or different sectors, or time series.

Country-level analysis

So far as individual country-level analysis is concerned, Pata (2021) searched for the impact of economic development, globalisation, renewable and non-renewable energy consumption on CO_2 emissions, as well as the ecological footprint through EKC in the United States. A cointegration test, fully modified least squares (FMOLS), dynamic least squares (DOLS) and canonical cointegrating regression (CCR) tests were used for statistical analysis. The results of the research confirmed that the inverted U-shaped EKC relationship between economic development and environmental pollution is valid for the United States. Furthermore, globalisation and renewable energy consumption led to reducing

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environmental pollution. Conversely, non-renewable energy consumption causes ecological stress.

Furthermore, Burakov (2019) applied an Autoregressive Distributed Lag (ARDL) time series model for Russia, suggesting that energy consumption and the agricultural sector stimulate climate change. In their models, economic growth was in line with the assumptions of the inverted U-shaped EKC. Finally, by conducting wavelet analysis, Adebayo *et al.* (2021) confirmed that renewable energy consumption helps curb CO_2, while trade openness, technological innovation, and economic growth contribute to higher CO_2. Furthermore, renewable energy consumption has been shown to decrease CO_2 in the medium and long term in Portugal. For Pakistan, Mahmood *et al.* (2019) underlined that income, trade openness, and renewable energy motivate emissions while human capital diminishes CO_2 emissions by estimating the three-stage least squares and ridge regression. Meanwhile, Rehman *et al.* (2021) measured the asymmetric effect of CO_2 emission on expenditures, trade, FDI, and renewable energy consumption using a nonlinear ARDL and Granger causality tests on Pakistani data. The findings revealed that the different shocks of renewable energy consumption were exposed to an increase in CO_2 emission in the short term. On the other hand, positive shocks from renewable energy consumption showed an adverse relationship with CO_2 emissions. Lastly, trade showed a statistically insignificant link with environmental degradation. Turning to China, Chandio *et al.* (2020), by employing the auto-regressive distributed lag (ARDL), fully modified ordinary least squares (FMOLS), canonical cointegration regression (CCR), and Granger causality tests, point out that crop and livestock production stimulates CO_2 emissions while electric power consumption in agriculture reduces emissions in China. Complementing this, Lei *et al.* (2021) analysed the impacts of Chinese energy efficiency and renewable energy consumption on CO_2 emissions by applying nonlinear ARDL models. They suggest that a positive shock in terms of renewable energy consumption has a depressing impact on CO_2 pollutants as compared to a negative shock, as it serves to strengthen environmental quality by decreasing short-term CO_2 emissions in China. Finally, Gokmenoglu (2019) explored a similar result in China using the same econometric technique, suggesting that real income, energy consumption and agricultural development have a positive impact on CO_2 emissions.

Cross-country analysis

Among cross-country analyses, several research investigated the impacts of economic development and different types of energy consumption on carbon dioxide emission (a proxy for climate change) in both developed and developing economies. Ahmed et al. (2021) used cross-sectional augmented autoregressive distributed lag (ARDL) analysis and demonstrated that economic growth and fossil fuel consumption increased CO_2 emissions, while renewable energy helped moderating emissions in 22 OECD countries. Addressing the impacts of non-renewable energy in the G-20, Ibrahim and Ajide (2021) found that fossil fuels and imports increased, while exports and technological innovation reduced per capita carbon emissions, examined by the augmented mean group (AMG), the common correlated effect mean group (CCEMG), and the mean group (MG). In the case of developing countries, Haldar and Sethi (2021) show that institutional quality moderates energy consumption and reinforces the drop in carbon emissions. Moreover, renewable energy consumption reduces emissions in the long run. They utilised mean group (MG), augmented mean group (AMG), common correlated effects mean group (CCEMG) estimator, dynamic system General Method of Moment (GMM), panel grouped-mean FMOLS and panel Quantile Regression approach. Parajuli (2019) applied the dynamic panel model (Arellano–Bond panel GMM) for 86 countries from Africa, Asia, Latin America and Europe at various stages of development, demonstrating that energy consumption and agriculture are positively correlated with carbon dioxide emissions while forest activities reduce the level of pollution in the long run.

Investigations carried out in emerging economies were also widespread. For example, Eyuboglu and Uzar (2020) researched the impacts of agriculture and renewable energy on CO_2 emissions for seven new emerging countries (Malaysia, Indonesia, India, Kenya, Mexico, Colombia, and Poland) using panel-based vector error correction model (VECM) techniques. The authors found that agriculture increases CO_2 emissions, while renewable energy reduces CO_2 in the region studied. Furthermore, economic growth and energy consumption enhance CO_2 emissions. The results indicate that the variables produced CO_2 emissions in the long run and economic growth indicated CO_2 emissions in the short term. In the developing world, You and Kakinaka (2021) discovered the relation of renewable energy to CO_2 emissions by using the ARDL model for 31 emerging countries according to the income classification. They suggest that CO_2 emissions have negative associations with renewable energy in the long term and are more exposed to modern renewable energy sources than traditional ones. Therefore, contemporary renewable energy sources can be an effective target for environmental and energy policies in emerging countries. Zafar *et al.* (2019) have studied the renewable and non-renewable energy sector, trade openness, and its impact on CO_2 emissions using the EKC in emerging economies. Their analysis applies cross-sectional dependence, second generation panel unit root, Pedroni, Westerlund panel cointegration tests along with continuously updated fully modified (CUP-FM), continuously updated bias-corrected (CUP-BC) estimations, and the vector error correction model (VECM). They have found that renewable energy consumption negatively affects, while fossil energy consumption positively affects CO_2 emissions. In contrast, the impact of trade openness on CO_2 is unfavourable.

Country group studies

Rasoulinezhad *et al.* (2018) examined long-term causal links between economic growth, CO_2 emissions, renewable and fossil energy consumption, trade openness, financial openness for the Commonwealth of Independent States (CIS) using DOLS and FMOLS panel cointegration estimation methods. According to their findings, the use of fossil fuel is the most significant factor in increasing CO_2 emissions in the long run in these countries. Moreover, the contribution of fossil energy consumption in improving economic growth is more important than the impact of CO_2 emissions and renewable energy consumption in the long run. Balsalobre-Lorente *et al.* (2019) identified agriculture, energy use, trade openness, and mobile use as the main drivers behind environmental degradation in Brazil, Russia, India, China, and South Africa (BRICS). The authors observed the inverted U-shaped EKC pattern between income level and carbon emissions and the damaging impact of agriculture on the environment. In the case of MERCOSUR, de Souza *et al.* (2018) evaluated the impact of energy consumption and income on emissions through an EKC framework on panel data. The authors point out that the consumption of renewable energy (biogas, solar, and wind) indicates a negative impact, while the consumption of non-renewable energy positively impacts carbon dioxide emissions. The validity of the EKC hypothesis for the MERCOSUR states was also proved. Mehmood (2021) found that globalisation, economic growth, and financial inclusion increased carbon dioxide emissions. However, the consumption of renewable energy moderated the emissions in Pakistan, India, Bangladesh, and Sri Lanka, investigated using the CS-ARDL approach. Similarly to individual country cases, development-energy-trade-emission patterns were identified at the regional level.

Studies focusing on EU emissions

Finally, limited number of studies explored the economic-energy-trade-emission linkage in European Union countries. In this context, Balsalobre-Lorente and Leitão (2020) analysed the effects of renewable energy, trade, carbon dioxide emissions and international tourism on economic growth in the EU using panel fully modified least squares (FMOLS), panel dynamic least squares (DOLS) and fixed effects (FE) estimation. Results suggest that trade openness, international tourism and renewable energy encourage economic growth, but the CO_2 and the use of green technologies are also associated with economic growth. Mert *et al.* (2019) investigated the association between CO_2 emissions and GDP, the use of renewable and fossil energy, and foreign direct investment in 26 EU countries by means of panel co-integration. The results confirmed the validation of the environmental Kuznets curve and the pollution haven hypothesises for EU countries. They argue that environmental regulations do not play an essential role in the validity of pollution havens but are significant elements in the EKC in the EU. They concluded that the EU should improve green technology and energy efficiency for sustainable development but narrow the environmental regulations on FDI inflow.

Considering a comparative analysis between EU and non-EU regions, Ponce and Khan (2021) considered the connection between CO_2 emissions and renewable energy, energy efficiency, fossil fuels, economic growth, property rights in 9 developed countries (Germany, Norway, Sweden, Switzerland, Australia, Canada, Japan, New Zealand, and the US), tested by the FMOLS. The outcomes shed light on a long-term equilibrium in developed European countries (Germany, Norway, Sweden, Switzerland). Still, it is not true for developed non-European countries (Australia, Canada, Japan, New Zealand, and the US). Estimates suggest a positive link between fossil fuel consumption, GDP, property rights, and CO_2 emissions. Meanwhile, renewable energy consumption and energy efficiency negatively influenced CO_2 emissions.

Previous studies have frequently focused on factors of economic growth via EKC, renewable energy and fossil fuel consumption, energy efficiency, trade, the financial and agricultural sector in various geographical areas. The selected literature suggests that economic growth, renewable energy, trade openness, export activity, and forest area all contribute to decreasing emissions while fossil fuel consumption, agriculture and imports all stimulate air pollution. Nearly all studies confirmed the inverted U-shaped EKC curve. Taking methodologies other than VECM into consideration, panel FMOLS, DOLS, CCR, nonlinear ADRL, panel MG, AMG, CCEMG, GMM and Quantile Regression were applied, and accompanied by unit root, cointegration, and Granger causality tests. However, only a limited number of studies (Mert *et al.* 2019, Balsalobre-Lorente and Leitão 2020) have investigated the environmental issues in the EU member states while taking into consideration the impacts of agricultural trade.

Methodology and data

We started our research by verifying the properties of the variables used in this empirical study. Consequently, we used unit root tests on panel data and the Pedroni cointegration test to observe long-term cointegration between the variables. Then, we analysed the explanatory factors of carbon dioxide emission in the European Union using Panel Fully Modified Least Squares (FMOLS), and Quantile Moments Regression Estimates suggested by Machado and Silva (2019). The estimated models investigated economic development, renewable energy, energy intensity, and agricultural exports as factors offering an explanation for carbon dioxide emissions. The selected database includes balanced panel data for the 27 EU member states between 1990 and 2018. The panel regression equation (1) captures the impact of economic development (GDP per capita), the level of primary energy intesity (in megajoules per GDP), agricultural exports (measured as export value in US dollars) and renewable energy consumption as a percentage of total energy consumption. Based on the empirical literature (Burakov, 2019; Balsalobre-Lorente *et al.,* 2019), the following equation is estimated:

$$\ln(CO_2pc) = \alpha + \beta_1 \ln(EI)_{ij} + \beta_2 \ln(GDPpc)_{ij} + \\ + \beta_3 \ln(agrexport)_{ij} + \beta_4 ln(RE)_{ij} + \varepsilon_{ij} \quad (1)$$

where
i denotes the EU member state,
j is the given year,
α is the constant,
β captures estimated coefficients,
and ε is the error term.

A detailed description of the variables is presented in Table 1.

Table 1: Description of variables.

Variables	Description	Source
CO_2pc	per capita CO_2 emissions in million tons	World Bank (2022) WDI
EI	primary energy intensity level (megajoules per GDP in 2011 US dollars, Purchasing Power Parity)	World Bank (2022) WDI
GDPpc	per capita GDP in 2011 US dollars, Purchasing Power Parity	World Bank (2022) WDI
AGREXPORT	agricultural exports in thousand current U.S. dollars	World Bank (2022) WITS
RE	renewable energy consumption as a percentage of total energy consumption	World Bank (2022) WDI

Note: The intensity level of primary energy is the ratio between the energy supply and the gross domestic product measured at purchasing power parity (PPP). Intensity is an indication of how much energy is used to produce one unit of economic output. A lower ratio indicates that less energy is used to produce one unit of output.
Source: Own composition

Based on the literature review, we formulate the following hypotheses in this empirical study.

H1: Economic development by increasing energy production and consumption stimulates CO_2 emissions in the EU.

More recently, studies by Balsalobre-Lorente *et al.* (2021), Leitão *et al.* (2021) and Burakov (2019) have found that economic growth has a positive impact on carbon dioxide emissions.

H2: The increased energy intensity of primary energy consumption leads to a higher level of CO_2 emission in the EU.

The intensity of the energy captures the amount of energy used to produce one unit of economic output. A higher proportion of energy intensity indicates that more energy is used to produce one unit of output. These assumptions are supported by Burakov (2019), Ponce and Khan (2021) and Haldar and Sethi (2021).

H3: The expansion of agricultural exports decreases CO_2 emissions in the member states.

Although in general, agricultural production stimulates emissions (Chen *et al.,* 2021; *Ansari et al.,* 2020 and Yu *et al.,* 2019), trade in agricultural products, especially agricultural intra-industry trade, may have been related to cleaner energies that help reduce CO_2 emissions in the EU (Leitão and Balogh, 2020).

H4: A higher share of renewable energy consumption contributes to a decrease in air pollution in the EU.

Several researchers (Pata, 2021; Burakov, 2019; Ahmed *et al.,* 2021; Eyuboglu and Uzar, 2020 and Zafar *et al.,* 2019) have suggested that increasing renewable energy consumption contributes to climate mitigation through emissions reduction.

Results

Figure 1 shows that, in line with the reduction in CO_2 emissions, the EU has generally experienced a small decrease in fossil energy use and an increase in renewable energy consumption, while agricultural trade was also developing.

The summary statistics are shown in Table 2. Based on the mean values, we can see that agriculture exports (LnAGR_EXPORT) and income per capita (LnGDPpc) represent the highest values. In addition, the variables of agricultural exports (LnAGR_EXPORT), income per capita (LnGDPC), and renewable energy (LnRE) have the highest maximum values.

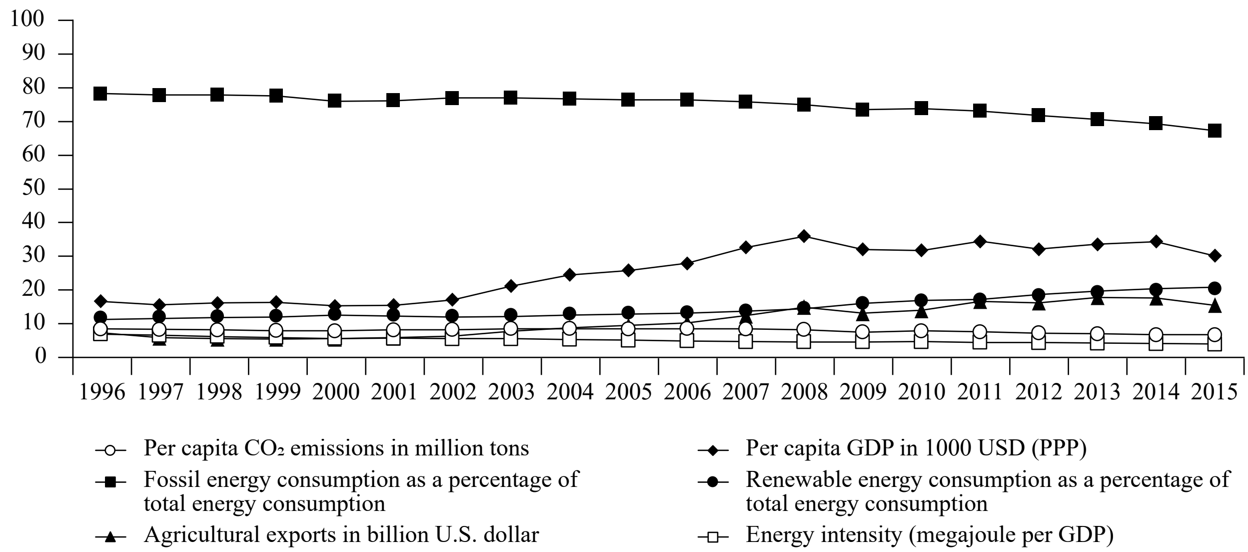

Figure 1: Evolution of indicators selected in the EU-27, mean, 1996-2015.
Source: Own composition based on World Bank (2022) data

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The Pearson correlation coefficients are given in Table 3. Variables of energy intensity (LnEI), income per capita (LnGDPC), and agricultural exports (LAGR_EXPORT) demonstrate a positive statistically significant effect on carbon dioxide emissions per capita (LCO_2pc). Furthermore, renewable energy (LnRE) is negatively correlated with per capita carbon dioxide emissions.

Table 4 presents the results obtained by the panel unit root test as well as Levin, Lin and Chu, ADF–Fisher Chi-square, Phillips-Perron, and Im–Pesaran–Shin tests to evaluate the proprieties of the variables used in this investigation. Here, we can observe that carbon dioxide emissions per capita (LnCO_2pc), energy intensity (LnEI), income per capita (LnGDPpc), renewable energy consumption (LnRE), and agricultural exports (LAGR_EXPORT) have been integrated into the first difference.

Table 2: Summary statistics.

Variable	Observation	Mean	Std. Dev.	Min	Max
Ln(CO_2pc)	737	0.869	0.172	0.429	1.438
Ln(EI)	727	0.716	0.161	0.257	1.261
Ln(GDPpc)	793	4.245	0.401	3.042	5.075
Ln(AGR_EXPORT)	609	6.536	0.797	3.952	7.949
Ln(RE)	716	0.929	0.474	-1.059	1.726

Source: Own composition based on World Bank (2022) data

Table 3: Pearson's correlation coefficients.

Variable	Ln(CO_2pc)	Ln(EI)	Ln(GDPpc)	Ln(AGR_EXPORT)	Ln(RE)
Ln(CO_2pc)	1.000				
L(EI)	0.102*	1.000			
Ln(GDPpc)	0.399*	-0.639*	1.000		
Ln(AGR_EXPORT)	0.176*	-0.259*	0.481*	1.000	
Ln(RE)	-0.432*	0.008	-0.024	-0.043	1.000

* p<0.05.
Source: Own composition based on World Bank (2022) data

Table 4: Panel unit root tests.

Variable	Levin, Lin & Chu t		Im, Pesaran and Shin W-stat		ADF–Fisher Chi-square		PP - Fisher Chi-square	
	Null: Unit root (assumes common unit root process)		Null: Unit root (assumes an individual unit root process)					
	Statistic	p-value	Statistic	p-value	Statistic	p-value	Statistic	p-value
Ln(CO_2pc)	3.876	0.999	4.647	1.000	30.398	0.998	59.344	0.355
Ln(EI)	1.758	0.961	7.453	1.000	8.915	1.000	7.030	1.000
Ln(GDPpc)	-3.182	0.001***	1.861	0.969	26.088	0.999	23.454	1.000
Ln(RE)	0.188	0.574	3.592	0.999	67.053	0.148	74.695	0.048**
Ln(AGR_EXPORT)	-2.843	0.002***	2.138	0.984	26.246	0.999	51.449	0.573
D(Ln(CO_2pc))	-6.992	0.000***	-10.609	0.000***	227.691	0.000***	528.232	0.000***
D(Ln(EI))	-10.852	0.000***	-12.878	0.000***	267.838	0.000***	523.711	0.000***
D(Ln(GDPpc))	-13.88	0.000***	-13.179	0.000***	275.494	0.000***	324.392	0.000***
D(Ln(RE))	-9.827	0.000***	-10.144	0.000***	212.019	0.000***	386.886	0.000***
D(Ln(AGR_EXPORT))	-10.50	0.000***	-9.483	0.000***	192.724	0.000***	292.380	0.000***

*** p<0.01, ** p<0.05, * p<0.1
Source: Own composition based on World Bank (2022) data

Pedroni residual cointegration tests are reported in Table 5. Consistent with the results, we can conclude that the variables in this investigation are cointegrated in the long run.

The results of panel fully modified least squares (FMOLS) are shown in Table 6. The variable of energy intensity consumption (LnEI) is statistically significant at a 1% level and is positively correlated with carbon dioxide emissions per capita (β_1>0). Therefore, the growth in energy consumption stimulates emission of 0.318%. According to previous studies (see, e.g., Rasoulinezhad *et al*., 2018; Balsalobre-Lorente *et al*., 2019 and de Souza *et al*., 2018), this result shows that primary energy consumption stimulates the increase of carbon dioxide emissions, which validates the hypothesis formulated.

Income per capita (LnGDPpc) has a positive effect on carbon dioxide emissions and the variable is statistically significant (β_2>0). According to empirical studies by Balsalobre-Lorente *et al.* (2021), Leitão *et al.* (2021) and Burakov (2019), economic growth and their activities encourage climate changes and global warming. The empirical literature is inconclusive in relation to the coefficient of agricultural exports (LnAGR_EXPORT). Some studies found a positive impact on agricultural export (e.g. Himics *et al.,* 2018; Chen *et al.,* 2021 and Ansari *et al.,* 2020); however, the result with FMOLS showed that expanding agricultural trade decreases carbon dioxide emissions in the EU. Subsequently, renewable energy (LnRE) has a negative effect (β_4<0) on carbon dioxide emissions and is statistically significant at a level of 1%. Estimates indicate that renewable energy consumption aims to reduce greenhouse gas emissions. The works of Leitão (2021), Balsobre Lorente *et al.* (2021) and Koengkan and Fuinhas (2020) also found a negative impact between renewable energy and carbon dioxide emissions.

Table 7 illustrates the results with the method of Quantile Regression. Considering the energy intensity (LnEI), the variable is statistically significant at 1% level for three quantiles (25%, 50% and 75%). Recent studies by Pata (2021) and Eyuboglu and Uzar (2020) found the same trend. As previous studies shown (Haldar and Sethi, 2021; Ponce and Khan, 2021), a positive relationship is revealed between economic growth (LnGDPpc) and carbon dioxide emissions, demonstrating that economic growth stimulates pollution emissions. Furthermore, the coefficient of renewable energy

Table 5: Pedroni Residual Cointegration Test.

Alternative hypothesis: common AR coefficient (within-dimension)							
Panel v-Statistic		**Panel rho-Statistic**		**Panel PP-Statistic**		**Panel ADF-Statistic**	
Statistic	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**
3.456	0.000***	-0.545	0.293	-3.760	0.000***	-1.981	0.024**
-0.644	0.740	-1.044	0.148	-7.346	0.000***	-4.227	0.000***
Alternative hypothesis: individual AR coefficient (between-dimension)							
Group Rho-Statistic		**Group PP-Statistic**		**Group ADF-Statistic**			
Statistic	p-value	Statistic	p-value	Statistic	p-value		
1.5304	0.937	-7.005	0.000***	-3.780	0.000***		

*** p<0.01, ** p<0.05, * p<0.1.
Source: Own composition based on World Bank (2022) data

Table 6: Panel Fully Modified Least Squares (FMOLS).

Variables	Coefficients
Ln(EI)	0.318 ***
	(0.000)
Ln(GDPpc)	0.227***
	(0.000)
Ln(AGR_EXPORT)	-0.063**
	(0.015)
Ln(RE)	-0.138***
	(0.000)
S.E. of regression	0.003
Long-run variance	0.003
Mean dependent variable	0.871
S.D dependent variable	0.165
Sum squared residual	0.549
Observations	491

P-values in parentheses
*** p<0.01, ** p<0.05, * p<0.1.
Source: Own composition based on World Bank (2022) data

Table 7: Quantile regressions.

	25%	50%	75%
Variables	**tau 0.25**	**median**	**tau 0.75**
Ln(EI)	0.572***	0.698***	0.844***
	(0.000)	(0.000)	(0.000)
Ln(GDPpc)	0.320***	0.351***	0.423***
	(0.000)	(0.000)	(0.000)
Ln(AGR_EXPORT)	0.009	0.008	-0.055***
	(0.556)	(0.314)	(0.000)
Ln(RE)	-0.147***	-0.123***	-0.189***
	(0.000)	(0.000)	(0.000)
Constant	-0.891***	-1.045***	-0.893***
	(0.000)	(0.000)	(0.000)
Observation	520	520	520
Pseudo R-squared	0.313	0.315	0.322

P-values in parentheses
*** p<0.01, ** p<0.05, * p<0.1.
Source: Own composition based on World Bank (2022) data.

(LnRE) negatively correlated with carbon dioxide emissions was statistically significant at a level of 1%. You and Kakinaka (2021) and Rehman *et al.* (2021) as well as Ponce and Khan (2021) also had a similar result.

Discussion and Conclusions

The European Union has committed to becoming carbon neutral by 2050. To achieve this target, a significant reduction in greenhouse gas emissions is needed. This article analysed the relationship between economic growth, energy intensity, agricultural exports, and CO_2 emission in the EU-27. The research used panel data, and panel cointegration models such as Fully Modified Least Squares (FMOLS) and Quantile Regression as a methodology applied for a period of 1990 and 2018. The panel unit root tests showed that the variables used in the investigation are integrated into the first difference. Besides, the Pedroni test revealed that there was a long-term cointegrated relationship between variables. The FMOLS estimate suggests that growth in energy consumption stimulates carbon emission by 0.318% in the EU. Income per capita had a positive effect on carbon dioxide emissions indicating that economic development produces higher emission levels in line with previous analyses (Balsalobre-Lorente *et al.,* 2021; Leitão, 2021 and Burakov, 2019). The result of the FMOLS regression demonstrated that expanding agricultural trade decreases carbon dioxide emissions in the EU, suggesting that intra EU trade induces less emission. The estimates indicated that renewable energy consumption helps cut GHG emissions, aids the transition to a green economy and decreases environmental pollution (Leitão, 2021; Balsobre-Lorente *et al.,* 2021; Koengkan and Fuinhas, 2020).

The result of Quantile Regression revealed that energy intensity (LnEI) is statistically significant at a 1% level for three quantiles (25 %, 50 % and 75%), following Pata (2021) and Eyuboglu and Uzar (2020), who found the similar tendency. A positive relationship between economic growth and carbon dioxide emissions is explored in the EU, indicating that economic growth stimulates greenhouse gas emissions (Haldar and Sethi, 2021; Ponce and Khan, 2021). Furthermore, renewable energy aims to decrease climate change, as You and Kakinaka (2021) and Rehman *et al.* (2021) as well as Ponce and Khan (2021) pointed out. Quantile Regression estimation discovered that increasing energy intensity (LnEI) stimulates emission (coefficient was statistically significant at a 1% level for three quantiles) in line with Pata (2021) and Eyuboglu and Uzar (2020). A positive relationship between economic growth and carbon dioxide emissions is explored, indicating that economic growth stimulates greenhouse gas emissions (Haldar and Sethi, 2021; Ponce and Khan, 2021). Furthermore, renewable energy consumption aims to reduce climate change (air pollution) as You and Kakinaka (2021), Rehman *et al.* (2021) and Ponce and Khan (2021) proved. The estimates revealed that the export of agricultural products decreases carbon dioxide emissions within the EU, referring to the fact that the intra EU agricultural trade is more environmentally friendly. Finally, higher renewable energy consumption was confirmed as contributing to United Nations climate mitigation goals by reducing emissions.

The findings presented in this investigation allow us to draw conclusions associated with agricultural and trade policy, as well as a more sustainable Common Agricultural Policy. The analysis concludes that economic development and rising energy intensity are strongly associated with carbon dioxide emissions; thus, the green transition, and increasing the share of renewable energies in the energy mix are needed. However, the climate law and Common Agricultural Policy of the EU mainly puts emphasis on reducing the impacts of climate change; member states' climate policies should therefore focus on reducing growth-related emissions, slowing the increase in energy intensity, and decreasing the footprint of agricultural production and trade. In this context, reducing the use of fossil energy production (coal and gas), dependency and its consumption is crucial. Moreover, diminishing long distance agri-food trade could be the way forward for EU member countries, as has been the role of the Common Agricultural Policy. Moderating long-haul agricultural export and supporting the consumption of low-carbon food products can be another solution in the EU climate policy. The findings suggest that the effect of renewable energy adoption on carbon emissions reduction in and of itself is limited and not enough to achieve carbon neutrality; investments in green technology, R&D and greater improvements in energy efficiency are also needed across economic sectors, industry, agriculture and services. Moreover, consumption choices can also significantly influence the European Union's emissions; their promotion can be supported by sustainable food certificates and ecological products.

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How improving the technical efficiency of Moroccan saffron farms can contribute to sustainable agriculture in the Anti-Atlas region

The saffron sector as a sustainable farming system plays a primordial agro-ecological and socio-economic role in the Anti-Atlas region in Morocco. Under the Green Morocco Policy, the saffron area has more than tripled; however, productivity is still very low. To evaluate the efficiency of Moroccan saffron farming and its determinants, we estimated a stochastic frontier model using survey data collected in the production area. The results show that saffron farms suffer from technical inefficiencies. More time dedicated to saffron field operations, a higher number of saffron plots and a greater distance to the urban centre increase farm efficiency, while the age of the farmer and the presence of off-farm activities decrease it. Building on our results, we argue that the new policy "Generation Green" should be focused on younger farmers as they are more likely to improve their skills and crop management techniques. To upscale the adoption of saffron as a sustainable farming system, an improvement in farmers' market access is necessary which would facilitate farm specialisation, convert saffron to a major source of income and reduce dependence on off-farm activities. Strengthening the role of saffron cooperatives could represent an important step in this direction, but this requires improved knowledge dissemination and technology access.

Keywords: saffron farms, sustainable agriculture, stochastic frontier model, technical efficiency, Anti-Atlas Mountains

JEL classification: Q12

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Introduction

The saffron crop (*Crocus sativus*) is traditionally grown in low input farming systems, and is characterised by specific agronomical and biological traits, such as low fertiliser requirements and high adaptation to poor soils (Gresta *et al.,* 2008). The cultivation of saffron in Morocco has increased considerably over the past few years. According to the Moroccan Ministry of Agriculture, the cultivated saffron area increased and reached 1,826 hectares in 2019 (MAPM, 2022), making Morocco the world's fourth-largest producer of saffron. Saffron production in Morocco is concentrated in the regions of Taliouine and Taznakht, which are located in the mountainous provinces of Ouarzazate and Taroudant in the Anti-Atlas mountain area. The climate of this area is continental, semi-arid to arid with low rainfall (220 mm to 300 mm) and temperature variation from -1°C in winter to +40°C in summer. The predominant soil types are light, shallow soils that are rich in limestone.

Farmers practice subsistence agriculture based on diversified farming systems with cereal production (barley, durum wheat and soft wheat), saffron cultivation and market gardening. As an endemic species in Morocco, the saffron crop is highly adapted to the pedoclimatic conditions of the region, and requires no specific phytosanitary measures, chemical fertilisation, or chemical weed treatments. These features highlight the fact that saffron plays an important agro-ecological role in preserving local biodiversity. The main field operations of this type of farming are carried out manually (particularly harvesting), a factor which contributes to the high price of saffron and hence increases the land value in the Anti-Atlas region. Women play a crucial role in saffron production, a situation that possibly contributes to rural women's empowerment. As a labour-intensive crop, saffron production demands around 258,000 working days per year (MAPM, 2022), thereby contributing to the alleviation of poverty and inequality in the region, while at the same time promoting local and socio-economic development.

Furthermore, the saffron sector plays an important cultural role which goes beyond agricultural production, extending to tourism and gastronomic activities, as well as social and cultural events. The Moroccan government has recognised these distinctive features that characterise the saffron sector and has introduced specific regulations along with support measures bundled together within the framework of the Green Morocco Policy (GMP), which include the creation of a new Protected Designation of Origin (PDO) Saffron of Taliouine quality scheme in 2010 with a view to supporting the saffron production system and the economy of the saffron territory. Since then, the saffron area has more than tripled in only 10 years, now exceeding the target set in the agricultural strategy by 35%. The current Moroccan annual average production has reached 6.5 tons, of which 1.2 tons are exported, mainly to Spain and Switzerland (MAPM, 2022). However, Morocco's productivity is still very low if it is compared to other countries, with yields of approximately 3.5 kg/ha compared to, for example, 8.4 kg/ha in Italy (MAPM, 2022; Kothari *et al.,* 2021). This low output implies that there is considerable unexploited potential to improve the productivity of the saffron sector in Morocco. It also raises the question of how to sustainably intensify production without compromising agroecological benefits.

Although there is a large body of literature dealing with productivity and technical efficiency analysis, the causes of the low saffron productivity, and thus potential entry points for its improvement, are still insufficiently studied. Recent studies have examined farm efficiency mostly in the context of developing countries, and have linked it to sustainable farming, climate change and precision agriculture (Adetoyinbo and Otter, 2022; Carrer *et al.,* 2022; Endalew *et al.,* 2022; Shahbaz *et al.,* 2022). However, most of the studies on the saffron crop have focused on plant physiology and biology (e.g. Abu-Izneid *el al.,* 2022; El Midaoui *et al.,* 2022; Rather *et al.,* 2022). A recent study examined the influence of dense planting on the technical efficiency of saffron production in Iran using data envelopment analysis (Ramezani *et al.,* 2022). Studies on Moroccan saffron have meanwhile tended to analyse crop cultivation techniques primarily from an agronomic point of view, or in terms of farm strategies for adapting to climate change (e.g. Aziz and Sadok, 2015; Lage, 2009). A recently published study carried out a strategic analysis of the Moroccan saffron sector and investigated marketing prospects as well as the perceptions of Moroccan consumers and their willingness to pay for this product (Lambarraa-Lehnhardt and Lmouden, 2022).

No previous studies have examined the technical efficiency of Moroccan saffron farms and its different determinants; this is therefore the main objective of the current study. As specific objectives, we estimate the technical efficiency of the main regions of saffron production in Morocco and analyse the impact of various farm and socioeconomic factors. Results from the analysis are expected to provide valuable insights into the causes of low saffron productivity in Morocco which could help policy makers designing policies aiming at the improvement of Moroccan saffron productivity and its upscaling as a sustainable farming system in the climatic and edaphic conditions of the Anti-Atlas area.

Methodology

Technical efficiency is defined as the capacity of an economic unit to produce the maximum attainable output from a given set of inputs and technology. Farrell (1957) provided a standard reference, enabling comparison of the efficiency of multiple firms using the concept of the frontier. According to the author, the measurement of firm efficiency is based on the comparison of a firm's performance with other similar firms belonging to the same sector, while the best ones define this frontier.

To apply this concept to saffron farms, we chose to build on the stochastic frontier model (SFM), which was originally introduced by Aigner *et al.* (1977) and Meeusen and van den Broeck (1977). SFM seeks to address the shortcomings of deterministic approaches (e.g. Data Envelopment Analysis, DEA) by distinguishing between exogenous shocks outside the farm's control, and inefficiency. The model assumes that, for a given combination of inputs, the maximum attainable production by a firm is delimited from above by a parametric function of known inputs involving unknown parameters and a measurement error. Based on this, a stochastic frontier production model can be expressed as follows:

$$y_i = f(x_i, \beta)e^{v_i - u_i} \tag{1}$$

where y_i is the output of the i-th firm (i=1,…,N), $f(x_i, \beta)$ represents the production technology, x_i is a $(1\times k)$ vector of inputs and other factors influencing production associated with the i-th firm β is a $(1\times k)$ vector of unknown parameters to be estimated. The disturbance term is composed of two parts: v_i is a symmetric component, which permits random variations of the frontier across firms and captures the effects of statistical noise outside the firm's control, is assumed to be normally distributed with the error term $N(0, \sigma_v^2)$, (i.e., statistical noise), and the term of inefficiency u_i is an independently and identically distributed one-sided random error term representing the stochastic shortfall of the i-th farm output from its production frontier due to the existence of technical inefficiency $N^+(0, \sigma_u^2)$ (i.e., farm-specific output-oriented technical inefficiency). It is further assumed that the two error terms are independently distributed from each other.

The specification that we are going to adopt is the model proposed by Battese and Coelli (1995), where technical efficiency is explained by specific factors. Thus, the term of technical inefficiency responds to the following pattern of behaviour:

$$u_i = \delta z_i + \eta_i \tag{2}$$

δ is an $(1\times m)$ vector of unknown coefficients of the firm-specific inefficiency variables. η_i random variable defined by the truncation of the normal distribution with zero mean and variance σ^2, such that the point of truncation is $-z_i\delta$. The explanatory variables z_i is a $(m\times 1)$ vector of firm-specific variables.

Maximum likelihood techniques are used for a simultaneous estimation of the stochastic frontier and the technical inefficiency model. This model is widely implemented using panel data and some studies exploited the nature of such data by assessing the dynamic technical efficiency of the farm (e.g. Lambarraa *et al.,* 2016; Tsionas *el al.,* 2019).

Technical efficiency is then used to predict conditional expectation, which allows calculating the individual efficiency of each producer. Then, the Technical efficiency (TE) ratio of the i-th producer firm is defined by equation (3):

$$TE_i = \frac{y_i}{f(x_i,\beta)} = \frac{f(x_i,\beta)e^{-u_i}}{f(x_i,\beta)} = e^{-u_i} \tag{3}$$

This ratio measures the proportion of actual production (output) to the maximum potential production if the farm used their resources efficiently. Finally, we used the generalised likelihood-ratio statistic to test several hypotheses related to the model:

- First, the functional form must accurately describe the production technology: if $\beta_{ij} = 0$ then the Cobb-Douglass is the convenient functional form for the model.
- Second, if $\delta = 0$ technical inefficiency effects are non-stochastic and the model (1) reduces to the average response function in which the explanatory variables in the technical inefficiency model are also included in the production function.
- Third, if $\sum_{ij} \beta_{ij} = 1$, then we have a constant return to scale.

The test statistic is calculated using this equation: $\lambda = -2\{ln\, L\,(H_0) - ln\, L\,(H_1)\}$, where $L\,(H_0)$ and $L\,(H_1)$ denote the values of the likelihood function under the null

(H_0) and the alternative (H_1) hypothesis, respectively. The LR has an asymptotic Chi-square distribution with degrees of freedom equal to the number of restrictions on the parameters if the null hypothesis is true (Coelli, 1995; Kodde and Palm, 1986).

Data collection

The database used in this study is based on a field survey on technical and socio-economic information conducted in 2018 among Moroccan saffron farmers (n = 125) in the regions of Taliouine and Taznakht (administrative district of Ouarzazate), which represent 95 % of the national farmers producing saffron. The data were collected in face-to-face interviews in Amazigh language. The area of study is difficult to access and involves complicated logistics. The methodology used to determine the number of farmers to be surveyed is based on stratified sampling method with two levels of stratification.

The first level of stratification is determined by the Agricultural Development Centre "ADC". These centres belong to the Moroccan ministry of agriculture and each centre is responsible for a specific area of production and farmers. Three ADCs operate in the study region:

- Agricultural Development Centre of Taliouine: It is the most important one in terms of farmers' number and the total surface of produced saffron. It includes six rural communes (RC), representing 51% of the total farmers, and 74.6% of the total surface of saffron;
- Agricultural Development Centre of Askaoune: This centre includes two RC and represents approximately 23.7% of saffron producers, and 9.7% of the total surface of saffron;
- Agricultural Development Centre of Taznakht: This centre includes four RC representing approximately 25.3% of saffron producers, and 15.7% of the total surface of the saffron.

The weighting basis used for the determination of the number of farmers to be surveyed per ADC corresponds to the ratio of the relative area per Agricultural Development Centre to the total area of saffron:

$$N_{zi} = N_t * (S_{zi}/S_t) \quad (4)$$

where
N_{zi}: is the number of farmers for the ADC_i
N_t: is the total number of farmers to be interviewed in the study area
S_{zi}: is the area of saffron in the ADC_i (ha)
S_t: is the total area of saffron in the study area (ha).

The second level of stratification corresponds to the rural communes producing saffron within each ADC (first level). Thus, for each ADC, the number of farmers to be interviewed per commune is determined on the basis of the weighting of the saffron area per commune to the total area at the ADC:

$$N_{cj} = N_{tzi} * (S_{cj}/S_{tzi}) \quad (5)$$

where:
N_{cj}: is the number of farmers for commune j
N_{tzi}: is the total number of farmers to be surveyed for the ADC_i
S_{cj}: is the area of saffron in commune j (ha)
S_{tzi}: is the total area of saffron in the ADC_i (ha)

Following this stratification technique, a total of 130 farmers needed to be interviewed, which represents 2.5% of the farms producing saffron. However, giving the time and logistics limitations, we were able to carry out 125 surveys from which we excluded a total of 8 incomplete questionnaires.

Empirical application

To analyse the efficiency of Moroccan saffron farms, we modelled the saffron production and efficiency using the collected farm-level data. To specify the model, we carried out different statistical tests using the generalised likelihood-ratio (L-R). Table 1 presents the results. The null hypotheses that the second order coefficients are zero ($\beta_{ij} = 0$) is accepted at the 5% significance level, which reduces the model to the Cobb-Douglass functional form. The second hypothesis tested $H'_0: \gamma = \delta_i = 0$ is rejected, which reveals that inefficiency effects are not absent from the model, confirming that Moroccan saffron farms suffer from inefficiencies. Both systematic and random technical inefficiency effects explain output variability. The third tested hypothesis of the presence of constant returns to scale ($\sum_{ij} \beta_{ij} = 1$) is accepted at the 5% significance level for the total sample, which means that there are constant returns to scale which speaks against expanding the saffron farms size as a possible strategy to increasing productivity.

Table 1: Model specification tests.

Hypothesis	LR test-statistic	Critical value (α = 0.05)	
Cobb-Douglas form, i.e.,: ($H_0: \beta_{ij} = 0$ for all j and i)	20.5	25	AH_0
Absence of inefficiency effects, i.e.,: ($H'_0: \gamma = \delta_i = 0$)	31.3	12.59	RH'_0
Constant returns-to-scale, i.e., : ($H''_0: \Sigma\beta_{ij} = 1$)	0.69	3.84	AH''_0

Source: Own composition

Thus, the production frontier function is specified as a Cobb-Douglas takes the form:

$$\ln(y_i) = \beta_0 + \sum_{k=1}^{p} \beta_k \ln(x_{ki}) + v_i - u_i \quad (6)$$

Production y_i is defined as the total saffron production in kilograms. Vector x_{ki} is defined as a (1x4) vector composed of four inputs. β is a $(K \times 1)$ vector of unknown parameters to be estimated, and the disturbance term is composed of two parts: v_i and u_i. The following input variables were used:

- Labour (x_L), since the production of saffron is known to be very labour-intensive (e.g. hand-picked harvesting). This variable is introduced in the model as the total number of working hours.

- Plantation (x_P), which is the total quantity of bulbs (in tons) planted in the considered area.
- Land (x_L), which is the total area occupied by saffron (in ha). In the region of study, the area devoted by farms to saffron cultivation is very variable, and generally small.
- Expenditure on organic fertilisers (x_F), which is approximated using the cost of manure in Moroccan Dirhams since there is no use of mineral fertilisation.
- Other inputs (x_{OI}), which includes e.g. the cost of diesel, and farming overheads, all measured in Moroccan Dirhams.

The technical inefficiency effects function is specified as:

$$u_i = \delta_0 + \sum_{i=1}^{m} \delta_i z_i + w_i \quad (7)$$

Vector (z_i) in the technical inefficiency effects function is a (1x6) vector that specifies the Constant (Z_1), the Farmer age (Z_2), Management practices (Z_3) expressed by the number of days by year spent for saffron management practices, Distance to the urban centre (Z_4), Number of saffron plots (Z_5), and Off-farm activities (Z_6). Following the literature, older farmers are expected to be less efficient in comparison to younger ones, since younger farmers tend to be more willing or have greater ability to introduce changes in farm management techniques (Battese and Coelli, 1995; Lambarraa *et al.,* 2007). As suggested by previous studies (Bloom *el al.,* 2013; Shuhao, 2005), the number of plots and the time spent on management practices also could influence technical efficiency. Both variables could be considered as indicators of specialisation and full-time commitment to this farming activity which could improve farms' efficiency (Bloom *el al.,* 2013), while off-farm activities are expected to have a negative impact on technical efficiency.

Results and discussion

Characteristics of the farm sample

Summary statistics for the sample of saffron farms are given in Table 2, showing that the average annual saffron produce per farm is around 1.88 kg. The sample farms employ 4,322 labour hours per year, 60.2% of which are family labour. The sample farms use more than 4 tons of saffron bulb for the plantation per year and spent 943 Moroccan Dirhams on fertilisers and 659 Moroccan Dirhams on other specific costs. The land average is around 1.39 ha. The average farm distance to the urban centre is around 35 km with a maximum of 97 km and a minimum of 12 km. The average age of farmers is 52 years.

Table 3 shows the characteristics of saffron plots as reported by the Agricultural Development Centre. Generally, there are no major differences regarding the saffron area between the different centres. Taliouine farmers have on average a larger saffron area per farm, but the land is more fragmented with an average of 12 plots per farm compared to Askouan with only 7 plots per farm. The oldest saffron is observed among Askouan farmers with an average age of 9 years, while the Taznakht saffron with an average age of 4 years appears to be the youngest.

The majority of the interviewed saffron households (62%) have between 4 and 10 members, 31% have more than 10 members and only 7% have less than 4 persons in their families. The overall average number of family members per farm household in the sample is around 9 persons. The majority of farmers (44.5%) have no formal school education, 20% have a Koranic-level education, while only 1.7% of the farmers have a university degree. The saffron farmers are well experienced in agriculture: 19% have experience

Table 2: Description of the sample data.

Variable	Unit of measure	Mean	Std Dev	Minimum	Maximum
Production	Kg	1.88	2.68	0.1	16
Labour	h	4322.4	2108.61	496	18,640
Land	ha	1.39	1.23	0.05	8
Plantation (Saffron bulb)	t	4.43	5.65	0.34	40
Fertilisation	dirhams	943.50	793.19	240	6,000
Other costs	dirhams	658.92	978.10	1	7,680
Farmer age	years	52.48	15.02	25	85
Distance to the urban centre	km	35.38	12.84	18	97

Source: Own composition

Table 3: Characteristics of saffron plots.

Agricultural Development Centre (ADC)	Saffron area (ha)	Plots (number)	Age of saffron (years)
ADC-Taliouine	1.51	12.74	7.21
ADC-Askaoune	1.08	7.85	9.77
ADC-Taznakht	1	6.19	4.44
Total Average	1.39	11.30	7.11

Source: Own composition

in agriculture of more than 50 years, 76% have experience between 10 and 50 years, while only 5% have less than 10 years of experience. Most of the interviewed farmers (60%) are not involved in off-farm activities. The remainder carry out parallel activities, such as trade, masonry, and others. The distribution by ADC shows that most farmers having off-farm activities are primarily located in Askaoune (61.5%), followed by the farmers of Taliouine (37.5%), while the farmers of Taznakht are most dedicated to farming, with only 12.5% being involved in off-farm activities. The Membership rate in cooperatives is around 57%; the farmers of Taznakht are the most to adhere to cooperatives (87%), followed by the farmers of Taliouine (54.6%), and finally the farmers of Askaoune (38.5%).

Regarding the farming technical itinerary; most farms grow barley (61.5%) or maize (36.8%) as previous crop to saffron and only 1.7% use market gardening. A quasi-totality of the farmers (82 %) plant their saffron in September, 8.6 % in August and the remainder between May and April. The average depth of plantation is 21.25 cm and the average space between bulbs is 14.74 cm. The majority of farmers (55.6%) use between 4 to 10 tons of bulbs per hectare, 27.4% use less than 4 tons per hectare, and 17.1% use more than 10 tons per hectare. The largest dose of planting is used in Taznakht with an average of 11.13 t/ha, followed by Askaoune with an average of 6.85 t/ha, and finally Taliouine where farmers use only 5.4 t/ha of bulbs on average. The sample farmers irrigate their saffron 10 times on average and the majority (60.7%) control weeds mechanically in March, 20.5% in April and 13.7% in May. Almost all farmers (90.6 %) report no disease occurrence related to the saffron, while 9.4 % declare bulbs rot called “Bayoud”. Half of the farms declare having rats or hare attacks, but they consider such damage not be significant. More than half of the interviewed farmers (58%) dry their saffron produce in the shade, 34% do so in the sun and only 8% use electric dryers. The vast majority of the farmers in the entire region (93.2 %) have limited access to the major markets since they sell their saffron to local markets (“souks”); the remainder sells it to other Moroccan cities aiming to take advantage of a higher price. The average contribution of family labour is around 60%; farmers of Taznakht seem to make the most use of family labour (82% of the total work), followed by Askaoune (70%) and Taliouine (55%).

Technical efficiency assessment

Results derived from the estimated Cobb-Douglas stochastic frontier model are presented in Table 4.

First-order parameters, β_k are all positive and statistically significant. This result indicates that the Moroccan saffron production increases with all inputs: plantation, labour, land, fertilisers, and other inputs. These estimations also suggest that the quantity of planted bulbs and the allocated working time are the most relevant factors affecting saffron production with coefficients of the order of 0.317 and 0.310 respectively, followed by Land (0.163) and Fertilisers (0.109). The sum of the partial production elasticities of these factors is equal to 1. This result is compatible with the likelihood-ratio test (see Table 1), confirming the presence of constant returns to scale which make an increase in the saffron farms’ size unattractive (as this would require increasing returns to scale).

The second part of the model regarding the estimated determinants of technical inefficiency helps revealing which factors affect farm efficiency. The goal is to explore

Table 4: Maximum Likelihood Estimates of Production stochastic frontier model for Moroccan saffron farms.

Variables	Parameters	Estimate	Standard Error
Production Frontier Model			
Constant	β_0	3.1348	(0.6822)***
Plantation	β_P	0.3170	(0.0690)***
Labour	β_{LB}	0.3104	(0.0722)***
Land	β_{LND}	0.1634	(0.0773)**
Fertilisers	β_F	0.1093	(0.0674)*
Other variable inputs	B_{OI}	0.0382	(0.0135)***
Inefficiency effects model			
Constant	δ_0	-0.6270	(1.7235)
Number of saffron plots	δ_{NP}	-0.2481	(0.1336)*
Off-farm activities	δ_{OF}	1.6557	(0.8365)**
Management practices	δ_{MT}	-0.4247	(0.2508)*
Age	δ_A	0.0201	(0.0223)
Distance to urban centre	δ_{DU}	-0.0089	(0.0361)
sigma-squared	σ^2	0.3413	(0.0284)***
gamma	γ	0.7304	
log ML = -50.6057			

Notes:***,** and * indicate that the parameter is significant at the 1, 5 and 10%, respectively.
Source: Own composition

the impact of a variety of factors on the efficiency of saffron farms, as specified in the section empirical application. The number of saffron plots, management practices and the distance to the urban centre are associated with a higher saffron farm efficiency, while the age of the farmer and having off-farm activities decrease it. Management practices, maintenance, and technical control effort such as corn planting, flower harvest and irrigation are expressed by the number of days that the farmer dedicated to these activities. The efficiency of saffron farms improves when farmers are more engaged in controlling different management practices. This result could be explained by the specialisation-effect; which argues that the more time is dedicated by the farmers to their farming activity, the better is the accumulated learning experience, which improves the efficiency of saffron production.

The negative sign of this variable shows that the number of plots has a negative impact on saffron farm inefficiency, which could be explained by the fact that saffron farmers who own more plots are more specialised in this farming activity, and hence more efficient, which is in line with other studies (e.g. Jha *et al.,* 2005).

The negative effect of distance to the urban centre on the level of technical inefficiency is statistically significant. Farmers with the greatest distance to the urban centre are the most efficient compared to farms in close peri-urban areas. This result can be explained by the fact that the farmers located in closest distance to the urban centre tend to be more often engaged in off-farm activities (e.g. masonry, electricity) and spend less time on saffron farming. Since saffron farming is labour-intensive, this situation leads to an increase in the inefficiency of the farms.

The effect of off-farm activities on technical inefficiency is statistically significant. The positive sign of this variable shows that farmers' engagement in off-farm activities increases technical inefficiency. This result is consistent with other studies (e.g. Sabasi *et al.,* 2019) and demonstrates that producers having other off-farm activities have an extra opportunity-cost expressed as the lost time on managing their saffron farm. This time reallocation leads to changes in management practices resulting in reduced effectiveness (Bloom *el al.,* 2013). Spending less time on the farm means that the production decisions may then be based on less information, which could lead to technical inefficiencies (Mayen *et al.,* 2010; Kumbhakar *et al.,* 1989). Other studies have found that off-farm income has a negative impact on farm technical efficiency due to the changes that take place in the farm household's work ethic and performance (Chang and Mishra, 2013). Farms managed by older farmers are less efficient than those managed by younger ones, which suggests that younger farmers may be more likely to introduce efficiency-enhancing management techniques on their farms. Another factor could be the inability of older farmers to concentrate on the labour-intensive saffron crop farming activity. This result is consistent with Lambarraa *et al.* (2007, 2009) who also found that age had a negative effect on technical efficiency.

Figure 1 and 2 show the predicted technical efficiency rates distributed by interval and Agricultural Development Centre (ADC). The technical efficiency in the farm sample takes an average value of 51%, implying that the production of Moroccan saffron farms could increase considerably, if technical inefficiencies were eliminated through more efficient use of inputs. Figure 2 shows that the majority of saffron farms (59%) have a TE rate less than 50% and only 20% of saffron producers have a TE -rate of greater than 80%.

The distribution of technical efficiencies by development centre, as shown in Figure 1, indicates that the most efficient farms are located in Taznakhte (TE= 67%), followed by Talioune (TE= 49%) and finally Askaoune (TE= 44%). These results could be explained by the fact that the Taliouine region has the highest rate of younger farmers adhering to the cooperatives with full engagement to the farming activity with lowest off-farm activities and highest family labour input.

A recent strategic analysis of the Moroccan Saffron sector shows that it has good potential to grow and expand further, particularly as regards the Moroccan and international markets (Lambarraa-Lehnhardt and Lmouden, 2022). However, on the production side, our study demonstrates that Moroccan saffron farms are inefficient. There is a need to improve

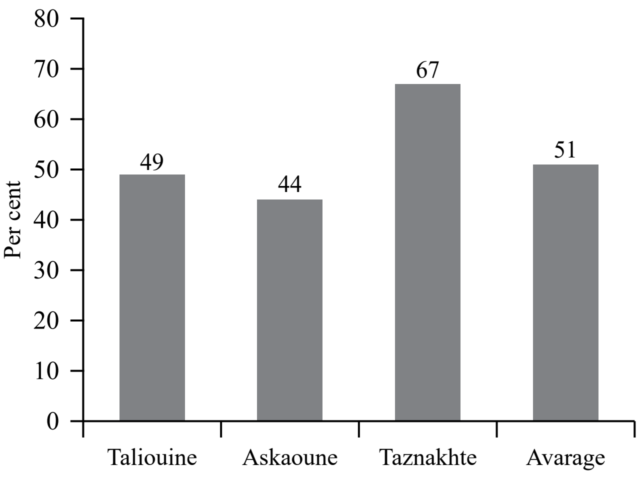

Figure 1: The distribution of the technical efficiency (TE) level by ADC.

Source: Own composition

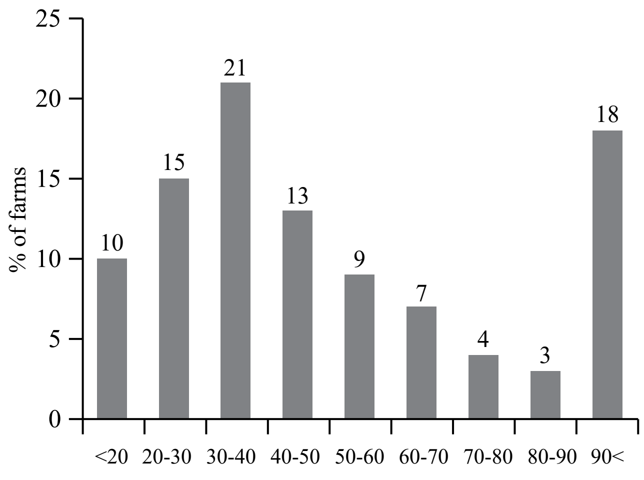

Figure 2: Distribution of the technical efficiency (TE) level by farms.

Source: Own composition

the farmer's efficiency and productivity to meet the increasing demands from the domestic market and to profit from the opportunities existing in the international export market. The new agricultural policy "Generation Green" launched in 2020 needs to achieve a sustainable intensification of saffron farming by improving farmers' specialisation. The saffron cooperatives could play a crucial role in reaching this objective by attracting more farmers to dedicate themselves fully to this farming activity and by providing them with the training programmes necessary to improve their skills and technical conduct. Moreover, more regulation is needed at the local market level to establish formal market channels under the Protected Designation of Origin (PDO) "Saffron of Talouine", which would serve to guarantee saffron farming as farmers' main source of income as well as to reduce off-farm activities.

The main limitation of this study relates to its use of cross-sectional data to analyse farmers' technical efficiency. The use of panel data can detect and measure the technical inefficiency over time. It also makes it possible to apply a more sophisticated modelling approach, such as the dynamic technical efficiency model and the decomposition of the farms' productivity and its evolution over time. Thus, we recommend that future studies collect data over a period of time. This could be facilitated by the establishment of a techno-economic observatory for monitoring the evolution of saffron production by the Moroccan Ministry of Agriculture and Fisheries. Such an observatory could provide researchers and policy makers with the necessary data to obtain better insights into the evolution of the Moroccan saffron sector.

As we anticipate future research, we need to consider analysing farmer technical and economic efficiency and productivity over time. The analysis of economic efficiency will reveal more information regarding the efficiency of saffron farms in relation to the market. The consideration of behavioural factors will complement the economic analysis to help explain farmers' decision-making in relation to the adoption of saffron farming.

Conclusions

Saffron farming plays an important agro-ecological and socioeconomic role in the marginal area of the Anti-Atlas mountain area. In this study, we assessed the technical efficiency of Moroccan saffron farms using a stochastic frontier model. A survey to 125 saffron producers was conducted in the production region of Taliouine and Taznakht according to a stratified sampling method. The main results of the estimated Stochastic Frontier Model and hypothesis tests are that the production of saffron is characterised by constant returns to scale and the main factors affecting the production are the corms planting dose, labour, land, and fertilisers. The estimated average efficiency level for the farm sample was about 50%, which means that there is ample scope to double the production of saffron without the need to increase required inputs or alter the production technology. The Taznakht region was found to perform more efficiently relative to Taliouine or Askaoune. Only 41% of the producers had a technical efficiency rate above 50 %, and among them, 18 % achieved a rate that was greater than 90 %. This large gap in efficiency levels shows that there is considerable potential to increase saffron production based on the factors affecting farm inefficiency. Among these factors, we find that the number of saffron plots, the frequency of use of different management practices and the distance to the urban centre increase saffron farms' efficiency, whereas the age of the farmer and the existence of off-farm activities decrease it.

In view of these results, we see a need to set up an appropriate strategy in the framework of the new agricultural policy "Generation Green" oriented towards improving the efficiency of the saffron sector. This strategy needs to be focused on activating the role of the cooperatives by attracting more farmers, especially younger ones, as they are more prone to introducing changes in crop management techniques. These farmers can improve their set of skills and technical conduct through knowledge dissemination by cooperatives (e.g. through trainings and other support measures, such as getting access to high quality saffron bulbs). However, more regulation is also needed in relation to farmers' access to the market. This would ensure that saffron production becomes the main source of income for farmers, thereby reducing off-farm activities and increasing specialisation through full-time commitment.

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Returns to Scale and Technical Efficiency in Colombian Coffee Production: Implications for Colombia's Agricultural and Land Policies

This paper applies a parametric approach to estimate technical and scale (in)efficiencies using input and output data at the level of 850 individual Colombian coffee-farms. Different Stochastic Production Frontier functions are estimated using a two-step procedure that corrects the endogeneity that has been ignored in previous works, leading to more reliable (i.e. unbiased and consistent) results. We conclude that small and medium coffee farmers are technically inefficient and exhibit increasing returns to scale, whereas large coffee farmers are close to being quasi-technically efficient and exhibit decreasing returns to scale. The corrected-for-endogeneity estimation also indicates that small and medium-sized units must prioritise primarily the land factor, whereas large farms should concentrate their efforts on increasing the labour factor. Based on these results, several agricultural and land policy recommendations are made.

Keywords: coffee production, stochastic production frontier, endogeneity, technical efficiency, returns to scale

JEL classification: Q12

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Introduction

Colombia is the World's third largest producer of coffee after Brazil and Vietnam and the highest in terms of the Arabica bean (Giovanucci *et al.*, 2002; ICO, 2021). From the time the commercial production of coffee first began in 1870, coffee has traditionally played an important role in the economic growth of Colombia. Today, it plays a smaller economic role, but it is still a primary source of income for nearly half a million rural families.

A great deal of Colombian coffee is produced on small and medium-sized family farms. This may be the consequence of the existence at the beginning of the twentieth century of large quantities of unclaimed land on the slopes of (particularly) the central cordillera, the relative scarcity of large accumulations of capital, and the country's inability to attract foreign immigrants. Whatever the precise reason for the growth of small and medium-sized coffee farms in Colombia, currently units of small size comprise the great bulk of coffee farms of the nation. Thus, the National Federation of Coffee Growers of Colombia estimates that there are 560,000 coffee growing families, where small farmers with less than 5 hectares of land are responsible for approximately 69 percent of coffee production in Colombia. This feature can in the future be exacerbated by virtue of the peace deal signed by the Government of Colombia with the Revolutionary Armed Forces of Colombia (FARC) at the end of 2016, that pledges to address unequal land ownership and foster development in neglected rural areas hit hard by violence.

Some reports indicate that agricultural productivity in general, and the productivity of coffee plantations in particular, are relatively low in Colombia (OECD, 2015). Hence, it is essential to assess what possibilities exist for improving the efficiency of coffee production. It is particularly interesting to analyse if providing land to a wider share of the rural population has a positive effect in terms of improving the productivity of coffee plantations. For that analysis, it is important to focus on the relationship between land size and productivity in Colombian coffee production.

This study aims to shed some light in this direction by examining the technical efficiency of small, medium- and large-sized coffee farms as well as testing for economies of scale in each of these groups. For that purpose, we apply a parametric approach to estimate technical and scale (in) efficiencies using input and output data at the level of 850 individual farms (556 small, 200 medium and 94 large-sized) in the Departments of Risaralda, Caldas, and Quindío in Colombia in year 2003. As far as we know, this database is the most recent to have been applied to coffee farms and, although a more current database may be desirable, no updated database exists with the same level of detail.

This study draws on the extensive literature on technical efficiency and returns to scale in agricultural production in developing countries following the seminal finding by Sen (1962) that yields per acre and farm size were inversely related for small Indian farms. This inverse relationship has been confirmed by studies in Africa (Barrett, 1996; Kimhi, 2006), Asia (Carter, 1984; Heltberg, 1998; Akram-Lodhi, 2005; Besley and Burgess, 2000), Europe (Alvarez and Arias, 2004) and Latin America (Berry and Cline, 1979) and contested by others, such as Bhalla and Roy (1988), who have shown that when differences in land quality are taken into consideration this phenomenon disappears. Lamb (2003) has additionally attributed these findings to labour market imperfections and measurement errors. More recent studies have imposed greater theoretical structure on the empirical work and have found that large farms are more efficient and more productive than small farms (Adamopoulos and Restuccia, 2014).

A subset of the literature on technical efficiency and returns to scale has focused on coffee production. Thus, Data Envelopment Analysis (DEA) techniques have been used to compute farm-level technical efficiency measures in Costa

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Rica by Mosheim (2002), in Côte d'Ivore by Binam *et al.* (2003), in Colombia by Perdomo and Mendieta (2007), and in Vietnam by Rios and Shively (2006) and Garcia and Shively (2011). Vedenov *et al.* (2007), Nchare (2007) and Perdomo and Hueth (2011), instead of using non-parametric mathematical programming, have made use of Stochastic Frontier Analysis (SFA) to estimate an input distance function and evaluate production efficiency in Mexico, Cameroon, and Colombia, respectively.

Perdomo and Hueth (2011) and Perdomo and Mendieta (2007) constitute two preliminary attempts to study the production function, returns to scale and technical efficiency of Colombian coffee farms using SFA and DEA. They found that small- and medium-sized coffee farms presented technical inefficiency and increasing returns to scale, whereas the larger coffee farms presented technical efficiency and decreasing returns to scale. Nevertheless, some authors have raised concerns about endogeneity in production function estimation (Kutlu, 2010; Tran and Tsionas, 2013). Stochastic production frontier models usually assume that input choices are independent of the efficiency and productivity terms. However, if a producer observes some factors – unobservable by the econometrician – that affect a farm's efficiency and/or its productivity, the input choices may also be influenced by this knowledge, resulting in an endogeneity problem in the stochastic production frontier estimation (Shee and Stefanou, 2015). This situation may therefore lead to a biased inference on input elasticities, economies of scale and technical efficiency. In this paper we follow Kutlu (2010) (see also Amsler *et al.*, 2016) to deal with endogeneity when estimating the SFA to assess the technical and scale (in)efficiencies of Colombian coffee farms.

The rest of the paper is organised as follows: the empirical model for the estimation of technical and scale efficiency is presented in the next section. The data set is described in the third section and the empirical results are discussed in the fourth section. Some recommendations for agricultural and land policies and concluding remarks follow in the fifth and sixth sections, respectively.

Empirical Model

Consider the following general form of the stochastic production frontier (SPF) function:

$$q_i = f(x_{i1}, \cdots, x_{im}, \beta)e^{\mu_i - \omega_i} \qquad i = 1, \cdots, n \tag{1}$$

where q_i is the observed output produced by the i-th farm, x_{ij} is the quantity of the j-th input used by the i-th farm ($j=1,\cdots,m$), β is a vector of parameters to be estimated, and $\mu_i - \omega_i$ is a composite error term. The μ_i term corresponds to the statistical noise (assumed to be independently and identically distributed) and ω_i is a non-negative random variable associated with technical inefficiency. Regarding $f(\cdot)$, the Transcendental and Cobb-Douglas functions are the two most commonly used functional forms in empirical studies of production, which include frontier analyses (Battese and Broca, 1997). The Cobb-Douglas stochastic frontier model takes the form:

$$q_i = A \prod_{j=1}^{m} x_{ij}^{\beta_j} e^{\mu_i - \omega_i} \tag{2}$$

which can be estimated as a linear relationship using the following expression:

$$ln\, q_i = \beta_0 + \sum_{j=1}^{m} \beta_j\, ln\, x_{ij} + \mu_i - \omega_i \tag{3}$$

Similarly, the logarithmic transformation of the Transcendental SPF model takes the following form:

$$\begin{aligned} ln\, q_i = \beta_0 + \sum_{j=1}^{m} \beta_j\, ln\, x_{ij} + \tfrac{1}{2}\sum_{j=1}^{m} \beta_{jj}(ln\, x_{ij})^2 + \\ + \sum_{j=1}^{m}\sum_{k>j}^{m} \beta_{jk}\, ln\, x_{ij}\, ln\, x_{ik} + \mu_i - \omega_i \end{aligned} \tag{4}$$

Note that the usual procedures for estimating SPF models depend on the assumption that the inputs are exogenous. However, in many situations this assumption is difficult to maintain because some inputs can be influenced by unobserved factors such as expected rainfall in the farm's location, managerial ability of the farmer etc. that obviously have an impact also on the produced output. To overcome this endogeneity problem, we follow Kutlu (2010) and Amsler *et al.* (2016) and estimate the SPF in a two-step procedure. In the first step, we estimate the reduced form of the inputs demand function system, where the endogenous variables ($x_{i1},\cdots,x_{im}$) are log- linear functions of their prices ($p_{x_{i1}}, \cdots, p_{x_{im}}$) and a set of unobserved factors, which have the characteristics of providing good instruments for the log inputs. Note that the error terms of such regressions, denoted as $\varepsilon_{i1}, \cdots, \varepsilon_{im}$, are possibly contemporaneously correlated, and consequently the system requires an estimation by means of seemingly unrelated regression (SUR) using iterative generalised least squares to obtain unbiased, consistent, and efficient estimators (Rosales *et al.*, 2013). In the second step the residuals from the SUR estimation, denoted as $\hat{\varepsilon}_{i1}, \cdots, \hat{\varepsilon}_{im}$, are used as controls in an operational version of equation (1):

$$q_i = f(x_{i1}, \cdots, x_{im}, \hat{\varepsilon}_{i1}, \cdots, \hat{\varepsilon}_{im}; \beta^*)e^{\mu_i - \omega_i} \tag{5}$$

Following Battese and Coelli (1992), the specification of the technical efficiency of production for the i-th farm (TE_i) is defined by:

$$TE_i = \frac{f(x_{i1},\cdots,x_{im},\hat{\varepsilon}_{i1},\cdots,\hat{\varepsilon}_{im};\beta^*)e^{\mu_i - \omega_i}}{f(x_{i1},\cdots,x_{im},\hat{\varepsilon}_{i1},\cdots,\hat{\varepsilon}_{im};\beta^*)e^{\mu_i}} = e^{-\omega_i} \tag{6}$$

$TE_i \in [0,1]$ provides a measure of the shortfall of observed output from maximum feasible output in an environment that allows for variation across farms.

The elasticity of output[1] of the i-th farm with respect to the j-th input ($e_{q_i x_{ij}}$) is defined by:

$$e_{q_i x_{ij}} = \frac{\partial\, ln\, q_i}{\partial\, ln\, x_{ij}} \tag{7}$$

[1] Whereas the elasticity is constant for the Coob-Douglas specification, the form of the translog in equation (4) implies that the elasticity depends on the level of the inputs. Following general conventions (see Greene, 2012) the elasticity is here calculated at the average inputs as $\frac{\partial\, ln\, \hat{q}_i}{\partial\, ln\, x_{ij}} = \hat{\beta}_j + \sum_{k=1}^{m} \hat{\beta}_{jk}\, ln\bar{x}_{ik}$ where, $ln\, \bar{x}_{ij}$ and $ln\bar{x}_{ik}$ are the averages log-inputs.

As a result, the returns to scale (RTS) are expressed by:

$$RTS_i = \sum_{j=1}^{m} e_{q_i x_{ij}} \quad (8)$$

It measures the proportional change in output resulting from a unit proportional increase in all inputs. Then $RTS>1$ shows the presence of increasing returns to scale, $RTS<1$ indicates the existence of decreasing returns to scale and $RTS=1$ implies constant returns to scale.

Data Description

The data used in the present study are from a survey undertaken by the Department of Agricultural and Resource Economics (AREC) of the University of Maryland[2] (United States) during the year 2004 in the Departments of Risaralda, Caldas, and Quindío in Colombia. It contains information obtained from 850 coffee farms of which 556 are small-sized (below 2 hectares), 200 are medium-sized (between 2 and 7 hectares) and 94 are large-sized (above 7 hectares). The information collected corresponds to the 2003 crop year[3].

For the purposes of the present study, output is measured in annual arrobas[4] produced. Four inputs are included in the production frontier function, namely land measured in hectares, labour (including family, hired workers and coffee pickers) measured in full time equivalents, intermediate inputs (fertiliser and pesticides) measured in kilograms, and capital stock (machinery) measured through a synthetic index of capital intensity. We use this index because the information in the survey only includes the number of machines used by each farm, without discriminating between different types of machines. This index, called Index of Machinery Intensity (IMI), is constructed by means of Principal Component Analysis (PCA) and feature scaling or minmax scaler process as follows (see details in Johnson, 1998, Ch. 5 and Perdomo *et al*. 2016, p. 42-44). The relative weights across different factors of machinery used in coffee growing (total number of coffee pulper machines, water pump machines, coffee demucilager machines, motors, coffee silo machines, fumigation machines, scythes machines and chainsaws) were estimated with PCA, because their units of measurement are heterogeneous, so their direct aggregation or sum is unsuitable for determining machinery intensity (MI). Once MI is calculated, values are normalised (between zero and one) using feature scaling or min-max scaler (see details in Perdomo *et al*., 2016, p. 42) as

$$IMI_i = \frac{MI_i - MI_{min}}{MI_{max} - MI_{min}} \quad (9)$$

where MI_i are obtained from PCA, MI_{min} and MI_{max} are their minimum and maximum values and $IMI_i \to 1$ indicates more intensity of machinery.

Several additional variables have been included in the regression in the first step to obtain the residuals used as controls in the second step. First, the number of people per household is used as a proxy of rural population density. Second, three dummy variables have been used to indicate (i) if the farm obtains income from activities other than coffee production, (ii) if the main source of income comes from coffee activity, and (iii) if the farm has road access to the municipal centre. The sample mean of these, and the rest of variables are given in Table 1.

Empirical Results

Table A1 in the Appendix shows the SUR estimates (first stage) of the input demand functions. The residuals in this regression are incorporated in the SPF function in the second step. Tables 2, 3 and 4 show the maximum likelihood

Table 1: Sample mean values of model variables.

Variable	Small-sized farms	Medium-sized farms	Large-sized farms
Output (arrobas year)	160.31	481.97	2726.11
Land (hectares)	1.44	3.53	14.33
Labour (workers, full time equiv.)	9.09	21.87	99.02
Chemicals (Kgs)	3.48	23.59	102.33
Machinery (capital intensity index-IMI-)	0.13	0.23	0.18
Price of Land (US$ per hectare)	22,184.28	41,378.20	52,852.84
Price of Labour (US$ weekly per worker)	100.44	179.76	188.55
Price of Chemicals (US$ per Kg)	7.22	7.66	8.82
Price of Machinery (index)	0.87	0.93	0.83
Family size (persons)	4.00	3.92	3.24
Diversification (dummy variable)	0.28	0.42	0.50
Specialisation (dummy variable)	0.87	0.80	0.74
Road Access (dummy variable)	0.66	0.79	0.98
Sample size	556	200	94

Source: Own composition

[2] The survey strategy was conducted by Prof. Darrell Hueth.

[3] Unfortunately, similar surveys have not been conducted since then.

[4] Arroba is a Portuguese and Spanish unit of weight, mass, or volume, representing a weight of around 25 pounds or 12.5 kilograms.

estimates of the different specifications for the SPF function for small-, medium- and large-sized farms, respectively. The standard errors from the two-stage method employed here are inconsistent because the estimates are conditional on estimated standardised error terms from the first stage. Hence, we only present bootstrap standard deviations as proposed by Kutlu (2010). The tables also include values of the Hausman test indicating that endogeneity exists in equation (3) in the three groups of farms. The general significance of the control functions reinforces the hypothesis of endogeneity of the inputs. The results of the Sargan test evidence as well the validity of the instruments used in the first step to control for the endogeneity of the input variables. For the sake of comparison, the estimation of the SPF function with and without correction of endogeneity are included. Even though not all the inputs are individually significant, we keep them in all the functional specifications for comparative purposes.

Table 2: Stochastic Production Frontier estimates (Second Stage) for small-sized farms.

Dependent Variable: (Coffee Production)	Translog without endogeneity corrected	Translog with endogeneity corrected	Cobb Douglas without endogeneity corrected	Cobb Douglas with endogeneity corrected
Explanatory Variables	**Coefficients (β)**	**Coefficients (β*)**	**Coefficients (β)**	**Coefficients (β*)**
Intercept	6.0258***	3.0936	3.5793***	2.2199**
Land	1.3551	1.5594	0.6171***	1.7572***
Labour	0.3007	0.8253	0.6322***	0.5204**
Chemicals	-0.2040	0.5583	0.1770***	0.7259***
Machinery	1.6073**	0.5774	-0.0076	-0.3369
Land^2	-0.4230	-0.3396	-	-
Labour ^2	-0.3609***	-0.4252***	-	-
Chemicals^2	-0.0750	-0.1472**	-	-
Machinery^2	0.1415	0.0448	-	-
Land*Labour	-0.0884	0.0654	-	-
Land*Chemicals	-0.2521**	-0.1670*	-	-
Land*Machinery	0.0431	-0.0833	-	-
Labour*Chemicals	0.1450**	0.1366***	-	-
Labour*Machinery	-0.4579*	-0.2568	-	-
Chemicals*Machinery	-0.1355	-0.1059	-	-
Residual first stage land	-	-1.0262*	-	-1.2548**
Residual first stage labour	-	-0.0145	-	0.1328
Residual first stage chemicals	-	-0.7090***	-	-0.6492***
Residual first stage machinery	-	0.2310	-	0.3001
Natural logarithm of v_i	-1.9760***	-2.1502***	-1.868013***	-2.0444***
Natural logarithm of u_i	-1.6106***	-1.7686***	-1.56359***	-1.7063***
AIC	950.76	860.62	974.04	886.66
Wald test (chi-square)	792.46***	1,690.14***	569.20***	1,562.62***
LR test of sigma_u=0 (chi-square)	55.25***	78.62***	47.97***	66.59***
Hausman test for endogeneity (chi-square)	-	62.97***	-	56.42***
Sargan test (F statistic)	-	0.01	-	0.06
RTS	2.15	3.17	1.42	2.67
TE (50th percentile)	0.75	0.75	0.74	0.75
Observations	555	550	555	550

Note: *, ** and *** Significant at 0.10, 0.05 and 0.01 levels, respectively
Source: Own composition

Table 3: Stochastic Production Frontier estimates (Second Stage) for medium-sized farms.

Dependent Variable: (Coffee Production)	Translog without endogeneity corrected	Translog with endogeneity corrected	Cobb Douglas without endogeneity corrected	Cobb Douglas with endogeneity corrected
Explanatory Variables	**Coefficients (β)**	**Coefficients (β*)**	**Coefficients (β)**	**Coefficients (β*)**
Intercept	6.1810***	7.0956***	4.1913***	5.5284***
Land	0.7045	2.1543**	0.5397***	1.7836***
Labour	-0.0810	-0.3845	0.5087***	0.1133
Chemicals	-0.6445***	-1.1043***	0.0655*	-0.2826**
Machinery	0.4215**	0.7649*	0.0551	0.5864***
Land^2	0.3019	0.2633	-	-
Labour ^2	-0.0544	-0.0969	-	-
Chemicals^2	0.0173	0.0493	-	-
Machinery^2	0.0692***	0.0336	-	-
Land*Labour	-0.0292	0.0360	-	-

Dependent Variable: (Coffee Production)	Translog without endogeneity corrected	Translog with endogeneity corrected	Cobb Douglas without endogeneity corrected	Cobb Douglas with endogeneity corrected
Explanatory Variables	**Coefficients (β)**	**Coefficients (β*)**	**Coefficients (β)**	**Coefficients (β*)**
Land*Chemicals	-0.1599	-0.1309	-	-
Land*Machinery	0.0165	0.0352	-	-
Labour*Chemicals	0.2848*	0.2533**	-	-
Labour*Machinery	-0.0410	-0.0501	-	-
Chemicals*Machinery	-0.0237	-0.0151	-	-
Residual first stage land	-	-1.6827***	-	-1.3040***
Residual first stage labour	-	0.4826**	-	0.4709***
Residual first stage chemicals	-	0.4527***	-	0.3273***
Residual first stage machinery	-	-0.5292***	-	-0.5967***
Natural logarithm of v_i	-2.0833***	-2.2288	-1.820015***	-1.8495***
Natural logarithm of u_i	-1.1813***	-1.2933	-1.294065**	-1.6848
AIC	307.72	289.64	310.17	288.78
Wald test (chi-square)	295.25***	570.08***	243.33***	215.98***
LR test of sigma_u=0 (chi-square)	5.66***	5.59***	3.05***	1.52
Hausman test for endogeneity (chi-square)	-	15.09***	-	26.82***
Sargan test (F statistic)	-	1.45	-	1.14
RTS	1.26	2.44	1.17	2.20
TE (50th percentile)	0.70	0.71	0.71	0.75
Observations	199	199	199	199

Note: *, ** and ***Significant at 0.10, 0.05 and 0.01 levels, respectively
Source: Own composition

Table 4: Stochastic Production Frontier estimates (Second Stage) for large-sized farms.

Dependent Variable: (Coffee Production)	Translog without endogeneity corrected	Translog with endogeneity corrected	Cobb Douglas without endogeneity corrected	Cobb Douglas with endogeneity corrected
Explanatory Variables	**Coefficients (β)**	**Coefficients (β*)**	**Coefficients (β)**	**Coefficients (β*)**
Intercept	7.3622***	8.5448***	4.2502***	5.7954***
Land	0.2053	0.0035	0.2628***	0.7685***
Labour	-0.4440	-0.5065	0.6300***	0.2026**
Chemicals	-0.1954	-0.2082	0.0799**	-0.0210
Machinery	0.4661	0.3550	-0.0068	0.2878**
Land^2	-0.3158	-0.2698	-	-
Labour ^2	0.0611	0.0280	-	-
Chemicals^2	-0.0594	-0.1003	-	-
Machinery^2	-0.0118	-0.0611	-	-
Land*Labour	0.2351*	0.2633	-	-
Land*Chemicals	0.0560	0.0325	-	-
Land*Machinery	0.1685	-0.0305	-	-
Labour*Chemicals	0.0122	0.0431	-	-
Labour*Machinery	-0.1023	0.0773	-	-
Chemicals*Machinery	-0.1184**	-0.1313**	-	-
Residual first stage land	-	-0.4821	-	-0.6583***
Residual first stage labour	-	0.6750***	-	0.6954***
Residual first stage chemicals	-	0.0624	-	0.0797
Residual first stage machinery	-	-0.3359**	-	-0.3273***
Natural logarithm of v_i	-2.1385***	-3.0192	-2.412315***	-3.6032
Natural logarithm of u_i	-9.1123	-3.2178	-1.858953***	-1.7887
AIC	99.77	49.26	99.12	54.97
Wald test (chi-square)	519.94***	953.60***	409.40***	537.59***
LR test of sigma_u=0 (chi-square)	0	0.12	1.24	3.34***
Hausman test for endogeneity (chi-square)	-	35.37***	-	71.76***
Sargan test (F statistic)	-	0.27	-	1.79
RTS	0.90	0.99	0.97	1.24
TE (50th percentile)	0.99	0.86	0.77	0.77
Observations	94	94	94	94

Note: *, ** and ***Significant at 0.10, 0.05 and 0.01 levels, respectively.
Source: Own composition

Table 5 contains the estimated elasticities and RTS defined in equations (7) and (8), for small-, medium- and large-sized farms. The RTS obtained from the SPF without endogeneity correction is underestimated in every situation. Focusing on the estimates with endogeneity correction, Table 5 shows that small- and medium-sized farms are subject to increasing RTS. It is also noteworthy that land is by far the most important input, especially in small- and medium-sized farms, whereas labour is especially important in large farms.

Implications for Colombia's Agricultural and Land Policies

In general, agricultural policies in post-conflict situations prioritise improvements in productivity and competitiveness with the aim of increasing the incomes of households whose livelihoods come from agriculture and guaranteeing food production (Adam-Bradford *et al.*, 2020; Jimenez *et al.*, 2021). This is precisely why it is pertinent to analyse in detail what effect the land distribution measures proposed in the 2016 peace accord in Colombia could have on the strategic sector of coffee production in terms of productivity. The results shown in the previous section suggest that small and medium coffee farmers in Colombia are technically inefficient in their production process and moreover, these production units exhibit increasing returns to scale. The challenge for agricultural and land policies is therefore to increase the scale of these farms in a way that does not conflict with another major objective of the proposed reform, which is to establish a more equitable distribution of land in rural areas (Faguet *et al.*, 2017).

It is beyond the scope of this article to carry out a detailed study of the direct and indirect effects of the different ways in which land reform can be implemented in Colombia. However, it does seem pertinent to comment that some concrete proposals in the literature and in the peace agreement itself, such as the formalisation of communal property regimes in rural settings, can make it possible to reconcile the objective of expanding access to land ownership with ensuring that the scale of farms is not sub-optimal.

Another important challenge is to enable the largest farms to improve their productivity through better access to labour. In fact, some reports attribute a reduction in factor endowments to the decline in coffee output that the country has suffered in the past decades (Saenz *et al.*, 2021). With a large mass of potential workers fleeing conflict zones, the wages of the remaining rural workers rose, leading to higher costs for coffee producers (World Bank, 2002). In addition, rural labour shortages have complicated the control of crop pests and the harvesting of the crop at the optimal time (Ocampo-Lopez and Alvarez-Herrera, 2017).

The resolution of the armed conflict may alleviate to some degree the depopulation of these rural areas and reduce some labour supply tensions. However, there are many more issues that need to be resolved in order to improve labour productivity indicators, which is the way in which the economic performance of every farm, but primarily the large plantations, can be improved. There are several studies promoted by companies and associations in the coffee

Table 5: Production elasticities and RTS.

SMALL-SIZED FARMS	Translog with endogeneity corrected	Translog without endogeneity corrected	Cobb Douglas with endogeneity corrected	Cobb Douglas without endogeneity corrected
Output elasticity of land	1.59***	0.758	1.76***	0.62***
Output elasticity of labour	0.67***	0.64***	0.52***	0.63**
Output elasticity of chemicals	0.85***	0.20	0.73***	0.18***
Output elasticity of machinery	-0.15	0.313	-0.34	-0.01
RTS	2.95***	1.90**	2.67***	1.42***
MEDIUM-SIZED FARMS	**Translog with endogeneity corrected**	**Translog without endogeneity corrected**	**Cobb-Douglas with endogeneity corrected**	**Cobb-Douglas without endogeneity corrected**
Output elasticity of land	2.20***-	0.58-	1.78***	0.54***
Output elasticity of labour	0.06-	0.46**	0.11	0.51***
Output elasticity of chemicals	-0.40-	0.05	-0.28**	0.07*
Output elasticity of machinery	0.57**-	0.15	0.59***	0.06
RTS	2.43***-	1.24***-	2.20***	1.17***
LARGE-SIZED FARMS	**Translog with endogeneity corrected**	**Translog without endogeneity corrected**	**Cobb-Douglas with endogeneity corrected**	**Cobb-Douglas without endogeneity corrected**
Output elasticity of land	0.62**	0.27	0.26***	0.77***
Output elasticity of labour	0.24	0.63***	0.63***	0.20**
Output elasticity of chemicals	-0.05	0.02	0.08**	-0.02
Output elasticity of machinery	0.24	0.04	-0.01	0.29**
RTS	1.05**	0.95**	0.97***	1.24***

Source: Own composition

sector that point to another series of factors as determinants to address the shortage and low productivity of labour in the Colombian coffee sector (Rocha, 2014).

In order to increase labour productivity on all types of plantations, but especially the larger ones, it is necessary to implement the following actions: (1) accompanying policies to hire more salaried workers with the formalisation of contracts that are more in line with labour regulations, (2) develop strategies to improve competitiveness in international markets that allow for wage improvements, and (3) offer training programmes to encourage specialisation among workers in the sector and prevent them from having to combine their activity with other complementary activities[5], without any signs of considering coffee growing as a long-term activity.

Conclusions

Two main contributions have been made in this work. On the one hand, the analysis of returns to scale, elasticities and technical efficiency previously carried out by other authors has been refined, correcting for endogeneity biases through a two-stage process to estimate the stochastic production frontier, in line with the proposal of Kutlu (2010) and Amsler *et al*. (2016). The correction for endogeneity is crucial, as it substantially conditions the conclusions of the analysis. We show that small and medium coffee farmers in Colombia are technically inefficient in their production process. In addition, these production units exhibit increasing returns to scale. Besides, large coffee farmers are close to being technically efficient and exhibit decreasing returns to scale. The corrected-for-endogeneity results also indicate that the input intensity that small and medium-sized units must prioritise in their agricultural activity is primarily the land factor, whereas large farms should concentrate their efforts on increasing the labour factor.

On the other hand, in this paper we try to translate these empirical results into agricultural and land policy recommendations in a context as special as the current one, where peace talks revolve around proposals to facilitate access to agricultural land for the poorest peasants in violence-affected areas.

We are aware that there are many aspects and challenges affecting the coffee sector in Colombia that are not addressed in this analysis and that could be analysed in future extensions of this paper. To the productivity analysis in this article should be added an analysis of competitiveness in international markets, as some of the aforementioned challenges relate to the need to attract investment from international suppliers, to accommodate the rapid expansion of coffee farms in low-income areas that have largely remained remote and isolated from international markets, as well as to cope with coffee's high dependence on foreign exchange rates.

[5] It should be borne in mind that many small farmers are in fact usually part farmers, part workers. The income of small farmers is based partly on the sale of crops and livestock, and partly on wage employment, whether on a farm or plantation or in some other rural occupation. Therefore, a sustainable development strategy for the coffee sector must also take into account, as a component, the wages of workers in coffee plantations.

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Appendix

Appendix 1: SUR model first stage results.

Dependent variable: LN(chemicals)	**Farm size**			**Dependent variable: LN(machinery)**	**Farm size**		
	Small	**Medium**	**Large**		**Small**	**Medium**	**Large**
Explanatory Variables	**Coefficients**	**Coefficients**	**Coefficients**	**Explanatory Variables**	**Coefficients**	**Coefficients**	**Coefficients**
Intercept	-2.6856***	2.4852	11.4980**	Intercept	-1.8679***	-5.0786**	-7.2970*
LN (price land)	0.0816***	0.2327***	0.3093**	LN (price land)	0.0059	0.1334*	0.2799**
LN(price labour)	0.1029	0.0512	-0.4464*	LN(price labour)	0.0054	0.1107	-0.0729
LN(price chemicals)	0.0734	-0.5258***	-0.5917**	LN(price chemicals)	-0.0335	-0.1401	-0.0310
LN(price machinery)	-0.1247	-0.0618	-0.0409	LN(price machinery)	-0.3825***	-0.1098	-0.3022**
Specialisation (dummy variable, yes=1 and no=0)	0.1606**	0.0270	-0.1620	Specialisation (dummy variable, yes=1 and no=0)	-0.0687**	0.3221*	0.3203
Road access (dummy variable, yes=1 and no=0)	0.1759***	0.0132	-1.4296*	Road access (dummy variable, yes=1 and no=0)	0.0130	0.4808***	0.6713
Diversification (dummy variable, yes=1 and no=0)	0.0315	0.2114	0.1909	Diversification (dummy variable, yes=1 and no=0)	-0.0689**	0.3780**	0.1635
LN(family size)	-	-	-0.3102	LN(family size)	-	-	0.2463
Global fit (chi-square)	68.09***	36.91***	20.15***	Global fit (chi-square)	126.29***	35.94***	14.90*
Observations	551	200	94	Observations	551	200	94

Dependent variable: LN(land)	**Farm size**			**Dependent variable : LN(labour)**	**Farm size**		
	Small	**Medium**	**Large**		**Small**	**Medium**	**Large**
Explanatory Variables	**Coefficients**	**Coefficients**	**Coefficients**	**Explanatory Variables**	**Coefficients**	**Coefficients**	**Coefficients**
Intercept	-0.4910	0.7622	2.0774	Intercept	2.0310**	5.0348	12.6031
LN (price land)	0.0380*	0.0401	0.1838**	LN (price land)	0.1366***	0.0748	0.2808***
LN(price labour)	0.0579***	-0.0188	-0.1025	LN(price labour)	-0.0167	-0.3373***	-0.9355***
LN(price chemicals)	-0.0602	-0.0022	-0.1047	LN(price chemicals)	-0.2160***	0.0561	-0.1737
LN(price machinery)	-0.0558	0.0221	-0.1557*	LN(price machinery)	-0.1147	-0.0185	-0.1501
Specialisation (dummy variable, yes=1 and no=0)	-0.0160	-0.0633	0.2205	Specialisation (dummy variable, yes=1 and no=0)	-0.1649*	-0.1929	0.6042***
Road access (dummy variable, yes=1 and no=0)	0.0282	-0.0539	-0.7360*	Road access (dummy variable, yes=1 and no=0)	0.0664	0.3056**	-0.1615
Diversification (dummy variable, yes=1 and no=0)	-0.0574	0.1249*	0.2022	Diversification (dummy variable, yes=1 and no=0)	-0.1237*	0.2988**	0.4497**
LN(family size)	-	-	-0.2391**	LN(family size)	-	-	-0.2370
Global fit (chi-square)	26.41***	9.27	21.81***	Global fit (chi-square)	32.78***	47.64***	66.36***
Observations	551	200	94	Observations	551	200	94

Note: *, ** and ***Significant at 0.10, 0.05 and 0.01 levels, respectively.
Source: Own composition

Boris O.K. LOKONON*, and Aklesso Y.G. EGBENDEWE****

Global warming, intermediary market power, and agricultural exports: Evidence for cotton and cashew nuts in West Africa

This research aims at analysing the extent to which climate change affects cotton and cashew nuts production and exports in West African countries in the presence of intermediary market power. To that end, the paper uses a combination of approaches to calibrate a price endogenous regional bio-economic optimisation model and handles uncertainties inherent to future socio-economic scenarios through Monte Carlo simulations. The results show that the effects of climate change on cotton and cashew nuts land use are mixed under the two simulated climate change scenarios. In fact, the effects vary across countries, ranging from experiencing only a decline, or only an increase to both a decline and an increase in land use. Similarly, the effects of climate change on the quantities of cotton and cashew nuts exported are also mixed, with the positive effects being more pronounced for cotton. Simulations of reductions in the market power exerted by intermediaries on cotton producers also show that such a scenario could to some extent mitigate the negative effects of climate change on cotton exports for some countries. Therefore, actions that include corrections to cotton market imperfection could be undertaken to mitigate the negative effects of climate change on cotton and cashew nuts production in West Africa.

Keywords: climatic change, intermediary market power, Monte Carlo simulations, price endogenous partial equilibrium, agricultural exports

JEL classifications: Q15, Q17

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Introduction

Climate change constitutes the most significant of all environmental externalities, and is particularly pernicious as it involves so many activities of daily life, and affects the entire planet (Nordhaus, 2019). Thus, this environmental externality is acknowledged in the economics literature as affecting both agricultural production and trade (Dallmann, 2019; Nordhaus, 2019). The effects of climate change on agricultural production could continue without adequate adaptation as well as mitigation strategies (Huang *et al.*, 2011). Meanwhile, agricultural trade could also be affected by changes in climatic conditions (Dallmann, 2019). Indeed, climate change might affect trade both indirectly – via its impact on production – and directly by impacting transport and distribution channels (Dellink *et al.*, 2017), and also prices (Willenbockel, 2012). It should be noted that developing countries are typically characterised – economically speaking – by the export of raw agricultural products and also tend to regulate the domestic markets of those products insofar as these constitute the means of foreign exchange generation (Mbaye *et al.*, 2018; Delpeuch, 2009). However, in the absence of competition, intermediary firms could exert market power and hold prices above marginal costs (De Loecker *et al.*, 2020; Chen and Yu, 2019). Thus, imperfect competition is characterised by higher prices relative to the perfect competition benchmark and this has welfare and resource allocation implications. In fact, farmers growing cash crops in developing countries do not directly export these to the international markets. Instead, there are intermediaries that buy these crops from farmers and even transform them partially before shipping them abroad. Therefore, the intermediaries often exert oligopsonitic market power on farmers that could affect production and the quantities traded, over and above the effects of climate change.

The international trade literature acknowledges that countries must be integrated into the world economy. Differences in technology (Ricardo and Ricardo-Viner) and differences in endowments of production factors (Heckscher-Ohlin-Samuelson) are traditionally emphasised by trade theorists as determinants of international trade (Jones, 2014; Huang *et al.*, 2011; Morrow, 2010). In fact, under the international trade paradigm, endowments in resources drive product specialisation, all else being equal, and countries specialise in the production and the export of products requiring intensive use of relatively abundant resources. It should be noted that agriculture is highly sensitive to the climate, particularly in areas where irrigation is not widespread. Therefore, due to the climate change threat, crop yields are expected to fall in the future in many regions for many crops. The fall in crop yields could affect production levels and influence international trade, as well as trade within countries. In fact, the potential changes in patterns of geographical specialisation of production are driven by changes in the returns to factors of production employed in agriculture such as land (Huang *et al.*, 2011). These returns would be negatively affected in the agricultural sector, this mostly being so in low-latitude countries, where the impacts of climate change on agriculture are expected to be more pronounced (Nordhaus, 2019; Rosenzweig and Parry, 1994).

The Intergovernmental Panel on Climate Change (IPCC) points out that the implications of climate change on agriculture are expected to result in higher trade flows from mid- to high-latitude products (e.g. cereal and livestock) to low latitudes which are expected to experience a fall in yields (Huang *et al.*, 2011; IPCC, 2007). The West African countries are among the countries around the world that are expected to be adversely affected by global climatic change (Nordhaus, 2019). In addition, these countries rely on the exports of raw agricultural products such as cocoa, coffee, cotton, and cashew nuts due to their thin industrial sector. For instance, cotton constitutes an important crop for some West African countries such as Benin, Burkina Faso, Mali and Togo which are among the leading African exporters. This crop is considered as a 'white gold' for these countries. The evidence shows that most of these countries are specialised in cotton production (Mbaye *et al.*, 2018).

In addition, some West African countries may desire to invest in cashew nuts production for export diversification purposes, as Côte d'Ivoire has done recently. Certainly, integration into the world economy represents a powerful means for countries to promote economic growth, development, and poverty reduction (World Bank, 2007). Moreover, cotton markets in the West African countries have been strongly regulated by governments (Mbaye *et al.*, 2018; Staritz and Tröster, 2015). As a result, the cotton sector in West African countries is characterised by a high degree of vertical integration (Staritz and Tröster, 2015). Even if the market structure of cotton has evolved with the liberalisation since 1990, there is still a presence of market power exerted by intermediaries to the detriment of producers. Thus, the cotton markets in these countries are still somehow characterised by imperfect competition. In fact, the typology differentiates between national monopolies in Mali and Senegal, local monopolies or 'concessions' in Burkina Faso, Côte d'Ivoire and Ghana, and hybrid systems in Benin (Delpeuch, 2009). The situation of the market structure of cashew nuts is similar to that of cotton (Ton *et al.*, 2018); although countries such as Benin in the past largely left the cashew sector to market forces, the paradigm has since changed and the State is very actively intervening in this sector.

This research aims at analysing the extent to which climate change affects cotton and cashew nuts production and exports in West African countries. Meanwhile, a combination of approaches for a regional bio-economic model calibration is developed; uncertainties inherent to future socio-economic conditions are introduced through Monte Carlo simulations and intermediary market power exertion in cotton domestic markets is taken into account. Specifically, this paper seeks to (i) evaluate the implications of global climatic change on cotton and cashew nuts land use, (ii) assess the effect of climate change on the quantities of cotton and cashew nuts exported, and (iii) investigate the extent to which the reduction of intermediary market power in cotton domestic markets would mitigate the effects of climate change on cotton and cashew nuts exported quantities. To our knowledge, no study investigating individual export crops in the African context has yet taken market imperfection into account in the assessment of climate change effects on agricultural trade. Most of the previous literature accounting for imperfect competition is related to developed countries (e.g. Baker *et al.*, 2018; Kawaguchi *et al.*, 1997), to global models and models at the level of Sub-Saharan Africa without there being any disaggregation showing the individual cash crops (e.g. Calzadilla *et al.*, 2013). In addition, the previous literature tends to focus on the effects of climate change on agricultural trade (e.g. Egbendewe *et al.*, 2017). This paper therefore contributes to the existing literature by filling a gap relating to the impacts of climate change on the international trade in agricultural commodities.

To reach these objectives, a bio-economic optimisation model is developed for 13 West African countries. The model includes 21 crops that are not traded internationally by these countries, four crops that are mainly produced for export, and rice importation. This paper makes several new contributions to the existing literature. First, the exertion of market power by intermediaries in domestic markets for cotton has been modelled based on econometric regressions. Second, the optimisation model has been calibrated by drawing on the calibration techniques of computable general equilibrium (CGE) models and the positive mathematical programming (PMP) approach. Third, future socio-economic scenarios are included through the use of Monte Carlo simulations, with adaptive expectations being assumed. Fourth, it contributes to our understanding of the international trade in cotton and cashew nuts, a domain which has not been studied in the previous literature, yielding insights as to the impacts of climate change on the export of these products from West Africa.

The remainder of the paper is organised as follows. The modelling techniques developed in the paper are presented in Section 2. Section 3 presents the findings of the simulations and discusses these findings in the light of earlier literature. The last section concludes the paper and comments on the policy implications.

Materials and methods

Researchers face challenges in building economic models that take both the plant growth process and economic optimisation behaviour across the supply chain into account in order to develop simulations capable of informing decision makers in relation to critical agricultural, energy and environmental policies. In fact, several agricultural economic models such as the Forestry and Agricultural Sector Optimisation Model (FASOM) with its subsequent version featuring greenhouse gas emissions (McCarl and Schneider, 2001) as well as the Global Biosphere Model (GLOBIOM) (Havlík *et al.*, 2013; Havlík *et al.*, 2011) among others have been built for such a purpose. This paper extends these modelling efforts, in order to suggest improvements to the calibration aspects as well as better ways to handle future socio-economic conditions, while accounting for market imperfections in the markets for some products. Hence, this research relies on a bio-economic modelling framework involving a representative risk-neutral economic agent in an integrated assessment setting. Biophysical and geographic information system (GIS) data are integrated into a regional, price-endogenous mathematical programming model. Crop yields are supplied to the optimisation model by an econometric crop yields simulator. The GIS component supplies to the bio-economic model parameters related to available land (for the 3 soil types within 39 agro-climatic zones - ACZs).

The economic component is a spatially-explicit price-endogenous mathematical programming model which uses production costs and biophysical parameters from the first two components, while still accounting for imperfect competition in cotton markets. The whole model is then optimised to determine optimal land allocations among available cropping systems so as to maximise the net present value of

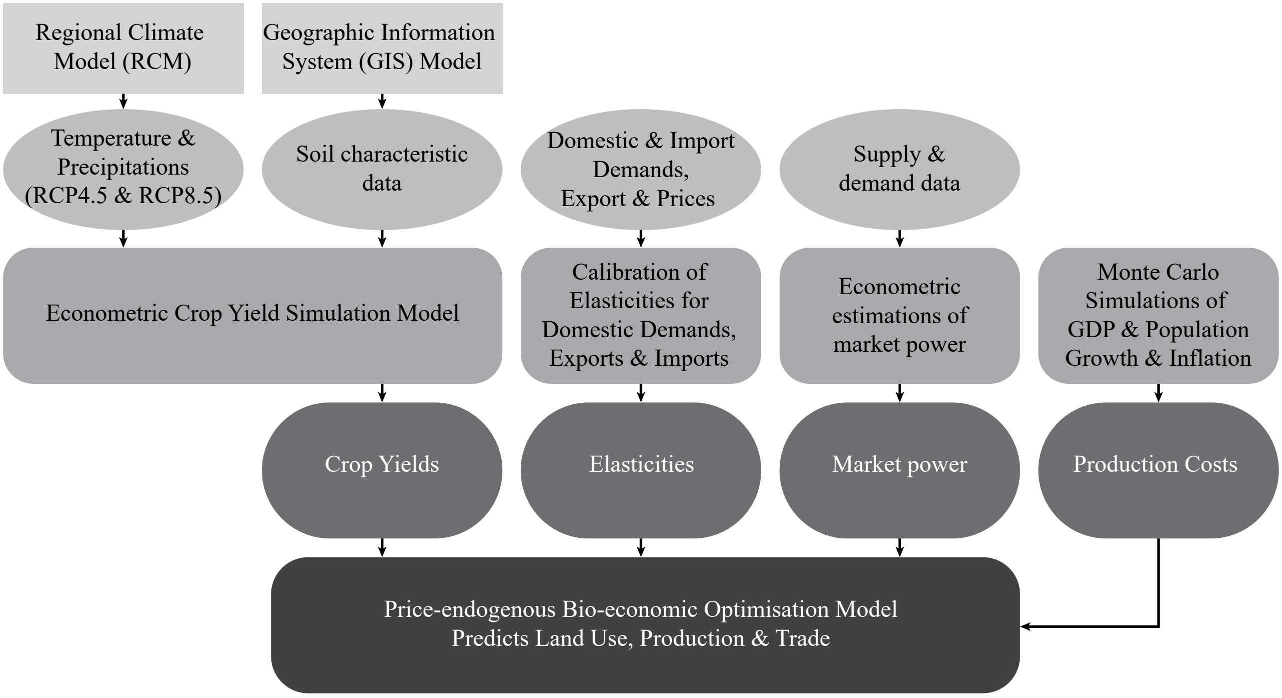

Figure 1: Structure of the regional bio-economic optimisation model.

Source: Own composition

the sum of consumers' and producers' surpluses. Figure 1 describes the general structure of the bio-economic model.

Crop yield model

The paper adopts an econometric regression approach to estimate crop yields following Chang (2002), as this research does not aim to estimate environmental outcomes like agricultural runoffs and emissions. In this framework[4], it is assumed that crop yields depend only on climate and soil conditions. This assumption is valid due to the characteristics of agriculture in West African countries. In these countries, agriculture is mostly rain-fed, and the use of fertilisers and mechanisation is not widespread and remains marginal. This research makes use of the average 2010 crop yields from the 39 ACZs under three soil types as well as of long-run (1981-2010; 30 years) average temperature and rainfall from May to November, given that these are the major climatic factors prevailing during the phenological stages of crop development. Nevertheless, technological change may induce variations under similar environmental conditions; consequently, this research adjusts the crop yields to take into account the effects of technological change. In fact, even with an unchanged climate, crop yields do not remain constant. The crop yields model used to estimate the yields of each of the 25 crops included in the bio-economic model is specified as follows:

$$Yield_i = f(temp_i, temp_i^2, vtemp_i, rain_i, \\ rain_i^2, vrain_i, clay_i, loam_i) + \varepsilon_i \qquad (1)$$

where *Yield* refers to crop yield per ha, *temp* is the average monthly temperature (in degrees Celsius), *vtemp* refers to the monthly variability of the temperature captured by the variance from April to November, *rain* stands for total rainfall from April to November (in mm), *vrain* is the monthly variability of rainfall captured by the variance, *clay* and *loam* are dummy variables that help to account for the effect of land characteristics on crop yields, and *i* stands for the ACZ. The non-linear effects of temperature and rainfall are included in equation (1) through their quadratic terms to be consistent with the notion of the physiological optimum (McCarl *et al.*, 2008; Chang, 2002; Kaufman and Seth, 1997). Moreover, the implications of the variability of climate factors on crop yields are taken into account by including temperature and rainfall variations, since their omission may lead to biased estimations (Mendelsohn *et al.*, 1996). The estimation results by the ordinary least squares (OLS) of cotton and cashew nuts yield regressions are presented in Table A1 of the Appendices. Future crop yields are simulated based on the estimation results of crop yields. It should be noted that, as previously mentioned, future crop yields are adjusted for technological change that allows an average annual yield increase of 1% (Lokonon *et al.*, 2019; Egbendewe *et al.*, 2017), implying a doubling of crop yields after 70 years. This adjustment is in line with the deceptive technological change rate observed in the West African region's agriculture (Nin-Pratt *et al.*, 2010; Nin-Pratt and Yu, 2008).

GIS component of the model

This study uses GIS to design a consolidated map of ACZs, soils, land use, and countries. The West African region is divided into 39 ACZs based on homogeneity in

[4] The econometric regressions do not take into account crop rotations and other management practices which may improve or deteriorate environmental conditions, such as the contents of soil nutrients.

weather conditions having the greatest effect on crop growth and yields. ACZs aim more adequately to distinguish among the diversity of practices, particularly in terms of different climates, regarding similar agricultural systems within larger agro-ecological zones (van Wart *et al.*, 2013). In the bio-economic model, agricultural production decisions take place at the ACZ level within the countries. However, in actuality crop production decisions take place at farm level. However, as the ACZ part of a country is the smallest unit based on the GIS component of the model (given that this study does not rely on household surveys), this means that the model considers a farmer at ACZ level within the countries to be representative. This assumption of a representative farmer is consistent with the literature (e.g. Calzadilla *et al.*, 2013; Havlík *et al.*, 2013) and in the case of this study takes advantage of the ACZs within the countries. Nonetheless, country information relating to ACZs is used for the disaggregation of land resources per country and per soil type. Cropland information per ACZs has been obtained from land use maps produced by previous research (FAO, 2015; Sebastian, 2014; van Wart *et al.*, 2013).

Economic optimisation model

Economic behaviour is modelled from the standpoint of a representative risk-neutral economic agent that is endowed with land resources, and has to choose among a set of crop production activities in order to maximise the combined sum of producers' and consumers' welfare. Under budget constraints, consumers derive utility from the consumption of crops if separable utility functions are assumed. In line with the assumptions made in large agricultural optimisation models (McCarl and Schneider, 2001), demand functions are assumed to take the form of constant elasticity. Vertical supply functions derived from a Leontief production are then used (Chen and Önal, 2012). This paper assumes that all produced quantities are brought to the market, so it does not assume a semi-subsistence agriculture characterised by the fact that only part of the production is marketed and the remainder is self-consumed by the households. Consequently, self-consumption is valued similarly to the part that is marketed. In this framework, the total welfare obtained from the market for each locally produced crop is equivalent to the area underneath the demand curve minus the production costs. Crops such as cashew nuts, cocoa, coffee and cotton are exported, and vertical supply functions are also used for them. However, for these exported crops, producer welfare is derived from constant elasticity export functions. Constant elasticity import demand and export supply functions are assumed for the imported rice, and the domestic welfare derived from rice import is computed as the consumer surplus from these imports. It is important to point out that a partial equilibrium economic model that simulates market clearing prices using price endogenous modelling (McCarl and Spreen, 1980) has been utilised. This modelling approach was originally initiated by Enke (1951) and Samuelson (1952) and was later fully developed by Takayama and Judge (1964). The optimisation problem can be expressed as follows:

$$\begin{aligned}
&\underset{x_{jklmt}}{Max\,\Omega} \sum_t \sum_l \sum_j \sum_k \exp(-\rho t) \\
&\Bigg[\Bigg((1+\theta\lambda_{kt}+\emptyset\eta_{kt})^{t/\epsilon}\int_0^{q_{klt}^d} p_{klt}^d(\cdot)\,dq_{klt}^d - \\
&-\sum_m \pi_{kt}c_{klt}x_{jklmt}\Bigg) + \\
&+\Bigg((1+\theta\lambda_{kt}+\emptyset\eta_{kt})^{t/\epsilon}\int_0^{q_{kt}^r} p_{kt}^r(\cdot)\,dq_{kt}^r - \\
&-(1+\gamma)p_{kt}^r q_{kt}^r\Bigg) + \\
&+\Bigg(\sum_n \{p_{knt}^e q_{knt}^e - \int_0^{q_{kt}^e} p_{knt}^e(\cdot)\,dq_{knt}^e\}\Bigg)\Bigg]
\end{aligned} \tag{2}$$

$$q_{klt}^d = \sum_j \sum_m (\beta_{jkl}x_{jklmt} - \delta_{jkl}x_{jklmt}^2) \;, \forall\, t,k,l \tag{3}$$

$$q_{knt}^e = \sum_j \sum_m (\psi_{jkl}x_{jklmt} - \alpha_{jkl}x_{jklmt}^2) \;, \forall\, t,k,n \tag{4}$$

$$\sum_l x_{jklmt} = L_{kjt}, \forall t,k,m,j \tag{5}$$

$$q_{kt}^r + S_{kt}^r = (1+\theta\lambda_{kt}+\emptyset\eta_{kt})^{t/\epsilon} D_{kt}^r, \forall t,k \tag{6}$$

$$\begin{aligned}
&p_{knt}^e = (\varphi_{kn}\omega_{kn}^1 + \omega_{kn}^2)q_{knt}^e + \omega_k^3 Q_{knt}^e + \\
&+\vartheta_{kn}, n = cotton, \forall t,k
\end{aligned} \tag{7}$$

The objective function, equation (2), maximises the total welfare that is the sum over time (t), crops (l), ACZs (j) and countries (k) of the welfare of domestically produced crops apart from exported crops (the first parenthesis), the welfare from rice imports (the second parenthesis), and the welfare from exported crops (the third parenthesis). The welfare computed in the first parenthesis is the sum of the areas underneath the demand curves of the domestically produced crops $p_{klt}^d(\cdot)$ minus the total costs over the three soil types (m) with being the unit production cost (per ha). This research indexes the total costs by the inflation rate (π). In the second part of the objective function (second parenthesis), the welfare from rice imports is computed as the areas underneath the import demand curves $p_{kt}^r(\cdot)$ minus the total value of imports that is subject to the common external tariff (CET) applied in the ECOWAS zone (γ).

The welfare derived from exported crops (the third parenthesis) is calculated as the sum of the total value of exports minus the areas underneath the export supply curves for the n exported crops. The demand and supply balance for locally produced and consumed crops q_{klt}^d and the exported crops q_{knt}^e are respectively captured by equations (3) and (4). A PMP calibration approach (Howitt, 1995) is used to obtain the quadratic form of the right-hand side of equations (3) and (4), and β,δ,ψ and α are calibration parameters. Equation (5) refers to land demand and supply balance, and equation (6) is rice import demand computed as the residual demand.

The demand is projected into the future using the expression $(1 + \theta\lambda_{kt} + \emptyset\eta_{kt})^{t/\epsilon}$ under the assumption that demand grows at the rate of gross domestic product (GDP) growth (η) and population growth (λ). θ and $\emptyset$ are respectively the elasticity of demand coefficients with respect to population and GDP growth. D^r_{kt} and S^r_{kt} are the base year total rice demand and total domestic rice supply, respectively. Equation (7) equalises price to marginal costs plus a part that depends on market power (φ) exerted by the intermediaries on cotton producers. The quantity of cotton exported by the intermediaries is captured by Q^e_{knt}. The market power coefficient (φ) and the remaining parameters of equation (7) (ω^1, ω^2, ω^3 & ϑ) are obtained from econometric regressions following Bresnahan (1989). The value of the market power coefficient is between 0 and 1. If $\varphi = 0$ then, the market is competitive. As its value become greater than 0, $0 < \varphi < 1$, there is a departure from the competitive equilibrium to a market characterised by imperfect competition. If $\varphi = 1$, full monopoly power is being exerted in cotton markets. The parameter ρ is a discount coefficient.

Calibration and dynamics via Monte Carlo simulations

This paper innovates first through the ways that the calibration of the model is carried out for improvement in the precision of the simulation results. Several efforts have been made in the literature to improve the capability of agricultural sector models to replicate closely the base year data, and escape a corner solution. Thus, the PMP calibration technique has been developed by Howitt (1995) which relies on the hypothesis that crop yields are decreasing functions of cultivated land areas. Other researchers have made many attempts to improve the PMP calibration approach, such as Mérel *et al.* (2011) and Mérel and Bucaram (2010). Moreover, other evidence on calibration methods has been provided from the experience of working with CGE models, which are based on the generalised axiom of revealed preference theorem (Afriat, 1967). For this theorem, if data from choices made by consumers or producers on prices and quantities are observed, then it is certain that these choices are based on rational preferences, and that utility and production functions are well behaved. Consequently, the optimisation problem described above can be solved for the elasticities of demand and supply functions, based on a given set of observed base year data on prices and quantities. This paper operationalises the optimisation problem following the three steps of the quadratic PMP as shown in equations (3) and (4). Thus, the calibration procedure relies both on the revealed preference approach of the CGE models, and the PMP approach. With this calibration method, there is no need for external estimations of the elasticities, and it works with better precision, particularly in an environment with a limited dataset.

Second, the dynamics of the bio-economic model are built through several channels of transmissions. Crop yields, which are one of the future drivers of the model, are projected based on climate scenarios using equation (1). Population and economic growth are then assumed to drive future demand. Finally, future production costs are assumed to be driven by growth in inflation rates. This paper assumes that future realisations of population growth, economic growth and inflation rates are drawn randomly from their values in past years. This assumption is made since only past information exists on the population growth, economic growth and inflation, and is equivalent to the hypothesis that the representative agent uses adaptive expectations (Nerlove, 1958) in the prediction of future realisations of these parameters by drawing them from past observations. Therefore, parametric distributions could be estimated from empirical distributions to simulate these parameters through Monte Carlo simulations, with observations of the past years. With this technique, thousands of simulations can be done with thousands of draws, and the values for average key outputs as well as their confidence intervals can be estimated. Nevertheless, this approach increases the computation time, given the number of simulations. The elasticities of demand coefficients with respect to population and GDP growth are obtained from the literature (Regmi and Meade, 2013; Johnson, 1999).

Empirical results and discussion

The empirical section consists of calibrating the model with data on land use, prices and quantities of the base year which is 2010 (2010 being chosen due to data availability). The time horizon of the model is 2100 with windows of 10 years. The use of the revealed preference approach of the CGE models helps in estimating all the elasticity values (Table 1). This approach, coupled with the PMP technique, has minimised the calibration error of the model; a percentage absolute deviation (PAD) of the calibrated model is about 5.42%. Note that the PAD could have been higher without using the combination of these two calibration approaches. Subsequently, simulated crop yields under the representative concentration pathways (RCP) 4.5 and RCP 8.5, population and economic growth as well as inflation rates projected up to 2100 are introduced into the model to govern the dynamics of the model. Thus, the two climate scenarios are run against a baseline scenario which is assumed to be the business-as-usual (BAU) scenario. In the BAU scenario, technological change is the key element that drives crop yields until the end of the century. These two RCPs are chosen owing to data availability in terms of disaggregation per ACZ.

Table 1: Calibrated elasticity of export supply of cashew nuts and cotton.

	Cashew nuts	Cotton
Benin	1.83	1.53
Burkina Faso	1.65	1.67
Côte d'Ivoire	2.03	1.55
The Gambia	1.04	--
Ghana	1.72	--
Guinea	1.32	--
Guinea Bissau	1.57	--
Mali	1.27	1.47
Nigeria	1.34	--
Togo	1.11	1.38

Source: Own composition

Monte Carlo simulations are often used to account for uncertainties in outcomes such as future socio-economic scenarios that govern the dynamics of this model. Therefore, the paper uses 31 years' data (1980-2010) on population growth, economic growth, and inflation rates for the 13 West African countries included in the study (Benin, Burkina Faso, Côte d'Ivoire, The Gambia, Ghana, Guinea, Guinea Bissau, Mali, Niger, Nigeria, Senegal, Sierra Leone and Togo) from the World Development Indicators. Cape Verde and Liberia which are also members of the Economic Community of West African States (ECOWAS) are not included in the research due to the lack of consistent dataset during the period of study. For the choice of the best parametric distributions, this paper compares the goodness-of-fit between the empirical distributions of the observed data against a set of eight parametric distributions (Egbendewe-Mondzozo *et al.,* 2013). The goodness-of-fit test used penalises the distributions at the tails (Anderson and Darling, 1952). Table A2 of the Appendices reports the selected parametric distributions. Three hundred random draws from these parametric distributions are simulated and averaged for each key output variable under consideration (cashew nuts production and exports, and cotton production and exports under the BAU scenario and the two RCPs). Experimentations show that Monte Carlo simulations above 300 random draws do not change the average values of the key output variables.

These elasticity values suggest that the supply of cashew nuts and cotton exports are elastic in the ten countries studied for cashew nuts and the five for cotton. Countries with no elasticity values reported for cotton do not export it at all. Where cashew nuts elasticity values are concerned, marginal producing countries are also intentionally included as some countries may desire to invest in its production in the future for export diversification purposes, as Côte d'Ivoire has done recently. It is noteworthy that the values of market power coefficients estimated for Benin, Burkina Faso, Côte d'Ivoire, Mali, and Togo amount to 0.006, 0.006, 0.001, 0.001, and 0.134 respectively. This shows that market power is being exerted by intermediaries even if the degree of the power might be low. The highest market power exerted by intermediaries is in Togo, and the lowest is in Côte d'Ivoire and Mali.

Simulation results under RCP 4.5 relative to the BAU

It should be recalled that in the BAU scenario, no climate effects are assumed, and cotton and cashew nuts yields increase every year from their 2010 values in line with technological change at a rate of 1%. The findings presented here relate to a climate scenario where a moderate level of GHG forcing (moderate climate change) is assumed. To shed light on how they differ from the BAU scenario, the simulation results (land use and exported quantities) under RCP 4.5 are presented relative to the BAU scenario (in percentage terms).

Cotton simulation results under RCP 4.5 relative to the BAU

Cotton land use tends to be sensitive to moderate climate change (Table 2). In fact, under RCP 4.5, cotton land use might decrease in some years and might increase in some other years relative to the BAU scenario in Benin and Mali. Under this scenario, Mali could experience mainly a drop in cotton land use relatively to the BAU except in the last three decades of the century. In Benin, cotton land use might decline relatively to the BAU in 2020, 2030, 2050 and 2080. At the same time, increased cotton land use might be observed in Burkina Faso, Côte d'Ivoire and Togo relatively to the BAU scenario. As for the exported quantities, the findings suggest that cotton exports from West African countries could experience mixed effects under a moderate climate change scenario (Table 3). Overall, cotton exports are projected to increase in most countries except in Mali and in Benin where exports might decline in some years. These mixed effects (regarding cotton land use and cotton exported quantities) underline the fact that under a medium GHG forcing scenario (RCP 4.5), the distribution of precipi-

Table 2: Cotton land use under RCP 4.5 relative to the BAU scenario (%).

	2020	2030	2040	2050	2060	2070	2080	2090	2100
Benin	-35.21	-8.64	27.06	-23.23	79.73	13.72	-51.59	4.21	4.21
Burkina Faso	23.21	33.01	39.48	47.51	49.70	41.96	29.31	20.90	15.30
Côte d'Ivoire	4.21	4.21	4.21	4.21	4.21	4.21	4.21	4.21	4.21
Mali	-89.33	-84.77	-84.58	-75.91	-66.79	-56.99	1.88	2.97	3.39
Togo	612.42	509.48	204.78	235.04	126.96	22.49	274.26	180.53	2.98

Source: Own composition

Table 3: Cotton exports under RCP 4.5 relative to the BAU scenario (%).

	2020	2030	2040	2050	2060	2070	2080	2090	2100
Benin	-11.96	29.88	84.94	14.25	183.95	99.90	-5.08	108.92	94.10
Burkina Faso	41.62	60.75	72.05	85.71	103.46	116.09	128.10	119.61	92.56
Côte d'Ivoire	56.40	59.12	64.18	75.22	90.42	94.43	100.60	102.09	93.57
Mali	-87.71	-81.40	-81.30	-70.72	-56.68	-36.81	84.92	93.77	78.37
Togo	1,221.02	1,055.01	500.05	557.80	378.74	164.51	807.35	589.25	140.25

Source: Own composition

tations may be very random and could cause some countries to have better yields than others (Egbendewe *et al.*, 2017).

Cashew nuts simulation results under RCP 4.5 relative to the BAU

Cashew nuts land use also exhibits dissimilarities across countries under a moderate climate change scenario relative to the BAU scenario (Table 4). Ghana and Guinea Bissau are expected to face a decline in cashew nuts land use under a moderate climate change scenario relative to the BAU from 2040 to the end of the century and in 2080 and 2090, respectively, and might experience an increase in the other years. Cashew nuts land use would only increase under a moderate climate change scenario in the remaining countries. However, the effects on cashew nuts exports are different compared with those on land use (Table 5). Cashew nuts exports could decline over the simulation period under RCP 4.5 in The Gambia, Guinea, Nigeria and Togo. The effects of a moderate climate change on cashew nuts exports are positive in every period for Benin, Côte d'Ivoire and Mali. Burkina Faso, Ghana and Guinea Bissau could record positive effects as well as negative effects due to moderate climate change, depending on the years.

Moreover, the findings indicate that cashew nuts export patterns are not affected in Senegal. The mixed results across countries underline the random nature of the uneven distribution of rainfall, leading some countries to do better than others. The uneven distribution of rainfall might affect cashew nuts yields and the increase in land use may not be enough to maintain the same level of exports in the BAU scenario in many countries, while other countries gain from their comparative advantage in terms of cashew nuts exports. It should be noted that exported quantities of cashew nuts are more negatively affected by moderate climate change than exported quantities of cotton. This suggests that the share of the West African countries in the world cashew nuts market could decline, everything else being equal.

Simulation results under RCP 8.5 relative to the BAU

These results correspond to a harsh climate scenario characterised by higher degrees of GHG forcing. The simulation results are presented following the same strategy as with the moderate GHG forcing scenario. That is, the figures for land use and the export of cotton and cashew nuts are presented relative to the BAU scenario and are calculated as the ratio

Table 4: Cashew nuts land use under RCP 4.5 relative to the BAU scenario (%).

	2020	2030	2040	2050	2060	2070	2080	2090	2100
Benin	69.60	42.42	51.89	36.13	25.25	57.73	164.29	100.99	105.32
Burkina Faso	2.34	4.21	4.21	4.21	4.21	4.21	4.21	4.21	4.21
Côte d'Ivoire	33.68	24.66	18.21	13.71	11.26	8.87	4.94	4.70	4.21
The Gambia	0.19	0.13	0.20	0.29	0.42	0.60	0.84	1.15	1.52
Ghana	0.89	169.57	-9.19	-8.05	-5.51	-5.09	-3.43	-1.81	-0.35
Guinea	5.23	4.64	4.49	4.40	4.34	4.29	4.27	4.22	4.21
Guinea Bissau	10.51	13.61	1.58	26.15	14.50	12.16	-2.99	-6.43	23.48
Mali	4.21	4.21	4.26	4.24	4.22	4.21	4.16	4.13	4.18
Nigeria	6.35	5.51	4.27	4.24	4.23	4.22	4.22	4.21	4.21
Senegal	8.29	5.49	4.21	4.21	4.21	4.21	4.21	4.21	4.21
Togo	14.38	6.42	4.18	13.83	4.20	4.20	4.21	4.20	4.21

Source: Own composition

Table 5: Cashew nuts exports under RCP 4.5 relative to the BAU scenario (%).

	2020	2030	2040	2050	2060	2070	2080	2090	2100
Benin	275.89	210.90	201.31	126.36	94.22	166.87	441.42	357.73	345.86
Burkina Faso	-1.33	-3.14	-10.94	-25.25	-31.16	-28.62	-12.68	1.41	0.04
Côte d'Ivoire	128.88	109.46	83.77	52.33	37.26	47.49	64.03	68.20	62.33
The Gambia	-57.06	-58.54	-62.16	-68.22	-70.63	-69.08	-62.05	-56.37	-57.16
Ghana	34.82	255.47	8.95	-5.17	-8.82	0.29	17.89	23.93	20.84
Guinea	-20.25	-21.65	-28.66	-39.72	-44.58	-38.51	-28.27	-27.53	-29.11
Guinea Bissau	-17.88	-5.61	-11.75	-21.64	-35.74	-16.76	-3.08	3.55	31.59
Mali	116.90	109.61	93.37	61.46	47.86	52.69	86.55	117.37	115.62
Nigeria	-68.77	-69.69	-72.35	-76.81	-78.82	-77.48	-73.13	-70.23	-70.80
Senegal	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Togo	-43.67	-48.16	-54.09	-56.06	-63.64	-60.25	-52.44	-48.39	-50.91

Source: Own composition

of the difference between RCP 8.5 and the BAU to the latter and are expressed as a percentage.

Cotton simulation results under RCP 8.5 relative to the BAU

The patterns of cotton land use are also sensitive to a harsh climate change scenario (Table 6). Land use is expected to decline and to increase depending on the countries and the time periods, except in Côte d'Ivoire. Overall, the negative effects seem to be less frequent than the positive ones with the exception of Burkina Faso and Togo that may not experience any decrease in cotton land use. As of the exported quantities (Table 7), negative effects of a harsh climate change on cotton exports would be observed only in Benin in 2070, and in Mali from 2020 to 2060. Overall, cotton exports are positively affected by a harsh climate change, and there is a certain degree of fluctuation in the positive effects over years; the highest effects being observed at the end of the century for all countries except for Togo. These findings suggest that land productivity (cotton yield) could be higher under RCP 8.5 than under the BAU scenario in some countries, and these countries could take advantage of it to export more cotton. It appears that cotton exports are higher under RCP 8.5 than under RCP 4.5. These results underline the fact that distribution of rainfall under RCP 8.5 favours some ACZs within countries in terms of cotton production relative to RCP 4.5 (rendering them more suitable for cotton production). Such a positive effect of climate change on cotton yields is also found in the literature (Amouzou *et al.*, 2018; Gérardeaux *et al.*, 2013).

These countries are expected to be differently affected by a harsh climate change in terms of cashew nuts land use (Table 8). Cashew nuts land use could be low under RCP 8.5 compared with the BAU scenario in few countries regardless of the time periods (in The Gambia and Ghana). Moreover, cashew nuts land use is negatively affected by a harsh climate change in 2040 in Guinea Bissau and from 2040 to 2080 in Senegal. Two countries are expected to not experience in some extent any change in cashew nuts land use under RCP 8.5 (Guinea and Mali), while Burkina Faso and Togo would record no change in the land use under this climate scenario. The remaining West African countries could experience mostly or only increase in cashew nuts land use under RCP 8.5 relatively to the BAU scenario. As for exported quantities, a harsh climate change may be detrimental to cashew nuts exports in several countries (Table 9). Indeed, when compared to the BAU scenario, a contraction in cashew nuts exports is expected under RCP 8.5 in Burkina Faso, The Gambia, Guinea, Guinea Bissau, Nigeria and Togo. Nonetheless, Senegal may not experience any change in cashew nuts exports patterns, while Benin, Côte d'Ivoire, Ghana and Mali are expected to increase cashew nuts exports under a harsh climate change scenario relative to the BAU. It should be noted that the highest increase in percentage is expected from Benin. Overall, cashew nuts exported quantities are expected to be lower under a harsh climate change than under a moderate climate change.

The findings presented above show the disparities in the effects of climate change across climate scenarios, countries and crops. Sometimes the observations show that climate impacts may be less severe in equatorial regions than temperate regions, though accounting for water use, adaptation potential, and adaptation capability alters this conclusion (Reilly and Hohmann, 1993). These findings are in line with the fact that there is a spatial dimension to the effects of global climatic change on agricultural production and trade (Lokonon *et al.*, 2019; Reilly *et al.*, 1994). Notably, Dellink *et al.* (2017) point out that the production of all commodities of the economy, including those that are heavily traded internationally, could be affected by the adverse impacts of climate change, but this is not the case with cotton and cashew nuts in West African countries. In fact, West African countries would potentially experience positive as well as negative effects of climate change, although there are disparities across countries, climate scenarios and crops.

Table 6: Cotton land use under RCP 8.5 relative to the BAU scenario (%).

	2020	2030	2040	2050	2060	2070	2080	2090	2100
Benin	3.00	22.12	-15.95	-14.18	-12.71	-52.35	17.72	0.00	146.87
Burkina Faso	51.05	47.38	36.39	26.05	14.04	0.00	0.00	0.00	0.00
Côte d'Ivoire	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mali	-43.44	-36.47	-33.65	-39.40	-37.50	-38.58	0.00	-0.04	0.00
Togo	898.45	545.36	341.17	344.67	227.00	40.91	291.92	169.24	0.00

Source: Own composition

Table 7: Cotton exports under RCP 8.5 relative to the BAU scenario (%).

	2020	2030	2040	2050	2060	2070	2080	2090	2100
Benin	39.70	77.42	24.74	36.00	51.03	-3.03	212.08	188.32	788.79
Burkina Faso	74.15	80.98	72.53	69.93	70.46	82.93	131.24	179.29	196.29
Côte d'Ivoire	49.01	54.06	59.64	76.83	91.89	103.34	118.26	144.07	157.72
Mali	-35.30	-22.51	-16.56	-20.15	-8.81	10.00	141.52	195.61	214.91
Togo	1,754.76	1,147.86	774.40	838.76	641.94	261.72	1,040.88	784.94	243.03

Source: Own composition

Actually, cotton is a C_3 crop, and so CO_2 fertilisation effects could sometimes compensate for yield loss resulting from climatic parameters, and even may reverse it (Amouzou *et al.*, 2018; Gérardeaux *et al.*, 2013). Nevertheless, cashew nuts are expected to be more negatively affected than cotton. Rupa *et al.* (2013) point out that as cashew nuts are grown in ecologically sensitive areas (e.g., areas with high rainfall and humidity), climate change may be detrimental to them. The major factors that adversely affect cashew yields and the quality of cashew nuts include unseasonal rains and heavy dew during the flowering and fruiting period (Rupa *et al.*, 2013).

Comparison of the findings, with and without taking into account cotton intermediary market power

The simulation results presented above with cotton intermediary market power effects accounted for are compared with those where these imperfections have not been taken into consideration. This sheds light on the errors made when intermediary market power in cotton domestic markets is not modelled. Under RCP 4.5, it appears that the countries would experience a decline in cotton exports relative to the BAU in some years, except for Côte d'Ivoire, in whose case accounting for market power does not have any significant effect. Overall, not accounting for intermediary market power may lead one to over-estimate or under-estimate the effect of a moderate climate change on cotton exports, depending on the time periods. Not accounting for cotton market imperfections would have a slight effect on cashew nuts exports under a moderate climate change, except in Benin, where it under-estimates the positive effect. The simulation results show that the non-inclusion of intermediary market power would lead to the under-estimation and the over-estimation of the effect of a harsh climate change on cotton production depending on the countries and the time periods. Furthermore, the positive effect of RCP 8.5 on cashew nuts exports is over-estimated by the non-inclusion of intermediary market power in cotton domestic market in Benin, Côte d'Ivoire and Mali. Nonetheless, the null effect under RCP 8.5 turns out negative overall in Burkina Faso and Togo. Consequently, it can be seen that ignoring cotton market imperfections in the modelling affect the simulation results.

Table 8: Cashew nuts land use under RCP 8.5 relative to the BAU scenario (%).

	2020	2030	2040	2050	2060	2070	2080	2090	2100
Benin	59.15	35.99	30.88	25.89	34.51	75.61	114.57	108.90	92.77
Burkina Faso	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Côte d'Ivoire	31.79	22.06	15.10	10.24	7.25	4.79	3.18	2.11	0.00
The Gambia	-96.70	-95.81	-94.48	-92.70	-91.32	-89.97	-86.77	-82.69	-77.80
Ghana	-2.18	-2.46	-2.35	-2.15	-1.90	-1.61	-1.32	-1.04	-0.79
Guinea	0.96	0.40	0.26	0.18	0.12	0.08	0.05	0.00	0.00
Guinea Bissau	3.04	6.81	-2.33	10.97	1.89	14.48	7.93	10.68	4.44
Mali	0.00	0.00	0.02	0.01	0.01	0.01	0.00	0.00	0.00
Nigeria	2.10	1.28	0.06	0.03	0.02	0.01	0.01	0.00	0.00
Senegal	1.67	0.38	-0.06	-0.04	-0.03	-0.02	-0.01	0.00	0.00
Togo	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Source: Own composition

Table 9: Cashew nuts exports under RCP 8.5 relative to the BAU scenario (%).

	2020	2030	2040	2050	2060	2070	2080	2090	2100
Benin	256.53	198.24	154.77	104.56	103.78	200.06	358.36	382.49	301.10
Burkina Faso	-3.65	-6.35	-15.82	-29.08	-35.48	-29.76	-12.36	2.10	-2.24
Côte d'Ivoire	127.96	102.68	74.61	41.58	27.66	37.72	54.57	50.37	34.94
The Gambia	-98.43	-98.12	-97.79	-97.61	-97.42	-96.83	-94.99	-92.86	-91.57
Ghana	31.77	26.81	14.90	-2.58	-8.19	2.12	17.73	16.46	6.25
Guinea	-23.24	-27.01	-33.41	-45.46	-49.43	-44.24	-35.29	-36.60	-42.63
Guinea Bissau	-19.33	-12.13	-20.72	-32.21	-42.04	-13.20	4.77	11.36	-3.56
Mali	107.84	102.03	82.07	53.10	38.54	49.96	86.79	119.18	112.12
Nigeria	-69.90	-71.14	-74.21	-78.55	-80.37	-78.50	-73.98	-71.95	-73.91
Senegal	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Togo	-50.24	-51.78	-56.89	-63.86	-66.15	-62.07	-53.75	-51.62	-56.62

Source: Own composition

Sensitivity of exports to the reduction of intermediary market power in cotton domestic markets

A reduction in intermediary market power in cotton domestic markets is simulated. That is, two simulations are run assuming respective reductions of 25% and 50% in intermediary market power under the two climate scenarios, in order to investigate to what extent reducing market imperfections could mitigate the effects of climate change on the quantities of cotton exported. To shed light on the differences from the climate scenarios, the simulation results under the climate scenario coupled with the reduction of intermediary market power are presented relative to cotton exports under the corresponding climate scenario in percentages (ratio of the difference between the RCP coupled with the reduction in intermediary market power and the RCP to the RCP, expressed as percentages). The simulation results indicate that under the two climate scenarios, reductions in market imperfections could mitigate the negative effects of a moderate climate change or strengthen a country's ability to benefit from the opportunity arising from this climate change scenario in terms of increasing these exports, depending on the countries (Tables A3 & A4 of the Appendices). It is noteworthy that the 50% reduction in cotton market imperfections has to a certain extent different effects only under RCP 4.5 climate scenario, but the trend is similar to what is found with the 25% reduction (Table A5 of the Appendices). Such a reduction could have indirect effects on cashew nuts exports (Tables A6, A7 & A8 of the Appendices). Decreasing intermediary market power in cotton domestic markets could affect countries' capacity to increase cashew nuts production and exports in the presence of climatic change and could exacerbate the negative effect of climate change, depending on the country and the climate change scenario. It should further be noted that reducing market imperfections may not automatically lead to higher returns to farmers (Delpeuch, 2009). In fact, a perfectly competitive sector performs well in terms of cost efficiency and provides relatively high prices to farmers but performs badly in terms of quality, input provision, extension and yields. However, a public monopoly performs poorly in terms of ginning cost-efficiency but does well in terms of inputs provision, extension, yields and farmers' welfare (Delpeuch, 2009).

Conclusion and policy implications

Given the importance of West African countries' integration with the world agricultural supply chain to the promotion of economic growth, development and poverty reduction, this paper has aimed to analyse the extent to which climate change affects cotton and cashew nuts production and exports in the West African countries using a regional bio-economic model, while also accounting for the presence of intermediary market power in cotton domestic markets. This paper has addressed three specific objectives. First, the paper has shown that the countries would be differently affected under RCP 4.5 and RCP 8.5 in terms of cotton and cashew nuts land use. The effects vary across countries, ranging from experiencing only a decline, or only an increase to experiencing both a decline and an increase in land use. Second, the paper has revealed that the effects of climate change on the quantities of cotton and cashew nuts exported are similar to those it has on land use, with the positive effects being more pronounced for cotton exports in particular. Third, the paper has found that a reduction in cotton market imperfections can either mitigate the negative effects of climate change or lessen a country's ability to take advantage of the opportunities arising from climate change in terms of increasing cotton exports, or strengthen this capacity, or have mixed effects depending on the countries. Therefore, actions need to be taken to mitigate the negative effects of climate change on cotton (especially in Mali) and cashew nuts (in Burkina Faso, The Gambia, Guinea, Guinea Bissau, Nigeria and Togo under conditions of moderate climate change) production and exports and also to take advantage of the beneficial effects involving these crops given climatic change. In the case of moderate climate change, the countries may only correct for cotton market imperfections, while under harsh climate change, they may combine this with an increase in cotton and cashew nuts land productivity. The main limitation of this paper is that cashew nuts market imperfections are not taken into account. Thus, future investigations could include intermediary market power in cashew nuts domestic markets in the regional bio-economic model in order to improve the precision of the model.

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Appendix

Appendix 1: Cotton and cashew nuts yield functions' parameters (dependent variable: ln(yield)).

Variables	Cotton		Cashew	
	Coefficients	T-statistics	Coefficients	T-statistics
Temperature	-1.12*	-1.95	-0.86	-0.89
Temperature^2	0.02*	1.72	0.01	0.70
Rainfall	-0.01***	-3.14	6.60e-04	1.37
Rainfall^2	1.68e-07	1.20	-5.37e-07**	-2.11
Temperature*Rainfall	2.26e-04***	3.50		
Variance of temperature	0.01	0.66	0.06	1.25
Variance of rainfall	-6.95e-05**	-2.57	9.92e-05***	2.61
Clay	-0.04	-1.03	-0.07	-0.80
Sandy	0.03	0.60	0.01	0.07
Constant	14.96**	2.14	11.69	1.04
Observations	297		291	
R^2	0.07		0.08	

Note: *** p<0.01, ** p<0.05, * p<0.1. These estimations results are used to project crop yields for agro-climatic zones, soils and countries from 2020 to 2100. For crop yield projections, future climate data with respect to RCP 4.5 & RCP 8.5 are used and holding soil variables equal to their means.
Source: Own composition

Appendix 2: Selected parametric distributions used in the Monte Carlo simulations

	GDP growth			Population Growth			Inflation rate		
	Distrib.	Mean	Std. Dev.	Distrib.	Mean	Std. Dev.	Distrib.	Mean	Std. Dev.
Benin	Normal	4.04	3.05	Normal	3.01	0.21	Normal	0.04	0.07
Burkina Faso	Beta	1.10	1.11	Normal	2.74	0.20	Normal	0.03	0.05
Côte d'Ivoire	Normal	1.00	3.39	Normal	3.05	0.86	Normal	0.04	0.05
The Gambia	Normal	3.70	2.91	Normal	3.42	0.59	Normal	0.09	0.10
Ghana	Beta	1.77	1.01	Normal	2.72	0.29	Normal	0.33	0.30
Guinea	Normal	3.67	1.67	Normal	2.85	1.28	Normal	0.19	0.14
Guinea Bissau	Uniform	0.98	5.42	Normal	2.17	0.24	Normal	0.02	0.04
Mali	Normal	3.98	5.39	Normal	2.49	0.61	Normal	0.03	0.07
Niger	Normal	2.06	5.23	Normal	3.36	0.35	Normal	0.03	0.09
Nigeria	Normal	3.17	5.89	Normal	2.57	0.80	Normal	0.21	0.18
Senegal	Normal	1.66	1.08	Normal	2.78	0.23	Normal	0.04	0.07
Sierra Leone	Logistic	5.03	3.43	Normal	3.12	1.08	Normal	0.09	0.09
Togo	Normal	2.55	6.10	Normal	2.90	0.38	Normal	0.05	0.09

Source: Own composition

Appendix 3: Sensitivity of cotton exports to 25% reduction of market power in cotton domestic markets under RCP 4.5 (%).

	2020	2030	2040	2050	2060	2070	2080	2090	2100
Benin	5.71	7.40	9.06	0.02	0.40	-9.55	0.33	0.00	0.00
Burkina Faso	6.49	6.84	4.08	4.69	5.30	4.92	3.59	2.54	1.77
Côte d'Ivoire	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mali	360.76	271.42	245.94	158.89	111.02	76.15	2.13	1.15	0.76
Togo	13.70	-10.15	15.75	-0.38	19.46	15.22	1.63	0.98	1.10

Source: Own composition

Appendix 4: Sensitivity of cotton exports to 25% reduction of market power in cotton domestic markets under RCP 8.5 (%).

	2020	2030	2040	2050	2060	2070	2080	2090	2100
Benin	-15.20	-43.09	-14.73	-10.82	-7.97	134.90	-0.71	0.00	-0.63
Burkina Faso	0.03	0.03	0.03	0.03	0.03	0.00	0.00	0.00	0.00
Côte d'Ivoire	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mali	-40.76	-39.11	-35.64	-35.08	-30.04	-22.81	0.00	0.03	0.00
Togo	-0.47	-0.41	-0.38	-0.38	-0.29	-0.15	0.61	0.00	0.00

Source: Own composition

Appendix 5: Sensitivity of cotton exports to 50% reduction of market power in cotton domestic markets under RCP 4.5 (%).

	2020	2030	2040	2050	2060	2070	2080	2090	2100
Benin	5.71	7.40	9.06	0.02	0.41	-9.58	0.33	0.00	0.00
Burkina Faso	6.49	6.84	4.08	4.69	5.30	4.92	3.59	2.54	1.77
Côte d'Ivoire	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mali	360.76	271.42	245.94	158.89	111.02	76.15	2.13	1.15	0.76
Togo	8.10	-9.87	8.30	1.02	13.88	0.33	1.05	0.89	1.46

Source: Own composition

Appendix 6:: Sensitivity of cashew nuts exports to 25% reduction of market power in cotton domestic markets under RCP 4.5 (%).

	2020	2030	2040	2050	2060	2070	2080	2090	2100
Benin	-0.75	0.99	-1.97	-0.01	-0.06	-0.06	-2.29	-0.17	0.23
Burkina Faso	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Côte d'Ivoire	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mali	0.01	0.00	-0.05	-0.03	-0.02	-0.02	0.05	0.07	0.03
Togo	-8.58	1.46	0.04	-11.19	0.01	0.01	-0.02	0.00	0.01

Source: Own composition

Appendix 7: Sensitivity of cashew nuts exports to 25% reduction of market power in cotton domestic markets under RCP 8.5 (%).

	2020	2030	2040	2050	2060	2070	2080	2090	2100
Benin	-0.53	-3.99	-6.07	-2.20	3.75	-0.35	-0.44	-4.47	-0.06
Burkina Faso	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Côte d'Ivoire	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mali	-0.46	-0.31	-0.24	-0.16	-0.11	-0.07	-0.05	-0.03	-0.02
Togo	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Source: Own composition

Appendix 8: Sensitivity of cashew nuts exports to 50% reduction of market power in cotton domestic markets under RCP 4.5 (%).

	2020	2030	2040	2050	2060	2070	2080	2090	2100
Benin	-0.76	0.99	-1.97	-0.02	-0.06	-0.04	-2.26	0.14	0.19
Burkina Faso	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Côte d'Ivoire	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mali	0.01	0.00	-0.05	-0.03	-0.02	-0.02	0.05	0.07	0.03
Togo	-8.50	-2.26	0.04	-11.18	0.01	0.01	0.00	0.01	0.01

Source: Own composition

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MIS adoption and its effects on the technical efficiency of agribusiness firms in Cameroon

This paper intends to determine the factors influencing the adoption of Management Information Systems (MIS) as well as the effects such systems have had on the technical efficiency of agribusiness firms in Cameron. 183 MIS users and 300 non-users were sampled through a multistage sampling procedure. An Ordered Logit model was employed to show that the user's level of satisfaction, the purchase price of equipment and technological performance all have a positive effect on MIS adoption. Conversely, fear of change in firm management, access to government regulations, and complexity of MIS equipment discourage the adoption of MIS. The Cobb-Douglas stochastic production function meanwhile revealed that ICT expense, firm size and number of customers were positively significant for the revenue of MIS users. For MIS non-users, ICT expense, firm size and quantity purchased also had a positive significance for revenue. However, the average technical efficiencies were 0.96 and 0.55 for MIS users and non-users, respectively, meaning that MIS users were far more technically efficient than MIS non-users. Also, the Tobit regression model on MIS users revealed that MIS improved the technical efficiency of agribusiness firms adopting them. This study therefore recommends that agribusiness firms in Cameroon invest in MIS; moreover, they should encourage its adoption by training their staff in how to use it optimally.

Keywords: adoption, Management Information Systems, technical efficiency, Agribusiness firms

JEL classification: Q12

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Introduction

All firms need information to better understand themselves, their environment and to make informed decisions. Although some information is meaningless, the right amount of information at the right time is a key factor for every organisation (Lapiedra and Devece Carañana, 2012). It is undeniable that information systems have revolutionised virtually every sector of the economy in which they have been applied (Sopuru, 2015). In developed and developing countries, there is a crucial need for organisations to transform their traditional bureaucratic management style into a modern management information system that is performant and efficient in the decision making process (Azeez and Yaakub, 2005). However, in Africa, due to lack of awareness, which restricts access to information and its proper dissemination (Sopuru, 2015), agribusiness firms have shown only a slight improvement, despite advances in agricultural innovations. The Cameroon government is encouraging investments in agribusiness both to promote effective strategies in relation to improved food security and as a vital source of economic development. This has made the agribusiness sector one of the major sectors in the economy of Cameroon. Emphasis is given to good agricultural practices, prescriptive agronomic recommendations, data-based farming, and other precision farming applications.

The definition of management information system (MIS) varies depending on authors. According to Lapiedra and Devece Carañana (2012), management information systems are information systems that provide managers with the information they need to make decisions and solve problems. Therefore, a management information system is a system that collects, processes, stores, retrieves, and disseminates the information needed to make decisions and solve problems in an organisation.

Today, the role of the computer system is essential to the company's information system, given that companies' information systems have to handle a large quantity of data and make structured information available to multiple decision-makers in the company (Lapiedra and Devece Carañana, 2012). Berisha-Shaqiri (2014) mentioned five tasks of computer operating system: data collection; data processing; data management; control and security of data and information generation. Management information systems have an increasingly crucial role to play in improving the operations of agribusiness firms in making goods and services readily available to the market.

Several studies have been carried out to explore factors affecting the adoption of management information systems and its effects on technical efficiency. Zide and Jokonya (2022) affirm that the implementation and adoption of innovation in organisations are influenced by technological, organisational, and environmental factors. Out of the six technological factors that affect the adoption of data management information systems in small and medium enterprises (SME) in South Africa, the security technological factor was the most highlighted. Among organisational factors, cost was the most frequently mentioned factor affecting the adoption of data management information services in SMEs. Lastly, among the five environmental factors that affect the adoption of data management information services in SMEs, government regulations were most often mentioned.

In Sweden, Imre (2016) also indicated that in addition to the well-known factors such as organisational size and IT

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readiness, social norms and ownership characteristics of the firm played a prominent role in information systems adoption. Sepahvand and Arefnezhad (2013), in their study on factors affecting the success of information systems in Isfahan Province of Iran, focused on organisational factors – such as top management support, resource allocation, decision-making structure, management style, alignment of goals and knowledge of IT management – that in turn, affected the success factors of information systems (system quality, user satisfaction, perceived usefulness and quality of information). Based on expert choices, the results showed that the most important organisational factor affecting the success of organisational information system was top management support and amongst the success factors of information systems, user satisfaction was the most important. Similarly, Ghaderi *et al.* (2017) found that environmental, organisational and human factors are, respectively, the most important factors affecting the use of MIS in 22 districts of Tehran municipality. Munirat *et al.* (2014) examined the factors affecting the implementation of MIS in selected financial cooperatives in Nairobi. The study found out that the effects of training, cost, infrastructure and regulations were the highest in the implementation of MIS. In Nigeria, Irefin *et al.* (2012) analysed the vital influential factors affecting the adoption of information and communication technology from adopter and non-adopter perspectives in small and medium size enterprises located in different parts of Lagos State. The results indicated that, among the adoption inhibiting factors (cost, business size, availability of ICT infrastructure, government support and management support), cost was the major barrier for small and medium size enterprises adopting ICT. Conversely, Lal (2007) found that one of the major factors limiting the adoption of ICT in SMEs in Nigeria was poor hardware infrastructure.

The growing body of theoretical and empirical literature on firm efficiency has identified numerous other variables such as ownership structures, investment in fixed capital, soft budget constraints, firm trade orientation, quality of labour and competition among others, as determinants of firm performance and consequently firm efficiency (Aw *et al.,* 2000; Djankov and Murrell, 2002; Frydman *et al.,* 1999). Badunenko *et al.* (2006) investigated factors that explain the level of technical efficiency of a firm in 35,000 firms over the years 1992-2004 in Germany. The study revealed that industry effects accounted for one third of the explanatory power of the model; whereas the firm's size and headquarters' location accounted for one quarter and ten percent of the variation in efficiency, respectively. Other firm characteristics such as ownership structure, legal form, age of the firm and outsourcing activities were found to have small explanatory power, while research and development activities were neutral as regards technical efficiency.

Mbusya (2019) in an analysis of small and medium sized Kenyan enterprises found that physical capital is one of the major determinants of firms' efficiency, although its impact is weak. He further showed that labour force, age of the firm, and legal status all have positive and significant effects on the technical efficiency of the firms. In contrast, Alvarez and Crespi (2003) in an analysis of micro, small, and medium-sized Chilean manufacturing firms in 1996 found that efficiency was positively associated with the modernisation of physical capital, the experience of workers and product innovation activity. Also, variables such as outward orientation, the education level of the owner, and corporate social responsibility did not affect the efficiency of the firms.

The analysis of efficiency is mostly associated with the quality of human capital, due to its importance in the production process and consequently, economic growth. According to Ismail *et al.* (2014), an increase in human capital investment through education and training will produce a more knowledgeable labour force. Human capital will improve productivity and ultimately improve the efficiency of manufacturing firms. Likewise, Ismail *et al.* (2014) argued that firms that have a high number of educated workers are in an advantageous position to keep up with, control and adapt to new technologies.

Several studies have examined the effects of management information systems on the efficiency of firms. Shao and Lin (2002) investigated the effects of information technology on technical efficiency in a firm's production process in USA through a two-stage analytical study with a firm-level data set. It was found that information technology exerts a significant favourable impact on technical efficiency and in turn, gives rise to the productivity growth. In Nigeria, Tantua and Osuamkpe (2019) in a cross-sectional survey in Rivers State, revealed a significant relationship between the management information system and office productivity of the Print Media in Rivers State. Acknowledging that productivity is understood to be a measure of the efficiency of production, the study further encouraged the use of office automation systems such as computers, websites, and scanners to help boost the operational efficiency and profitability of Print Media in Rivers State. Based on an analysis of the impact of MIS on the performance of business organisations in Nigeria, Munirat *et al.* (2014) concluded that MIS has direct effects on the performance and efficiency of business organisations since 60% of them agreed that a lack of adequate knowledge and skill relating to MIS is one of the major factors affecting the efficient performance of management information systems in Nigeria. According to Alene (2018), MIS provides information that manages the organisation effectively and efficiently. Meanwhile, the study of Handzic (2001) focused on the efficiency of business decision making, based on information availability and people's ability to use information in short and long-term planning. The results showed that the higher the availability of information, the better the impact on both the efficiency and accuracy of business decisions. Likewise, Awan and Khan (2016) investigated the impact of management information system on the performance of the organisation by analysing 31 different organisations of Pakistan. Their results showed that having a management information system affected positively the performance and efficiency of organisations in Pakistan.

This study aims to fill a knowledge gap by examining the complexity related to the adoption of MIS in agribusiness firms in Cameroon and by investigating the effects of MIS on agribusiness firms' performance. Several empirical and conceptual studies have been carried out worldwide to examine this disputed but important issue. A big debate continues regarding the suitability of a set of variables that could be used to determine the users' perception of successful adoption of MIS in agribusiness firms. According to Zide and Jokonya (2022), the successful adoption of MIS in companies is more dependent on technology, organisational, and environmental characteristics. However, these factors are much neglected by organisations, especially among small MIS users, where social and human characteristics play an important role. Moreover, little is known about the existing level of inefficiency among MIS users and non-users. These must be known to improve the efficiency of MIS users in the study area. Lastly, as far as the study area is concerned, there is insufficient literature that examines the effects of MIS on the technical efficiency of MIS users in Cameroon. It is against this backdrop that this study intends to fill the research gap by analysing the MIS adoption and its effects on the technical efficiency of MIS users in Cameroon.

This study intends to determine the potential factors that influence the adoption of a management information system in Cameroon; to estimate and compare the firms' technical efficiencies of MIS users and non-users; and to assess the effects of MIS on the technical efficiency of MIS users. This will provide a critical understanding of the complexity of MIS adoption. Estimating indicators associated with different technical efficiencies of MIS users and non-users is imperative, to enable the two groups to be compared. Moreover, the study will also give a sound demonstration of the importance of MIS in agribusiness firms, as well as identifying the various constraints and factors that affect the adoption of MIS in firms.

Methodology

The study area was Cameroon, located in the central part of Africa within latitudes 2 and 13 North and longitude 9 and 16 east of the equator. It covers a total land area of 475,442 square kms. The country has ten regions: Centre; Littoral; Adamawa; Far-North; North; South; East; West; North-West, and South-West (Djomo *et al.,* 2021; Farris *et al.,* 2010). The country has great potential for agricultural production thanks to its agroecological diversity. The sector employs around 70% of Cameroonians (Abia *et al.,* 2016) and its contribution to GDP in 2020 represented 17.38%. The population of the study comprised all registered agribusiness firms in Cameroon.

Sample size, sampling procedure and data collection

Multi-stage sampling technique was used based on purposive, stratified, simple random sampling technique for sample selection. Firstly, three out of the ten regions that make up the country were purposively selected, given that these regions are agriculture-based and have a high number of agribusiness firms. Secondly, two major towns were randomly selected in each of the three regions previously selected, amounting to six towns in total. Thirdly, from each of the towns selected, respondents were selected after stratifying them into MIS users and non-users.

For sample selection purposes, lists of all registered firms involved in agribusiness were obtained from the respective Regional Registries for Commerce and Industry in Cameroon. The sample sizes of the various strata were obtained using the Taro Yamane formula (Yamane, 1973). Should a listed firm not be available, other not yet selected firms might replace them.

The Taro Yamane formula was used from a sample frame of 340 registered MIS users and 1200 non-users involved in agribusiness (Yamane, 1973). The formula is expressed as follows:

$$n = \frac{N}{1+N(e^2)} \quad (1)$$

where:
n = sample size
N = real or estimated size of the population
e = level of significance (5% or 0.05)

To achieve proportional distribution of samples according to strata, the following formula was used:

$$n_h = \frac{nN_h}{N} \quad (2)$$

where:
n = sample size.
N_h = population size in each stratum.
n_h = number of questionnaires needed for each stratum.

Primary data was used for this study. These data were collected through well-structured questionnaires and interview techniques administered to managers or owners of agribusiness firm. We obtained data on physical quantities and monetary value of firms. We also collected firm data on technology, organisational and environmental characteristics of MIS. In addition, we collected socio-economic data on employees of the firms. The questionnaires were divided into sections based on information needed. It was administered to the respondents with the aid of trained enumerators.

Data Analysis and Estimation Techniques

The data collected for this study was analysed using inferential statistics. An ordered logistic regression model was used to determine potential factors that influence the adoption of MIS. A multiple regression model based on Stochastic Frontier Profit Function which assumed Cobb-Douglass specification form and inefficiency function model was employed to determine the technical efficiency of both agribusiness firms using MIS or not. A logistic regression model was used to assess the effects of MIS on technical efficiency of MIS users. And lastly, a t-test was used to test the hypothesis of no significant difference in technical efficiency among MIS users and non-users.

Ordered Logistic regression model

In determining factors influencing the adoption of MIS in agribusiness firm in the study area, this research employed an ordered logit model (OLM). The OLM is employed when the dependent variable has more than two categories and the values of each category have sequential pattern in which one category is greater in value than the next (Otekunrin, 2022). This was done because the dependent variable was ordinal and categorical in nature, derived from a Likert rating scale which required the respondents to indicate the steps an individual goes through in adopting MIS in his agribusiness firm under five categories as (Adekoya and Tologbonse, 2011): Awareness stage = 1, Interest stage= 2, Evaluation stage = 3, Trial stage = 4 and Adoption stage = 5.

Ordered logistic regression and ordinal logit models are interchangeable when determining ordinal survey data (Cordero-Ahiman *et al.,* 2020; Samim *et al.,* 2021). Empirically, it has been argued that using either of the two models basically depends on the purpose of choice and convenience (Long, 1997; Samim *et al.,* 2021). The main assumption of the ordered logistic regression model (OLM) is the Proportional Odds Model (POM), where the association between each pair of outcome groups is identical. This is also known as a parallel regression assumption. Violations of the parallel proportional odds assumption might result in inconsistent estimates of the model variables (Chowdhury, 2021). If a POM assumption is violated by one or more explanatory variables, an unconstrained generalised ordinal logit (gologit) model, partial proportional odds model, or multinomial logit model (MNLM) can be used as an alternative.

The observed ordinal variable in the model is given as Y and it is a function of another variable y* not measured. As specified by (Long, 1997) and Otekunrin (2022), the y* has various threshold points as presented in (1):

$$y_i^* = x_i^{'}\beta + \varepsilon_i \tag{3}$$

where y_i^* is the hidden variable of the MIS adoption levels of the firm $i, x_i^{'}$ is a vector of explanatory variables describing firm i, β is a vector of parameters to be estimated, and ε_i is a random error term which follows a standard normal distribution.

Stochastic Frontier Model

The stochastic frontier production function model of Cobb-Douglas functional form was employed to estimate the efficiency of the firm. Many empirical studies particularly those relating to developing countries used the Cobb-Douglas functional form because its functional form meets the requirement of being self-dual, i.e. it allows an examination of efficiency (Ambali *et al.,* 2012).

The Stochastic Frontier Production (SFP) function used in this study is defined as follows:

$$\begin{aligned} \mathrm{LnY} &= \beta_0+\beta_1\mathrm{Ln}X_1+\beta_2\mathrm{LnX}_2+\beta_3\mathrm{LnX}_3+ \\ &+\beta_4\mathrm{LnX}_4+\beta_5\mathrm{LnX}_5+\beta_6\mathrm{LnX}_6+\mathrm{V}_i-\mathrm{U}_i \end{aligned} \tag{4}$$

where; L_n= natural logarithm to base 10; Y_i = operating revenue in FCFA; X_1 = the expenditures in information and communication technology (ICT) in FCFA; X_2 = Labour used measured in man days per hectare; X_3 = expenditure in power supply in FCFA; X_4 = firm size in FCFA, X_5 = number of customers measured in number of people; X_6 = is retailed or wholesale, measured in quantity purchased.

The inefficiency of production was modelled in terms of factors such as:

$$\mathrm{U}_i= \sigma_0+\sigma_1 Z_{1i}+\sigma_2\mathrm{Z}_{2i}+\sigma_3\mathrm{Z}_3+\sigma_4\mathrm{Z}_{4i} \tag{5}$$

where: σ = a vector of unknown parameters to be estimated; Z_1= Level of Education measured in number of years spent in formal education, Z_2= manager experience in years, Z_3= gender of manager (1 is male and 0 is female), Z_4= corporate body (1 is yes, 0 is No).

According to Battese and Coelli (1995), technical efficiency occurs when there is possibility to reduce inputs used without negatively affecting output. On the contrary, technical inefficiency is defined as the amount by which the level of production for the firm is less than the frontier output (Usman *et al.,* 2013). TE takes values between 0 and 1.

Tobit Regression Model

The study used a Tobit regression to analyse the effects of MIS on technical efficiency of agribusiness firm. This model was used given the fact that technical efficiency has both the lower and upper bounds (from 0 to 1). According to Gujarati and Porter (2010), using the ordinary least squares (OLS) method would cause major violations of the assumptions of the OLS model (normality of distributions, homoscedasticity of errors, and exogeneity of independent variables) and lead to inconsistent parameter estimates. Moreover, the Tobit model has the advantage of using the maximum likelihood estimation (MLE) procedures to estimate errors in the presence of non-normal distribution, which is the most efficient estimator for asymptotically distributed dependent variable (Okello *et al.,* 2019; Wooldridge, 2002).

$$Y_i^*=\lambda_0 + \lambda_1 V_{1i} + \lambda_2 V_{2i} +...+ \lambda_{15} V_{15i} + \lambda_{16} V_{16i} + \rho_i \tag{6}$$

with $Y_i^* = TE_i$, λ_0 intercept, taking the value of TE_i when other variables are null. λ_i= are the parameters to be estimated, V_1 ease of use, V_2= response time, V_3 reliability, V_4= accuracy, V_5 precision, V_6= timeless, V_7= number of failures, V_8= repair time. ρ_i is an error term which is assumed to be independent and identically distributed.

Results and Discussion

Factors affecting the adoption of management information systems

The analysis of factors influencing the adoption of MIS is presented in Table 1. Although 10 variables were hypothesised to have an influence in MIS adoption, the ordered Logistic regression result confirmed that only 6 factors were statistically significant (at 1% level) in influencing MIS adoption. These variables are government regulation, users' satisfaction, purchased price, complexity, technology performance and fear of change.

The explanatory power of the independent variables as expressed by Pseudo R^2 was relatively high (40%). The overall goodness of fit as rejected by Prob > Chi2 (0.0000) was also good. The estimated cut-off points (μ) satisfy the conditions that $\delta_1 < \delta_2 < \delta_3 < \delta_4$. This implies that these categories were ranked in an ordered way. In terms of consistency with a priori expectations on the relationship between the dependent variable and the explanatory variables, the model seems to have behaved well.

The government regulation was negative and significant in explaining the level of MIS adoption. This indicates that the more the government investigates in MIS firms, the lower the firms adopt MIS. This means that agribusiness firms are not ready to increase the use of MIS to prove their various activities. The findings are in line with Zide and Jokonya (2022), who found that government regulation was the highest environmental factor that affects positively the adoption of data management information service in small and medium enterprises in South Africa.

User satisfaction was positive and significant at 1% level of probability. This implies that the more agribusiness firms are satisfied with the use of MIS, the more they adopt it. The finding is in line with Sepahvand and Arefnezhad (2013) who found that the most important organisational factor affecting successful adoption of MIS was user satisfaction. The coefficient of purchased price was positive and statistically significant at 1% level of probability. This indicates that high cost would result in more adoption of MIS, implying that the equipment used for MIS in agribusiness firms are considered as Veben goods or luxury goods, whose demand increase as price increases.

Our study found a negative and significant relationship between complexity of MIS equipment's and the adoption level of MIS in agribusiness firms. This indicates that the more complex are MIS equipment, the less agribusiness firms are willing to adopt MIS in their firms. This might be explained by the fact that a complex MIS equipment would increase the complexity of tasks, as a wide array of hardware and software has to be managed. Moreover, greater heterogeneity of MIS equipment could complicate the task of migrating to more sophisticated systems because technologies change over time and this may offset any positive effects (Chau and Tam, 1997). This could then discourage firms to adopt such complex MIS equipment. This result conflicts with the findings of Chau and Tam (1997), who did not find a significant relationship between complexity of MIS equipment and adoption.

Results also revealed a positive and significant relationship between technology performance and MIS adoption in the firm. This means that farmers' perception of the performance of technologies significantly influences their decision to adopt them. In other words, farmers who perceive technology as being consistent with their needs and their environment are likely to adopt it, since they view it as a positive investment (Mwangi and Kariuki, 2015). A similar result was found by Wandji *et al.* (2012) who examined the famers' perception towards the adoption of aquaculture technology in Cameroon, as well as Adesina and Zinnah (1993) who studied the influence of how farmers perceived a modern variety of rice on their decision on whether to adopt it.

The coefficient of fear of change was negatively and significantly related with the level of MIS adoption. That is the more the users of MIS fear change in their management system, the more they are afraid of MIS adoption in their firm activities. This result is in disagreement with the findings of Zide and Jokonya (2022), who showed that fear of change in the management system was not a significant factor affecting the adoption of MIS in firms in South Africa.

Table 1: Determinants of MIS adoption.

Variable	Coefficient	Standard error	T-value	P-value
Constant	0.431	0.033	13.070***	0.000
Risk perception	-0.220	0.183	-1.190	0.232
Government regulation	-0.167	0.045	-3.670***	0.000
Self sufficiency	-0.252	0.229	-1.100	0.270
User satisfaction	0.450	0.152	2.770***	0.006
Education	0.035	0.053	0.670	0.504
Purchased price	0.0001	$5.45e^{-06}$	8.020***	0.000
Experience	$2.48e^{-11}$	$2.79e^{-10}$	0.090	0.929
Complexity	-1.030	0.250	-4.060***	0.000
Technology performance	0.793	0.220	3.610***	0.000
Fear of change	-0.783	0.223	-3.510***	0.000
Pseudo R^2	0.397			
LR chi2(8)	165.160			
Prob > chi2	165.160			
Log likelihood	-125.316			
δ_1	1.290			
δ_2	6.850			
δ_3	8.010			
δ_4	9.430			

***, ** and * significant at 1, 5 and 10%, respectively.
Source: own survey.

Estimates of parameters in the Stochastic Production Function

The result on technical efficiency of MIS users in the study area is presented in Table 2. The analysis revealed that there were technical inefficiency effects as shown by the gamma value of 0.99 and 0.16 for users and non-users respectively. The significant gamma (γ) estimates indicate that 99% and 16% of the technical inefficiencies can be explained jointly by the socio-economic variables in the technical inefficiency equation. The estimated sigmas squared were significant at 1% level of probability. This indicated a good fit and correctness of the specified distribution assumption of the model.

For MIS users, the coefficients of ICT, firm size and number of customers were positive and statistically significant at 1%, 5% and 10% levels, respectively. That means that a unit expense in ICT under static condition of other independent variables will result in decrease of revenue by 0.09. This result is in conformity with Delina and Tkáč (2015) who concluded that using ICT for doing business leads to positive impact of ICT on revenue growth. Similarly, ICT not only improve the revenue but also the productivity and competitiveness of the firm (Bernroider *et al.,* 2011; Cardona *et al.,* 2013; Hall *et al.,* 2013; Tarutė and Gatautis, 2014). In the same way, the coefficient of number of customer (0.407) implies that a unit increase of customer will lead to an increase of 0.407 in the revenue. This result concurs with the work of Sharp and Allsopp (2002), who found that increases in sales are due more to growth of the size of the customer rather than increased rates of buying frequency. Likewise, a unit increase in firm size – i.e. a firm's capital – will increase revenue by 0.90. This shows that capital is a determinant of the technical efficiency of agribusiness firms in South Cameroon. Comparable result were reported by Mbusya (2019) who found that found that capital was one of the major determinants of firm's technical efficiency although its impact is weak. For MIS non-users, technical efficiency has a significant relationship with ICT, firm size and quantity purchased. Unlike MIS users, quantity purchased is statistically significant and positively related to revenue. This implies that a unit increase in quantity purchased will increase the revenue by 0.15.

The estimated coefficient from the inefficiency model included in the stochastic production frontier estimation revealed that for MIS users, only experience was found to exert a statistical influence on the inefficiency of agribusiness firms. The results showed that the estimated coefficient of experience (-0.47) had a negative sign for technical inefficiency and was statistically significant at 1% level of probability. The negative sign implies that the higher the level of experience is, the more the inefficiency decreases. In other words, a negative sign of experience means that experience has a positive effect on technical efficiency. This implies that increase in experience will improve the ability of the firms to optimally combine the available inputs to maximise their revenue. Specifically, a unit increase in experience will increase the revenue by 0.47. This result is conformed to the findings of Kaka *et al.* (2016), who found a negative and significant relationship between the experience and profit inefficiency of paddy farmers in Malaysia.

Technical efficiency distribution of agribusiness firms

The frequency distribution of technical efficiency (TE) scores for agribusiness firms is presented in Table 3. The technical efficiency scores were not fairly distributed with all firms having their technical efficiency within the bracket of 0.90 to

Table 2: Maximum Likelihood Estimates of the Parameters in the Stochastic Frontier Analysis.

Variables	Users		Non-Users	
	Coefficient	t-ratio	Coefficient	t-ratio
Constant	1.639	-4.530***	1.893	0.030
ICT	0.088	4.190***	0.205	1.760*
Labour	-0.029	-0.450	-0.019	-0.140
Power supply	-0.0396	-1.480	-0.007	-0.050
Farm size	0.902	51.960***	0.358	6.210***
Number of customers	0.407	1.660*	0.167	0.920
Quantity purchased	-0.011	-0.050	0.147	1.670*
Inefficiency model				
Constant	-0.637	-0.240	0.744	0.010
Education	-0.118	-0.620	-0.018	-4.480***
Experience	-0.047	-2.650***	-0.005	-4.090***
Sex	-1.157	-0.690	-0.096	-3.290***
Corporate body	-0.260	-0.280	0.103	4.710***
Sigma-square	0.352	47.560***	0.344	17.200***
Gamma	0.988	13.530***	0.157	17.440***
LR test	263.260		7.975	

***, **and * significant at 1, 5 and 10%, respectively.
Source: Own survey

1.00 for MIS users and 0.40 to 0.75 for MIS non-users. The means TE were 0.96 and 0.55 for MIS users and non-users, respectively. From the result, MIS users are highly technically efficient than MIS non-users. This might be explained by the efficient use of resources due to the use of management information system. However, there is room for improvement in technical efficiency of MIS users by 0.04 and more especially for MIS non-users, whose average technical efficiency is low compared to the one of MIS users. The mean technical efficiency of MIS non-users might increase by 0.45, through the efficient use of management information system.

Effects of MIS on technical efficiency of MIS users

To assess the effects of MIS on technical efficiency of MIS users, Tobit regression model was estimated. The results were presented in Table 4. The sigma revealed the fitness of the model at 1% ($p < 0.01$) level of significance. The likelihood ratio chi-square of 39.13, with a p-value of 0.000, tells us that our model is statistically significant overall. In other words, it fits significantly better than a model with no predictors. The result of the model shows that four out of the eight MIS variables were found to have a significant influence on technical efficiency of MIS users in the study area. These variables included use of office automation system, availability of information, skill on management information system and number of failures.

Results showed that the use of office automation system was positive and statistically significant at 1% level of probability. This implies that technical efficiency increases when office automation system was used in agribusiness firms in the study area. This result confirms our expectations and is in line with Tantua and Osuamkpe (2019), who found that the use of office automation system such as computers, websites and scanners has a positive effect on efficiency and profitability of print media in Rivers State of Nigeria.

The coefficient of availability of information was positive and statistically significant at 1% level of probability, indicating that better access to information would result in high technical efficiency of MIS users. In that case, MIS provides information in short and long term for both accuracy and efficiency of business decisions of the firm. The positive effect of availability of information on technical efficiency of MIS users confirms the results of Handzic (2001) who claimed that the better the availability of information, the better the impact on both accuracy of business decisions and efficiency of the firm.

The coefficient of skill on MIS revealed that an increase in skill on MIS increases the technical efficiency of agribusiness firms. This means that knowledge on MIS improve the performance of management information system. Comparable results were reported by Munirat *et al.* (2014) who

Table 3: Percentage distribution of technical efficiency.

TE	Users		Non-Users	
	Frequency	Percentage	Frequency	Percentage
[0.40 - 0.50]			63	21.2
[0.50 - 0.60]			168	57.3
[0.60 - 0.70]			62	20.8
[0.70 - 0.75]			2	0.7
[0.90 - 0.93]	3	1.6		
[0.93 - 0.96]	39	21.4		
[0.96 - 1:00]	183	100	300	100
Maximum	0.99		0.75	
Minimum	0.90		0.40	
Mean	0.96		0.55	
Standard deviation	0.02		0.60	

Source: Own survey

Table 4: Effect of MIS on technical efficiency.

Variable	Coefficient	Standard error	t-value	p-value
Constant	0.939	0.0060	157.8800	0.0000
Easeofuse	0.0010	0.0009	1.0900	0.2760
Use of office auto syst	0.0035	0.0012	2.9100***	0.0040
Reliability	0.0005	0.0013	-0.3900	0.6970
Availability of inform	0.0036	0.0014	2.6300***	0.0090
Skill on MIS	0.0047	0.0013	3.7200***	0.0000
Timeliness	0.0021	0.0073	1.6300	0.1040
Numberoffailures	-0.0028	0.0013	-2.6000**	0.0320
Repairtime	-0.0034	0.0011	-0.3100	0.7590
Sigma	0.0140	0.0008	19.0100***	0.0000
LR chi2(8)	39.1300			
Prob > chi2	0.0000			
Log likelihood	512.6000			

***, **and * significant at 1, 5 and 10%, respectively.
Source: Own survey

reveals that majority of firms agreed that lack of adequate knowledge and skill on information technology and the ability to manage the MIS process is one of the major factor that reduce the efficient performance of management information system in Nigeria. Results also showed a negative and significant relationship between number of failures and technical efficiency of MIS users. This means that the more the number of failures increases, the more the technical efficiency of agribusiness firm decreases. However, some apparent failures might be a consequence of a limited appreciation of the uses for which MIS can be put into practice (Malmi, 1997).

Two samples t-test

A two-sample Student's *t*-test assuming unequal variances using a pooled estimate of the variance was performed to test the hypothesis that the means technical efficiency scores for MIS users and non-users were equal. From the result in Table 5, we reject the null hypothesis, since t (364.43) = 114.3, p = 0.000 and $t$cal>$t$tab. We conclude there is significant difference in technical efficiency between MIS users and non-users.

Table 5: Two samples t-test for differences in technical efficiency

Levene's test on equality of variances		T-test on significance of means			
F	**Sig.**	**t**	**Sig. (bilateral)**	**Difference in means**	**Difference in variances**
164.256	0.000	92.286	0.000	0.4164	0.0045
		114.275	0.000	0.4164	0.0036

Note: t tab at 1% is 2.576.
Source: Own survey

Conclusions

This paper has analysed the factors influencing the adoption of MIS and its effects on technical efficiency of agribusiness firms in Cameroon. The results reveal that users' satisfaction, purchased price of equipment and technology performance have a positive effect on MIS adoption, while fear of change in firm management, government regulation and complexity of MIS equipment discourage the adoption of MIS in agribusiness firms in the area studied. MIS users are far more technically efficient than MIS non-users. The difference in technical efficiency might be explained by a more efficient use of resources that can be attributed to the use of management information system by MIS users. However, there is room for improvement in technical efficiency more especially for MIS non-users, whose average technical efficiency is very low compared to MIS users. The application of a Tobit regression model to MIS users reveals that the use of an office automation system, the availability of information, skill in making use of the management information system and numbers of failures have a significant influence on the technical efficiency of MIS users in the study area. More explicitly, the use of an office automation system, the availability of information and skill in making use of MIS all play a crucial role in improving the technical efficiency of agribusiness firms adopting MIS.

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