Agricultural-Induced Environmental Kuznets Curve for South Africa: A Threshold Regression and ARIMA Forecasting Approach

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The purpose of the paper is to examine the impact of the agricultural sector on agricultural emissions in South Africa. To this end, we estimate an agricultural-induced environmental Kuznets curve (EKC) for South Africa between 1990 and 2022 using conventional and threshold regression frameworks. Our regression estimates reveal a 'humped-shaped' relationship between agricultural production and agricultural emissions whereby agricultural production produces lower agricultural emissions above threshold estimates of 4,876 and 6,100 metric tons of CO_2 emissions. Further investigations show that the South African economy has consistently remained above these thresholds since 2010. Moreover, a forecast analysis of the time series using ARIMA models shows that agricultural production is (emissions are) on an upward (a downward) trajectory. However, the forecasting analysis also shows that the South African agricultural sector is not scheduled to reach the net-zero emissions target by 2050. Altogether, these findings imply that whilst South Africa had followed a trajectory of sustainable development prior to the COVID-19 pandemic, the current trajectory may not be sufficient to attain the 2050 Sustainable Development Goals.

Keywords: agricultural sector, agricultural emissions, environmental Kuznets curve (EKC), threshold regression model, ARIMA forecasting, South Africa
JEL *Classification:* C22; C51; Q19; Q56

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Introduction

Our study examines the agricultural-induced environmental Kuznets curve (EKC) for South Africa with the purpose of determining whether the country's agricultural sector is on a path towards being climate neu-

tral. Notably, there has been much research focused on the impact of climate change on South Africa's agricultural production, and the general consensus drawn is that climate change has decreased the country's production yields of staple foods such as maize, soya beans, dry beans, and sunflower (Walker and Schulze 2006; Calzadilla et al. 2014; Tagwi 2022) whilst increasing crop water requirements for sustainable agricultural production (Olabanji et al. 2021). However, very little attention has been paid to the impact of South Africa's agricultural sector on climate change through greenhouse gas (GHG) emissions. Examining the latter, using the EKC, is equally if not more important for the fight against global warming, as such an analysis can reveal whether the technological advancements in the agricultural sector – that make production activities resilient to climate change – can simultaneously reduce GHG emissions from the agricultural sector whilst ensuring sustainable agricultural productivity.

Indeed, the agricultural sector has been the focal point of global policy discussion at the most recent COP28 meeting, with emphasis being placed on the role that sustainable agricultural systems can play in reducing GHG emissions whilst enhancing food security and production systems. These discussions are more relevant for African countries who are mainly dependent on climate-sensitive, traditional sectors like agriculture and mining for their livelihood and are thus more vulnerable to the adverse repercussions of climate change such as prolonged droughts, increased temperatures, soil degradation and crop diseases (Doku et al. 2021; Doku and Phiri 2022). The importance of the agricultural sector in promoting sustainable development in Africa has also been a focal point for African policymakers, as demonstrated at the inaugural 2023 Africa Climate Summit which birthed the 'Nairobi declaration' centred on '… *boosting agricultural yields through sustainable agricultural practices to enhance food stability while minimizing negative environmental impacts* …' (Dal 2023).

We take South Africa as a case study since the country has the highest emissions in Africa (Phiri and Nyoni 2023; Phiri and Sesoai 2024) whilst simultaneously boasting the largest agricultural land on the continent. Therefore, any actions taken by South Africa in her fight towards reducing the country's emissions have the potential to influence the trajectory of Africa's GHG emissions on a global scale. It is also not surprising that South Africa has received a bulk majority of climate financing from Annex I nations committed to the African continent, since the country has

in place the necessary infrastructure and governance to better operationalize the funding for adapting to and mitigating against climate change (Doku et al. 2021; Doku and Phiri 2022; Doku and Phiri 2023; Phiri and Doku 2024).

Figure 1 shows that emissions from South Africa's agricultural sector have been on a slightly downward trajectory since the commitment of climate financing to the country by Annex I nations during the 2009 Copenhagen accord. Conversely, agricultural production has mainly been on an uptrend and yet experienced the most significant surge in the post-2015 period despite the country facing severe drought episodes.

Moreover, the scatterplot between agricultural production and emissions in figure 2 reveals a 'humped-shaped' relationship reminiscent of the EKC, which theoretically hypothesizes on a two-phased emissions-productivity relationship where (i) 'scale effects' dominate during the earlier stages of development when there is much dependency on dirty energy usage for production (i.e. a positive relationship between agricultural production and emissions), (ii) 'technical effects' appear at a later stage of development when the economy is more reliant on cleaner energy technologies that increase productivity without damaging the environment (i.e. a negative relationship between agricultural production

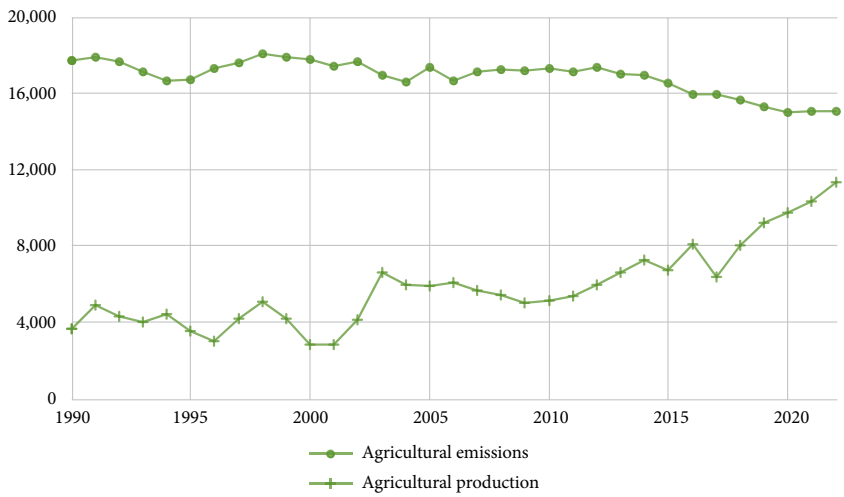

FIGURE 1 Time Series Plot Between Agricultural Emissions and Production (1990–2020)

NOTES Agricultural emissions is measured as carbon dioxide emissions from agriculture in Mt CO_2e. Agricultural production is measured as agricultural value added in millions of US$. Data is sourced from the World Bank Development Indicators.

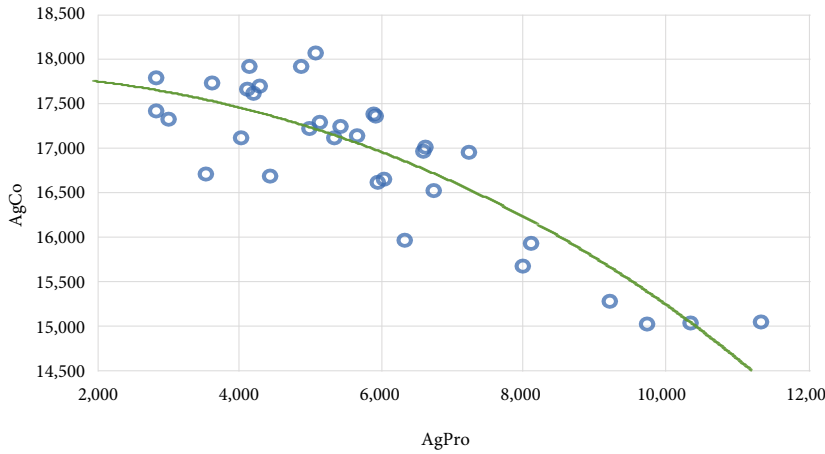

FIGURE 2 Scatterplot Between Agricultural Emissions and Production (1990–2020)
NOTES Agricultural emissions is measured as carbon dioxide emissions from Agriculture in Mt CO_2e. Agricultural production is measured as agricultural value added in millions of US$. Data is sourced from the World Bank Development Indicators.

and emissions). We therefore question whether there exists a significant agricultural-induced EKC relationship for the South Africa economy and, if so, which part of the curve the country is situated on?

The rest of the paper is structured as follows. The second section presents the literature review and the contribution of our study to existing knowledge in this field. In the third section the empirical framework and estimation methods are outlined. The fourth section describes data and presents a preliminary overview of the time-series. The fifth section presents empirical analysis whilst the sixth section concludes the study in the form of policy implications and avenues for future research.

Literature Review and Contribution of This Study

Several previous studies have investigated different forms of the agricultural-induced EKC curve (see table 1). We note that none of the studies presents country-specific research for the South African economy. In fact, all empirical evidence for South Africa is restricted to that presented in panel studies which include the country amongst a host of developing, emerging and industrialized economies (Ogundari et al. 2017; Parajuli et al. 2019; Cetin et al. 2022; Shah et al. 2022; Trofimov 2024). Most of these studies use the conventional method of regressing emissions on economic growth and its squared term whilst including agricultural production as a control variable in the regression. In this sense,

TABLE 1 Summary of Previous Literature on Agricultural-Induced EKC

Author	Scope	Dependent variables	Independent variables	Methods	Results
Ogundari et al. (2017)	43 SSA countries (1990–2009)	AGRIC.CO_2	GDP, GDP^2, FOR, AGRIC, POP, TRADE, POL	FGLS	+ve effect of AGRIC on emissions
Zafeiriou et al. (2017)	Bulgaria, Czech Republic, Hungary (1970–2014)	CO_2	AGRIC, $AGRIC^2$	ARDL	Significant U-shaped agriculture-emissions relationship for Bulgaria and Czech Republic but insignificant for Hungary
Gokmenoglu and Taspinar (2018)	Pakistan (1971–2014)	CO_2	GDP, GDP^2, EC, AGRIC	FMOLS	+ve effect of AGRIC on emissions
Gokmenoglu et al. (2019)	China (1971–2014)	CO_2	GDP, GDP^2, AGRIC	ARDL	+ve effect of AGRIC on emissions
Gurbuz et al. (2021)	Azerbaijan (1992–2014)	CO_2	GDP, GDP^2, EC, AGRIC	ARDL	+ve effect of AGRIC on emissions
Parajuli et al. (2019)	86 countries (1990–2014)	CO_2	GDP, GDP^2, EC, FOR, AGRIC	GMM	+ve effect of AGRIC on emissions
Kułyk and Augustowski (2020)	6 CEE countries (1992–2012)	COS	AGRIC, $AGRIC^2$, GDP, POP, TRADE	GLS	Humped shaped agricultural-emissions relationship
Aziz et al. (2020)	Pakistan (1990–2018)	EF	GDP, GDP^2, FOR, AGRIC, RENEW	QARDL	AGRIC has a +ve and significant (insignificant) effect on CO_2 at quantiles below (above) 0.5
Cetin et al. (2022)	47 developing countries (1976–2017)	CO_2	AGRI., GDP, GDP^2	PMG, DOLS, FMOLS	+ve effect of AGRIC on emissions

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TABLE 1 *Continued from the previous page*

Author	Scope	Dependent variables	Independent variables	Methods	Results
Ntim-Amo et al. (2022)	Ghana (1980–2014)	CO_2	GDP, GDP^2, EC, AGRIC	ARDL	+ve effect of AGRIC on emissions
Shah et al. (2022)	BRICS (1990–2019)	CO_2	GDP, GDP^2, AGRIC, RENEW, ICT, HC	PMG	+ve effect of AGRIC on emissions
Ganie et al. (2024)	4 South Asian countries (1990–2019)	CO_2	GDP, GDP^2, AGRIC, $AGRIC^2$, RENEW, FIN	CS-ARDL	U-shaped agriculture-emissions relationship
Trofimov (2024)	74 developed and 70 developing countries (1990–2018)	$AGRIC.CO_2$	AGRIC, $AGRIC^2$	FMOLS, DOLS, PMG, POLS, Quantile regressions	Humped shaped agriculture-emissions relationship

NOTES GDP – Economic growth; GDP^2 – Square of GDP; AGRIC – Agricultural production; $AGRIC^2$ – Square of AGRIC; CO_2 – Carbon emissions; $AGRIC.CO_2$ – Carbon emissions from Agricultural sector; RENEW – Renewable energy consumption; FOR – Forestry land; ICT – Information communications technology; HC –Human capital; EC – Energy consumption; ELEC – Electricity consumption, POP – Population growth, TRADE – Trade openness, POL – Political stability, FIN – Financial development. ARDL – Autoregressive distributive lag; POLS – Pooled ordinary least squares; FMOLS – Fully modified ordinary least squares; DOLS – Dynamic ordinary least squares; PMG – Pooled mean group; CS-ARDL – Cross sectional autoregressive distributive lag; QARDL – Quantile autoregressive distributive lag; FGLS – Feasible generalized least squares; GLS – Generalized least squares.

asymmetric EKC dynamics are modelled between economic growth and emissions whilst the impact of agriculture on emissions is restricted to being linear, with most studies finding a positive effect on emissions. Only a few other studies directly model asymmetric relationships between emissions and agricultural productivity and yet the empirical evidence is mixed, with Zafeiriou et al. (2017) and Ganie et al. (2024) finding humped-shaped relationships, whereas Kułyk and Augustowski (2020) and Trofimov (2024) find U-shaped curves.

We build on previous studies by determining the fit of the agricultural-based EKC for South Africa between 1990 and 2022. Unlike previous studies, we make use of the threshold regression model of Hansen (2000) which endogenously estimates the turning point in the EKC and presents formal testing procedures to validate the significance of the estimated 'threshold value'. Notably, several studies have modelled EKC effects using threshold regressions (Sirag et al. 2018; Şentürk 2020; Simionescu 2021; Wang et al. 2022; Li et al. 2023; Yong et al. 2023; Çatik et al. 2024) and these methods are favoured since they provide a more rigorous search for turning points in the data compared to those produced by conventional 'kinked' regressions. Moreover, threshold regressions are preferable to other nonlinear methods such as the quantile regressions used by Aziz et al. (2020) which capture differences in the agricultural productivity–emissions relationship at various locational asymmetries and yet fall short of estimating the precise 'turning point' at which the relationship switches dynamics. This is important for our study as we intend to use the threshold estimates obtained from the threshold regressions as benchmarks to determine '*if and when*' the South African economy transitions from 'scaling' to the 'technical' phase of the EKC (Phiri et al. 2024).

Altogether, our study presents novel evidence validating a 'humped-shaped' relationship between agricultural production and agricultural emissions in South Africa. We specifically find that the country's agricultural sector has transitioned from 'scale effects' to 'technical effects' on the EKC at thresholds of between 4,876 and 6,100 metric tons and the country has consistently remained above these threshold levels in the post-2010 period. These findings, in isolation, imply that the South African agricultural sector has been on a path of sustainable development since the 2009 Copenhagen accord. However, in further conducting a time series forecast of the agricultural production and emissions variables using autoregressive integrated moving average (ARIMA) modelling

techniques, we observe that agricultural production has (emissions have) been on a downward (an upward) trajectory since the COVID-19 pandemic. The main policy implication drawn from these findings is that South Africa has not been on a development path since the COVID-19 pandemic, and the country is not positioned to achieve the SDG 2030 targets of doubling agricultural production by 2030 and reaching net-zero emissions by 2050.

Empirical Framework

TRADITIONAL FRAMEWORK

To examine the agricultural-induced Kuznets curve in South Africa, we follow the works of Kułyk and Augustowski (2020) and Trofimov (2024) and specify the traditional agricultural-induced EKC as:

$$AGRIC.CO2 = \beta 0 + \beta 1\, AGRIC + \beta 2\, AGRIC.SQ + \beta X\, CONTROLS + error \tag{1}$$

where CO_2 is greenhouse emissions from the agricultural sector, AGRIC is the agricultural production, AGRIC.SQ is the squared term on agricultural production which is intended to capture the nonlinear dynamics, CONTROLS are the conditioning variables as determined by theory and economic intuition, and error is a well-behaved error term with $N(0, \sigma^2)$ properties. Following the works of Ogundari et al. (2017), Kułyk and Augustowski (2020), Aziz et al. (2020), Shah et al. (2022), and Ganie et al. (2024) we select human capital (HUMAN), information and communications technology (ICT), renewable energy consumption (RENEW), foreign direct investment (FDI), and trade (TRADE). In line with theory, we expect negative coefficient estimates on the HUMAN, ICT, and RENEW variables and positive ones on the FDI and TRADE variables.

Based on the EKC regression (1), the β coefficients govern the nonlinear dynamics between agricultural production and emissions, with $\beta_1 > 0$, $\beta_2 < 0$, indicating traditional EKC dynamics (i.e. a humped U-shaped relationship), whereas $\beta_1 < 0$, $\beta_2 > 0$ indicates inverse EKC dynamics (i.e. a U-shaped relationship). To compute the turning point, we take the first derivative of equation (1) and equate to zero, i.e.

$$\frac{\partial (AGRIC.CO2)}{\partial (AGRIC.)} = \beta 1 + 2\beta 2\, AGRIC = 0, \tag{2}$$

and solving for the above, we obtain the turning point as:

$$AGRIC^{*} = \frac{-\beta_1}{2\beta_2}. \tag{3}$$

3.2 THRESHOLD REGRESSION

The second framework we use in our study is based on the threshold regression framework of Hansen (2000) from which we specify our 2-regime EKC regression model as:

$$\begin{aligned} AGRIC.CO2 = {} & \alpha_0 + \alpha_1 AGRIC + \alpha_2 HUMAN + \alpha_3 ICT \\ & + \alpha_4 RENEW + \alpha_5 FDI \\ & + \alpha_6 TRADE\ I.(qt \leq AGRIC) \\ & + \beta_0 + \beta_1 AGRIC + \beta_2 HUMAN \\ & + \beta_3 ICT + \beta_4 RENEW + \beta_5 FDI \\ & + \beta_6 TRADE\ I.(qt > AGRIC) + \varepsilon_t, \end{aligned} \tag{4}$$

where I. is an indicator function governing the regime-switching dynamics and q_t is the endogenous threshold value of the threshold variable, AGRIC. We compactly specify regression (4) in matrix format:

$$Y_t = \Theta' x_t + \delta' x_t(\gamma) + \varepsilon_t, \tag{5}$$

where the stacked values are θ' = α's and δ' = α'- β, and θ, δ and γ are the regressions parameters which are estimated as minimization of the sum squared errors function, $S_n(\theta, \delta, \gamma)$, i.e.

$$S_n(\Theta, \delta, \gamma) = (Y - X\Theta - X_\gamma \delta)'(Y - X\Theta - X_\gamma \delta). \tag{6}$$

The optimum value of γ is further obtained by minimizing of the concentrated sum of squared errors function, $S_n(\gamma)$, i.e.

$$S_n(\gamma) = S_n(\hat{\Theta}(\gamma), \hat{\delta}(\gamma), \gamma), \tag{7}$$

where and are the estimated values of θ and δ, and the true value of is obtained as:

$$\hat{\gamma} = \underset{\gamma \in \Gamma_n}{\operatorname{argmin}} S_n(\gamma). \tag{8}$$

A direct way of testing the significance of a threshold effect is to formulate the following null hypothesis:

$$H_0: \alpha_i = \beta_i \tag{9}$$

However, since the threshold is not identified under the null hypothesis in (9), conventional F-tests are unreliable as they produce non-standard distributions. Hansen (1996) thus proposes the use of the bootstrap technique to simulate the asymptotic distribution of a likelihood ratio (LR) test on the following hypothesis:

$$H_0: \gamma = \gamma_0 \tag{10}$$

and to reject for large values of LR(γ) where:

$$LR(\gamma) = \frac{S(\gamma) - S(\hat{\gamma})}{\hat{\sigma}^2}. \tag{11}$$

ARIMA FORECASTING MODEL

Lastly, we use an autoregressive integrated moving average (ARIMA) framework to forecast the future trajectories of the agricultural emissions and production time series. The baseline ARIMA model can be specified as:

$$\Delta Y_t = \alpha_o + \sum_{i=0}^{p} a_i \Delta Y_{t-i} + \sum_{j=0}^{q} b_i \Delta u_{t-i}, \tag{12}$$

where Y_t represents the main time series, u_t denotes the white noise error process, and p and q are the optimum lag lengths of the Y_t and u_t variables, respectively. Equation (12) can be expressed in backshift notation as:

$$(1 - \varphi_1 B - \ldots - \varphi_p B^p)(1-B)^d Y_t = c + (1 + \varphi_1 B + \ldots + \varphi_p B^p) u_t. \tag{13}$$

In modelling the ARIMA model we follow the Box et al. (1974) three-step procedure which consists of (i) identifying the optimal AR and MA lags of the model by selecting the model which produces the lowest Alkaike and Schwarz information criterion, (ii) estimating the ARIMA model using the maximum likelihood (ML) estimators, (iii) forecasting the ARIMA to use the model to iteratively generate h-ahead forecasts based on past values of Y_t and u_t.

Data Descriptions and Preliminary Analysis

To conduct our empirical analysis, we make use of 9 time series variables whose description and source are provided in table 2.

Table 3 summarizes the summary statistics and integration properties of the time series. The standard deviations are relatively large numbers compared to their mean values, implying that the series are highly volatile. Moreover, the reported p-values of the Jarque-Bera statistics all reject the hypothesis of a non-normally distributed series and hence indicate possible nonlinearity in the series. This warrants the use of nonlinear estimators in our empirical analysis. Moreover, the Augmented Dickey-Fuller (ADF) and Dickey-Fuller Generalized Least Squares (DF-GLS) unit root test, which test the null hypothesis of non-stationary behaviour in the time series, all fail to reject the unit root hypothesis in all series except for GOVERN, FDI and trade variables. We therefore log-linearize

TABLE 2 Description of the Data Used

Variable	Symbol	Source
Carbon dioxide emissions from Agriculture (Mt CO_2e)	AGRIC.CO_2	WDI
Agriculture value added (Constant 2015 US$)	AGRIC.PROD	WDI
Squared term of agriculture value added (Constant 2015 US$)	AGRIC.$PROD^2$	OWN
Human capital index	HUMAN	PWT
Governance effectiveness index	GOVERN	WGI
Individuals using internet as a % of the population	ICT	WDI
Renewable energy consumption as a % of total energy consumption	RENEW	WDI
Foreign direct investment as a % of GDP	FDI	WDI
Trade as a % of GDP	TRADE	WDI

NOTES WDI – World Development Indicators; WGI – World Governance Indicators; PWT – Penn World Tables; OWN – own computation.

TABLE 3 Summary Statistics and Unit Root and Preliminary Correlations

Series	Mean	Standard deviation	Jarque-Bera	ADF	DF-GLS
AGRIC.CO^2	16874.65	879.4622	0.00	−1.68	−0.32
AGRIC.PROD	5806.302	2145.229	0.12	−1.84	−2.08
AGRIC.$PROD^2$	38175691	29343363	0.00	−1.47	−1.08
HUMAN	2.372978	0.348474	0.22	−1.95	−2.08
GOVERN	0.484620	0.391872	0.26	-3.94^{**}	-3.46^{**}
ICT	23.93101	26.58919	0.10	−2.01	−1.82
RENEW	12.19394	4.184117	0.12	−1.36	-2.92^{*}
FDI	0.606259	0.921935	0.00	-3.56^{**}	-3.62^{**}
TRADE	49.39234	8.483135	0.64	-3.48^{*}	-3.24^{**}

NOTES '***', '**', '*' denote the 1%, 5% and 10% significance levels, respectively.

the remaining time series to obtain stationarity of the variables, which is crucial for ensuring compatibility with our estimators.

Empirical Results

CONVENTIONAL EKC REGRESSION ESTIMATES

Table 4 presents the findings from the conventional OLS estimators. Note that we estimate 8 regressions, with regression (1) presenting the agricultural-based EKC regression estimated with no control variables, and regressions (2) – (7) including each control variable, whilst regression (8) includes all control variables. Recall that the agricultural emissions and production variables are estimated in their natural logs and therefore we exponentiate the estimated turning values to obtain the true values of these 'optimum points'. To ensure that the regression is robust to serial correlation and heteroscedasticity we use 'Newly-West' standard errors.

In all regressions, we find positive (negative) and significant coefficients on the AGRIC (AGRIC.SQ) and estimate a variety of threshold values ranging from 3,103 (regression 4) to 4,273 (regressions 5 and 7). These findings of a humped-shaped relationship between agricultural production and emissions imply significant fit of the EKC for South Africa's agricultural sector and these findings complement those similarly found in the panel-based studies of Kułyk and Augustowski (2020) and Trofimov (2024). We also find some control variables, such as human capital governance and trade, become statistically significant once all controls are entered into the regression, i.e. regression (8). The positive (negative) signs on the trade (human capital and governance) variables imply that these control variables are harmful towards (helpful for) the environment and these findings concur with those in Ogundari et al. (2017) and Shah et al. (2022).

So far, we have only determined the shape of the EKC curve for South Africa's agricultural sectors and yet we have not determined on which part of the curve the economy currently lies. Therefore, we further analyse the results by plotting the time series for agricultural production between 1992 and 2022 against the range of threshold estimates to determine 'if and when' South Africa transitioned from the 'scale' to 'technical' phases of the EKC. From figure 3, we observe that South African production has continuously lay above the 'range of threshold' estimates reported in table 4 since early 2000. These observations depict that South Africa transitioned to the 'technical' phase of the agricultural-induced

TABLE 4 Threshold Regression Results

Dependent Variable: AGRIC.CO2								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.31	1.01	0.30	1.83	0.12	−0.37	0.20	0.91
	(0.83)	(0.58)	(0.85)	(0.45)	(0.94)	(0.87)	(0.89)	(0.67)
AGRIC. PROD	2.31	2.14	2.31	1.93	2.34	2.47	2.34	2.32
	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***
AGRIC. PROD^2	−0.14	−0.13	−0.14	−0.12	-0.0.14	−0.15	−0.14	−0.14
	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***
HUMAN		0.26						−0.35
		(0.26)						(0.00)***
GOVERN			−0.0009					−0.089
			(0.96)					(0.01)**
ICT				−0.0005				0.002
				(0.29)				(0.02)*
RENEW					0.0004			−0.004
					(0.83)			(0.29)
Log(FDI)						−0.003		−0.003
						(0.45)		(0.48)
TRADE							0.0005	0.001
							(0.44)	(0.09)*
Turning point	8.25	8.23	8.25	8.04	8.36	8.23	8.36	8.29
	[3844]	[3752]	[3844]	[3103]	[4273]	[3752]	[4273]	[3959]
R^2	0.80	0.82	0.80	0.82	0.81	0.81	0.81	0.90

NOTES '***', '**', '*' denote the 1%, 5% and 10% significance levels, respectively. P-values of regression estimates are reported in (). Natural value of threshold variable reported in [].

EKC, ultimately implying that country's agricultural sector is on a long-term environmentally sustainable path.

THRESHOLD REGRESSION ESTIMATES

Next, we present the results obtained from estimating 2-regime threshold regressions in table 5. Note that we estimate the same sequence of regressions used in our traditional analysis, thus yielding 8 regressions. The upper (lower) part of table 5 reports the coefficient estimates of the upper (lower) regimes of the nonlinear regression and captures the relationship between agricultural production and other control variables on agricultural emissions above (below) the threshold estimates. The estimated values of the thresholds, along with the LR statistics used to verify significant threshold effects, are reported at the bottom of table 5 and all reported statistics exceed their critical values at a 5% level of signifi-

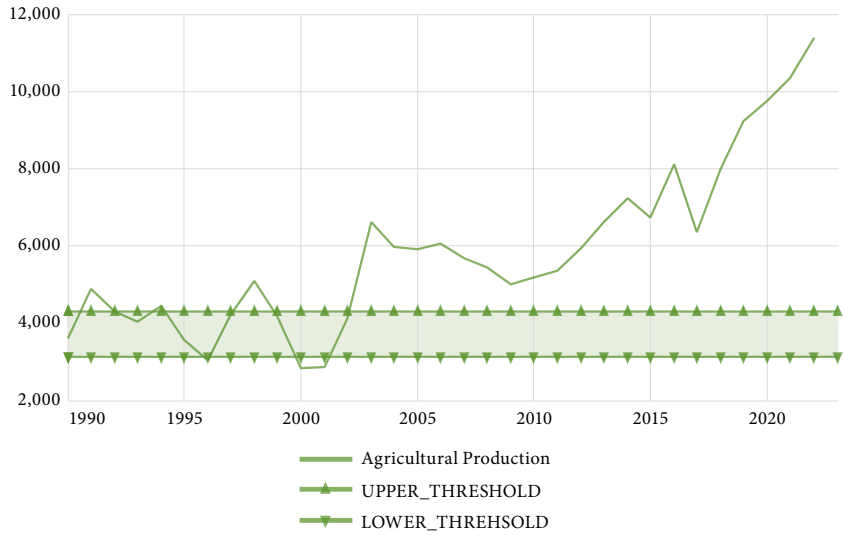

FIGURE 3 Agricultural Production Versus Estimated Thresholds (Conventional Model)

NOTE Vertical axis measures agricultural value added in millions of US$.

cance. Also bearing in mind that the main dependent and independent variables are in logarithm format, we exponentiate these values to obtain their 'original values'.

From table 5, we observe that the threshold estimates obtained from the threshold regressions range between 4,876 and 6,100, and these values are much larger compared to those obtained from the conventional estimators. Below these thresholds, agricultural production and the control variables produce insignificant estimates in regressions (1) to (7), yet produce a positive (negative) and significant effect of agricultural production and human capital (governance and trade) in regression (8). Above the threshold the dynamics switch, with agricultural production and human capital (governance and trade) variables producing positive (negative) coefficient estimates as observed in regressions (2), (3) and (8). Altogether, these findings from the threshold regressions confirm a humped-shaped relationship similarly obtained using traditional estimators. Considering that we obtain higher threshold estimates compared to the 'turning-points' computed by conventional estimators, this suggests the possibility of the economy transitioning from the lower regime to the upper regime at a later stage of development than previously thought. To test this possibility, we once again compare the evolution of agricultural

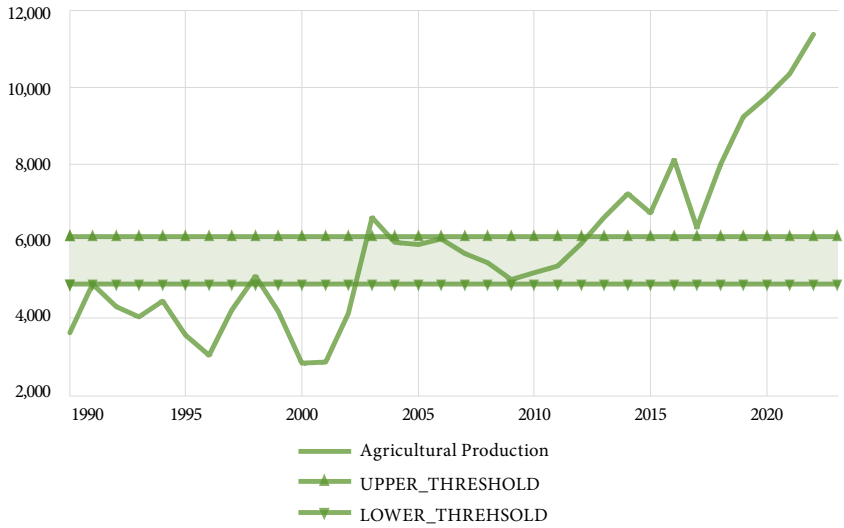

FIGURE 4 Agricultural Production Versus Estimated Thresholds (Threshold Model)
NOTE Vertical axis measures agricultural value added in millions of US$.

production against the estimated threshold points using the time series plot presented in figure 4. As can be observed, South Africa's agricultural production is found to be consistently higher than the range of threshold estimates in the post-2010 period.

ARIMA FORECASTS

Thus far, we have estimated the EKC and their optimum 'turning points' and have further found that the South African sector has already transitioned from the 'scale' phase to the 'technical' phase of the curve, which we treat as evidence of the agricultural sector being on a path of sustainable development. However, the analysis does not give a depiction of the trajectory of these variables in the long-term future, which has important policy implications since the Sustainable Development Goals (SDGs) are geared towards doubling agricultural productivity by 2030 whilst attaining zero-emissions by 2050. We therefore conduct an ARIMA forecasting exercise to determine the path of South Africa's agriculture emissions and production by 2050.

As a first step in the modelling process, we need to identify the optimum number of lags which produces the best fit of the ARIMA (p, d, q) regression for both agricultural emissions and production time series. Recall that the unit root tests found both series to be nonstationary,

TABLE 5 Threshold Regression Results

	Dependent variable: AGRIC.CO2							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Below threshold								
Constant	9.84 (0.00)***	9.58 (0.00)**	9.73 (0.00)***	9.64 (0.00)***	9.80 (0.00)***	9.84 (0.00)***	9.81 (0.00)***	9.97 (0.00)***
AGRIC. PROD	0.009 (0.69)	8.46E−05 (0.99)	0.009 (0.83)	0.01 (0.76)	0.009 (0.83)	0.009 (0.71)	0.0003 (0.87)	0.004 (0.00)***
HUMAN		0.09 (0.34)						0.18 (0.00)***
GOVERN			−0.05 (0.12)					−0.089 (0.01)**
ICT				0.004 (0.14)				0.002 (0.76)
RENEW					−0.007 (0.15)			−0.078 (0.29)
FDI						0.0001 (0.98)		0.003 (0.48)
TRADE							−0.0003 (0.62)	−0.001 (0.09)*
Above threshold								
Constant	11.46 (0.00)***	11.26 (0.00)***	11.31 (0.00)***	11.25 (0.00)***	11.47 (0.00)***	11.32 (0.00)***	11.55 (0.00)***	12.67 (0.00)***
AGRIC. PROD	−0.19 (0.00)***	−0.16 (0.00)***	−0.18 (0.00)***	−0.17 (0.00)***	−0.20 (0.00)***	−0.18 (0.00)***	−0.22 (0.00)***	−0.24 (0.00)***
HUMAN		−0.06 (0.04)*						−0.04 (0.00)***
GOVERN			0.04 (0.09)*					0.89 (0.01)**
ICT				−0.0004 (0.23)				−0.001 (0.42)*
RENEW					0.002 (0.21)			0.004 (0.29)
FDI						0.006 (0.55)		−0.003 (0.48)
TRADE							0.002 (0.17)	0.001 (0.09)*
R^2	0.83	0.86	0.86	0.85	0.85	0.83	0.84	0.88
Threshold value	8.69 [5984]	8.49 [4876]	8.49 [4876]	8.49 [4876]	8.49 [4876]	8.69 [5984]	8.69 [5984]	8.71 [6100]
LR test	33.32***	32.12***	41.75***	21.28***	37.87***	29.89***	35.60***	46.71***

NOTES '***', '**', '*' denote the 1%, 5% and 10% significance levels, respectively. P-values of regression estimates are reported in (). Natural value of threshold variable reported in [].

I(1) processes, hence, we model variables using the autoregressive moving-average (ARMA) processes in their first differences i.e. d = 1. Moreover, we select the optimal lags for the ARIMA model by the minimization of AIC and SC information criterion, which find ARIMA (1, 1, 1) and ARIMA (1, 1, 2) processes to be most suitable for the agriculture emissions and productivity series, respectively.

Table 6 presents the maximum likelihood (ML) estimates of the ARIMA models and for both variables we observe a significant and positive coefficient on the AR part of the model and insignificant values for the MA processes. The Jarque-Bera and Ljung-Box statistics further indicate no autocorrelation in the ARIMA process and 'non-normality' of the regression's residual terms. Collectively, these findings imply that we can rely on our ARIMA models for forecasting purposes.

The forecast values of the agriculture emissions and productivity time series variables over a window period of 2023 to 2050 are presented in figures 5 and 6, respectively, and show that the future trajectory of agricultural production (emissions) is on a downward (upward) trend. This is interesting to note since agricultural production (emissions) was on an upward (downward) trajectory for periods prior to the COVID-19 pandemic and our forecast values indicate a switch in these trajectories over the long run. Notably, Kour (2023) similarly observes an upward future

TABLE 6 ARIMA (p, d, q) Models of Agricultural Production and Emissions

Coefficients	AGRIC.CO2 ARIMA (1, 1, 1)	AGRIC.PROD ARIMA (1, 1, 2)
C	0.39 (0.00)***	0.34 (0.00)***
AR(p)	0.91 (0.00)**	0.95 (0.00)***
MA(q)	0.26 (0.53)	−0.08 (0.68)
σ^2	0.79 (0.00)***	0.89 (0.00)**
Diagnostic tests (p-values)		
Jarque-Bera	0.42	0.81
Ljung-Box[4]	0.54	0.82
Ljung-Box[8]	0.78	0.96
Ljung-Box[12]	0.84	0.99

NOTES '***', '**', '*' denote the 1%, 5% and 10% significance levels, respectively. P-values of regression estimates are reported in (). Lag lengths of Ljung-Box test are reported in [].

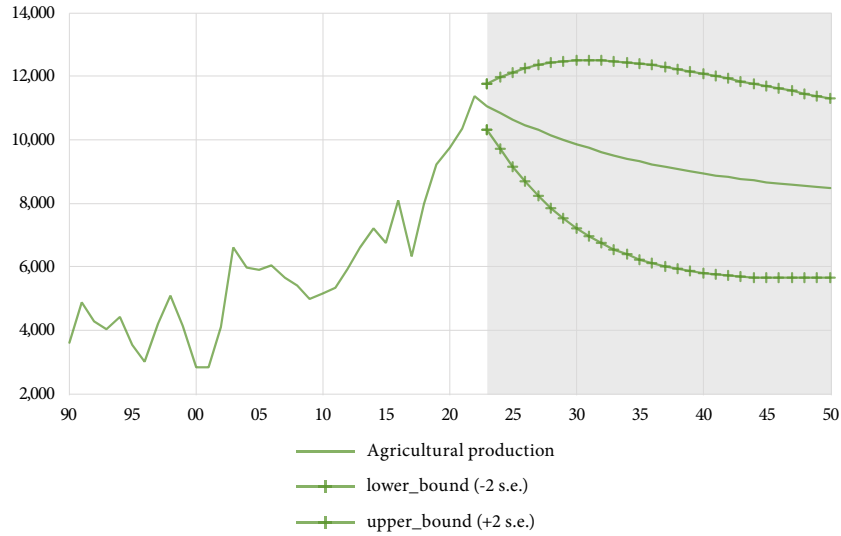

FIGURE 5 ARIMA (1, 1, 1) Forecast of Agricultural Production
NOTE Vertical axis measures agricultural value added in millions of US$.

trajectory of carbon emissions for the South African economy using similar ARIMA forecasting techniques. Moreover, our finding of a lowered future trajectory for agricultural production in South Africa is novel to the literature. Altogether, these trajectories still imply a negative relationship between the variables as they seem to move in opposite future directions, and yet these future paths are highly unsustainable and are not on course to achieving the SDGs.

Conclusion

There has been increasing awareness from global policy makers of the role which the agriculture sector can play in combatting climate change whilst ensuring sustainable food systems and security. To attain these global objectives, the SDGs highlight the need to double the current agricultural productivity by 2030 whilst achieving net zero emissions by 2050. The EKC presents a convenient theoretical framework which can be used to determine whether an economy or sector is on a path of sustainable development. We therefore estimate an agricultural-induced EKC for the South African economy between 1992 and 2022 using conventional and threshold regression analysis and use our results to examine whether the South African agricultural sector has crossed its inflexion point on the EKC.

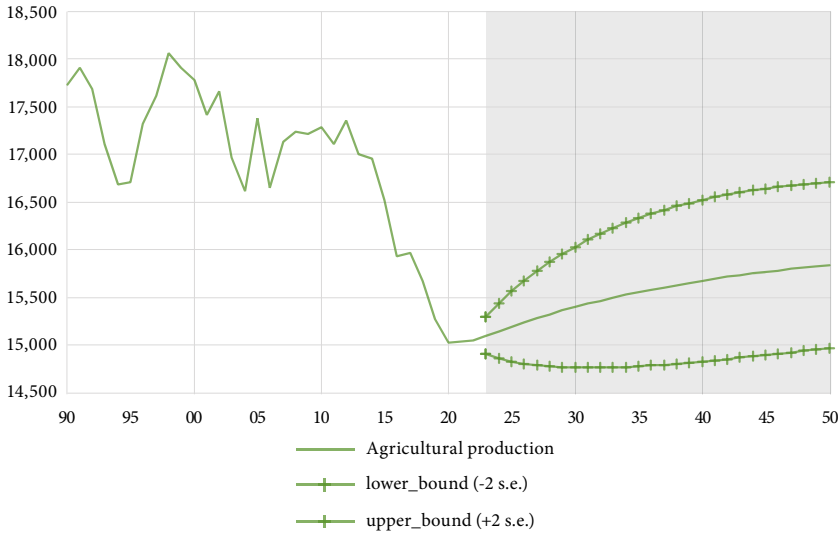

FIGURE 6 ARIMA (1, 1, 2) Forecast of Agricultural Emissions
NOTE Vertical axis measures agricultural value added in millions of US$.

Our study reveals that the South African agricultural sector crossed its inflexion point and has consistently remained above its threshold in the post-2010 period. These findings imply that South African agricultural emissions and productivity have maintained an inverse relationship since crossing its thresholds and these dynamics adhere to the theoretical underpinnings of the traditional EKC. However, our forecasting exercises show that the COVID-19 pandemic may have distorted the previous trajectory of increasing agricultural production whilst reducing emissions. Therefore, these variables are expected to have adverse trajectories in the long-term future whilst maintaining their 'expected' negative relationship.

Overall, our findings imply that whilst the South African agricultural sector had previously been on a sustainable development path, the forecasts of the productivity and emissions variables after the pandemic indicate otherwise. Importantly, we observe that the agriculture production (emissions) is (are) expected to decline (increase) in the long-term future and hence the economy is not on a sustainable path towards achieving the 2030 and 2050 SDG targets. Therefore, policymakers need to focus their energies on finding ways of changing the adverse trajectories of both agriculture production and emissions forecast after the COVID-19 pandemic.

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