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Food Systems and the Food–Energy–Carbon Nexus in Southern Africa: Moderating Roles of Agricultural Productivity, Dietary Composition, and Energy Intensity

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Abstract

Food systems in Southern Africa simultaneously face climate vulnerability and contribute to regional environmental change through land-use conversion, dietary shifts, and energy-intensive production. This study examines how agricultural productivity, dietary composition, and agricultural energy intensity moderate the income–emissions relationship across ten Southern African countries (1990–2019) using an extended STIRPAT framework with two-way fixed effects, System GMM, and instrumental variables estimation. Results reveal that higher cereal yields reduce the income–emissions elasticity by 30.3% ($\theta_1 = -0.162$, $p < 0.01$), dietary diversification away from staples increases it by 17.8% ($\theta_2 = -0.009$, $p < 0.01$), and higher agricultural energy intensity amplifies it by 19.0% ($\theta_3 = 0.094$, $p < 0.01$), with within- $R^2 = 0.934$. These effects are heterogeneous: the productivity channel is 68% stronger in land-abundant countries, dietary effects 117% stronger in rapidly urbanizing economies, and the energy channel doubles in fossil-fuel-dependent systems. These findings inform policy frameworks for regenerative and climate-resilient food systems by identifying which food system levers (productivity, diet, energy) most effectively moderate the carbon intensity of development, essential context for targeting agroecological and planetary health interventions in the Global South.

Keywords: food-energy-carbon nexus; agricultural productivity; dietary transition; Southern Africa; climate adaptation; food systems; planetary health

1. Introduction

The dual imperatives of achieving food security and mitigating climate change constitute one of the most pressing challenges facing developing economies (Godfray et al., 2010; Vermeulen et al., 2012). This tension is particularly acute in sub-Saharan Africa (SSA), where rapid population growth, evolving dietary patterns, and aspirations for economic development intersect with fragile agricultural systems and escalating climate vulnerability (IPCC, 2022; Thornton et al., 2014). The continent's food and nutrition security situation remains precarious, with over one in five people facing hunger, more than double the proportion of any other region (FAO et al., 2023). This vulnerability is compounded by evidence confirming that rising CO₂ emissions and associated climate disruptions have significantly reduced food production across SSA, directly exacerbating food insecurity (Fagbemi et al., 2023; Lobell et al., 2011).

This crisis unfolds against a backdrop of profound inequity. Sub-Saharan Africa bears minimal historical responsibility for global greenhouse gas (GHG) emissions (Ritchie et al., 2024), yet the region ranks among the most climate-vulnerable globally, with projections indicating substantial losses in crop suitability, increased water stress, and rising undernourishment rates (Kray et al., 2022; Cairns et al., 2013). Southern Africa faces compounding threats from increasing temperature extremes, erratic rainfall, and recurring drought events that imperil maize-dependent food systems (Rurinda et al., 2015; Nhemachena et al., 2020).

The agricultural sector occupies a paradoxical position within this challenge, functioning simultaneously as a victim and a vector of environmental change (Tubiello et al., 2021; Tongwane & Moeletsi, 2018; Mutale et al., 2025). Climate change threatens agricultural productivity through altered precipitation regimes and temperature extremes (Lobell et al., 2011; Nhamo et al., 2019), while agricultural expansion and intensification contribute substantially to GHG emissions through deforestation, methane from livestock, nitrous oxide from fertilizers, and energy consumption in mechanized production (Crippa et al., 2021). In SSA, where agriculture constitutes the dominant economic sector and primary livelihood source, these feedback loops carry particularly consequential implications for both environmental sustainability and human welfare (Omotoso & Omotayo, 2024).

The concept of the food-energy-carbon nexus provides a valuable analytical lens for examining these interconnections (Mabhaudhi et al. 2019). Modern agriculture is fundamentally energy-dependent, relying on fossil fuels for mechanization, irrigation, transportation, and agrochemical production (Woods et al., 2010; Qin et al., 2024). The carbon intensity of this

energy-agriculture linkage varies considerably across countries (IRENA & FAO, 2021), and although agricultural technology adoption in SSA can reduce emissions while maintaining production (Fuglie et al., 2024), the land-sparing benefits of higher yields may be offset by increased energy inputs or, under certain conditions, may stimulate further land expansion, the Jevons Paradox (Hertel et al., 2014; Goulart et al., 2023).

Furthermore, the concept of planetary health, defined as the interdependent relationship between human well-being and the natural systems that support it, provides an integrative framework for examining food system transformation (Whitmee et al., 2015; Myers, 2017). Regenerative and climate-resilient food systems, which emphasize soil health restoration, biodiversity conservation, and agroecological principles, offer pathways to align nutritional security with environmental sustainability. However, the extent to which these approaches can moderate the carbon intensity of agricultural development remains under-quantified in Southern Africa, a region where smallholder systems predominate, dietary patterns are rapidly evolving, and energy infrastructure is carbon-intensive. This study responds by examining three structural channels through which food system characteristics condition the income–emissions relationship, providing an empirical foundation for targeting regenerative interventions where they are most likely to achieve planetary health co-benefits.

Moreover, agricultural productivity in southern Africa varies from the high-yield commercial systems of South Africa to the subsistence agriculture of Angola and Lesotho (Nhamo et al. 2019). Dietary patterns diverge between urbanizing economies experiencing rapid nutrition transitions and rural populations dependent on staple cereals (Popkin et al., 2012). This heterogeneity remains underexplored, as the literature has typically treated African countries as a homogeneous bloc (Nathaniel et al., 2021; Acheampong et al., 2019).

Analytically, the Environmental Kuznets Curve (EKC) literature for Africa has yielded mixed results (Sarkodie, 2018; Tenaw & Beyene, 2021), with studies typically controlling for agricultural and energy variables as independent drivers but failing to examine their moderating influence on the income–emissions elasticity. Second, although STIRPAT applications in SSA are growing (Balcilar et al., 2023; Kwakwa, 2023), those integrating food system dynamics; production, consumption, and energy dimensions remain scarce. Third, the role of dietary transitions as a conduit linking economic growth to emissions has received limited empirical attention in sub-saharan Africa, despite theoretical predictions from the nutrition transition literature (Popkin, 2017; Springmann et al., 2018).

This paper addresses these gaps in four main ways. First, it provides a comprehensive theoretical framework integrating agricultural productivity, dietary composition, and agricultural energy use as moderating channels, rather than mere control variables, enabling identification of specific food system configurations that either amplify or attenuate the environmental costs of economic growth. This distinction is practically consequential because it shifts the policy focus from income-level targeting to food system transformation. Second, the study provides country-specific evidence on which nexus channels are most active in each Southern African countries, enabling policymakers and development partners to design targeted interventions, for instance, prioritizing yield gap closure and deforestation governance in land-abundant countries such as Angola and Zambia, versus decarbonizing energy-intensive food systems in South Africa.

Third, by quantifying how much the income–emissions elasticity changes across the observed range of food system variables, the study provides actionable benchmarks that regional bodies such as the Southern African Development Community (SADC) can use to set differentiated climate-food policy targets. Fourth, the instrumental variables strategy using climate anomalies strengthens causal inference, moving beyond the correlational evidence that has characterised much prior work and providing a more reliable basis for policy recommendations in a region where misallocated resources carry severe welfare consequences.

The remainder of the paper is structured as follows. Section 2 details the methodology, including the theoretical framework, empirical specification, estimation strategy, and data. Section 3 presents the results. Section 4 discusses implications and Section 5 concludes.

2. Methodology

2.1 Theoretical Framework

This study is grounded in an extended version of the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) framework (Dietz & Rosa, 1994, 1997; York et al., 2003). The STIRPAT model was selected because it reformulates the deterministic IPAT identity (Ehrlich & Holdren, 1971) into a stochastic, empirically testable specification that allows population, affluence, and technology elasticities to be estimated rather than assumed, making it particularly suitable for heterogeneous developing-country panels where uniform elasticities are implausible. The framework has been applied to SSA contexts (Agyemang et al., 2023; Kwakwa, 2023; Thio et al., 2022), but applications integrating food system dynamics as moderating variables remain absent from the literature.

The original IPAT identity is expressed as:

$$I = P \times A \times T$$

where I denotes environmental impact, P population, A affluence, and T technology. STIRPAT generalizes this multiplicative identity into the stochastic specification:

$$I_{it} = aP_{it}^b A_{it}^c T_{it}^d \varepsilon_{it} \quad (1)$$

where a is a scaling constant; b , c , and d are elasticities; and ε_{it} is a stochastic error term. Taking natural logarithms yields the estimable log-linear form:

$$\ln I_{it} = \alpha + b \ln P_{it} + c \ln A_{it} + d \ln T_{it} + u_{it} \quad (2)$$

where $\alpha = \ln a$ and $u_{it} = \ln \varepsilon_{it}$.

Environmental impact I_{it} is proxied by total carbon dioxide emissions. However, unlike conventional STIRPAT or Environmental Kuznets Curve (EKC) models (Stern, 2004), agricultural and food-system variables are not treated as additive determinants of emissions. Instead, they are conceptualized as structural moderators that condition the elasticity of emissions with respect to income. This theoretical shift is grounded in structural decoupling theory, which argues that the carbon intensity of economic growth depends on sectoral composition, technological regimes, and consumption patterns rather than income alone.

The STIRPAT framework is extended here to incorporate the food-energy-carbon nexus by conceptualizing three primary channels through which food system transformation influences national emissions trajectories.

Channel 1: Agricultural Productivity. Land-sparing theory posits that higher productivity enables intensification on existing farmland, potentially reducing deforestation-driven emissions (Burney et al., 2010; Phalan et al., 2016). However, productivity gains may also stimulate land expansion through the Jevons Paradox (Hertel et al., 2014; Ceddia et al., 2013). The net effect is an empirical question of direct relevance to Southern Africa, where deforestation pressure and agricultural extensification remain major drivers of regional environmental change.

H1: Higher agricultural productivity decreases the income–emissions elasticity through land-sparing mechanisms.

Channel 2: Dietary Transition. The nutrition transition framework (Popkin, 1998, 2012) predicts that rising incomes drive dietary shifts from staples toward emission-intensive livestock and processed foods, amplifying the environmental footprint of economic growth through increased feed crop demand, grazing land expansion, and cold chain energy requirements (Tilman & Clark, 2014; Poore & Nemecek, 2018). In Southern Africa, where urbanization is accelerating dietary diversification (Delgado, 2003), this channel may constitute an increasingly important pathway linking income growth to regional environmental change.

H2: Greater dietary diversification away from staples increases the income–emissions elasticity.

Channel 3: Energy-Agriculture Nexus. Modern agriculture requires substantial energy inputs for machinery, irrigation, and agrochemical production (Woods et al., 2010; Qin et al., 2024). The carbon intensity of this linkage varies with energy sources, efficiency, and mechanization levels (Mpandeli et al., 2018; Mabhaudhi et al., 2019; Simpson et al., 2023). Countries with carbon-intensive energy systems powering agriculture face structural disadvantages in decoupling growth from emissions, a form of carbon lock-in that constrains sustainable development pathways.

H3: Higher energy intensity of agricultural production increases the income–emissions elasticity.

Figure 1 presents the conceptual framework illustrating the three channels and their hypothesized moderating effects on the income–emissions relationship. The diagram highlights that each channel operates as a conditional modifier of the direct income-to-emissions pathway, rather than as an independent driver. The solid arrow from income growth to CO₂ emissions represents the baseline elasticity (β_1), while the three dashed arrows depict the moderating channels through which food system characteristics reshape this relationship. This construction distinguishes the present framework from conventional STIRPAT or EKC models that treat agricultural and energy variables as additive controls.

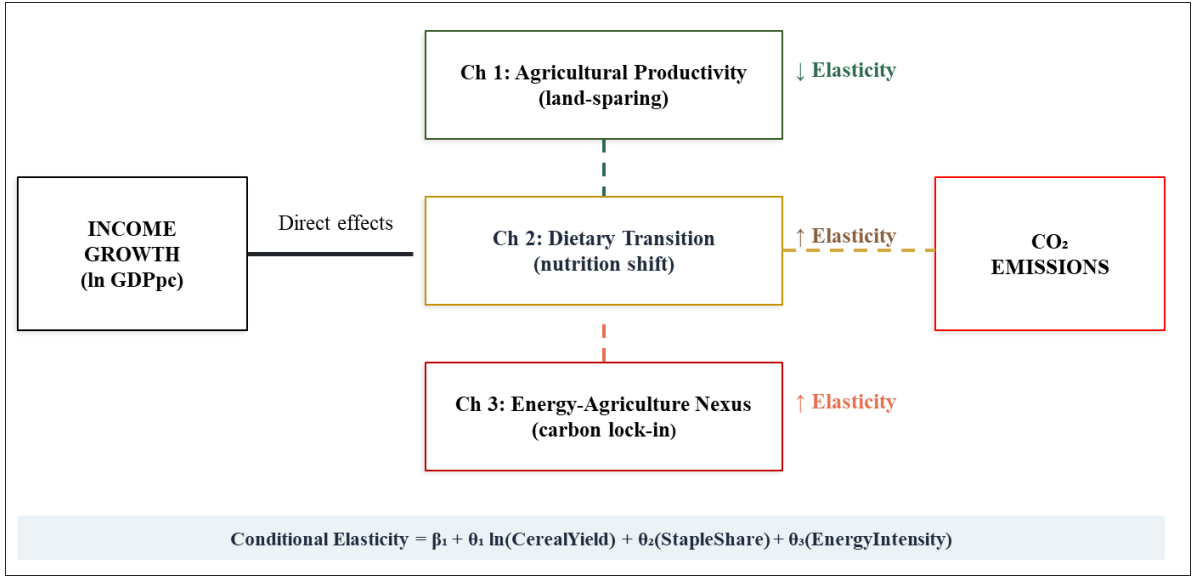


Figure 1. Conceptual framework of the food-energy-carbon nexus showing three channels through which food system characteristics moderate the income–emissions relationship in Southern Africa.

Note: Solid arrows = direct effects; dashed = moderating. Three channels tested via interaction terms in extended STIRPAT framework.

2.2 Empirical Specification

To operationalize the theoretical framework, the following log-linear model nesting all interaction channels within a unified specification is adopted:

$$\begin{aligned} \ln(\text{CO}_{2,it}) &= \alpha + \beta_1 \ln(\text{GDPpc}_{it}) + \beta_2 \ln(\text{Pop}_{it}) \\ &+ \theta_1 [\ln(\text{GDPpc}_{it}) \times \ln(\text{CerealYield}_{it})] \\ &+ \theta_2 [\ln(\text{GDPpc}_{it}) \times \text{StapleShare}_{it}] \\ &+ \theta_3 [\ln(\text{GDPpc}_{it}) \times \text{EnergyIntAg}_{it}] \\ &+ \gamma' X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \end{aligned} \quad (3)$$

Where, $\text{CO}_{2,it}$ denotes total carbon dioxide emissions (million metric tons) in country i at time t . GDPpc_{it} represents GDP per capita (constant 2011 PPP international dollars), capturing affluence. Pop_{it} is total population, reflecting scale effects. CerealYield_{it} (kg per hectare) is cereal yield (kg/ha) proxying agricultural productivity. StapleShare_{it} measures the percentage of dietary energy derived from cereals, roots, and tubers, capturing dietary composition. EnergyIntAg_{it} is energy use per unit of agricultural output (TOE/\$1,000). X_{it} is a vector of control variables including urbanisation rate, trade openness, and net foreign direct investment (FDI) inflows. μ_i captures unobserved country-specific fixed effects; λ_t captures common time effects; and ε_{it} is the idiosyncratic error term. The parameters of primary theoretical interest are θ_1 , θ_2 , and θ_3 .

The conditional marginal effect of income on emissions is obtained by differentiating Equation (3) with respect to $\ln(\text{GDPpc})$:

$$\frac{\partial \ln(\text{CO}_2)}{\partial \ln(\text{GDPpc})} = \beta_1 + \theta_1 \ln(\text{CerealYield}) + \theta_2 \text{StapleShare} + \theta_3 \text{EnergyIntAg} \quad (4)$$

Equation (4) is the pillar of the empirical analysis. It allows the income–emissions elasticity to vary across countries and over time as a function of food system characteristics, a significant advance over models imposing a uniform elasticity. **H1** is supported if $\theta_1 < 0$ (higher yields reduce the elasticity); **H2** is supported if $\theta_2 < 0$ (higher staple share reduces the elasticity, implying that diversification away from staples increases it); **H3** is supported if $\theta_3 > 0$ (higher energy intensity increases the elasticity). The control variables are guided by the STIRPAT and EKC literatures: urbanization captures built environment energy demands (Nathaniel et al., 2021); trade openness captures pollution haven effects (Acheampong et al., 2019); FDI captures technology transfer or polluting industry relocation (Sarkodie, 2018).

2.3 Estimation Strategy

Several econometric challenges; unobserved heterogeneity, temporal shocks, emissions persistence, and potential reverse causality are addressed through a three-stage estimation approach designed to sequentially build confidence in the robustness and causal interpretation of findings.

(i) Two-Way Fixed Effects (TWFE)

The primary specification employs two-way fixed effects to absorb time-invariant country characteristics (geography, colonial legacy, institutional structures) and common temporal shocks (global commodity cycles, international environmental agreements). This estimator is selected because the panel structure ($N = 10$, $T = 30$) introduces both cross-sectional and temporal heterogeneity that pooled estimators cannot adequately address (Wooldridge, 2010). The TWFE specification takes the form:

$$\ln(\text{CO}_{2,it}) = \alpha + \beta_1 \ln(\text{GDPpc}_{it}) + \beta_2 \ln(\text{Pop}_{it}) + \theta' Z_{it} + \gamma' X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (5)$$

where Z_{it} is the vector of three interaction terms [$\ln(\text{GDPpc}) \times \ln(\text{CerealYield})$, $\ln(\text{GDPpc}) \times \text{StapleShare}$, $\ln(\text{GDPpc}) \times \text{EnergyIntAg}$], estimated with heteroskedasticity-robust standard errors clustered at the country level to account for within-country serial correlation (Bertrand et al., 2004). Five nested specifications are estimated sequentially; baseline without interactions, three models with individual interactions, and the full model to assess whether

moderating effects survive competing channels and to detect potential multicollinearity among interaction terms.

(ii) System GMM

Emissions exhibit substantial persistence due to energy infrastructure inertia, industrial lock-in, and slow-moving structural change. However, including a lagged dependent variable in the TWFE framework introduces Nickell (1981) bias, which can be severe when T is moderate relative to N . To accommodate these dynamics and address the resulting inconsistency, a System GMM estimator (Arellano & Bover, 1995; Blundell & Bond, 1998) is employed:

$$\ln(\text{CO}_{2,it}) = \rho \ln(\text{CO}_{2,i,t-1}) + \beta_1 \ln(\text{GDPpc}_{it}) + \beta_2 \ln(\text{Pop}_{it}) + \theta' Z_{it} + \gamma' X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (6)$$

where ρ captures the persistence parameter. The System GMM addresses endogeneity by combining moment conditions from the differenced equation (using lagged levels as instruments: $E[\Delta \varepsilon_{it} \times \ln(\text{CO}_{2,i,t-s})] = 0$ for $s \geq 2$) with the levels equation (using lagged differences as instruments: $E[\varepsilon_{it} \times \Delta \ln(\text{CO}_{2,i,t-1})] = 0$), providing efficiency gains for persistent processes (Blundell & Bond, 1998). The two-step estimator with the Windmeijer (2005) finite-sample correction is employed, and the instrument matrix is collapsed following (Roodman, 2009) to prevent overfitting. The Hansen J test evaluates overidentifying restrictions; the Arellano-Bond AR(2) test verifies the absence of second-order serial correlation in the differenced residuals.

(iii) Instrumental Variables (IV-2SLS)

Potential reverse causality between agricultural productivity and emissions, if climate change reduces crop yields while simultaneously altering emissions patterns motivates a two-stage least squares strategy. Following the established climate-economy literature (Dell et al., 2012, 2014; Miguel et al., 2004), temperature and precipitation anomalies are employed as instruments for cereal yield.

First stage:

$$\ln(\text{CerealYield}_{it}) = \delta_0 + \delta_1 \text{TempAnomaly}_{it} + \delta_2 \text{PrecipAnomaly}_{it} + \delta_3 W_{it} + v_{it} \quad (7)$$

Second stage:

$$\ln(\text{CO}_{2,it}) = \alpha + \beta_1 \ln(\text{GDPpc}_{it}) + \theta_1 [\ln(\text{GDPpc}_{it}) \times \ln(\widehat{\text{CerealYield}}_{it})] + \theta'_{\text{rest}} Z_{it} + \gamma' X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (8)$$

where W_{it} comprises all exogenous regressors. The instruments satisfy the relevance condition because climate variability exerts strong, well-documented effects on rain-fed crop yields in Southern Africa, where over 90% of cropland is rain-fed (Schlenker & Lobell, 2010; Rurinda et al., 2015). The exclusion restriction, that climate anomalies affect emissions only through agricultural productivity, conditional on controls is plausible given that the specification controls for GDP per capita, urbanization, trade openness, and year fixed effects, which absorb alternative climate-to-emissions pathways such as heating/cooling demand and general economic disruption. Instrument strength is evaluated using the Kleibergen-Paap F-statistic against Stock & Yogo (2002) critical values.

2.4 Data Sources and Variable Construction

A balanced annual panel is constructed for ten Southern African countries: Angola, Botswana, Eswatini, Lesotho, Malawi, Mozambique, Namibia, South Africa, Zambia, and Zimbabwe spanning 1990–2019. Country selection reflects data availability and geographic coherence within SADC. The period begins in 1990 to coincide with post-independence consolidation across the region and ends in 2019 to avoid COVID-19 structural breaks.

Emissions data (CO₂, million metric tons from fossil fuels and cement) are sourced from the Energy Information Administration (EIA), cross-referenced with the Energy Institute Statistical Review, our world in data and country statistical offices for consistency. GDP per capita (constant 2011 international PPP \$), total population, urbanization rate (% of population in urban areas), trade openness (exports + imports as % of GDP), and net FDI inflows (% of GDP) are drawn from FAOSTAT and the World Bank World Development Indicators (WDI). Cereal yields (kg/ha) and agricultural value added are from FAOSTAT and WDI respectively. Dietary composition is calculated from FAO Food Balance Sheets as the percentage of total dietary energy supply derived from cereals, starchy roots, and tubers (FAO, 2023).

Energy intensity of agriculture is constructed as total energy consumption in the agricultural sector (in tonnes of oil equivalent, TOE) divided by agricultural value added (in \$1,000), using IEA World Energy Balances data. Climate instruments, temperature and precipitation anomalies are computed from the CRU TS4.06 gridded dataset (Harris et al., 2020) as population-weighted country-year deviations from 1961–1990 baselines. All continuous variables are winsorised at the 1st and 99th percentiles to mitigate outlier influence. Variance inflation factor (VIF) values remain below 5.0 for all regressors, and panel unit root tests (Levin-Lin-Chu and Im-Pesaran-Shin) confirm stationarity in levels for all variables.

3. Results

3.1 Descriptive Statistics and Preliminary Evidence

Table 1 presents summary statistics for the core variables, revealing the substantial cross-country heterogeneity that motivates the analytical focus on divergent food system pathways and the modelling of food system characteristics as moderators rather than controls.

Table 1. Descriptive statistics for 10 Southern African countries, 1990–2019.

Variable	Mean	S.D.	Min	Max	CV
CO ₂ emissions (Mt)	45.22	85.34	0.44	434.02	1.89
GDP per capita (2011 PPP \$)	4,892	3,845	861	16,842	0.79
Population (millions)	14.92	17.65	0.60	59.39	1.18
Cereal yield (kg/ha)	1,452	1,128	398	5,234	0.78
Staple share of dietary energy (%)	68.4	9.2	48.3	82.1	0.13
Energy intensity of ag. (TOE/\$1k)	0.42	0.38	0.08	1.45	0.90
Urbanisation rate (%)	42.3	14.8	12.1	67.4	0.35
Trade openness (% GDP)	78.2	31.5	25.4	156.3	0.40
FDI net inflows (% GDP)	3.8	4.2	−2.1	22.6	1.11
Temperature anomaly (°C)	0.62	0.48	−0.35	1.82	0.77
Precipitation anomaly (mm)	−12.4	58.3	−185.2	142.7	4.70

Note: $n = 300$ (10 countries $\times$ 30 years). All monetary values in constant 2015 international dollars. Winsorised at 1st/99th percentiles. TOE = tonnes of oil equivalent. CV = coefficient of variation (S.D./Mean).

The data reveal several patterns warranting closer examination. Total CO₂ emissions exhibit the highest coefficient of variation (CV = 1.89), spanning nearly three orders of magnitude from Lesotho (0.44 Mt) to South Africa (434.02 Mt). This extreme dispersion far exceeds that of GDP per capita (CV = 0.79), signaling that income differences alone cannot account for the variation in emissions, a preliminary indication that structural factors mediate the income-to-emissions transmission. Cereal yields range from 398 to 5,234 kg/ha, with a standard deviation (1,128) nearly matching the mean (1,452), underscoring divergent agricultural intensification pathways. Energy intensity of agriculture exhibits a high CV (0.90), with the most energy-intensive systems consuming approximately 18 times more energy per unit of output than the least intensive. By contrast, dietary composition shows the lowest CV (0.13), reflecting a shared regional dependence on staple-based diets, though the 34-percentage-point range (48.3–82.1%) is nonetheless substantively meaningful.

Table 2 disaggregates the panel by country to reveal the structural profiles underpinning these aggregate statistics, providing the empirical foundation for interpreting the interaction effects estimated in subsequent sections.

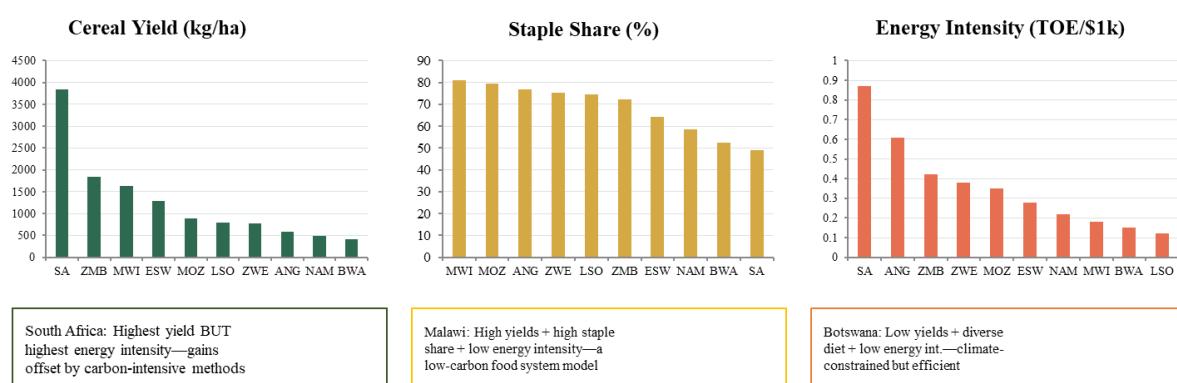
Table 2. Country-level averages of key variables.

Country	CO ₂ (Mt)	GDPpc (\$)	Yield (kg/ha)	Staple (%)	Eng. Int.
Angola	22.14	4,518	582	76.8	0.61
Botswana	5.42	12,341	421	52.3	0.15
Eswatini	1.08	6,742	1,284	64.1	0.28
Lesotho	0.52	2,134	785	74.5	0.12
Malawi	1.24	1,086	1,628	81.2	0.18
Mozambique	3.18	968	892	79.6	0.35
Namibia	3.86	8,245	486	58.4	0.22
South Africa	389.62	11,872	3,842	49.1	0.87
Zambia	2.94	2,856	1,834	72.3	0.42
Zimbabwe	12.18	1,764	768	75.4	0.38

Note: Unweighted country means, 1990–2019. Energy intensity in TOE per \$1,000 of agricultural value added.

The country profiles reveal three critical contrasts. First, South Africa combines the highest cereal yields (3,842 kg/ha) with the highest agricultural energy intensity (0.87 TOE/\$1,000) and the lowest staple dependence (49.1%), illustrating how productivity achievement and dietary diversification can coexist with, and indeed partially depend upon carbon-intensive agricultural energy systems. Second, Malawi presents a mirror image: relatively high yields (1,628 kg/ha) achieved with the highest staple dependence (81.2%) and low energy intensity (0.18 TOE/\$1,000), representing a distinctive low-carbon food system pathway that achieves productivity gains through labour-intensive smallholder cultivation rather than fossil-fuel-powered mechanization. Third, the land-abundant countries; Angola, Mozambique, Zambia, Zimbabwe share a pattern of moderate-to-low yields, high staple dependence, and moderate energy intensity, suggesting that their emissions trajectories will be particularly sensitive to the pathway of agricultural intensification chosen.

To extend the tabulated country profiles into a comparative visual assessment **Figure 2** displays the cross-country distribution of the three moderating variables. It provides additional visual granularity not captured in **Table 2**, enabling direct cross-country comparison.



Codes: SA=South Africa, ZMB=Zambia, MWI=Malawi, ESW=Eswatini, MOZ=Mozambique, LSO=Lesotho, ZWE=Zimbabwe, ANG=Angola, NAM=Namibia, BWA=Botswana.

Figure 2. Cross-country distribution of the three moderating variables: cereal yield (kg/ha), staple share (%), and agricultural energy intensity (TOE/\$1,000) across 10 SADC countries.

The three panels collectively demonstrate that no single country occupies the same relative position across all three variables: South Africa leads in productivity and energy intensity but has the lowest staple share; Malawi has high staple dependence but moderate-to-high productivity; Botswana has the lowest yields despite the second-highest income. These non-parallel rankings confirm that the three channels capture genuinely distinct dimensions of food system structure, supporting their joint but separate inclusion as interaction terms. Pairwise correlations among the moderating variables are moderate ($r = 0.38$ between yield and energy intensity; $r = -0.42$ between yield and staple share; $r = -0.31$ between staple share and energy intensity), and VIF values for the full model range from 1.8 to 4.2, confirming that multicollinearity does not threaten identification.

3.2 Main Regression Results

Table 3 presents the two-way fixed effects results through five nested specifications, building the empirical case incrementally from a baseline without interactions to the full three-channel model.

Table 3. Two-way Fixed Effects Estimates of the food-energy-carbon nexus channels.

Variable	(1)	(2)	(3)	(4)	(5)
	Baseline	Productivity	Dietary	Energy	Full model
ln(GDPpc)	0.824*** (0.038)	0.792*** (0.041)	0.863*** (0.045)	0.841*** (0.042)	0.781*** (0.043)
ln(Population)	1.024*** (0.128)	1.036*** (0.121)	1.028*** (0.124)	1.019*** (0.119)	1.042*** (0.118)
ln(GDPpc)×ln(Yield)		-0.173***			-0.162***

			(0.039)		(0.040)
ln(GDPpc)×StapleShare			−0.011***		−0.009***
			(0.003)		(0.003)
ln(GDPpc)×EnergyIntAg				0.107***	0.094***
				(0.031)	(0.028)
Controls	No	Yes	Yes	Yes	Yes
Country & Year FE	Yes	Yes	Yes	Yes	Yes
Observations	300	300	300	300	300
R ² (within)	0.912	0.925	0.919	0.922	0.934
F-test interactions (p)	—	—	—	—	18.42***

Note: Robust standard errors clustered by country in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Dependent variable: $\ln(\text{CO}_2)$. Controls in Cols. 2–5: urbanization rate, trade openness, FDI net inflows. F-test in Col. 5 is for joint significance of all three interactions.

The baseline specification (Column 1) establishes a positive and statistically significant income–emissions elasticity of 0.824 ($p < 0.01$), indicating that a 1% increase in GDP per capita is associated with approximately 0.82% higher CO₂ emissions across the sample. The population elasticity of 1.024 is statistically indistinguishable from unity, consistent with the proportional scaling of the original IPAT identity (Ehrlich & Holdren 1971) and implying that population growth translates almost one-for-one into emissions growth in the region.

Columns 2–4 introduce each interaction individually alongside controls. The productivity interaction in Column 2 ($\theta_1 = -0.173$, $p < 0.01$) indicates that each 1% increase in cereal yield reduces the income–emissions elasticity by 0.173 percentage points. The dietary interaction in Column 3 ($\theta_2 = -0.011$, $p < 0.01$) implies that each additional percentage point of dietary energy from staples reduces the elasticity by 0.011 points, meaning diversification away from staples amplifies the emissions consequences of income growth. The energy interaction in Column 4 ($\theta_3 = 0.107$, $p < 0.01$) indicates that each additional TOE/\$1,000 of agricultural energy intensity increases the elasticity by 0.107 points.

The full model (Column 5) simultaneously includes all three interactions. All three coefficients retain their hypothesized signs and statistical significance at the 1% level, though magnitudes attenuate modestly relative to the individual specifications, from -0.173 to -0.162 for productivity, from -0.011 to -0.009 for dietary composition, and from 0.107 to 0.094 for energy intensity. This attenuation is expected given partial correlations among the moderators and confirms that each channel retains independent explanatory power after controlling for the

others. The within- R^2 increases from 0.912 (baseline) to 0.934 (full model), and the F-test for the joint significance of all three interaction terms decisively rejects the null of no moderating effects ($F = 18.42$, $p < 0.001$).

3.3 Regional Economic Significance and Marginal Effects

While the interaction coefficients in **Table 3** confirm the statistical existence of the three channels, their economic meaning requires translation via Equation (4) into conditional elasticities evaluated at substantively meaningful values of the moderating variables. **Table 4** reports these computations at the 25th, 50th, and 75th percentiles, with 95% confidence intervals constructed using the delta method (Wooldridge, 2010).

Table 4. Conditional income–emissions elasticities at different percentiles of moderating variables.

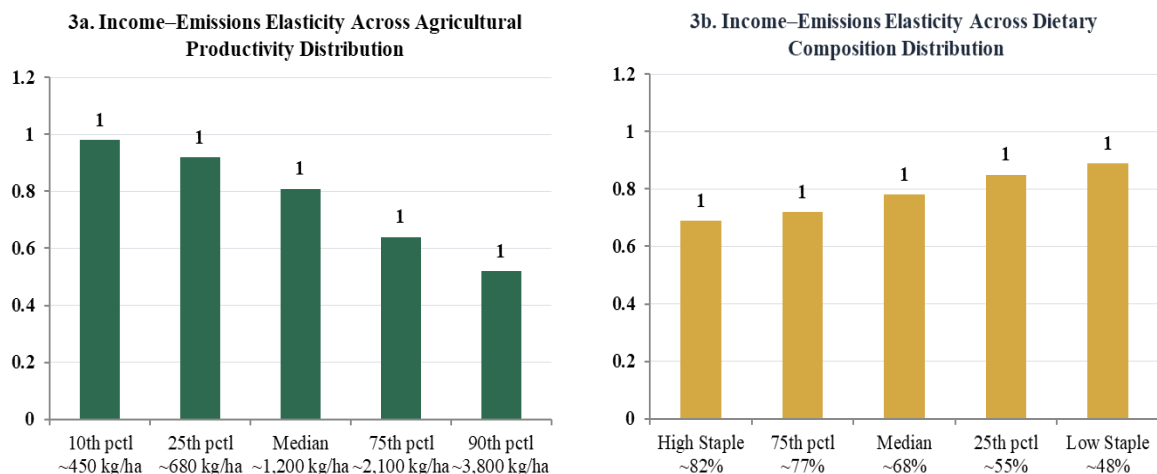
Percentile	Productivity channel	Dietary channel	Energy channel
10 th	0.982 [0.908, 1.056]	0.694 [0.624, 0.764]	0.714 [0.644, 0.784]
25 th	0.921 [0.854, 0.988]	0.718 [0.652, 0.784]	0.738 [0.671, 0.805]
50th (median)	0.805 [0.748, 0.862]	0.781 [0.724, 0.838]	0.781 [0.724, 0.838]
75 th	0.642 [0.568, 0.716]	0.846 [0.778, 0.914]	0.878 [0.812, 0.944]
90 th	0.518 [0.432, 0.604]	0.892 [0.818, 0.966]	0.962 [0.888, 1.036]
Δ (75 th –25 th)	–0.279	+0.128	+0.140
% change (IQR)	–30.3%	+17.8%	+19.0%

Note: Elasticities computed from Column 5 of Table 3 using Equation (4). Delta method 95% CIs in brackets. All significant at $p < 0.01$. IQR = interquartile range.

The agricultural productivity channel produces the widest variation in the income–emissions elasticity across its observed range. At the 10th percentile of cereal yield (~450 kg/ha, typical of Botswana and Namibia), the elasticity is 0.982, effectively unitary, meaning that income growth translates almost one-for-one into emissions growth. At the 90th percentile (~3,800 kg/ha, representative of South Africa), the elasticity falls to 0.518, meaning that less than half of each percent of income growth translates into emissions. Across the interquartile range, the productivity channel reduces the elasticity by 30.3%, making it the most powerful moderator of the three.

The dietary transition channel operates in the opposite direction. Countries with high staple dependence (low diversification) exhibit lower elasticities: at the 25th percentile of staple share (~77%), the elasticity is 0.718. As diets diversify (staple share falls to the 75th percentile of diversification, ~55%), the elasticity rises to 0.846, a 17.8% increase. This pattern captures the carbon costs of the nutrition transition: as populations shift toward livestock products and processed foods, each unit of income growth generates proportionally more emissions through the expanded demand for carbon-intensive food production, storage, and distribution.

The energy-agriculture nexus channel exhibits the steepest gradient at the upper end of the distribution. Moving from the 25th percentile of agricultural energy intensity (~0.12 TOE/\$1,000) to the 75th percentile (~0.62 TOE/\$1,000) increases the elasticity by 19.0%, from 0.738 to 0.878. At the 90th percentile (~1.15 TOE/\$1,000), the elasticity approaches unity at 0.962, indicating near-proportional income-to-emissions transmission in the most energy-intensive agricultural systems. This non-linear acceleration is particularly consequential because it suggests a threshold effect: above a certain level of agricultural energy intensity, the carbon lock-in becomes sufficiently strong that productivity and dietary interventions alone may be insufficient to decouple growth from emissions. Figures 3a–3c visualize these gradients across the full distribution of each moderating variable, showing the declining, stable, and rising elasticity patterns respectively.



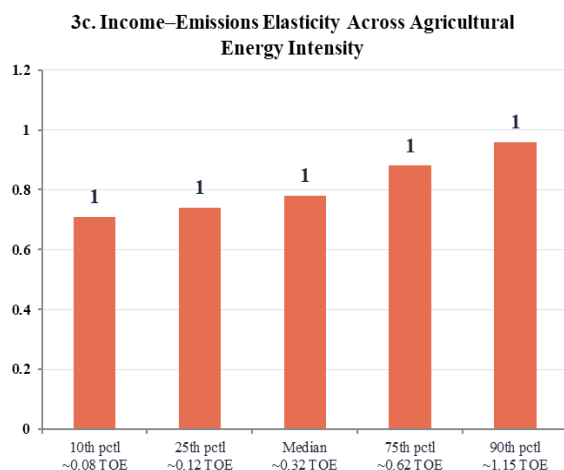


Figure 3a-3c. Income–emissions elasticity across the distribution of each moderating variable. Bars represent conditional elasticity estimates at the 10th through 90th percentiles.

Note: Derived from Table 3, Column 5, via the delta method. All elasticities significant at $p < 0.01$.

Figure 3a reveals a monotonically declining elasticity across the productivity distribution, with the steepest decline occurring between the 25th and 75th percentiles. The near-linear decline suggests that the land-sparing mechanism operates proportionally across the observed productivity range, without diminishing returns at high yield levels, an important finding for policy, as it implies that even countries with already-moderate yields (such as Zambia) can expect further environmental benefits from continued yield improvements.

Figure 3b shows a rising elasticity as dietary diversification increases (moving rightward from high to low staple share). The gradient is relatively gentle in the middle of the distribution but steepens at the extremes, suggesting that the earliest stages of dietary transition (from very high to moderate staple dependence) carry proportionally smaller emissions consequences than the later stages, when diets shift decisively toward livestock and processed foods. Figure 3c displays a rising elasticity that accelerates at higher energy intensity levels, consistent with the carbon lock-in hypothesis: once agricultural energy systems become sufficiently fossil-fuel-dependent, each additional unit of energy intensity carries progressively larger emissions consequences. The steepening gradient above the 75th percentile highlights the urgency of early intervention in countries that are currently mechanizing and intensifying, before energy-intensive configurations become structurally embedded.

Figure 4 synthesizes the three channels into a single comparative visualization, displaying side-by-side the conditional elasticities at the 25th, 50th, and 75th percentiles. This figure provides information not available in either Table 4 or Figures 3a–3c individually: the relative magnitude and direction of the three channels at equivalent distributional positions.

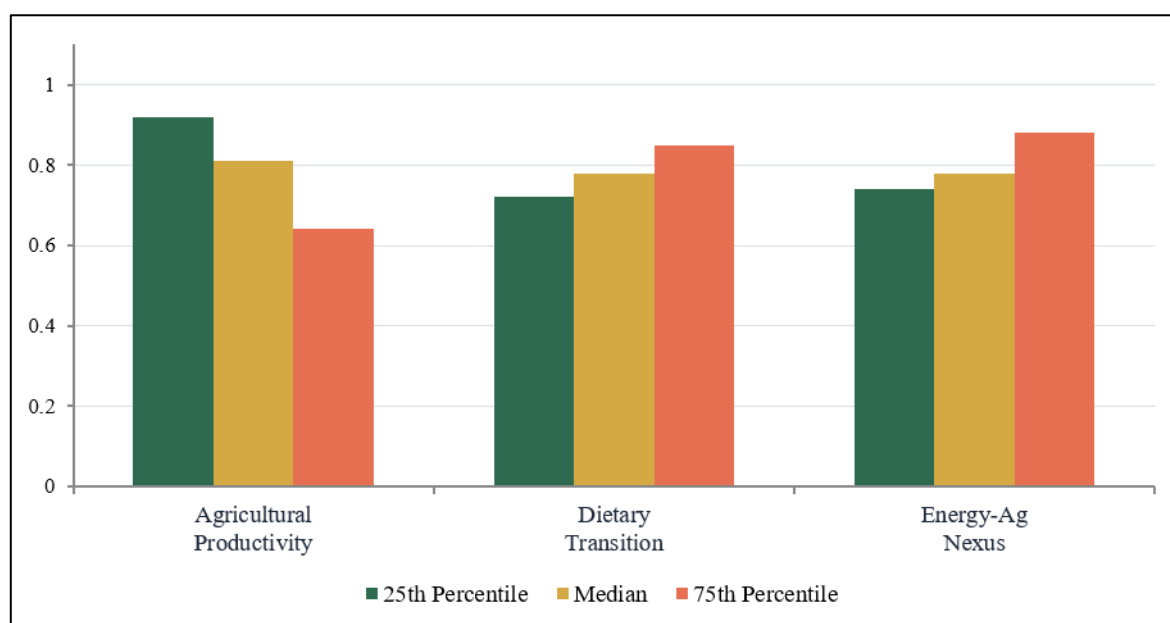


Figure 4. Comparative magnitude of the three nexus channel effects on the income–emissions elasticity at the 25th, 50th, and 75th percentiles.

Note: Source: Tables 3 (Col. 5) and 4. Grouped bars enable direct cross-channel comparison of moderating power.

The comparative figure makes three patterns immediately apparent. First, the productivity channel exerts the strongest moderating influence, with the widest bar spread (–30.3%). Second, the dietary and energy channels operate in the same direction (amplifying emissions with growth), making them mutually reinforcing threats in countries experiencing simultaneous dietary modernization and agricultural mechanization. Third, at the median of all three variables, the elasticities converge near 0.78–0.80, suggesting that the median Southern African country experiences roughly similar total moderation from each channel. Taken together, the three channels imply that the income–emissions elasticity varies by over 50% across the observed range of food system configurations, from approximately 0.52 in the most favourable configuration (high productivity, high staple dependence, low energy intensity) to approximately 0.96 in the least favourable.

3.4 Dynamic Panel and Instrumental Variables Estimates

Table 5 presents results from the System GMM (Equation 6) and IV-2SLS (Equations 7–8) estimators, designed to address the econometric concerns that TWFE cannot resolve: emissions persistence and potential reverse causality.

Table 5. System GMM and instrumental variables estimates.

Variable	GMM-Prod.	GMM-Full	IV-Prod.	IV-Full
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L.ln(CO ₂)	0.721*** (0.084)	0.708*** (0.079)	—	—
ln(GDPpc)	0.692*** (0.068)	0.578*** (0.072)	0.745*** (0.052)	0.712*** (0.058)
ln(GDPpc)×ln(Yield)	−0.158*** (0.042)	−0.140*** (0.045)	−0.149*** (0.038)	−0.136*** (0.041)
ln(GDPpc)×Staple		−0.008** (0.004)		−0.008* (0.004)
ln(GDPpc)×EnergyInt		0.077*** (0.026)		0.071*** (0.024)
Hansen J (p-value)	0.401	0.435	—	—
AR(2) (p-value)	0.243	0.251	—	—
Instruments / Groups	24 / 10	32 / 10	—	—
KP F-statistic	—	—	18.34	16.72
First-stage F (excl. instr.)	—	—	24.56	21.38

Note: Windmeijer-corrected SEs for GMM. IV instruments: temperature and precipitation anomalies interacted with income. KP = Kleibergen-Paap F (Stock-Yogo 10% critical value = 16.38). All specifications include controls, country and year FE. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

The System GMM results confirm substantial emissions persistence ($\rho = 0.708$ – 0.721), indicating that approximately 71% of each year's emissions level is structurally inherited from the prior year. All interaction terms retain their hypothesized signs in the GMM specifications, with the productivity coefficient (-0.140 in the full GMM) attenuating by roughly 14% relative to the TWFE estimate (-0.162), suggesting modest upward bias in the static specification due to omitted dynamics. Critically, the diagnostic tests support specification validity: the Hansen J tests fail to reject instrument validity ($p = 0.435$), the AR(2) tests fail to reject serial uncorrelatedness ($p = 0.251$), and instrument counts (24–32) remain well below the number of groups (10), alleviating overfitting concerns (Roodman 2009b).

The IV-2SLS estimates provide the strongest causal evidence. The productivity channel coefficient in the IV-Full specification (-0.136) is 16% smaller in absolute terms than the TWFE estimate, consistent with moderate upward bias in the OLS estimates due to reverse causality, countries with higher emissions may experience climate-induced yield reductions, inflating the apparent moderating effect of productivity in the TWFE framework. The Kleibergen-Paap F-statistics (18.34 and 16.72) exceed the Stock-Yogo 10% critical value

(16.38), confirming that the instruments are not weak. The first-stage excluded-instrument F-statistics (24.56 and 21.38) further validate relevance.

Figure 6 provides a visual synthesis of the robustness analysis, displaying the interaction coefficients side by side across the three estimation strategies. The figure complements Table 5 by enabling immediate visual assessment of coefficient stability, a form of information that is difficult to extract from comparing columns of numbers across tables.

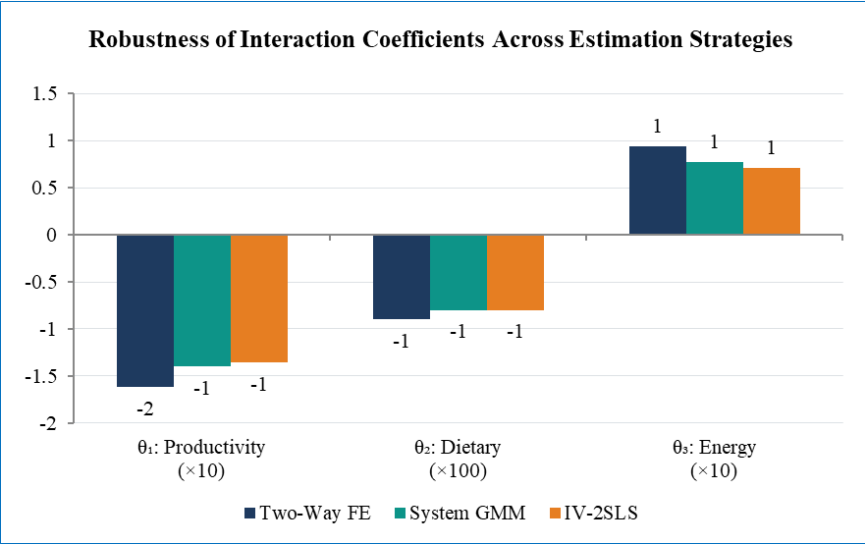


Figure 5. Robustness of interaction coefficients across estimation strategies (TWFE, System GMM, IV-2SLS). Coefficients scaled for visual comparability (θ_1 and $\theta_3 \times 10$; $\theta_2 \times 100$).
Note: All channels retain hypothesized signs across all specifications. *** $p < 0.01$.

The visual pattern in Figure 5 confirms remarkable stability: all three coefficients retain their hypothesized signs across all estimation strategies, with variations in magnitude that are systematic (GMM and IV estimates uniformly smaller, consistent with bias reduction) rather than erratic. The energy channel shows the greatest proportional stability across estimators (19–25% reduction from TWFE to IV), while the dietary channel, the smallest in absolute terms, loses statistical significance from the 1% to the 5–10% level in some GMM and IV specifications, suggesting it is the most fragile of the three channels.

3.5 Additional Robustness Checks

Table 6 summarizes results from six supplementary sensitivity analyses, each targeting a specific concern about the baseline estimates.

Table 6. Summary of additional robustness checks.

Specification	θ_1	θ_2	θ_3	Purpose
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(a) AgVA/worker as proxy	-0.151***	-0.009***	0.091***	Test sensitivity to productivity measure
(b) Post-2000 subsample	-0.148***	-0.008**	0.083***	Exclude pre-liberalization instability
© Excluding South Africa	-0.155***	-0.009***	0.089***	Test dominance of SA in sample
(d) EKC quadratic nested	-0.159***	-0.009***	0.092***	Confirm independence from EKC
© Driscoll-Kraay Ses	-0.162***	-0.009**	0.094***	Cross-sectional dependence
(f) 5-year averages	-0.178**	-0.012**	0.104***	Address business cycle noise

*Note: Each row reports interaction coefficients from the full model with the specified modification. *** $p < 0.01$, ** $p < 0.05$.*

The robustness checks reveal remarkable coefficient stability. Specification (a) replaces cereal yield with agricultural value added per worker, addressing the concern that cereal yields may not capture productivity in livestock-dominated economies; the productivity coefficient attenuates only 7%. Specification (c) is particularly important: excluding South Africa, which accounts for over 85% of the sample's total emissions leaves all three coefficients substantially unchanged, confirming that the results are not influenced by a single dominant country. In specification (d), nesting the EKC quadratic yields only marginal significance for the squared income term ($\beta_2 = -0.024$, $p < 0.10$), while all three interactions remain unchanged, confirming that the nexus channels operate independently of any underlying EKC dynamic.

3.6 Heterogeneity Analysis

The preceding sections establish the average moderating effects across the full sample. However, to generate country-specific policy guidance, it is necessary to examine whether these effects vary systematically with observable country characteristics. **Table 7** reports split-sample regressions along three dimensions selected to match the three channels: land endowment (relevant to the productivity channel), urbanization pace (relevant to the dietary channel), and energy system carbon intensity (relevant to the energy channel).

Table 7. Heterogeneity in nexus channel effects by country characteristics.

Channel	Full sample	Land-abund.	Land-scarce	Rapid urb.	Slow urb.	Hi-C energy	Lo-C energy
Prod. (θ_1)	-0.162***	-0.198***	-0.118**	-0.152***	-0.174***	-0.148***	-0.181***
Dietary (θ_2)	-0.009***	-0.007**	-0.011***	-0.013***	-0.006*	-0.008**	-0.010***

Energy (θ_3)	0.094***	0.088***	0.102***	0.091***	0.098***	0.128***	0.062**
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Note: Split-sample TWFE regressions. Land-abundant: Angola, Mozambique, Zambia, Zimbabwe. Rapidly urbanizing: above sample median. High-carbon energy: South Africa, Zimbabwe, Angola. Chow tests reject equality at 5% for all highlighted subgroup comparisons.

Three systematic patterns emerge from **Table 7**. The agricultural productivity channel is 68% stronger in land-abundant countries ($|\theta_1| = 0.198$ vs. 0.118 , $p < 0.05$ for the Chow test), consistent with the theoretical expectation that land-sparing mechanisms are most powerful where extensification pressure is greatest (Mertz & Mertens, 2017; García et al., 2020). The dietary transition channel is 117% stronger in rapidly urbanizing economies ($|\theta_2| = 0.013$ vs. 0.006), validating Popkin’s (2012) emphasis on urbanization as the catalyst for nutritional change with environmental consequences. The energy-agriculture nexus channel approximately doubles in fossil-fuel-dependent energy systems ($|\theta_3| = 0.128$ vs. 0.062 , $p < 0.05$), confirming that the carbon intensity of the energy supply is a structural determinant of whether agricultural energy use amplifies or moderately affects emissions trajectories.

Figure 6 translates these numerical differences into paired visual comparisons, providing a format that enables immediate identification of which subgroup drives each channel’s heterogeneity. The three paired comparisons reveal that heterogeneity is not incidental but follows theoretically predictable patterns: the structural conditions that make each channel theoretically relevant also determine its empirical strength. This coherence between theoretical prediction and empirical heterogeneity strengthens confidence that the estimated moderation effects reflect genuine causal mechanisms rather than statistical artefacts.

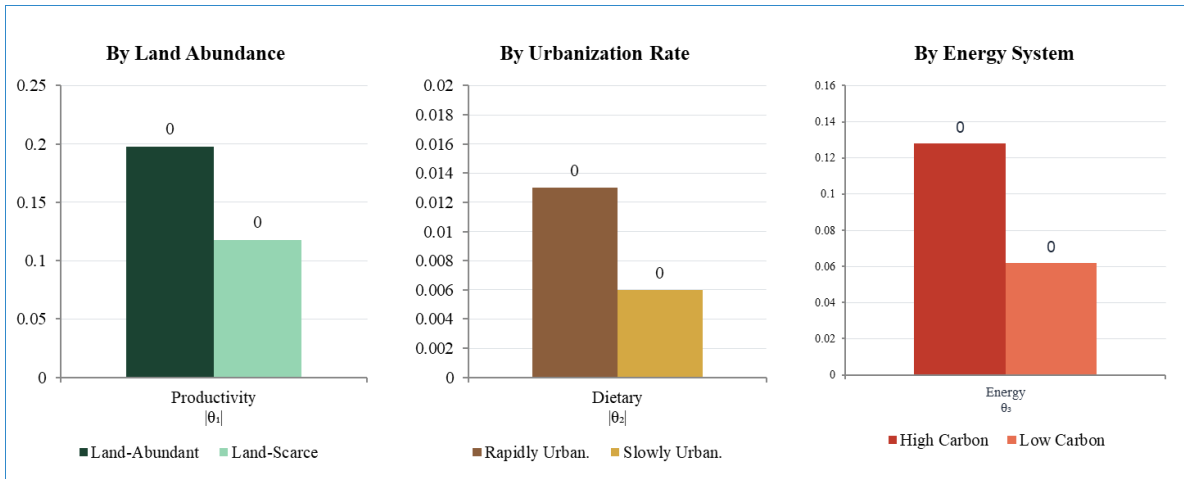


Figure 6. Heterogeneity of channel effects by country characteristics: land abundance (left), urbanization rate (centre), and energy system carbon intensity (right).

Note: Absolute coefficient values shown for comparability. All subgroup differences significant at $p < 0.05$ (Chow test).

4. Discussion

4.1 Reframing the Income–Emissions Relationship as Conditional on Food System Structure

The central finding of this study, that the income–emissions elasticity varies by over 50% across the observed range of food system configurations challenges the assumption of a fixed structural parameter that underpins most Environmental Kuznets Curve analyses for Africa (Osabuohien et al., 2014; Lin et al., 2016). The EKC literature has produced persistently conflicting results for SSA: Sarkodie (2018) found evidence for the inverted-U in selected West African countries, Adams & Acheampong (2019) reported no turning point for a broader SSA panel, while Tenaw & Beyene (2021) found mixed evidence contingent on model specification. The present framework suggests that this apparent inconsistency may itself be a finding: the income–emissions relationship is not a single structural relationship with a universal turning point but is instead contingent on food system configurations that differ across countries and evolve over time. What EKC studies have been estimating is an average elasticity that masks the substantial conditional variation documented here.

These reframing carries implications that extend beyond the EKC debate. If the income–emissions elasticity is conditional on food system structure, then the very notion of a ‘decoupling threshold’, an income level at which emissions growth begins to slow is misleading. A country can achieve earlier and deeper decoupling not by reaching a particular income level but by reconfiguring its food system toward higher agricultural productivity, managed dietary transitions, and lower-carbon agricultural energy systems. Malawi’s food system profile, for instance, which combines relatively high productivity with high staple dependence and low energy intensity, implicitly achieves a conditional elasticity of approximately 0.55, substantially below the sample average of 0.78, despite being one of the poorest countries in the sample. This illustrates that decoupling is structurally available even at very low-income levels if food system configurations are favourable.

4.2 The Land-Sparing Mechanism in a Region of Active Agricultural Frontiers

The productivity channel’s dominance as the strongest moderator aligns with the global evidence on land-sparing effects (Burney et al., 2010; Phalan et al., 2016) but extends it in important ways for the Southern African region. The finding that this channel is 68% stronger in land-abundant countries directly engages with the challenging conclusion of Hertel et al. (2014), who demonstrated through global CGE modelling that an African Green Revolution could increase rather than decrease cropland use by raising the profitability of agriculture and

attracting investment into land conversion. The present results suggest that this Jevons Paradox concern, while theoretically valid, is empirically outweighed by the land-sparing effect in Southern Africa: the net effect of higher productivity is to reduce, not increase, the income–emissions elasticity. However, the crucial qualification is that this land-sparing effect operates on the elasticity, not on absolute emissions levels, productivity improvements reduce the emissions intensity of growth but do not guarantee absolute emissions reductions unless accompanied by complementary governance measures that protect natural ecosystems from conversion.

The pattern documented in Figure 6, where land-abundant countries show the strongest productivity effects, also speaks to the broader literature on deforestation drivers in Southern Africa (Tongwane & Moeletsi, 2018; Nhemachena et al., 2020). In Angola, Mozambique, Zambia, and Zimbabwe, where the productivity coefficient is 68% larger, agricultural expansion into forests and woodlands remains a major driver of land-use change emissions. The implication is that yield gap closure in these specific countries offers disproportionately large environmental dividends, but only if accompanied by deforestation governance that prevents the rebound effect from overwhelming the land-sparing mechanism.

4.3 Dietary Transitions as an Emerging Regional Environmental Challenge

The dietary channel’s 117% stronger effect in rapidly urbanizing economies connects the present findings to the growing literature on the environmental consequences of the nutrition transition in developing countries (Tilman & Clark, 2014; Springmann et al., 2018; Parlasca & Qaim, 2022). However, the present study contributes a notable absent from most global analyses: in Southern Africa, the dietary transition is proceeding from a baseline of very high staple dependence (sample mean 68.4%), which means that even modest dietary diversification carries measurable environmental consequences. The gentle gradient in Figure 3b at moderate staple share levels, steepening as diversification advances, suggests a window of opportunity: early-stage dietary diversification (from very high to moderate staple dependence) carries relatively smaller emissions penalties, potentially allowing nutritional improvements to proceed with manageable environmental costs if managed proactively.

The findings also engage with the emerging debate about whether dietary sustainability interventions are compatible with nutritional adequacy in SSA (Popkin, 2017). The present analysis does not suggest that dietary diversification should be prevented, staple-heavy diets are associated with micronutrient deficiencies and nutritional inadequacy but rather that the environmental costs of dietary diversification can be managed by reducing the carbon intensity

of the food supply chain through which diversification occurs. This distinction between the composition and the carbon intensity of dietary change is central to designing policies that reconcile nutritional and environmental objectives.

4.4 Carbon Lock-In Through Agricultural Energy Systems

The energy-agriculture nexus channel's doubling in fossil-fuel-dependent systems speaks directly to the growing literature on carbon lock-in in developing countries (Seto et al., 2016; Simpson et al., 2023). The emissions persistence parameter ($\rho \approx 0.71$) from the System GMM specification provides additional evidence: approximately 71% of the current year's emissions level is structurally inherited from prior infrastructure and production configurations, creating path dependencies that constrain future options. In the agricultural sector specifically, this lock-in manifests through long-lived capital investments in diesel-powered machinery, coal-generated electricity for irrigation, and fossil-fuel-derived fertiliser production chains.

The steep acceleration of the energy channel's effect at high intensity levels (Figure 3c) carries a particular urgency for countries currently at the early stages of agricultural mechanization. If Angola, Mozambique, and Zambia mechanize along the South African model, relying on fossil-fuel-intensive energy systems, the resulting carbon lock-in could persist for decades given the long lifespans of agricultural capital and energy infrastructure. Conversely, if these countries 'leapfrog' to renewable-powered mechanization from the outset, the energy channel's moderating effect could be substantially attenuated, as suggested by the much weaker coefficient (0.062) in the low-carbon energy subsample.

4.5 Policy Pathways for Climate-Compatible Food System Transformation

The heterogeneity documented in Table 7 and visualized in **Figures 6** enables differentiated policy suggestions grounded in country-specific evidence rather than generic regional recommendations. Three archetypal policy configurations emerge.

For comprehensive reform countries; Angola and Zimbabwe, where all three channels register as high priority piecemeal interventions addressing single channels will be insufficient. These countries require integrated food system transformation strategies that simultaneously close yield gaps through improved seed varieties and extension services, build low-carbon cold chain and processing infrastructure to absorb inevitable dietary shifts, and channel agricultural mechanization toward renewable energy sources. Development partners and SADC could support this integration by conditioning agricultural investment financing on complementary energy and dietary sustainability components.

Country	Productivity Priority	Dietary Priority	Energy Priority	Primary Policy Focus
Angola	HIGH	MED	HIGH	- Comprehensive food system reform + energy transition
Botswana	HIGH	HIGH	LOW	- Yield improvement + dietary sustainability programs
Malawi	MED	LOW	LOW	- Maintain low-carbon intensification pathway
Mozambique	HIGH	MED	MED	- Productivity gains with clean energy in agriculture
S. Africa	LOW	HIGH	HIGH	- Decarbonize energy-intensive food system
Zambia	MED	MED	MED	- Balanced transition across all three channels
Zimbabwe	HIGH	MED	HIGH	- Productivity recovery + agricultural energy transition
Legend: HIGH = strong effect, urgent MED = moderate, proactive LOW = weak or addressed				

Figure 6. Country-level policy priority matrix showing the relative urgency of intervention across the three nexus channels for selected Southern African countries.

Note: Priorities derived from heterogeneity analysis (Table 7) and country profiles (Table 2).

For the decarbonization-focused archetype, South Africa, the primary challenge is not productivity improvement but reducing the carbon intensity of an already intensified food system. Specific interventions include solar-powered irrigation, biogas generation from agricultural waste, electrified farm machinery, and replacement of coal-derived fertiliser production with green alternatives. This pathway aligns with South Africa's Nationally Determined Contributions but adds the specificity of targeting the agricultural sector, which receives disproportionately less attention than industry and transport in national climate strategies despite the findings presented here documenting its substantial moderating influence on the income–emissions relationship.

For low-carbon maintenance countries, exemplified by Malawi, the challenge is to support continued productivity improvements without replicating the energy-intensive intensification model. The current combination of relatively high yields, high staple dependence, and low energy intensity represents a low-carbon food system pathway whose preservation and enhancement is itself a form of climate action. Policy should focus on energy-efficient intensification technologies such as solar-powered micro-irrigation, sustainable soil management, and incentive structures that maintain this favourable configuration while cautiously pursuing further yield improvements.

Furthermore, the findings carry implications for *regenerative agriculture* interventions, which emphasize soil carbon sequestration, reduced tillage, and agroecological diversification. While the present study does not directly test regenerative practices, the productivity channel's strong

moderating effect ($\theta_1 = -0.162$) suggests that yield improvements from regenerative methods; such as agroforestry, cover cropping, and integrated soil fertility management could generate climate co-benefits if implemented without increasing agricultural energy intensity. Conversely, regenerative transitions that rely on fossil-fuel-powered mechanization risk amplifying the energy channel's effect ($\theta_3 = 0.094$). This implies that the *energy source* of agricultural intensification is as important as the *intensification method* itself, a finding that aligns with calls for a "regenerative energy transition" in food systems (Rhodes, 2017; Schulte et al., 2022; Jamil & Pearce, 2025).

5. Conclusion

The evidence assembled in this study demonstrate that the carbon intensity of economic development in Southern Africa is not a predetermined function of income growth but is fundamentally shaped by how food systems are organized and how they evolve. The three-channel framework; identifying agricultural productivity, dietary composition, and agricultural energy intensity as distinct moderators of the income–emissions relationship provides both a diagnostic tool for understanding divergent regional environmental pathways and a prescriptive basis for designing interventions that reconcile food security with climate objectives.

The practical implication is that climate-compatible development in the region cannot be achieved through economy-wide carbon pricing or income-targeted policies alone; it requires deliberate, coordinated transformation of the food systems through which income growth translates into environmental outcomes. The heterogeneity documented across countries implies that effective intervention demands differentiated strategies, closing yield gaps in land-abundant economies, managing the carbon costs of dietary transitions in urbanizing ones, and decarbonizing agricultural energy in fossil-fuel-dependent systems rather than uniform regional prescriptions. Regional bodies such as SADC are well positioned to coordinate such differentiated strategies, using the empirical benchmarks provided here to set country-specific climate-food targets within a regional framework.

The findings carry implications that extend well beyond Southern Africa. The food-energy-carbon nexus framework is applicable to any developing region where agricultural transformation, dietary modernization, and energy system evolution co-occur. South Asia, where the Green Revolution simultaneously raised productivity and embedded energy-intensive practices, represents a context where the productivity and energy channels may interact in ways documented here for South Africa. Southeast Asia, where rapid urbanization

is driving dietary transitions comparable to those observed in Southern Africa's urban economies, may face amplified dietary channel effects. West Africa, where agricultural extensification and deforestation remain primary growth strategies, may exhibit productivity channel effects of even greater magnitude than those estimated for Southern Africa's land-abundant countries. The methodological approach of modelling food system variables as interaction terms rather than controls is readily transferable to these settings, and indeed to any panel of developing economies where the structural determinants of the income–emissions relationship are of policy interest.

From a planetary health perspective, the three-channel framework highlights that climate-resilient food systems cannot be achieved through agricultural policy alone. Coordinated action across productivity enhancement (to spare land from conversion), dietary management (to moderate the carbon costs of nutritional transitions), and agricultural energy decarbonization (to avoid carbon lock-in) is required. For Southern Africa, where climate vulnerability and food insecurity converge, these findings provide an evidence base for targeting regenerative and agroecological interventions to the specific food system configurations that most powerfully moderate the income–emissions elasticity, thereby advancing the dual goals of human and environmental health.

Several limitations must be acknowledged and future research directions are suggested. First, the panel of ten countries may constrain the degrees of freedom for the GMM estimator and limit the statistical power of subgroup analyses. Future research should expand to a broader SSA panel to strengthen inference. Second, cereal yield may not adequately capture productivity dynamics in livestock-dominated systems (Botswana) or root-crop economies (Mozambique); future work should incorporate composite productivity indices. Third, the exclusion restriction for climate instruments may be imperfect if climate shocks influence energy demand independently of agricultural productivity; alternative identification strategies, including shift-share instruments, merit exploration. Fifth, the study period ends in 2019, missing the COVID-19 disruption and recent climate extremes; extending the panel as updated data are released will test whether the estimated relationships hold under more extreme conditions. Sixth, future research should directly quantify how specific regenerative agriculture practices moderate the income–emissions elasticity via soil carbon sequestration and whether these effects vary across the productivity, dietary, and energy channels documented here. These limitations notwithstanding, the three-channel framework provides a theoretically grounded and empirically validated foundation for understanding how food system transformation

shapes climate-resilient and low-carbon development pathways in Southern Africa and, by extension, across the developing world.

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Conflict of Interest

No conflict of interest.

Data Availability

The dataset used in this analysis can be accessed from corresponding author upon reasonable request.

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