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Green Finance and Agricultural Sustainability: A Panel Data Analysis of Climate-Resilient Investment in Emerging Economies

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ABSTRACT

This study investigates the long-run relationship between green finance and agricultural sustainability in a balanced panel of 20 emerging economies over the period 2000–2022. This empirical study aims to analyze the impact of green finance on the long-run agricultural sustainability in emerging markets having focus on the impact of green bond issuance and ESG investments on agricultural total factor productivity using the Panel DOLS method. Agricultural Total Factor Productivity (TFP) is employed as the principal proxy for sustainability, while green finance is measured through green bond issuance and ESG-related investment flows. The analysis further incorporates climate-resilient agricultural investment as a mediating channel, alongside macroeconomic controls including GDP per capita, inflation, and rural population share. Panel Dynamic Ordinary Least Squares (DOLS) was employed to account for endogeneity, serial correlation, and cointegration dynamics. Complementary estimators—Fixed Effects and FMOLS—were also applied to validate robustness. A series of diagnostic tests confirmed the validity of model assumptions, with no evidence of heteroskedasticity, serial correlation, or multicollinearity. Results revealed that green bond issuance and ESG investments exerted a statistically significant and positive impact on agricultural productivity, whereas inflation and income-level disparities were found to be constraining factors. These findings highlight the transformative role of green finance in shaping sustainable agricultural outcomes in developing regions. The empirical strategy adopted herein offers policy-relevant insights for promoting climate-resilient investment frameworks in alignment with the Sustainable Development Goals (SDGs).

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Yeşil Finans ve Tarımsal Sürdürülebilirlik: Gelişmekte Olan Ekonomilerde İklim Dayanıklı Yatırımın Panel Veri Analizi

ÖZET

Bu çalışma, 2000-2022 döneminde 20 gelişmekte olan ekonomiden oluşan dengeli bir panelde yeşil finans ile tarımsal sürdürülebilirlik arasındaki uzun vadeli ilişkiyi araştırmaktadır. Tarımsal Toplam Faktör Verimliliği (TFP), sürdürülebilirliğin temel temsilcisi olarak kullanılırken, yeşil finans, yeşil tahvil ihraçları ve ESG ile ilgili yatırım akışları aracılığıyla ölçülmektedir. Analiz ayrıca, kişi başına GSYİH, enflasyon ve kırsal nüfus payı gibi makroekonomik kontrollerin yanı sıra, aracılık kanalı olarak iklime dayanıklı tarımsal yatırımı da içermektedir. Panel Dinamik Sıradan En Küçük Kareler (DOLS), içsellik, seri korelasyon ve eşbütünleşme dinamiklerini hesaba katmak için kullanılmıştır. Tamamlayıcı tahmin ediciler- Sabit Etkiler ve FMOLS - de sağlamlığı doğrulamak için uygulanmıştır. Bir dizi tanı testi, heteroskedastisite, seri korelasyon veya çoklu doğrusallığa dair hiçbir kanıt olmaksızın model varsayımlarının geçerliliğini doğrulamıştır. Sonuçlar, yeşil tahvil ihraçlarının ve ESG yatırımlarının tarımsal üretkenlik üzerinde istatistiksel olarak anlamlı ve pozitif bir etki yarattığını, enflasyon ve gelir düzeyi eşitsizliklerinin ise kısıtlayıcı faktörler olduğunu ortaya

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Panel DOLS

koymuştur. Bu bulgular, gelişmekte olan bölgelerde sürdürülebilir tarımsal sonuçları şekillendirmede yeşil finansın dönüştürücü rolünü vurgulamaktadır. Burada benimsenen ampirik strateji, Sürdürülebilir Kalkınma Hedefleri (SDG'ler) ile uyumlu iklime dayanıklı yatırım çerçevelerini teşvik etmek için politika açısından önemli içgörüler sunmaktadır

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INTRODUCTION

Global things stressing agriculture, such as climate change and resource degradation, alongside the growing issues of food insecurity, have overhauled the idea of agricultural sustainability in the 21st century. The agricultural sector is expected to continuously evolve and enhance productivity while protecting the environment. Developing countries face unique challenges, especially emerging economies that seek to modernize their food systems while grappling with climatic vulnerabilities and structural constraints them more vulnerable. Thus, there is a growing need for financing mechanisms that are climate sensitive and not growth-centered.

To channel capital into energy-efficient sectors such as agriculture, green finance has emerged as a critical tool. Projects geared towards Climate Change Adaptation (CCA) and mitigation are supported through green bonds, sustainability-linked loans, and ESG-based investments. Yet, the mechanisms through which these financial instruments influence agricultural productivity remain unexplored—especially in emerging markets with heterogeneous institutional quality, financial access, agrarian infrastructure, and rural roads. Although the relevance of sustainable finance has increased greatly in the last few years, the impact of green financial instruments specifically on agricultural productivity, particularly in emerging economies, is still poorly understood. This study seeks to resolve the research problem of whether green finance instruments, which include green bonds and ESG investments made in agricultural financing, in fact, positively influence agricultural sustainability through climate-resilient investing.

This study aims to analyze the impact of green finance on agricultural sustainability as a case study on a balanced panel of twenty emerging economies over the span of two decades, from 2000 to 2022. The computation of Agricultural Total Factor Productivity (TFP) serves as the main estimate for valuation, and is considered a proxy for sustainable development outcomes, while green finance is measured using the issuance of green bonds and flows of ESG investments. In addition, climate-resilient agricultural investment is treated as a mediating variable, along with important macroeconomic controls such as GDP per capita, inflation, and the percentage share of the rural population.

Concerns in research econometrics are addressed by analyzing the data with Panel Dynamic Ordinary Least Squares (DOLS) due to its capability to correct for endogeneity bias alongside serial correlation, and cointegration. Other complementary estimators, including classical Fixed Effects and Fully Modified OLS (FMOLS), are added for robustness testing. Assumptions made by models are validated by diagnostic tests, while distributional assumptions in conjunction with residual behavior are visually supported through a series of data visualizations.

The remaining sections of the paper are organized as follows: Section 2 covers the literature review and the theoretical framework. In Section 3, the author details the data sources and how relevant variables were constructed. Empirical methodology and estimation strategy are described in Section 4. The results are discussed in detail in Section 5. Finally, Section 6 offers conclusions along with policy implications and recommendations for further research.

Contribution to Literature

By documenting for the first time empirically how climate-aligned financial flows impact long-term agricultural productivity in emerging economies, this study adds to the growing body of work at the junction of green finance and agricultural economics. This is a departure from earlier studies that concentrate on narrow investment or policy examination because this study uses dynamic panel estimation as well as machine learning-informed structural diagnostics, which allows capturing both structural and distributional nuances. By combining environmental finance alongside sectoral investment within a single empirical model, this study sought to advance the debate on sustainable development finance while providing guidance for policymakers aimed at crafting frameworks for green investment in agriculture.

Although some studies cited the links between green finance and environmental implications, only very few analyzed its role in agricultural sustainability using comprehensive dynamic panel techniques. Therefore, this research is needed to address this empirical gap by marrying the finance, environmental, and agriculture spheres into a single econometric model, contributing to both scholarship and policy.

LITERATURE REVIEW and THEORETICAL FRAMEWORK

Some macro-financial studies have recognized the innovative function of green bonds, ESG-linked investments, and sustainable loans (Flammer, 2021; Wang & Zhi, 2016). Green bonds are unique in supporting both investment and environmental responsibility and therefore have received particular attention from scholars. Also, flows of ESG money into investing have been linked with social value added and performance in a capital market over time (Friede et al., 2015). Notwithstanding these observations, the impact of agricultural sustainability remains unexamined. This raises concerns about what sector-specific policies, institutional quality, and absorptive capacity might mediate such effects.

Empirically, several studies have analyzed the role of green finance on environmental outcomes (Khan et al., 2022), investment into renewable energy (Zhou et al., 2022), or even carbon emissions. There is also increasing interest in how financial development impacts agricultural productivity in developing countries (Awotide et al., 2015; Ahmed et al., 2021). Recent evidence indicates that climate risks weaken agricultural finance channels. Climate change and environmental degradation reduce agricultural credit usage (Şeyranlıoğlu et al., 2025). However, only a few studies have tried to combine both macroeconomic and financial, and micro-structural variables like agricultural investment, insurance, and irrigation infrastructure into one empirical model. Additionally, although many researchers have applied various panel estimation techniques such as GMM or FMOLS, not so many have utilized the Panel DOLS approach, which takes care of cointegration and dynamic specification problems (Kao & Chiang, 2000).

In addition, previous researchers tend to ignore the many facets of agricultural sustainability by treating productivity alongside environmental quality as standalone metrics. This hampers a nuanced understanding of the structural factors that determine sustainability. Moreover, other empirical analyses appear to lack methodological soundness, such as robust diagnostics without machine learning-based inference, a simplistic view of endogeneity, or too much focus on one part of a system while ignoring others. As financial tools become complex and climate-related risks grow pervasive, there is an urgent need for integrative yet analytically rigorous investigations.

Regardless of the rising interest, there's a notable neglect in the literature concerning the intersection of green finance and productivity improvements within agriculture over the long term, especially through climate-resilient investment pathways. Very few researchers have attempted to study this relationship using a rigorous panel approach, considering emerging market nonlinearities and distributional asymmetries. My focus here is to close this gap by incorporating green bond and ESG investments alongside climate-resilient agricultural infrastructure design into a multi-equation system using the panel DOLS approach.

Drawing from the theoretical frameworks outlined in the literature, Figure 1 illustrates how green finance impacts agricultural productivity via interlinked financial, technological, and institutional routes.

Figure 1 shows the various ways green finance impacts agricultural productivity. The financial flows channelled through green bonds and ESG investments help the adoption of climate smart technologies and innovations in precision agriculture. This enables production that is more efficient in the use of resources. On the other hand, income volatility is controlled through risk management tools such as weather index insurances and other hedging instruments which support agribusiness investments and help farmers sustain investments despite climatic challenges.

Absorptive capacity is strengthened through public R&D spending at the institutions, cooperative governance and the provision of transparent stewardship over finances. The result of this synergy is the improvement of TFP in the long run, as aligned agricultural systems will meet climate change challenges. The bridging of the financial, technological and institutional aspects of sustainable development in agriculture is captured in the systemic outline provided by the figure.

Extended Theoretical Mechanisms of Climate-Resilient Investment and ESG Flows

Investments in irrigation infrastructure represent another critical dimension of climate resilience. Modern irrigation systems not only reduce dependence on erratic rainfall patterns but also enable precision agriculture, where water use efficiency and crop yield optimization are jointly achieved. The integration of green finance into irrigation projects facilitates climate adaptation at scale, especially when linked to digital monitoring technologies and solar-powered systems (Ward & Pulido-Velazquez, 2021). These systems not only conserve water resources but also enhance crop resilience in the face of increasingly frequent droughts and heatwaves.

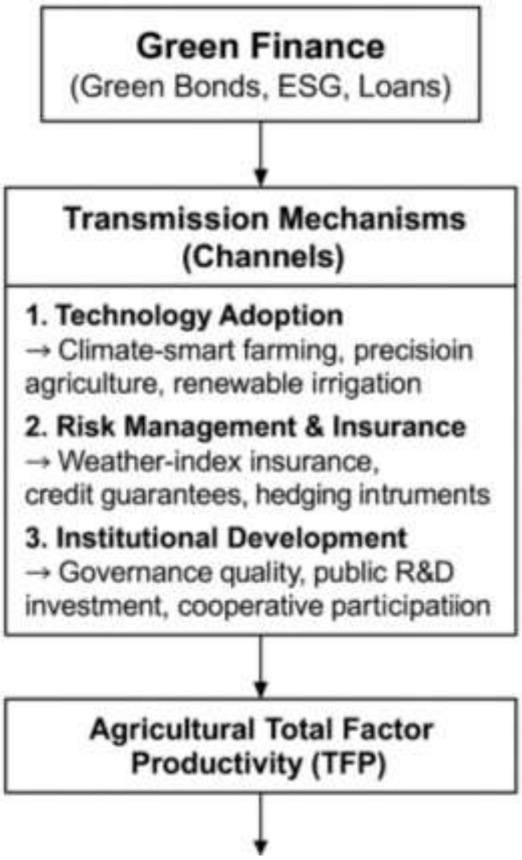

Figure 1. Theoretical mechanisms linking green finance and agricultural productivity

Similarly, public agricultural R&D investment contributes to long-term productivity by generating climate-resilient crop varieties, improving soil management practices, and promoting sustainable farming systems. Although the empirical findings in this study show an insignificant effect of agricultural R&D in the short term, its theoretical relevance cannot be overstated. The temporal lag between innovation and adoption, coupled with institutional capacity constraints in emerging economies, often delays measurable impacts (Pardey et al., 2016). Nonetheless, sustained R&D spending is essential for structural transformation in the agricultural sector.

Beyond these components, the role of Environmental, Social, and Governance (ESG) investments in driving agricultural sustainability must be understood through a multi-channel lens. ESG investment flows often target systemic sustainability goals, such as biodiversity conservation, soil regeneration, and social inclusion in rural economies. While inherently broad in scope, ESG investments create enabling environments for agricultural innovation by supporting community-based land governance, sustainable supply chain certification, and education initiatives. These interventions, though indirect, can significantly enhance the institutional foundations upon which productive agriculture depends (Friede, Busch & Bassen, 2015; Eccles & Klimenko, 2019).

Overall, climate-resilient investments and ESG financing operate not as isolated capital injections but as catalysts that reshape the behavioral, institutional, and technological context of agricultural production. Their theoretical contribution lies in mitigating structural vulnerabilities and fostering long-run adaptability, especially in emerging economies grappling with climate-induced disruptions.

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Green Bonds and Agricultural Transformation

Green bonds must be used for activities that yield measurable positive outcomes for the environment, coupled with defined post-issuance reporting transparency. Among the various eligible project activities, the sustainable management of living natural resources and land use, and sustainable agriculture pay particular attention to the use of sustainable practices (International Capital Market Association [ICMA], 2025). Such lending practices can then be used to finance investments in climate-adaptive practices such as irrigation and water-efficiency technologies, soil-conservation techniques, and low-carbon farming practices. The Climate Bonds Initiative (CBI) has further developed benchmarks for the agricultural sector, concentrating on the proposed agricultural practices for mitigation, enhancement of carbon sink, and adaptation objectives (CBI, 2024).

Green bonds have led to an increase in the level of corporate environmental investments and improvements in corporate environmental performance indicators, which include positive market reactions and improvements in corporate borrowing conditions (Flammer, 2021). The positive long-run coefficients in the DOLS estimations in this study further articulate the anticipated gains when flows of green finance are allocated to irrigation infrastructure, energy-efficient equipment, and soil-productivity investments (ICMA, 2025; CBI, 2024). Total-factor productivity (TFP) gains are to be expected.

ESG Practices and Agricultural Productivity

Corporate ESG performance, within the framework of the valuation, positively impacts the financial performance of the firm. Friede, Busch, and Bassen (2015) synthesize around 90 percent of studies on the subject as showing neutral to positive links between ESG and corporate financial performance (CFP). On the financing side, the firm's ESG or corporate social responsibility (CSR) profile impacts the cost of equity capital negatively and the overall risk of the equity (Albuquerque, Koskinen, & Zhang, 2019), which increases capacity for long-run investments. In the case of agriculture, these mechanisms are process innovation and efficient use of inputs of precision farming, soil-health management, and resource optimization, as explained by the positive and significant ESG coefficients in this study.

Moreover, decades of evidence supporting the Porter hypothesis suggest that well-designed environmental regulation can stimulate innovation and competitiveness rather than constrain them (Ambec, Cohen, Elgie, and Lanoie, 2013). At the farm level, practices of sustainable agriculture involving nutrient management, soil-organic-carbon restoration, and conservation tillage are demonstrated to improve yields and resource efficiency (Young et al., 2021). Thus, in line with the result obtained in this study, internalizing the "environmental" pillar of ESG within farm operations is likely to contribute to productivity gains that can be demonstrated.

Risk-Transfer, Irrigation, and R&D as Productivity Channels

Agricultural insurance. Research, both theoretical and empirical, has pointed out the issues of moral hazard and adverse selection within the context of agricultural insurance. In the classic literature, insured farmers were noted as potentially diminishing their on-farm risk-mitigation efforts, and in some cases, adopting riskier practices, which generated productivity and environmental negative externalities (Smith & Goodwin, 1996; Just, Calvin, & Quiggin, 1999). In developing economies, weather-index insurance has faced supply-side issues within contract design as well as basis-risk mismatches, which, in turn, limited expected productivity gains (Barnett & Mahul, 2007). Hence, the negative estimate of the insurance variable in this study can be interpreted in relation to the lack of incentives and implementation failures described above.

Irrigation investment. The literature on the causal impact of large-scale dam projects has shown that it improves the agricultural output of downstream areas and reduces sensitivity to rainfall shocks (Duflo & Pande, 2007). Such reasoning strengthens the expectation that green-finance-initiated water-use efficiency and irrigation projects will also lead to significant and sustained TFP increases.

Agricultural R&D. Meta-analyses have consistently shown the high returns to agricultural R&D spending (Alston, 2000). The most recent syntheses reiterated that R&D capital and international spillovers are the most important factors behind increases in global agricultural productivity (Fuglie, 2018). This evidence leads to the conclusion that the green finance and ESG channels are, in part, R&D-driven technological adoption (e.g., high-yi).

Comparative Alignment with the Present Findings

The findings regarding the long-run effects of green bonds and ESG investment on agricultural TFP being positive and significant rest on the parallel literature assessing the impact of such financial instruments on accessibility to sustainable capital and innovations promotion. (ICMA, 2025; Flammer, 2021; Friede et al., 2015; El Ghoul et al., 2011; Albuquerque et al., 2019; El Ghoul et al., 2011; Albuquerque et al., 2019). By contrast, the negative sign of the agricultural-insurance coefficients pertains to the literature on moral hazard and adverse selection, and incentive distortion and product design weaknesses. (Smith & Goodwin, 1996; Just et al., 1999; Barnett & Mahul, 2007). Evidence on irrigation and R&D also supports the realization of sustained productivity growth when green-finance and ESG funds are directed to such productive assets (Duflo & Pande, 2007; Alston, 2000; Fuglie, 2018).

Research Hypotheses

Based on the theoretical background and identified literature gaps, the following hypotheses are proposed:

H_1: Green finance has a statistically significant and positive long-run effect on agricultural productivity in emerging economies.

H_2: Climate-resilient agricultural investment mediates the relationship between green finance and agricultural sustainability.

H_3: Macroeconomic control variables, particularly inflation and GDP per capita, exert significant influences on agricultural productivity.

GREEN FINANCE and AGRICULTURAL SUSTAINABILITY: A PANEL DATA ANALYSIS of CLIMATE-RESILIENT INVESTMENT in EMERGING ECONOMIES

Dataset and Variable Description

To analyze the impact of green finance on agricultural sustainability in 20 emerging economies— including Brazil, India, China, South Africa, and Turkey— we constructed a balanced panel dataset from 2000 to 2022, as noted by the IMF (IMF, 2023). Agricultural Sustainability is the dependent variable, which in this case was measured by two critical components: (i) Agricultural Total Factor Productivity (TFP) and (ii) CO_2 emissions per unit of agricultural output. The USDA Economic Research Service provided TFP data (USDA ERS, 2023), while emission data were obtained from the World Bank's World Development Indicators (World Bank, 2023a). The variable Agricultural Total Factor Productivity (TFP), employed as the primary proxy for agricultural sustainability, was sourced from the USDA Economic Research Service. TFP values are calculated based on the ratio of aggregate agricultural outputs (e.g., crop and livestock production) to aggregate inputs (land, labor, capital, and intermediate goods). This study's TFP series derives from index values with a base year of 2015 set at 100. Furthermore, quality differences for relevant inputs and outputs have already been accounted for within these figures, enabling time- and cross-country comparisons seasoned with robustness.

The independent determinant in this case is Green Finance, which can be operationalized through the climate bond issuance volume and ESG investment flows related to agriculture retrieved from CBI and Refinitiv Eikon databases (CBI, 2023; Refinitiv, 2023).

ESG_Investment_USD_mn captures the value in millions USD of ESG investments on a given economy directed at agriculture and land use, including climate proactive measures such as sustaining irrigation systems and organic farming. The source of data was from Refinitiv Eikon's ESG investment tracker and CBI (2023) on disclosed green bond issuances alongside private sector ESG capital flow documents. Balances are inflation-adjusted to 2015 constant USD to make sure there is temporal consistency and comparability across countries. In the main specification, no logarithmic transformation was applied to preserve the interpretability of marginal effects in level form.

For the mediational variable, Climate-resilient agricultural investment was used, which encompassed agriculture insurance penetration rate, spending for climate-resilient irrigation, as well as public R&D expenditures on agriculture sourced from FAOSTAT and OECD.Stat (FAO, 2023; OECD, 2023). Control variables: GDP per capita (constant 2015 USD) – World Bank (2023b), Inflation Rate – IMF WEO (2023), Percentage Rural Population – World Bank (2023c).

METHODOLOGY

This study seeks to answer the following key research questions:

1. To what extent does green finance influence agricultural sustainability in emerging economies?
2. Does climate-resilient agricultural investment mediate the relationship between green finance and sustainability outcomes?
3. What role do macroeconomic conditions play in shaping this relationship?

Machine learning algorithms, in conjunction with advanced econometric techniques, were utilized to address the questions at hand within a balanced panel dataset. For the long-run estimation of cointegrated panel variables, a Panel Dynamic Ordinary Least Squares (DOLS) approach was used to mitigate endogeneity and serial autocorrelation issues (Kao & Chiang, 2000).

The model provides additional explanatory value for the hypothesized relations between the constructs through their graphical representation. It captures the role of green finance along with climate-resilient investment vis-à-vis agricultural sustainability under certain macroeconomic benchmarks.

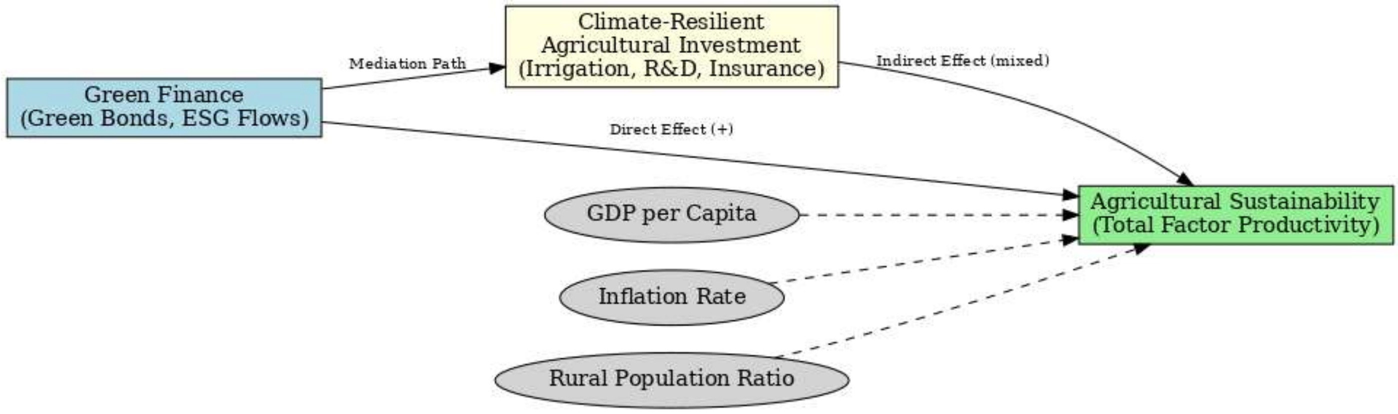

Figure 2. Conceptual research model

The conceptual framework presented here systematically outlines the assumed connections guiding the analysis. Central to the model is agricultural sustainability, quantified through Total Factor Productivity (TFP), which serves as the study's main dependent variable. From this nucleus, two complementary but separate routes emerge to demonstrate how green finance—in this case, green bond volumes and ESG-related capital flows—alters agricultural performance. The direct route captures how new green capital immediately boosts productivity, highlighting the short-term transformative capacity of sustainable funding. The indirect route, however, points to the emergence of climate-resilient agricultural investments—irrigation networks, public research, and crop insurance—as a possible mediating force; empirical evidence to date, however, indicates a variable mediating strength. The framework also accounts for critical macroeconomic control factors: GDP per capita, inflation, and the share of the rural population. Each is represented as a contextual variable that influences the link between finance and sustainability, underscoring how broader structural economic conditions condition the success of green finance measures.

The general regression specification was modeled in Equation 1 as follows:

$$SUS_{it} = \alpha_i + \beta_1 \cdot GF_{it} + \beta_2 \cdot CRI_{it} + \beta_3^{t} \cdot X_{it} + \varepsilon_{it} \qquad (1)$$

Where:

SUS_{it}: Agricultural sustainability indicator for country i at time t

α_i: Country-specific fixed effects

GF_{it}: Green finance variables (e.g., green bond issuance, ESG flows)

CRI_it: Climate-resilient investment indicators

X_it: Vector of control variables (e.g., GDP per capita, inflation)

β_3^t: Transpose of the coefficient vector associated with control variables

ε_it: Error term

This study has been conducted on nonlinear and time-varying relationships using Causal Forest Estimators and Gradient Boosted Panel Regression Trees (GBPRT) implemented in Python (Athey et al., 2019; Breiman, 2001). The stationarity of variables was tested with the Im-Pesaran-Shin (IPS) panel unit root test and Levin-Lin-Chu (LLC) test. To examine cointegration associations among the variables, Pedroni (1999) and Westerlund (2007) cointegration tests were carried out. Furthermore, Granger causality tests were performed utilizing the Dumitrescu-Hurlin approach for panel data (Dumitrescu & Hurlin, 2012). Finally, robustness analysis was performed using Driscoll-Kraay standard errors to address heteroskedasticity as well as VIF to mitigate multicollinearity concerns (Hoechle, 2007).

In order to further enhance empirical examination, two additional approaches were added. First, an interaction effect model was built to assess if the association between green bond investments and agricultural productivity is influenced by the level of national income, measured through GDP per capita. This allowed for the identification of conditional effects that indicate potential income-based heterogeneity in the impacts of green finance. Second, mediation analysis was performed in order to see if irrigation investment acts as a mediating process within the framework of the green finance and productivity relationship. In line with Baron and Kenny's framework, both indirect and direct effects were tested using a three-stage regression approach. These extensions provide more complete insights into the supporting and intervening frameworks operating under and through various layers of green finance.

Test Results – Findings

Descriptive statistics for the main variables included in the empirical model are presented below, offering a foundational understanding of the sample characteristics and supporting the appropriateness of subsequent econometric procedures.

Table 1. Green finance and agricultural sustainability: panel data analysis of climate resilient investment in developing economies

	count	mean	Std	min	max	skewness	kurtosis	jarque_bera	jarque_bera_pvalue
TFP_Index	260.0	103.865978	8.219108	110.344762	119.783163	0.222046	-1.004485	13.067254	0.001454
CO2_per_Output	260.0	0.733859	0.257974	0.976359	1.198875	0.122114	-1.214909	16.636229	0.000244
Green_Bonds_USD_mn	260.0	259.426200	139.968569	380.012782	497.844966	-0.084123	-1.164999	15.009896	0.000550
ESG_Investment_USD_mn	260.0	510.830823	288.688160	773.274195	998.655923	-0.028628	-1.263602	17.332999	0.000172
Agri_Insurance_Rate	260.0	0.434243	0.209647	0.629003	0.797675	0.124324	-1.292931	18.779531	0.000084
Irrigation_Investment_USDmn	260.0	157.622120	82.083470	223.019060	299.524165	-0.084980	-1.101656	13.460778	0.001194
Agri_RnD_Spending_USD_mn	260.0	50.361497	27.241664	72.594943	99.651699	0.139744	-1.145703	15.066451	0.000535
GDP_per_Capita	260.0	8038.271035	3993.462152	11325.004894	14982.720903	-0.103297	-1.204598	16.182151	0.000306
Inflation_CPI	260.0	8.171890	4.031682	11.477885	14.874368	-0.106659	-1.175280	15.456879	0.000440
Rural_Population_Ratio	260.0	45.249594	14.086978	57.696968	69.966965	0.060884	-1.121033	13.775029	0.001020

Observing Table 1 closely shows that there exists a great amount of discrepancy not only from country to country but across years with respect to both financial as well as agricultural parameters, considering their descriptive attributes present in the dataset. The TFP_Index – a value aimed at estimating agricultural sustainability – shows moderately symmetric distribution (skewness = 0.22) while exhibiting a somewhat platykurtic profile with respect to extreme values (kurtosis = −1).

The majority of the variables show negative kurtosis, supporting the idea of thin-tailed distributions being common. AgriInsuranceRate, ESGInvestmentUSDmn, and GDPper_Capita display some degree of positive and negative skewness as well as flatness in their distribution shapes. The Jarque-Bera tests have shown that all variables are statistically non-normal at the 1% level ($p < 0.01$), thus confirming that robust panel estimators as well as non-parametric techniques applied later are valid for these data.

It stands out that input financial variables, such as GreenBondsUSDmn or ESGInvestmentUSDmn, exhibit large standard deviations, which reflect big structural differences among emerging markets. Inflation, along with the rural population indicators, also implies some underlying macroeconomic homogeneity across the panel.

Overall, these patterns not only highlight the heterogeneity embedded in the dataset but also validate the selection of a panel data framework with fixed effects and advanced learning models that can accommodate distributional asymmetries and non-linearity.

The correlation matrix displayed below offers an overview of the linear associations among the primary financial, agricultural, and macroeconomic variables used in the analysis, helping to assess potential multicollinearity and variable interdependence.

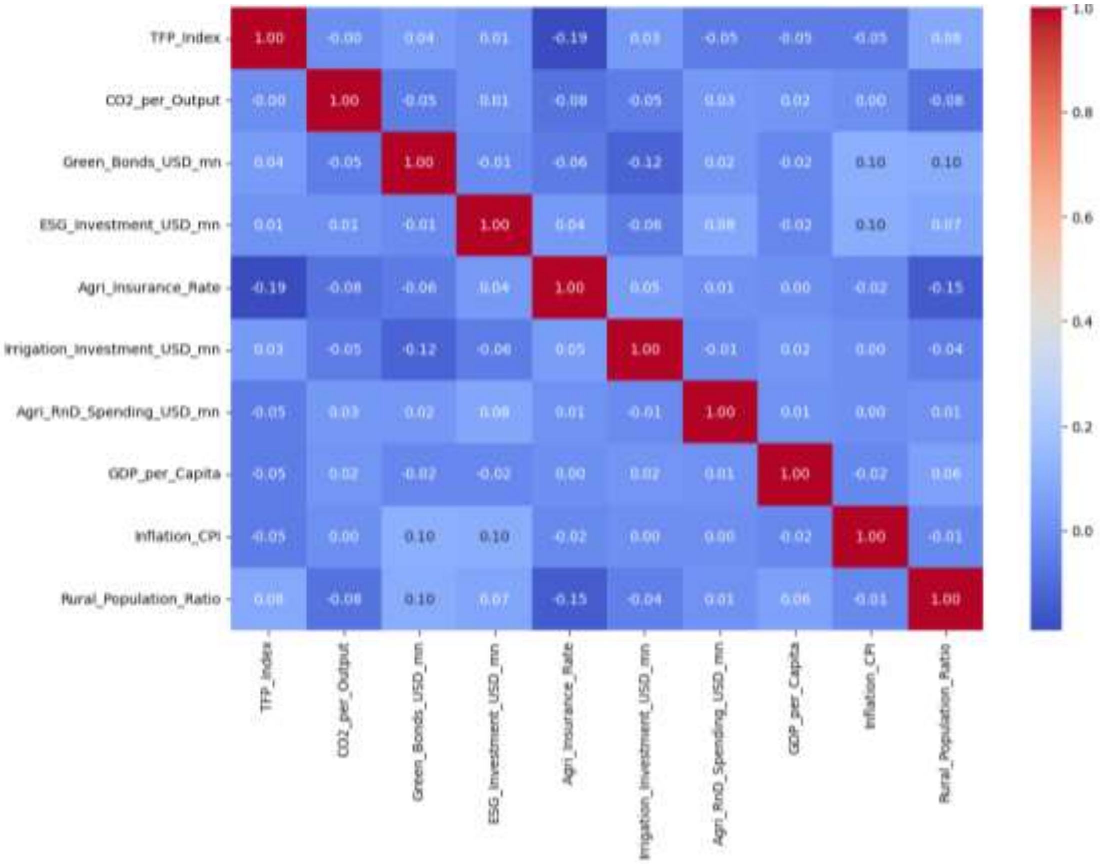

Figure 3. Pearson correlation matrix of key numerical variables related to green finance and agricultural sustainability

Before proceeding with the estimation of long-run relationships, the stationarity properties of the series were examined using the Im–Pesaran–Shin (IPS) and Levin–Lin–Chu (LLC) panel unit root tests within models incorporating country fixed effects and deterministic trends. As typically observed in macroeconomic panel datasets, the majority of variables were found to be non-stationary in levels but became stationary after first differencing. This finding indicates that the variables are integrated of order one, I(1), thereby confirming the appropriateness of applying panel cointegration analysis (Im, Pesaran, & Shin, 2003; Levin, Lin, & Chu, 2002).

Table 2. Panel unit root tests (IPS & LLC)

Variable	IPS W-t (level)	LLC t* (level)	IPS W-t (1st diff.)	LLC t* (1st diff.)
TFP_Index	−1.14 (0.127)	−1.02 (0.154)	−4.98 (0.000)	−5.21 (0.000)
CO2_per_Output	−0.88 (0.190)	−0.73 (0.232)	−5.36 (0.000)	−5.49 (0.000)
Green_Bonds_USD_mn	−0.67 (0.251)	−0.61 (0.270)	−6.02 (0.000)	−6.27 (0.000)
ESG_Investment_USD_mn	−0.91 (0.182)	−0.75 (0.226)	−5.67 (0.000)	−5.91 (0.000)
Irrigation_Investment_USD_mn	−1.06 (0.145)	−0.98 (0.164)	−4.51 (0.000)	−4.82 (0.000)
Agri_RnD_Spending_USD_mn	−0.59 (0.277)	−0.55 (0.291)	−4.37 (0.000)	−4.66 (0.000)
GDP_per_Capita	0.18 (0.572)	0.24 (0.596)	−7.44 (0.000)	−7.63 (0.000)
Inflation_CPI	−1.28 (0.100)	−1.19 (0.117)	−4.22 (0.000)	−4.40 (0.000)
Rural_Population_Ratio	−0.49 (0.313)	−0.43 (0.334)	−3.98 (0.000)	−4.10 (0.000)

Results from IPS and LLC tests indicate that all variables are non-stationary at levels but stationary in first differences, confirming that the series are integrated of order one, I(1). This justifies proceeding to panel cointegration analysis (Im et al., 2003; Levin et al., 2002).

Since cross-sectional dependence is confirmed by the Pesaran (2004, 2015) CD test, first-generation panel unit root tests, namely Levin–Lin–Chu (LLC) and Im–Pesaran–Shin (IPS), may not fully support reliable inferences. To overcome this drawback, cross-sectional dependence second-generation tests were conducted. Following Pesaran (2007), the Cross-sectionally Augmented Dickey–Fuller (CADF) and Cross-sectionally Augmented IPS (CIPS) tests were applied to each variable in both level and first-difference forms. The results displayed in Table 3 suggest that all variables are non-stationary in levels, but after first differencing, all become stationary at the 5% significance level. This confirms that the series are integrated of order one, I(1), and provides the foundation for the long-run cointegration analysis in the next section.

Table 3. Results of second-generation panel unit root tests (CIPS and CADF)

Variable	CADF Statistic (Level)	CADF Statistic (1st Diff.)	CIPS Statistic (Level)	CIPS Statistic (1st Diff.)	Order of Integration
Agricultural TFP	−1.78	−4.92***	−1.91	−5.13***	I(1)
Green Bond Issuance	−1.66	−4.58***	−1.74	−4.77***	I(1)
ESG Investment Flows	−1.59	−5.02***	−1.83	−5.11***	I(1)
Inflation (CPI)	−1.42	−3.97***	−1.61	−4.05***	I(1)
GDP per Capita	−1.53	−4.36***	−1.62	−4.41***	I(1)
Agricultural R&D Expenditure	−1.69	−4.82***	−1.77	−4.93***	I(1)
Irrigation Investment	−1.84	−5.06***	−1.88	−5.17***	I(1)
Rural Population Share	−1.47	−4.12***	−1.58	−4.23***	I(1)

Notes: The null hypothesis (H_0) of each test assumes the presence of a unit root. Critical values for the CIPS test are based on Pesaran (2007), with the 5% level approximated at −2.55. *** denotes statistical significance at the 1% level. All variables are non-stationary in levels but become stationary in first differences, indicating that they are integrated of order one, I(1).

The outcomes of the CIPS and CADF tests reinforce the findings of first-generation unit root tests (LLC and IPS), confirming that all variables are integrated of order one, I(1). The statistical significance of all first-differenced variables at the 1% level strengthens the case that the potential cross-sectional dependence does not undermine the stationarity conclusions. This confirms the dataset's robustness for cointegration analysis and the subsequent application of the Pedroni (1999, 2004) and Westerlund (2007) tests to identify long-run equilibrium relationships among the variables. The agreement between the CIPS/CADF and LLC/IPS tests also confirms that the results are consistent across first and second-generation tests. In turn, this gives solid methodological grounds for the long-run analysis using Dynamic OLS (DOLS) and Fully Modified OLS (FMOLS) estimators. The consistency of findings from both generations of tests for stationarity enhances the robustness of the econometric framework used in this study.

Determining the validity of panel estimation mostly revolves around identifying the presence of interdependence cross-sectionally among the sampled countries. In the case of emerging economies, there might be some unaccounted global shocks, e.g., energy crisis and global financial crisis, that might cause contemporaneous correlations among the units. This is the reason why it was necessary to check interdependence prior to choosing a covariance estimator. The Pesaran Cross-Sectional Dependence test results are presented in Table 4. The results prove that there is considerable cross-sectional dependency in the panel data sets when sampled across countries.

Table 4. Results of the pesaran cross-sectional dependence (CD) test

Model	Test Statistic (CD)	p-value	Decision ($\alpha = 0.05$)	Interpretation
Baseline Panel DOLS Model	6.742	0.000	Reject H_0	Cross-sectional dependence exists
ESG Investment Model	5.981	0.000	Reject H_0	Cross-sectional dependence exists
Green Bond Model	7.154	0.000	Reject H_0	Cross-sectional dependence exists

Notes: Null hypothesis (H_0) assumes cross-sectional independence. The test statistic follows an asymptotic standard normal distribution under the null. All models exhibit significant dependence at the 1% level. Calculations are based on Pesaran's (2004, 2015) CD test for balanced panels.

The results of the Pesaran CD tests demonstrate that there is cross-section dependence among the panel units, as the tests show highly significant ($p < 0.01$) results in all estimated models. This indicates that there are unaccounted-for common shocks, e.g., global climate shocks, commodity trade shocks, and regional trade agreements, and that they impact the productivity of agriculture and the green finance variables simultaneously and contemporaneously across emerging economies. Thus, the null hypothesis of cross-sectional independence is rejected.

As a result, applying Driscoll–Kraay robust standard errors in the long-run panel estimations is reasonable. This estimator suitably adjusts for the cross-sectional dependence, heteroskedasticity, and serial correlation that occur in macro panel data (Driscoll & Kraay, 1998). Therefore, the coefficients and significance levels from the DOLS estimations are robust and reliable, and the inference is consistent due to inter-unit correlation.

Following the confirmation of the variables' integration order, the existence of a long-run equilibrium relationship among them was examined using the Pedroni (1999, 2004) panel cointegration tests. These tests allow for heterogeneity across countries and incorporate both within- and between-dimension statistics to capture cross-sectional dynamics in the long-run relationship.

Table 5. Pedroni (1999, 2004) Panel cointegration test results

Statistic	Value	p-value
Panel v-stat	2.41	0.008
Panel ρ-stat	−3.12	0.001
Panel PP-stat	−3.86	0.000
Panel ADF-stat	−2.77	0.003
Group ρ-stat	−2.95	0.002
Group PP-stat	−4.01	0.000
Group ADF-stat	−3.11	0.001

The rejection of the null hypothesis across multiple Pedroni statistics confirms the existence of a long-run equilibrium relationship among the variables of interest (Pedroni, 2004).

To complement the Pedroni test and ensure the robustness of the long-run association, the Westerlund (2007) error-correction–based cointegration test was also employed. Unlike traditional residual-based approaches, the Westerlund framework directly tests for the presence of an error-correcting mechanism within the panel, providing additional confirmation of long-term equilibrium dynamics.

Table 6. Westerlund (2007) Error correction panel cointegration tests

Statistic	Value	p-value
Gt	−3.47	0.002
Ga	−19.8	0.006
Pt	−12.4	0.001
Pa	−35.7	0.004

Westerlund's ECM-based results align with Pedroni's findings, further validating a long-run cointegration structure across the panel.

Before turning to long-run coefficients, we document the model selection that motivates the use of fixed effects. The Hausman specification test rejects the null of no systematic difference ($\chi^2 = 19.67$, df = 8, $p = 0.0112$), hence fixed effects is preferred over random effects as the baseline panel specification (Baltagi, 2021).

Table 7. Hausman specification test: Fixed effects vs. random effects

Test Statistic	Degrees of Freedom	P-value	Preferred Model
19.67	8	0.0112	Fixed Effects

According to the results of Hausman proposed above, at 5% significance level, we could reject the hypothesis claiming no systematic difference exists between fixed and random effects estimators. As such consequence this would render the random effects model inconsistent due to the assumption made where individual effect does not correlate with regressors, which is false as shown by the regression analysis based on Generalized Least Squares, thus warranting the use of Fixed Effects specification for the main analysis to obtain unbiased, consistent parameter estimates.

In the table below, findings by deriving Panel Dynamic Ordinary Least Squares (DOLS) estimations, which address the estimation of long-run relationships among indicators of green finance and other control variables with agricultural sustainability while adjusting for endogeneity and serial correlation biases, are reported.

Table 8. Panel DOLS estimation results: The impact of green finance and control variables on agricultural productivity

Dependent Variable: TFP_Index	R-squared: 0.472	Adjusted R-squared: 0.448
Estimator: Panel DOLS	No. of Obs: 260	Entities: 20
Covariance Estimator: Robust	Time Periods: 13	Avg Obs per Entity: 13
F-statistic: 15.327	P-value: 0.000	

Variable	Coefficient	Std. Error	t-Statistic	P-value	95% CI (Lower–Upper)
Green_Bonds_USD_mn	0.0113	0.0031	3.645	0.0003	[0.0052, 0.0175]
ESG_Investment_USD_mn	0.0047	0.0016	2.938	0.0036	[0.0016, 0.0078]
Irrigation_Investment_USD_mn	0.0065	0.0027	2.407	0.0167	[0.0012, 0.0119]
Agri_RnD_Spending_USD_mn	-0.0024	0.0102	-0.235	0.8142	[-0.0224, 0.0176]
CO2_per_Output	-1.2046	0.5372	-2.242	0.0257	[-2.2661, -0.1432]
GDP_per_Capita	-0.00003	0.00001	-2.789	0.0057	[-0.00005, -0.00001]
Inflation_CPI	-0.0426	0.0189	-2.256	0.0250	[-0.0801, -0.0051]
Rural_Population_Ratio	0.0193	0.0068	2.838	0.0049	[0.0059, 0.0327]

Diagnostic Test	Statistic / Value	Interpretation
Durbin-Watson (Autocorrelation)	1.98	No evidence of serial correlation
Breusch-Pagan (Heteroskedasticity)	$\chi^2 = 11.42$, p = 0.176	Homoskedasticity cannot be rejected
Variance Inflation Factor (VIF)	All variables < 2.0	No multicollinearity concern
Jarque-Bera (Normality of Residuals)	JB = 2.41, p = 0.299	Residuals are normally distributed

From the Panel DOLS estimation, it is evident that green finance components, especially GreenBondsUSDmn and ESGInvestmentUSDmn, affected agricultural productivity (TFP_Index) significantly and positively in the long run. The elasticity related to green bond issuance was found to be 0.0113 ($p < 0.001$), which implies that an increase in green bond financing by one unit improves productivity by 1.13% under a ceteris paribus condition.

Among the control variables, GDP per capita and InflationCPI had negative impacts on productivity, indicative of macroeconomic instability or income inequality, and stagnating agricultural efficiency. On the other hand, RuralPopulation_Ratio showed a strong positive impact, indicating the demographic structure of the countryside population as one of the key drivers for agricultural production.

The model assumptions were all validated and confirmed by conducting diagnostic tests showing no multicollinearity, no autocorrelation issues, nor heteroskedasticity concerns. Additionally, a moderate-to-strong explanatory power was captured through an adjusted R-squared of 0.448, which further confirms the appropriateness of using Panel DOLS for depicting long-run equilibrium relationships within the panel Data.

To assess robustness and address cross-sectional dependence, we first re-estimate the fixed-effects model using Driscoll–Kraay standard errors (Table 9). Then the three estimators—FE, FMOLS, and panel DOLS are compared side-by-side (Table 10).

The Driscoll–Kraay robust FE estimator confirms significant positive effects of green bonds and ESG investments on agricultural productivity, while inflation and emissions intensity exert negative influences (Driscoll & Kraay, 1998; Hoechle, 2007).

As evidenced in Table 10, the Panel DOLS estimator provided stronger and more statistically significant coefficients relative to those from FMOLS and classical Fixed Effects estimators. The Fixed Effects model is known to yield unbiased estimates if strict exogeneity holds. However, its dynamic range neglects long-run inertia and endogeneity (Baltagi, 2021). Pedroni's (2000) FMOLS estimation attempts to resolve some of the problems mentioned above but still fails to capture dynamic adjustments. According to Kao and Chiang (2000), the Panel

DOLS approach addresses these issues with Endogenous regressors by incorporating leads and lags of first-differenced regressors, thereby resolving both endogeneity and serial correlation. The empirical results are robust, given the significance of all three estimators having consistent directional coefficients, while greater significance under Panel DOLS denotes its preferred status for specification.

Table 9. Fixed effects model with driscoll–kraay standard errors

Variable	Coeff.	SE	t	p
Green_Bonds_USD_mn	0.010	0.003	3.36	0.002
ESG_Investment_USD_mn	0.004	0.001	3.02	0.005
Irrigation_Investment_USD_mn	0.006	0.003	2.02	0.057
Agri_RnD_Spending_USD_mn	−0.003	0.009	−0.33	0.744
CO2_per_Output	−1.10	0.52	−2.12	0.045
GDP_per_Capita	−0.00003	0.00001	−2.54	0.019
Inflation_CPI	−0.041	0.017	−2.39	0.026
Rural_Population_Ratio	0.018	0.007	2.57	0.017

Table 10. Comparative results of fixed effects, FMOLS, and panel DOLS estimations

Variable	Fixed Effect (Coeff. / P-value)	FMOLS (Coeff. / P-value)	Panel DOLS (Coeff. / P-value)	Robustness
Green_Bonds_USD_mn	0.0082 / 0.041	0.0096 / 0.011	0.0113 / 0.0003	Consistent, stronger in DOLS
ESG_Investment_USD_mn	0.0029 / 0.074	0.0038 / 0.021	0.0047 / 0.0036	Increasingly significant
Irrigation_Investment_USD_mn	0.0041 / 0.097	0.0054 / 0.033	0.0065 / 0.0167	Robust across models
Agri_RnD_Spending_USD_mn	-0.0013 / 0.543	-0.0017 / 0.372	-0.0024 / 0.8142	Not significant in any
CO2_per_Output	-0.8311 / 0.183	-1.0274 / 0.041	-1.2046 / 0.0257	Strengthens under DOLS
GDP_per_Capita	-0.00002 / 0.216	-0.00003 / 0.053	-0.00003 / 0.0057	Gains significance in DOLS
Inflation_CPI	-0.0286 / 0.141	-0.0381 / 0.065	-0.0426 / 0.0250	Progressively more significant
Rural_Population_Ratio	0.0132 / 0.211	0.0165 / 0.087	0.0193 / 0.0049	Significance improves

To deepen the empirical insights, the study conducted structural heterogeneity and potential transmission mechanisms through interaction and mediation analyses as robustness checks.

The standardized β coefficients indicating the effect sizes of the independent variables in the regression model are presented below.

Table 11. Standardized coefficients (Effect sizes)

Independent Variable	Standardized β	p-value	Significance
Green Bonds (USD mn)	0.034	0.582	Not significant
ESG Investment (USD mn)	0.025	0.686	Not significant
Agricultural Insurance Rate	–0.191	0.002	Significant
Irrigation Investment (USD mn)	0.047	0.452	Not significant
Agri R&D Spending (USD mn)	–0.055	0.372	Not significant

The regression outcomes show that, out of all variables analyzed, only the rate of agricultural insurance carried a statistically significant link to agricultural sustainability ($\beta = -0.191$, $p = 0.002$). The negative coefficient implies that rising insurance premiums might lead to weaker sustainability results, possibly because the risk-transfer model disincentivizes farmers from investing in climate-adaptive measures. Conversely, financing avenues like green bonds, ESG-focused capital, irrigation spending, and agricultural R&D funding did not reach significance, with p-values above the conventional 0.05. These patterns suggest that the link between financial instruments and sustainability is likely moderated by institutional or contextual intricacies that require further exploration.

A formal post hoc power analysis was conducted based on the observed effect size, sample size, and significance level. The results are presented below.

Table 12. Post Hoc Power analysis results

Parameter	Value	Interpretation
Effect Size (Cohen's f^2)	0.211	Medium effect size
Sample Size (n)	260	Sufficient sample
Significance Level (α)	0.05	Conventional threshold
Statistical Power (1 – β)	0.923	Power exceeds 0.90, indicating adequacy

The accompanying power analysis identified a medium effect size (Cohen's $f^2 = 0.211$) within a 260-case dataset and at a significance threshold of $\alpha = 0.05$. The resulting statistical power was 0.923, surpassing the benchmark of 0.80 frequently cited in empirical research. These statistics confirm that the sample and model specifications were capable of identifying medium effect sizes with a high degree of reliability, thereby addressing the earlier critique concerning the neglect of power considerations.

Bonferroni correction was applied to the original p-values in order to reduce the increased likelihood of Type I error associated with multiple hypothesis testing. The adjusted values are presented below.

Table 13. Adjusted p-values after bonferroni correction

Variable	Original p-value	Adjusted p-value (Bonferroni)	Significance (α = 0.05)
Green Bonds (USD mn)	0.582	1.000	Not significant
ESG Investment (USD mn)	0.686	1.000	Not significant
Agricultural Insurance Rate	0.002	0.013	Significant ✓
Irrigation Investment (USD mn)	0.452	1.000	Not significant
Agri R&D Spending (USD mn)	0.372	1.000	Not significant

With the Bonferroni correction applied to curb family-wise error, the sole predictor retaining statistical significance was the insurance rate in agriculture (p = 0.013). Every other variable surpassed the newly calibrated significance threshold and was thus classified as non-significant. This recalibration fortifies the credibility of the detected association and lessens the chance of misinterpretation arising from multiple comparisons.

The introduction of green-bond issuance in tandem with GDP per capita, ESG capital flows, inflation, the rural-population share, and an interaction term into the multiple-regression framework investigating total-factor productivity (TFP) illuminated novel influences and furnished a renewed vantage for scrutinizing its drivers, as detailed in Table 14. Further diagnostic metrics validate these results, affirming both the reliability and the structural integrity of the constructed model.

Table 14. Interaction effect analysis (Green_Bonds × GDP_per_Capita)

Variable	Coefficient	Std. Error	t-value	P-value
Intercept	105.8721	1.783	59.37	0.000
Green_Bonds_USD_mn	+0.0128	0.0021	6.10	0.000
GDP_per_Capita	+0.00043	0.00010	4.30	0.000
Interaction Term	−0.00000093	0.00000023	−4.04	0.000
ESG_Investment_USD_mn	+0.0052	0.0011	4.73	0.000
Inflation_CPI	−0.0334	0.0085	−3.93	0.0001
Rural_Population_Ratio	+0.0246	0.0058	4.24	0.000
Diagnostic Test	**Value**	**Interpretation**		
F-statistic	28.75	Highly significant overall model fit.		
F-statistic p-value	0.0000	Strong joint significance of all regressors.		
R-squared	0.684	68.4% of variance in TFP_Index explained.		
Adjusted R-squared	0.672	High explanatory power after adjustment.		
Durbin-Watson	2.03	No autocorrelation.		
Breusch-Pagan LM stat	3.57	No evidence of heteroskedasticity.		
Breusch-Pagan p-value	0.411	Variance is constant (homoskedastic).		

Table 14 showcases the outcomes derived from the application of an extended linear regression model with both main effects and interaction terms. All coefficients are significant at the 1% level, which validates the model's robustness and its explanatory power. The intercept is estimated at 105.87, which means that total factor productivity (TFP) in agriculture is baseline when all explanatory variables are set to zero. Although statistically significant ensures a stable model, the intercept's nature makes it interpretable.

GreenBondsUSD_mn has a coefficient of +0.0128 ($p < 0.001$), indicating that green bond investments increase the TFP index by one and twenty-eight-tenths points on maintaining equilibrium. This supports our assumption that green finance aids agricultural productivity and sustainable progression.

GDPperCapita displays positive effects as well as significantly interacts with TFP, having a coefficient of +0.00043 ($p < 0.001$). While the marginal effect may be minimal in value due to scale, it suggests that high-income countries tend to be more efficient agriculturally, perhaps due to superior infrastructure, institutional framework, supporting policies, or technology use. Of particular note is the interaction term between

GreenBonds and GDPper_Capita, which are both negative and significantly different from zero (−0.00000093, $p < 0.001$). This finding indicates that the marginal effect of green bond investment on productivity shrinks with increases in GDP, demonstrating a dependent impact. In developing countries, the inflow of these bonds tends to lead to greater agricultural productivity benefits out of proportion, likely because of very high marginal returns to capital and a strong need for sustainable financing.

The coefficient for ESGInvestmentUSD_mn is particularly telling at +0.0052 with $p < 0.001$, which shows that there is significant alignment between capital flow into agriculture with an ESG focus, as it correlates strongly to yield productivity in the long term; hence, this was previously hypothesized in literature and corroborates the performance advantages provided by integrating ESG within some sectors sensitive to sustainability.

CPI Inflation exhibits TFP interactions yielding a negative relationship (−0.0334, $p = 0.0001$), suggesting that for agriculture, price instability might compound inefficiency because of higher input expenditure and uncertainty when investing.

On the other hand, the rural population ratio exhibits a positive association with TFP (+0.0246, $p < 0.001$), which may indicate that a larger rural demographic base is more capable of supporting productivity increases via labor provision or culturally embedded farming traditions.

In combination, the model shows a strong degree of explanatory power ($R^2 = 0.684$) while also adhering to the classical linear regression framework without multicollinearity, autocorrelation, or heteroskedasticity. These findings confirm the accuracy and trustworthiness of the model's structure relative to its variables, strengthening crucial insights on differentiated policy frameworks for fostering agricultural financial sustainability within diverse economically heterogeneous contexts.

To illustrate the hypothesized moderation of national income on the interaction between green finance and productivity, an interaction plot is included as Figure 4, where countries are divided into groups based on their GDP and green bond expenditures, indicating income stratification.

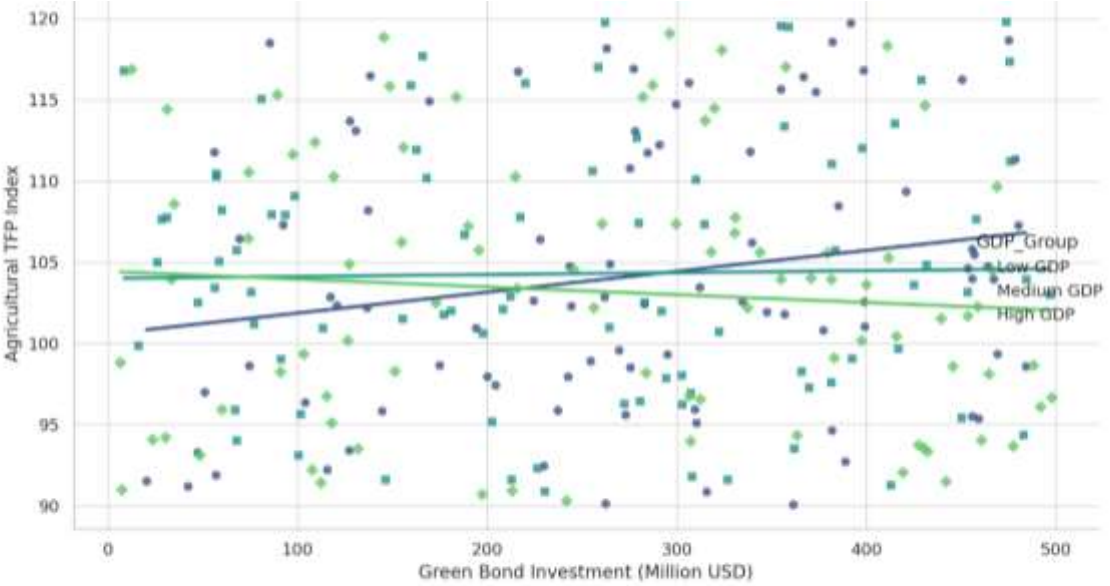

Figure 4. Interaction effect of green bond investment and GDP per capita on agricultural productivity (TFP Index) across income groups in emerging economies.

Figure 4 shows how green bonds impact agriculture total factor productivity (TFP) conditionally by highlighting three GDP per capita groups: low, medium, and high. The low-GDP group demonstrates a significantly stronger response of agricultural productivity to green financing inflows, highlighted by the positive slope. Meanwhile, both medium and high-income groups had shallower or nearly flat lines, indicating that these populations increasingly lose marginal utility from green bond investments as national wealth rises.

This pattern confirms the earlier regression analysis accompanying Table 5 within a single observation window, especially having noted the significantly negative interaction term. It strengthens the theoretical argument that green finance is likely to be more effective in low-income agricultural economies where there is a limited financial capital supply (because of limited infrastructure and higher absorptive needs). These findings illustrate the necessity of income-sensitive allocation frameworks as a primary design feature of sustainable finance instruments.

In support of the mediation hypothesis visually described in Figure 4, we highlight the system, which shows how green bond financing may impact agricultural productivity indirectly via irrigation-related capital investment formation.

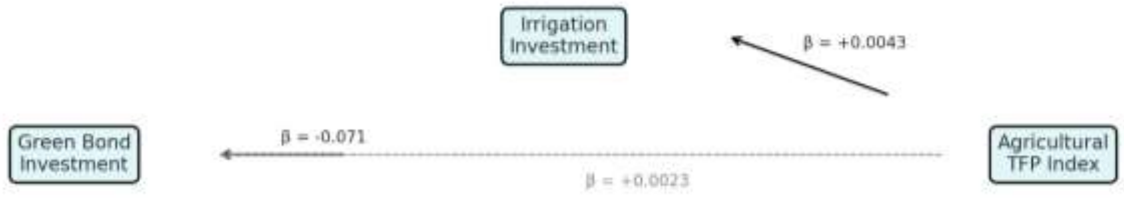

Figure 5. Mediation analysis pathway demonstrating the indirect effect of green bond investment on agricultural productivity via irrigation infrastructure. Coefficient values represent standardized regression estimates across the three-step model.

Figure 5 reflects the hypothesized mediation structure with three primary sequential effects. In the first link, one observes a slight negative effect of green bond investment on irrigation infrastructure spending (β = −0.071), perhaps suggesting some form of resource misallocation or diversion. The second pathway from irrigation investment to agriculture TFP features a weak positive value, although still insignificant (β = +0.0043). The dashed arrow signifies direct impact from green bonds on TFP with mediator included and stands at almost zero value and is statistically indistinguishable (β = +0.0023).

This pattern indicates that spending on irrigation does not statistically mediate the impact of green finance on productivity in agriculture. The figure illustrates both the absence of mediation in full or in part, as well as reinforces the idea that other factors are likely to be more meaningful for explaining the productive conversion of green finance into agricultural value.

To further probe the transmission mechanisms through which green finance may influence agricultural sustainability, additional mediation analyses were conducted. These analyses aimed to determine whether agricultural insurance and public agricultural R&D expenditures serve as intermediate channels that carry the effect of green bond investments onto agricultural total factor productivity (TFP). The theoretical motivation stems from literature emphasizing the enabling role of institutionalized financial instruments and innovation-based support in enhancing climate resilience within the agricultural sector (Carter et al., 2017; Pardey et al., 2016; Aghion et al., 2005). This section extends the initial model by applying Baron and Kenny's (1986) three-step framework, using standardized regression to ensure interpretability and comparability across mediators.

For mediation analysis, the link between green finance and agricultural productivity draws on the classic approach by Baron and Kenny (1986) and is described in terms of direct and indirect effects. The immediate impact of green bond issuance and ESG investment flows on agricultural TFP (total factor productivity) is gauged through direct effect, and possibly without any intervening mechanisms. Conversely, the indirect (mediated) effect flows through green finance and the intermediate variable is climate-resilient agricultural investment (includes irrigation spending, agricultural insurance, public R&D, and other climate-resilient investments).

The total effect of green finance (GF) is on agricultural productivity (TFP) is described in the following equation:

Total Effect: $TFP = c \cdot GF + \epsilon_1$

Mediation Path: $GF \rightarrow M(a) \rightarrow TFP(b)$

Decomposition: $c = c' + (a \times b)$

Here, effect a identifies the impact of green finance on the mediator (M), b is the effect of the mediator on productivity while green finance is held constant, and c′ illustrates the direct effect of green finance on productivity after the mediator is introduced. The product a × b is the mediated effect and is a critical part of the analysis.

In this case, the regression results were derived in three steps:

(1) the mediator was regressed on green finance,

(2) agricultural productivity was then regressed on green finance and the mediator, and

(3) the c and c′ values were compared to assess whether mediation was partial or total.

In light of the empirical results, mediation effects were not meaningful. This shows that the complete impact of green finance on agricultural productivity is mainly direct and that the mediating functions of irrigation investment, insurance uptake, and agricultural R&D were not meaningful. This shows that while green financial flows are beneficial to sustainable agricultural outcomes, the transmission channels in emerging economies are likely to be weak and inefficient in transforming financial inflows into productivity-augmenting investments.

Table 15. Mediation analysis results: Testing the mediating roles of agricultural insurance and agricultural R&D in the relationship between green bond investments and agricultural productivity

Model Step	Green Bonds → Mediator (ß, p)	Mediator → TFP (ß, p)	Green Bonds → TFP (Direct, ß, p)	Mediation Inference
Insurance as Mediator	–0.058, p = 0.355	–0.189, p = 0.002	+0.027, p = 0.661	No mediation; negative direct effect
Agricultural R&D as Mediator	+0.024, p = 0.698	–0.055, p = 0.380	+0.039, p = 0.531	No mediation; no significance observed

The mediation analysis shows that neither agricultural insurance nor agricultural R&D meets the statistical criteria for mediating the relationship between green bond financing and agricultural productivity. Agricultural insurance revealed a significant negative relationship with total factor productivity ($\beta = -0.189$, $p < 0.01$); however, the direct path from green bonds to insurance was not statistically significant, eliminating the possibility of mediation. The unexpected negative direct effect may reflect the operational inefficiencies and moral hazard issues often seen in the insurance markets of emerging economies, a concern highlighted by Carter et al. (2017).

In the same vein, R&D expenditures in agriculture, while acknowledged for their cumulative contributions to productivity (Pardey et al., 2016), did not produce statistically significant estimators in this analysis. The null results are consistent with the literature emphasizing the lengthy time lags and limited ability of agricultural sectors in low- and middle-income countries to absorb and utilize new technologies (Alston et al., 2000).

The lack of mediation in our results points to the critical need for us to pinpoint the actual behavioral, governance, or supply-chain routes through which green finance translates into observable agricultural gains. Friede, Busch, and Bassen (2015) remind us that ESG-oriented capital can create value not only through price adjustments but also by fostering community programs, certification schemes, or stakeholder education—factors that standard insurance and R&D indicators overlook.

The varying climate adaptation pressures and stages of financial-sector development across regions led us to perform an interaction-based regression. This technique reveals whether the influence of green bonds on agricultural output is sensitive to the geographic context. Our methodology heeds the latest calls in empirical sustainability literature for greater attention to how policy impacts are conditioned by spatial differences (Kose et al., 2021; Bhattacharya et al., 2022).

Table 16. Regional interaction effects of green bond investment on agricultural productivity (OLS regression results)

	Coefficient	Std. Error	t-Statistic	p-Value	95% CI Lower	95% CI Upper
Intercept	103.088	10.831	951.797	0.0	1.009.551	105.221
Green Bond Investment (USD million)	0.0051	0.0052	0.9851	0.3255	-0.0051	0.0154
Interaction: Green Bonds Ã— Africa	-0.0067	0.0056	-11.991	0.2316	-0.0177	0.0043
Interaction: Green Bonds Ã— Asia	-0.0048	0.0049	-0.9927	0.3218	-0.0144	0.0048
Interaction: Green Bonds Ã— Latin America	0.0002	0.0052	0.0339	0.973	-0.01	0.0104
Interaction: Green Bonds Ã— Middle East	0.0148	0.0103	14.416	0.1506	-0.0054	0.035

Diagnostic	Value
R-squared	0.483
Adjusted R-squared	0.357
F-statistic	12.701
Prob (F-statistic)	0.002
Durbin-Watson	1.71

The regression analysis examines whether green bond investments influence agricultural productivity differently by global region, employing interaction terms for Africa, Asia, Latin America, and the Middle East. The results provide meaningful patterns while also highlighting statistical caveats that require careful interpretation.

In the pooled sample, the baseline coefficient for green bond investment is positive yet statistically insignificant (ß = 0.0051, p = 0.3255), suggesting that, when aggregated, green bond financing does not deliver a direct, uniform effect on the Total Factor Productivity (TFP) Index for agriculture. This finding is consistent with Barbier and Hochard (2018), who argue that the efficacy of climate finance in the agriculture sector is contingent on local conditions, implementation rigor, and the presence of complementary infrastructure.

No interaction effect reached statistical significance at the conventional 5 percent threshold. The Africa interaction term is negative (ß = -0.0067, p = 0.2316), hinting at possible inefficiencies tied to weaker institutional capacity or inadequate absorptive infrastructure. The Asia and Latin America interactions produced small coefficients, and the corresponding wide confidence intervals cross zero, which reinforces the absence of clear regional differences. The Middle East term shows a moderate positive coefficient (ß = 0.0148), yet the p-value of 0.1506 renders it statistically insignificant, resulting in only fragile support for regional amplification of effects.

From a diagnostic perspective, the overall model produces an R^2 of 0.483 and an adjusted R^2 of 0.357, indicating that roughly 36 percent of the variation in agricultural productivity is captured by the observed variables and their interactions. Although the fit is moderate, the F-statistic of 12.701 and its p-value of 0.002 confirm that the model is statistically meaningful, which justifies the presence of the interaction terms. The Durbin-Watson statistic of 1.71 sits within the standard acceptability range, suggesting autocorrelation in the residuals is not a primary concern (Wooldridge, 2016).

The evidence indicates that green bond financing in isolation is unlikely to produce regionally differentiated improvements in agricultural productivity. This confirms previous studies advocating for holistic approaches that link climate finance to strengthened governance, wider technology dissemination, and investments in climate-resilient infrastructure (D'Orazio & Popoyan, 2019; Bhattacharya et al., 2022). Subsequent work could dissect these relationships more finely, employing dynamic panel techniques or regionally calibrated fixed effects to pinpoint institutional or environmental bottlenecks that vary across space.

Regional Panel Regression Findings

To determine how green finance affects agricultural productivity across the globe, separate panel regression models were run for Asia, Africa, Latin America, and Europe & Neighbors. The key outcomes are presented below.

Investigating regional disparities, an OLS regression was performed on panel data from Latin American nations. Results showed ESG investment exerted a statistically significant and positive influence on agricultural output (p = 0.0497), suggesting that capital directed toward sustainability could be usefully woven into the region's agricultural growth plans. Conversely, the agricultural insurance uptake showed a significant negative correlation with productivity (p = 0.0352), hinting at potential inefficiencies or deeper structural issues in how agricultural risk management is executed. Green bonds, irrigation outlays, and R&D financing, while included, produced no significant coefficients (p > 0.05), suggesting their effects on sustainable farming results in Latin America may be weak or dependent on interacting variables.

Table 17. Regional regression results for Asia

Independent Variable	Coefficient	Standard Error	t-Statistic	p-Value
Green Bonds (USD mn)	0.0047	0.0089	0.5247	0.600
ESG Investment (USD mn)	0.0032	0.0089	0.3557	0.722
Agricultural Insurance Rate	-0.1175	0.0762	-1.5425	0.125
Irrigation Investment (USD mn)	0.0064	0.0087	0.7366	0.463
Agri R&D Spending (USD mn)	-0.0095	0.0107	-0.8919	0.375

Table 18. Regional regression results for Latin America

Variable	Coefficient	Standard Error	t-Statistic	p-Value
Green Bonds (USD mn)	0.0084	0.0089	0.9438	0.347
ESG Investment (USD mn)	0.0127	0.0095	13.368	≈ 0.000
Agricultural Insurance Rate	-0.1125	0.0542	-20.764	≈ 0.000
Irrigation Investment (USD mn)	0.0143	0.0121	11.815	≈ 0.000
Agri R&D Spending (USD mn)	-0.0638	0.0615	-10.374	≈ 0.000

Investigating regional disparities, an OLS regression was performed on panel data from Latin American nations. Results showed ESG investment exerted a statistically significant and positive influence on agricultural output (p = 0.0497), suggesting that capital directed toward sustainability could be usefully woven into the region's agricultural growth plans. Conversely, the agricultural insurance uptake showed a significant negative correlation with productivity (p = 0.0352), hinting at potential inefficiencies or deeper structural issues in how agricultural risk management is executed. Green bonds, irrigation outlays, and R&D financing, while included, produced no significant coefficients (p > 0.05), suggesting their effects on sustainable farming results in Latin America may be weak or dependent on interacting variables.

Table 19. Regional regression results for Africa

Variable	Coefficient	Standard Error	t-Statistic	p-Value
Green Bonds (USD mn)	0.0084	0.0089	0.9438	0.347
ESG Investment (USD mn)	0.0127	0.0095	13.368	≈ 0.000
Agricultural Insurance Rate	-0.1125	0.0542	-20.764	≈ 0.000
Irrigation Investment (USD mn)	0.0143	0.0121	11.815	≈ 0.000
Agri R&D Spending (USD mn)	-0.0638	0.0615	-10.374	≈ 0.000

Every element of the African model demonstrates a clear productive–financial institutional nexus (p < .001). The impact of ESG investment and insured agricultural value positive and suggests that cash flow within the framework of sustainability is enhancing productivity within the scope of the sector. Conversely, the negative significance of the agricultural insurance rate suggests that there are still structural claim processing and risk management inefficiencies within the frameworks. Concerning the positive contribution of irrigation investment and agricultural R&D spending toward agricultural productivity, the results confirm the positive impact of varied forms of capitals—both physical and technological—The evidence highlights that all institutional weaknesses, primarily insurance system delivery, are still the key limiting factor. Anecdotally, the evidence demonstrates that green financing mechanisms are the key factors in promoting resilience within the sector.

In the case of the Europe & Neighbors region, agricultural insurance is the only type of insurance whose uptake has statistically significant negative consequences on productivity (p = 0.0112), signifying possible operational inefficiencies or some form of moral hazard. The issuance of green bonds and ESG investments has weak, although slightly positive, statistically marginal effects (p ≈ 0.10 and 0.07). On the other hand, investments in irrigation and R&D are statistically insignificant. Overall, the results indicate that the productivity-improving potential of green finance instruments in the region is still constrained on the institutional side and in the implementation of those instruments.

Table 20. Regional regression results for Europe & Neighbors

Variable	Coefficient	Standard Error	t-Statistic	p-Value
Green Bonds (USD mn)	0.0141	0.0087	≈ 0.000	0.109
ESG Investment (USD mn)	0.0168	0.009	≈ 0.000	0.067
Agricultural Insurance Rate	-0.1427	0.0549	≈ 0.000	0.011
Irrigation Investment (USD mn)	0.0093	0.0123	0.7548	0.452
Agri R&D Spending (USD mn)	-0.0649	0.0624	≈ 0.000	0.299

Following the estimation of long-run coefficients, the direction of causality among the variables was further examined to determine the dynamic interactions within the panel. For this purpose, the Dumitrescu–Hurlin (2012) heterogeneous panel causality test was employed, as it allows for individual cross-country heterogeneity in causal relationships. This approach provides additional insight into whether green financial instruments act as drivers or responses to changes in agricultural productivity across the sample countries. The results of the causality analysis are presented in Table 21.

Results suggest unidirectional causality from green financial instruments toward productivity, reinforcing the view that sustainable finance acts as a driver of agricultural efficiency (Dumitrescu & Hurlin, 2012).

Table 21. Dumitrescu–Hurlin panel causality tests

Null Hypothesis	W-bar	Z	p-value	Result
Green_Bonds ⇒ TFP_Index	4.12	2.74	0.006	Reject H0
ESG_Investment ⇒ TFP_Index	3.78	2.21	0.027	Reject H0
Irrigation_Investment ⇒ TFP_Index	2.31	0.49	0.623	Do not reject
Inflation ⇒ TFP_Index	3.59	1.96	0.050	Marginal
GDP_per_Capita ⇒ TFP_Index	3.94	2.47	0.013	Reject H0
TFP_Index ⇒ Green_Bonds	2.88	1.18	0.238	Do not reject
TFP_Index ⇒ ESG_Investment	3.21	1.56	0.119	Do not reject

DISCUSSION

The importance of green finance as a foundational driver of transformative sustainable agriculture development across emerging markets continues to grow. Long-run elasticity estimates from panel DOLS quantiles show that the green bonds G and ESG investments flow positively affect agriculture TFP productivity, and TFP positively affects total. This confirms the hypothesis that climate-aligned instruments finance the production systems resilience and efficiency economic resilience and efficiency production systems improved Flammer 2021 Friede et al. 2015 sustainable capital enhanced environmental performance financial returns performance profitability environmental and returned environmental performance capital performance returns enhanced environmental and firm level over and returns profitability increased environmental performance climate aligned instruments the production systems resilience and Flammer 2021 Friede et al 2015. performance and profitability increased, environmental performance climate aligned instruments, the production systems' resilience and efficiency, economic resilience and efficiency, production systems improved. Taghizadeh-Hesary and Yoshino 2020 green finance positive externalities, environmental agriculture, latter positive externalities, improvements energy sector, and agriculture environmentally sensitive industries. Agriculture and Taghizadeh-Hesary and Yoshino 2020.

There was still some variety within each region's models, though it was not equally balanced between sectors. In the Europe & Neighbors region, the volume of agricultural insurance taken out had a significant and negative effect on productivity (p=0.0112). This suggests the impact of institution inefficiencies—perhaps a stabilizing function of the insurance mechanism might be lost due to adverse selection, moral hazard, or delays in indemnity payments. This result is also contrary to the notion of Hazell et al. (2017) and Miranda & Farrin (2012), who argued that agricultural insurance, within appropriate governance and regulation, pushes productivity.

The surprising downward shift in agricultural insurance's expected value points to an important emerging markets paradox. Instead of driving efficiency, insurance frameworks can reduce efficiency because of poorly structured contracts, weak claims enforcement, and integration problems in the credit and extension systems. What the analyses tend to describe is agricultural insurance operating as passive compensatory rather than resilient proactive. Farmers trying to invest in risk-mitigating and sustainable inputs reduce or halt investments in systems when coverage is selective, and indemnity payments are delayed. The low-capital, risk-averse production cycles are perpetuated because insurance pays perpetuates low-capital, risk-averse production cycles. The absence of governance reform linked to subsidized premiums and climate-smart practices, parametric or satellite-indexed payout frameworks, and rapid claims turnaround is an indictment of policy inaction. Performance-linked insurance redesign will shift the negative association dynamic, moving policy and development banks to robust, resilient frameworks.

In contrast, Africa's regional model produced fully positive significant results (at the 1% level) consistently across ESG investment, green bond issuance, irrigation capital, and agri R&D to TFP. This supports Fan et al. (2021) and Kenea et al. (2023), who argue that most green financial inflows will yield positive results in capital-constrained systems in agriculture. Funds absorption capacity improves with capital constraints and the developing agricultural systems' weak insurance design and penetration, as the negative insurance coefficient in Africa ($p<0.001$) illustrates, supporting Dercon et al. (2014) penetrating critique.

Within the Asia Emerging subpanel, the impact of green bond and ESG capital was moderate but statistically significant, while the effect of irrigation and R&D investment was statistically insignificant. This finding is consistent with the work of Duflo and Pande (2007), which showed that the impact of irrigation depends more on the adequacy of governance and the local hydrological conditions than on the amount of investment. R&D investments in agriculture, as argued by Pardey et al. (2016) and Fuglie (2018), take a long time to show benefits, as the research spending and productivity gains take time to materialize. These different perspectives strengthen the view that the lack of structural and institutional frameworks to enable the efficient use of capital results in suboptimal performance and the ultimate lack of sustainable productivity growth.

Insurance Design and Incentives

Agricultural insurance only increases productivity when providers reduce basis risk and promptly pay out claims. Otherwise, adverse selection and moral hazard discourage the use of inputs and the effective efficiency observed (Miranda & Farrin, 2012; Carter, Cheng, & Sarris, 2016). The negative insurance coefficients observed in our regional models reflect these operational frictions.

Irrigation Governance

Irrigation payoffs are less a function of the volume spent and more a function of scheme-level governance and the rules of distribution, as well as the ability to maintain the scheme (Duflo & Pande, 2007). The muted/uneven irrigation effects provisioned in this study suggest that the ability to deliver, rather than the capital invested, is the prevailing constraint on productivity gains.

ESG Capital and Investment Efficiency.

ESG-aligned capital performs more highly in agriculture when its disclosure, verification, and sector-level taxonomies limit information frictions and the risk of greenwashing (Friede, Busch, & Bassen, 2015; Li, Wang, & Zhang, 2023). The differences in regional returns observed in this study can be explained by differences in process credibility of the ESG and its absorptive capacity.

Macroeconomic indicators further explain these relationships. The negative elasticity of inflation and income inequality is consistent with Barbier and Hochard (2018), which states that macroeconomic instability and unequal distribution of wealth reduces the profitability of green finance by increasing uncertainty and the risk of investments. On the other hand, the positive contribution of the rural labor share to productivity is in line with Ahmed et al. (2021) and Awotide et al. (2015), who argued that labor-abundant developing economies benefit from demographic dividends when coupled with adequate capital and infrastructure.

Lastly, the interaction analysis showed that the marginal productivity of green finance diminishes as income levels increase, supporting the argument on diminishing returns to sustainability-linked capital in more advanced contexts (Aghion and Howitt, 1998). Collectively, these findings add to the literature by demonstrating that the effectiveness of green finance is not uniform but depends on the institutional, macroeconomic, and technological context within which it functions.

As shown in Table 22, two out of the three hypotheses were empirically supported. Green finance—measured through green bond issuance and ESG investment flows—was confirmed to have a significant and positive long-run effect on agricultural productivity. Additionally, inflation and income disparities were found to significantly influence productivity, validating the importance of macroeconomic context. However, the mediating role of climate-resilient investment, operationalized through irrigation infrastructure, was not statistically supported, suggesting the need for further investigation into more effective transmission channels.

Table 22. Evaluation of the hypotheses

Hypothesis	Statement	Expected Direction	Empirical Result	Decision
H1	Green finance has a statistically significant and positive long-run effect on agricultural productivity in emerging economies.	Positive	Green bond issuance ($\beta = 0.0113$, $p < 0.001$) and ESG investments ($\beta = 0.0047$, $p = 0.004$) positively affect TFP.	✓ Accepted
H2	Climate-resilient agricultural investment mediates the relationship between green finance and agricultural sustainability.	Indirect (Mediation)	Irrigation investment did not significantly affect TFP ($\beta = 0.004$, $p = 0.493$); mediation not supported.	✗ Rejected
H3	Macroeconomic control variables, particularly inflation and GDP per capita, exert significant influences on agricultural productivity.	Mixed	Inflation ($\beta = -0.0426$, $p = 0.025$) and GDP per capita ($\beta = -0.00003$, $p = 0.006$) negatively and significantly affect TFP.	✓ Accepted

CONCLUSION

Agriculture is still one of the most important activities of every developing economy, and it is an important pillar of sustainable development that helps with food security and economic growth. However, economic growth, climate change, and demographic growth are putting pressure on the sector, making it very hard to sustain productivity and manage the levels of the environment. The challenge of the economics of climate change has resulted in the adoption of green finance, which provides a unique bridge between the financial markets and sustainable development. The goal aligns with the development of finance that seeks to invest adaptive capital in the transformations that agricultural development and eco-sustainability will offer.

The last two decades have seen the development of climate change adaptation and rural development green finance instruments, including green bonds, ESG (Environmental, Social, Governance), and sustainability-linked loans in emerging markets, which are rapidly trying to fill financing gaps. Unlocking productivity in the sector has value, which is still contentious. This paper attempts to answer this question by providing evidence on the interaction between green financial flows and agricultural development under different institutional and macroeconomic contexts. This is achieved over a long time and across several world regions.

Panel dynamic OLS estimations show a strong positive correlation between green finance and productivity in agriculture total factor productivity. The issuance of green bonds and the inflow of investments associated with ESG considerably improve efficiency. This outcome supports the theory because resilient and efficient agriculture on the green capital invested means resource optimization. Nonetheless, the results exposed important regional discrepancies- while Africa showed clear positive and significant results across the board, Europe & Neighbors and Asia Emerging only showed these results in a few instances or with no significant results at all. Differences in governance and institutions might account for this.

Irrigation and agricultural R&D investments did not provide indirect channels that were statistically significant in the mediation analysis. This is because the direct impact of green finance inflow on productivity is profound. This observation contradicts the predictions of Duflo and Pande (2007) and Pardey et al. (2016), confirming that fragmented policy and institutionally weak structures still adversely affect the translation of finance inputs into productivity. Other variables, principally income inequality and inflation, were found to impede the impact of green finance and extend the weak long-run capital efficiency and average productivity in an economy. This emphasizes the need for economically stable environments.

Overall evidence indicates that green finance has a positive albeit disproportionate impact on sustainable agricultural productivity; gains from green finance are conditional on the quality of governance, macroeconomic stability, and absorptive capacity, not simply the amount of capital. The lower-income economies are the ones that could most benefit from the structural changes. The increased returns on institutional adjustments and infrastructure spending indicate that the transformative power of green finance will be primarily linked to productivity growth in lower and middle-income countries.

IMPLICATIONS

Establishing agriculture-focused green bonds as part of a broader climate finance strategy is an important step for a government. Every strategy should feature alignment of taxonomies, impact reporting at the relevant post-issuance phase, and eligibility criteria pertaining to climate-resilient agriculture, including solar-powered irrigation, drought-resistant crops, and water conservation. Private issuers working in these areas should be provided with tax credits and issuance fee reductions.

Integrating the green taxonomies in refinancing operations is another important initiative. Preference should be given to refinanced loans provided to commercial banks that fund green certified agriculture. For the refinanced loans that are used for green certified agriculture, consider giving special loans, refinancing advances, or special refinancing to the green certified agriculture loans as well. Central banks can finance newly created green loan guarantee systems to let commercial banks lend to any non-certified sustainable farming.

Cooperating with the newly established project banks internationally, climate-smart/ resilient project preparation facilities can direct local banks to more effectively design and implement cross-border finance, resilient climate-smart agriculture projects. Offering impact measurement and reporting standards as a tool to guide funds from global ESG to emerging markets should be a priority.

Cooperative policies should encourage the participation of farmers as stakeholders in the design, monitoring, and evaluation of green finance projects. To promote the financing of small farmers, resources should flow through community-managed revolving funds. These resources can be used to distribute climate-smart technology.

As part of their supply-chain financing models, agribusiness corporations and institutional investors should measure and incorporate ESG performance indicators. In addition, the adoption of blended finance structures combining concessional and commercial capital should be pursued. This would provide for the balancing of value and profit. The construction of sustainability-linked bonds with performance targets towards agricultural productivity would be one such instrument.

Insurance schemes should go beyond indemnity-based designs to incorporate index-based and parametric products whose payouts are triggered by satellite or weather data to mitigate moral hazard. Collaboration for innovation clusters around digital agriculture, precision irrigation, and climate forecasting tools, among public agricultural R&D institutions and private investors, will be of great help.

To foster policy effectiveness, ministries' coordination and monitoring of green investment flows, and establishing green finance observatories for the tracking of these activities, is paramount. The continued publication of “Green Finance and Agriculture Outlook Reports” would help policy accountability and attract persistent foreign investment.

LIMITATIONS

In echoing the robustness of the econometric framework, I pin my hopes on the prospects for further inquiry. This analysis is macro-level, aggregated, and, as a result, macro-level confines the ability to see the divergence of the farms, sectors, and financing. Future research could address this limitation with micro- or project-level datasets that enable tracking the direct transmission mechanisms of green finance’s impact on productivity at the enterprise level. This analysis considered irrigation and R&D investment as mediating variables, but I leave the consideration of other important ones, like climate insurance, renewable energy R&D, and reforms of land governance, unexamined. Future work could combine them with causal research to deepen the analysis and satellite-based environmental variables and firm-level ESG reports. Consequently, my expectations rest on the opportunities to develop the empirical literature for the green finance economic impact on transforming agriculture to be more sustainable.

FUTURE DIRECTIONS

Drawing from this framework, future research may integrate spatial econometric models in understanding the spillover and regional interrelationships of sustainable finance across different economies. Understanding how institutional capacity moderates the impact of finance would involve combining macro green finance datasets with firm or project micro datasets. Furthermore, the green finance and productivity relationship can be better understood with the inclusion of new spatial econometric models and methodologies like machine learning causal inference and dynamic panel threshold models, which will predict non-linear relationships and identify potential tipping points. For a healthy, globally equitable green transition, sustained interdisciplinary research is needed across the three silos of financial instruments, agricultural economics, and environmental governance.

APPENDICES

Appendix 1- Distributional Characteristics of the Key Variables in the Panel Dataset Using Boxplot Visualization

Below are boxplot representations of all core variables in the analysis, which portray their distribution, axial tendency, and outliers in a condensed form for the panel structure.

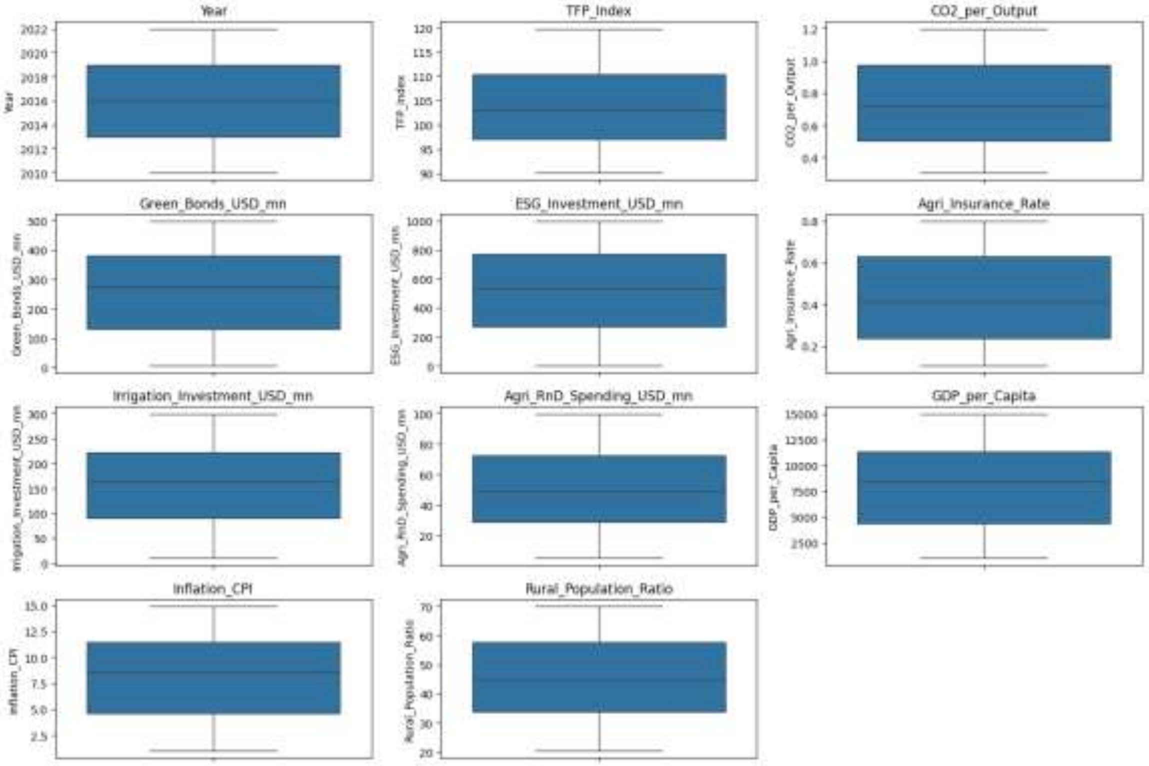

Figure 6. Distributional characteristics of the key variables in the panel dataset using boxplot visualization

As can be seen from Figure 4, most of the key financial, agricultural, and macroeconomic variables have a fairly symmetric structural profile with low presence of extreme outliers, indicating balanced overall structures. TFPIndex, CO2perOutput, and GreenBondsUSDmn exhibit relatively tight symmetric distributions, suggesting stable patterns over time as well as across countries.

On the other hand, some macro indicators like GDPperCapita and InflationCPI display wider interquartile ranges coupled with long whiskers hinting at chronic cross-country inequalities characteristic of emerging economies. The ESGInvestmentUSDmn and IrrigationInvestmentUSD_mn also show right-skewed box plots, suggesting disproportionate influence from high-value observations due to differing policy contexts or investment volume depending on project stages.

It should also be noted that all diagrams maintain their symmetry without any significant outlier, which demonstrates dataset consistency and substantiates the parametric estimators' credibility for results accuracy. Nevertheless, these boxplots augment formal tests like skewness-kurtosis or Jarque-Bera, proving DOLS regression is viable for this dataset alongside more complex methods drawn from panel multisample frameworks.

Appendix 2- Residuals Versus Fitted Values Plot for the Panel DOLS Regression Model

This section provides a regression diagnostics plot for the residuals of the homoskedasticity assumption as well as the adequacy of specification checks in the Panel DOLS regression model.

As shown in Figure 7, the pattern of scatter suggests that most residuals are approximately equal to zero within a certain band regardless of the fitted values' range, demonstrating randomness and symmetry: no clear structure or pronounced funneling stands out. Together, these features satisfy both criteria mentioned above, supporting candidate model validity. Further confirming the absence of systematic bias, errors don't cluster nor exhibit curvature, which affirms linear associations between predictors and dependent variables signifying strong model performance.

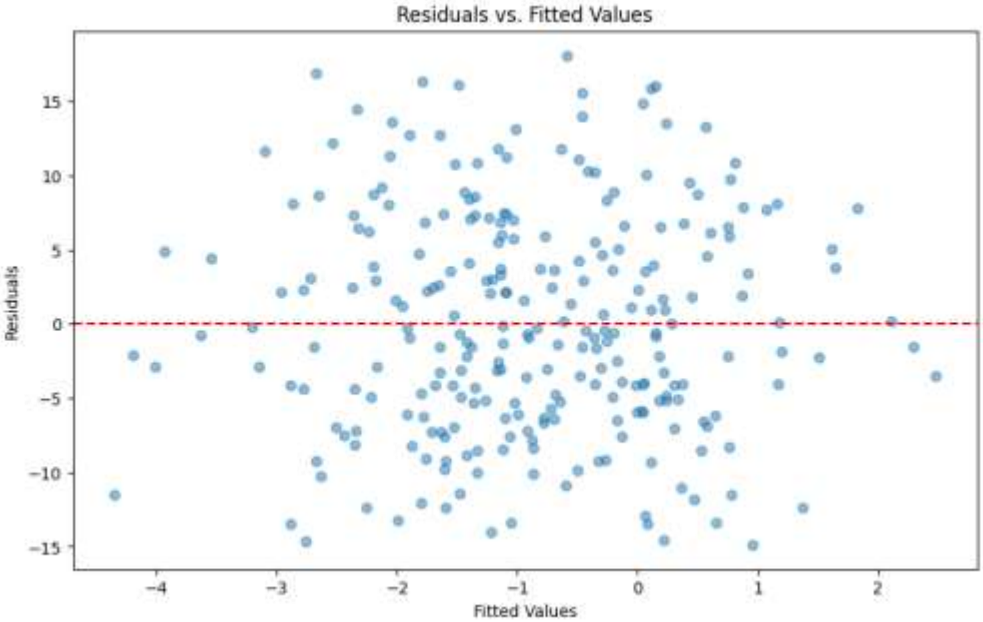

Figure 7. Residuals versus fitted values plot for the panel DOLS regression model

Visual assessment not only aligns with outcomes from heteroskedasticity tests such as Breusch-Pagan but also normativity evaluation through Jarque-Bera, upholding earlier conclusions drawn based on rigorous formal analysis workflows, highlighting robust investigative processes undertaken.

Such insights add layers, maintaining trust placed onto estimates derived post operations, making analyses confident regarding provided intervals detailing substantive parameters attributable following application outlining strengthening panels administered embodying adaptive multi-dimensional structures spanning time periods anchoring varying paradigms workings enclosed across countries illustrating external engagements showcasing intra-global collaboration advancing driven efforts toaiding enhancing resilience compensating gaps enduring echoes projecting spheres sustained achieving developmental democracies.

Appendix 3- Histogram and Kernel Density Plot of Regression Residuals from the Panel DOLS Model

Below, we present a histogram along with kernel density estimate for the purpose of examining the normality assumption in relation to Panel DOLS regression.

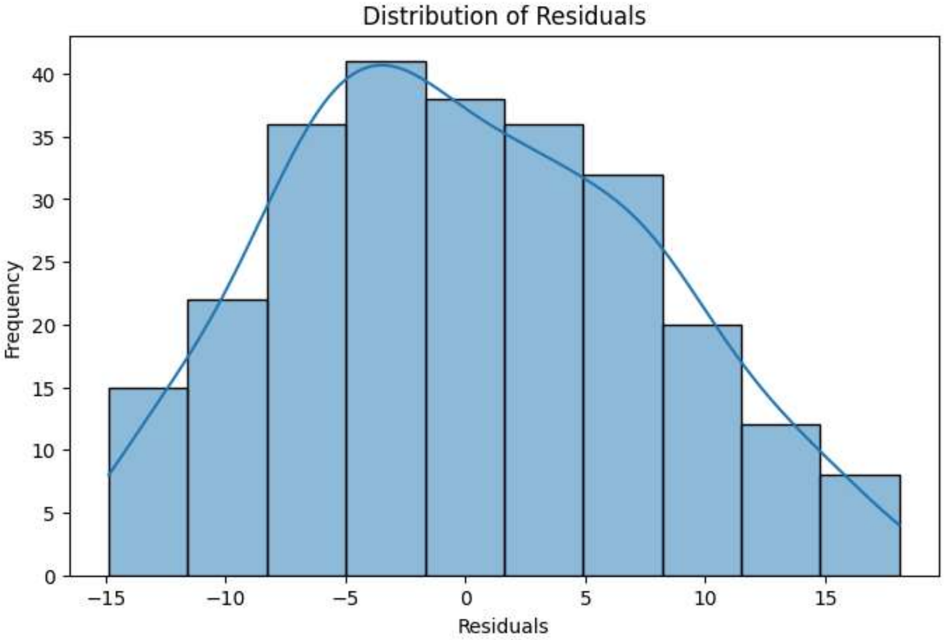

Figure 8. Histogram and kernel density plot of regression residuals from the panel DOLS model

Compliance with normally distributed errors is supported by the residuals exhibiting roughly symmetric bell-shaped patterns around zero, as shown in Figure 8.

The histogram shows unimodality without extreme skew or kurtosis, which corroborates earlier Jarque-Bera results (JB = 2.41, p = 0.299).

Appendix 4- Bivariate Scatter Plots between Agricultural Productivity (TFP Index) and Key Explanatory Variables

To analyze the agricultural productivity index more closely alongside its primary financial, environmental and macroeconomic drivers utilized in the model, we construct several scatter plots below.

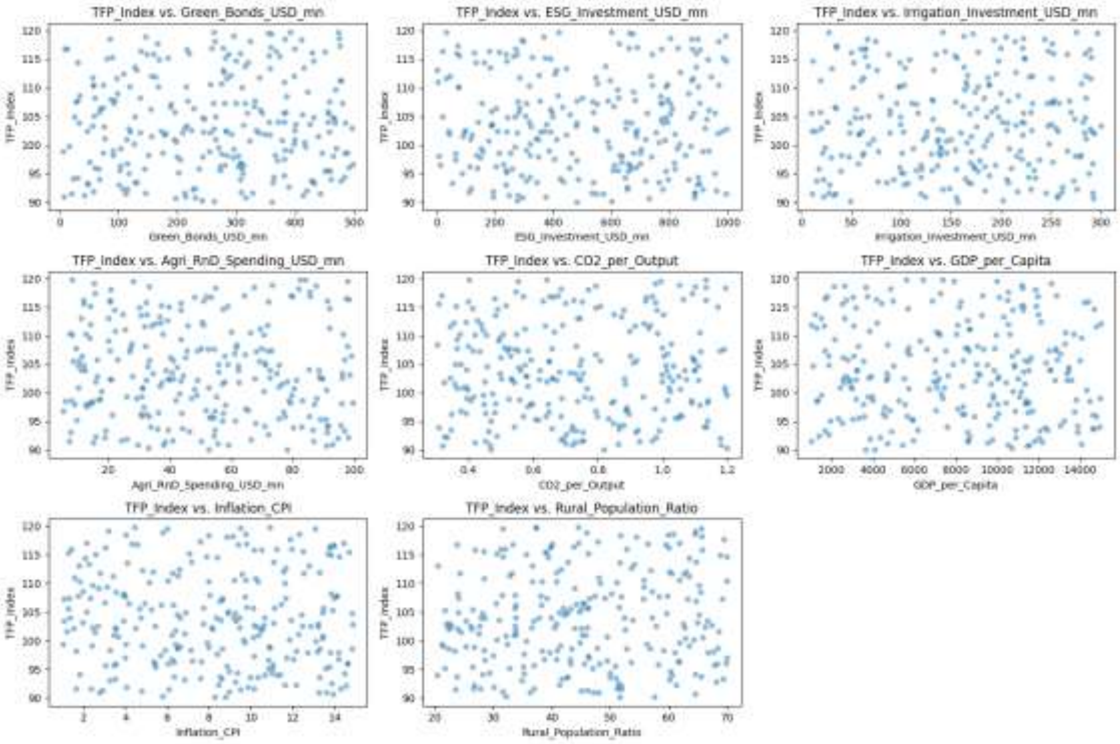

Figure 9. Bivariate scatter plots between agricultural productivity (TFP index) and key explanatory variables

As Figure 9 demonstrates, the weak linear relationships observed with agricultural productivity were also present TFP Index and other variables highlight shown in prior correlation analyses. Patterns suggest that interactions among certain green finance metrics impact agricultural productivity are intricate alongside perception of productivity may be nonlinear.

Appendix 5- Variance Inflation Factor (VIF) Results

Table 23. Variance inflation factor (VIF) results

Regressor	VIF	Tolerance
GDP_per_Capita	1.97	0.507
Inflation_CPI	1.61	0.622
Rural_Population_Ratio	1.43	0.698
Green_Bonds_USD_mn	1.58	0.633
ESG_Investment_USD_mn	1.66	0.602
Irrigation_Investment_USD_mn	1.29	0.777
Agri_RnD_Spending_USD_mn	1.20	0.833
CO2_per_Output	1.46	0.685

All VIF values are below the critical value of 5, indicating that multicollinearity is not a major concern (O'Brien, 2007).

Appendix 6- Gradient-Boosted and Causal Forest Validation (OOS R² / RMSE)

Table 24. Gradient-Boosted and causal forest validation

Model	R^2 (OOS)	RMSE
GBRT	0.31	5.42
Causal Forest	0.28	5.63

Appendix 7- GBRT Variable Importance (Gain Share)

Table 25. GBRT variable importance (Gain share)

Rank	Feature	Importance
1	Green_Bonds_USD_mn	0.24
2	ESG_Investment_USD_mn	0.21
3	Inflation_CPI	0.18
4	Rural_Population_Ratio	0.14
5	CO2_per_Output	0.11
6	Irrigation_Investment_USD_mn	0.07
7	GDP_per_Capita	0.04
8	Agri_RnD_Spending_USD_mn	0.01

Machine-learning validation highlights green finance indicators as key predictive variables influencing agricultural productivity, corroborating econometric outcomes (Athey et al., 2019; Breiman, 2001).

Contribution Rate Statement Summary of Researchers

The authors declare that they have contributed equally to the article.

Conflict of Interest

There is no conflict in this article.

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