

Green Growth through Microcredit: The Climate Adaptation Potential of Indonesia's Kredit Usaha Rakyat Policy

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This study examines the correlation between the People's Business Credit (KUR) policy and climate adaptation, as well as the promotion of green total factor productivity (GTFP) in Indonesia's agricultural sector. Utilizing a balanced panel dataset covering 34 provinces from 2016 to 2023, green productivity was measured using the Malmquist–Luenberger Productivity Index (MLPI) with a Data Envelopment Analysis (DEA) framework. The empirical findings indicate that although the KUR policy is not significantly associated with improvements in agricultural GTFP, it exhibits a positive and statistically significant effect on technological change. Moreover, the positive impact of KUR on technological advancement is amplified under higher temperature conditions, underscoring its potential role as an instrument for climate adaptation. These findings suggest that KUR primarily operates as a driver of technological progress rather than as a direct catalyst for green productivity enhancement in agriculture, offering significant policy implications for aligning agricultural credit schemes with climate resilience initiatives.

Keywords: Agriculture, climate change, Malmquist-Luenberger, People's Business Credit, productivity, technological change

JEL Classification : Q12

1. INTRODUCTION

The impact of microcredit on economic indicators, including productivity and poverty levels, has been widely documented (Choudhury et al., 2017; Debnath et al., 2019; Luoyindoula et al., 2023). Empirical evidence typically suggests that microcredit positively impacts economic outcomes. However, limited research has explored the role of microcredit in climate change adaptation, presenting a substantial gap in the literature. Investigations into the impacts of climate change on agriculture require a comprehensive environmental and climate economic analysis. Approaches, such as the Computable General Equilibrium (CGE) model and Integrated Assessment Models (IAM), notably the Dynamic Integrated Model of Climate and the Economy (DICE) and the Regional Integrated Model of Climate and the Economy (RICE)

developed by Nordhaus and Moffat (2017), have been employed to integrate the interplay between climate and economic sectors (Tol, 2014). Nonetheless, the application of these models to explain the transmission mechanisms between microcredit and agricultural productivity—particularly in terms of technological advancement and resource utilization in the context of climate change—remains underexplored.

The assessment of agricultural productivity has consistently evolved. Initially, productivity was often assessed through simple ratios of output to input, including labor or land area (Chiarella et al., 2022; Luoyindoula et al., 2023). However, Total Factor Productivity (TFP) is increasingly seen as a more comprehensive metric, encompassing all production inputs (Zhen et al., 2024). The use of TFP is particularly pertinent in addressing the climate change, as it can incorporate carbon emissions as undesirable outputs, thereby enabling the measurement of green productivity—Green Total Factor Productivity (GTFP)—through the Malmquist-Luenberger Productivity Index (MLPI) (Wang et al., 2022). The MLPI offers an appropriate metric for agricultural productivity aligned with the challenges posed by climate change.

Diverse agricultural credit programs across countries have shown positive effects on productivity. In the Republic of Congo, three major agricultural credit schemes—the Commercial Agriculture Development Support Project (PDAC), Fonds de soutien à l'agriculture (FSA), and the French Development Agency (AFD)—have contributed to enhanced agricultural productivity (Luoyindoula et al., 2023). In India, the Kisan Credit Card (KCC) scheme, which integrates government and banking sector credit facilities with interest subsidies and group lending mechanisms to mitigate default risks, has also proven effective (Agriculture Institute, 2023; Ezhar, 2020). In contrast, in Nigeria, where microcredit is predominantly provided by non-profit organizations, its impact has been less pronounced in rural agricultural regions (Idewawumi & Ademola, 2015).

In Indonesia, the government places a high priority on the People's Business Credit (Kredit Usaha Rakyat/KUR) policy as a strategic instrument to expand financial access for segments of the population that do not meet conventional credit criteria. This commitment is reflected in the steadily increasing disbursement of KUR funds. The realization of KUR financing in 2023 reached IDR 259.8 trillion, representing a tenfold increase from IDR 22.8 trillion in 2015. This significant growth is attributed to the broadening of the policy's target beneficiaries—initially focused on micro, small, and medium enterprises (MSMEs) in the trade sector—now extended to include strategic production sectors, such as agriculture.

Kredit Usaha Rakyat (KUR) was officially introduced by the Indonesian Government in 2007 as a national policy initiative aimed at expanding credit accessibility for productive micro, small, and medium enterprises (MSMEs) that do not meet conventional lending criteria. The program was launched under a coordinated policy framework involving the central government, state-owned banks, and credit guarantee institutions, with the government providing partial guarantees to mitigate lenders' credit risk. Initially, KUR focused primarily on supporting MSMEs in trade, services, and small-scale production sectors to foster financial inclusion, employment creation, and poverty reduction. Over time, the scope of KUR expanded in both scale and sectoral coverage, ultimately incorporating strategic sectors, such as agriculture as part of broader economic development and resilience strategies.

The Agricultural Sector-specific KUR Policy was formally introduced in 2018 through the Regulation of the Minister of Agriculture Number 16/Permentan/SR.230/4/2018. This program offers farmers preferential credit terms, including subsidized low-interest loans, thereby augmenting their capacity to engage in both productive and consumptive economic activities. During the COVID-19 pandemic, KUR played a critical role in accelerating economic recovery initiatives and improving social conditions. Notably, in 2022, the government introduced an additional 3% interest subsidy specifically for agricultural KUR loans, highlighting the

program's significance as a policy instrument in improving productivity in the agricultural sector.

The Agricultural People's Business Credit (Kredit Usaha Rakyat / KUR Sektor Pertanian) is a government-backed financing program designed to provide working capital and investment loans to individuals, groups, or enterprises engaged in productive and viable activities but lacking sufficient collateral (Ika et al., 2016). The program is distributed through commercial banks and designated financial institutions, including cooperatives. So as to reduce financial risk, the government guarantees up to 70% of potential loan defaults, with the remaining 30% borne by the lending institution. The overarching aim of KUR is to expand financial inclusion by broadening access to credit for individuals excluded from conventional banking systems.

According to Ministry of Agriculture Regulation No. 16/Permentan/SR.230/4/2018, KUR is classified into several categories. Micro KUR provides loans up to 25 million Rupiah, with repayment terms of three years for working capital and five years for investment. Small KUR and Special KUR offer loans up to 500 million Rupiah, with repayment terms ranging from four to five years. The agricultural subsectors eligible for financing include upstream production (e.g., seed, fertilizer, pesticide, and machinery provision), cultivation (planting and harvesting of biological resources), and downstream activities (post-harvest processing, storage, and marketing). Within this structure, KUR directly supports productive activities, including the procurement of agricultural inputs and mechanization, underscoring its pivotal role in strengthening agricultural production systems.

From a theoretical standpoint, KUR has implications for the agricultural supply-demand equilibrium. By facilitating access to modern inputs and technologies, KUR shifts the agricultural supply curve outward, thereby increasing production capacity. Higher output levels can exert downward pressure on commodity prices, which in turn affects farm incomes and ultimately farmer welfare. This dynamic indicates that farmer well-being is largely determined by improvements in agricultural productivity, positioning KUR as both a financing instrument and a catalyst for structural transformation in rural economies.

Eligibility criteria vary across financial institutions. For instance, Bank Rakyat Indonesia (BRI) stipulates that applicants must be individuals or MSMEs engaged in productive and viable activities, with a minimum age of 17 years. Additionally, applicants must have operated their businesses for at least six months, and eligibility is restricted if the borrower is already receiving other forms of credit. In the agricultural sector, eligibility is also defined by production cycles that correspond with seasonal farming patterns.

Importantly, KUR has the potential to serve as a financing mechanism for regenerative agriculture aimed at climate adaptation. As stipulated in Regulation No. 16/Permentan/SR.230/4/2018, KUR can be utilized for both working capital and investment purposes, thereby supporting capital formation in agriculture through the acquisition of fixed assets and inputs. This enables farmers to adopt disaster-resilient and eco-friendly technologies, aligning agricultural finance with the objectives of the Long-Term Strategy for Low Carbon and Climate Resilience 2050 (LTS-LCCR 2050). Therefore, agricultural KUR is not merely a financial inclusion policy but also a potential instrument for advancing climate adaptation and mitigation strategies in Indonesia's agricultural sector.

The Long-Term Strategy for Low Carbon and Climate Resilience (LTS-LCCR) 2050 designates agricultural credit financing as a pivotal component in the adaptation and mitigation strategies for the agricultural sector. Agricultural productivity is projected to improve through the intensification of agricultural inputs and the adoption of improved technologies. So as to increase production, farmers are urged to leverage financial access, such as credit from banks or other financial institutions, to replace or supplement existing production inputs. The People's

Business Credit (Kredit Usaha Rakyat/KUR) program offers an accessible financing alternative for farmers. Specifically, the agricultural sector KUR policy aims to support farmers in implementing adaptation strategies in response to climate change. Within the LTS-LCCR 2050 framework, access to credit is positioned as a critical enabler for the adoption of agricultural technologies, rendering it a strategic priority for continued development.

Beyond facilitating the use of agricultural inputs, KUR also plays a potential role in enhancing farmers' competencies to implement regenerative agricultural practices or Climate Smart Agriculture (CSA) approaches. Consequently, the KUR program holds significant potential as an integral policy instrument in achieving Indonesia's 2050 carbon emission reduction targets.

The agricultural sector is a primary focus in Indonesia, with over 50% of the workforce engaged in agriculture, as per the 2025 Sakernas figures. Given agriculture's strong dependence on climate cycles, it remains the most vulnerable sector to climate-related impacts. The sector's susceptibility, combined with its large labor force, highlights the extensive socio-economic risks posed by climate change. Therefore, mitigating climate impacts in agriculture has emerged as a crucial policy concern for the government.

The Long-Term Strategy for Low Carbon and Climate Resilience (LTS-LCCR) 2050 identifies credit financing in agriculture as a pivotal component of both adaptation and mitigation strategies. Enhancing agricultural productivity is envisioned through improved access to inputs and technologies, for which credit plays an enabling role. Farmers can utilize credit from banks or financial institutions to invest in or replace production inputs. Thus, the People's Business Credit (KUR) program serves as a potentially accessible funding alternative for farmers. Specifically, agricultural KUR policies are not yet formulated to support farmers in adapting to climate change. LTS-LCCR 2050 highlights farmer credit access as a central mechanism in promoting technological adaptation, establishing it as a strategic priority for continued development.

This study emphasizes agricultural output in relation to the impact of KUR on agricultural productivity, rather than assessing output productivity relative to input. Moreover, the investigation of KUR as an adaptation strategy of climate changes remains limited in Indonesia. Therefore, analyzing KUR within the framework of climate adaptation offers a valuable contribution to the climate policy literature in Indonesia. This study aims to provide a benchmark for evaluating the climate-related effectiveness of KUR policy on agricultural sector productivity.

This study seeks to contribute to the academic discourse on climate change policy by offering novel insights into the role of the People's Business Credit (KUR) as a mechanism for both adaptation and mitigation strategies. It provides an innovative perspective on green economics, particularly by introducing an alternative approach to measuring green productivity beyond conventional methods. Through this analysis, the relevance of KUR in tackling climate change challenges is empirically examined.

Furthermore, the findings are expected to guide stakeholders, particularly policymakers, in the design and management of agricultural KUR policies. The study offers empirical evidence that could contribute to the ongoing development and refinement of KUR initiatives in the future. In so doing, the agricultural KUR initiative can be managed more effectively and efficiently in support of sustainable development goals.

2. LITERATURE REVIEW

Studies examining the impact of credit on agricultural productivity have reported mixed findings. Numerous studies have highlighted negative effects, including labor inefficiency caused by excessive credit absorption (Seven & Tumen, 2020), or insignificant impacts where recipients already have adequate access to agricultural inputs (Nakano & Magezi, 2020). Nonetheless, most data support a positive relationship between credit and productivity in the agricultural sector (Ahmad, 2020; Idewawumi & Ademola, 2015). Agricultural credit has demonstrated the capacity to augment productivity through increased investment and capitalization (Akudugu, 2016), while also promoting the adoption of advanced agricultural technologies, including high-quality seeds, modern machinery, irrigation systems, pesticides, and fertilizers (Kipkoge et al., 2025; Luoyindoula et al., 2023; Mariyono, 2020). Research by Mariyono (2018) and Mariyono et al. (2019) further underscored that farmers who received credit were more inclined to adopt improved technologies, thereby boosting agricultural output. Moreover, the adverse impacts of climate change on agricultural productivity can be mitigated through the adoption of climate-resilient technologies, which play a significant role in enhancing productivity in the agricultural sector (Song et al., 2022).

To analyze the impact of climate change on agriculture, the Ricardian analysis is frequently employed as a policy-relevant framework (Mendelsohn et al., 1994). This quantitative approach initially utilized cross-sectional data to compare the effects of climatic variation across farming locations and growing seasons (Abidoye et al., 2017; Burke & Emerick, 2016; Huong et al., 2019; Passel et al., 2017; Shakoor et al., 2011). However, cross-sectional data may be susceptible to bias from unobserved, time-invariant variables. In contrast, panel data offer a methodological advantage by reducing omitted variable bias stemming from factors such as weather patterns, time variation, or spatial differences in agricultural settings (Bozzola et al., 2017; Burke & Emerick, 2016). For instance, Bozzola et al. (2017) applied the Ricardian model using land values per hectare across crop and livestock farmers through a panel data approach.

In assessing the impact of the People's Business Credit (Kredit Usaha Rakyat or KUR) through the Ricardian framework, policy assessment entails examining the factors affecting production input variables and the variables related to climate change impact. The use of panel data enables more accurate modeling and simulation compared to cross-sectional data. Furthermore, prior policy studies on agricultural subsidies in Indonesia often presumed a linear correlation between temperature and productivity. However, in climate impact analysis, temperature generally has a nonlinear effect, necessitating quadratic specification (Abidoye et al., 2017; Huong et al., 2019). Therefore, adapting the model to account for climate change impacts in the analysis of KUR policy introduces a novel contribution to agricultural research in Indonesia, particularly for the government.

3. RESEARCH METHODS

Building upon the aforementioned empirical studies, this research integrated climate variables with microcredit variables. We introduced a set of control variables to address concerns over omitted variables, including the Incremental Capital Output Ratio (ICOR), the consumer price index, the KUR variable (Nchake & Shuaibu, 2020; Tumen & Seven, 2020), along with financial and social characteristics (Ruzzante *et al.*, 2021). Green Total Factor Productivity (GTFP) was estimated using the Malmquist-Luenberger Productivity Index (MLPI), grounded in the metrics of output, emissions, and production inputs (Jiang *et al.*, 2024; Song *et al.*, 2022; Wang & Qian, 2024).

The data spanned the period from 2016 to 2023, corresponding to the transition of KUR with an interest subsidy scheme. The dataset comprised a panel of 34 provinces across Indonesia. Provincial-level data were employed as they provided the most comprehensive and granular information for our investigation. All data were obtained from the Ministry of Finance, the Ministry of Agriculture, the Meteorology, Climatology, and Geophysical Agency (BMKG), and the Central Statistics Agency (BPS).

Green productivity was estimated using the Malmquist-Luenberger Productivity Index (MLPI) approach. MLPI offers an advantage over conventional indices, including the Fisher and Tornqvist indices, in that it does not require input or output price information (Chung *et al.*, 1997). MLPI assessed dynamic productivity by comparing decision-making units (DMUs) across two time periods, t and $t+1$, using Data Envelopment Analysis (DEA). A DMU is considered to have experienced productivity growth when the MLPI score exceeds 1, and a decline when the score falls below 1. For ease of interpretation, MLPI values were multiplied by 100% to represent productivity as a percentage.

The use of DEA in productivity estimation offers key advantages in handling datasets with multiple inputs and outputs across different time periods (Shah *et al.*, 2024). Moreover, in contrast to Stochastic Frontier Analysis (SFA), DEA does not enforce strict assumptions, including the requirement for error decomposition to be uncorrelated with inefficiency. Thus, MLPI with the DEA approach can be applied without the necessity to adhering to such restrictive assumptions.

Table I: List of Variables

Main Variables	Measurement	Description
GTFP	Percent	Change of Green Total Factor Productivity
TECH	Percent	Change of Technical Efficiency
TECCH	Percent	Change of Technology Progress
KUR	Billion Rupiah	Value of KUR in agriculture sector
Td	Celsius	Yearly average temperature
Rd	mm ³	Yearly average precipitation rainfall
Productivity Variables		
GDP	Billion Rupiah	Value of real GDP (base year 2010)
Carbon Emission	Gigagram	Value of carbon emission in agriculture sector
Labor	Person	Number of labors in agriculture sector
Land	Hectare	Agriculture land area
Control Variables		
CPI	Index	Consumer Price Index (base year 2018)
ICOR	Ratio	Incremental capital output ratio
Year of School	Year	Average school year
Population	Person	Number of populations
Bank	Office	Number of bank offices
BTS	Percent	Percentage of villages with <i>Base Transceiver Station</i>
CPI	Index	Consumer Price Index (base year 2018)

COVID	Category	1 = Covid Period (2020-2022) 0 = Non-Covid Period (2016-2019 & 2023)
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MLPI illustrates the correlation between production inputs and outputs through a Data Envelopment Analysis (DEA) approach. In the agricultural sector, relevant production inputs typically include land, labor, fertilizers, water, pesticides, machinery, and plastic film (Huang et al., 2022; Jiang et al., 2024; Zhou & Zhang, 2024). Nonetheless, due to data limitations, this study employed solely labor and harvested land area as proxy for production inputs. The desirable output was measured by the Gross Regional Domestic Product (GRDP) at constant prices (Lu et al., 2024; Zhou & Zhang, 2024), while the undesirable output was represented by the value of greenhouse gas (GHG) emissions (Huang et al., 2022; Jiang et al., 2024). We also used the proportion of the village with access to the internet network via Base Transceiver Station to control farmer's technology adoption.

A notable advantage of the MLPI is its ability to disaggregate productivity into two primary components: technical efficiency change (TECH) and technological change (TECCH). This disaggregation underpins the basis for using MLPI as a tool to estimate green productivity (Wang et al., 2022). MLPI evaluates productivity by measuring the distance from the decision-making unit (DMU) to the production frontier based on a specified directional vector. This study applied the directional vector $g = (0, Y, -B)$, adopting an output-oriented approach under the premise of relatively similar scale efficiencies across DMUs. Green Total Factor Productivity (GTFP) was estimated using the MLPI-DEA model, following the specification established by Chung et al. (1997), as detailed below:

$$D_r(x, y, b; g) = \max_{\beta, \lambda} \beta \dots \dots \dots (1)$$

$$s. t. \sum_{\tau \in \Gamma_t} \sum_{j=1}^J \lambda_{j\tau} x_{j\tau} \leq x + \beta g_x$$

$$\sum_{\tau \in \Gamma_t} \sum_{j=1}^J \lambda_{j\tau} y_{j\tau} \leq y + \beta g_y$$

$$\sum_{\tau \in \Gamma_t} \sum_{j=1}^J \lambda_{j\tau} b_{j\tau} \leq b + \beta g_b$$

$$\lambda_{j\tau} \geq 0, j = 1, \dots, J$$

$$GTFP = \left\{ \frac{1+D_r^t(x^{t+1}, y^{t+1}, b^{t+1}; g)}{1+D_r^t(x^t, y^t, b^t; g)} \times \frac{1+D_r^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; g)}{1+D_r^{t+1}(x^t, y^t, b^t; g)} \right\}^{\frac{1}{2}} \dots \dots \dots (2)$$

In this context, D denotes the directional distance function, j represents unit, t refers to time, x represents inputs, y denotes desirable outputs, and b stands for undesirable outputs.

The two fundamental components of the MLPI—TECH and TECCH—capture technical efficiency change (the “catching-up” effect) and technological change (the “frontier-shift” effect), respectively. TECH refers to changes in a unit’s ability to utilize production inputs—viz. labor and harvested land in this study—to produce outputs under a given technology. Other inputs are assumed to have proportional usage patterns to labor and land. On the other hand, TECCH reflects changes in the global production frontier over time, which also captures the effects of adopting new technologies or resource innovations beyond conventional inputs—including drought-resistant seeds and organic pesticides. The estimation of TECH and TECCH follows the model proposed by Chung et al. (1997), as outlined below:

$$TECH = \frac{1+D_r^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; g)}{1+D_r^t(x^t, y^t, b^t; g)} \dots \dots \dots (3)$$

$$TECCH = \left\{ \frac{1+D_r^t(x^{t+1}, y^{t+1}, b^{t+1}; g)}{1+D_r^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; g)} \times \frac{1+D_r^t(x^t, y^t, b^t; g)}{1+D_r^{t+1}(x^t, y^t, b^t; g)} \right\}^{\frac{1}{2}} \dots \dots \dots (4)$$

Subsequent to the green productivity estimation, the analysis proceeded with a fixed effects model to examine the correlation between the KUR policy, climatic variables, and productivity change. After estimating green productivity through the MLPI framework, we employed a fixed effects (FE) panel model to analyze the correlation between the People's Business Credit (KUR) policy, climate variables, and productivity dynamics across provinces. The FE specification was selected to control for unobserved, time-invariant heterogeneity at the provincial level, including agro-ecological conditions, historical land institutions, and structural differences in agricultural production systems, as well as common macroeconomic and policy shocks through year fixed effects. This approach enables the analysis to focus on within-province variations over time, thereby reducing bias stemming from persistent cross-sectional differences that could affect productivity outcomes. We acknowledge, however, that the correlation between KUR and productivity may remain subject to bias. To further mitigate these concerns, the model incorporated a comprehensive array of time-varying control variables, climate indicators, and lagged variables. Although these strategies did not fully eliminate endogeneity, they substantially improved identification by isolating short-run within-province co-movements between KUR, climate conditions, and productivity change. Accordingly, the FE estimates were interpreted as conditional associations rather than causal effects.

Based on the conceptual framework, the empirical model applied a Ricardian analysis specifically tailored to the agricultural sector, formulated as follows:

$$GTFP_{it} = \alpha + \rho_i + \gamma_1 KUR_{it} + \gamma_2 Td_{it} + \gamma_3 Td^2_{it} + \gamma_4 Rd_{it} + \gamma_5 Rd^2_{it} + \gamma_6 KUR_{it} x Td_{it} + \gamma_7 KUR_{it} x Td^2_{it} + \gamma_8 KUR_{it} x Rd_{it} + \gamma_9 KUR_{it} x Rd^2_{it} + X_{it} + \varepsilon \dots \dots \dots (5)$$

$$TECH_{it} = \alpha + \rho_i + \gamma_1 KUR_{it} + \gamma_2 Td_{it} + \gamma_3 Td^2_{it} + \gamma_4 Rd_{it} + \gamma_5 Rd^2_{it} + \gamma_6 KUR_{it} x Td_{it} + \gamma_7 KUR_{it} x Td^2_{it} + \gamma_8 KUR_{it} x Rd_{it} + \gamma_9 KUR_{it} x Rd^2_{it} + X_{it} + \varepsilon \dots \dots \dots (6)$$

$$TECCH_{it} = \alpha + \rho_i + \gamma_1 KUR_{it} + \gamma_2 Td_{it} + \gamma_3 Td^2_{it} + \gamma_4 Rd_{it} + \gamma_5 Rd^2_{it} + \gamma_6 KUR_{it} x Td_{it} + \gamma_7 KUR_{it} x Td^2_{it} + \gamma_8 KUR_{it} x Rd_{it} + \gamma_9 KUR_{it} x Rd^2_{it} + X_{it} + \varepsilon \dots \dots \dots (7)$$

In this context, GTFP denotes green total factor productivity, TECH indicates technical efficiency change, TECCH refers to technological change, KUR represents the disbursed amount of People's Business Credit, Td refers to temperature, Rd signifies rainfall, X constitutes a vector of control variables, μ_i and δ_t denote province and time fixed effects, respectively, while ε_{it} is the error term.

The effect of KUR on productivity is assessed through the KUR coefficient. Meanwhile, the climate adaptation role of the KUR policy is analyzed through the interaction terms between KUR and climate variables. If γ_6 is negative and γ_7 is positive, the impact of KUR on productivity increases as temperature rises. Conversely, if γ_6 is positive and γ_7 is negative, the correlation weakens with higher temperatures. The identical interpretation applies to γ_8 and γ_9 : a negative γ_8 and positive γ_9 suggesting that KUR has a stronger association with productivity at higher

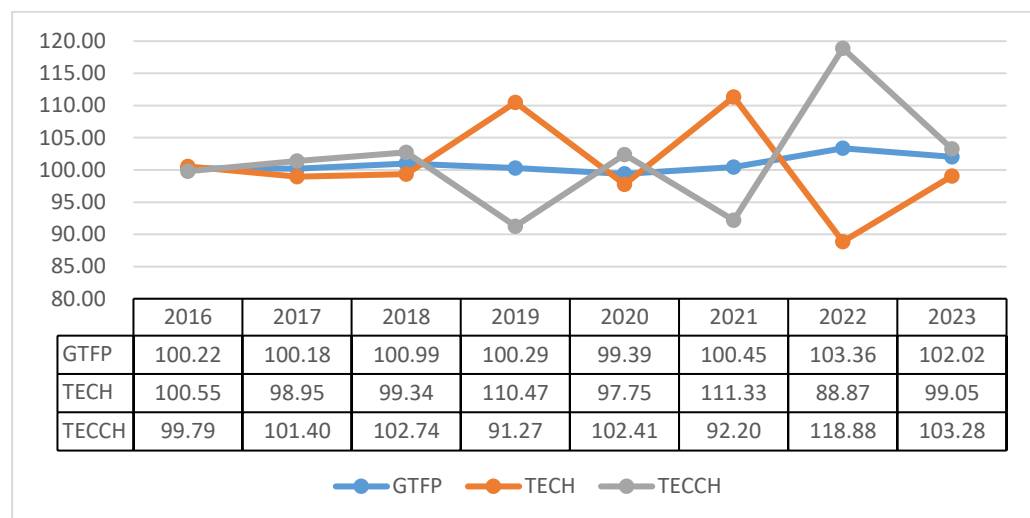
rainfall levels, whilst a positive γ_8 and negative γ_9 indicate a diminishing impact of KUR as rainfall increases.

4. RESULTS AND DISCUSSION

The national averages of GTFP, TECH, and TECCH were calculated to assess the progress of productivity change in Indonesia, as illustrated in Figure 1. TECH, as an indicator of technical efficiency in resource management, exhibited a notable declining trend. A notable decline occurred in 2022, with a value of 88.87%, indicating a regression relative to 2021. The decline in TECH values suggests inefficiencies in the management of agricultural land and labor. Such inefficiency may stem from a decrease in labor productivity or the unproductive use of agricultural land. This inefficiency in utilizing production inputs was reflected in the estimated TECH values.

In contrast to the decline in technical efficiency, TECCH, which assesses technological change, displayed an upward trajectory. The most significant increase occurred in 2022, reaching 118.8%. This suggests that notable technological transpired during that year, possibly attributable to the adoption of higher-quality agricultural machinery and more productive seed varieties adapted to warmer climatic conditions.

Figure 1: Average Green Productivity by Province 2016-2023



Source: Author own work

According to the GTFP estimates, Jakarta recorded the highest productivity value at 169% in 2022, whereas Jambi reached 133% in the same year. In 2023, Gorontalo and North Sulawesi recorded the highest GTFP values at 105% and 119%, respectively. In 2021, North Maluku and West Sulawesi emerged as the top-performing provinces, with GTFP values of 106%.

In 2022, Jakarta implemented urban farming initiatives focusing on horticultural commodities, including chiles, vegetables, and fruits. These commodities require relatively minimal land, thus enhancing productivity. According to the Performance Report of the Jakarta Provincial Food Security, Marine, and Agriculture Office, the realized budget for agricultural infrastructure amounted to IDR 16.2 billion. Development efforts were focused in the Thousand Islands area, designated as a strategic agricultural zone for Jakarta in 2022.

Jambi has emerged as a pioneer of green strategies through the Jambi Sustainable Landscape Management Project, funded by the BioCarbon Fund Initiative for Sustainable Forest

Landscapes (BioCF-ISFL). One of the project's components entailed reducing land allocated for palm oil plantations. In 2023, North Sulawesi progressed the development of Sustainable and Inclusive Agricultural Commodity Areas and Value Chains (ICARE), particularly for coconut and maize. According to the Agricultural Instrument Standardization Implementation Office in North Sulawesi, project implementation reached IDR 2.3 billion in 2023. Gorontalo witnessed a sharp decline in palm oil plantation productivity in 2023, whilst sugarcane production increased. The Agricultural Instrument Standardization Implementation Office in Gorontalo introduced higher-quality maize seeds in the same year.

Table II: Regression Summary

Variables	GTFP	TECH	TECCH
KUR	0.00587 (0.143)	-0.670** (0.314)	0.918*** (0.302)
Temperature	9.298 (22.77)	-70.19 (49.89)	141.7*** (47.94)
Temperature Squared	-0.170 (0.420)	1.391 (0.921)	-2.673*** (0.885)
KUR_Temperature	-0.000393 (0.0105)	0.0497** (0.0230)	-0.0670*** (0.0221)
KUR_TemperatureSquared	2.80e-06 (0.000192)	-0.000917** (0.000421)	0.00122*** (0.000405)
Precipitation	-0.00219 (0.00353)	0.000288 (0.00773)	-0.000658 (0.00742)
Precipitation Squared	3.74e-07 (6.51e-07)	-4.04e-10 (1.43e-06)	1.57e-08 (1.37e-06)
KUR_Precipitation	1.60e-06 (1.59e-06)	-1.61e-06 (3.48e-06)	3.18e-06 (3.34e-06)
KUR_PrecipitationSquared	-2.16e-10 (2.68e-10)	0 (5.87e-10)	-2.99e-10 (5.64e-10)
Controls	Yes	Yes	Yes
Observations	272	272	272
R-squared	0.047	0.161	0.259

Note: For all the regressions, year fixed effects are controlled; t statistics in parentheses; *p<0.1, **p<0.05, ***p<0.01. Source: Stata

The regression results presented in Table 2 indicate that KUR policy was not statistically significantly correlated with green productivity in the agricultural sector. However, KUR showed a markedly negative correlation with technical efficiency. An increase of IDR 1 billion in KUR disbursement correlated with a 0.67 percentage point decrease in technical efficiency, on average, *ceteris paribus*. This negative correlation may arise from inefficiencies in the use of agricultural labor. The figures indicated an increase in the number of agricultural workers relative to the change in cultivated land area. Such inefficiency might be attributed to the creation of a labor market surplus in the agricultural sector, driven by credit expansion, which ultimately reduces labor productivity (Seven & Tumen, 2020). In addition, land ownership

remains a barrier for farmers, particularly those leasing land, which limits their ability to fully optimize agricultural land (Mariyono, 2019). The barrier of land acquisition, coupled with the higher other input use, likely cause the diminished marginal returns, highlighting the inefficiency problem in resource utilization. Consequently, access of inputs, particularly land, significantly plays the major role in technical efficiency.

Climate variables, including temperature and rainfall, were not found to be significantly correlated with productivity through technical efficiency. This suggests that the efficiency of resource management is not directly related to climatic conditions, such as temperature or rainfall. The lack of a notable climate-to-efficiency transmission aligns with the findings of Shaibu & Nchake (2020) and Yin et al. (in Song et al., 2022), indicating that temperature and precipitation do not substantially influence agricultural productivity. This may be attributed to the presence of adequate irrigation infrastructure that buffers climate variability (Zhou et al., 2024).

KUR, however, exhibited a significantly positive correlation with technological progress in the agricultural sector. A one-billion-rupiah increase in KUR disbursement correlated with a 0.91 percentage point increase in technological progress, on average, *ceteris paribus*. Luoyindoula et al. (2023) argue that credit accelerates the adoption of agricultural technologies, thereby enhancing productivity. Higher levels of KUR can facilitate farmers' access to mechanized inputs and more efficient agricultural systems relative to current alternatives. The adoption of more advanced technology leads to higher agricultural productivity.

Temperature was significantly and positively associated with productivity through technological progress. However, at higher temperatures, the marginal effect of climate on productivity turned negative. This implies that while temperature increases may initially boost productivity through innovation, continued temperature rise ultimately reduces productivity due to accelerated depreciation or obsolescence of technologies. Song et al. (2022) argue that rising temperatures may shorten the effective lifespan of agricultural machinery, especially when used on climate-affected land.

Rainfall was not significantly associated with technological change. Zhou et al. (2024) suggest that robust agricultural infrastructure could help mitigate the effects of fluctuating rainfall, thereby neutralizing its impact on technological progress.

The correlation between KUR policy and climate change in relation to technological advancements is illustrated in Figure 2. The regression results also showed that KUR has a negative direct correlation with agricultural productivity in technology, which progressively turns positive as temperature rises. The Marginal Impact (MI) of temperature on technological progress is derived as follows:

$$MI_{Td} = \left[\frac{\partial TECCH}{\partial Td} \right] = \gamma_2 + 2\gamma_3 Td_{it} + \gamma_6 KUR_{it} + 2\gamma_7 KUR_{it} x Td_{it} \dots \dots \dots (8)$$

$$\Delta MI_{Td} = MI_{Td+1} - MI_{Td} \dots \dots \dots (9)$$

$$\begin{aligned} \Delta MI_{Td} = & [\gamma_2 + 2\gamma_3 Td_{td+1} + \gamma_6 KUR_{it} + 2\gamma_7 KUR_{it} x Td_{td+1}] \\ & - [\gamma_2 + 2\gamma_3 Td_{td} + \gamma_6 KUR_{it} + 2\gamma_7 KUR_{it} x Td_{td}] \end{aligned}$$

$$\Delta MI_{Td} = [2\gamma_3 Td_{td+1} + 2\gamma_7 KUR_{it} x Td_{td+1}] - [2\gamma_3 Td_{td} + 2\gamma_7 KUR_{it} x Td_{td}]$$

$$\Delta MI_{Td} = 2\gamma_3 (Td_{td+1} - Td_{td}) + 2\gamma_7 KUR_{it} x (Td_{td+1} - Td_{td})$$

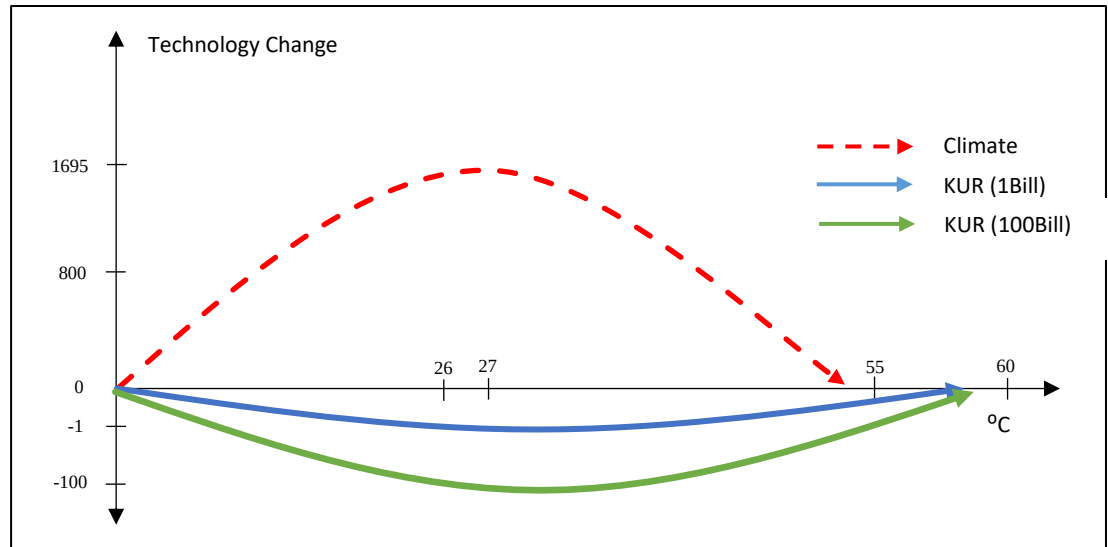
Based on the formula, the change in MI corresponding to a 1°C increase in temperature and an IDR 1 billion increase in KUR is calculated as follows:

$$\Delta MI_{Td} = 2\gamma_3 + 2\gamma_7 = 2(-2.673) + 2(0.001) = -5.34$$

This means that a 1°C temperature increase, combined with a KUR value of IDR 1 billion, correlates with a 5.34 percentage point decline in productivity through technological change. This association exceeds the 2.3–3.4 percentage points reported by Song et al. (2022). The adverse effects of climate are more pronounced in hotter regions compared to cooler ones (Pasel et al., 2017).

The interaction between KUR and temperature indicates that KUR has a marginally positive relationship with productivity, suggesting the adaptation of climate change. The increased expenditure in KUR would correlate with a lower marginal relationship of climate change. This suggests that KUR may help mitigate the relationship of climate on agricultural productivity through the adoption of climate-resilient technologies (Song et al., 2022; Mariyono, 2020). Thus, KUR policy is significantly and positively associated with climate adaptation in agriculture, primarily due to its contribution to technological progress. The findings encourage Government to put more concern on KUR in agricultural sector, particularly on adaptation and mitigation strategies of climate change.

Figure 2 The role of KUR in impact of climate to technology change



Source: Author own work

The explicit integration of Agricultural Credit (KUR) into the Long-Term Strategy for Low Carbon and Climate Resilience 2050 (LTS-LCCR 2050), which outlines Indonesia's climate adaptation and mitigation policies to achieve national emission targets, is currently lacking. Nevertheless, the LTS-LCCR 2050 acknowledges the potential of agricultural credit as a financing mechanism for adaptation and mitigation initiatives through agricultural inputs and technologies. In terms of agricultural technologies, mechanization includes the use of tractors, water pumps, transplanters, cultivators, and irrigation machinery. For post-harvest operations, credit financing is used for equipment, including harvesters, dryers, and milling machines. Furthermore, climate-adaptive agricultural inputs comprise drought-resistant seeds, organic fertilizers, plastic film, and low-carbon pesticides.

Considering the current requirements of KUR and the strategic goals of the LTS-LCCR 2050, KUR exhibits strong potential to serve as a green financing mechanism to bolster governmental

climate initiatives. By embedding green production criteria into KUR disbursement for the agricultural sector, the government can improve climate adaptation and mitigation activities at the farm level. This alignment is crucial, as the intersection between KUR policy and LTS-LCCR 2050 enables farmers to engage in environmentally conscious production while simultaneously improving productivity. Empirical findings further corroborate the positive interaction between KUR allocation, temperature variation, and green technology productivity in agriculture.

In addition to financing agricultural inputs and technologies, KUR can also support the development of farmers' capacity in adopting regenerative agricultural practices. This contributes to expanding the agricultural production frontier by advancing the green technological change. Climate-Smart Agriculture (CSA) embodies a holistic approach for sustainable farming practices designed to tackle climate change adaptation in the sector. As argued by Okolie et al. (2023), CSA pursues three interconnected goals: development, adaptation, and mitigation, and constitutes the most suitable set of techniques for farmers facing climate-related challenges.

In this regard, KUR in the agricultural sector holds considerable promise for operationalizing CSA in Indonesia. CSA practices may include technological adoption, input selection, and/or adaptive cultivation management. Based on the findings of Okolie et al. (2023) in the Africa, several CSA techniques are identified as potentially suitable for KUR financing in Indonesia. These are summarized in Table 3.

Table III Potential KUR Financing for Climate-Smart Agriculture (CSA)

No	CSA Technique	Climate Adaptation Objective	Potential KUR Utilization
1	Water Conservation	Reducing water usage and improving drought resilience	Financing drip irrigation systems, water pumps, recharge wells
2	Crop Varieties	Enhancing climate-resilient agricultural production	Procurement of superior seeds and funding varietal research
3	Land Management	Maintaining soil fertility and reducing carbon emissions	Capital for organic fertilizer production and agroforestry training
4	Agricultural Mechanization	Improving efficiency, productivity, and climate responsiveness	Financing fixed assets such as tractors, cultivators, and precision monitoring tools
5	Agricultural Down-streaming	Enhancing value-added production	Funding for marketing management training and commodity processing equipment

In light of these financing potentials, the current implementation and utilization of agricultural KUR in addressing climate challenges require further evaluation. Nurdin et al. (2025) examined KUR's contribution to agricultural development, revealing that while KUR improves farm efficiency and crop yields, farmers receiving KUR report lower net incomes compared to non-recipients. This indicates suboptimal utilization, primarily due to limited technical assistance

and financial literacy. Although KUR positively affects productivity through the purchase of fertilizers, seeds, and equipment, it is also associated with negative outcomes when funds are diverted toward debt repayment, non-agricultural business activities, or household consumption.

Therefore, agricultural KUR policies should be reoriented to align more explicitly with green production activities and climate adaptation and mitigation strategies. Strengthening this alignment will enable agricultural financing to serve as a strategic tool in promoting sustainable, climate-resilient farming systems in Indonesia.

5. CONCLUSION AND POLICY RECOMMENDATIONS

This study addressed the question of how the People's Business Credit (KUR) policy affects agricultural productivity. By employing the Malmquist-Luenberger Productivity Index (MLPI) approach, productivity was decomposed into two distinct components: technological change and technical efficiency. The analysis revealed that agricultural productivity in Indonesia remained relatively stagnant from 2016 to 2023. This stagnation was attributed to gains in productivity from technological progress being offset by declines due to technical inefficiencies in resource utilization. The highest productivity gains were observed in Java and Sulawesi, indicating that resource management in these regions is more effective compared to others.

The correlation between the KUR policy and agricultural productivity showed two contrasting relationships with the sources of productivity. While the amount of KUR disbursed was positively associated with technological progress, it was negatively associated with technical efficiency. This indicates that productivity gains driven by technology adoption are constrained by inefficient use of production resources. As a climate adaptation strategy, KUR has a stronger association with technological progress in regions with higher temperatures. This suggests that KUR plays a significant role in supporting climate change adaptation through the adoption of agricultural technologies that are better suited for hot climates.

Based on these findings, several policy recommendations can be proposed to improve agricultural productivity. First, increasing the credit ceiling of KUR could support broader and more impactful investments. Second, in response to rising temperatures, the adoption of climate-resilient agricultural technologies should be prioritized to mitigate environmental impacts. Providing technical assistance is essential to ensure that KUR funds are effectively used to finance the adoption of more productive technologies. Furthermore, the effectiveness of KUR in improving resource utilization necessitates augmented access to other production inputs. Expanding access to a wider and more comprehensive set of agricultural inputs can improve the efficiency of resource use funded by KUR.

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