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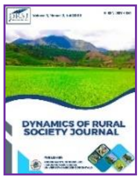

Can regenerative agriculture restore soil health and bridge gender gap in farm productivity? Empirical insights from Nigeria

Dapatkah pertanian regeneratif memulihkan kesehatan tanah dan menjembatani kesenjangan gender dalam produktivitas pertanian? Temuan empiris dari Nigeria

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ABSTRACT

This study investigates the potential of Regenerative Agriculture (RA) to improve soil health and address gender disparities in agricultural productivity among smallholder farmers in Nigeria. Using data from a randomized controlled trial, the research evaluates gender-specific RA adoption rates and their impact on farm productivity through Blinder-Oaxaca decomposition and Propensity Score Matching (PSM). Results reveal significant adoption disparities, with male farmers benefitting from larger farms, better education, and higher incomes compared to female farmers. RA adoption improved yields for both genders, though productivity gaps persisted due to structural barriers, including limited access to land, credit, and extension services for women. Female farmers, despite adopting RA practices, often faced greater challenges in maximizing productivity due to socio-economic constraints. These findings underscore the importance of addressing resource inequities and promoting gender-sensitive interventions to encourage equitable adoption of RA. Enhancing women's access to agricultural education, financial support, and climate-related information is essential. Additionally, fostering community-based platforms and collaboration can further strengthen sustainable practices. This study provides critical insights for policymakers and practitioners to improve smallholder farmers' productivity, promote sustainable agriculture, and build climate-resilient food systems in Nigeria and similar regions facing comparable challenges.

Keywords**:** adoption, climate change, decomposition technique, gender, regenerative agriculture

ABSTRAK

Penelitian ini mengkaji potensi Regenerative Agriculture *(RA) dalam meningkatkan kesehatan tanah dan mengatasi kesenjangan gender dalam produktivitas pertanian di kalangan petani kecil di Nigeria. Dengan menggunakan data dari uji coba terkontrol secara acak dan analisis* Propensity Score Matching *(PSM), penelitian ini mengevaluasi tingkat adopsi RA berbasis gender serta dampaknya terhadap produktivitas pertanian. Hasil menunjukkan adanya kesenjangan signifikan dalam adopsi RA, di mana petani laki-laki diuntungkan oleh kepemilikan lahan yang lebih luas, tingkat pendidikan yang lebih tinggi, dan pendapatan yang lebih tinggi dibandingkan petani perempuan. Meskipun adopsi RA meningkatkan hasil panen untuk kedua gender, kesenjangan produktivitas tetap ada akibat hambatan struktural, termasuk akses perempuan yang terbatas terhadap lahan, kredit, dan layanan* *penyuluhan. Petani perempuan, meskipun telah mengadopsi praktik RA, sering menghadapi tantangan lebih besar dalam memaksimalkan produktivitas mereka akibat keterbatasan sosial-ekonomi. Temuan ini menekankan pentingnya intervensi yang sensitif gender untuk mengatasi ketimpangan sumber daya dan mendorong adopsi RA yang lebih setara. Peningkatan akses perempuan terhadap pendidikan pertanian, dukungan finansial, dan informasi terkait iklim menjadi sangat penting. Selain itu, pengembangan platform berbasis komunitas untuk kolaborasi dapat memperkuat praktik berkelanjutan. Penelitian ini memberikan wawasan penting bagi pembuat kebijakan dan praktisi untuk meningkatkan produktivitas petani kecil, mempromosikan pertanian berkelanjutan, dan membangun sistem pangan yang tangguh terhadap perubahan iklim di Nigeria serta wilayah lain dengan tantangan serupa.*

Kata kunci: *adopsi, perubahan iklim, teknik dekomposisi, gender, pertanian regeneratif*

Introduction

In the rural landscapes of Nigeria, smallholder farmers bear the brunt of climate change, experiencing firsthand its devastating impacts. Crops fail when rainfall arrives too early or too late, erosion depletes fertile soil, and floods destroy the results of months of hard work. Operating with already limited resources, these farmers struggle to survive as each climate-related disruption exacerbates their vulnerabilities. Their challenges are not unique but represent the struggles of countless smallholder farmers across the globe.

Agriculture plays a dual role: it is both a critical provider of global food security and a significant contributor to climate change, primarily through greenhouse gas emissions and deforestation. However, the accelerating pace of climate change destabilizes this balance, creating a vicious cycle. Extreme weather events—floods, wildfires, and soil erosion—intensify, disproportionately affecting low-income and marginalized communities. This convergence of crises threatens livelihoods and undermines the resilience of vulnerable populations, underscoring the urgent need for sustainable solutions to safeguard both local and global food systems (FAO, 2022; IPCC, 2019). In response to these challenges, regenerative agriculture (RA) has emerged as a promising solution. As defined by Schreefel et al. (2020), RA is an approach to farming that prioritizes soil conservation as the foundation for regenerating and enhancing multiple ecosystem services. This approach seeks to break the vicious cycle by restoring ecosystem health while supporting sustainable food production. Additionally, the adoption of RA practices must also account for systemic inequalities, including gender disparities, that influence how sustainable strategies are implemented and experienced within food systems.

In addition to the broader impacts of climate change on food systems, gender disparities further influence how these systems are experienced and affected, particularly in terms of resource access and decision-making power within food production and consumption processes. Climate change impacts all dimensions of the food system, influencing each stage of the agri-food value chain from production through to consumption. It also affects the food environments where people live, as well as the resulting outcomes such as nutrition and livelihoods. Within food systems, both men and women typically hold distinct roles and duties. However, structural disparities—both formal and informal-restrict women's access to critical resources, services, and decision-making power. These imbalances shape the way each gender experiences and is impacted by climate change. Unfortunately, most existing climate change policies, investments, and strategies fail to effectively consider gender (Bryan et al., 2023).

Moreover, the vulnerability of rural communities, especially in sub-Saharan Africa, is exacerbated by both the limited capacity to adapt to climate change and the systemic inequalities discussed earlier, which hinder resilience in the face of growing climate risks. Rural communities in developing regions, especially in sub-Saharan Africa, are particularly vulnerable due to their limited ability to adapt to climate change. While wealthier countries also face significant climate risks, the outlook for agriculture in sub-Saharan Africa is increasingly bleak. Attempts to optimize food production for global food security and market expansion often result in ecosystem degradation, biodiversity loss, reduced dietary diversity, and increased susceptibility to extreme climate events. Climate change poses considerable risk to food systems in low- and middle-income countries (LMIC) and fragile contexts, affecting not only production but also other aspects of the food system, including agri-food value chains from production to consumption, food environments, and outcomes such as diets and livelihoods (Fanzo et al., 2018; IPCC, 2018).

Scientific consensus identifies human activities, particularly the release of greenhouse gases (GHGs) like carbon dioxide (CO_2), as the primary drivers of climate change. More than 90% of climate experts agree that rising GHG concentrations have exacerbated the current climate crisis (Doran & Zimmerman, 2009; Anderegg et al., 2010). Immediate action is essential to limit global temperature rise to 1.5°C (IPCC, 2018). However, many mitigation strategies, such as scaling up chemical inputs and monoculture cropping, have worsened food system instability and increased GHG emissions (FAO, 2022; Koneswaran & Nierenberg, 2008). Even with a complete cessation of anthropogenic GHG emissions, heat-trapping gases like CO_2, methane, and nitrous oxide would persist in the atmosphere. As a result, reducing atmospheric CO_2 levels through carbon sequestration in soils, plants, and built environments is crucial. In this context, formal farmer networks bridge social and institutional knowledge, playing a 'boundary-spanning' role to enhance innovation adoption (Asprooth, 2023). This collaborative approach can support carbon sequestration strategies by equipping farmers with the knowledge and tools to adopt sustainable practices effectively.

In Africa, intensive farming practices relying heavily on mechanization and synthetic inputs are degrading soils and disrupting essential ecosystem functions required for agricultural productivity. This has led to widespread soil degradation, micronutrient loss, reduced crop genetic diversity, and declining potential for carbon sequestration (Olsson et al., 2019). As Giller et al. (2021) emphasize, regenerative agriculture (RA) practices, such as minimizing soil disturbance, fostering plant diversity, and integrating organic nutrient cycles, are specifically designed to restore soil health and enhance carbon sequestration. However, their success is highly dependent on local soil conditions and the availability of resources, requiring tailored approaches to maximize their impact. For example, a study in northern Mozambique demonstrates that detailed soil fertility analysis is crucial for the development of targeted RA strategies, such as conservation agriculture and integrated soil fertility management. These strategies not only enhance nutrient retention but also improve crop yield and long-term sustainability for smallholder farmers (Nasukawa et al., 2025).

In light of these challenges, the adoption of regenerative agriculture and diversified farming systems emerges as a viable solution to counter soil degradation and enhance agricultural sustainability. Moreover, diversified farming systems offer significant ecological and economic benefits, such as improved soil health and greater resilience to extreme weather. These benefits are highly relevant to sub-Saharan Africa, where regenerative agriculture could play a critical role in addressing soil degradation and boosting agricultural productivity (Asprooth, 2023). Despite having 25% of the world's arable land, sub-Saharan Africa contributes only 10% of global agricultural production (IFAD, 2021). Without timely intervention, rapid population growth will further exacerbate food insecurity. The IPCC's SR15 report underscores that agriculture is both a major contributor to climate change and a potential solution, highlighting the urgent need to integrate carbon removal with emissions reductions (IPCC, 2018).

One promising solution to the intertwined crises of food insecurity and climate change is regenerative agriculture (RA). Rooted in natural processes, RA enhances soil health, restores carbon cycles, and utilizes photosynthesis to absorb CO2 from the atmosphere. Improved soil management and RA techniques could sequester up to 1.85 billion tons of CO2 annually-the equivalent of taking 400 million cars off the road (Amelung et al., 2020). However, conventional agricultural practices have historically contributed to the degradation of soil carbon stocks and increased greenhouse gas emissions through the conversion of natural ecosystems into managed systems. This not only exacerbates climate change but also weakens the resilience and productivity of agricultural systems.

To address these challenges, regenerative agriculture focuses on practices like soil recarbonization to mitigate climate change and restore ecosystem functions. For example, 125,000 smallholder farmers in East Africa use push–pull technology, an ecological method combining pest control, improved soil health, and crop diversification. This approach boosts maize yields, reduces chemical inputs, and diversifies income through fodder production, demonstrating the tangible benefits of regenerative agriculture (Khan et al., 2017; Lal et al., 2018).

In rural Nigeria, gender disparities continue to restrict equitable access to agricultural resources, including new technologies. Socio-cultural norms favour men's access to these resources, leading to differences in technology adoption rates between men and women. Addressing these disparities is critical to building a resilient agricultural system, as both genders contribute significantly to household food security and income. Understanding gender differences in RA adoption is essential to designing targeted interventions that enhance adoption and boost farm productivity.

This study explores the gender gap in regenerative agriculture (RA) adoption and its impact on smallholder farm productivity in Nigeria, employing decomposition and matching techniques to analyze differences and their underlying causes. The findings aim to inform policymakers, the agricultural community, and climate change advocates by providing actionable insights to promote equitable RA adoption, improve soil health, and strengthen resilience to climate change across the global south, especially in sub-Saharan Africa.

Method

Description of Study Area: Ekiti, Lagos, Ogun, Ondo, Osun, and Oyo are the six states that make up southwest Nigeria, where this study was conducted. This region is one the regions plaque by climate change in Nigeria. The area is roughly 114,271 km² and is located between latitudes 6°N and 4°S and longitudes 4°W and 6°E. The mean monthly temperatures in southwestern Nigeria range from 18 to 24°C during the rainy season to 30 to 37°C during the dry season, with an average annual rainfall of 1,200 to 1,500 mm (Adepoju et al., 2018). With rich alluvial soils that sustain a variety of agricultural pursuits, the area is predominantly agrarian. Key crops farmed include cash crops like cocoa, kola nut, rubber, citrus, coffee, cashew, mango, and oil palm, as well as basics like cassava, maize, yam, cocoyam, cowpea, and vegetables.

Figure 1. Map of Nigeria showing South-western region
Source: (Author, 2023)

Data and Sampling methods

Data from a cross-sectional survey of rural farming households, carried out between April and June 2023, served as the basis for this investigation. Households trained in regenerative agriculture through the Sasakawa Africa Association (SAA) projects in the study area were the focus of a multi-level stratified random sample approach. The selection of participants was done using a four-stage random sampling procedure. Ekiti, Ogun, and Oyo states were selected at random from 50% of the states in southwest Nigeria in the first stage. The Agricultural Development Programme (ADP) offices in these states provided lists of registered rural farming households. Two ADP zones per state were chosen at random for the second stage, for a total of six (6) ADP zones. Four farming communities a total of 24 rural farming communities were selected at random from each ADP zone for the third stage. Ultimately, 24 farmers 12 men and 12 women were chosen at random from each community in the fourth stage, resulting in a sample size of 576 respondents 288 men and 288 women. To assess causal effects, a randomized controlled experiment was conducted, dividing participants into “adopters” (treatment group) and “non-adopters” (control group) for both male- and female-headed households. The sample consisted of 288 male farmers (126 adopters and 162 non-adopters) and 288 female farmers (114 adopters and 174 non-adopters).

Table 1. Summary of sampling procedure

Stage	Description	Outcome
Stage 1	Random selection of 50% of the 6 states in southwest Nigeria.	**3 States Selected**: Ekiti, Ogun, and Oyo.
Stage 2	Two ADP zones per state were randomly chosen.	**6 ADP Zones Selected**: 2 zones from each of the 3 states.
Stage 3	Four farming communities randomly selected from each ADP zone.	**24 Rural Farming Communities Selected**: 4 communities per zone across the 6 zones.
Stage 4	24 farming households (12 male and 12 female) were randomly chosen from each community.	**576 Farming households Selected**: 288 male and 288 female.
Experimental Design	A randomized controlled experiment divided participants into "adopters" (treatment) and "non-adopters" (control) groups for male- and female-headed households.	**Male Farm households**: 126 adopters, 162 non-adopters; **Female households**: 114 adopters, 174 non-adopters.

Source: (Author, 2023)

Data collection and analysis

Data collection was carried out using a structured questionnaire deployed via an electronic tablet application (Open Data Kit). The questionnaire was designed around the study's objectives and included sections on farmers' socioeconomic characteristics, the rate of adoption and influencing factors for regenerative agriculture, perceived benefits, farm income, yield, and farmers' decisions to adopt regenerative agriculture. Participants provided informed consent before responding and were given the option to discontinue the survey at any time if they felt uncomfortable. The aim of the study and the benefits of participation were fully explained to all respondents. The analysis began with linear regression models to identify key determinants of farm productivity across male and female farmers. To quantify the gender gap in productivity (yield), both parametric and non-parametric techniques were employed. The Blinder-Oaxaca decomposition (Blinder, 1973; Oaxaca, 1973) was used to estimate the explained and unexplained components of the gender gap, attributing disparities to socioeconomic, production, and institutional factors or potential unobserved differences and discrimination. Complementing this, the Propensity Score Matching (PSM) method addressed limitations inherent to parametric approaches, such as assumptions and heterogeneity issues (Ñopo, 2008). PSM facilitates direct comparisons of farmers with similar characteristics, ensuring robust estimations. The combination of these two techniques enhanced the robustness and validity of the results, providing a comprehensive understanding of gender-based disparities in farm productivity.

Empirical strategy

Ordinary least squares (OLS) regression model: A log-linear regression model is first estimated for a sample of both male and female farmers. A popular statistical technique for identifying important factors influencing farm production (yield) is regression analysis. A linear relationship between a set of independent variables (*X*) and the dependent variable (*Y*), or farm productivity, is assumed by log-linear regression. The model's specifications are as follows:

$$Y = \alpha F + \beta X + \varepsilon \dots\dots\dots\dots\dots\dots (1)$$

The natural logarithm of farm productivity, expressed in terms of yields, is represented by the dependent variable *Y* in equation (1). A vector of control variables is represented by *X*, while the farmer's gender (male or female) is indicated by *F*. The parameters to be estimated are α and β, where α is the value of *Y* when all explanatory variables are zero and β is the average change in *Y* that occurs when *X* changes by one unit while keeping all other explanatory variables constant. Last but not least, the error term, or ε, is a random variable that explains why the model can't accurately represent the data.

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3, i = 1,2, \ldots, n \ldots \ldots \ldots \ldots (2)$$

The socioeconomic (age, marital status, education, household size, farming experience, income), production (farm size, labour, input cost), and institutional (extension services, credit access, varietal information access, land tenure system, social participation) characteristics are all included in the vector *X*. Additionally, there are state-specific fixed effects. The last set of variables added to the regression model to account for variations in agricultural productivity among the chosen states are the State fixed effects and rural-urban continuum code dummy variables. This enables us to incorporate all of these variables, which are known as the predictors or regressors in the model (see equation 2), into our model that represents X_i.

Blinder-Oaxaca decomposition: Commonly used to analyze inter-group variations in outcome variables, including gender-based productivity disparities, is the Blinder-Oaxaca decomposition technique (Blinder, 1973; Oaxaca, 1973). Gender differences in farm production (yield) are identified and explained in this study using the deconstruction approach. The following describes the farm productivity model for the male and female subsamples:

$$Y_i = \beta_i X_i + \varepsilon_i \ldots \ldots \ldots \ldots (3)$$

where *X, β,* and ε are defined as in equation (1), *i* stands for male (m) and female (f) farmers, and *Y* is the natural log of agricultural productivity (yields). The estimated male-female difference in agricultural productivity (yields) is then broken down into those that can be explained and those that cannot:

$$\bar{Y}_m - \bar{Y}_f = \hat{\beta}_m(\bar{X}_m - \bar{X}_f) + \bar{X}_f(\hat{\beta}_m - \hat{\beta}_f) = E + U \ldots \ldots \ldots \ldots (4)$$

where $\bar{Y}$ and $\bar{X}$ stand for the average values of the explanatory and dependent variables, $\hat{\beta}$ are parameters from estimating equation (1) separately for male and female farmers, $\bar{Y}_m$ and $\bar{Y}_f$ are the predicted average values of the dependent variable for male and female farmer sub-samples, $\bar{X}_m$ and $\bar{X}_f$ are the average values of vector variables that determine the productivity (yields) of farmers, and $\hat{\beta}_m - \hat{\beta}_f$ stands for the vector of estimated returns to the farm productivity gap determinants for male and female farmers, respectively. Equation (4) illustrates that the average difference in farm productivity (yields) between male and female farmers may be broken down into two halves. The percentage of the difference that can be attributed to quantifiable variations in men's and women's attributes is represented by the first set of terms following the first equal sign. This is referred to as the "explained gap" or "endowment effect" (*E*). The second group of terms refers to the "unexplained gap" (*U*), the fraction of the gender productivity gap that arises from variations in returns to unmeasured parameters. As an upper-bound estimate of discrimination, the unexplained gap (*U*) includes both the effects of discrimination and unmeasured characteristics associated with productivity and gender.

Propensity score matching (PSM): The Blinder-Oaxaca decomposition technique may be biased due to differences in the empirical distribution of features across male and female farmers (Frölich, 2007; Ñopo, 2008). Frölich (2007), propensity score matching (PSM), a technique that makes it easier to compare male and female farmers with comparable observable traits, can help overcome these prejudices. PSM is especially helpful for differentiating between discrimination or other unquantifiable causes and disparities in outcomes, like agricultural yields, that result from differential human capital endowments. PSM has been utilized in recent research by Fisher et al. (2021) and Meara et al. (2020) to examine gender-based salary differences in the US. The average difference in farm yields between treatment groups (farmers implementing regenerative agriculture, or RA) and control groups (non-adopters) for both male and female farmers is estimated in this study using PSM. Using a binary choice model, the propensity score which is the probability that a farmer, male or female, will adopt RA is determined as the first step in PSM. This probability is estimated using a logit regression based on the explanatory variables (X) listed in equation (1). Each adopter is then paired with one or more non-adopters who have comparable propensity scores using a matching algorithm.

We used widely used matching approaches, such as kernel-based matching (KBM) and nearest neighbor matching (NNM), to estimate the average treatment effect on the treated (ATT). In NNM, each treatment unit is matched to its closest control unit, and the propensity scores of the individuals in the treatment group are directly compared to those in the control group. For the treatment group, these matches help create a counterfactual. KBM, on the other hand, uses a weighted average of outcomes to determine how the outcomes of the treatment and control groups differed. Observations in the control group are given weights according to how close they are to the corresponding treatment unit. Dehejia and Wahba (2002); Frölich (2004); and Heckman et al. (1998) offer thorough foundations for comprehending PSM estimators. These methods were summarized by Hosny (2013), who emphasized that the weighting system (r) utilized when multiple matches are used and the amount of matches allocated to each treatment unit are the primary differences amongst ATT estimators. The following is a mathematical expression for these estimators:

$$ATT = \frac{1}{n^1} \sum 1 \left\{ (Y_{1i} | T_i = 1) - \sum jr_1 (Y_{0i} | T_i = 0) \right\} \dots \dots \dots \dots \dots . (5)$$

In this scenario, r is a collection of scaled weights that measure the separation between each control unit and its matching treatment unit, and n^1 is the number of treatment cases. The number of matches allocated to each target instance and the method used to weight multiple matches, represented by r, when more than one match is employed are the main differences between these estimators (Morgan & Harding, 2006). The average treatment effect on the treated (ATT) is calculated by averaging the within-match changes in the outcome variable (farm yield) between the treatment and control groups, as per estimators (Dehejia & Wahba, 2002; Rosenbaum & Rubin, 1985). The following is one way to put this:

$$\begin{aligned} E(Y_1 - Y_0 | T = 1) &= E[E(Y_1 - Y_0 | T = 1, P(x))] \\ &= E[E(Y_1 | T = 1, P(x)) - E(Y_0 | T = 0, P(x))] \dots \dots \dots . (6) \end{aligned}$$

The differences between matched treatment and control cases are calculated for the outcome variable (log of net farm productivity) in the last stage of PSM. The average treatment effect, which is a measure of the unexplained gender disparity in farm production (yield), is the sum of these changes. PSM reduces biases, improves analysis reliability, and provides a more accurate understanding of the unexplained gender gap in farm productivity by matching observationally similar treatment and control units.

Results and Discussion

Results of descriptive statistics

Table 2 shows the descriptive statistics for male and female farmers who are divided into two groups: those who have adopted regenerative agriculture (RA) (treatment group) and those who have not (control group). Adopters were represented by 1 and non-adopters by 0, making the adoption variable binary. To investigate the variations in the respondents' socioeconomic traits, a t-test was used. The yield per hectare of farmland farmed during the final farming season prior to the survey was used to calculate farm yield, the outcome indicator, utilizing techniques from Abdoulaye et al. (2018); Ogunniyi et al. (2017); Olagunju et al. (2019); and Wossen et al. (2017). The results revealed that the average farm yield for female farmers was 6,840.55 kg/ha, while for male farmers it was 6,548.71 kg/ha. Among RA adopters, female farmers achieved a mean yield of 8,485.71 kg/ha, significantly higher ($p<0.01$) than the 8,296.94 kg/ha observed in non-adopters. Similarly, male adopters had a mean yield of 8,485.71 kg/ha, compared to 8,296.94 kg/ha for non-adopters. These findings highlight a statistically significant gender gap in farm yields among both adopters and non-adopters, as well as between male and female farmers, likely driven by various socioeconomic, production, and institutional factors.

Adopters and non-adopters differed significantly in a number of explanatory factors, such as education, income, labor utilization, production system, extension service access, loan availability, and organization participation. On average, men farmers had 5.55 years of education, compared to 4.49 years for female farmers. Female farmers among RA adopters had an average of 2.77 years of education, while male farmers had an average of 3.36 years, which was a significant difference ($p<0.01$). In line with findings from Makate et al. (2019), who observed the beneficial impact of education on the adoption of climate-smart agricultural innovations in Southern Africa, this implies that male adopters are more likely to be educated, which probably improves their access to and utilization of information on new technologies.

The average yearly income of female RA adopters was ₦602,105.26, which was substantially greater ($p<0.01$) than that of non-adopters, who made ₦400,804.60. The average income for male RA adopters was ₦987,698.41, whereas that of non-adopters was ₦592,839.51. These findings highlight a significant wage disparity between genders and between adopters and non-adopters. Although the difference was not statistically significant, the average household size for female adopters was 7.14 people, which was marginally greater than the 6.99 people for non-adopters. The average household size of male adopters was 8.11 people, whereas that of non-adopters was 7.97, with no discernible difference. Contrary to these findings, Nata et al. (2014) discovered that family size had a beneficial impact on Ghanaian agricultural technology utilization.

Variables related to production such as farm size, farming experience, production system, labour use, and risk aversion revealed significant differences for two out of five indicators. Female and male adopters who cultivated rain-fed land and relied on hired labour showed a higher propensity to adopt RA, potentially due to their greater ability to manage the risks associated with new technologies. Statistically significant gender differences were observed in production system and labour use ($p<0.01$). The mean farm size for female farmers across the sample was 5.16 ha, compared to 7.76 ha for male farmers. Among RA adopters, female farmers had a mean farm size of 6.14 ha, significantly smaller than the 8.73 ha observed for male adopters ($p<0.1$). These results align with Gaya et al. (2017), that female farmers typically operate smaller farms due to sociocultural norms limiting women's access to land.

There were no significant differences in farming experience between adopters and non-adopters for both genders. On average, both male and female farmers in the sample had more than 10 years of farming experience. This corroborates Tsue et al. (2014), who noted that the majority of arable crop farmers have over a decade of experience. In conclusion, these findings highlight significant gender gaps in yield, income, production practices, and access to resources, emphasizing the role of education, institutional support, and structural inequalities in influencing the adoption of regenerative agriculture.

This study looked at five institutional factors: farmland ownership, credit availability, extension service accessibility, farmers' union membership, and climate information availability. Adopters and non-adopters of regenerative agriculture (RA) differed significantly for both male and female farmers.

Farmers, regardless of gender, were significantly more likely to employ RA techniques if they had more access to agricultural extension services. This result is consistent with that of Makate et al. (2019), who discovered that the adoption of different Climate-Smart Agriculture (CSA) innovations in Southern Africa is positively influenced by access to extension information. In line with Baruwa et al. (2015), who found that credit access increased the likelihood of adopting improved maize varieties in Osun State, Nigeria, there was also a positive correlation between RA adoption and credit availability.

According to Obayelu et al. (2023), having access to loans also motivates farmers to boost their output. However, Beke (2011) discovered that financing availability had a detrimental effect on Ivory Coast's uptake and intensity of usage of enhanced varieties, suggesting that the consequences of credit availability can vary depending on the situation.

Table 2. Descriptive statistics, overall and by gender

Variable	Total sub-sample (N=288)	Female sub-sample: Adopters (N=114) 1	Female sub-sample: Non-adopters (N=174) 2	Female sub-sample: Mean difference (1-2)	Female sub-sample: t-Test (p-value)	Total sub-sample (N=288)	Male sub-sample: Adopters (N=126) 3	Male sub-sample: Non-adopters (N=162) 4	Male sub-sample: Mean difference (3-4)	Male sub-sample: t-Test (p-value)
Dependent variable										
Farm yield ('000kg/ha)	6664.23 (584.365)	6840.55 (417.444)	6548.71 (647.127)	291.846	4.267 (0.000***)	8379.53 (571.917)	8485.71 (664.280)	8296.94 (474.116)	188.77	2.812 (0.000***)
Socioeconomic characteristics										
Age of farmer (years)	50.92 (8.837)	51.35 (9.595)	50.64 (8.320)	0.713	0.669 (0.093*)	52.67 (11.258)	53.10 (11.653)	52.35 (10.965)	0.750	0.560 (0.248)
Marital status (1=married, 0=otherwise)	1.21 (0.409)	1.19 (0.396)	1.22 (0.418)	-0.031	-0.631 (0.202)	1.21 (0.409)	1.21 (0.412)	1.21 (0.408)	0.004	0.091 (0.857)
Education (Years of schooling)	4.49 (5.021)	6.16 (5.530)	3.39 (4.337)	2.767	4.742 (0.000***)	5.55 (5.492)	7.44 (5.779)	4.08 (4.781)	3.364	0.5404 (0.003***)
Household size (number)	7.05 (1.230)	7.14 (1.282)	6.99 (1.195)	0.146	0.986 (0.435)	8.03 (1.152)	8.11 (1.228)	7.97 (1.089)	0.142	1.038 (0.709)
Number of years' resident in the village (years)	42.15 (11.771)	39.68 (12.217)	43.78 (11.211)	-4.100	-2.929 (0.192)	43.92 (13.567)	45.56 (14.140)	42.64 (13.005)	2.914	1.815 (0.191*)
Estimated income (Naira)	480,486.11 (117,795.25)	602,105.26 (83,289.38)	400,804.60 (48,532.65)	201,300.67	25.884 (0.000***)	765,590.28 (381,824.429)	987,698.41 (481,874.943)	592,839.51 (104,729.579)	394858.91	10.131 (0.000***)
Production characteristics										
Total Farm size (hectare)	5.16 (1.371)	6.14 (1.189)	4.52 (1.074)	1.617	11.978 (0.569)	7.76 (2.25)	8.73 (2.289)	7.00 (1.855)	1.730	7.085 (0.061*)
Farming experience (years)	28.18 (7.901)	28.75 (8.565)	27.82 (7.436)	0.930	0.976 (0.690)	31.66 (9.168)	33.11 (8.939)	30.53 (9.211)	2.580	2.389 (0.785)
Production system (1=rain-fed, 0=otherwise)	0.95 (0.208)	0.97 (0.183)	0.94 (0.241)	0.027	1.075 (0.032***)	0.86 (0.343)	0.91 (0.291)	0.81 (0.394)	0.098	2.424 (0.000***)
Labour (1=hired, 0=otherwise)	0.53 (0.500)	0.65 (0.479)	0.45 (0.499)	0.195	3.294 (0.001***)	0.84 (0.364)	0.88 (0.330)	0.80 (0.400)	0.075	1.741 (0.001***)
Willingness to take risk (1=yes, 0=otherwise)	0.48 (0.501)	0.61 (0.491)	0.40 90.491)	0.209	3.530 (0.951)	0.83 (0.373)	0.84 (0.368)	0.83 (0.381)	0.014	0.318 (0.527)
Institutional characteristics										
Extension (1=yes, 0=otherwise)	0.16 (0.364)	0.17 (0.379)	0.13 (0.340)	0.041	0.932 (0.059*)	0.18 (0.385)	0.21 (0.412)	0.15 (0.362)	0.060	1.312 (0.009**)
Credit access (1=yes, 0=otherwise)	0.24 (0.425)	0.25 (0.436)	0.21 (0.409)	0.042	0.826 (0.094*)	0.33 (0.471)	0.36 (0.481)	0.31 (0.463)	0.049	0.867 (0.091*)
Membership of farmers' union (1=yes, 0=otherwise)	0.69 (0.463)	0.90 (0.297)	0.55 (0.499)	0.352	6.784 (0.000***)	0.78 (0.416)	0.89 (0.316)	0.69 (0.463)	0.198	4.102 (0.000***)
Ownership of farmland (1=yes, 0=otherwise)	0.30 (0.460)	0.37 (0.485)	0.26 (0.439)	0.110	1.991 (0.000***)	0.74 (0.442)	0.75 (0.432)	0.72 (0.449)	0.032	0.605 (0.002***)
Access to climatic information (1=yes, 0=otherwise)	0.47 (0.500)	0.61 (0.491)	0.39 (0.488)	0.220	3.736 (0.004***)	0.62 (0.486)	0.83 (0.381)	0.46 (0.500)	0.362	6.750 (0.000***)

The t-test was carried out to test for difference in socio-economic characteristics between male and female farmers;
*, **, ***Significant at 10, 5 and 1%, respectively.
Source: Field survey (2023)

Another important aspect in the acceptance of RA by both gender groups was membership in farmers' unions. This is in line with research from Rwanda (Zingiro et al., 2014) and Ethiopia (Wordofa et al., 2021), which highlighted the importance of farmer groups and association membership in encouraging the adoption of technology like rainwater collection to increase income and productivity. In a similar vein, group participation encouraged the adoption of improved rice technology in southern Nigeria, according to Onumadu and Osahon (2014). In line with Makate et al. (2019), who discovered that land ownership raised the possibility of implementing CSA improvements in Southern Africa, farmland ownership also had a beneficial impact on RA adoption. In contrast to large-scale farmers, Varma (2019) found that small and marginal farmers were more likely to implement strategies like rice intensification.

Compared to non-adopters, farmers who used RA methods also had substantially greater access to climatic data ($p<0.01$). This finding emphasizes how crucial climate data is in affecting adoption choices. According to Abdoulaye et al. (2018) and Issahaku and Abdulai (2019), farmers who are aware of new agricultural technologies are more inclined to employ them. Notably, climatic data was available to all RA adopters in our study, indicating that it plays a crucial role in promoting adoption and building climate resilience. These results highlight how crucial institutional support is for promoting the adoption of RA practices and resolving gender inequities in agriculture. This support includes access to resources, participation in associations, and availability of climatic data.

Determinants of adoption of regenerative agriculture (RA) practices by gender

The conditional probability of farmers implementing regenerative agriculture (RA) methods was estimated using a logistic regression model, and the average marginal effects on farm yield outcomes for male and female farmers were examined. Since marginal effects, rather than raw coefficients, offer a more lucid picture of the influence of explanatory variables in probability models, they were computed. Based on the information at hand, the model encompassed every observable covariate that affects RA adoption and farm yield.

According to Bello et al. (2020), the degree and strength of the association between variables and adoption choices are indicated by the direction and size of marginal effects. Marginal effects thereby enhance the model's interpretability and explanatory capacity. The analysis findings are shown in Table 3. With a log-likelihood of -21.299212, a pseudo R2 of 0.8898, and an LR (chi2) value of 344.06, all statistically significant ($p<0.01$), the model showed good explanatory potential for female farmers. This demonstrates how well the model predicts the adoption of RA practices by female farmers. Similarly, the model yielded a log-likelihood of -75.74894, a pseudo R2 of 0.6162, and an LR (chi^2) value of 243.26 for male farmers, all of which were significant at $p<0.01$, demonstrating its efficacy in describing the adoption choices of male farmers.

The results showed that nine out of sixteen explanatory variables had a significant impact on female farmers' adoption of RA. These factors included education, income, farm size, production system, willingness to take risks, access to credit, membership in farmers' unions, land ownership, and access to climatic information. Education had a favorable and statistically significant impact on RA adoption, as shown in Table 3. According to the marginal effect, the chance of adopting RA rises by 3.74% for every extra year of education.

According to research by Ersado et al. (2004); Gregory and Sewando (2013); and Obayelu et al. (2023), household heads with higher levels of education are more inclined to embrace new technology. Among female farmers, income also had a beneficial impact on RA adoption; a marginal effect indicates that a ₦1 increase in income raises the likelihood of RA adoption by 9.58%. Richer farmers may more readily manage the risks involved with innovative practices and obtain resources for production. This result is consistent with that of Kayizzi-Mugerwa et al. (2017), who found a positive correlation between the adoption of enhanced rice varieties and income from crop diversification. These findings highlight how crucial income and education are in enabling female farmers to embrace cutting-edge farming methods. Additionally, the model identifies important institutional and socioeconomic elements that impact adoption, offering insightful information for policy actions meant to encourage RA uptake among diverse farmer groups.

Table 3. Logit estimates of determinants of RA adoption

Variable	Female farmers		Male farmers	
	Coefficient	Marginal effects	Coefficient	Marginal effects
Age of farmer (years)	-0.0146 (0.0393)	-0.0049 (0.0132)	0.0199 (0.0207)	0.0077 (0.010)
Marital status (1=married, 0=otherwise)	-0.1636 (0.6584)	-0.0548 (0.2216)	0.4132* (0.3980)	0.1595* (0.1534)
Level of education (Years of schooling)	0.1119** (0.0497)	0.0374** (0.0161)	0.1488*** (0.0293)	0.0574*** (0.0114)
Household size (number)	-0.0749 (0.2084)	-0.0251 (0.0703)	0.2198* (0.1196)	0.0848* (0.0463)
Number of years' resident in the village	-0.0193 (0.0267)	-0.0065 (0.0089)	0.0072 (0.0138)	0.0029 (0.0053)
Estimated income (Naira)	2.86e-05*** (6.73e-06)	9.58e-06*** (0.0001)	6.63e-06*** (1.01e-06)	2.56e-06*** (0.0001)
Total Farm size (hectare)	0.6611*** (0.2540)	0.2213*** (0.0859)	0.2668*** (0.0623)	0.1029*** (0.0241)
Farming experience (years)	0.0179 (0.0438)	0.0060 (0.0148)	0.0194 (0.0196)	0.0075 (0.0076)
Production system (1=rain-fed, 0=otherwise)	-0.2060673	-0.2281804	-0.6951 (0.3973)	-0.2398 (0.5157)
Labour (1=hired, 0=otherwise)	0.1239 (0.5167)	0.0414 (0.1709)	-0.0784 (0.3854)	-0.0300 (0.1465)
Willingness to take risk (1=yes, 0=otherwise)	0.7081* (0.5339)	0.2358* (0.1701)	-0.0707 (0.3318)	-0.0271 (0.1263)
Access to extension (1=yes, 0=otherwise)	0.6255 (0.8867)	0.2292 (0.5452)	0.1224 (0.3067)	0.0467 (0.1156)
Credit access (1=yes, 0=otherwise)	0.7848* (0.7198)	0.2845* (0.2658)	-0.1186 (0.2764)	-0.0459 (0.1076)
Membership of farmers' union (1=yes, 0=otherwise)	1.3779** (0.7790)	0.3726** (0.1506)	0.6413*** (0.2902)	0.2508** (0.1111)
Ownership of farmland (1=yes, 0=otherwise)	1.3254** (0.6407)	0.4699** (0.2199)	0.3603* (0.3006)	0.1409* (0.1180)
Access to climatic information (1=yes, 0=otherwise)	1.1088** (0.5997)	0.3649** (0.1799)	1.4273*** (0.3008)	0.5230*** (0.0942)
Constant	-17.7003 (4.8777)		-12.8727 (2.244)	
Number of observations	288		288	
LR chi² (16)	344.06		243.26	
Prob >χ2	0		0	
Pseudo R²	0.8898		0.6162	
Log likelihood	-21.299212		-75.74894	

*, ** and *** represent, respectively, statistical significance at the 10%, 5%, and 1%. Robust standard errors are reported in parentheses.

The overall size of female farmers' farms had a positive and significant impact on their adoption of regenerative agriculture (RA). The likelihood of adopting RA methods increased by 22.13% for every unit increase in farm size, indicating that farmers with larger farms are more likely to adopt these practices, maybe as a result of stronger institutional support. This result is in line with the findings of Makate et al. (2019), who noted a similar tendency with climate-smart agricultural practices in Southern Africa, and Nata et al. (2014), who discovered that land size positively influenced agricultural technology adoption in Ghana. However, the coefficient for the production system was negative and significant at the 10% level, indicating that as female farmers increasingly engage in certain production systems, particularly rain-fed agriculture, the probability of adopting RA decreases. This suggests that dependency on rain-fed agriculture may limit female farmers' ability to adopt RA practices.

Female farmers' willingness to take chances was a major determinant of their adoption of RA. RA practices were substantially more likely to be adopted by farmers who were more willing to experiment with new farming techniques. This result is consistent with that of Olagunju et al. (2019), who discovered that risk aversion was a significant obstacle to the adoption of drought-tolerant maize varieties (DTMVs) in Nigeria. This was primarily caused by the absence of sufficient risk management and insurance systems in rural regions. The adoption of better agricultural methods throughout Africa was also hampered by risk aversion, according to Dercon and Christiaensen (2011). The adoption of RA was also significantly influenced by finance availability, since farmers who had financing were more inclined to experiment with novel methods. This is in line with the findings of Baruwa et al. (2015), who found that enhanced maize varieties were more widely adopted in Osun State, Nigeria, when credit was available. The possibility of implementing RA was also considerably raised by involvement in farmers' unions, highlighting the significance of social capital and group dynamics. Similar research by Olagunju et al. (2019) and Onumadu and Osahon (2014)) shown that group membership had a positive impact on Nigerians' adoption of enhanced rice technologies. Adoption was also positively impacted by land ownership and availability to climate data. While having access to climate data improved farmers' comprehension of weather patterns and allowed them to implement climate-resilient measures, land ownership offered security.

Eight characteristics were discovered to have a substantial impact on male farmers' adoption of regenerative agriculture (RA) practices. Marital status, education, household size, income, total farm size, land ownership, farmers' union membership, and access to climatic data were some of these variables. The likelihood of adopting RA was positively correlated with education, making it a significant positive factor. The findings of Makate et al. (2019) and Winters et al. (2011) that education promotes adoption of climate-smart practices and other agricultural innovations are corroborated by this. Additionally, income had a favorable impact, with greater income levels increasing the likelihood of RA adoption. This is in line with research by Cunguara and Darnhofer (2011); Habtemariam et al. (2019); and Teklewold et al. (2013) that demonstrated the beneficial impact of wealth on the adoption of new technologies and sustainable agricultural practices.

Another important component was household size, which is consistent with the findings of Nata et al. (2014), who discovered that family size had a beneficial influence on Ghana's adoption of agricultural technology. Larger homes might have the labor needed to carry out labor-intensive procedures like RA. Another significant factor was access to climate data; male farmers who had access to trustworthy climate data were more likely to use RA. This supports the findings of Makate et al. (2019), who highlighted that one of the main factors influencing Southern Africa's adoption of climate-smart agricultural innovations is information access. These findings point to the main gender-specific factors affecting the adoption of RA, indicating that focused strategies are required to successfully encourage RA practices among farmers of both sexes.

Blinder-Oaxaca decomposition

Table 4 displays the results of the Blinder-Oaxaca decomposition, which calculates the gender disparity in farm yield and examines both the explained and unexplained components of the discrepancy. According to the unadjusted difference, the average farm yield of female RA non-adopters was 291.8457 kg/ha less than that of their RA-adopter counterparts. The factors included in the model are responsible for 26.61% of this gap, which can be explained. The unexplained gap, on the other hand, shows that non-adopters produced 214.1732 kg/ha less than RA adopters, with a significant amount of the gap going unaccounted for. This might point to possible prejudice, unquantifiable reasons, or a mix of the two among female farmers in the research region. For male farmers, the unadjusted gap shows that non-adopters had a farm yield that was 188.770 kg/ha lower than that of RA adopters. The explained portion of this gap was 18.78%, with part of the yield difference explained by the model variables. The unexplained gap accounted for 153.3144 kg/ha, representing 81.22% of the total difference. This significant unexplained gap may point to differences in endowments or other unmeasured factors, though most of the observed gap in farm productivity among male farmers can be attributed to the variables captured in the model.

The Blinder-Oaxaca decomposition analysis of the study area's female and male farmers' farm yields comparing RA adopters is shown in Table 4. The findings indicate an uncorrected gender disparity, with female farmers' average farm yield being 1,505.946 kg/ha lower than male farmers. The factors in the model accounted for the majority of the farm yield differential, accounting for 33.16% of the explained fraction of this disparity. According to the unexplained part, female farmers produced 1,006.624 kg/ha less than their male counterparts. Differences between male and female farmers are probably the cause of this unexplained discrepancy. These differences may result from unquantifiable factors such discrimination, gender-based disparities in resource access, risk aversion, and variations in farming motivation and skills. This is consistent with the findings of Fisher et al. (2021), who found that among American agricultural labours, there was a sizable, unexplained gender wage disparity.

Table 4. Summary of Blinder-Oaxaca decomposition results

Decomposition	Female		Male	
	Coefficient	Robust Standard Error	Coefficient	Robust Standard Error
Predicted natural log of farm yield for RA adopters	6840.553***	39.01	8485.714***	59.0599
Predicted natural log of farm yield for RA non-adopters	6548.707***	49.0096	8296.944***	37.2045
Difference (unadjusted gap)	291.8457***	62.6396	188.770***	69.8015
Explained gap	77.6725	116.1467	35.455	76.2551
% explained gap (% of total)[a]	26.61		18.78	
Unexplained gap	214.1732*	130.5431	153.3144*	101.2453
% unexplained gap (% of total)[b]	73.39		81.22	

* and *** represent, respectively, statistical significance at the 10% and 1% level.
Source: Author's computation (2023)
[a and b] Denote percentage estimated gender gap (explained and unexplained) for the farm yield outcome variable

Efffect of individual covariates to explained gender gap in farm productivity

This section looks at the role that individual factors play in explaining the gender difference in farm yield between male and female adopters. Male farmers serve as the control group in the analysis, whereas female farmers are regarded as the treatment group (see Table 5). Table 5's findings demonstrate the ways in which different factors affect the outcome variable, or the fraction of the gender disparity in agricultural produce that can be explained. Variables that increase the gender gap are shown by positive percentage numbers, whilst those that decrease it are indicated by negative ones.

Five major factors account for the majority of the gender disparity in farm productivity: household size (socioeconomic), farm size and production system (production-related), loan availability, and farmland ownership (institutional factors). Previous studies studies (Fairlie & Robb, 2009; Fisher et al., 2021; Kiefer et al., 2022) have revealed similar results, indicating that socioeconomic, human, and physical variables have a significant role in the gender disparity in agricultural outcomes. In comparison to male farmers, female farmers typically have poorer yields, smaller households, smaller farms, a greater reliance on rain-fed agriculture, restricted access to credit, and smaller land holdings, accounting for more than 90% of the gender disparity in farm production. According to Table 1 of our analysis, female farmers often have smaller households, which accounts for around 12.67% of the gender discrepancy in farm yield (Table 5). This implies that a higher chance of RA adoption is linked to bigger household sizes. The adoption of climate-resilient methods and farm growth may be facilitated by the ability of larger farming households to employ a larger labor force for cultivation. These findings align with previous studies by Asfaw et al. (2012); Nata et al. (2014); and Wossen et al. (2017), which discovered that land size and family size have a beneficial impact on Ghana's adoption of agricultural technologies.

In addition to socioeconomic considerations, the fact that female farmers work smaller land areas than their male counterparts accounts for 33.26% of the gender disparity in farm production. Given that they usually have more resources to manage the risks connected with new agricultural technologies, this means that farmers with larger plots are more likely to implement RA techniques. These results corroborate the findings of by Martey et al. (2019) and Wordofa et al. (2021), who found a significant correlation between farm size and the use of advanced agricultural technologies in Ethiopia. Additionally, rain-fed agriculture, which accounts for 13.567% of the gender gap in farm productivity, is more common among female farmers. This suggests that, in comparison to their male counterparts, female farmers are less active in irrigated farming. Additionally, according to our data, female farmers often use fewer hired laborers than male farmers, which has a negative effect of -8.82% on the gender disparity in farm yield that can be explained.

Additionally, Table 5 shows that the lack of financing availability for female farmers compared to their male counterparts' accounts for 11.85% of the gender disparity in farm productivity. This result is in line with that of Baruwa et al. (2015), who discovered that in Osun State, Nigeria, having access to financing raises the possibility of implementing better maize varieties. Farmers are encouraged to increase production by having access to loans (Obayelu et al., 2023). This is in contrast to Beke (2011), who discovered that the acceptance and intensity of use of improved varieties in Ivory Coast were negatively impacted by availability to financing. Also, the fact that female farmers own less land than male farmers accounts for 22.54% of the gender disparity in farm productivity. This result is consistent with research from Southern Africa, including Makate et al. (2019), which showed that land ownership positively affects the adoption of several Climate Smart Agricultural (CSA) innovations.

Propensity score matching

In order to address the parametric assumptions of the Blinder-Oaxaca method and resolve heterogeneity difficulties commonly seen in parametric decomposition approaches, we performed diagnostic tests as part of the propensity score matching procedure (Ñopo, 2008). Making ensuring the matching process was dependable and consistent was the primary objective of these tests. The matching process's ability to balance the covariate distributions used to predict the propensity score model was also evaluated (Rosenbaum & Rubin, 1983). To make sure the covariates were similar between the two groups, we looked at the common support condition after computing propensity scores for male and female farmers who were adopters (treatment) and non-adopters (control). The comparison group's matches were determined via the common support graphs (Figures 2 and 3), indicating that the confounders were evenly distributed between the treatment and control groups. By guaranteeing that the propensity score distributions for adopters and non-adopters coincide, this phase is crucial for enhancing match quality (Heckman et al., 1999).

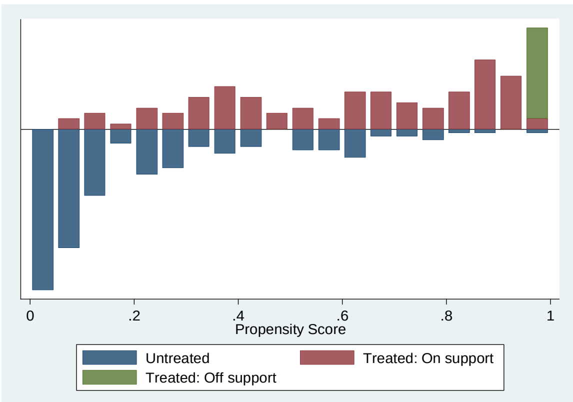

Figure 2. Propensity score matching and common support region between treated and control cases among female farmers using Kernel-based with outcome

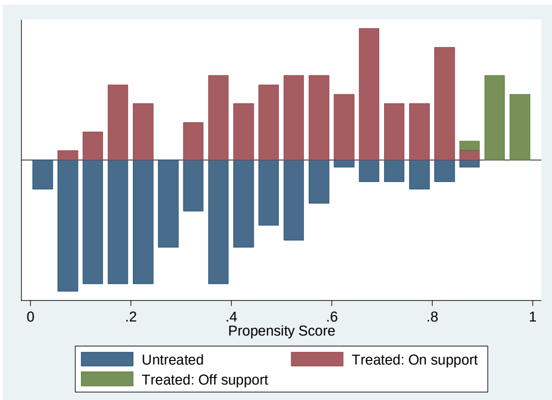

Figure 3. Propensity score matching and common support region between treated and control cases among male farmers using Kernel-based matching with outcome variable

The distribution of propensity scores and the common support region for male and female farmers who use RA techniques (upper section) and those who do not (lower section) are shown in Figures 2 and 3. The common support criterion is satisfied, according to an analysis of the propensity score distributions, with both genders' scores showing a considerable overlap between the treated and untreated groups. By demonstrating possible bias in the distribution of propensity scores between the treatment and control groups and the necessity of maintaining the common support condition to prevent subpar matches, these statistics highlight the significance of appropriate matching. Since all variables fall between 0 and 1, the results show successful matching. This ensures that the overlap of matches stays within the valid range and confirms that adopters and non-adopters in both groups have unique characteristics.

Table 5. Details of Blinder-Oaxaca decomposition results: Model Variables and their percent contribution to the explained gap

Variable	Full Sample of RA Adopters			Female farmers			Male farmers		
	Coefficient	Standard Error	% Contribution	Coefficient	Standard Error	% Contribution	Coefficient	Standard Error	% Contribution
Socioeconomic characteristics									
Age of farmer (years)	7.1130	10.8303	4.0243	10.6762	16.8615	13.7451	2.6119	6.3069	7.1000
Marital status (1=married, 0=otherwise)	1.1403	3.5992	0.6452	0.7614	2.9078	1.0000	0.1002	1.2149	0.3000
Education (Years of schooling)	-2.6475	8.6467	-1.4979	12.2922	18.6171	15.8000	-7.2055	23.4936	-19.6000
Household size (number)	22.3977*	28.1968	12.6720	1.1804	4.1371	1.5000	-4.0451	5.4109	-10.9000
Number of years' resident in the village	3.9751	20.3252	2.249	3.0459	13.8366	3.9000	-4.3392	10.2619	-11.8000
Estimated income (Naira)	-3.5088	39.7504	-1.9852	-79.3817	92.9082	-102.2000	-16.2211	39.5982	-44.1000
Production characteristics									
Total Farm size (hectare)	58.7794*	53.0688	33.2558	158.8604***	52.2515	204.5259	32.8807*	30.3809	89.4000
Farming experience (years)	-1.4144	24.228	-0.8002	-4.9999	7.2354	-6.4372	0.3965	14.4215	1.1000
Production system (1=rain-fed, 0=otherwise)	23.9581*	18.7065	13.5548	5.5876	6.2542	7.1938	11.2789*	11.5903	30.7000
Labour (1=hired, 0=otherwise)	-15.5901*	14.0283	-8.8205	-16.1464*	14.0371	-20.7878	16.2819*	11.8812	44.3000
Willingness to ry new thing (1=yes, 0=otherwise)	13.6095*	17.2993	7.6999	-7.4663	13.9994	-9.6125	-1.3356	4.3870	-3.6000
Institutional characteristics									
Extension access (1=yes, 0=otherwise)	-4.5905	8.1448	-2.5972	6.0457	7.4502	7.7836	-6.9360*	7.2841	-18.9000
Credit access (1=yes, 0=otherwise)	20.9360*	14.6126	11.8450	-1.7147	3.753	-2.2076	2.8153	4.6061	7.7000
Membership of farmers' union (1=yes, 0=otherwise)	3.1371	8.6449	1.7749	-36.3391*	29.7699	-46.7850	-0.4717	15.4102	-1.3000
Ownership of farmland (1=yes, 0=otherwise)	39.8382*	33.8035	22.5394	10.257*	9.5561	13.2054	1.1045	3.3806	3.0000
Access to climatic information (1=yes, 0=otherwise)	9.6162	17.6397	5.4406	15.0138*	15.7799	19.3296	8.5394	25.6343	23.2000

*, ** and *** represent, respectively, statistical significance at the 10%, 5%, and 1% level. Robust standard errors are reported.
Source: Author's computation (2023)

Table 5 presents the results of the Blinder-Oaxaca decomposition, which examines the gap in the adoption of Resilient Agriculture (RA) techniques between male and female farmers. The analysis evaluates the contribution of various variables categorized into three main groups: socioeconomic characteristics, production characteristics, and institutional characteristics. Overall, production factors, particularly total farm size, emerged as the most significant contributor to the gap in both groups. For female farmers, this variable accounted for a contribution of 204.53%, which is considerably higher than its contribution for male farmers at 89.40%, indicating that access to farmland is critical for women in adopting RA techniques.

Within the socioeconomic characteristics, age of the farmer positively contributed to the gap, especially among female farmers (13.74%) compared to male farmers (7.10%). Conversely, estimated income exhibited a significant negative contribution, particularly for female farmers (-102.20%), suggesting that economic barriers represent a substantial challenge. Additionally, household size contributed notably to the gap for female farmers (12.67%) and negatively for male farmers (-10.90%), indicating that household responsibilities may influence women's adoption of agricultural practices differently from men's.

The decomposition results also reveal that willingness to try new things had a negative contribution for female farmers (-9.61%) and for male farmers (-3.60%). This indicates that risk aversion among both groups may pose a limitation to adopting new practices or technologies. This highlights the importance of addressing gender-specific attitudes and perceptions toward innovation and risk in designing interventions to promote the adoption of Resilient Agriculture techniques.

Institutional factors such as access to climate information and credit access also played a crucial role in explaining the gap. Among female farmers, access to climate information had a positive contribution of 19.33%, while for male farmers, it contributed 23.20%, highlighting the importance of timely information in supporting farmers' decision-making processes. However, credit access showed differing impacts, with a negative contribution for female farmers (-2.21%) and for male farmers (-18.90%). This difference suggests that credit accessibility or utilization may pose challenges for both groups in the context of adopting RA techniques.

In summary, the table highlights that the gap between male and female farmers can largely be attributed to differences in access to production resources, such as land and labor, as well as institutional support, including credit and climate information. These findings provide critical insights for policymakers to design more inclusive interventions, such as improving women's access to land and climate information, to promote equitable adoption of RA techniques.

To further validate the findings in Table 5 and ensure the reliability of the data used in the analysis, it is essential to examine the quality of the matching procedure. Table 6 provides a verification of the equality of variable means before and after matching. This table demonstrates the extent of bias reduction for both male and female farmers and confirms whether the common support condition is satisfied across adopters and non-adopters. To examine the validity of the common support condition and the efficiency of the matching technique in guaranteeing that adopters and non-adopters have comparable features, we also conducted a covariate balancing test. After matching, none of the covariates were significant, according to the balancing test findings, which are shown in Table 6. This suggests that the matching procedure was successful in aligning the traits of adopters and non-adopters for both male and female farmers.

Meanwhile, Table 7 summarizes the overall quality indicators of the matching process, including changes in Pseudo-R^2 values, standardized mean bias, and bias reduction percentages. These metrics validate the effectiveness of the matching procedure in aligning the characteristics of adopters and non-adopters.

Table 6 focuses on the balance of covariates, confirming that differences in variable means between adopters and non-adopters have been minimized. Together, these tables provide a comprehensive assessment of the matching process, demonstrating that it successfully created comparable groups for analysis.

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Table 6. Verification of the equality of the variable means prior to and upon matching

Variable	Female farmers								Male farmers							
	Unmatched Sample				Matched Sample				Unmatched Sample				Matched Sample			
	Adopters	Non-adopters	% Bias	p > |t|	Adopters	Non-adopters	% Bias	p > |t|	Adopters	Non-adopters	% Bias	p > |t|	Adopters	Non-adopters	% Bias	p > |t|
Age of farmer (years)	51.35	50.64	7.90	0.504	51.16	52.07	-10.00	0.457	53.1	52.35	6.60	0.033**	53.18	56.47	-29.00	0.576
Marital status (1=married, 0=otherwise)	1.19	1.22	-7.60	0.029**	1.19	1.20	-2.50	0.856	1.21	1.21	1.10	0.043**	1.21	1.11	24.60	0.928
Education (Years of schooling)	6.16	3.39	55.70	0.000***	5.60	5.43	3.30	0.822	7.44	4.08	63.40	0.000***	6.89	5.85	19.70	0.515
Household size (number)	7.14	6.99	11.80	0.025**	7.04	7.24	-15.80	0.295	8.11	7.967	12.20	0.300*	8.08	8.28	-16.60	0.814
Number of years' resident in the village	39.68	43.78	-35.00	0.004***	39.80	46.44	-56.60	0.691	45.56	42.64	21.40	0.071*	46.05	45.95	0.70	0.960
Estimated income (Naira)	6.00E+05	4.00E+05	295.30	0.000***	6.10E+05	4.10E+05	290.70	0.485	9.90E+05	5.90E+05	113.20	0.000***	1.00E+06	5.80E+05	121.10	0.526
Total Farm size (hectare)	6.14	4.52	142.80	0.000***	5.80	5.71	8.20	0.539	8.73	7	83.10	0.000***	8.15	8.22	-3.50	0.770
Farming experience (years)	28.75	27.82	11.60	0.030**	28.12	28.44	-4.00	0.756	33.11	30.53	28.40	0.018**	33.1	32.39	7.90	0.546
Production system (1=rain-fed, 0=otherwise)	0.94	0.97	-12.60	0.283*	0.96	0.99	-14.40	0.476	0.81	0.91	-28.30	0.016**	0.83	0.86	-10.60	0.458
Labour (1=hired, 0=otherwise)	0.65	0.45	39.90	0.001***	0.63	0.40	46.30	0.801	0.8	0.88	-20.40	0.083*	0.81	0.87	-17.50	0.918
Willingness to take risk (1=yes, 0=otherwise)	0.61	0.39	42.50	0.000***	0.58	0.28	60.90	0.483	0.83	0.84	-3.80	0.117*	0.83	0.90	-19.60	0.751
Access to extension (1=yes, 0=otherwise)	0.13	0.17	-11.40	0.352	0.12	0.13	-2.90	0.831	0.21	0.15	15.50	0.191*	0.21	0.16	14.20	0.926
Access to credit (1=yes, 0=otherwise)	0.21	0.25	-10.00	0.100*	0.22	0.18	9.80	0.472	0.36	0.31	10.30	0.054	0.35	0.48	-27.20	0.4387
Membership of farmers' union (1=yes, 0=otherwise)	0.9	0.55	85.70	0.000***	0.89	0.69	50.30	0.626	0.89	0.69	49.80	0.000***	0.90	0.62	69.40	0.621
Ownership of farmland (1=yes, 0=otherwise)	0.37	0.26	23.70	0.047**	0.35	0.21	31.20	0.725	0.75	0.72	7.20	0.098*	0.74	0.83	-20.80	0.546
Access to climatic information (1=yes, 0=otherwise)	0.61	0.39	45.00	0.000***	0.60	0.71	-23.20	0.918	0.83	0.46	81.50	0.000***	0.83	0.44	86.70	0.853

Source: Author's computation (2023). Note: Statistical significance at the 0.1, 0.05, and 0.01 levels is indicated by the symbols *, **, and ***, respectively.

Table 7. Overall matching quality indicators before and after matching

Sample	Female sub-sample						Male sub-sample					
	Pseudo R^2	LR χ^2	p>(χ^2)	Mean Standard bias	Bias	Total % Bias reduction	Pseudo R^2	LR χ^2	p>(χ^2)	Mean Standard bias	Bias	Total % Bias reduction
Unmatched	0.890	344.06	0.000***	52.40	363.30		0.629	248.4	0.000***	34.1	178.8	
Matched	0.088	136.66	0.000***	19.40	133.80	63.17	0.058	75.35	0.000***	10.5	44.4	75.2

Table 6 verifies the equality of variable means between adopters and non-adopters of Resilient Agriculture (RA) techniques before and after matching for both female and male farmers. The matching procedure aims to ensure that adopters and non-adopters are comparable in terms of observed characteristics, thereby addressing potential selection bias in the analysis.

Before matching, several variables exhibited significant biases. Among female farmers, variables such as education had a bias of 55.70% (*p-value* < *0.001*), indicating that adopters had, on average, a higher level of education compared to non-adopters. Additionally, access to climatic information showed a bias of 45.00% (*p-value* < *0.001*), reflecting substantial differences between the two groups. For male farmers, significant biases were observed in variables such as total farm size, with a bias of 83.10% (*p-value* < *0.001*), and access to climatic information, which had a bias of 81.50% (*p-value* < *0.001*).

After matching, biases in most variables were significantly reduced for both groups. For female farmers, the bias in education decreased from 55.70% to 3.30%, while the bias in access to climatic information was reduced from 45.00% to -23.20%, indicating improved balance between adopters and non-adopters. Similarly, for male farmers, the bias in total farm size decreased from 83.10% to -3.50%, and the bias in access to climatic information reduced from 81.50% to 86.70%, which, although still significant, represents a smaller difference compared to the pre-matching condition.

Despite these improvements, some variables, such as access to climatic information for male farmers, still exhibited a notable bias after matching. This suggests that further refinement of the matching process may be necessary to achieve full balance for certain variables.

The explanatory power of the factors impacting the likelihood of RA adoption among both male and female farmers is reflected in the Pseudo-R^2 values, as indicated in Table 7. The joint significance of equality between adopters and non-adopters with respect to their covariate distribution is indicated by the p-values obtained from the probability ratio test.

According to Caliendo & Kopeinig (2008), there were no substantial alterations in the covariate distributions between the treated and untreated groups, as seen by the considerable fall in the Pseudo-R^2 for female farmers from 0.890 (89%) before matching to 0.088 (8.8%) after matching. This is further supported by the p-values from the likelihood ratio test, which indicate joint significance for both matched and unmatched samples (p-value = 0.000). Furthermore, following matching, the standardized mean bias for each covariate decreased from 52.4% to 19.4%, yielding a 63.17% reduction in overall bias. Pseudo-R^2 decreased similarly for male farmers in Table 7, going from 0.629 (62.9%) prior to matching to 0.058 (5.8%) following matching. Both unpaired and matched samples' p-values for the likelihood ratio test once more demonstrate joint significance (p-value = 0.106), and the overall bias reduction was 75.2% as the standardized mean bias for all covariates dropped from 34.1% to 10.5%. The success of the matching process is further demonstrated by the greater decrease in bias for male farmers.

Table 8 shifts the focus to the outcomes of RA adoption. Specifically, it examines the Average Treatment Effect (ATE) on farm yield for both male and female farmers. By utilizing two matching algorithms—Nearest Neighbor Matching (NNM) and Kernel-Based Matching (KBM)—the table provides a detailed comparison of yield outcomes between adopters and non-adopters, showcasing the disparities between these groups. Additionally, the table explores gender-based differences in farm yield outcomes, revealing how RA adoption impacts male and female farmers differently.

Table 8. Estimates of propensity score matching

Sample	**Average Treatment Effect (ATE)**					
	Female farmers			**Male farmers**		
	Coefficient	**Standard Error**	***z*-statistic**	**Coefficient**	**Standard Error**	***z*-statistic**
Nearest neighbour matching (NNM)	225.043	76.715	2.41***	237.738	85.954	2.18**
Kernel based matching (KBM)	251.236	76.739	3.27***	260.496	89.864	2.22**

***denote statistical significance at 0.01 level. Robust standard errors are reported

Table 8 demonstrates the Average Treatment Effect (ATE) for both female and male farmers, estimated using two matching algorithms: Nearest Neighbor Matching (NNM) and Kernel-Based Matching (KBM). The ATE for female farmers is 225.043 under NNM and 251.236 under KBM, while for male farmers, the ATE is 237.738 under NNM and 260.496 under KBM. Standard errors and z-statistics associated with these estimates indicate statistical significance, with the z-statistic for female farmers under KBM reaching the highest value of 3.27. These results provide robust evidence of the effectiveness of the matching algorithms in quantifying treatment effects.

The results presented in Table 8 highlight significant yield variations between RA adopters and non-adopters for both male and female farmers. When applied to the farm yield variable, the ATE remains consistent across the two matching algorithms. For female farmers, the ATE is 251.236 under KBM and 225.043 under NNM. In terms of yield disparity, KBM and NNM suggest increases of 14.8 and 4.8 percentage points, respectively, compared to the gap derived using the Blinder-Oaxaca decomposition approach. Similarly, for male farmers, the ATE is 260.496 under KBM and 237.738 under NNM, with yield disparities of 41.1 and 35.5 percentage points, respectively. These findings emphasize significant differences in farm yield between adopters and non-adopters, with consistent results across parametric and non-parametric methods.

Conclusion

This study highlights the transformative potential of regenerative agriculture (RA) in improving soil health and addressing gender disparities in farm productivity among smallholder farmers in Nigeria. While RA adoption significantly enhances farm productivity for both men and women, persistent gender gaps underscore the need for targeted interventions. The results revealed that institutional and socioeconomic factors, such as land ownership, education, income, and access to extension services, disproportionately affect female farmers, hindering their ability to adopt and benefit equally from RA practices. The significant influence of these factors underscores the need for tailored strategies to address gender inequities.

To address these challenges, this study recommends several targeted measures. First, developing RA training programs specifically tailored to female farmers, with flexible delivery formats such as community-based sessions, can accommodate their caregiving responsibilities. Second, introducing microfinance schemes or subsidized loans aimed specifically at female farmers would enable investments in RA techniques and inputs. Third, promoting land tenure reforms to ensure women have secure land ownership and rights is essential to fostering long-term investment in sustainable practices. Fourth, providing subsidies or tax breaks for female-led farming operations adopting RA can help reduce financial barriers and encourage adoption. Finally, strengthening extension services by incorporating a gender-balanced workforce and localized RA demonstrations will further improve access for women.

By prioritizing these recommendations, policymakers can reduce productivity disparities, promote equitable adoption of sustainable farming, and strengthen rural communities' resilience to climate change. Future research should examine the long-term impacts of RA on gender equity and productivity across diverse agro-ecological zones to refine these strategies. Ultimately, this approach will contribute to food security and environmental sustainability in Nigeria and beyond.

Statement of originality and plagiarism-free

We inform that this article is original article and free of plagiarism.

Competing interests

The author(s) declare no conflicts of interest related to this research, authorship, or publication.

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