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Analysis of the factors influencing the adoption of improved rice seeds on farm resilience to climate change in the Tandjile Province of Chad

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ABSTRACT

In the face of climate change threatening food security in Chad, improved seeds are promoted as a key innovation to enhance farmer resilience. However, their adoption remains limited in the province of Tandjile. This study aims to analyze the socio-economic and institutional determinants of the adoption of improved rice seeds and to assess their causal impact on agricultural productivity, as an indicator of resilience. Based on a sample of 270 farm households and 68 qualitative interviews in the province of Tandjile, an Endogenous Switching Regression model was employed to correct for selection biases and estimate the impact of adoption on yield. Our findings reveal a significant causal impact: adoption increases yield by an average of 624 kg/ha for adopters (Average Treatment Effect on the Treated). The potential impact for non-adopters amounts to 665 kg/ha (Average Treatment Effect on the Untreated), suggesting that the most vulnerable farmers would have the most to gain. Adoption is primarily determined by access to credit, extension services, membership in a farmer organization, education level, and the complementary use of fertilizer. The analysis reveals significant selection bias: adopting farmers exhibit inherently higher productive capacities, independent of the technology's effect. Improved seeds are effective in enhancing productive resilience. The main challenge lies in their equitable adoption. Policies must shift from a mere dissemination of seeds towards an integrated approach, specifically targeting access to credit, strengthening extension services and farmer organizations, and removing barriers for vulnerable groups (smallholders, women, less-educated farmers) to realize the full potential of this innovation.

Key words: Technology adoption, Improved seeds, Agricultural resilience, Endogenous switching regression model, Chad

INTRODUCTION

Climate change is one of the primary challenges confronting agriculture today. Extreme weather events, such as droughts and floods, are adversely affecting agricultural productivity and food security. According to the Food and Agriculture Organization of the United Nations (FAO), climate change could lead to a 2% to 6% decline in agricultural productivity by 2050 (FAO, 2017). Agricultural performance is heavily dependent on climatic and rainfall factors, which are becoming increasingly erratic (Fayama and Maïga, 2017). Global cereal productivity growth has slowed, characterized by yield stagnation and declining profitability of high-input production systems (FAO, 2016). This slowdown could have deleterious effects on food security and producer welfare if incentive measures promoting the use of improved seeds are not implemented, particularly in Africa where cereal yields are less than half the global average (FAO, 2017).

Chad, a Sahelian country, is highly dependent on an agricultural sector that is pivotal to its economy and food security (World Bank, 2020), employing approximately 80% of the labour force. However, the country faces significant challenges related to climate change, including rainfall variability, droughts, and floods. These extreme events substantially impact agricultural productivity and food security. Improved seeds are perceived as a potential solution to enhance the resilience of farm holdings against these hazards. Engineered to withstand environmental stresses (e.g., drought, diseases) and to offer higher productivity, they could play a crucial role.

Research on the impact of climate change indicates that extreme events can cause significant productivity losses and threaten food security (Schlenker and Roberts, 2009). Improved seeds, by bolstering farm resilience, could thereby help mitigate these effects (Ceccarelli *et al.*, 2010).

They can indeed increase productivity, enhance food security, and improve crop resistance to droughts and floods. Nevertheless, their adoption in Chad remains constrained by several factors:

(i) limited access for smallholder farmers, (ii) high cost, (iii) a lack of knowledge and skills for effective utilization, and (iv) agricultural policies and rural development programs that are inadequately tailored to farmers' needs.

Chadian farmers primarily rely on the informal seed sector, which is based on family and community systems of seed conservation and exchange. These systems constitute the principal source of seeds in the medium and long term. Their impact on food security and agricultural production is fundamental, and their enhancement would represent an effective strategy for combating poverty among farming households (PNS, 2016). Although the seed sector is a national priority supported by the government and development partners, the seed value chain remains disorganized. Seed centres produce basic and commercial seeds, yet demand frequently outstrips supply, as seed producers struggle to meet it.

The rate of improved seed utilization in Chad remains very low, accounting for only about 2% of potential demand (PNS, 2016). The primary causes identified are: a marked deficiency in human, material, infrastructural, and financial resources for agricultural research, extension services, and quality control; seed systems that are ill-adapted to the needs of smallholder farmers, who are responsible for over 95% of agricultural production; and still-nascent initiatives to structure agricultural value chains (PNS, 2016).

Within this context of constrained access to improved seeds, Chadian farming households predominantly use local seeds and planting materials. The situation is particularly critical for cereals. The failure to adopt improved seeds is likely attributable to a lack of adequate infrastructure for the efficient multiplication and distribution of improved cultivars, such as those derived from hybridization, which would necessitate stronger involvement from the private sector.

Agricultural economics research demonstrates that adoption rates and the factors influencing farmers' decisions to adopt a technology vary considerably due to the heterogeneity of their preferences (Roussy *et al.*, 2015). Furthermore, numerous studies indicate that the adoption of improved seeds can lead to increased production, enhanced food security, and higher farmer incomes (Moti *et al.*, 2015; Tesfaye *et al.*, 2016). However, the available literature, particularly concerning Chad, has not yet specifically addressed the adoption and impact of improved seeds for cereals. This study therefore aims to fill this gap by analyzing the level, determinants, and impact of improved seed adoption on agricultural productivity in the Tandjile Province of Chad, using survey data and an econometric approach.

This research seeks to understand the impact of adopting improved seeds on the resilience of farm holdings to climate change in Tandjile Province. More specifically, it aims to address the following questions: What is the impact of this adoption on crop productivity and resilience? Which factors influence farmers' decisions? How can agricultural policies and rural development programs support this adoption to strengthen the resilience of farm holdings? By analyzing this impact, the study intends to provide actionable insights for policymakers and rural development practitioners to enhance the climate resilience of Chadian agriculture.

Understanding the factors influencing the adoption of improved seeds is essential for assessing their impact on resilience. Smallholder farmers often face access barriers due to high costs or limited availability. They require training, financing, and market access to utilize these seeds effectively, manage climate risks, and commercialize their produce. To increase productivity and ensure food self-sufficiency, it is crucial to enhance yields through the introduction and adoption of climate-adapted seeds. Researchers and policymakers regard these seeds as an indispensable factor for increasing production (FAO, 2017). The decision to adopt an innovation can be influenced by producers' preferences for specific varieties.

To identify the determinants of improved seed adoption, we postulate that the low adoption of improved rice varieties can be explained by a combination of several factors: i) socio-cultural factors (perceptions, culture, dietary habits); ii) technical and economic factors (production costs, insufficient mastery of cultivation techniques); iii) communication factors (lack of awareness of improved varieties, information deficits); iv) political factors (inadequate support for farmers); and v) factors related to the farmer-based approach (participatory selection, dissemination and extension methods, linkages between research, extension services, and producers) (Fayama and Maïga, 2017). This study focuses more specifically on the socio-technical determinants that hinder the adoption of varieties that have demonstrated efficacy at the research level. Fieldwork results reveal that Tandjile Province is characterized by a low level of uptake of improved seeds, an observation that warrants the attention of the political class and development stakeholders.

MATERIALS AND METHODS

Study area

This study was conducted in the TANDJILE Province of Chad. This area represents a significant rice-growing basin characterized by a Sahelian climate, with a single rainy season conducive to rice cultivation, which is a strategic activity for local and regional food security.

The selection of the five study sites was carried out in close collaboration with the Departmental Agricultural Services, following a rigorous methodology based on four main criteria: the importance of rice production in the local economy, a history of improved seed distribution by the state or development projects over the past five years, the presence of local initiatives for the production or dissemination of improved seeds, and the existence of at least one private actor involved in the seed sector.

Sample distribution and sampling rate

The sample size was determined using Cochran's formula (1977) for finite populations, adapted for agricultural studies following the recommendations of Singh and Masuku (2014):

$$n = \frac{(t^2 * p)(1-p)}{m^2} \quad (1)$$

N = sample size

t = confidence level

p = proportion size

m = margin of error

From a total population of 1,321 agricultural households surveyed in the study area, a sample of 270 households was interviewed using the simple random sampling method without replacement. Table 1 shows the detailed distribution by site:

Table 1. Distribution of the sample by study site

Study site	Total population of households	Number of households surveyed	Sampling rate (%)
LAÏ	420	86	20,48%
BERE	285	58	20,35%
KELO	315	64	20,32%
BATCHERO	180	37	20,56%
HAM	121	25	20,66%
Total	1 321	270	20,43%

Given logistical constraints and following the approach of Kothari (2004), which recommends a minimum sampling rate of 20% for agricultural studies in the Sahelian context, a sample of 270 households was selected. The sample size (270 households) and the overall sampling rate of 20.43% meet the methodological standards for studies in agricultural economics (Malhotra and Grover, 1998). The simple random sampling method applied uniformly across all sites ensures statistical representativeness with a margin of error of ±5% and a confidence level of 95%.

Data collection

In Chad, rice cultivation relies on the use of various improved seed varieties, introduced by a range of actors including research institutions, development partners, agricultural services, and the private sector. As highlighted by recent work on the adoption of agricultural innovations in sub-Saharan Africa (Dandonougbo *et al.*, 2023; Kabore, 2022), assessing the impact of these technologies requires a rigorous methodological approach. The present study specifically aims to assess the level of adoption of these seeds, identify their determinants, and measure their impact on the productivity of rice-farming households.

The quantitative survey targeted the heads of agricultural households. The construction of the sample, a crucial phase for representativeness (Dossou *et al.*, 2024), was based on lists of households per village. For some sites, these lists were created from scratch for the study, while for others, administrative lists provided by the Agricultural Services were used after careful updating in the field with village chiefs and key informants—a practice recommended to overcome the frequent obsolescence of official registers. The reference population amounts to 1,321 enumerated households. The final sample comprises 270 households, selected by the probabilistic method of simple random sampling without replacement after numbering all households (from 1 to N) in each village. This represents a sampling rate of 20.43%, deemed sufficient for good statistical precision in agricultural studies (Mutungamere, 2023).

The administered questionnaire was designed to collect multidimensional data, inspired by frameworks for analyzing technology adoption (Bassogog *et al.*, 2023). It covered the socio-economic and demographic characteristics of households, farming practices, the use of improved seeds, the perception of risks and attributes of these seeds, production levels, input usage, and constraints encountered during the 2024-2025 agricultural season. In addition, the qualitative approach captured the complexity of farmers' perceptions and strategies, as advocated by the literature on mixed methods (Phelan, 2022). Informal interviews, in the form of open discussions, were conducted opportunistically with producers, thus providing an in-depth understanding of local contexts.

Finally, to ensure the validity and reliability of the data, in accordance with the principles of methodological triangulation widely supported (Ouedraogo, 2023), several measures were taken.

Among others, direct observations were carried out in the fields, and the collected information (primary and secondary data) was systematically cross-referenced and compared.

Factors influencing innovation adoption, potential impacts, and theoretical framework

The adoption of an agricultural technology can be defined as the degree of effective and sustained use of an innovation by farmers after fully understanding its benefits and constraints. Although often measured quantitatively (e.g., the area cultivated with an improved variety), it can also be considered as a binary decision (adoption or non-adoption). Seeds, as a fundamental input, play a crucial role. Access to quality seeds for a diversity of crops allows farmers to increase their productivity and income, while strengthening their resilience to climate shocks and diseases (FAO, 2018). The adoption of agricultural technologies is a complex process influenced by the interaction of multiple factors. Recent research identifies the following key determinants:

Age of the producer: Effects remain mixed. A study by Wossen *et al.* (2023) on smallholder farmers in sub-Saharan Africa confirms an inverted U-shaped relationship, where middle-aged farmers adopt more frequently than the young (lack of capital) and the elderly (increased risk aversion).

Gender of the farm manager: According to Doss and Meinzen-Dick (2020), gender gaps persist but are mainly attributable to differences in access to productive assets rather than an intrinsic reluctance to innovate.

Education level: Formal education improves the ability to process technical information, with a threshold effect often observed at the secondary level (Nakano *et al.*, 2023).

Size of cultivated land: Land area remains an important proxy for the capacity to absorb risk. Larger farms show a higher probability of adoption, as confirmed by Mbeche *et al.* (2024) in the East African context.

Access to credit: Financing helps overcome liquidity constraints, especially for costly inputs. A meta-analysis by Ogutu *et al.* (2023) emphasizes that credit products tailored to the cropping cycle increase adoption by 25 to 40%.

Membership in farmer organizations: These structures reduce transaction costs and facilitate collective access to inputs. Sibhatu and Qaim (2023) demonstrate their crucial role in peer-to-peer information diffusion.

Contact with extension services: The digitalization of services (mobile-based extension) is emerging as a determining factor, particularly for reaching young farmers (Agyekum *et al.*, 2024).

Perceived relative advantage: Anticipated profitability and the observability of results on neighboring plots remain primary drivers (Tumusiime *et al.*, 2023).

Compatibility with the existing system: Mismatch with local farming practices still explains the majority of early disadoptions (Kansime *et al.*, 2023).

Availability and price of inputs: The reliability of certified seed supply chains is identified as the main bottleneck in many regions (Abdoulaye *et al.*, 2024).

Subsidy policies: Targeting subsidies towards the most vulnerable producers proves more effective than universal subsidies (Liverpool-Tasie *et al.*, 2023).

Concurrent use of fertilizer:The synergy between improved seeds and fertilizers is systematically correlated with sustained adoption (Sheahan and Barrett, 2023).

Exposure to climate change: The perception of climate risks accelerates the adoption of resilient varieties (Shikuku, 2024).

The adoption process is neither immediate nor universal. It generally follows a diffusion curve over several years, where farmers gradually evaluate the innovation against their existing practices (Kuehne *et al.*, 2017). Even when benefits are demonstrated, adoption rarely reaches 100% of potential farmers. The adoption of agricultural technologies, such as improved seeds, generates positive impacts at multiple levels. Economically, it directly affects productivity by increasing yields and farmers' incomes, which helps reduce poverty and stimulate local development through job creation in processing and marketing value chains (Manda *et al.*, 2020). Socially and environmentally, it strengthens food security and constitutes a crucial adaptation strategy by improving the resilience of farms to climate shocks, such as droughts or pest infestations (IPCC, 2019).

The decision to adopt an innovation is a complex process. According to modern adoption theory, farmers evaluate an innovation based on the utilities they assign to its different characteristics (yield, taste, resistance, etc.), an approach inherited from Lancaster's characteristics theory (1966). The process generally involves information gathering, opinion formation, and decision-making, which is influenced by the perception of risks and benefits (Kuehne *et al.*, 2017). Effective demand for adoption only emerges when farmers, once informed, are able to access the technology, without being hindered by market failures (limited access to inputs, credit) or inadequate agro-ecological constraints (Abate *et al.*, 2018).

Analysis method

Evaluating the impact of adopting improved seeds faces the challenge of selection bias, where both observable and unobservable characteristics simultaneously influence the adoption decision and agricultural performance. Unlike standard methods (OLS, PSM) that struggle to fully correct for this bias, the Endogenous Switching Regression (ESR) model was selected for its ability to simultaneously estimate selection and outcome equations, while allowing for a nuanced counterfactual analysis (TT and TU effects). This choice aligns with recent work, such as that of Khonje *et al.* (2018) on agricultural technologies in Africa, Wiredu *et al.* (2021) on the adoption of improved maize seeds, or Mishra *et al.* (2022) in assessing the impact of agricultural innovations, which highlight the robustness of ESR for estimating differentiated causal effects and informing targeted policies.

The selection equation, modeled by a probit model, specifies the determinants of the decision to adopt improved seeds. Adoption is modeled by a latent variable A_i^*. Adoption is modeled using a latent variable Ai^*. The observed variable is A_i. $A_i = 1$ si $A_i^* > 0$.

$A_i^* = \beta Z_i + u_i$,

$Ai = 1$

where $A_i^* > 0$, and $Ai = 0$ otherwise (2)

The outcome equations for each regime, specified below, allow for the estimation of production function parameters conditional on adoption status. Agricultural yields (per hectare) for the two groups are modeled separately:

Regime 1 (Adopters): $Y1_i = \boldsymbol{\alpha}1\, \boldsymbol{X}_i + \varepsilon1_i$ (3)

Regime 2 (Non-adopters): $Y2_i = \boldsymbol{\alpha}2\, \boldsymbol{X}_i + \varepsilon2_i$ (4)

Where:

Y_{1i}, Y_{2i} are agricultural yields per hectare for adopters and non-adopters, respectively.

$\boldsymbol{X}_i$ is a vector of exogenous variables affecting yield.

$\mathrm{Z}_{\mathbf{i}}$ is a vector of exogenous variables influencing the adoption decision (which may include variables not present in X_i for identification purposes).

u_i, $\varepsilon1_i$ and $\varepsilon2_i$ are the error terms of the equations.

The maximum likelihood estimation procedure requires specific distributional assumptions regarding the error terms of the model's equations. To correct for endogenous selection bias, equations (2), (3), and (4) are estimated simultaneously using the full information maximum likelihood (FIML) method (Lokshin and Sajaia, 2004). This approach assumes that the error terms $(u_i, 1_i, \varepsilon2_i)$ follow a trivariate normal distribution with a zero mean vector and covariance matrix Ω:

$$\Omega = \begin{pmatrix} \sigma_\mu^2 & \sigma_{1\mu} & \sigma_{2\mu} \\ \sigma_{1\mu} & \sigma_1^2 & \sigma_{12} \\ \sigma_{2\mu} & \sigma_{12} & \sigma_2^2 \end{pmatrix} \quad (5)$$

σ_u^2 is the variance of the error term in the selection equation;

σ_1^2 and σ_2^2 are the variances of the error terms in the continuous outcome equations;

$\sigma_u^1$is the covariance between u_I and v_{1i};

σ_u^2 is the covariance between u_i and v_{2i}.

The covariance between v_{1i} and v_{2i} is not defined because Y_{1i} and Y_{2i} are never observed simultaneously.

Counterfactual analysis allows for the construction of impact measures by estimating what the outcomes for the farmers would have been in the alternative situation to the one actually observed. Following the literature (Asfaw *et al.*, 2012), the endogenous switching regression model is used to calculate the conditional expected yields for four crucial scenarios, presented in the Table 2 below.

Table 2. provides a detailed description of the variables used to estimate the endogenous switching regression model.

Variables	Descriptions	Measurements
Production variables	Area sown	Hectares (ha)
	Quantity of fertilizer	Kg / ha
	Quantity of herbicide	Liters / ha
	Labor	Man-days
	Yield	Kg / ha
	Quantity of improved seed used	Kg / ha
	Farmer's Income	CFA Francs
	Price of improved seed	CFA Francs
Farmer characteristics	Age	Years
	Sex	1= Male, 0= Female
	Experience	Years
	Agricultural training	1= Yes, 0= No
Institutional variables	Access to credit	1= Yes, 0= No
	Education	1= Yes, 0= No
	Extension services contact	1= Yes, 0= No
	Membership in a farmer organization	1= Yes, 0= No

Table 3. Conditional expectations, treatment and heterogeneity effects

Subgroup	Adoption decision (Potential outcome)		Impact measure
	Adoption Y_1	Non adoption Y_2	
Adopters (A=1)	(a) $E(y_{1i}\|A_i = 1)$ (Observed outcome)	(c) $E(y_{2i}\|A_i = 1$ (Counterfactual)	TT (Treatment effect on the treated)
Non-Adopters (A=0)	(d) $E(y_{1i}\|A_i = 0)$ (Counterfactual)	(b) $E(y_{2i}\|A_i = 0$ (Observed outcome)	TU (Treatment effect on the untreated)
Heterogeneity effects	BH1 (Selection bias of adopters)	BH0 (Selection bias of non-dopters)	TH (Treatment Heterogeneity)

$A_i = 1$ if the farmer adopted improved seeds; $A_i = 0$ otherwise.

$Y1_i$: Potential yield if the farmer adopts (adoption regime).

$Y2_i$: Potential yield if the farmer does not adopt (non-adoption regime).

TT (Average Treatment Effect on the Treated): The average benefit gained by the adopters due to adoption. TT = (a) - (c).

TU (Treatment Effect on the Untreated): The potential average benefit that non-adopters would gain if they were to adopt. TU = (d) - (b).

BH1 (Selection Heterogeneity of Adopters): Measures whether adopters possess observable and unobservable characteristics that predispose them to achieve better (or worse) outcomes than the average, irrespective of adoption. BH1 = (a) - (d).

BH0 (Selection Heterogeneity of Non-Adopters): Measures whether non-adopters possess observable and unobservable characteristics that predispose them to achieve better (or worse) outcomes than the average, irrespective of non-adoption. BH0 = (c) - (b).

TH (Treatment Heterogeneity): Measures whether the impact of adoption is different for the adopters (TT) compared to what it would be for the non-adopters if they were to adopt (TU).

A significant TH value indicates that the treatment effect is not homogeneous across the population. TH = TT - TU.

This counterfactual analysis is essential for assessing the true impact of adoption and for informing seed policies. From these expected values, we can calculate two key impact measures:

The Average Treatment effect on the Treated (TT): This effect measures the impact of adoption specifically for the farmers who actually adopted. It is given by the difference between their observed outcome (a) and their counterfactual situation (c) had they not adopted.

$$TT = (y1i|Ai = 1) - E(y2i|Ai = 1) \tag{6}$$

The Average Treatment effect on the Untreated (TU): This effect measures the potential impact that adoption would have had on the farmers who did not adopt. It is given by the difference between their counterfactual situation (d) had they adopted and their observed outcome (b). Similarly, the difference between cases (d) and (b) is the Average Treatment effect on the Non-adopters (TU) (Equation 7):

$$TU = (y_{1i}|A_i = 0) - (y_{2i}|A_i = 0) \quad (7)$$

Table 3 summarizes the key estimates from the model: the treatment effects and the heterogeneity effects. The endogenous switching regression model allows for the isolation and separate quantification of the causal effect of adoption (treatment effect) and the pre-existing productivity advantage of the adopters (heterogeneity effect). This methodology disentangles the causal effect of adoption itself (TT and TU) from the effect of selection or unobserved heterogeneity (Asfaw *et al.*, 2012).

For example, adopters might have higher yields than non-adopters not because of the seeds, but simply because they are more competent, more motivated, or have better land (unobservable factors). This intrinsic advantage, independent of the technology, is captured by the heterogeneity effect BH1 (Equation 8):

$$EH1 = (y1i|Ai = 1) - (y1i|Ai = 0) \quad (8)$$

Similarly, the BH0 effect (Equation 9) measures the intrinsic advantage (or disadvantage) of non-adopters in the non-adoption regime:

$$EH2 = (y2i|Ai = 1) - (y2i|Ai = 0) \quad (9)$$

Finally, the treatment heterogeneity (TH), calculated as the difference between TT and TU (Equation 10), indicates whether the impact of adoption is systematically stronger for one group than the other. A significant TH suggests that the gains expected from a policy promoting adoption would be different for current non-adopters compared to the gains realized by current adopters

RESULTS

Descriptive comparison of adopting and non-adopting groups

Table 4 presents the descriptive statistics of the main variables for the total sample, as well as for the subgroups of adopters and non-adopters.

The descriptive statistics highlight marked differences between farmers who adopted improved seeds and those who did not. Regarding outcome variables, the average yield of adopters was 2150.60 kg/ha, which is significantly higher (at the 1% level) than that of non-adopters (1120.30 kg/ha), representing a raw difference of 1030.30 kg/ha. A similar disparity is observed for rice income, with the average income for adopters (537,650 FCFA) being nearly double that of non-adopters (280,075 FCFA).

Analysis of producer characteristics reveals that adopters are, on average, younger (45.1 years vs. 49.6 years for non-adopters), a difference significant at the 5% level. Furthermore, the proportion of males is significantly higher among adopters (89%) than among non-adopters (73%). The level of formal education is also a distinguishing factor: 55% of adopters are educated compared to only 26% of non-adopters. Substantial gaps are also observed for economic and institutional variables. The average cultivated area for adopters (2.5 ha) is significantly larger than that of non-adopters (1.5 ha). Access to support services is markedly higher for the adopter group: 49% of them have access to credit (vs. 18%), 75% had contact with extension services (vs. 26%), and 62% are members of a farmer organization (vs. 18%). Finally, fertilizer use is a much more widespread practice among adopters (82%) than among non-adopters (21%).

Determinants of improved seed adoption

Table 5 presents the results of the endogenous switching regression model estimation, starting with the determinants of the adoption decision.

The results of the logistic regression on the determinants of adoption show that the farmer's age influences the decision in a non-linear manner. The negative coefficient for the "Age" variable (-0.021) and positive for "Age Squared" (0.0002) indicates an inverse U-shaped relationship, significant at the 5% and 10% levels, respectively. Gender has a significant effect at the 10% level, with males having a higher probability of adopting. Education level is a key determinant: having a secondary level education or higher significantly increases (at the 1% level) the probability of adoption, unlike primary education, whose effect is not statistically significant.

Table 4. Descriptive statistics and comparison of adopting and non-adopting groups

Variable	Total sample (n=270)	Adopters (n=85)	Non-adopters (n=185)	Difference (t-test)
Outcome variables				
Yield (kg/ha)	1450.75	2150.60	1120.30	1030.30***
Rice income (FCFA)	362,687	537,650	280,075	257,575***
Producer characteristics				
Age (years)	48.2	45.1	49.6	-4.5**
Gender (1=Male)	0.78	0.89	0.73	0.16**
Expérience (années)	22.5	20.1	23.6	-3.5*
Éducation formelle (1=Oui)	0.35	0.55	0.26	0.29***
Variables économiques et institutionnelles				
Superficie cultivée (ha)	1.8	2.5	1.5	1.0***
Accès au crédit (1=Oui)	0.28	0.49	0.18	0.31***
Contact vulgarisation (1=Oui)	0.41	0.75	0.26	0.49***
Membre organisation paysanne (1=Oui)	0.32	0.62	0.18	0.44***
Utilisation d'engrais (1=Oui)	0.40	0.82	0.21	0.61***

Table 5. Determinants of improved seed adoption

Variable	Coefficient	Standard Error
Age of producer	-0.021**	(0.009)
Age squared	0.0002*	(0.0001)
Gender (1=Male)	0.415*	(0.242)
Education level		
Primary	0.288	(0.231)
Secondary and above	0.752***	(0.285)
Farming experience	-0.015	(0.011)
Total cultivated area (ha)	0.204***	(0.062)
Access to credit (1=Yes)	0.638***	(0.198)
Contact with extension (1=Yes)	0.821***	(0.215)
Member of a farmer organization (1=Yes)	0.594**	(0.236)
Fertilizer use (1=Yes)	0.967***	(0.224)
Constant	-2.145***	(0.542)
Number of observations	270	
Log pseudolikelihood	-285.34	

Table 6. Impact of improved seed adoption on yield (kg/ha)

Subgroup	Expected outcome		Treatment effect
	Adoption regime (Y_1)	Non-adoption regime (Y_2)	
Adopters (A=1)	2151 (a) (Observed outcome)	1527 (c) (Counterfactual)	TT= 624* (Effet sur les traités)
Non-adopters (A=0)	785 (d) (Counterfactual)	1120 (b) (Observed outcome)	TU= 665* (Effet sur les non-traités)
Heterogeneity effects	BH_1 = 366 (Adopters' base advantage)	BH_0 = 407 (Non-adopters' base disadvantage)	TH= -41 (Treatment heterogeneity)

Among economic variables, total cultivated area exerts a positive and highly significant (at the 1% level) effect on the probability of adoption. Fertilizer use is the factor most strongly associated with adoption, with a highly significant positive coefficient (0.967, $p<0.01$). Regarding institutional variables, access to credit, contact with an extension agent, and membership in a farmer organization all have a positive and highly significant impact (at the 1% and 5% levels) on the decision to adopt improved seeds. Farming experience, however, has no statistically detectable effect.

Causal impact on yield

Table 6 presents the results of the yield equations for the adopter and non-adopter regimes, as well as the counterfactual analysis used to calculate the causal impact.

The estimation of the endogenous switching regression model allows for the calculation of the causal impact of adoption. For farmers who adopted (the treated), the observed mean yield in the adoption regime (Y_1) is 2151 kg/ha. The estimated counterfactual scenario (what they would have obtained without adoption, Y_2) is 1527 kg/ha. The difference between these two values, the Average Treatment Effect on the Treated (TT), is 624 kg/ha, a positive impact significant at the 5% level.

For non-adopters (the untreated), the observed yield without adoption (Y_0) is 1120 kg/ha. The counterfactual scenario (what they would have obtained if they had adopted, Y_1) is estimated at 785 kg/ha. The difference, the Average Treatment Effect on the Untreated (TU), is 665 kg/ha, also significant at the 5% level. The analysis reveals a significant positive selection bias. Adopting farmers possess characteristics (observable and unobservable) that confer a base advantage (BH_1) of 366 kg/ha, meaning they would obtain higher yields even without adoption. Conversely, non-adopters suffer from a base disadvantage (BH_0) of 407 kg/ha. The treatment effect heterogeneity (TH), i.e., the difference between TT and TU, is small (-41 kg/ha) and not statistically significant.

DISCUSSION

Farmer profiles and determinants of adoption

The descriptive comparison confirms the existence of significant structural differences between adopters and non-adopters, validating the concern of selection bias and justifying the use of a robust econometric method like the endogenous switching regression model. The profile of adopters – younger, more educated, better connected to institutions, and managing larger farms – is a consistent finding observed in many studies in sub-Saharan Africa. The very strong correlation between seed adoption and fertilizer use underscores that farmers often adopt a coherent "technology package," where innovations are complementary for maximizing productivity gains.

The estimated determinants of adoption align well with the literature consensus. The inverse U-shaped relationship with age corroborates findings by Kansime *et al.* (2021) in Uganda, suggesting that middle-aged farmers combine sufficient experience with a greater propensity to take risks. The crucial importance of secondary education, well-documented by Mazuze *et al.* (2021) in Mozambique, confirms its role in the ability to understand and evaluate complex technical innovations. The determining influence of institutional factors (credit, extension, farmer organizations) supports the foundational work of De Janvry *et al.* (1991) and recent studies like that of Awel and Azomahou (2020) in Ethiopia, who identify access to credit as a major constraint. Similarly, the positive impact of extension, demonstrated by Kondylis *et al.* (2017) in Kenya, highlights its role in reducing uncertainty associated with a new technology. These results clearly indicate that the adoption decision is deeply embedded in a favorable institutional environment.

Causal impact and its implications

The significant causal impact of 624 kg/ha (TT) demonstrates the real effectiveness of improved seeds in the context of Tandjilé Province. This effect is substantial and consistent with the impact ranges reported by meta-analyses, such as that of Tambo and Mockshell (2021) in West Africa.

The most notable finding with strong policy implications is the slightly higher Treatment Effect on the Untreated (TU) of 665 kg/ha. This suggests that the potential gain for current non-adopters is, on average, greater than the gain actually realized by adopters. This phenomenon, observed by authors like Suri (2011) in Kenya, is explained by the theoretical framework of Magruder (2018): when the first adopters are those who are already better endowed, their measured gain (TT) may underestimate the average benefit the technology could bring to the entire farming population, and particularly to the most vulnerable. The presence of a significant selection bias (base advantage of adopters of 366 kg/ha) confirms this interpretation. Non-adopters, although structurally disadvantaged, would therefore ultimately have more to gain from adoption. Improved seeds could thus act as a "leveler," helping to bridge part of the productivity gap linked to structural disadvantages. The fact that the treatment effect heterogeneity (TH) is not significant reinforces this conclusion by indicating that the technology itself is not biased in favor of a particular group; its benefits are potentially universal.

This finding is crucial for public policy. It argues for targeted interventions to remove the specific barriers (access to credit, information, complementary inputs) that hinder adoption among the most vulnerable farmers, as they are precisely the ones who could derive the greatest benefit, thereby contributing to both equity and the overall efficiency of the agricultural sector.

CONCLUSION

This study on the adoption of improved rice seeds in the Tandjilé Province of Chad has yielded significant conclusions regarding their impact on the resilience of farms in the face of climate change. The results demonstrate that the adoption of these seeds is an effective lever for improving agricultural productivity, strengthening food security, and increasing the incomes of rural households.

The analysis revealed that improved seeds lead to a substantial increase in yields, with an average gain of 624 kg/ha for adopting farmers. More significantly, the study highlighted that non-adopters could benefit from an even greater impact (665 kg/ha) if they adopted this technology, thus underscoring the untapped potential of these seeds for the most vulnerable farmers. The identified determinants of adoption—including education, access to credit, agricultural extension, membership in farmer organizations, and fertilizer use—shed light on the structural barriers that currently limit wider adoption. The presence of a significant selection bias confirms that adopting farmers already possess better productive capacities, independent of their use of improved seeds.

The results of this study call for a reconfiguration of seed and agricultural policies in Chad, shifting from an approach focused solely on seed availability to an integrated strategy aimed at removing the structural barriers to adoption. The following recommendations are priorities: (i) Improve access to seeds for the most vulnerable: Design dissemination programs that explicitly target underrepresented groups, such as women and small-scale farmers. (ii) Develop tailored support mechanisms: Develop adapted microcredit mechanisms (guaranteed loans, warehouse receipt financing) and commercialize small, subsidized seed packets. (iii) Expand access to credit by supporting microfinance institutions and developing digital financial products tailored to the cropping cycle.

This study has certain limitations. It focuses on one province and a specific crop; a national survey would allow for the generalization of the results. Furthermore, the analysis focused on yield as an indicator of immediate resilience. Future research could: (i) Quantify the impact on other dimensions of resilience, such as income stability, dietary diversification, and adaptive capacity to specific climate shocks. (ii) Conduct a more in-depth analysis of the specific constraints to adoption by women, using an intersectional gender lens.

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