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Unveiling the resilience of smallholder farmers in Senegal amidst extreme climate conditions

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Abstract

In Senegal, agriculture is an important sector underpinning the socioeconomic fabric of the populace. Notably, the agricultural production in this region exhibits heightened sensitivity to climatic perturbations, particularly droughts and heat waves. This study aims to determine the resilience of different agronomic interventions for farmers practicing mixed farming that produce both crops (i.e., groundnut (*Arachis hypogaea* L.) and pearl millet (*Pennisetum glaucum* (L.) R. Br.)) and raise animals in the Groundnut Basin in Senegal, which holds historical and socioeconomic significance. To understand the current situation regarding demographics, economics, consumption behavior, and farm operations for smallholder farmers, data were comprehensively collected from government and nongovernment organizations (NGO) reports, scientific papers, organization databases, and surveys. Additionally, the Agricultural Production Systems sIMulator (APSIM) was used to understand how combinations of three planting dates, three plant densities, and six urea nitrogen (N) fertilizer rates affected the yield of pearl millet, which were used as the alternative scenarios to the baseline in the farm modeling and analyses. All the collected and generated data were used as inputs into the Farm Simulation Model (FARMSIM) to generate economic, nutritional, and risk data associated with mixed farming systems. The generated data were then used to determine the resilience of the alternative scenarios against the baseline. Initially, a multi-objective optimization was employed to meet nutritional needs while maintaining a healthy diet at the lowest cost. Then, the scenarios that met the population's nutritional requirements were evaluated based on four economic indicators: net cash farm income (NCFI), ending cash reserves (EC), net present value (NPV), and internal rate of return (IRR). Lastly, those that passed the economic feasibility test were ranked based on risk criteria certainty equivalent (CE) and risk premium (RP). The analyses found N fertilizer rates of 0, 20, and 100 kg N ha^{-1} were generally economically not feasible. Additionally,

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medium (early-July to late-August) and late (late-July to mid-September) planting dates generally performed better than early (early-June to late-July) planting dates, while plant densities of 3.3 and 6.6 pL m^{-2} performed better than 1.1. The robust resilience approach introduced in this study is easily transferable to other regions.

KEYWORDS
drought, farm modeling, nitrogen fertilizer, nutrition, plant density, planting date

1 | INTRODUCTION

Extreme events (e.g., high temperatures, floods, and prolonged drought), climate change and variability, major natural disasters, mass pandemics, and civil unrest and political instability, including the war in Ukraine, have had a profound impact on global food and nutrition security (FAO et al., 2022; IFPRI, 2023; Kogo et al., 2021; Lin et al., 2022). These events can disrupt agricultural production, damage infrastructure, compromise supply chains, decrease food availability, access, and increase food prices (FAO et al., 2022; IFPRI, 2023; WFP, 2021). Meanwhile, over 50% of the world's malnourished population live in conflict affected regions (Mehrabi et al., 2022; WFP, 2021). Extreme events often exacerbate existing social and economic inequalities, as poor communities are disproportionately affected and often lack the resources to cope with food shortages (FAO et al., 2022; IFPRI, 2023). Ultimately, these events pose significant challenges to food security, jeopardizing the access, availability, and stability of nutritious food for populations worldwide. Therefore, the resilience of communities, households, and individuals must be improved to better adapt these unforeseen events.

Climate change and its associated extreme events have profoundly affected Africa, exacerbating existing vulnerabilities and posing significant challenges across the continent (Trisos et al., 2022; WMO, 2022a). Rising temperatures, changing rainfall patterns, and increased frequency and intensity of droughts, floods, and storms have disrupted agricultural systems, decreased crop yields, and affected livestock health and productivity (FAO, 2021; WMO, 2022b). This has resulted in the regions' food insecurity, malnutrition, and economic instability (Nhemachena et al., 2020; Schilling et al., 2020; Trisos et al., 2022; Waha et al., 2017). Vulnerable communities, including smallholder farmers (Ayanlade et al., 2017; Mogomotsi et al., 2020), pastoralists (Ayanlade & Ojebisi, 2019; Wangui, 2018), and fishing communities (Belhabib et al., 2016; Muringai et al., 2019), bear the brunt of these impacts, often lacking the resources and capacity to adapt and recover (Trisos et al., 2022; WMO, 2022b). Meanwhile, multiple climate risks (e.g., temperatures, drought, pest, and disease outbreaks) can interact and amplify impacts; therefore, cross-sectoral solutions are critical to support climate-resilient development (Liu et al., 2018). Climate change and extreme events in Africa are intertwined, creating a complex web of challenges that require urgent attention and comprehensive strategies for adaptation and resilience-building. Nonetheless, the extent to which these strategies remain effective during severe occurrences, such as prolonged droughts, has not been adequately evaluated. Therefore, considering the enormity of the issue, it is imperative to assess potential solutions to guarantee the resilience of the adaptation strategies.

Meanwhile, there is no consensus on measuring resilience and no universally accepted tool to quantify resilience across various scales (Eeswaran et al., 2021). Moreover, definitions of resilience can differ across disciplines and target groups. Therefore, it is necessary to establish a definition and approach for quantifying resilience before embarking on a study (Davoudi et al., 2013; FAO, 2016). A general definition of resilience is the ability of a system to recover from stressors (Holling, 1973). Resilience metrics help to gauge the extent of system improvement toward sustainable conditions, identify critical thresholds for potential issues, and aid in assessing the management of the system (Quinlan et al., 2016). According to the Committee on Sustainability Assessment (COSA), assessing resilience typically requires a comprehensive approach considering social, economic, and environmental dimensions of a system of interest (COSA, 2017). While there have been many studies on resilience, there are few studies that utilize risk as a metric to evaluate resilience (Slijper et al., 2020).

Conventional risk management methods rely on retrospective knowledge, incident reporting, and risk assessments using historical data probability calculations (Tong & Gernay, 2023). However, these approaches prove insufficient for modern socio-technical systems, particularly because numerous adverse events arise from unforeseen combinations of normal performance variability (Tong & Gernay, 2023). In addition, risk as a metric is not always used to determine resilience (FAO, 2016). Therefore, risk behavior is inherently related to resilience as farmers' risk-management strategies, risk preferences, and risk perceptions impact how they cope with risks (Slijper et al., 2020). Due to the intricate relationships and complexity within these dimensions, the assessment of food system resilience is often conducted using qualitative methods (Toth et al., 2016). Nevertheless, qualitative assessments are subjective and geographically limited, hence prone to discrepancies. Finally, the existing resilience indices can help with ranking different mitigation scenarios. However, they do not necessarily guarantee that all aspects of food and nutritional security are captured.

Therefore, this paper establishes resilience as the state wherein farmers are able to ensure their essential nutritional and economic needs with minimal risk. To achieve this, we propose a new paradigm to limit resilience solutions to those that are economically feasible and meet the nutritional requirements of society at the lowest level of uncertainty. Here, we consider a variety of relevant aspects, including food purchases consumed, donated food consumed, dietary diversity, costs associated for maintenance, insurance, taxes, loans, debt, school expenses, value of cropland and machinery, type of crops grown, crop variety, percent of a grown crop consumed by the farmers' family, and income generated from sales. These inputs cover social, environmental, and economic aspects of resilience. Subsequently, in contrast to established approaches, we refrained from computing the comprehensive resilience scores through arbitrary weighting of diverse metrics (such as economic and environmental factors) and their summation (Eeswaran et al., 2021). Our approach guarantees that the proposed solutions meet the nutritional and economic needs with the lowest risk to the smallholder farmers in the target area. This proposed approach is used in a case study to assess the viability of solutions to extreme drought events in Senegal. Specifically, the objectives of the study are to (1) evaluate and rank alternative scenarios based on the nutritional requirement of smallholders at the lowest cost, (2) determine the most feasible alternative systems that meet the economic needs of smallholder farmers, and (3) rank alternative scenarios based on the risk and resilience to extreme drought conditions.

2 | METHODOLOGY

2.1 | Study area

The Groundnut Basin in Senegal, containing the districts Thiès, Diourbel, Fatick, Kaolack, Kaffrine, and Kolda, is the target location of this study (Figure 1). This region is known for its high agricultural production (Faye & Du, 2021; Malou et al., 2020; Toure & Diakhate, 2020). Located in the central-western part of Senegal, the basin encompasses an extensive area and is primarily dedicated to pearl millet (*Pennisetum glaucum* (L.) R. Br.) (hereafter referred as millet) and groundnut (*Arachis hypogaea* L.) (or peanut) grown in rotation (HEA SAHEL, 2016; Ricome et al., 2017). This paper aims to study millet farmers in the Groundnut Basin, where they grow millet and groundnut in rotation, making it relevant to study both crops. Mineral fertilizer use is rare, and most agriculture is rainfed (Faye & Du, 2021; Ricome et al., 2017). Smallholder farmers typically have horses and oxen for traction power and cattle, goats, sheep, and chickens for their livelihood (HEA SAHEL, 2016; Ricome et al., 2017). Despite the Groundnut Basin's historical focus on groundnut production, there has been a lack of growth in recent years, which can be attributed to a challenging environment characterized by unpredictable rainfall patterns and soil degradation (Mills et al., 2021). Groundnuts serve as a lucrative cash crop and a significant export commodity for Senegal, while millet is a fundamental staple crop for local household consumption. Therefore, delving into the study of the Groundnut Basin becomes imperative for comprehending the resilience demonstrated by smallholder farmers engaged in millet and groundnut cultivation within the region.

2.2 | Modeling overview

The methodology presented in this study determines resilience employing a holistic approach. Therefore, we utilized two models (FARMSIM, Farm Simulation Model (Texas A&M, 2023); and APSIM, Agricultural Production Systems Simulator (Holzworth et al., 2018)) to obtain the required nutrition, economics, and risk data information. The modeling process started with data collection as FARMSIM requires about 500 inputs to simulate a representative farm for a region. The input data can be seen in Tables S1–S25. Briefly, some of the main variables include soil moisture (Eeswaran et al., 2021), climate conditions (FAO, 2016), market price fluctuations (Slijper et al., 2020), crop diversity (FAO, 2016), dietary diversity (Dillon et al., 2015; FAO, 2016), crop yield (Birthal et al., 2015; Martin & Magne, 2015), agricultural assets (FAO, 2016), revenue (Kandulu et al., 2012; Rigolot et al., 2017; Tibesigwa & Visser, 2015), profit (Browne et al., 2013; Komarek et al., 2015; Seo, 2010), and food consumption expenditures to meet food security (Alfani et al., 2015). In addition to regional farming inputs, APSIM was utilized to generate yield data across different districts as inputs to FARMSIM for a baseline management strategy and alternative scenarios. The APSIM

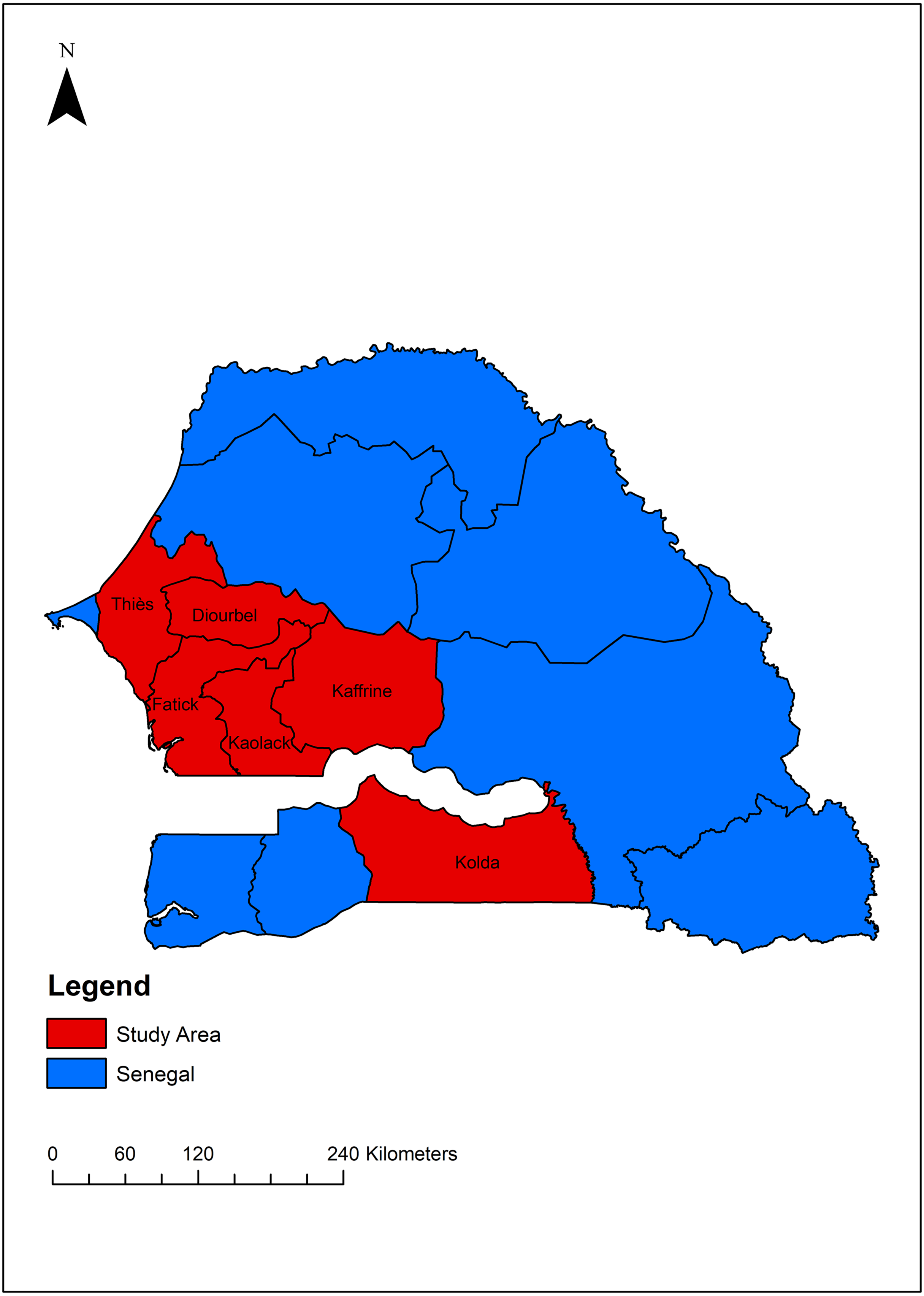

FIGURE 1 Senegal and the study area.

model was used to simulate millet yield only as the scope of this paper was to analyze how to improve millet production as millet is one of the most predominate crops across Senegal. Moreover, millet has a higher temperature ceiling than other cereal crops, which is especially relevant as climate change is expected to increase temperatures as well as heat wave frequency and intensity (Aissatou et al., 2017; Djanaguiraman et al., 2018; Lowe et al., 2011). Therefore, increasing millet production is relevant to improving Senegal farmers' livelihoods. However, in regard to FARMSIM, millet and groundnut were modeled together as these two crops are typically grown in rotation.

Based on the data obtained to build the aforementioned models, this study aims to analyze how varying planting dates, plant densities, and N fertilizer rates impact millet production and affect the resilience of smallholder farmers under extreme drought. The alternative scenarios have three planting dates, three plant densities, and six fertilizer N rates, resulting in a total of 54 management scenarios and a baseline for each district for a total of 324 simulations (Figure 2). The baseline was defined as an early planting date, 1.1 pL m^{-2} plant density, and 30 kg N ha^{-1} fertilizer rate. All scenarios and the baseline were simulated under rainfed conditions. The first rain higher than 20 mm after May 30 determined the early planting date. Subsequently, the remaining planting dates were spaced 20 days apart (medium and late). The baseline and alternative scenarios were based on Vieira Junior et al. (2023).

As described in the introduction section, resilience was determined when nutritional and economic conditions were satisfied at the lowest risk to the farmer. In the realm of nutrition, this criterion is fulfilled by meeting the minimum requirements for human nutritional needs, achieved through an optimization analysis (Objective 1). The optimization analysis was employed to enhance the deficient nutritional categories, ensuring they meet the minimum nutritional requirements. This demonstrates how farmers can allocate their income toward specific foods in order to fulfill their nutritional needs. A linear optimization was run to examine which solutions meet the minimum nutrition requirements at the lowest cost. Additionally, a multi-objective optimization was used to find minimum nutrition requirements at the lowest cost while maintaining a healthy, balanced diet. Under Objective 1, the alternative scenarios will then be ranked in terms of a nutrition-balanced diet at the lowest cost. The ultimate list comprises solely the solutions that outperformed the baseline scenario, which represents the current practices. After meeting the nutritional requirements for smallholder households, an economic analysis was performed to identify the most economically feasible solutions. The process starts by filtering out alternative solutions that are not economically feasible (Objective 2). Any alternatives with a negative internal rate of returns (IRR) are eliminated. Subsequently, the remaining options are

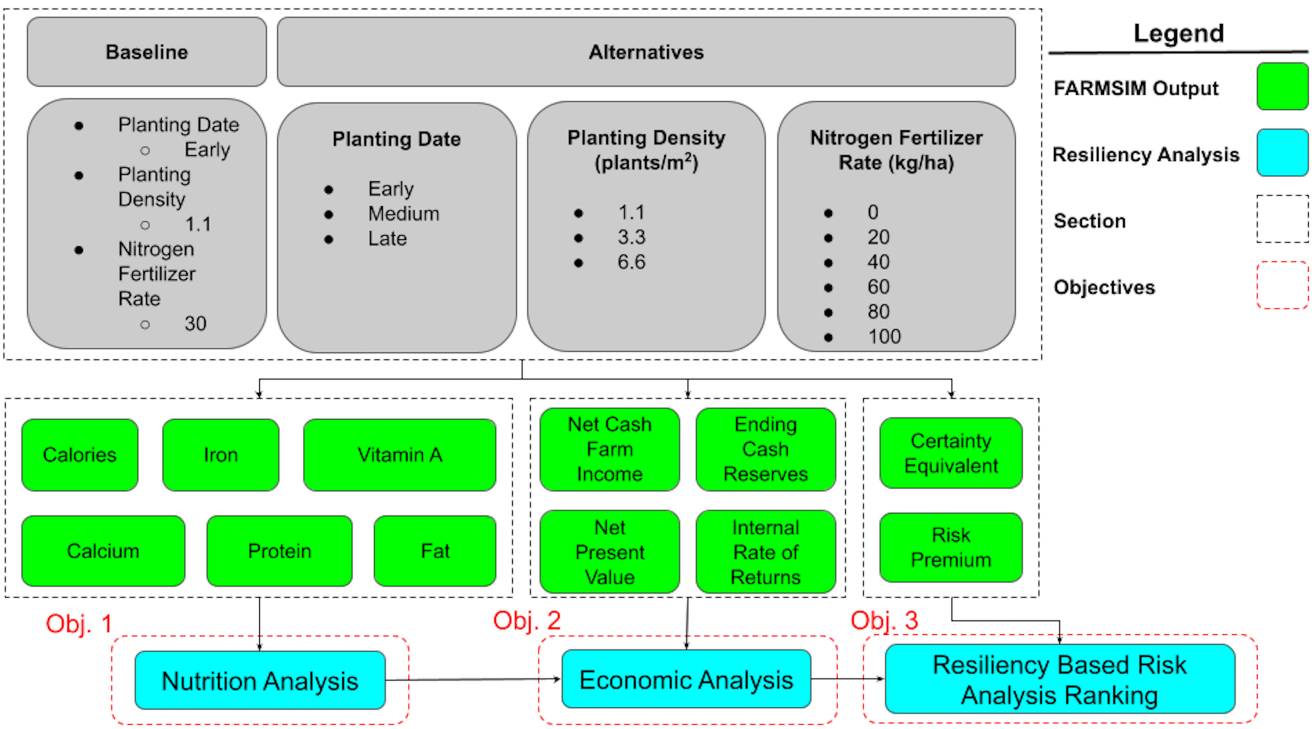

FIGURE 2 Schematic representation of variables and methodologies used to determine the resilience of smallholders to extreme drought.

evaluated according to three economic indicators: net cash farm income (NCFI), net present value (NPV), and ending cash reserves (EC). Finally, the top-ranked economically feasible alternatives were evaluated based on two risk factors, certainty equivalent (CE) and risk premium (RP) to identify the most resilient alternatives (Objective 3).

2.3 | Data collection

Primary and secondary data were utilized in this study. Primary data were obtained through household surveys and experts' opinions. Secondary sources that were utilized include L'Enquete Agricole Annuelle (EAA) reports from the Direction de l'Analyse, de la Prévision et des Statistiques Agricoles (DAPSA), other government reports, NGOs' reports, and peer-reviewed publications. Crop yield and cultivation extent data were obtained from DAPSA and the Ministère de l'Agriculture et de l'Equipement Rural (MAER) for the years 2016–2020. These data aided our comprehension of agricultural practices for each district and helped to establish representative farm operations, demographics, consumption patterns, and finances. The gathered data encompassed millet and groundnut production details, including crop yield, associated crop production costs, livestock numbers, livestock production costs, milk and egg production, purchased and donated foods, food consumption, fixed costs, alternative scenario costs, and assets. All these data elements were gathered according to the FARMSIM model requirements (Bizimana & Richardson, 2019).

2.4 | Farm income and nutrition simulator (FARMSIM)

FARMSIM is an integrated farm model, which uses Monte Carlo simulations and is widely employed to predict the potential effects of distinct agricultural interventions on household-level nutrition and financial stability (Bizimana & Richardson, 2019). This model assesses various facets of farming systems, including crop production, livestock rearing, food consumption, market structures, financial systems, and risk management (Richardson et al., 2008). To evaluate the risks associated with agricultural interventions, the model utilizes Simulation and Econometrics to Analyze Risk (Simetar) tools (Richardson et al., 2008). Furthermore, the model incorporates stochastic simulation techniques to account for system uncertainty, generating probabilistic outputs for different agricultural management scenarios. Following the simulation process, the outcome comprises 500 iteration values for each key output variable (KOV) over a 5-year planning horizon. Section A of the Appendix S1 provides the definitions of KOVs used in this study.

The Simetar function of FARMSIM allows for the evaluation of various alternative scenarios utilizing the Stochastic Efficiency with Respect to a Function (SERF). These values establish empirical probability distributions that are instrumental in comparing the baseline farming technologies or interventions with alternative ones. Moreover, decision makers can quantitatively assess the potential outcomes of introducing alternative technologies through a comparative analysis of the probability distributions. For this study, we are utilizing the following KOVs: NCFI, EC, NPV, IRR, calories, protein, fat, calcium, iron, and vitamin A. Additionally, the CE and RP will be utilized in this study to determine the risk of adapting the alternative scenarios.

The model has been extensively utilized in developing countries such as Ghana (Balana et al., 2020), Ethiopia (Bizimana & Richardson, 2019), Tanzania (Andrew et al., 2019), and Malawi (Chikafa et al., 2023), providing valuable support in decision-making. Its credibility and accuracy have been substantiated by its ability to simulate real agricultural data effectively. Notable applications include analyzing household-level food consumption impact in Ethiopia (Bizimana et al., 2020), utilizing farmer's risk factors to assess the adoption potential of technologies (Bizimana & Richardson, 2019), and evaluating the efficacy of farm-level agricultural technologies (Bizimana & Richardson, 2019). These abilities empower decision makers to devise financial and management strategies for the successful implementation, adoption, and sustainability of different technologies (van den Berg et al., 2019).

FARMSIM comprised four elements: crops, livestock, nutrition, and economics. The model simulates farming practices at the village, district, or regional level, offering plausible income and nutrition status at the household level. For nutrition analysis, the model accounts for how much a household consumes in terms of the number of livestock, livestock products, harvested crops, purchases from the market, and food donations. Moreover, FARMSIM utilizes simulations to calculate the potential income for households considering the livestock, livestock products, and crops sold by the household in the market. The model determines the nutritional requirements for families with Calories, protein, fat, calcium, iron, and vitamin A by utilizing the standard nutrient score. Table S2 provides a summary of the minimum nutrient requirements per adult equivalent used by the model for nutrition simulation.

2.5 | Agricultural Production Systems sIMulator (APSIM)

The simulations in this study were performed utilizing version 7.10 of the APSIM software platform (Holzworth et al., 2014). A previous calibration of the APSIM-Millet model (Van Oosterom et al., 2002; Van Oosterom, Carberry, Hargreaves, et al., 2001; Van Oosterom, Carberry, & O'leary, 2001) obtained by (Vieira Junior et al., 2023) was employed. This calibration was explicitly developed for the two most commonly adopted millet landraces in Senegal: Sanio and Souna. The model's performance was assessed by simulating grain yield and crop phenology (Vieira Junior et al., 2023). The soil parameters and initial conditions used in the simulations were defined based on the descriptions provided by Vieira Junior et al. (2023). These soil parameters include depth (0–150 cm), bulk density (1.27–1.64 g/cm^3), drained lower limit (0.06–0.17 mm/mm), drained upper limit (0.11–0.28 mm/mm), saturated water content (0.38–0.40), and pH (5.19–6.96).

Grain yield production simulation was conducted at five equidistant points within each of the six millet-producing departments in Senegal, resulting in a total of 95 simulated locations. A total of 54 management scenarios were simulated for the period spanning from 1990 to 2021. The simulated scenarios were defined based on the combination of (i) three planting dates (early (early-June to late-July), medium (early-July to late-August), and late (late-July to mid-September)), (ii) three plant densities (1.1, 3.3, and 6.6 pL m^{-2}), and (iii) six N fertilization levels (0, 20, 40, 60, 80, and 100 kg N ha^{-1}). The simulated nitrogen (N) fertilization source was urea, which was applied at two specific dates, 21 days and 45 days after sowing.

2.6 | Drought determination

Droughts can have devastating effects on crop production and farmers' livelihood. The primary threat to Senegal's agriculture comes from drought and the growing unpredictability of rainfall, which pose the most notable danger to crops and livestock (D'Alessandro et al., 2015). The increased frequency of extreme events, such as prolonged rainy breaks and droughts, as well as a delay in the start and duration of the rainy season, have increased the vulnerability of agricultural production systems (IPCC, 2019; Ndiaye et al., 2021). Moreover, floods occur more frequently than droughts; however, droughts have more pronounced impacts and affect more people per event (World Bank, 2011). Droughts will not only decrease crop yields and biomass production but also lead to food shortages, price increases, increases in bushfires, pest infestations, rural–urban migration, and destabilization of poor households' livelihoods (USAID, 2012).

We analyzed farmers' resilience to extreme drought conditions to better understand what combination of interventions better prepares farmers to mitigate the negative impacts of future droughts. We utilized precipitation data from 1990 to 2021 to determine the driest 5-year period within our study area. The growing season was determined by finding the average number of days for each district between the planting date and harvest date. The precipitation was summed over the growing season for each year, and the year with the lowest recorded precipitation was utilized as the third year in the 5-year analysis in FARMSIM. The drought period determined for each study district is as follows: Diourbel was 2012–2016, Fatick was 1995–1999, Kaffrine was 2012–2016, Kaolack was 1995–1999, Kolda was 2012–2016, and Thiès was 2012–2016. After finding the drought years, crop yields in those years were utilized in the simulations of FARMSIM. These drought periods are supported by literature as in 1996–1998 and in 2014, regional droughts were reported (D'Alessandro et al., 2015; Nébié et al., 2021).

2.7 | Statistical analysis

A Wilcoxon signed-rank test was used to calculate the adjusted p-value using the Bonferroni method (Wilcoxon, 1945). This test was used to determine the statistical significance between the baseline and alternative indicators. Indicators that had a p-value calculated for them include yield, RP, CE, NPV, NCFI, EC, calories, protein, fat, calcium, iron, and vitamin A. An indicator was determined to be significantly different than the baseline when the p-value was <0.05 ($p < 0.05$). The Wilcoxon signed-rank test is a nonparametric statistical test used to compare two related samples or analyze a single sample with a paired difference test of repeated measurements to assess whether the population mean ranks differ (Xia, 2020). The statistical method is the nonparametric equivalent of the parametric paired t-test (Scheff, 2016; Xia, 2020). The Wilcoxon signed-rank test is preferred for dealing with data made up of definite scores, which is the case of this research (Scheff, 2016).

2.8 | Comparison and evaluation of agricultural alternative scenarios

In this study, the indicators were categorized into four groups: yield (yield), risk (CE and RP), economics (NPV, NCFI, and EC), and nutrition (calories, protein, fat, calcium, iron, and vitamin A). The *p*-values obtained from the statistical tests were organized as follows: a value of one was assigned if there was a significant increase in the indicator, a value of minus one was assigned for a significant decrease in the indicator, and a value of zero was assigned if there was no significant difference in the indicator.

A comparison of the baseline and alternatives was conducted using the generated values. The values of −1, 0, and 1 were summed from each district into a table of comparisons with the 54 alternative scenarios. The summed number was averaged for the districts, which resulted in the average *evaluation percentage* for the alternative scenarios versus the baseline current situation. The percentage change (increase, decrease, or no significant difference) can be utilized to see how varying degrees of planting date, plant density, and N fertilizer performed compared to the baseline situation.

Additionally, a comparison using the generated values was conducted between the alternatives to understand better how the alternatives perform when compared to each other. The scenarios were separated into three categories: planting date and plant density, plant density and N fertilizer rate, and planting date and N fertilizer rate. Each category was further divided into four groups: yield, risk, economics, and nutrition. The total values of −1, 0, and 1 were summed for the alternatives and districts and then averaged among the districts. The percent change (increase, decrease, or no significant difference) can be utilized to see how varying degrees of planting date, plant density, and N fertilizer interact.

2.9 | Meet the nutritional requirements of smallholder farmers

Here, we proposed two optimization strategies to address the nutritional deficiency of smallholder farmers under the nutrition analysis section to identify (1) the cheapest alternative to meet the nutritional requirements and (2) the most balanced nutritional alternative that also costs the least.

2.9.1 | Linear optimization (meet nutritional deficiencies at the lowest cost)

The linear optimization was performed using the Python library Scipy. When a nutrition deficiency is identified at the individual level for each district, a thorough optimization analysis was performed to fulfill the minimum daily requirements as established in Table S2. Based on our knowledge of consumption behavior in each district, the foods considered for purchasing include fish, beef, milk, eggs, lettuce, peanuts, rice, maize, and millet. Table S26 shows the nutritional values for all considered products. Items included as inputs for the optimization algorithm include nutritional information (Table S26) and prices for crops and food purchases (Table S27) in addition to the minimum daily intake requirement per person (Table S2) and the nutritional data outputs from FARMSIM for calories, protein, fat, calcium, iron, and vitamin A. The objective of the optimization analysis was to fill the nutritional deficits experienced under the baseline and alternative scenarios by utilizing the cost, which will be incorporated into the analysis by adjusting EC and NPV values. Therefore, linear optimization was used to accomplish the objective. Linear programming employs linear equations and inequalities to determine potential solutions for current challenges (Mallick et al., 2020). Linear optimization was used to define decision variables, objective functions, and different constraints where the constraints were recognized and characterized as a collection of linear equations and inequalities. The constraints were defined as a set of inequalities and linear equations with the additional requirement that every decision variable must be positive. Thus, this framework was utilized to meet the required minimum nutrients at the lowest cost. The optimization analysis was completed using Pymoo's implementation of Nondominated Sorting Genetic Algorithm II (NSGA-II) (Blank & Deb, 2020). The analysis was run for all alternative scenarios for all six districts.

An optimization model (Equation 1) was formulated to minimize the purchasing cost of market goods (C). In this context, the decision variables, denoted as X_i, signify the quantity of consumptive products, while C_i represents the cost per unit of each product (as presented in Table S27). The alternatives were ranked based on cost, with the cheapest alternative being considered the best.

$$\begin{aligned} C = {} & X_1 \times C_1 + X_2 \times C_2 + X_3 \times C_3 + X_4 \times C_4 + X_5 \times C_5 \\ & + X_6 \times C_6 + X_7 \times C_7 + X_8 \times C_8 + X_9 \times C_9 \end{aligned} \tag{1}$$

2.9.2 | Multi-objective optimization (meet nutritional deficiencies by achieving a balanced nutritional intake at a minimum cost)

A second optimization analysis was conducted to determine the best use of income while restraining excess nutritional consumption. The multi-objective optimization analysis was completed using Pymoo's implementation of NSGA-II. The two parameters used in this optimization were the cost of additional food purchases to meet minimum nutritional requirements and the percent change in individual consumption above the required nutrition (Table S2). The percentage change in nutritional content was calculated by assessing the percentage change in each nutritional category from the minimum required nutritional values, followed by averaging these changes. After running the optimization, many possible solutions satisfied the criteria, so the chosen solution was at the closest point to the origin as this would be the most balanced position between meeting nutritional needs and cost. The solutions were ranked based on the cost and percent change in nutrition. This was done by normalizing the cost against the minimum cost and the percent change in nutrition values against their minimum, adding the normalized cost and normalized percent change in nutrition, and then ranking them in ascending order.

2.10 | Economic analysis to adjust cash income based on meeting nutritional needs

The economic analysis was performed on scenarios that meet the population's nutritional needs. Therefore, the cost of the optimization solution was subtracted from the EC and NPV to account for the additional food costs. At the start of the economic analysis, the alternative scenarios were filtered using IRR. IRR is a relevant measure of the feasibility of investments and interventions in regard to how they sustain themselves through generated profits from farm produce sales (Chikafa et al., 2023). Again, a negative and zero IRR were not considered economically feasible solutions. Meanwhile, the remaining alternative scenarios were ranked utilizing the sum of normalized NCFI, EC, and NPV.

2.11 | Resilience ranking of alternative scenarios based on risk

Adaptation of agricultural technologies involves an intrinsic element of risk. Various techniques can be employed to rank risky scenarios, encompassing measures like means, standard deviation, and coefficient of variation (Bizimana & Richardson, 2019). Nonetheless, while these approaches take risk into account, they often lack the resilience to consistently and conclusively prioritize scenarios, as they do not consider the decision maker's risk preferences (Chernobai & Rachev, 2006). Consequently, it is more advisable to integrate utility-based ranking approaches when comparing different farming scenarios, as they offer a superior approach to assist decision-makers in selecting among the options (Geissel et al., 2018). This aids decision makers in selecting the most favorable technology to adopt.

By employing the Simetar function, diverse alternative scenarios can be assessed. For this study, we utilized the SERF option due to its capacity to evaluate profits or certainty equivalence across various risk aversion levels (ranging from 0, indicating risk neutrality, to 1, indicating risk aversion). Decision makers can use this approach to evaluate the performance of various alternatives across different risk coefficients and choose the one that consistently yields the largest CE and has a higher RP across all levels of risk (Richardson et al., 2008). Thus, this was the approach utilized in this paper. The CE and RP for the different levels of farmers were averaged over the ARAC (alternative risk aversion coefficients) and were used in the final risk ranking.

The optimization analysis satisfied the nutritional needs of the farmer for the alternatives. The economic analysis ensured economic feasibility and income growth for the alternatives. Finally, the risk analysis eliminated alternative scenarios with a negative RP and determined the final ranking of the alternatives utilizing CE. The alternative scenarios that are ranked the best after these analyses will provide the farmers with the most resilient options to adapt in extreme drought conditions.

3 | RESULTS AND DISCUSSION

3.1 | Initial assessment of nutritional deficiency in the study region

The FARMSIM model simulated nutrition values for calories, protein, fat, calcium, iron, and vitamin A. The findings of the nutrition analysis (Table 1) indicate that only the baseline scenarios in the Fatick and Kaffrine districts fulfill just half of the population's nutritional needs. In contrast, all the other districts fall short of more than 50% of the required nutritional indicators (e.g., iron, vitamin A). All districts except Thiès had adequate nutrition for protein and fat. All districts were deficient in calcium, iron, and vitamin A. The nutrition values for the alternatives were similar to the baseline as the family consumption of millet was adjusted as yield changed. Several prior studies corroborate our findings. For example, a report from the International Food Policy Research Institute (IFPRI) found rural populations in Senegal deficient in calcium, iron, and vitamin A (Marivoet et al., 2021). Additionally, the rural population was slightly deficient in calories; however, they met their protein intake needs (Marivoet et al., 2021). The rural population was seen to have an excessive fat intake, though not as pronounced as in urban settings (Marivoet et al., 2021). Several other papers also confirm the nutritional results obtained in this study (Fiorentino et al., 2016; Giguère-Johnson et al., 2021).

TABLE 1 Nutrition per individual for baseline scenarios for all districts[a].

	Nutrition					
Districts	Calories (Cal)	Protein (g)	Fat (g)	Calcium (g)	Iron (g)	Vitamin A (g)
Diourbel	<2306.42	>52.10	>73.77	<1.45	<0.0137	<0.009
Fatick	>2306.42	>52.10	>73.77	<1.45	<0.0137	<0.009
Kaffrine	>2306.42	>52.10	>73.77	<1.45	<0.0137	<0.009
Kaolack	<2306.42	>52.10	>73.77	<1.45	<0.0137	<0.009
Kolda	<2306.42	>52.10	>73.77	<1.45	<0.0137	<0.009
Thiès	<2306.42	<52.10	<73.77	<1.45	<0.0137	<0.009

[a]Red represents not meeting nutritional requirements. Green represents meeting nutritional requirements.

3.2 | Comparison and evaluation of agricultural baseline and alternative scenarios using statistical analysis

3.2.1 | Comparison of agricultural baseline and alternative scenarios

The agricultural intervention scenarios were compared against the baseline and evaluated based on *p*-values. The results of this analysis can be seen in Figures 3–7 and Figures S1–S9. The figure shows the percentage of times the *p*-values determined significance for each alternative at each indicator for all six districts. A higher, positive value indicates the percentage of times the districts had a significant increase in the indicator at a particular alternative scenario, while a lower, negative value indicates the percentage of times the districts had a significant decrease in the indicator at a particular alternative scenario. A value of around 0 meant the alternative did not significantly increase or decrease the indicators for a particular alternative scenario from the baseline.

There were some trends of interest in this analysis. First, vitamin A showed no significant increase or decrease from the alternatives. Additionally, this was also true for calcium except for two alternative scenarios. A trend occurred within each fertilizer application rate and planting date where a plant density of 1.1 pL m^{-2} generally had a lower positive percent change than plant densities of 3.3 pL m^{-2} and 6.6 pL m^{-2}, which were generally similar. For N fertilizer, it was observed that as the fertilizer rate increased, so did the percent change of yield, calories, protein, fat, and iron for a given plant density and planting date. However, at a plant density of 1.1 pL m^{-2}, the CE, RP, NPV, NCFI, and EC all decreased with increasing N rate and constant planting date. This could be the result of yields increasing, but not enough to improve risk and economic indicators for smallholder farmers. For the planting date, a trend occurred where at a plant density of 1.1, the CE, RP, NPV, NCFI, EC, calories, protein, fat, and iron increased as the planting date increased, though at varying fertilizer rates. This trend was more pronounced at lower N fertilizer rates (0, 20, and 40 kg N ha^{-1}). Additionally, the late planting date saw a large increase in all the indicators except calcium and vitamin A, especially at the lower N fertilizer application rates of 0, 20, and 40 kg N ha^{-1}. With planting date, there was a relatively small effect on the indicators at high plant.

3.2.2 | Comparison and evaluation of agricultural alternative scenarios against each other

After comparing the alternative scenarios against the baseline, a further analysis was conducted to examine how the alternatives compared against each other. The analyses were separated into three comparisons with planting date versus plant density, plant density versus N fertilizer rate, and planting date versus N fertilizer rate. These were further analyzed through four categories: yield, risk, economics, and nutrition. Figures 4–6 provide a practical way to understand how the alternatives compare. A positive percentage value indicates that the alternative on the side of the figure (*y*-axis) had a significantly higher performance than the alternative on the bottom (*x*-axis). Additionally, a negative percentage value indicates that the alternative on the side of the figure (*y*-axis) had a significantly lower performance than the alternative on the bottom (*x*-axis). A near 0 percentage value indicated no significant difference in the performance of the two alternatives as assessed by categorical indicators, such as yield.

Effects of planting date and plant density on indicators

Figure 4 can be used to compare how changes in planting date and plant density affect the yield. Generally, alternatives with higher plant densities performed better in terms of yield, with plant densities 3.3 pL m^{-2} and 6.6 pL m^{-2} performing better than 1.1 pL m^{-2}, with 3.3 pL m^{-2} plant densities performing best with the *evaluation percentage*. The medium and late planting dates generally had higher

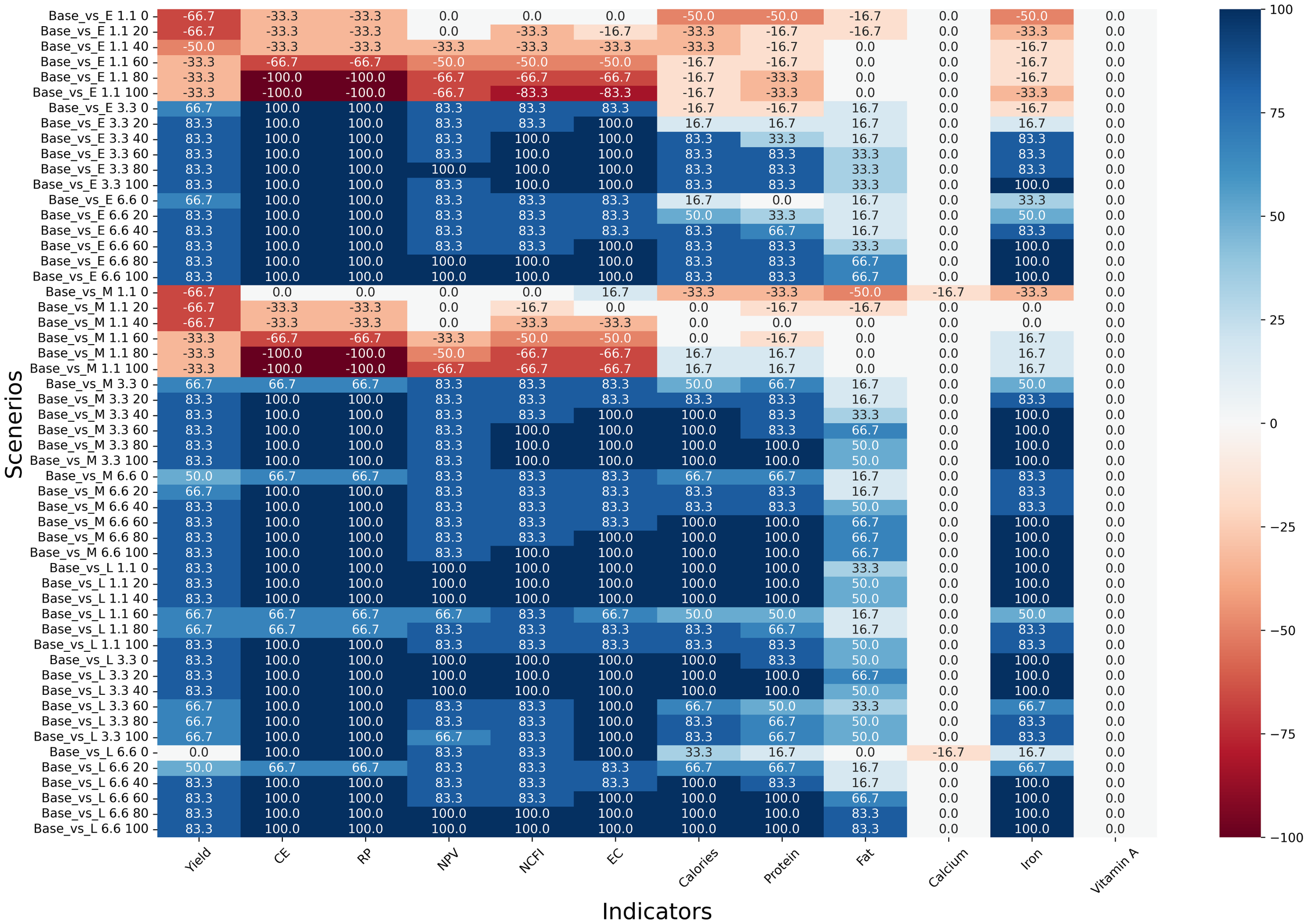

FIGURE 3 Intervention *evaluation percentage* across six districts for the baseline versus the alternatives. The scenario label shows planting date-plant density-N fertilizer rate). The *x*-axis scenarios are labeled as planting date (E (Early), M (Medium), L (Late)), plant density (1.1 pL m^{-2}, 3.3 pL m^{-2}, 6.6 pL m^{-2}), and N fertilizer rate (0 kg N ha^{-1}, 20 kg N ha^{-1}, 40 kg N ha^{-1}, 60 kg N ha^{-1}, 80 kg N ha^{-1}, 100 kg N ha^{-1}).

evaluation percentages versus the early planting dates. Additionally, late planting dates usually had higher *evaluation percentages* than early and medium planting dates. Compared to the other alternatives, the two worst alternatives were medium (M) planting date and 1.1 pL m^{-2} and early (E) planting date and 1.1 pL m^{-2} plant density. The alternative that performed the best was the late (L) planting date with a 3.3 pL m^{-2} plant density. These general trends were also observed for nutrition, economics, and risk (Figures S1–S3). This could be due to increased yield, improving nutrition and economic indicators while reducing risk. However, there are still differences between Figure 1, Figures S1–S3. Figure 1 and Figure S3, which represent yield and risk data, respectively, have similar *evaluation percentages*; however, Figures S1 and S2 (nutrition and economics) have more similar *evaluation percentages*. Figure 1 and Figure S3 have higher positive and lower negative values, indicating more pronounced effects with extreme values at both ends, while Figures S1 and S2 have smaller positive and higher negative *evaluation percentages*. This can signify that yield and risk data are more volatile when analyzed through changing planting date and plant density where varying dates and densities will have a more significant impact on yield and risk than nutrition and economics. Utilizing a poor performing planting date or density could significantly impact the yield and therefore the risk of the smallholder farmer to this variable yield could increase. Additionally, nutrition and economics had more muted *evaluation percentages* implying less significant impacts due to various planting dates and densities. This could be due to no associated costs for altering the planting date or that even with increasing yield the returns in the form of economics and nutrition were less pronounced and did not vary as much as yield and risk.

Effects of plant density and N fertilizer rate on indicators

Figure 5 compares alternative scenarios for all districts against each other concerning yield. Alternatives with

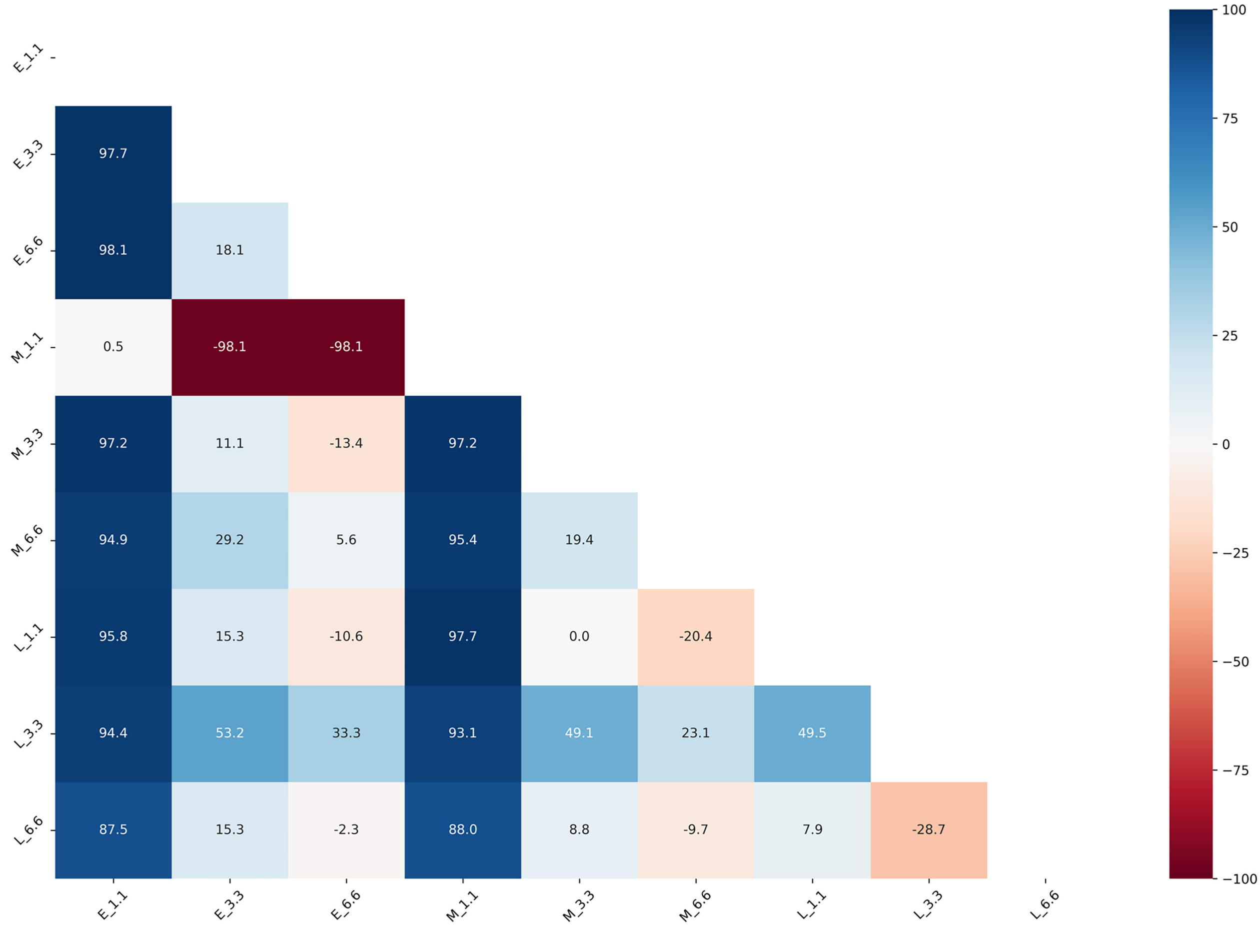

FIGURE 4 Intervention *evaluation percentage* for yield across six districts for the alternatives versus each other with varying planting dates and plant densities. The alternative labels are (planting date_plant density). The scenarios labeled as planting date (E (Early), M (Medium), L (Late)), plant density (1.1 pL m^{-2}, 3.3 pL m^{-2}, 6.6 pL m^{-2}), and N fertilizer rate (0 kg N ha^{-1}, 20 kg N ha^{-1}, 40 kg N ha^{-1}, 60 kg N ha^{-1}, 80 kg N ha^{-1}, 100 kg N ha^{-1}).

different planting dates were compared against each other at different plant densities and N fertilizer rates. In general, as the amount of N fertilizer increased, the percentage of improvement in yield became more evident, indicating the positive impact of a higher N fertilizer rate. There appears to be a trend where at N rates of 0, 20, and 40 kg ha^{-1}, the *evaluation percentage* increases when plant density increases from 1.1 pL m^{-2} to 3.3, but the *evaluation percentage* decreases between plant densities of 3.3 pL m^{-2} and 6.6 pL m^{-2}. Thus, the 3.3 pL m^{-2} plant density was superior to the other plant densities. This could be due to the associated costs of utilizing more fertilizer and seeds. However, at higher N fertilizer application rates such as 60 kg ha^{-1}, 80 kg ha^{-1}, and 100 kg ha^{-1}, the *evaluation percentage* increased as plant density increased. Some alternative agricultural scenarios with the lowest *evaluation percentages* include (plant density_N fertilizer rate) 1.1_60, 1.1_80, 1.1_100, 6.6_0, 6.6_20, and 6.6_40. Several of the alternative agricultural scenarios with the highest *evaluation percentages* include (plant density_N fertilizer rate) 3.3_20, 3.3_40, 3.3_100, 6.6_60, 6.6_80, and 6.6_100.

These trends were also observed for the risk, economic, and nutrition comparisons in Figures S4–S6. This could be due to increased yield, resulting in improved risk, economics, and nutrition indicators. However, there are still differences between Figure 5 and Figures S4–S6. Figure 5 and Figure S6 (yield and risk, respectively) generally have higher positive and lower negative *evaluation percentages* as compared to Figures S4 (nutrition) and S5 (economics). This can signify that yield and risk data are more volatile when analyzed through changing plant density and N fertilizer rate where varying densities and fertilizer rates will have a more significant impact on yield and risk than nutrition and economics. Opting for an unsuitable planting date or fertilizer rate can substantially impact the crop's output, consequently altering the smallholder farmer's exposure to risk and yield fluctuations. Additionally, nutrition and economics had more muted *evaluation percentages* implying less significant impacts due to various plant densities and fertilizer rates. This could be because even with increasing yield the returns in the form of economics and nutrition were less pronounced and did not vary

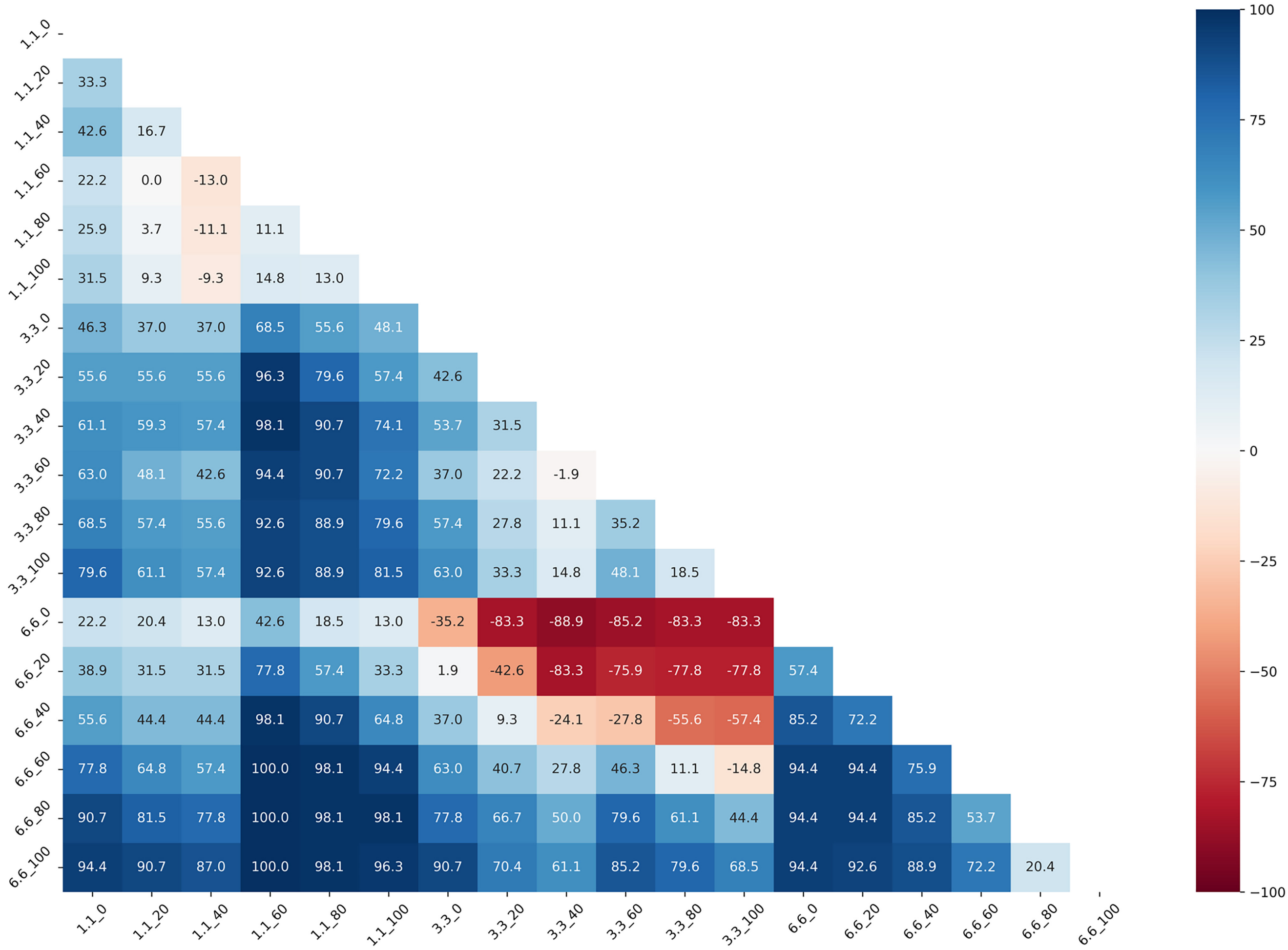

FIGURE 5 Intervention *evaluation percentage* for yield across six districts for the alternatives versus each other with varying plant densities and N fertilizer rates. The alternative labels are (plant density_N fertilizer application rate). The scenarios labeled as planting date (E (Early), M (Medium), L (Late)), plant density (1.1 pL m^{-2}, 3.3 pL m^{-2}, 6.6 pL m^{-2}), and N fertilizer rate (0 kg N ha^{-1}, 20 kg N ha^{-1}, 40 kg N ha^{-1}, 60 kg N ha^{-1}, 80 kg N ha^{-1}, 100 kg N ha^{-1}).

as much as yield and risk. Figure S6 had negative values for the 1.1 plant density, which could be attributed to the increased costs of increased fertilizer use not covering the increased yield and economics, thereby putting the farmers at risk.

Effects of planting date and N fertilizer rate on indicators

Figure 6 compares alternative scenarios for all districts against each other in relation to yield. Alternatives with different plant densities were compared against each other at different planting dates and N fertilizer rates. Generally, as the N fertilizer rate increases so does the *evaluation percentage*. Additionally, the *evaluation percentages* are highest at a late planting date. However, the medium planting date at N fertilizer rates of 0–40 generally has lower *evaluation percentages* than the early planting date, but at N fertilizer rates of 60–100 the *evaluation percentages* are generally higher than the early planting date. Some of the alternative agricultural scenarios with the lowest *evaluation percentages* include (planting date_N fertilizer rate) M_0, M_20, M_40, E_0, E_20, and E_40. Several of the alternative agricultural scenarios with the highest *evaluation percentages* include (planting date_N fertilizer rate) L_100, L_80, L_40, M_100, and M_80. These trends were also observed for the risk, economic, and nutrition comparisons in Figures S7–S9. This could be due to increased yield, which can result in improved risk, economics, and nutrition indicators. However, there are still differences between Figures S7–S9. Figure 6 and Figure S9 (yield and risk, respectively) generally have higher positive and lower negative *evaluation percentages* as compared to Figures S7 (nutrition) and S8 (economics). Figure S8 indicates that there was a muted *evaluation percentage* with less extremes seen in the *evaluation percentage*. This can signify that yield and risk data are more volatile when analyzed through changing planting date and N fertilizer rate where varying dates and fertilizer rates will have a

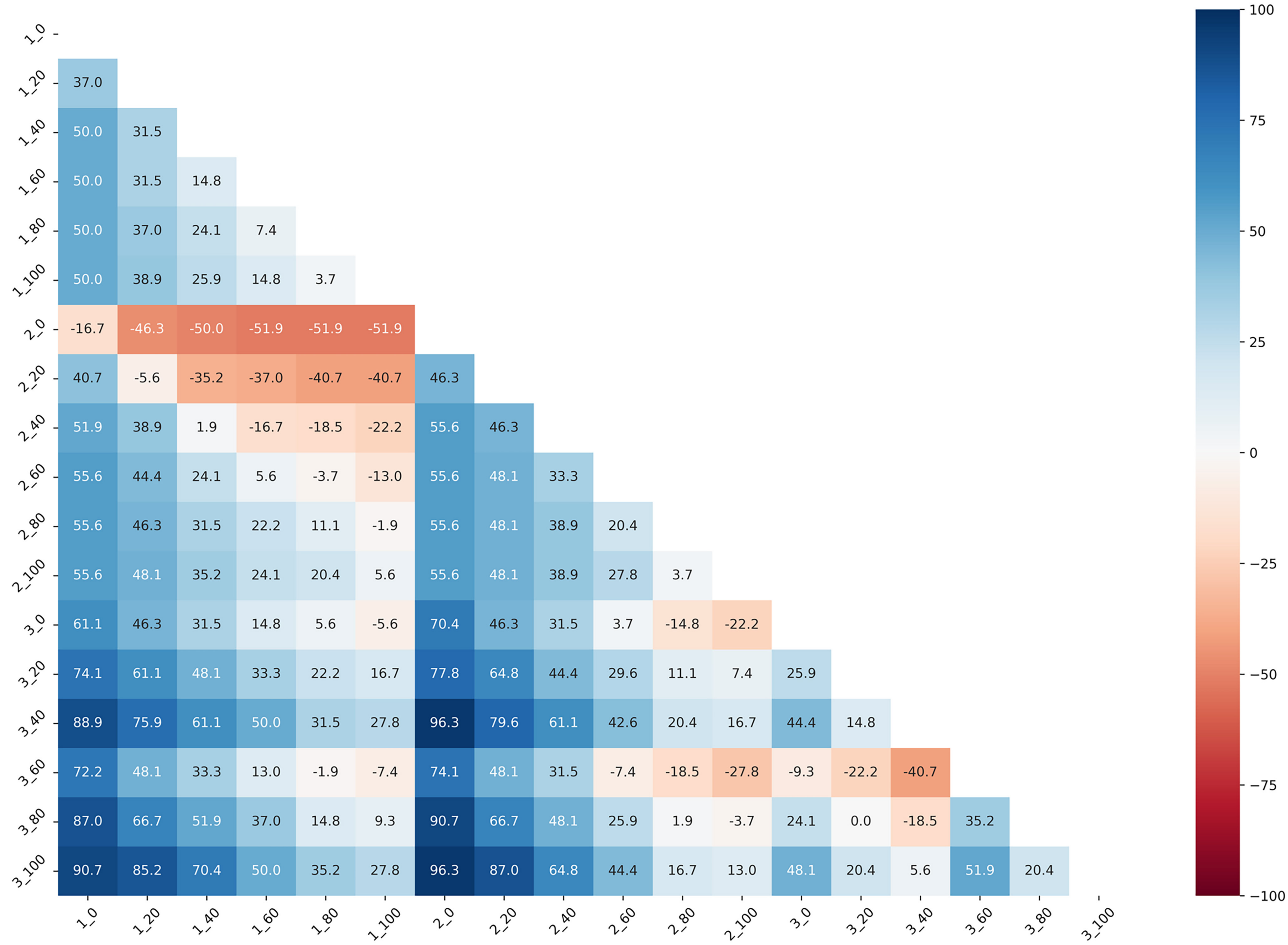

FIGURE 6 Intervention evaluation for yield across six districts for the alternatives versus each other with varying planting dates and N fertilizer rates. The alternative labels are (planting date_N fertilizer application rate). The scenarios labeled as planting date (E (Early), M (Medium), L (Late)), plant density (1.1 pL m^{-2}, 3.3 pL m^{-2}, 6.6 pL m^{-2}), and N fertilizer rate (0 kg N ha^{-1}, 20 kg N ha^{-1}, 40 kg N ha^{-1}, 60 kg N ha^{-1}, 80 kg N ha^{-1}, 100 kg N ha^{-1}).

more significant impact on yield and risk than nutrition and economics. Choosing an ineffective planting date or fertilizer rate can greatly influence the crop yield, thereby affecting the smallholder farmer's vulnerability to risk and yield variability. Additionally, nutrition and economics had more muted *evaluation percentages* implying less significant impacts due to various planting dates and fertilizer rates. This could be due to no associated costs for altering the planting date or that even with increasing yield the returns in the form of economics and nutrition were less pronounced and did not vary as much as yield and risk.

Overall summary

Several studies on millet in Senegal found that higher plant densities resulted in higher yields (Bastos et al., 2022; Faye et al., 2023; Pilloni et al., 2022; Vieira Junior et al., 2023), which is similarly found in this paper. Additional evidence for the potential benefits of delaying the planting date has on millet yield in Senegal can be seen in other studies, thus confirming our results (Araya et al., 2022; Vieira Junior et al., 2023). Finally, other studies in Senegal on the use of N fertilizer for millet found the range of the best fertilizer rates to go from 68 kg N ha^{-1} to 120 kg ha^{-1} (Araya et al., 2022; Bastos et al., 2022; Isah et al., 2020; Vieira Junior et al., 2023), which is in agreement with our results.

3.3 | Adjustment of nutrition by adding foods to meet the district nutrient requirements at the lowest cost

3.3.1 | Linear optimization (meet the nutritional deficiency at the lowest costs)

As seen in Table 1, the nutrition for individuals was deficient across the different nutrition values and districts for the alternative agricultural scenarios after running the FARMSIM simulations. Tables S28–S33 depict the recommended food purchases and associated costs to meet the objective of the linear optimization. Additionally, after the linear optimization the final nutrition values as depicted in Tables S34–S39 were above the minimum requirements in Table S2 and the initial nutrition in Table 1. This demonstrates how the excess income from the alternative scenarios can be used to meet nutrition gaps. However, with linear optimization, the process increases all nutrition to meet the minimum requirement, which can be excessively high, as seen especially with calories, protein, and fat. This is further shown in Table 2 as the cheapest cost was chosen as the rating criteria, though this caused the percent change in nutrition to be very high and ranged from 300% to 400%. The percent change in nutrition was largely affected by the excess calories, protein, and fat. Excess calories and fat can lead to obesity (Camacho & Ruppel, 2017; Wang et al., 2020), while excess protein can lead to an increased risk for type 2 diabetes (Fappi & Mittendorfer, 2020). This is important to note as in Senegal, the prevalence of overweight children under 5 years of age in 2020 was 2.1% and the prevalence of adult obesity (18 years and older) in 2016 was 8.8%, where both have increased with time, though have remained below the average for West Africa (FAO et al., 2022). Moreover, regarding food purchases, most alternative scenarios from all districts utilized only lettuce and peanuts to meet the nutritional gaps in the linear optimization, contributing to the excess nutrients. Therefore, multi-objective optimization may be ideal for understanding how to best utilize the additional income.

3.3.2 | Multi-objective optimization (meet nutritional deficiencies by achieving a balanced nutritional intake at a minimum cost)

The multi-objective optimization can determine solutions utilizing more determining parameters. This is important when optimizing scenarios, as multiple criteria need to be satisfied. The cost and percent change in nutrition were utilized in the multi-objective optimization. The results of the multi-objective optimization can be found in Table 3. The alternative scenarios were ranked based on the value of adding the normalized cost and the percent change in nutrition. The costs were relatively close, with Fatick having the lowest cost and Thiès having the highest. The percent change in nutrition varied, with Thiès having the lowest percent change in nutrition and Kolda having the highest change in nutrition. Moreover, food purchases for the alternative scenarios from all districts utilized all food options though primarily milk, lettuce, and peanuts were used to meet the nutritional gaps in the multi-objective optimization. Purchasing a larger variety of foods allowed farmers to meet their nutritional needs, but not in excessive amounts.

To facilitate a clearer comparison between the outcomes of the two optimization approaches, Figure 7 displays the cost and percentage change values for the most optimal scenarios in each district. The linear optimization had lower costs to meet nutritional needs than the multi-objective optimization; however, the percent change in nutrition was much higher in the linear optimization as opposed to the multi-objective optimization. This demonstrates how utilizing a linear optimization would miss a critical aspect of improving agriculture by increasing nutrition excessively. A multi-objective optimization met nutritional needs, while preventing excessive nutritional values and maintaining low costs. Thus, after the optimization analysis, the multi-objective analysis results were utilized in the economic analysis due to more accurately depicting relevant food purchases to meet nutrition.

3.4 | Economic analysis to adjust cash income after meeting the nutritional needs of the population

An economic analysis was used to examine the impact of increased food purchases from the multi-objective optimization on economic indicators. The alternative scenarios were filtered using IRR and ranked utilizing the sum of

TABLE 2 Linear optimization for identifying the cheapest alternative scenario and percent change in nutrition consumption.

District	Best alternative scenario	Cost (CFA/person/day)	Percent change in nutrition (%)
Thiès	3_3.3 40 kg	394.80	381.92
Diourbel	2_3.3100 kg	387.35	384.25
Kolda	3_3.3 40 kg	340.42	347.15
Kaolack	2_3.3 40 kg	385.77	394.62
Kaffrine	3_3.3 20 kg	350.09	366.95
Fatick	3_3.3 40 kg	320.30	330.29

District	Best alternative scenario	Cost (CFA/person/day)	Percent change in nutrition (%)
Thiès	1_3.3 0 kg	440.70	32.13
Kolda	2_6.6 80 kg	373.36	52.65
Kaolack	1_6.6100 kg	396.65	35.65
Kaffrine	1_1.1 60 kg	365.80	41.89
Fatick	1_3.3 40 kg	340.40	41.08
Diourbel	3_3.3 40 kg	414.94	36.04

TABLE 3 The best alternative scenario in each district was obtained from the multi-objective optimization, associated costs, and percent change in nutrition.

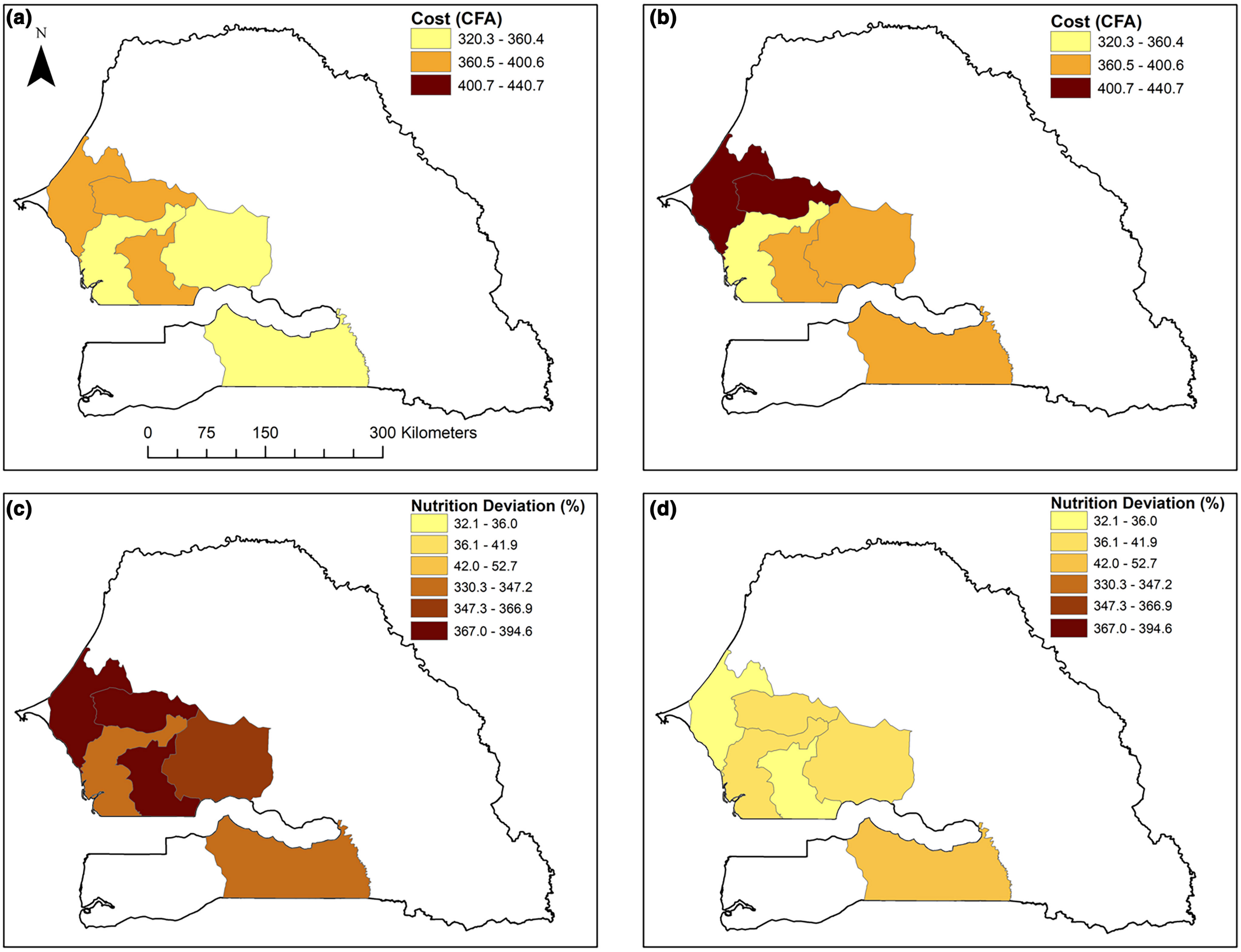

FIGURE 7 Final optimization maps (a) linear optimization cost values, (b) multi-objective optimization cost values, (c) linear optimization percent change in nutrition values, (d) multi-objective optimization percent change in nutrition values.

normalized NCFI, EC, and NPV. Tables S40–S45 show the economic values calculated after adjusting for the increased food purchases for each district in the study region. Figure 8 depicts the summarized economic ranking for all districts in the study region.

Based on the results from the economic assessment, only one alternative scenario was worse off than the baseline; therefore, the alternative with a medium planting date, 1.1 plant density, and 40 kg of N fertilizer would not be recommended. The best alternative scenario in terms of economics for 5 of the 6 districts was the late planting date, 3.3 plant density, and 40 kg of N fertilizer. This is further shown in Figure 9, which summarizes the districts in the region.

The alternatives with the highest IRR for 5 out of 6 districts were the alternatives with the late planting date, 3.3 plant density, and 40 kg of N fertilizer, signifying the validity of this alternative scenario. The Kolda district had

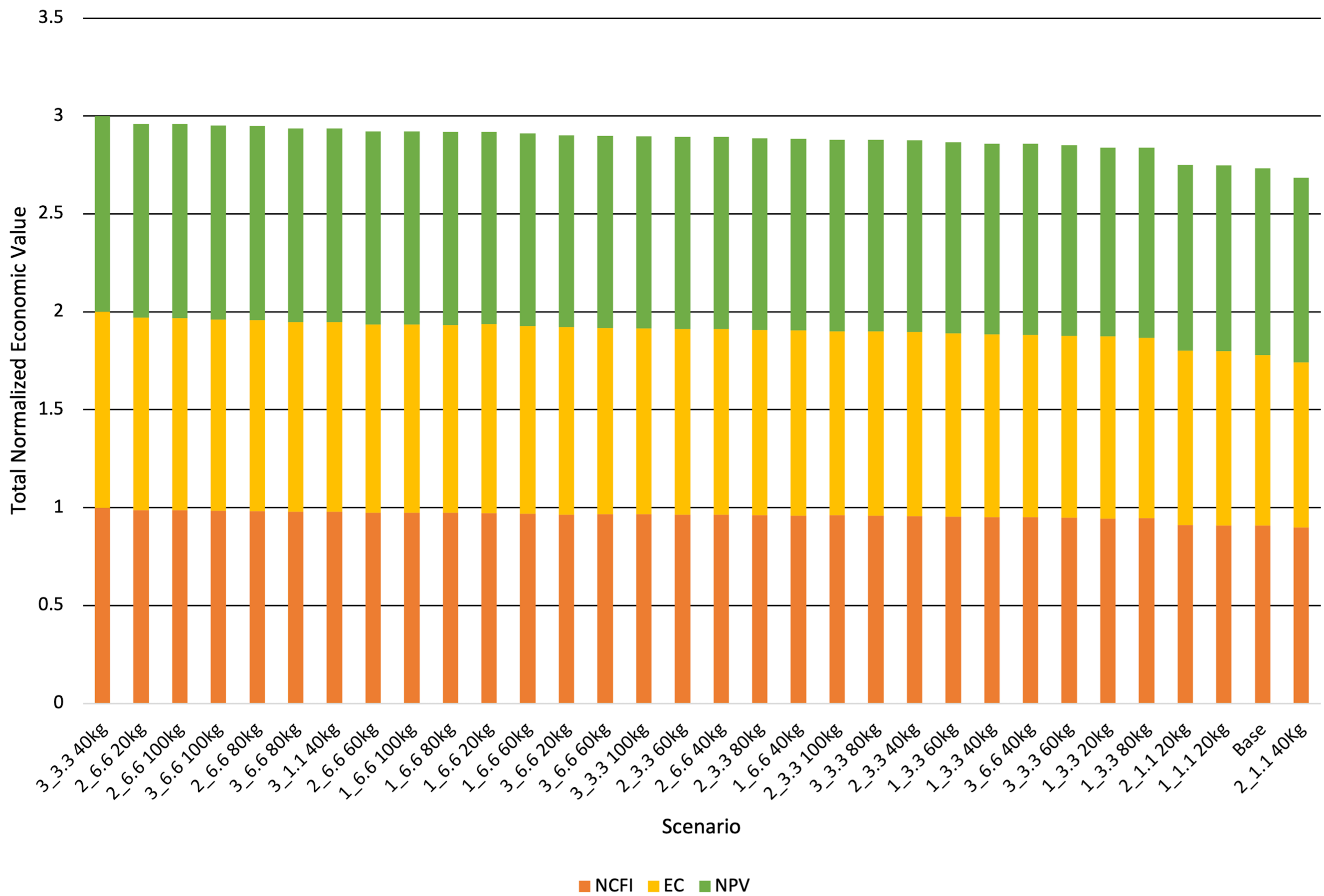

FIGURE 8 Final economic ranking of alternatives in terms of normalized NCFI, EC, and NPV summarized for all districts.

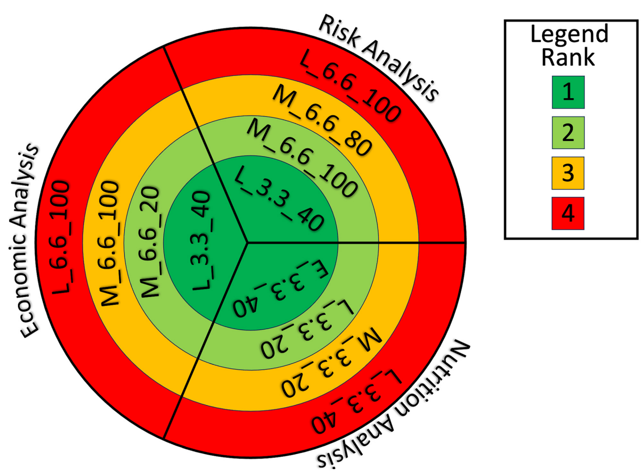

FIGURE 9 Overall top four ranking of alternatives from each of the nutrition analysis, economic analysis, and risk analysis summarized for all districts. The interior circle contains the highest ranked alternative scenario and proceeds to the outside circle with the fourth ranked alternative scenario.

the highest NPV, followed by Kaffrine, Fatick, Kaolack, Diourbel, and Thiès. In terms of EC and NCFI, the districts in order of highest to least were Kolda, Kaffrine, Fatick, Diourbel, Kaolack, and Thiès. The variations in economics could be due to the level of groundnut production per hectare, as this is highest in Kolda and lowest in Diourbel and Thiès. This in turn could be due to Kolda receiving more rainfall, which would boost production in the district.

Generally, alternatives with medium and late planting dates as well as alternatives with 3.3 and 6.6 plant densities, performed better in the ranking. This is a confirmation of the results found in the comparison of agricultural baseline and alternative scenarios comparison, as well as the evaluation of agricultural alternative scenarios against each other. Additionally, in terms of fertilizer scenarios, 0, 20, and 100 kg of fertilizer were generally filtered out as they had zero or negative IRR values. Scenarios that were ranked below the baseline all had 20 kg of fertilizer. For scenarios with 0 and 20 kg this could be attributed to lower yield increases due to low amount of fertilizer applications. For scenarios with 100 kg, this could be attributed to the increases in yield leveling off in comparison to the costs of the additional fertilizer. These trends were also observed in the resilience ranking based on risk.

3.5 | Resilience ranking of alternative scenarios based on risk

A further analysis was conducted to rank the alternative scenarios based on the CE and RP. Here, we first remove all RPs below 0 and then rank the overall risk performance based on CE. A higher CE and RP signifies a lower risk to the farmer. Here, the risk ranking does not consider alternative scenarios that were removed in the economic analysis through IRR elimination process. The results of this ranking analysis can be seen in Tables S46–S51. The baseline was included in the ranking, showing how some alternative scenarios had a higher risk than the baseline and thus were not preferred over the baseline. The best alternative scenario in terms of risk for 5 of the 6 districts was the late planting date, 3.3 plant density, and 40 kg of N fertilizer. This is similar to the best scenarios determined in the economic analysis, though not with the same districts. Table S52 contains the final overall ranking of alternative scenarios based on all optimization, economics, and risk analyses. Figure 9 shows the overall best four alternative scenarios for the study region as determined by nutrition, economic, and risk analysis. There is some overlap between the best scenarios from each type of analysis. The economic and risk analyses had the same 3 alternative scenarios in their top four, although these were not necessarily in the same order. The nutrition analysis only had one scenario in its top 4 scenarios, which is also in the other two analyses. The risk analysis was the most durable of the analyses, which is why it was used as the final ranking metric after the previous analyses. To fully understand the resilience of smallholder farmers in Senegal, it is essential to consider multiple facets. While nutritional analysis offers one perspective, it does not capture the economic and risk dimensions. Therefore, an economic analysis is crucial for a deeper understanding of resilience, and a risk analysis further refines this understanding.

4 | CONCLUSIONS

Existing metrics for resilience involve a holistic approach that covers nutritional, economic, and environmental aspects; however, there is no guarantee that a high-ranked approach meets the population requirements related to these aspects. In addition, many of the resiliency metrics do not account for risk as a variable. Therefore, the approach taken in this study tries to address these shortcomings, making the approach more robust. Meanwhile, utilizing a qualitative approach with integrated crop and animal models instead of arbitrary weighted metrics is an innovation, as the models can be calibrated for different technologies, practices, climates, conditions, and regions. The paper presents a novel method for determining farmer resilience to climate extremes. The major findings are as follows:

- Adopting and integrating multi-objective optimization methods in our strategic planning and implementation is recommended to ensure the nutritional well-being of smallholder farmers while maintaining budgetary constraints. This will ultimately guide us in designing a program that meets the population's nutritional requirements in a cost-effective manner while ensuring a balanced diet to combat malnutrition and obesity.
- Scenarios tended to be more resilient for millet production with increasing N fertilizer, plant density, and later planting dates, though this is not always the case, possibly due to diminishing marginal returns from increasing yield and increased costs.
- Considering the economic analysis, it is imperative for millet production to reconsider the promotion or subsidization of N fertilizer rates at 20 and 100 kg or promoting no fertilizer application, especially during drought years, given their zero or negative IRR values. Policymakers should prioritize rates that yield positive IRR to ensure economic viability and sustainability of agricultural practices.
- Given that the alternative scenario for millet with a late planting date, 3.3 plant density, and 40 kg of N fertilizer received the highest overall rating, policymakers should consider endorsing and possibly providing incentives for these specific agricultural practices when utilized together to enhance the resilience of smallholder farmers to extreme drought.
- The comprehensive method employed in this study offers a detailed and multifaceted assessment of farmers' resilience to climatic extremes. Therefore, it is crucial for the stakeholders to recognize and utilize this approach. By doing so, they can effectively address farmers' nutritional requirements without overshooting while ensuring affordability and minimizing risks for the farmers.

The novel approach utilized in this paper to determine the resilience of smallholder farmers can be expanded to cover more regions, climate conditions, and demographics in Africa. FARMSIM is well suited to be used for these purposes as it can be developed for different countries with many different alternative interventions. Therefore, more research must analyze specific solutions for specific situations and economic groups. For example, problems affecting very poor and poor farmers may not be the same problems facing middle-class and rich farmers. Therefore, future studies should address these shortcomings.

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CONFLICT OF INTEREST STATEMENT

The authors have stated explicitly that there are no conflicts of interest in connection with this article.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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