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Simulating maize yield gaps under variable climate scenarios in Ethiopia's semi-arid Central Rift Valley

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Abstract

Reducing maize yield gaps in Ethiopia's semi-arid regions requires a better understanding of nitrogen (N) responses under variable rainfall conditions. This study evaluated the effects of N management on maize yield level, yield variability, and yield gaps across contrasting rainfall scenarios using field experiments (2010–2021) and long-term DSSAT simulations (CERES-Maize) at Batu (1981–2017) and Melkassa (1980–2025). We classified seasonal rainfall into dry, normal, and wet years using a rainfall-tercile approach. The Average simulated potential yield (Yp) was higher at Melkassa (≈7.2 Mg ha⁻¹) than at Batu (≈6.7 Mg ha⁻¹), whereas water-limited yield (Yw) was greater and more stable at Batu (6.3 ± 1.0 Mg ha⁻¹) than at Melkassa (5.3 ± 2.7 Mg ha⁻¹), reflecting the much higher rainfall variability at Melkassa (CV = 57.4%) compared with Batu (19.9%). At Melkassa, rainfed yields under no nutrient limitation averaged only 2.96 ± 2.35 Mg ha⁻¹ in dry years but increased to 6.0 ± 2.03 and 7.1 ± 1.43 Mg ha⁻¹ in normal and wet years, respectively. Yield gap and the management approach to narrowing the yield gap vary by location and rainfall tercile. Across locations, the average yield gaps between farmers' yields and researchers' managed yields, simulated water-limited yields, and potential yields were 29.6%, 48%, and 57%, respectively. Long-term simulations confirmed that combined nutrient- and water-related yield gaps were higher (62.1–80.9%) in dry years than in wet years (50.7–74.0%). These findings demonstrate that maize N response and yield-gap closure are strongly rainfall-dependent, highlighting the need for climate-responsive fertilizer recommendations to improve productivity and reduce production risk in Ethiopia's semi-arid environments.

Keywords: Climate variability, DSSAT-CSM, nutrient-limited yield, rainfall-tercile, water-limited potential yield

1. Introduction

Maize (Zea mays L.) is one of the most important cereal crops in Ethiopia, serving as a major source of food, income, and livelihood for millions of smallholder farmers [1]. In the last two decades, maize production has increased from 2.4 million tonnes in 2004 to 10.8 million tonnes in 2022 [1, 2], a fivefold increase owing to improvements in the use of improved maize cultivars [1]. Despite the significant yield improvement, the current national average yield of maize is nearly 4.2 t ha^{-1} [2] which is below the estimated global average production of 5.8 t ha^{-1} [3] due to several factors. Among the major factors contributing to low maize yields and wide yield gaps in the country's semi-arid regions are high rainfall variability, low rates and inefficient use of fertilizer inputs, and suboptimal field management practices [4–7]. At the national level, the yield gap between the farmers' actual yield (3.27 Mg ha^{-1}) and the water-limited potential yield (14.96 Mg ha^{-1}) is estimated at around 78.1%, numerically equivalent to an 11.69 Mg ha^{-1} unmatched gap [8], representing a considerable unrealized production potential that warrants urgent attention through optimum nutrient, water, and crop management practices.

Yield-gap analysis provides a useful framework for identifying the relative contributions of management, nutrient, and water limitations to crop productivity [9] and to explore options that can narrow existing gaps. Some studies explored factors contributing to existing maize yield gaps in Ethiopia [4, 10, 11]. These studies, however, did not stratify yield gaps by rainfall class, despite the fact that both the magnitude of yield gaps and the effectiveness of their management strategies can vary substantially across different rainfall conditions. Integrating nutrient management with climate-scenario-based yield gap analyses can provide valuable insights by identifying the interacting factors that prevent crops from reaching attainable yields and the production risks associated with different management options under prevailing climate scenarios [12]. Such information is critical for designing site-specific and climate-tailored fertilizer management that enhances yield while minimizing input losses due to climate variability. Globally, few studies have explicitly classified cropping seasons into dry, normal, and wet years. However, recent yield-gap research increasingly incorporates seasonal rainfall variability and contrasting climatic conditions to quantify how attainable yields and yield gaps vary across seasons [13, 14]. This provides a strong rationale for stratifying yield-gap analyses by rainfall classes when developing climate-tailored fertilizer recommendations that we believe help in narrowing yield gaps in the region.

Process-based crop simulation models have become indispensable tools for evaluating crop responses to management and environmental conditions over long time periods that are difficult to study experimentally. These models are generally developed and applied for field-scale simulations and are adapted from local to global scales using different approaches and purposes [15]. The Decision Support System for Agrotechnology Transfer (DSSAT) model integrates crop growth, soil processes, weather conditions, and management practices to simulate crop performance under diverse production environments. Globally, there are numerous studies which evaluated the DSSAT model for climate change impact studies [15–17] and to explore adaptation options that can respond to climate change risks [18–22]. DSSAT has been widely applied to quantify yield responses to fertilizer management, assess climate risks, estimate yield gaps, and evaluate adaptation strategies across sub-Saharan Africa. Some studies also evaluated the application of DSSAT for different crop soils and agroecology in Ethiopia [23–27]. By combining long-term historical weather records with field-evaluated crop models, DSSAT provides a robust framework for exploring the interactions among climate variability,

nitrogen management, and crop productivity in rainfed maize systems. This study integrated field experiment data with DSSAT-based long-term simulations to quantify maize yield gaps under farmers' current management relative to potentially attainable yield levels across contrasting nitrogen and water management scenarios and variable rainfall conditions in the semi-arid maize-growing regions of Ethiopia.

2. Materials and Methods

2.1 Study sites

The field experiment for model validation and the DSSAT simulation experiment were conducted in the East Shewa zone of the Oromia region, Ethiopia. Two sites (Batu and Melkassa) with varying agroecology and soil type were selected. Geographically, the Batu site is situated at approximately 7.93° latitude and 38.7° longitude at an altitude of 1640 m above sea level, while the Melkassa site is located at approximately 8.4° latitude and 39.32° longitude at an altitude of 1550 m a.s.l. The sites differ markedly in major soil types and agroecology, as depicted in Figure 1.

The dominant soil type at the Batu site is classified as light Vertisols with a silty loam texture. Agroecologically, it is situated in the tepid sub-moist mid-highlands. In contrast, the Melkassa experimental site features Andosol soils (pH ranging from 7 to 8.2) with a dominant clay loam texture, which is suitable for crop production under optimum water availability [28]. Agroecologically, Melkassa falls under the warm sub-moist lowland zone, where erratic rainfall and in-season dry spells are most common [28].

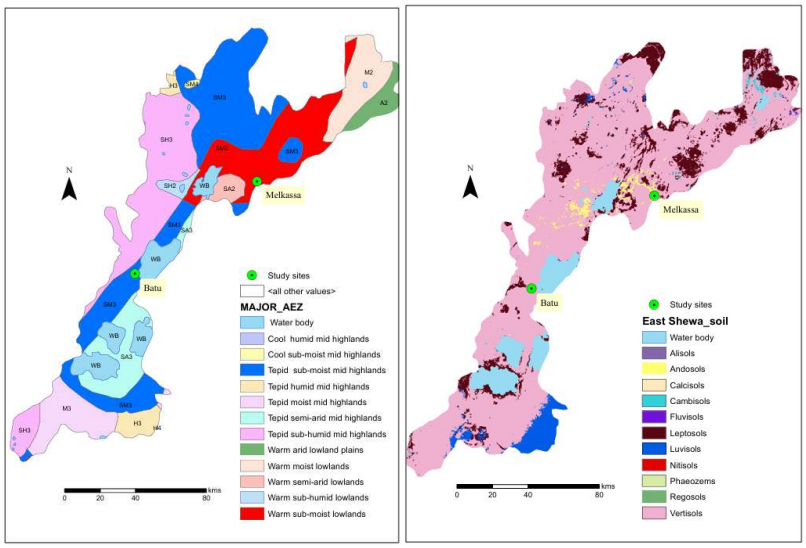


Figure 1. The major agroecological zones and soil types of the study area (FAO, WRB (2015))

2.2 Weather and soil data

Weather

Daily measured weather data for Batu (1981-2017) and Melkassa (1980-2025) were obtained from the National Meteorological Agency of Ethiopia (http://www.ethiomet.gov.et) and the Melkassa Agricultural Research Center's Agrometeorology department. The collected weather data include rainfall, temperature (Tmax and Tmin), solar radiation, relative humidity, and wind speed at a daily temporal resolution. Data quality was previously ensured and published by [28].

Soil

Soil profile data for each location were obtained from published sources [29, 30] and hydraulic limits, such as the lower limit (LL), drained upper limit (DUL), saturation, drainage coefficients, and runoff curve number, were generated from measured soil properties using the DSSAT internal pedo-transfer functions. Table 1 presents the soil data used for the DSSAT model.

Table 1. Soil profile properties of Melkassa and Batu soils used in DSSAT simulations

Depth	LL*	DUL	SAT	BD	Clay	Silt	OC	TN	P	pH	CEC
cm	$cm^3\ cm^{-3}$			$g\ cm^{-3}$	(%)				$mg\ kg^{-1}$		$cmol_c\ kg^{-1}$
Batu											
20	0.20	0.39	0.49	1.25	26.2	45.8	1.2	0.45	13.3	7.9	26.4
60	0.16	0.38	0.50	1..26	15.3	41.6	1.2	0.38	9.2	9.1	16.8
105	0.28	0.41	0.45	1.28	16.1	46.1	1.1	0.24	7.6	9.9	10.3
150	0.25	0.32	0.37	1.28	1.1	45.7	1.03	0.21	1.82	9.8	1.21
Melkassa											
15	0.094	0.343	0.393	1.19	20.1	45.2	1.06	0.12	17.3	7.3	33
30	0.188	0.337	0.387	1.23	19.4	47.1	1.04	0.16	12.4	7.5	32
60	0.162	0.348	0.398	1.24	19.2	49.3	1.03	0.21	10.1	7.6	34
100	0.186	0.352	0.401	1.25	18.3	51.3	1.01	0.2	7.4	7.8	34
200	0.209	0.378	0.428	1.24	18.5	51.1	1.01	0.16	6.6	7.9	34

*LL: lower soil water limit; DUL: drained soil water upper limit; SAL: saturated upper limit; BD: bulk density; OC: organic carbon; TN: total N; P: P-Olsen; and CEC: cation exchange capacity.

2.3 DSSAT model calibration and evaluation

Models that perform well in some locations should be evaluated before being used elsewhere [30]. The DSSAT model was primarily calibrated for the Melkassa-2 maize variety in the lowland and mid-highland maize-growing regions of Ethiopia [31]. Hence, we directly evaluated the model performance for the study area conditions after adjustments were made to the potential maximum number of kernels per plant (from 920 to 850 kernels per plant) and kernel filling rate under optimum conditions (from 7.1 to 6.1 mm d^{-1}). The calibration coefficients used for DSSAT genetic coefficient estimates of the maize Melkassa-2 variety are depicted in Table 2, adapted from [31].

Table 2. Genetic coefficients of the Melkassa-2 maize cultivar calibrated in the DSSAT model (Source: [31])

Coefficient	Description	Melkassa-2 (ZM-521)

P1	Thermal time from seedling emergence to the end of the juvenile stage (degree days above the base temperature of 8°C in the juvenile stage)	220.0
P2	Photoperiod sensitivity associated with delayed growth under unfavorable long-day conditions (no unit)	0.10
P5	Thermal time from silking to physiological maturity (degree days above the base temperature of 8°C in the maturity stage)	640.0
G2	Potential maximum number of kernels per plant	920.0/**850.0**
G3	Kernel filling rate under optimum conditions (mg d^{-1})	7.1/**6.1**
PHINT	Interval in thermal time between successive leaf appearance (degree days above a base temperature of 8°C)	38.9

*Values indicated in bold are coefficients changed from the original genetic coefficient and used in DSSAT simulation for the study

The model's seasonal performance was evaluated using five years of observed phenological and yield data derived from the treatment of locally applied fertilizer rate (23-20 NP kg ha^{-1}) during 2010-2015 experimental seasons. The evaluation was made using measured data for days to emergence, days to anthesis, days to physiological maturity, grain yield, and total above-ground biomass.

Performance of the models was evaluated by comparing the deviation between observed and simulated values. The following statistical indicators were employed based on [32]. The root mean square error (RMSE) (Eq 1) measures the average magnitude of the estimated errors, with lower RMSE values indicating greater central tendencies and generally smaller extreme errors.

$$\text{RMSE}= \left(\frac{\sum(\text{Yi-Zi})}{\text{n}}\right)^{0.5} \quad \text{(Eq 1)}$$

The normalized RMSE (nRMSE) (Eq. 2) provides a measure (%) of the relative difference between simulated and observed data. The simulation is considered excellent with nRMSE < 10%, good if between 10–20%, fair if between 20–30%, and poor if equal to or greater than 30%.

$$\text{nRMSE} = \frac{100 \text{ X RMSE}}{\hat{\text{Y}}} \quad \text{(Eq 2)}$$

The index of agreement (d) (Eq 3) determines the degree of agreement between the predicted and their respective observed values, and d = ∼1 is desirable.

$$\text{d} = 1- \frac{\sum(\text{Yi-Zi})^2}{\sum\left(\left|\text{Zi-}\hat{\text{Y}}\right|+ \left|\text{Yi-}\hat{\text{Y}}\right|\right)^2} \quad \text{(Eq 3)}$$

The mean error (ME) (Eq 4) estimates the average generated error, and a positive and negative ME show that the generated data were generally underestimated and overestimated, respectively.

$$ME = \frac{1}{n}\sum_{i=1}^{n}(Yi\text{-}Zi) \quad \text{(Eq 4)}$$

In addition, the Pearson correlation coefficient (r) (Eq 5) was used to evaluate how well the generated data correspond to the observed data.

$$r = \frac{\sum_{i=1}^{n}(Yi\text{-}\hat{Y})(Zi\text{-}\hat{Z})}{\sqrt{\left[\sum_{i=1}^{n}(Yi\text{-}\hat{Y})^2\right]\left[\sum_{i=1}^{n}(Zi\text{-}\hat{Z})^2\right]}} \quad \text{(Eq 5)}$$

Small values of RMSE were considered good, whereas d-values and r-values close to 1 were considered indicators of good performance of the DSSAT model.

where: Yi is the measured value, Zi is the simulated value, n is the number of observations, and $\hat{Y}$ and $\hat{Z}$ are the averages of the measured and simulated values, respectively.

2.4 Long-term DSSAT simulation experiments

A long-term DSSAT simulation experiment was conducted at Batu (n = 37 years) and Melkassa (n = 46 years) to evaluate the effects of nitrogen fertilizer rates on maize yield levels, yield variability, and yield-gap components under long-term climatic variability in the semi-arid maize-growing regions of Ethiopia. Four nitrogen treatments were considered: 23N, representing the farmers' current fertilizer rate; 69N, representing the recommended research-based rate; unlimited N under rainfed conditions, representing the water-limited yield potential (Yw); and unlimited N under irrigated conditions, representing the potential yield (Yp). Phosphorus was set at an unlimited level across all treatments to eliminate P limitation and isolate the effects of nitrogen availability and water supply on maize yield. Simulations were conducted assuming a previously cultivated soil with a history of poor management under continuous maize monoculture. The simulation experiment used the locally recommended maize plant population density (5.33 plants m^{-2}) and the planting date followed a locally accepted planting window that spanned from April 15 to July 30, and was triggered automatically when the soil moisture level reached at least 50% of the field capacity.

2.5 Data analysis

2.5.1 Yield gap analysis

Yield gap analysis involves quantifying the differences between simulated potential yield and farmers' yield levels and identifying those factors responsible for the yield differences [9]. Most researchers used references for calculating yield gaps, being yields under optimum management (i.e., no nutrient stress), which represent potential yields under irrigation conditions, or water-limited yields under rainfed conditions [4, 10, 11]. To capture management effects on yield differences, we included researcher-managed yields (experimental yields) under rainfed conditions with nutrient levels equivalent to the farmers' local application rate (23-20 kg NP ha^{-1}) [33].

For synthesizing the yield gap, we followed two approaches: 1) the field experimental data approach and 2) long-term DSSAT simulation experiments. For the field experiment-based approach, the average actual farmers' yields (Yf_a) in the yield gap calculation were based on fourteen years of observed data collected from the Central Statistical Agency (CSA) dataset for the cropping seasons 2007/08 to 2021/22[34]. Researcher-managed yields (Yr_a) were used from field trials conducted by Melkassa Agricultural Research Center (EIAR) under rainfed conditions and local fertilizer application rate (23-20 NP kg ha^{-1}) from 2010-2015/17, while simulated yields in the same scenario were supplemented for years with no field data (2007-2009 and 2016-2022).

Similarly, the yield gap under long-term simulated conditions was also analyzed for Batu (1981-2017) and Melkassa (1980-2025) by comparing simulated farmer yield (Yf), which is the equivalent of 23 kg N ha^{-1} simulated yield, research yield (Yr) simulated yield under 69 kg N ha^{-1}, water-limited yield potential (Yw), and potential yield (Yp). The simulated yield gap was decomposed into management, nitrogen, water, and total yield gaps based on long-term yield gap simulations. Yield gap due to N rate management (Gap_M) under farmer and research conditions was computed by subtracting the farmer yield (Yf) from the research yield (Yr). The percent yield gap due to N rate variation was applied as:

$$\mathrm{Gap_M} = \left(\frac{\mathrm{Yr}-\mathrm{Yf}}{Yr}\right) * 100\% \quad \text{(Eq 9)}$$

Yield gap due to N use variation (Gap_N) under the research N recommendation level and under no N limitation was computed by subtracting the research yield (Yr) from the water-limited yield (Yw), and the percent yield gap was computed using Eq. 10:

$$\mathrm{Gap_N} = \left(\frac{Yw-Yr}{Yw}\right) * 100\% \quad \text{(Eq 10)}$$

The yield gap due to water limitation (Gap_W) under the water-limited yield level and the potential yield was computed by subtracting the water-limited yield (Yw) from the potential yield (Yp). The percent yield-gap due to water availability was computed using Eq. 11:

$$\mathrm{Gap_W} = \left(\frac{Yp-Yw}{Yp}\right) * 100\% \quad \text{(Eq 11)}$$

Total yield gaps (Gap_{Total}) were partitioned into management, nutrient, and water-limitation components to identify the major constraints to maize productivity. The percent yield gap due to all the major constraints that affect maize yields was computed using equation 12:

$$\mathrm{Gap_{Total}} = \left(\frac{Yp-Yf}{Yp}\right) * 100\% \quad \text{(Eq 12)}$$

This framework follows established yield-gap methodologies widely applied in agricultural systems research (Van Ittersum et al., 2013).

2.5.2 Rainfall tercile analysis

We categorized simulation years into dry (seasonal rainfall below the 33rd percentile), normal (33rd–66th percentile), and wet seasons (seasonal rainfall above the 66th percentile) using terciles of seasonal

rainfall amount. We then analyzed yield levels, yield gaps, and risk indicators within each rainfall class to evaluate treatment performance under contrasting climatic conditions. Rainfall tercile classification is widely used in climate-risk and seasonal forecasting studies to characterize rainfall variability and assess its implications for agricultural production [35, 36].

3. Results

3.1 DSSAT model performance evaluation

Model evaluation with the calibrated cultivar parameters provided good agreement between simulated and observed values of crop phenology (Figure 2a) and yield components (Figure 2b) for all seasons at both locations. Days of emergence were simulated with no deviation, except for a single year with a one-day deviation at both locations. Dates of anthesis, however, were simulated with a deviation of 1 to 8 days at Melkassa and within 3 to 5 days at Batu during the 5-year validation periods. Dates of physiological maturity were simulated with a deviation of 1 to 8 days at Batu and 2 to 8 days at Melkassa for the Melkassa-2 maize variety.

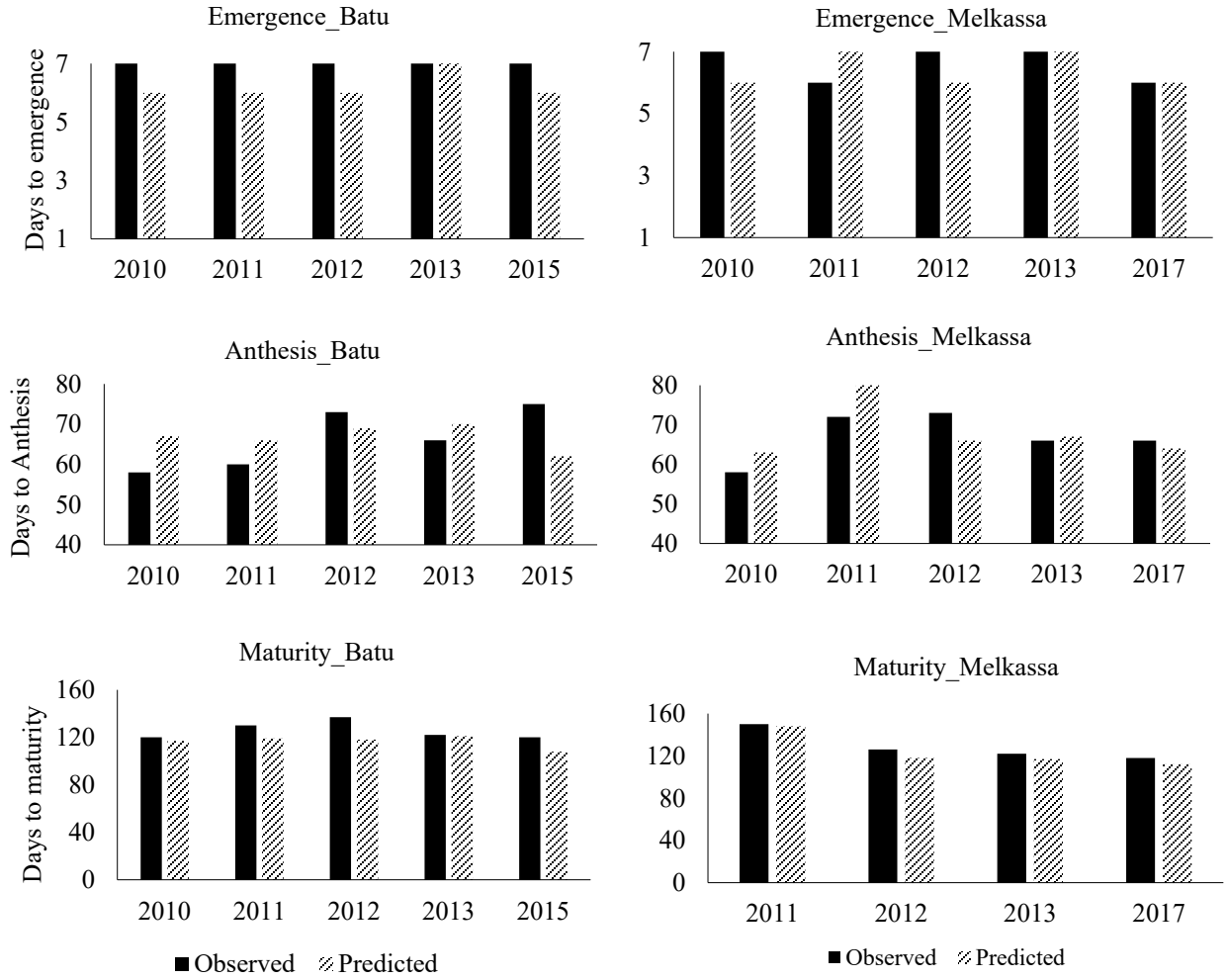


Figure 2a. Observed vs. simulated days to emergence, days to anthesis, and days to maturity at Batu and Melkassa for the Melkassa-2 maize variety.

On the other hand, the model simulated grain yield and yield components with reasonable agreement with the observed values. The deviation in simulated grain yield ranged from 0.1 to 0.7 Mg ha^{-1} at Batu and from 0.1 to 0.4 Mg ha^{-1} at Melkassa, while the deviation in above-ground biomass ranged from 0.1 to 3.2 Mg ha^{-1} at Batu and from 0.2 to 0.7 Mg ha^{-1} at Melkassa (Figure 2b).

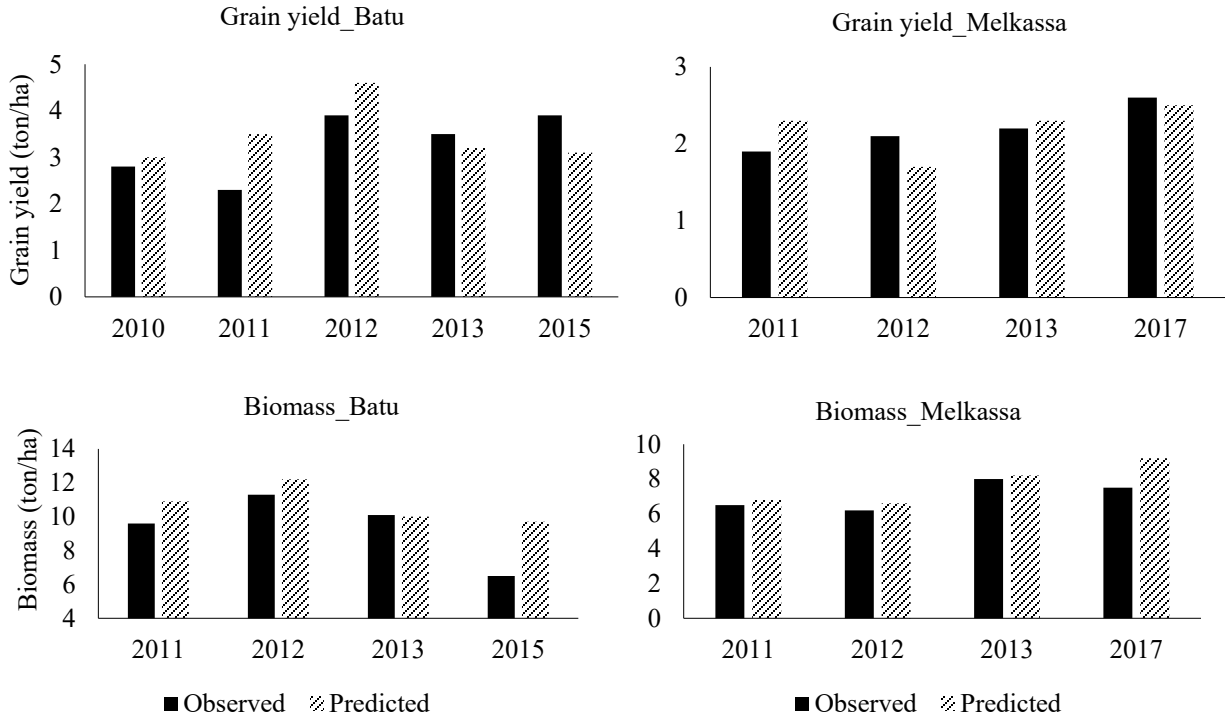


Figure 2b. Observed vs. simulated maize grain yield (Mg/ha) and biomass at Batu and Melkassa for the Melkassa-2 maize variety.

Table 3 presents the statistical performance indicators used to evaluate the model. The good agreement between simulated and observed grain yield was indicated by low values of the RMSE (0.4 Mg ha^{-1} at Batu, 0.3 Mg ha^{-1} at Melkassa), a close-to-one index of agreement (0.93 at Melkassa, 0.86 at Batu), and a high degree of correlation (0.83 at Batu, 0.74 at Melkassa) and corresponding high coefficient of determination (95% at Batu, 63% at Melkassa). In general, comparison of model-simulated water-limited yield and researcher-managed on-farm trial yield for the period 2010-2017 showed a very good agreement, whereby high simulated yields also had relatively high on-farm trial yields in the same years. However, the simulated yield in most cases was higher than the on-farm trial yield, as shown by statistically negative mean error (ME) values at both locations. This difference may be attributed to yield-reducing factors, as the yields observed in on-farm trials were not entirely free from the effects of pests, diseases, weeds, and other constraints. In contrast, the model assumes that such factors are perfectly controlled, and that crop management is optimal, thereby resulting in higher simulated yields.

Table 3. Simulations vs observed traits statistics for model evaluation

Validation for seasons	n	r	R^2	ME	RMSE	nRMSE (%)	d
Batu							
Days to emergence (days)	5	0.61	0.38	0.2	0.45	7	0.77
Days to anthesis (days)	5	0.73	0.53	2.2	4.1	6	0.78
Days to maturity (days)	5	0.81	0.66	3.6	4.4	3.7	0.69
Grain yield (Mg ha^{-1})	5	0.95	0.91	-0.24	0.4	10.9	0.87
Aboveground biomass (Mg ha^{-1})	4	0.77	0.6	-1.33	1.8	18.8	0.66
Melkassa							
Days to emergence (days)	5	0.58	0.33	-0.25	0.5	8.0	0.73
Days to anthesis (days)	5	0.98	0.97	-1.8	4.2	6.2	0.89
Days to maturity (days)	5	0.99	0.98	5.3	5.6	4.3	0.96
Grain yield (Mg ha^{-1})	4	0.63	0.39	0	0.3	13.3	0.74
Aboveground biomass (Mg ha^{-1})	4	0.98	0.97	-0.3	0.43	5.8	0.97

* N, number of data pairs used; r, Pearson correlation coefficient; R^2, coefficient of determination; ME, mean error; RMSE, root mean square error; nRMSE, normalized root mean square error; d, index of agreement.

3.2 Seasonal rainfall variability at Batu and Melkassa

The long-term average seasonal rainfall, interannual rainfall variability, and tercile rainfall distribution for the Batu and Melkassa sites are presented in Table 4. The seasonal rainfall analysis revealed variations in seasonal rainfall characteristics across sites and the three rainfall terciles. Batu exhibited relatively stable rainfall patterns, with mean seasonal rainfall increasing from 356 mm during dry years to 442 mm during normal years and 543 mm during wet years. The interannual variability, expressed by the coefficient of variation (CV), ranged from only 4.9% under normal conditions to 13.8% during dry years, indicating relatively low interannual rainfall variability. In contrast, Melkassa showed substantially greater seasonal rainfall amount and variability, with mean seasonal rainfall ranging from 179 mm in dry years to 322 mm in normal years and 645 mm in wet years. Rainfall variability was particularly high during dry years (CV = 49.6%) and remained elevated during wet years (CV = 22%). Overall, Melkassa exhibited much greater rainfall variability (CV = 57.4%) than Batu (CV = 19.7%). Furthermore, Melkassa experienced years with no effective seasonal rainfall during dry years, whereas Batu maintained a minimum seasonal rainfall of 232 mm. The wider range between the 5th and 95th percentile rainfall values at Melkassa (50–800 mm) compared with Batu (285–608 mm) further illustrates the higher climatic uncertainty at Melkassa.

Table 4. Seasonal rainfall amount and interannual variability under the different rainfall classes at Batu (n=37 years) and Melkassa (n=46 years).

Site	Rainfall class	Mean rainfall (mm)	Maximum rainfall (mm)	Minimum rainfall (mm)	Coefficient of variation (CV in %)	P5 (mm)	P95 (mm)
Batu	Dry	356	413	232	13.8	257	413
Batu	Normal	442	478	415	4.9	415	477

Batu	Wet	543	662	478	9.7	481	662
Melkassa	Dry	179	271	0	49.6	0	270
Melkassa	Normal	322	404	271	11.1	272	384
Melkassa	Wet	645	883	404	22.0	407	883
Batu	All	447	662	232	19.7	285	608
Melkassa	All	382	883	0	57.4	50	800

*P5 and P95 are the 5 and 95th percentiles of the rainfall amounts, respectively.

The contrasting rainfall characteristics between Batu and Melkassa highlight the strong spatial variability of rainfall across Ethiopia's semi-arid agricultural landscapes. Batu's relatively low interannual variability suggests a more dependable rainfall regime that can support stable crop production and improve the efficiency of agronomic inputs such as fertilizers. In contrast, the high rainfall variability observed at Melkassa indicates greater climatic risk, where frequent droughts and occasional excessive rainfall can substantially reduce crop productivity and increase year-to-year yield fluctuations. Such rainfall uncertainty is typical of semi-arid environments and necessitates climate-smart agricultural practices, including drought-tolerant cultivars, in situ moisture conservation, supplemental irrigation, and seasonal climate information to guide management decisions.

3.3 Maize yield levels and variability under different nitrogen rates and water conditions

The mean farmer-managed yield, research-managed yield, water-limited yield, and potential yield simulated for Batu and Melkassa are presented in Figure 3. The results showed that farmer-managed yields were relatively low at both Batu (2.87 ± 0.63 Mg ha^{-1}) and Melkassa (1.66 ± 0.70 Mg ha^{-1}), which can be attributed largely to the low rates of nitrogen fertilizer application under farmers' management. With the higher fertilizer rates recommended by research, yields increased substantially to 5.23 ± 0.83 Mg ha^{-1} at Batu and 3.50 ± 1.60 Mg ha^{-1} at Melkassa. The simulated potential yields were 6.7 ± 0.5 Mg ha^{-1} at Batu and 6.9 ± 1.6 Mg ha^{-1} at Melkassa, indicating considerable scope for increasing maize productivity through improved nutrient management and other agronomic practices. Simulated yield levels at Batu were lower than at Melkassa across the corresponding years. Conversely, the mean water-limited yield was higher and more stable for Batu (6.3 ± 1.0 Mg ha^{-1}) than Melkassa (5.3 ± 2.7 Mg ha^{-1}) during the simulation period. The highest water-limited yield simulated for Batu and Melkassa was 7.5 and 7.8 Mg ha^{-1}, while the lowest was 2.6 and 0 Mg ha^{-1}, respectively.

Water-limited maize yields varied considerably between sites and across the three rainfall terciles (Figure 3, right). At Batu, where interannual rainfall variability was relatively low, simulated yield levels remained largely stable across the rainfall terciles, ranging from 5.81 ± 1.3 Mg ha^{-1} during dry seasons to 6.67 ± 0.7 Mg ha^{-1} in the wet seasons. In contrast, water-limited yields at Melkassa were strongly influenced by rainfall conditions. Under wet conditions, maize achieved higher yields with relatively lower yield variability (7.1 ± 1.4 Mg ha^{-1}) than under normal (5.99 ± 2.03 Mg ha^{-1}) and dry (2.96 ± 2.4 Mg ha^{-1}) conditions. Under dry conditions, yields remained low despite unlimited nutrient availability, with a considerable risk of crop failure and markedly greater yield variability.

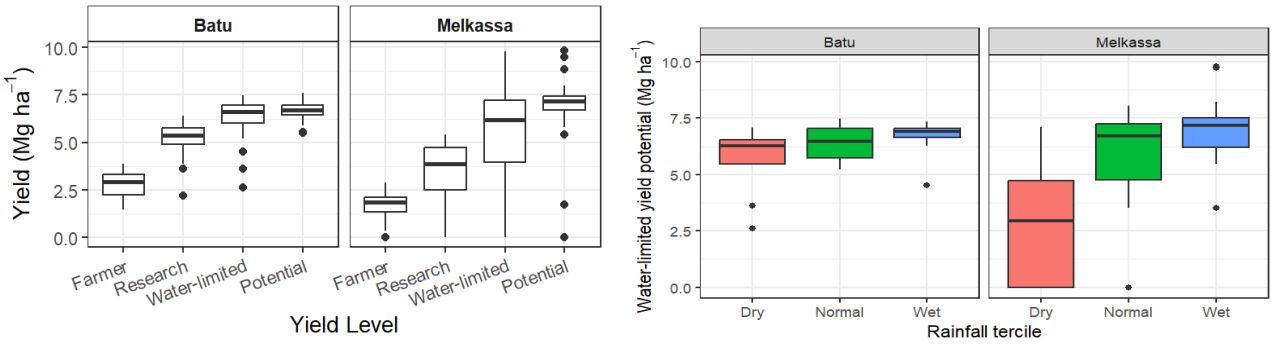


Figure 3. Yield level of maize from the farmers' yield (23N), research-recommended yield (N69), water-limited yield (Yw) and potential yield (Yp) (left) and water-limited yield under tercile rainfall (right) at Batu (n=37) and Melkassa (n=46)

3.5 Yield-gap decomposition

The yield gap analysis showed that farmers' actual maize yields were substantially lower than yields from researcher-managed fields and the simulated water-limited and potential yield levels (Figure 4). During 2007–2022, the average maize grain yield from farmers' fields receiving 23–20 kg NP ha^{-1} was 3.05 Mg ha^{-1}, compared with 3.69 Mg ha^{-1} at Batu and 4.97 Mg ha^{-1} at Melkassa under researcher-managed conditions. Consequently, researcher-managed yields exceeded farmers' yields by 21–63%, reflecting the benefits of improved crop and soil management practices. Furthermore, the average farmers' yield represented only 52% of the simulated water-limited yield and 43% of the simulated potential yield, demonstrating the existence of a substantial yield gap in the study region. The difference between actual and water-limited yields indicates considerable scope for increasing maize productivity through improved agronomic management, including optimum fertilizer application, timely planting, and effective pest and disease control under rainfed conditions. The even larger gap between actual and potential yields suggests that integrating irrigation with optimal nutrient and crop management could increase maize yields by more than double in areas where irrigation is feasible. These findings highlight the significant opportunity to enhance maize productivity and strengthen food security through improved crop management and the expansion of irrigation where water resources permit.

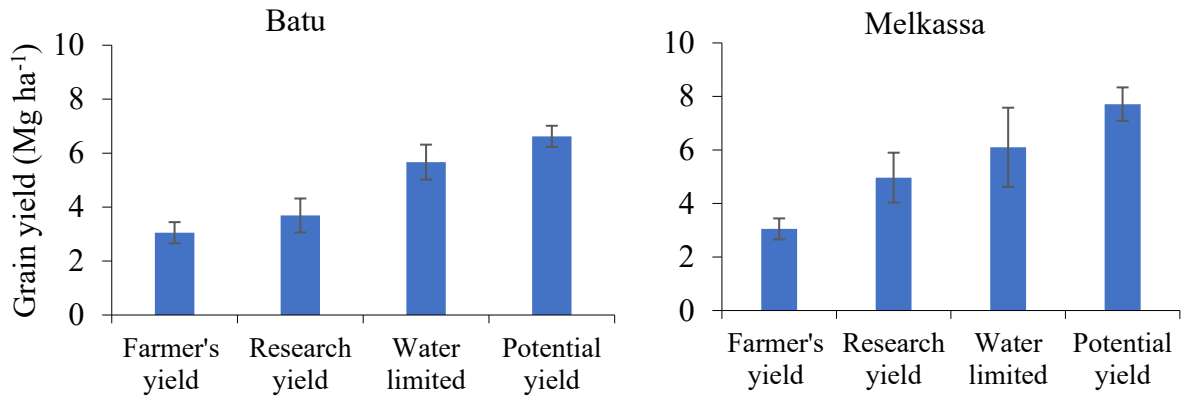


Figure 4. Yield gap of maize in the CRV of Ethiopia during the 2007-2022 season.

The long-term simulation also compared potential, water-limited yield simulations, research recommendations, and farmers' local fertilizer rates, indicating yield gaps due to seasonal rainfall variations (Table 5). The total yield gap (the yield difference between the farmers' yield level and the potentially attainable yield level) at Melkassa (5.54 Mg ha^{-1}) was higher than that of Batu (3.83 Mg ha^{-1}) for the prescribed simulation periods. The yield gap attributed to differences in variations of N application rates between the research and local farmers' practice under the prevailing rainfall conditions was higher at Batu (2.36 Mg ha^{-1}, 0.7 to 2.5 Mg ha^{-1}) than at Melkassa (1.81 Mg ha^{-1}, 0 to 2.5 Mg ha^{-1}). Consequently, the yield gap that can be narrowed by application of irrigation water varied from 0.4 Mg ha^{-1} at Batu (0.1 Mg ha^{-1} during good rainfall years to 2.9 Mg ha^{-1} during low rainfall years) to 1.9 Mg ha^{-1} at Melkassa (ranging from 2 to 5.4 Mg ha^{-1} for corresponding high and low rainfall years, respectively). Overall, irrigation water application could substantially enhance crop production, particularly at Melkassa during periods of severe rainfall deficits, whereas improved nitrogen management could have a greater impact at Batu. The high coefficient of variation in the yield gap foretells seasonality in irrigation water requirements at both locations. The wide yield gap, especially during lower rainfall years across the simulation periods, signifies the requirement of more dependable application of irrigation water and a potential shift to irrigated agriculture.

Table 5. Potential and water-limited maize yield during 1981-2017, n=37 for Batu and 1980-2025, n = 46 for Melkassa)

Variables	Batu					Melkassa				
	Mean	SD	CV	Min	Max	Mean	SD	CV	Min	Max
Potential yield (Mg ha^{-1}) (a)	6.7	0.5	7.7	5.5	7.6	7.2	0.9	13	5.4	9.8
Water-limited yield (Mg ha^{-1}) (b)	6.3	1.0	16	2.6	7.5	5.3	2.7	49.8	0	7.8
Researchers' managed yields (Mg ha^{-1}) (c)	5.23	0.8	15.9	2.2	6.4	3.47	1.5	44.6	0	5.4
Farmers' yields (Mg ha^{-1}) (d)	2.87	0.6	22	1.5	3.9	1.66	0.7	41.9	0	2.9
Yield gap due to irrigation (a-b)	0.4			2.9	0.1	1.9			5.4	2.0
Yield gap due to N (c-d)	2.36			0.7	2.5	1.81			0	2.5
Total yield gap (a-d)	3.83			4	3.7	5.54			5.4	6.9

SD: Standard deviation, CV: coefficient of variation (%), Min: Minimum value, Max: Maximum value

3.6 Yield gap of maize under dry, normal, and wet years

Long-term simulated yield gap of maize under dry, normal, and wet rainfall scenarios was synthesized, and the yield gaps due to applications of different rates of N (farmer rate (23N), research rate (69N), rainfed with unlimited N (Yw), and unlimited N and water (Yp)) are presented in Table 6. The yield gap generally varies by site and rainfall scenarios. For sites with relatively dependable rainfall, such as Batu, the highest yield gap was simulated during the dry season, followed by the normal and wet

seasons under each yield gap category. Yield gaps of 46.8%, 45.3%, and 41.1% can be narrowed through the adoption of research recommendation rates under the dry, normal, and wet seasons, respectively. Similarly, there exist 19, 17.2, and 15.2% potentially achievable yield gaps that still need to be explored by research to achieve the rainfed potential yield levels. The yield gap arising from water limitation alone contributes from 1.5% during wet seasons to 4.5% in normal seasons, up to 12% during the dry season. The total yield gap contributed by nutrient and water limitation is high, ranging from 62% during the dry years to 50.7% in the wet years

At the Melkassa site, on the other hand, the simulated yield gaps were higher during the wet seasons, where the responses to added fertilizer are governed by moisture level. The response of yield to applied N was minimal for all N levels under dry conditions. However, the farmers' N rate appears below optimal, where farmers can increase the yield level twofold only by adopting the research recommendation, even in the driest seasons. Under normal and wet seasons, higher yield gaps were simulated between the farmers' yield and the research yield (53.7-52.5%) and the rainfed potential yield (68.3-72.5%), which needs urgent attention to improve maize productivity. Likewise, the significance of water limitation alone is high, especially in the dry season (54%), and considerable even during the normal season (16.7%). The yield gap contributed by both nutrients and water is very high, spanning from 80.9% in the dry year to 74% during the normal and wet years, indicating that nitrogen response and yield-gap closure vary with seasonal rainfall.

Table 6. Simulated long-term maize yield gaps under dry, normal, and wet rainfall scenarios for Batu and Melkassa.

Site	Rainfall Class	Yf (a)	Yr (b)	Yw (c)	Yp (d)	Nutrient Gap (%)		Water Gap (%)	Total Gap (%)
						(b-a)	(c-b)	(d-c)	(d-a)
Batu	Dry	2.5	4.7	5.8	6.6	46.8	19.0	12.1	62.1
Batu	Normal	2.9	5.3	6.4	6.7	45.3	17.2	4.5	56.7
Batu	Wet	3.3	5.6	6.6	6.7	41.1	15.2	1.5	50.7
Melkassa	Dry	1.2	2.3	2.9	6.3	8.7	20.7	54.0	80.9
Melkassa	Normal	1.9	4.1	6.0	7.2	53.7	31.7	16.7	73.6
Melkassa	Wet	1.9	4.0	6.9	7.3	52.5	42.0	5.5	74.0

4. Discussions

4.1 Model performance evaluation

Performance of the DSSAT model in simulating different N rates was reported in different studies [37–39] for Africa and for the CRV areas [4, 30, 39]. The model accurately simulated yield and other phenological parameters during the evaluation period in the CRV. For the variables considered for evaluation, there was a very low RMSE and more than 60% of the coefficient of determination (R^2) and close to 1 d-value, reflecting a fair agreement between the observed and predicted values [30]. Therefore, the model can be used well to simulate yield of maize for N management in the variable climate of the Central Rift Valley of Ethiopia.

The mean potential yield (averaged over the site) of medium-maturing maize (7 Mg ha^{-1}, in the range 6.5 – 8.6 Mg ha^{-1}) simulated considerably agrees with previous studies made by [4], who simulated mean potential yield levels of early (6.8 Mg ha^{-1}) and late (8.2 Mg ha^{-1}) maturing cultivars of maize under the CRV conditions. Additionally, the results are also in good agreement with the highest yield of the cultivar reported from field experiments in the study areas. For instance, the potential yield of maize cultivar Melkassa-2 reported under irrigated conditions is about 8 Mg ha^{-1} [40].

4.2 Maize yield gap under variable climate

The results agree with previous works conducted in the CRV conditions and other similar agroecologies in Sub-Saharan Africa. For instance, [4] reported that actual farmers' yields were 28–30% of the simulated water-limited yield and 44–65% of the researcher-managed yields (on-farm trial) in the CRV of Ethiopia. The average yield gap of maize (6.5 t ha^{-1}) between farmers' yield and water-limited yield was reported during 2004-2009 in the central lowlands of the Rift Valley [10] Recent estimates also showed that farmer yield was only 46–54% of research yield, and research yield was 23.5–45.2% of water-limited yield in the southern part of the Rift Valley areas (Tesfaye et.al., 2023). Similarly, [41] reported that the average farmers' yield of maize in Kenya was 25% of the water-limited yield potential, indicating a high yield gap in the area. Some reports also identify these yield gaps as historical challenges that are still unresolved today. For example, Rötter (1993) and Rötter and Dreiser (1994) cited in [4] reported maize yields at moderate levels of N and P fertilizer application (e.g., 50 kg N ha^{-1} and 22 kg P ha^{-1}) reaching 40–60% of water-limited yields in semi-arid to sub-humid climatic zones of the Kenyan Rift Valley.

Studies indicated that nitrogen is widely recognized as the most limiting nutrient for maize production in Ethiopia's maize-growing belts, as evidenced by the results obtained from the nationally conducted nutrient omission trials [42–45]. High rates of nutrient mining from continuous cultivation without proper fertilizer replenishment have reduced soil fertility and substantially contributed to yield penalties across many maize-growing areas [4]. During the field experimental period, the average fertilizer rate used by Ethiopian farmers was about 21-23 kg N ha^{-1} [33], which is by far lower than the national recommendation rates of 60–100 kg N ha^{-1} [46]. [10] reported the insufficient application of fertilizers by farmers in the CRV of Ethiopia. The authors indicated that the actual nitrogen (N) and phosphorus (P) application on farmers' fields was low (2.6–16.5 kg N ha^{-1} and 2.2–17.3 kg P ha^{-1}), whereby the best-performing farmers, on average, apply 8–20 kg N ha^{-1} and 5–21 kg P ha^{-1} in the CRV maize growing areas. Smallholder farmers in Ethiopia currently apply an average of approximately 37 to 40 kg ha^{-1} N [6], a slight improvement from a decade ago.

The field results indicate that proper field management with the supply of required inputs (fertilizer and improved seed) and increasing resource use efficiency through agro-advisory services could increase crop yield and consequently narrow yield gaps [4]. However, increasing N application to recommended rates alone had only a small effect on narrowing the yield gap under current farmers' management, and without climate considerations [6, 10, 11]. Researchers do agree that crop responses vary considerably depending on seasonal rainfall conditions and soil moisture availability [47–49]. Understanding how nitrogen responds to maize productivity and yield stability under variable climatic conditions is, therefore, essential for developing climate-smart nutrient management strategies that improve both productivity and resilience [50] and narrow prevailing maize yield gaps [51] in Ethiopia.

4.3 Implications of climate variability on maize yield gap

Recent yield-gap studies increasingly incorporate seasonal rainfall variability [13, 52, 53], drought and wet-year conditions [54] or contrasting climate scenarios [14] to capture the influence of climate variability on attainable yields and yield-gap estimates. The reviewed literature consistently supports our analysis by highlighting the strong interrelationship between climate variability and maize yield variability, emphasizing the need to incorporate climatic variability into yield-gap assessments and the design of climate-tailored fertilizer recommendations. For example, For example Saketa et al. (2025) showed that maize yield in western Ethiopia responds differently under varying rainfall conditions, with rainfall increases improving yield while moisture deficits substantially reduce production. A study integrating the yield gap and rainfall scenario by [14] compared yield gaps under current and future climates and found that dry years experienced much larger yield penalties than average years in a study conducted at 10 sites across the globe. They also demonstrated that attainable yields vary considerably among years because of climate variability. Studies conducted in SSA also demonstrated that rainfall variability explains 50–60% of interannual maize yield variation and concluded that identifying dry and wet weather patterns is essential for climate-smart agricultural management and weather-related risk assessment [54].

Evidence from Malawi [55], Uganda [56], Brazil [57], and other rainfed maize systems shows that the magnitude of the gap between farmers' actual yield and water-limited yield potential changes substantially across rainfall regimes, with the largest gaps typically occurring during dry years. Evaluated adaptation options under contrasting climate scenarios, illustrating that attainable yields depend on seasonal climate conditions. Studies further demonstrate that both drought and excessive rainfall can reduce maize productivity, indicating that climate-specific yield-gap analysis provides a more realistic assessment of production opportunities and risks than a single long-term average yield-gap estimate.

5. Conclusions

This study demonstrated that maize yield gap in the semi-arid Central Rift Valley of Ethiopia is strongly influenced by the interaction between nitrogen application and seasonal rainfall variability. Raising nitrogen application from the prevailing farmer practice (approximately 23 kg N ha^{-1}) to research-based recommendations (69–92 kg N ha^{-1}) substantially increased maize productivity and reduced the exploitable yield gap. However, considerable gaps remained between the attained yield, water-limited yield potential, and potential yield, indicating that water scarcity and suboptimal nutrient management continue to constrain maize production. The long-term simulations further revealed that rainfall variability and fertilizer management are key factors to be considered in narrowing current yield gaps. Overall, the findings highlight that fixed fertilizer recommendations are unlikely to maximize productivity under highly variable rainfall conditions. Instead, climate-responsive, site-specific nitrogen management, complemented by improved water management through supplemental irrigation or other water-conservation practices, offers a more effective strategy for increasing maize productivity and narrowing yield gaps in the semi-arid regions of Ethiopia.

Declarations

Ethical Approval

This research involved standard field agronomic practices, soil sampling, and crop management, and did not involve human participants, endangered biological species, or animal testing. Therefore, formal ethical committee approval was not required. The field experiments were conducted in compliance with the institutional guidelines of the Ethiopian Institute of Agricultural Research, and all necessary permissions for land and field access were obtained prior to the study.

Availability of data

The datasets generated and/or analyzed in this study are available from the corresponding author upon reasonable request.

Author contributions

FA was involved in the conceptualization, data collection, DSSAT modeling, analysis, preparation of the original draft, and searching for resources and funding. AAB and GB were involved in the re-analysis, review, and editing.

Competing interests

The author declares that there are no competing interests.

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Consent to Participate

Not applicable.

Consent to Publish

Not applicable.

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