



# Assessment of Maize Yield Response to Agricultural Management Strategies Using the DSSAT–CERES–Maize Model in Trans Nzoia County in Kenya

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## Abstract

Maize production in low-yielding regions is influenced by climate variability, poor soil fertility, suboptimal agronomic practices, and biotic influences, among other limitations. Therefore, the assessment of yields to various management practices is, among others, critical for advancing site-specific measures for production enhancement. In this study, we conducted a multiseason calibration and evaluation of the DSSAT–CERES–Maize model to assess the maize yield response of two common cultivars grown in Trans Nzoia County in Kenya under various agricultural strategies, such as sowing dates, nitrogen fertilization, and water management. We then applied the Mann–Kendall (MK), and Sen’s Slope Estimator (SSE) tests to establish the yield trends and magnitudes of the different strategies. The evaluated model simulated long-term yields (1984–2021) and characterized production under various weather regimes. The model performed well in simulating the growth and development of the two cultivars, as indicated by the model evaluation results. The RMSE for yield was 333 and 239 kg ha<sup>-1</sup> for H614 and KH600-23A, respectively, representing a relative error (RRMSE) of 8.1 and 5.1%. The management strategies assessment demonstrated significant feedback on sowing dates, nitrogen fertilization, and cultivars on maize yield. The sowing date conducted in mid-February under fertilization of 100 kg of nitrogen per hectare proved to be the best strategy for enhancing grain yields in the region. Under the optimum sowing dates and fertilization rate, the average yield for cultivar KH600-23A was 7.1% higher than that for H614. The MK and SSE tests revealed a significant ( $p < 0.05$ ) modest downwards trend in the yield of the H614 cultivar compared to the KH600-23A. The eastern part of Trans Nzoia County demonstrated a consistent downwards trend for the vital yield enhancement strategies. Medium to high nitrogen levels revealed positive yield trends for more extensive coverage of the study area. Based on the results, we recommend the adoption of the KH600-23A cultivar which showed stability in yields under optimum nitrogen levels. Furthermore, we recommend measures that improve soil quality and structure in the western and northern parts, given the negative model response on maize yield in these areas. Knowledge of yield enhancement strategies and their spatial responses is of utmost importance for precision agricultural initiatives and optimization of maize production in Trans Nzoia County.

**Keywords** Calibration · CERES–Maize · DSSAT · GLUE · Maize · Trends

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## Introduction

Sub-Saharan Africa (SSA) faces food shortage problems due to highly variable and less predictable weather conditions, poor soil fertility, unsustainable agricultural practices, low adoption of technology, and pest and disease attacks (Connolly-Boutin & Smit, 2016; de Graaff et al., 2011; Kalele et al., 2021). These challenges, compounded by the fast-growing population, impede the region's capacity to meet the people's daily and seasonal nutritional and food security needs (Hall et al., 2017). Therefore, sound and sustainable agricultural strategies are feasible pathways for addressing the frequent agricultural challenges in the region (Garzon et al., 2020). These strategies, ideally aligned at the political level with the United Nations (UN) sustainable development agenda and other goals of national importance, can propel SSA to a self-sufficient food region. As a result, the region may experience poverty decline, hunger reduction, and increased resilience of agricultural systems to current and anticipated climate shocks (UN, 2015). Like any other developing nation, Kenya is witnessing a rapidly growing population and increasing climate change effects, including rapid inner migrations. Approximately 80% of the landmass constitutes arid and semi-arid lands (ASAL), with less favourable conditions for food production (Sombroek et al., 1982). The region is prone to environmental hazards such as droughts, soil erosion, floods, and biodiversity losses, which exacerbate land degradation and significantly lower agricultural potential (Kanyenji et al., 2020; Klisch & Atzberger, 2016). As a remedial measure, populations in the ASAL areas adopt climate-smart practices such as cultivating drought-resistant crops and livelihood diversification for their socioeconomic well-being (Karienyé & Macharia, 2020; Kirui et al., 2021). In contrast, Kenya's medium to high agricultural potential areas constitute only 12% of the total landmass (Kabubo-Mariara & Karanja, 2007). These areas exhibit optimal climatic conditions and improved soil structure and fertility compared to ASAL areas.

Maize is the primary cereal crop devoted to the productive zones in Kenya. As the most consumed and primary staple food, it accounts for one-third of the total per capita caloric intake (Mohajan, 2014). Additionally, it occupies more than half of the total land for crop production. Furthermore, it contributes to the food and household income needs of 98% of the population, who are the majority of smallholder farmers (Kiriimi et al., 2011). The average production of maize in Kenya has stagnated at 1.7 tonnes per hectare, below the world average of 4 tonnes under the same acreage (Mumo et al., 2018). The low yields have persisted despite some of the earliest yield enhancement strategies, such as the green revolution,

market liberalization and technology growth (Hugo De Groote et al., 2005). In response to poor production, the government is promoting policies for increasing production and ensuring household self-sufficiency. The services include the provision of subsidized agricultural inputs, expanded dissemination of extension services, devolution of agriculture, and promotion of research services (Bou-langer et al., 2022; Shelmith, 2019). These services are mainly policy-oriented and have been the focus of most literature. Despite their importance in quantifying yield effects in various environments, studies on Site-Specific Agricultural Management Strategies (SSAMS) and their spatiotemporal response across agricultural landscapes are lacking. Site-oriented target measures are critical in optimizing policy implementation and ensuring maximum economic returns in a particular production environment. Therefore, combining agronomic practices with site conditions enhances the understanding of local yield responses and aids decision-making.

The SSAMS matches inputs with spatially varying crop requirements and environmental conditions (Pringle et al., 2003). The strategy differs from conventional management, whereby field or landscape crop production conditions are considered to have a uniform influence on production. According to Olwande and Smale (2012), SSAMS are critical in enhancing maize production and bridging yield gaps. Long-term experimental trials are conventionally used to evaluate SSAMS and their responses to agricultural yields (Vilayvong et al., 2015). These trials are, however, costly to manage and incur substantial time and resources. Therefore, with the advent of low-cost crop modelling approaches, SSAMS evaluations have been made easier. In particular, they give continuous input to decision-maker's dialogue at various scales (Corbeels et al., 2018; Webber et al., 2014). Ideally, these crop models should be provided with the necessary inputs and accurately calibrated for reliable assessments. Calibration ensures that the model adequately mimics crop growth and yield output. Additionally, the process ascertains the transferability of the model parameters for use in various applications and under different environments. A range of agronomic measures have been embedded in existing crop models. For example, the Decision Support System for Agro-technological Transfer (DSSAT) model evaluates the response of various sowing dates, different cultivars, nitrogen fertilization levels, and different irrigation water amounts, among other measures. The highly ranked model combines crop models that simulate different cropping strategies (Jones et al., 2003). The DSSAT modelling system includes the Crop Environment Resource Synthesis (CERES-Maize) model used for simulating maize (*Zea mays* L.) growth and yield under various environmental conditions. The model has been used to address a range of applications, such as evaluating

strategies to cope with limited weather and soil conditions (Malik & Dechmi, 2019), evaluating climate change impacts on crop production (Babel & Turyatunga, 2015; Jiang et al., 2021; Lin et al., 2015), optimizing agronomic practices for increased production (Mubeen et al., 2016), and assessing the performance of various cultivars and their suitability in different environmental conditions (Chisanga et al., 2021c; Feleke et al., 2021). Researchers have tested the model under various production environments such as the Tropical, the Mediterranean, and Temperate regions (Ahmad et al., 2021; Arefi et al., 2017; Banterng et al., 2010; Getachew et al., 2021; Kothari et al., 2019; Vilayvong et al., 2015). The model application in these environments has been informed by its ability to characterize maize growth and development reasonably. However, to achieve reliable estimations and extend the model's applicability for various applications, it is essential to acquire multiple datasets for parameterizing the model. The datasets acquired via different means and the complexity of the model structure in approximating soil and crop processes often introduce uncertainties in model predictions (Dokoohaki et al., 2021). To address these uncertainties, techniques such as assimilation with external data sources have been suggested to constraint the model simulations over time (Joshi et al., 2019; Li et al., 2015). In addition, application of model ensembles has been adopted to characterize biophysical processes across agricultural landscapes (Chisanga et al., 2021b; Feleke et al., 2021). Another requirement for the DSSAT-CERES-Maize model is that investment in significant amount of experimental resources is necessary to account for the variability in various seasons (Hoogenboom et al., 2019). Nevertheless, the reliability of the DSSAT-CERES-Maize model has opened frontiers for assessing SSAMS and optimizing farm-level decisions for increasing maize yield in different regions.

Site-specific agricultural measures (SSAMS) have been the focus of most literature. Subsequently, process-based crop models have an essential function in assessing their effects on yield enhancement in various parts of the world. (Nóia Júnior & Sentelhas, 2019) evaluated the impacts of sowing dates on soybean-maize succession across Brazil using different crop models. Furthermore, Saddique et al., (2019) examined the sowing date and irrigation interaction effects on maize yield in China. In the Sudan Savanna region of Nigeria, Adnan et al., (2017) investigated the influence of sowing dates and different maturing varieties on maize yield. Additionally, in Tanzania, Volk et al., (2021) assessed management strategies, including full irrigation, deficit irrigation, mulching and nutrient management, to evaluate their effects on maize yield under current and projected climatic conditions using the DSSAT-CERES-Maize model. Although the literature has demonstrated the efficacy of the DSSAT-CERES-Maize model in assessing SSAMS,

existing evaluations have been conducted at a point scale. The assessments, therefore, do not account for the spatial responses of the practices on yield in more regionalized and heterogeneous contexts. Furthermore, there is a dearth of knowledge on the spatial response of SSAMS across diverse soil and climatic conditions in Kenya. Attempts to incorporate the spatial aspect into modelling are covered in the studies of Liu and Basso, (2017) & Ojeda et al., (2021) conducted in Malawi and Australia, respectively. However, these studies covered few agronomic measures and did not incorporate trend analysis in the considered strategies. Against this background, a comprehensive assessment of spatial responses to multiple/simultaneous crop management strategies remains a challenge for further future simulations to better adapt to climate change.

This study expanded on the scope of the literature in evaluating the spatial response of maize yield under various SSAMS in Trans Nzoia County in Kenya. Therefore, this research hypothesises that the application of SSAMS increases production and reduces interannual variability in maize yields. The objectives drawn from the hypothesis include; (i) to calibrate and evaluate the DSSAT-CERES-Maize model for simulating the growth and development of two maize cultivars using multiseason field experiments, (ii) to assess the response to various management measures, acting independently and in their interactions on maize yield, and (iii) to explore the spatio-temporal yield trends of various SSAMS.

## Materials and Methods

### Study Area, Weather, and Soil Data

The study was carried out in Trans Nzoia County, western Kenya, situated between longitudes 34° 35' E and 35° 21' E and latitudes 00° 48' N and 01° 16' N. The elevation ranges from 1500 m above sea level in the southern parts to above 4000 m in the Mt. Elgon region. The soil distribution varies from deep, well-drained Humic and Rhodic Nitisols in the slopes of Mt. Elgon region to deeply weathered Humic Ferralsols in the undulating central and southern parts. According to Koppen Geiger's climate zone classification, the climate of the study area is rainforest. The precipitation pattern is bimodal, with long rains occurring between April and July and short rains between October and December. Precipitation varies between 900 and 1700 mm. The annual mean temperature is 18 °C. The major crops grown include maize, wheat, barley, sunflower, coffee, potatoes, and beans. The county plays a significant role in both high crop production and a high ratio of agriculturally productive areas in Kenya. Although the region receives high rainfall,

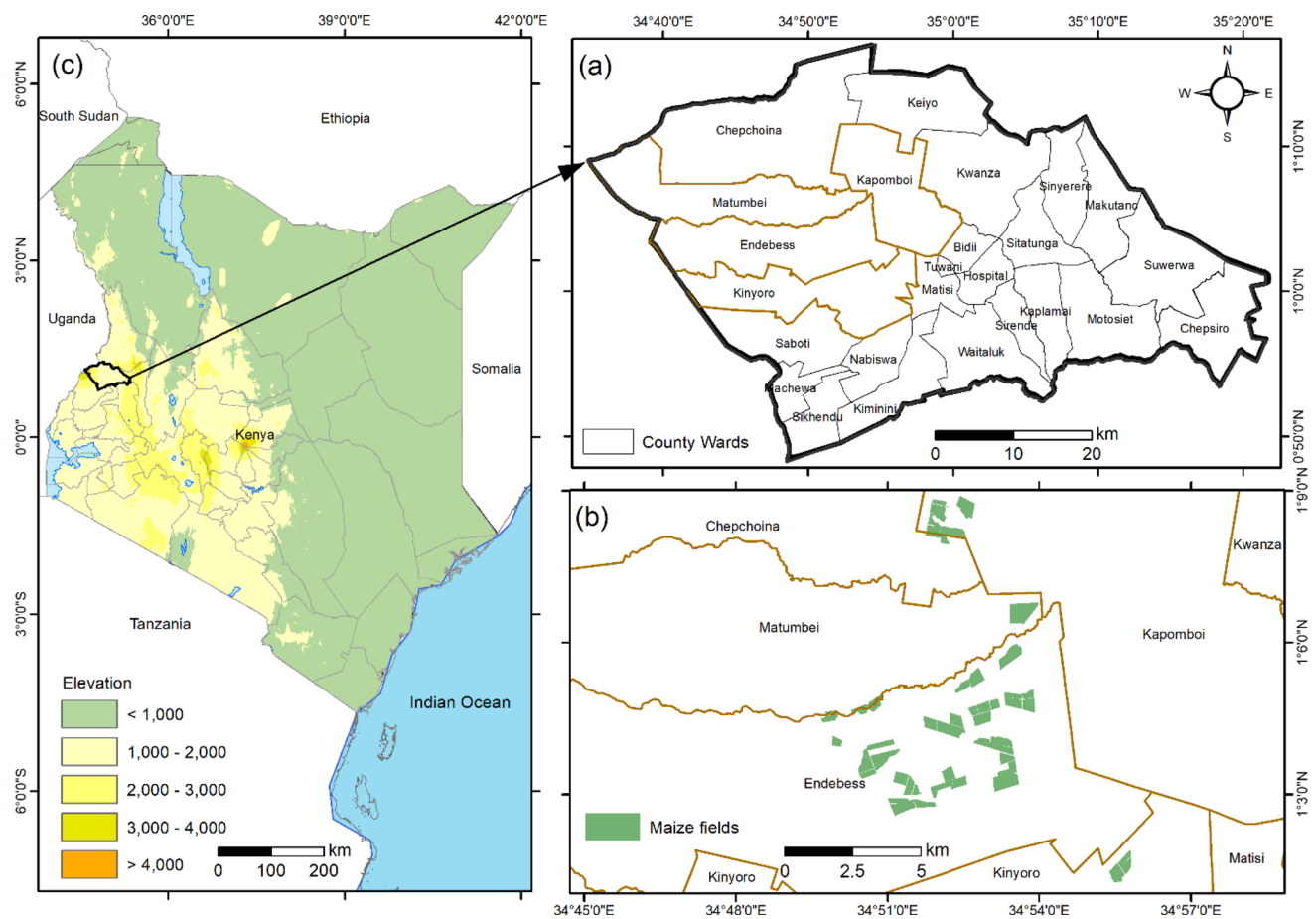
its potential for maize production has not been fully tapped, with current annual yields ranging between 3000 and 4000 kg ha<sup>-1</sup> (GOK, 2020).

### Field Experiments and Data Acquisition

The experimental data for calibrating and evaluating the DSSAT–CERES–Maize model were sourced from 42 pure-stand maize fields in various parts of the county (Fig. 1). The data collection was conducted between March and November 2021, coinciding with the long rainy season in Kenya. The cultivars that were grown in the fields were KH600-23A and H614. KH600-23A is a white, semiflint, late-maturing cultivar owned by the Agricultural Development Corporation (ADC) and first released in 2008. The H614 cultivar is relatively old, stable, and well adopted by farmers and was first released in 1976 in Kenya (Johnson, 1980). The two cultivars were selected mainly because of their high yield potential, resistance to pests and diseases, suitability

to local climatic conditions, and wide adoption by farmers in the region.

Ploughing of the fields was conducted between January and February following practices commonly adopted by farmers in the study area. Afterwards, harrowing was carried out to break up soil caps and obtain a fine seedbed. Sowing varied across the fields between early March and early May 2021. The planting density was 53,333 plants per hectare with a row spacing of 75 cm and a sowing depth of 10 cm. The sowing was conducted according to the recommended inorganic fertilizer rate of 75 kg N ha<sup>-1</sup> (Chebet et al., 2017). Calcium Ammonium Nitrate (CAN) at a rate of 60 kg N ha<sup>-1</sup> was used to provide an additional nitrogen dose at the sixth leaf collar stage (V6) in all fields. Other management practices, including pest, disease, and weed control, were conducted according to standard local procedures. Figure 2 shows maize growth and development at various phenological stages recorded across the experimental sites in the 2021 growing season.



**Fig. 1** Map of the study area: **a** Trans Nzoia County, **b** the distribution of fields used for calibrating and validating the DSSAT-CERES-Maize model, **c** the position of Trans Nzoia County within Kenya.

Background: A 30-m Shuttle Radar Topographic Mission (SRTM) digital elevation model showing the elevation variation



**Fig. 2** Maize growth at the V6, vegetative tasseling, and R1 phenological stages in Trans Nzoia County during the 2021 growing season. The photos were taken at the **a** Sabwani, **b** Olngatongo, and **c** Katuke sites

Independent data for the model evaluation were obtained from experiments conducted in the 2015 planting season for both cultivars as part of research work by Bartolomew et al., (2016). The experiments involved the collection of essential data, including field management, biomass, phenological stages, weather variables, and yield. Similarly, seasonal variables, including soil moisture and LAI, were obtained. Sowing in the 2015 growing season was conducted between 03 March and 28 April under the same nitrogen fertilization rates relative to the 2021 season. Soil analysis was also conducted, and therefore, the physical and chemical characteristics of the soils were adequately represented. The experimental fields in both planting seasons were kept free from weeds using the integration of both herbicides and manual weeding. A mixture of Gavana (Acetochlor 340 g L<sup>-1</sup>, Mesotrione 40 g L<sup>-1</sup>, and Atrazine 200 g L<sup>-1</sup>) and 2, 4-D at a rate of 1 L ha<sup>-1</sup> was applied immediately after sowing. The dates for data collection and recording of vital phenological stages are provided in Table 1.

### Weather and Soil Data

The daily weather variables (minimum and maximum temperatures (°C), precipitation (mm), average global radiation (W m<sup>-2</sup>), relative humidity (%) and daily wind speed (km/h)) for the 2015 and 2021 growing seasons were obtained from three weather stations distributed in the study area. The weather stations include Magero, Kenya Seed Company and Katuke. A complete set of weather variables was available at the Magero weather station (Fig. 3a, b), whereas precipitation amounts and temperature were available at the remaining stations. The data were adjusted to DSSAT format using the WeatherMan data utility program in DSSAT (Pickering et al., 1994).

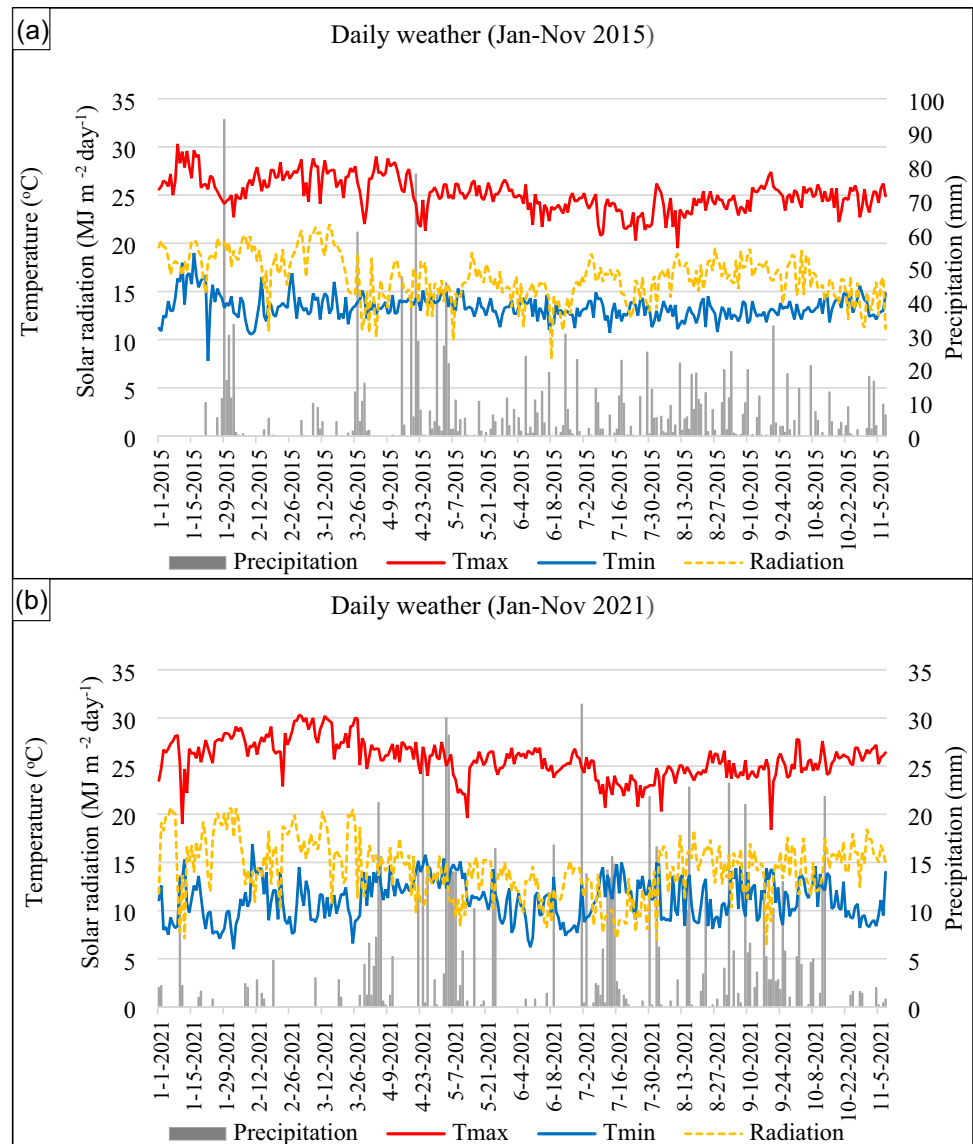
Soil sampling was conducted before sowing to determine both physical and chemical conditions. The physical properties measured include soil texture, water saturation content, and bulk density. The chemical properties were pH in water, cation exchange capacity (CEC), total

**Table 1** Summary of data collected from the experimental sites during the 2015 and 2021 growing seasons

Site	Katuke		Sabwani		Olngatongo	
Growing season	2015	2021	2015	2021	2015	2021
Land preparation	January–March	January–February	January–March	January	January–March	January
Planting/BD	03 March	10 March	28 March	08 March	03 March	27 April
Top dressing	09 May	28 April	13 May	12 May	07 May	02 June
PS						
Emergence	11 March	18 March	04 April	17 March	12 March	27 April
V4	09 April	11 April	01 May	16 April	02 April	20 May
R1	04 July	27 June	28 June	01 July	24 June	04 August
R6	28 October	14 October	29 October	28 October	26 October	06 November
BS						
V6	20 April	28 April	16 May	27 April	23 April	05 June
R1	04 July	14 July	01 August	12 July	08 July	15 August
R6	28 October	21 October	28 October	28 October	01 November	05 November
HS	16 October	23 October	24 October	21 October	22 October	11 November

BD basal dressing, PS phenological stages, BS biomass sampling, HS harvest sampling

**Fig. 3** Daily average air temperature, daily maximum and minimum temperatures, daily precipitation, and daily radiation during **a** 2015 and **b** 2021 maize growing seasons for Magero Weather station (34° 52' E, 01° 05' N)



nitrogen (%N), soil organic carbon (OC), and electrical conductivity (EC). The soil profile properties (each 20–100 cm depth) were obtained in all fields. Table 2 shows the study area's physical and chemical properties of the representative sites.

### DSSAT-CERES-Maize Model Calibration and Evaluation

The 2021 growing season data were used for model calibration and included crop phenology, grain yield, aboveground biomass and leaf area index. Cultivar Specific Parameters (CSPs) for the H614 and KH600-23A

cultivars were calibrated using the DSSAT-Generalized Likelihood Uncertainty Estimation (GLUE) submodule in DSSAT (Jones et al., 2011). The DSSAT-GLUE optimization process adjusts the CSPs (P1, P2, P5, G2, G3, and PHINT) by minimizing the difference between the simulated and observed yields, LAI, and the number of days to attain different phenological stages. In the present study, the phenological parameters (P1, P2, and P5) were calibrated by specifying 6000 runs, followed by a similar number of runs to estimate the growth parameters (G2, G3, and PHINT). The thresholds for phenological and growth parameters were guided by values obtained in other field experiments conducted in the East African region and

**Table 2** Physical and chemical soil analyses for Katuke, Sabwani, and Olngatongo

	TN (%)	PH (water)	OC (%)	EC (Ms/cm)	Sand (%)	Clay (%)	Silt (%)
Katuke							
0–20	0.1	5.48	2.1	0.36	62	24	14
20–40	0.09	5.49	1.3	0.20	64	27	9
40–60	0.08	5.48	1.02	0.29	60	32	8
60–80	0.10	5.64	1	0.27	56	34	10
80–100	0.05	5.78	0.61	0.24	55	37	8
Sabwani							
0–20	0.12	5.53	2.73	0.78	54	27	19
20–40	0.1	6.00	2.58	0.70	55	25	20
40–60	0.08	6.00	1.26	0.43	52	32	16
60–80	0.07	6.3	1.3	0.39	51	35	14
80–100	0.08	6.10	0.92	0.22	39	45	15
Olngatongo							
0–20	0.12	5.75	2.72	0.7	51	28	21
20–40	0.11	6.3	1.93	0.66	49	37	14
40–60	0.06	6.92	1.29	0.76	42	43	15
60–80	0.06	6.84	0.92	0.71	40	48	12
80–100	0.05	7.22	0.88	1.12	36	51	13

TN total nitrogen, OC organic carbon, EC electrical conductivity, and pH potential hydrogen ions in water

subsequently adjusted for in the parameter file (Gummadi et al., 2020; Mourice et al., 2014).

The DSSAT-CERES-Maize model was evaluated using observed grain yield from field experiments conducted in the 2015 growing season. The CSPs derived from the calibration process were used to assess the robustness of the model for both cultivars in Trans Nzoia County. The model's ability to simulate soil water content was also evaluated. In the three experimental sites, soil moisture analysis was conducted at sowing, emergence, sixth leaf collar stage, silking, and grain filling. The computed values were then compared with the DSSAT-CERES-Maize simulations of soil water balance. The evaluation of the DSSAT-CERES-Maize model was essential for model application.

### Statistical Evaluation and Model Performance Analysis

Statistical metrics, root mean square error (RMSE), relative mean square error (RRMSE) and mean absolute error (MAE), were used to quantify the goodness of fit of the DSSAT-CERES-Maize model simulations against the observed data (Ali & Abustan, 2021). The metrics evaluate the statistical distances and dispersion between the actual and simulated values to determine the model skill scores for model outputs. Additionally, we assessed the model skill score using Willmott's index of agreement (IOA) (Willmott, 1981). The statistical metrics are computed using Eqs. 1, 2, 3, 4, 5.

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^n (\hat{y}_i - y_i)^2}{n}} \quad (1)$$

$$\text{RRMSE} = \sqrt{\frac{\sum_{i=1}^n (\hat{y}_i - y_i)^2}{n}} \times \frac{100}{m} \quad (2)$$

$$\text{MAE} = 1/n \sum_{i=1}^n |\hat{y}_i - y_i| \quad (3)$$

$$\text{IOA} = 1 - \frac{\sum_{i=1}^n (\hat{y}_i - y_i)^2}{\sum_{i=1}^n (|\hat{y}_i - \bar{y}_i| + |y_i - \bar{y}_i|)^2} \quad (4)$$

where  $n$  is the number of observations,  $\hat{y}_i$  is the predicted value,  $y_i$  is the observed value, and  $m$  is the mean of the observations.

The root mean square error measures the average difference between the predicted values and the actual observations. The RRMSE statistical measure shows the error as a fraction of the average measured values, while MAE expresses the average absolute deviation between the predicted and measured values. RMSE and MAE values of zero indicate a perfect fit (Moriasi et al., 2007). A low value of RMSE and MAE indicates predicted values that tend to be close to the observed

values. A RRMSE value of less than 20% is considered good, while between 20 and 30% is considered fair. Wilmott's IOA represents the ratio between the sum of squared errors and a 'potential error' obtained by the sum of squared absolute values of deviations from the observed values to the mean observed values. A value of 1 indicates a perfect model fit, and a value of zero indicates a poor fit.

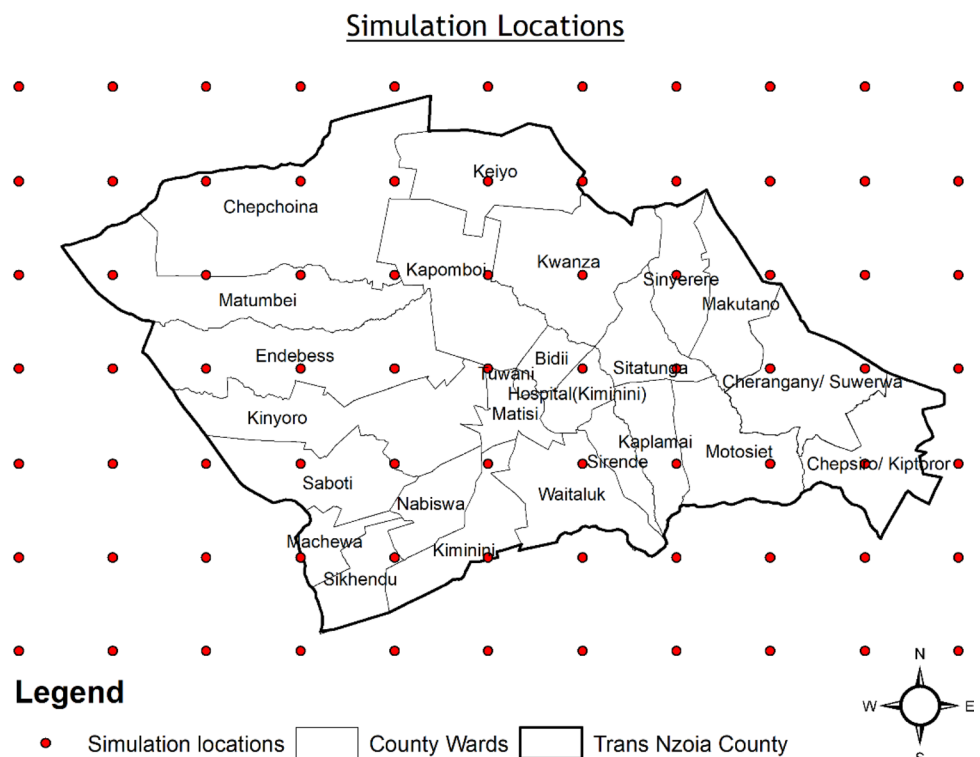
### Impact Assessment of the Agricultural Management Strategies

The responses of various management strategies to yield were evaluated at the county scale using the validated model. Accordingly, long-term (1984–2021) yield simulations were conducted at 77 sites in the study area (Fig. 4). The sites correspond to soil profile locations from the global high-resolution soil database for crop modelling applications (Han et al., 2015). The dataset was synergistically generated by combining ISRIC SoilGrids (<http://soilgrids.org/>) and the AfSIS (<http://africasoils.net/>) projects, yielding global soil information at a 10 km resolution ( $0.10^\circ \times 0.10^\circ$ ). Each selected location had the physical and chemical properties required by the DSSAT model simulations. The data attributes included bulk density, organic carbon, clay percentage, silt percentage, soil pH, and cation exchange capacity at various soil profile levels. In addition, soil hydraulic properties, including saturated hydraulic conductivity, soil water content at field capacity, wilting point, and saturation, were

estimated using pedo-transfer functions (Han et al., 2019). The global high-resolution soil database for crop modelling applications also contained country-specific data. SOL files. These files were merged with the point shapefile to extract the soil profile properties at various soil depths.

The 77 locations were also used to extract weather variables from weather databases. Long-term precipitation data were sourced from the Climate Hazards Infrared Precipitation (CHIRPS) (Funk et al., 2015). The global product has been generated by blending satellite and observed station data. CHIRPS has provided reliable weather data for conducting environmental assessments, especially in the context of SSA, where weather station coverage is poor and with incidences of missing data (Kiprotich et al., 2021; Sacré Regis et al., 2020). Daily CHIRPS precipitation datasets covering 1984–2021 were accessed and extracted for the selected locations using the Google Earth Engine (GEE) and saved in table format. Daily solar radiation and minimum and maximum temperature data for the same period were obtained from the National Aeronautics and Space Administration (NASA) Langley Research Center (LaRC) Prediction of Worldwide Energy Resources (POWER) using the *nasapower* package in R (Sparks, 2018). The weather files were prepared according to the DSSAT input-specific format using the Weatherman Version 4.7.5.0 tool in DSSAT (Pickering et al., 1994). Together with management and the imported soil grids, simulations for the strategies were conducted, and statistical yield metrics such

**Fig. 4** Locations used in simulating long-term (1984–2021) maize yield in Trans Nzoia County





as the mean, standard deviation, and variance were used for further analysis.

The present study evaluated 60 independent factorial combinations from four management strategies. The management strategies comprised five sowing dates (15 February, 01 March, 15 March, 01 April, and 15 April), two water management strategies (rainfed and irrigation at 40 mm 40 days after sowing), and three nitrogen levels (N1 = 30 kg ha<sup>-1</sup>, N2 = 50 kg ha<sup>-1</sup>, and N3 = 75 kg ha<sup>-1</sup>), all for the two different cultivars CV1 = H614 and CV2 = KH600-23A. The evaluation was conducted for each cultivar and covered 38 years (1984–2021). The five sowing dates correspond to very early, moderately early, early, mid, and late sowing dates, which are regular sowing practices in the region. The 30 N kg ha<sup>-1</sup> corresponds to the low nitrogen application rate, and the 50 and 75 N kg ha<sup>-1</sup> represent the conventional and the recommended nitrogen fertilization rates, respectively (Chebet et al., 2017). Four weeks after planting, an equal amount of nitrogen was top dressed in the form of urea for each fertilization strategy. The assessment of water management tested the effect of providing supplementary irrigation to support early growth under situations of late precipitation onset or inadequate precipitation.

The multi-factorial analysis of variance (ANOVA) analyzed the 60 management strategies to identify whether (a) individual management strategies and (b) whether multi-factorial feedback mechanisms impact maize yield (Chambers et al., 2017). ANOVA estimates multi-variate best-fitting linear combinations for the different combinations of management strategies on yield. Based on these linear combinations and residuals, the H<sub>0</sub>-hypothesis ‘there are no feedbacks between the management strategies’ was tested at a significance level (p = 5%). If the calculated p value is less than or equal to the significance, the test is significant, and the H<sub>0</sub>-hypothesis is to be rejected. This would indicate with a high probability that yield is not independent of the management strategies. For the multi-factorial ANOVA, the test shows whether feedbacks amongst multiple factors are detectable. The ANOVA variance was calculated using the ‘aov’ function in the ‘dplyr’ package (Wickham & François, 2014) of the R programming software (R Core Team, 2020).

### Maize Yield Trends and Stability

The trend of maize yield under the management strategies was analysed using the Mann–Kendall (MK) (Kendall, 1975; Mann, 1945) and Sen’s Slope Estimator (SSE) (Sen, 1968) statistical tests. MK is a nonparametric test that detects the monotonic trend in time series data. The method’s tau statistic shows whether the monotonic trend is increasing or decreasing. The p value score shows the significance or nonsignificance of the monotonic trend at a 5% significance level.

The MK test is mathematically expressed as:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sgn}(X_j - X_i) \tag{5}$$

where n represents the time series data points (X<sub>1</sub>, X<sub>2</sub>, …, X<sub>n</sub>) and sgn is a value assigned to each data point based on the difference between each pair of time series data. The conditions for sgn are:

$$\text{sgn}(X_i - X_j) = \begin{cases} 1 & X_j > X_i \\ 0 & X_j = X_i \\ -1 & X_j < X_i \end{cases} \tag{6}$$

Kendall’s tau τ is computed as:

$$\tau = \frac{S}{0.5n(n-1)} \tag{7}$$

Accordingly, τ ranges from – 1 for a monotonic negative trend to + 1 for a monotonic positive trend.

The SSE statistic (Eq. 8) indicates the magnitude and direction of the trend. The statistic is a ratio of the difference between data points and their respective ranks. SSE is expressed as:

$$\text{SSE} = \frac{X_j - X_k}{j - k} \quad j > k \text{ for } i = 1, 2, \dots, n \tag{8}$$

where n represents the time steps, and j and k represent the ranks of the data points. Accordingly, the n values are arranged from smallest to largest in the calculation of the SSE.

The SSE magnitude is computed as the median value of the slopes using Eq. 9.

$$Q = \begin{cases} \text{SSE}_{[(n+1)/2]} & \text{when } n \text{ is an odd number} \\ 0.5 * \left( \text{SSE}_{\frac{n}{2}} + \text{SSE}_{[\frac{n+1}{2}]} \right) & \text{when } n \text{ is an even number} \end{cases} \tag{9}$$

The MK technique is robust in handling outliers and can effectively model space–time data. Furthermore, it tolerates skewed distributed data and thus transcends the assumptions present in parametric tests (Hamed, 2008). The trend analysis was based on the long-term (1984–2021) annual maize yield simulations. The trend analysis was conducted at the pixel level to provide insights into spatial variation and involved only those strategies with significant effects based on the factorial ANOVA.

Mann Kendall and SSE statistical tests have currently gained traction in assessing maize yield responses to trends of meteorological variables (Gadedjisso-Tossou et al., 2020; Mumo et al., 2018). Other studies have extended the capabilities to evaluate maize yield trends in evolving climates

(Bekuma Abdisa et al., 2022; Ojara et al., 2022; Zhang & Lu, 2021). Therefore, the 38 years of yield simulations from a well-calibrated and evaluated DSSAT-CERES-Maize model were analysed in the study region. Point-based yield estimations were interpolated to produce continuous raster surfaces using the kriging technique in the ArcGIS environment. The raster surfaces for the management strategies were then subjected to trend analysis using the 'raster' and 'Kendall' packages in R statistical software (Hijmans et al., 2022; McLeod, 2005). The 'calc' function from the Kendall package generated surfaces of Kendall's tau, p values, and Sen's slopes. The raster surfaces for the p values (not shown) were significant at a 5% significance level.

## Results

### DSSAT–CERES–Maize Model Calibration

The DSSAT–CERES–Maize model calibration results using GLUE for cultivars H614 and KH600-23A are shown in Tables 3 and 4, respectively. The accuracy of the simulations from the calibrated CSPs (Table 3) was assessed by comparing the simulated days to anthesis, days to maturity, LAI, and dry weight at harvest to the corresponding observations (Table 4). The results revealed excellent agreement between the model simulations and the measured parameter values. The simulated days to

**Table 3** Calibrated CSPs for the H614 and KH600-23A cultivars

	P1 (°C day)	P2 (day)	P5 (°C day)	G2 (No. Kernels/ear)	G3 (mg/day)	PHINT (°C day)
H614	290.8	0.471	921.2	796.8	5.26	39.74
KH600-23A	345.6	0.5	971.2	777.3	7.12	36.78

P1-Thermal time from seedling emergence to the end of the juvenile phase (expressed in degree days above a base temperature of 8 °C) during which the plant is not responsive to changes in photoperiod

P2-Extent to which development (expressed as days) is delayed for each hour increase in photoperiod above the longest photoperiod at which development proceeds at a maximum rate (which is considered to be 12.5 h)

P5-Thermal time from silking to physiological maturity (expressed in degree days above a base temperature of 8 °C)

G2-Maximum possible number of kernels per plant

G3-Kernel filling rate during the linear grain filling stage and under optimum conditions (mg/day)

PHINT-Phyllochron interval, the interval in thermal time (degree days) between successive leaf tip appearances

**Table 4** The DSSAT–CERES–Maize model calibration statistics for anthesis, physiological maturity, LAI, and grain yield for maize cultivars H614 and KH600-23A

	H614					
	Observed mean n=42	Simulated mean n=42	MAE	RMSE	RRMSE (%)	IOA
Anthesis (DAS)	98	97	1	2	2.0	0.95
Maturity (DAS)	191	198	1	2	1.0	0.89
Maximum LAI (m <sup>2</sup> m <sup>-2</sup> )	3.82	3.70	0.29	0.35	9.2	0.69
Grain yield (kg DW ha <sup>-1</sup> )	4150	4134	264.8	332.9	8.1	0.75
	KH600-23A					
	Observed mean n=36	Simulated mean n=36	MAE	RMSE	RRMSE (%)	IOA
Anthesis (DAS)	106	108	7	8	3	0.92
Maturity (DAS)	209	206	6	7	3.4	0.48
Maximum LAI (m <sup>2</sup> m <sup>-2</sup> )	3.9	4.2	0.44	0.50	12.8	0.58
Grain yield (kg DW ha <sup>-1</sup> )	5209	5316	185.3	238.6	5.1	0.81

DW is dry weight, LAI is leaf area index, and DAS is days after sowing

anthesis were in close agreement with the observed days for both cultivars. However, the model slightly underestimated the anthesis for the H614 cultivar and overestimated the anthesis for the KH600-23A cultivar. The opposite was, however, noted in the simulation of the days to maturity. In this case, the model overestimated the days to physiological maturity for the H614 cultivar and underestimated those for KH600-23A.

The simulated and observed days to anthesis and maturity statistical values ranged between 1 and 7 days for MAE, 2 and 8 days for RMSE, and 0.48 and 0.95 for IOA for both cultivars. The IOA value for KH600-23A was low compared to that of the H614 variety, implying that the model simulations for the latter agreed well with the observations (Willmott, 1984). Additionally, the LAI and yield simulations for both cultivars were adequately simulated. The LAI RMSE was 0.35 (H614) and 0.44 (KH600-23A). Both cultivars displayed RRMSE values below 13% for the LAI, signifying good model performance. The grain yield RMSE values were below 350 kg ha<sup>-1</sup> for both cultivars, indicating excellent model performance. The obtained accuracies demonstrate the credibility of the CERES-Maize model in representing genetic variation in Trans Nzoia County.

### DSSAT-CERES-Maize Model Evaluation

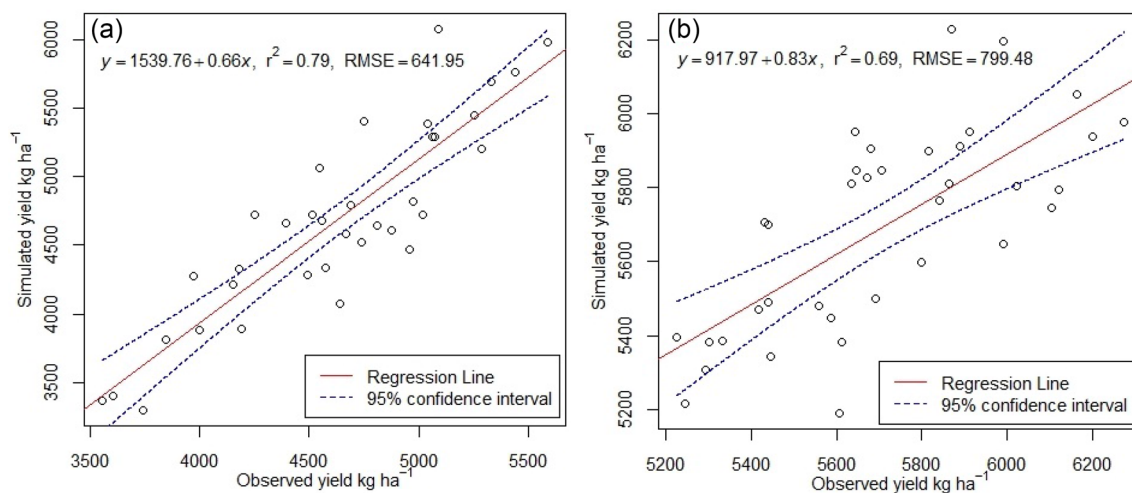
The model performance was evaluated independently using experimental data from the 2015 growing season. Grain yield (Fig. 5) and soil water content were the variables with complete data at all sites and were therefore used for the evaluation (Figures S3-S5 in the supplementary file). The assessment of the DSSAT-CERES-Maize model showed high accuracy, with RMSE values of 642 and 810 kg ha<sup>-1</sup>

for the H614 and KH600-23A cultivars, respectively. The plot showed that the model underestimated low yields and overestimated high yields for the H614 cultivar. For the KH600-23A cultivar, the overestimation of yields was more pronounced across the different yield ranges. For example, in some fields, the model overestimated yields by about 400 kg/ha (Fig. 5b). The overestimation increased the RMSE error and decreased the coefficient of determination relative to the H614 cultivar. However, the DSSAT-CERES-Maize model reliably characterized the maize growth conditions of the cultivar types in the study area. In addition, the model represented well the soil water content across the different crop phenological stages. The measured versus simulated soil water balance comparisons showed a close agreement between the measured and model simulated values (Figures S3-S5 in the supplementary file).

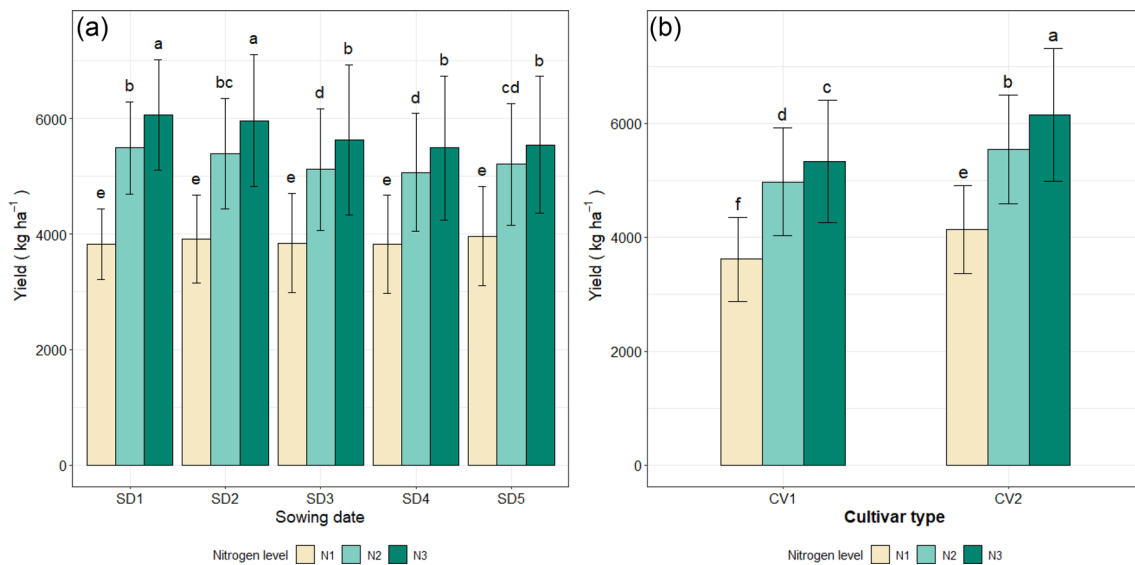
### Impact Assessment of the Agricultural Management Strategies

The calibrated and evaluated model identified feasible strategies for enhancing yields in the study region. The results from the Tukey-HSD (Fig. 6) and the factorial ANOVA (Table 5) are presented.

The main effects of three independent management strategies, sowing dates, cultivars, and nitrogen levels, were significant ( $p < 0.05$ ) based on the factorial ANOVA. However, the main effect of the water management strategy was not significant. The model simulated high yields and low yield variability for early sowing dates (Figure S1a of the supplementary file). The earliest sowing date (SD1) revealed the highest average yield of 5124 kg ha<sup>-1</sup> and the lowest standard deviation of 1244 kg ha<sup>-1</sup>. SD4 showed the lowest average yield of 4790 kg ha<sup>-1</sup>, while the



**Fig. 5** Comparison of observed and simulated grain yield for the **A** H614 and **B** KH600-23A cultivars using experimental data for the 2015 maize growing season. The solid red line indicates the regression line, and the dashed blue lines are the 95% confidence interval



**Fig. 6** DSSAT-CERES-Maize simulated yields under **a** various nitrogen fertilization rates and sowing dates interactions and **b** nitrogen fertilization rates and cultivars interactions. SD1, SD2, SD3, SD4, and SD5 are sowing dates corresponding to mid-February, early March, mid-March, early April, and mid-April, respectively. N1, N2,

and N3 nitrogen levels at 30, 50 kg ha<sup>-1</sup>, and N3=75 kg ha<sup>-1</sup>. CV1 and CV2 show H614 and KH600-23A cultivars. The bar charts represent the mean, and the error bars represent the standard deviation. Treatments that share a common letter are not significantly different ( $p > 0.05$ )

**Table 5** Results of the factorial ANOVA showing the main effects and their interactions on maize yield in Trans Nzoia County

Strategy	Df	Sum Sq	Mean Sq	F value	Pr (> F)
SD	4	7.76E+07	1.94E+07	21.754	<0.001**
CV	1	4.69E+08	4.69E+08	525.574	<0.001**
N	2	2.89E+09	1.45E+09	1620.523	<0.001**
WM	1	3.30E+06	3.30E+06	3.701	0.05
SD:CV	4	7.41E+06	1.85E+06	2.077	0.081
SD:N	8	4.98E+07	6.22E+06	6.978	<0.001**
CV:N	2	1.96E+07	9.78E+06	10.968	<0.001**
SD:WM	4	1.05E+05	2.63E+04	0.029	0.100
CV:WM	1	2.55E+03	2.55E+03	0.003	0.957
N:WM	2	1.28E+05	6.41E+04	0.072	0.930
SD:CV:N	8	1.40E+06	1.75E+05	0.196	0.992
SD:CV:WM	4	1.24E+05	3.11E+04	0.035	0.1
SD:N:WM	8	1.73E+05	2.17E+04	0.024	1
CV:N:WM	2	3.55E+04	1.77E+04	0.02	0.980
SD:CV:N:WM	8	4.51E+04	5.64E+03	0.006	1
Residuals	4560	4.07E+09	8.92E+05		

Significance. Codes: 0 '\*\*\*\*' 0.001 '\*\*\*' 0.01 '\*\*' 0.05 '\*' 0.1 '.' 1

SD sowing date, N nitrogen, CV cultivar, WM water management

highest variability was observed on the SD3 date (standard deviation = 1320 kg ha<sup>-1</sup>). The nitrogen fertilization effect on yield showed that the highest nitrogen rate (N3) could yield an average of 5738 kg ha<sup>-1</sup> (Figure S1b of the supplementary file). The variability under this nitrogen rate

was similarly high (standard deviation = 1195 kg ha<sup>-1</sup>). The lowest nitrogen application rate had the lowest average yield (3872 kg ha<sup>-1</sup>) and variability (standard deviation = 795 kg ha<sup>-1</sup>). The mean yield for cultivar CV1 was 4636 ha<sup>-1</sup> (Figure S2 of the supplementary file), with a

standard deviation of 1188 kg ha<sup>-1</sup>. CV2 revealed the highest average yield (5273 kg ha<sup>-1</sup>) and variability (standard deviation = 1291 kg ha<sup>-1</sup>).

The factorial ANOVA further revealed significant effects in the interactions of the main effects (Fig. 6). The interaction between sowing dates and nitrogen fertilization was significant at the 5% significance level. Early sowing dates and the highest nitrogen level revealed the highest yields. SD1 and N3 fertilization had the highest yield of approximately 6062 kg ha<sup>-1</sup>. SD1 and SD2 interaction with the highest nitrogen fertilization rate showed significantly higher yields than late sowing dates. Similarly, N2 fertilization interaction with early sowing dates showed significantly higher yields than late sowing dates. The average yields under the nitrogen levels N2 and N3 decreased as the sowing dates advanced gradually, and the variability also increased. The KH600-23A cultivar revealed high yields (6148 kg ha<sup>-1</sup>) under N3 nitrogen application. The H614 cultivar showed low yields (3611 kg ha<sup>-1</sup>) under the lowest nitrogen fertilization (N1). The results revealed the lowest yield deviation between the highest and the lowest fertilization levels compared to the KH600-23A cultivar. The results confirm nutrient availability as a yield-limiting factor in the study region.

The interaction effect of the sowing dates and cultivars was not significant. Additionally, sowing dates and water management interaction strategy did not show a significant effect. This was also similar to the third-order management interactions. Based on the evaluation of the management strategies, the combination of the early sowing dates, the KH600-23A cultivar, and the highest nitrogen fertilization was found to be a feasible strategy for enhancing maize yield in the study area. Sowing in late February and early March may be beneficial to farmers in boosting yields. The statistics showed that farmers could improve production by 52% if cultivar KH600-23A was planted in mid-February under nitrogen fertilization of 75 kg ha<sup>-1</sup> with equal top dressing amount compared to the latest sowing date, with low nitrogen level and the slightly low yielding H614 cultivar.

The application of supplementary irrigation did not substantially affect maize yield (Table 5). The main effect of water management showed no significant effect on maize yield. This means that the precipitation in the region is currently sufficient for maize growth, and any moisture enhancement at the early vegetative stage may not significantly impact maize production. Similarly, the water management interaction with both cultivar and nitrogen levels did not significantly affect maize yield. A similar effect was observed for the third-order interactions of water management and other strategies.

## Maize Yield Trends

The SSE was used to evaluate the yield trends for the high potential management strategies. Consequently, the early sowing date (SD1) was used to model the trend and magnitude of the long-term yield simulations. The analysis informed regions in our study area where particular management practices should be intensified. Maps (Fig. 7) were used to visualize the spatial variation in the magnitude results from the MK and SSE tests.

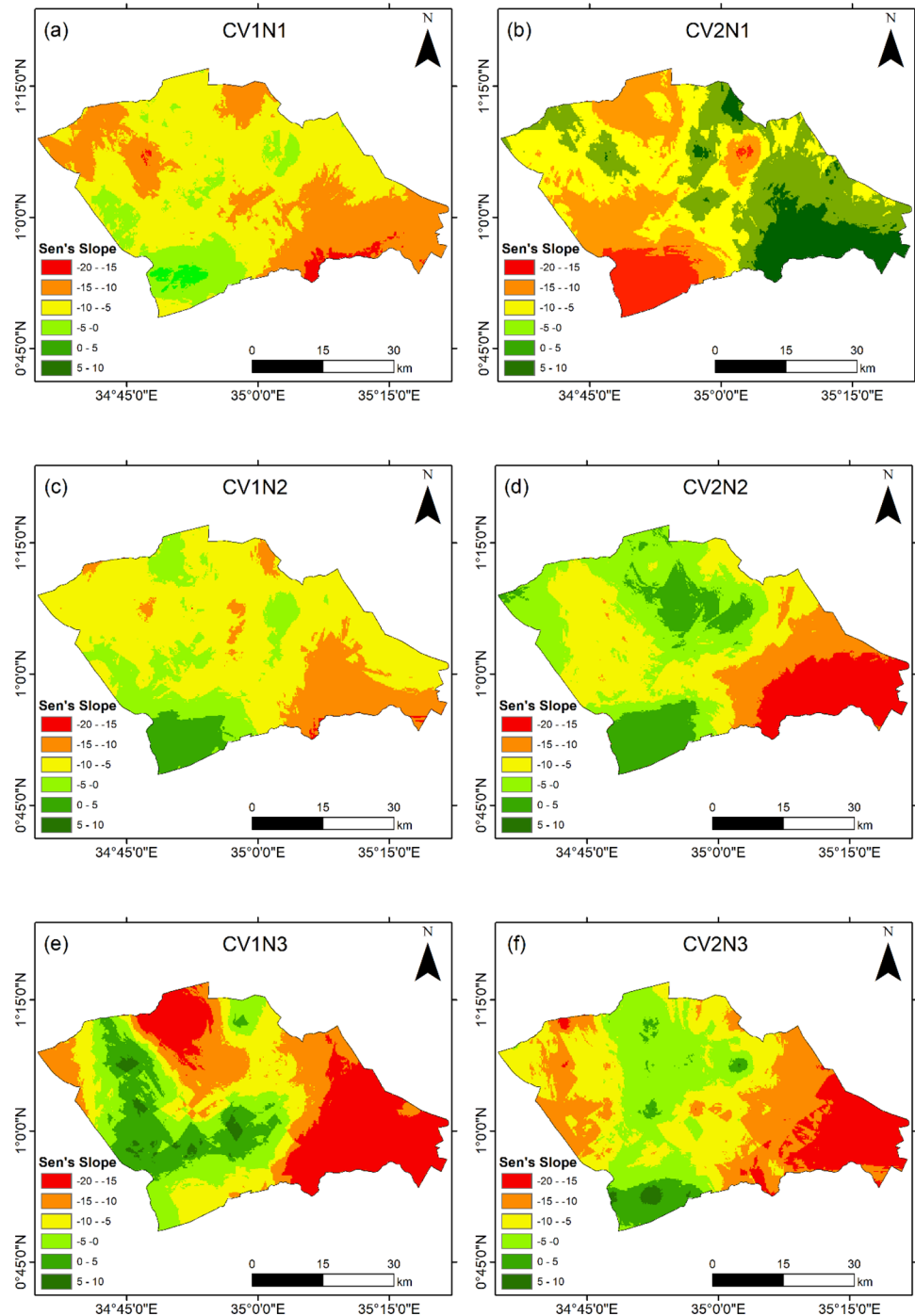
The SSE variation from the MK trend analysis revealed the varied magnitude of yield trends in the region. The maps showed a significantly decreasing trend in most parts of the study region (light green to red colour). Some areas in the northern and southern parts of the county indicated a significant increasing trend under various management practices. The eastern region of the county showed a significantly decreasing trend in yields, and the decrease was more pronounced under high nitrogen levels. The decrease influenced both cultivars in the eastern regions of the county. In contrast, the significant positive magnitude of the H614 cultivar was higher than that of KH600-23A in the western region under the high nitrogen level. In addition, the results revealed a modest yield decrease in the H614 cultivar under nitrogen levels N1 and N2.

## Discussion

### Calibration and Evaluation of the DSSAT-CERES-Maize Model

The present study calibrated and evaluated the DSSAT-CERES-Maize model using multiseason experimental data in Trans Nzoia County. The model was further applied to assess various agricultural management strategies and their effects on maize yield. Generally, the model statistics from the calibration and evaluation processes showed excellent performance of the DSSAT-CERES-Maize model in simulating maize growth and development in the study region. The model's credibility was indicated by the low RMSE and MAE values and a high IOA between the observed yield and the simulated values. Additionally, the simulation of phenological development and grain yield at maturity were within the acceptable thresholds (<10%) and (<20%), respectively, according to Jamieson et al., (1991). The accuracy of the DSSAT-CERES-Maize model for maize yield simulation aligned with other studies in Kenya that calibrated and evaluated the model for various applications (Aluoch et al., 2022; Gummadi et al., 2020). In addition, other studies conducted in the wider East Africa and SSA

**Fig. 7** Maps indicating the spatial variation in the magnitude of the maize yield trend for the study area under the early sowing date (SD1). Light green to red colour shows a monotonically decreasing trend, whereas forest green to dark green indicates a monotonically increasing trend in maize yields. The variations for cultivar H614 at nitrogen levels N1, N2, and N3 are represented by maps (a), (c), and (e), respectively. Maps (b), (d), and (f) show the variation in cultivar KH600-23A at nitrogen levels N1, N2, and N3. The generated surfaces were statistically significant at  $p$  value  $< 0.05$  (maps not shown)



regions found robust accuracies in the CERES-Maize model calibration and evaluation under various managements (Chisanga et al., 2020; Mourice et al., 2015; Volk et al., 2021). Other studies that tested nitrogen and irrigation applications achieved relative accuracies to our study in predicting maize yield (Malik et al., 2019). Similarly, studies that evaluated the model's performance in simulating phenological stages found comparable results to our findings (Feleke et al., 2021).

### Simulation of Agricultural Management Strategies

The main management strategies with respect to sowing dates, nitrogen levels, and cultivars revealed significant influences on maize yield in the region. Based on the results, early sowing dates, especially SD1, contributed to the highest yield outcome. The effect could be attributed to the interplay of factors, including the suitability of weather conditions at various plant stages and the duration of the

linear and exponential grain-filling phases (Tsimba et al., 2013). Sowing date is a critical factor in crop growth, as it influences the amount of intercepted radiation and its contribution to photosynthesis (Honnaiah et al., 2021). Additionally, the different sowing dates may have influenced the attainment of particular phenological stages, for example, the grain-filling stage, which is highly sensitive to weather variation (Zhou et al., 2017). The early sowing allows the vegetative and grain-filling stages to coincide with the high rainfall experienced in May and July in the region. Therefore, moisture deficiency is reduced, and the plant attains the maximum possible kernels per ear (Walne & Reddy, 2022). The benefits of early sowing dates on crop growth and yields have been confirmed by other studies conducted in western Kenya (Almekinders et al., 2021). Crop modelling applications in the African continent also revealed that production is highly dependent on planting windows (Chisanga et al., 2019; MacCarthy et al., 2018; Tofa et al., 2020).

The main effect of the cultivar revealed a huge potential of the KH600-23A cultivar for enhancing yields in the region. The cultivar is relatively new, with a yield potential between 9.5 and 15 tonnes per hectare, out-performing other cultivars that have been in existence (Wamalwa, 2013). H614 is one of the oldest cultivars and is popular among farmers, especially in high-altitude regions (Almekinders et al., 2021). According to Obunyali et al., (2019), new cultivars are slowly being adopted due to a lack of performance data under farmers' conditions. The assertion suggests that evaluating various cultivars in different production conditions is crucial for agrotechnology transfer and farmers' adoption. The calibration results from the present study showed that the KH600-23A cultivar needed more heat units to attain the juvenile and physiological maturity stages than the H614 cultivar. The difference in crop life cycles of the cultivars is a possible explanation for the variation in yield response. Other studies that assessed the response of maize growth cycles found differences in yield resulting from unique cultivar traits (Lana et al., 2017).

The contribution of the main effect of nitrogen application levels on the maize yields was also significant. The lowest nitrogen application level (N1) attained significantly lower yields than the recommended nitrogen level. In Kenyan and African landscapes, nitrogen is the most limiting factor in maize production, and its supply in optimum quantities improves yields (Yue et al., 2021). The nitrogen application rates in the region fall short of the required amounts for better yield production (Pasley et al., 2020). In addition to the poor soil fertility in Kenya, other nutrient enhancement barriers include soaring fertilizer prices and land degradation that exacerbate nutrient depletion (Chebet et al., 2017; Kiboi et al., 2021; Nathan et al., 2022). Therefore, soil nutrient mining without replenishment efforts

or amendments significantly hampers soil productivity and leads to lower yields. Consistent with the current assessment, studies conducted in nitrogen-limited conditions in Kenya's western region showed that an increase in inorganic and organic fertilizer resources significantly increased maize yield (Chebet et al., 2017). The same observations were also noted in other studies conducted in central Kenya (Jindo et al., 2020; Oduor et al., 2021). Therefore, opportunities for enhancing nitrogen fertilization are paramount, given the high nitrogen use efficiency in Kenyan environments (Bonilla-Cedrez et al., 2021).

Supplementary irrigation 40 days after sowing did not increase maize yields as anticipated. Trans Nzoia County falls within Kenya's humid and subhumid agroclimatic zones (Kabubo-Mariara & Karanja, 2007). These zones are characterized by sufficient moisture and low evapotranspiration levels. Deep and highly porous clay soils characterize the present study region with good water retention capacity (Muchena & Gachene, 1988). The current study tested the supplementary irrigation potential six weeks after sowing. The period coincides with the onset or continuity of the long rains; therefore, increasing the water supply in the model simulations may not impact the harvested yields. During this time, soil water is sufficient, and therefore, any additional amount of water has a minimal effect on yield. Based on a long-term assessment of rainfall characteristics in western Kenya by Mugalavai et al., (2008), Trans Nzoia County receives annual mean rainfall amounting to over 1200 mm and equally early rainfall onsets. Additionally, Bryan et al., (2013) reported that in humid sites with adequate rainfall, soil water conservation measures might have a limited effect on yield, sometimes resulting in reduced yield due to increased nitrogen leaching. Our findings are corroborated by Torrión and Stougaard, (2017), who found a poor irrigation response on the harvest index in the Montana region of the United States. The study found a positive influence of the practice on yields only during hot and dry years.

The interaction effects of sowing date and nitrogen level significantly impacted maize yield. Similarly, nitrogen levels and cultivar interactions had a significant effect on maize yield. The study revealed that high nitrogen levels and early sowing dates combined with the high-yielding cultivar increased regional production. Chisanga et al., (2021a) also noted the significance of the interaction of sowing dates and nitrogen fertilization on maize yield and yield components in the Zambian agricultural landscapes. Sowing dates affect the accumulated temperature units and duration of radiation interception, which influences nitrogen uptake and utilization efficiency (Caviglia et al., 2014). Synchronizing fertilizer amounts with sowing dates can increase nitrogen use efficiency, especially under optimum weather conditions (Hussain et al., 2022). Srivastava et al. (2018) also found

the significance of sowing dates and fertilization rate on nitrogen use efficiencies and losses in maize production. Similarly, the interaction effects of cultivar and nitrogen were significant, with KH600-23A and high nitrogen fertilization levels showing the most feasible strategy for increasing maize yields. Abera et al. (2017) similarly found a significant interaction effect between improved maize varieties and grain yield.

### Maize Yield Trend Analysis

Based on the trend analysis, the management strategies demonstrated spatial variation in yield variation. The response of the management strategies to the increasing and decreasing trends in yield varied across the study region. The results indicated that the southern and western parts of Trans Nzoia County respond better to maize yield increase than the eastern regions. Maize yield in the eastern region showed a decreasing trend of up to 20 kg ha<sup>-1</sup> annually. However, the trend in the western and southern parts demonstrated an increase of up to 10 kg ha<sup>-1</sup>. A possible explanation for this observation is the varying soil and weather conditions unique to the region. While the western part of Trans Nzoia County is characterized by soils of Humic Nitisol and Cambisol origin with high water-holding capacities, the eastern part is dominated by Ferralsols and Regosols with limited water-holding capacities and poor chemical properties. The poor condition of soils has motivated farmers to invest in organic manures and leguminous trees as alternatives to improving soil fertility (Nekesa et al., 2007). In addition, the western and southern regions of Trans Nzoia receive high rainfall (Trans Nzoia County Government, 2018).

The spatial assessment of the yield magnitude showed a modest decrease under low nitrogen fertilization than under high nitrogen fertilization, especially in the eastern parts of the county. A possible reason for this finding is that the combined precipitation and nitrogen effects may have resulted in a higher loss of nutrients. A study on leaching and fertilizer losses in western Kenya showed that leaching is significantly lower in drought seasons (Russo et al., 2017). Compounded with highly porous and well-drained soils in the eastern region of Trans Nzoia County, the leaching of nutrients might have been the reason for the high decrease in yields under the highest nitrogen level. Our study revealed yield enhancement spots where management needs to be upscaled to optimize resource use and enhance production. Tailored measures for improving nutrient use efficiency in the eastern region are feasible, whereas an increase in fertilizer application may improve yields in the northern parts. The testing of supplementary irrigation at different stages may also be conducted to investigate the effect of irrigation on yields in

this region. Our study found no significant impact of early irrigation on maize yield. However, examining scheduling and varying irrigation levels at various crop stages may further reveal significant effects.

The performance of the DSSAT–CERES–Maize in modelling maize growth conditions and production in Trans Nzoia County was evaluated with satisfactory model accuracies for yield and phenological stages predictions. However, it should be noted that crop models have inherent limitations that stem from input data, calibration processes, and evaluation procedures. As such, the model might not account for all the functions in the plant, soil, and atmosphere continuum. As such, some biotic and abiotic factors that influence plant growth and production may not be fully accounted for by the model. For example, the DSSAT–CERES–Maize has no modules for modelling pests, disease and weed effects (Lin et al., 2015). Also, the crop model parameters are relevant for regions where the data was sourced, calibrated and evaluated. The conditions underpin the validity of the model for application in local environments where environmental conditions are adequately represented. Transferring these parameters to other locations with significant shifts in environmental factors may result in large model uncertainties.

### Conclusion

This present study on multi-management maize yield assessment underpins the merits of cultivars, sowing dates, and nutrient management as potential strategies for improving maize yields in Trans Nzoia County. Cultivars, sowing dates and nutrient application were shown to increase yield by up to 600, 300 and 750 kg ha<sup>-1</sup>, respectively. Supplementary irrigation did not affect maize yield in the studied region implying sufficient water availability under no irrigation conditions. The study concludes that the application of 100 kg N ha<sup>-1</sup> and early sowing spanning mid-February to Mid-March has a greatest potential for enhancing yields in the study region. Also, cultivar KH600-23A is preferred for stabilizing yields in the area spanning the southern to northern parts of the county, whereas H614 is better for stabilizing yields in the western zone. Therefore, we recommend that agricultural extension services should be aligned with site-specific measures for optimal production returns. Additionally, low maize yield regions need to intensify integrated soil fertility measures, including organic manures, cereal–legume intercropping, agroforestry, and minimum tillage to improve soil fertility. These practices benefit resource-constrained smallholder farmers who cannot afford mineral fertilizers. The less costly measures that include early sowing and proper cultivar choice are critical in improving production and



maximising resource use by smallholder farmers. The assessment provided insights into the regional dimensional effects on maize yield and enhanced the understanding of yield enhancement measures at various locations. Based on the study's findings, farmers would benefit in particular in the low-yield response zones by aligning their production with better suited management practices for their region. Future studies could assess the SSAMS and its response to maize production in other agroclimatic zones in Kenya given field specific yield data. The findings of this study are of primordial importance to farmers, the government, and policy-makers in devising region-specific measures for improving maize production.

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**Author contributions** HKK: Conceptualization, investigation, formal analysis, methodology, Software, original draft, review, editing and visualization. SS, SDBK, ML, and MB: Supervision, review and editing, visualization, and Software. GG: Conceptualization, writing, review and editing. CBC: Conceptualization, writing, review and editing. RB: Formal analysis, writing, review, editing and visualization. BR: review and editing. All authors read and approved the final manuscript.

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**Data availability** The crop model driving and calibration data supporting this study's findings are available upon request from the corresponding author. The global high-resolution soil profile dataset can be derived from the Harvard University dataverse website (<https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/1PEEY0>). The CHIRPS (<ftp://ftp.chg.ucsb.edu/pub/org/chg/products/CHIRPS-2.0/>) and NASA POWER data are freely downloadable from GEE and the NASA POWER website (<https://power.larc.nasa.gov/>), respectively.

## Declarations

**Conflict of interest** The authors declare that they have no competing interests. Any suggestions, results, discussions, recommendations, and conclusions presented in this study are those of the authors and do not express the views of the funding agencies.

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