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Agronomic management response in maize (*Zea mays* L.) production across three agroecological zones of Kenya

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Abstract

Maize (*Zea mays* L.) productivity in Kenya has witnessed a decline attributed to the effects of climate change and biophysical constraints. The assessment of agronomic practices across agroecological zones (AEZs) is limited by inadequate data quality, hindering a precise evaluation of maize yield on a large scale. In this study, we employed the DSSAT-CERES-Maize crop model (where CERES is Crop Environment Resource Synthesis and DSSAT is Decision Support System for Agrotechnology Transfer) to investigate the impacts of different agronomic practices on maize yield across different AEZs in two counties of Kenya. The model was calibrated and evaluated with observed grain yield, biomass, leaf area index, phenology, and soil water content from 2-year experiments. Remote sensing (RS) images derived from the Sentinel-2 satellite were integrated to delineate maize areas,

Abbreviations: AEZ, agroecological zone; CERES, Crop Environment Resource Synthesis; DSSAT, Decision Support System for Agrotechnology Transfer; GEE, Google Earth Engine; GEOGLAM, Group on Earth Observations Global Agricultural Monitoring Initiative; OK, ordinary kriging; RS, remote sensing; SDs, sowing dates.

and the resulting information was merged with DSSAT-CERES-Maize yield simulations. This facilitated a comprehensive quantification of various agronomic measures at pixel scales. Evaluation of agronomic measures revealed that sowing dates and cultivar types significantly influenced maize yield across the AEZs. Notably, AEZ II and AEZ III exhibited elevated yields when implementing combined practices of early sowing and cultivar H614. The impacts of optimal management practices varied across the AEZs, resulting in yield increases of 81, 115, and 202 kg ha^{-1} in AEZ I, AEZ II, and AEZ III, respectively. This study underscores the potential of the CERES-Maize model and high-resolution RS data in estimating production at larger scales. Furthermore, this integrated approach holds promise for supporting agricultural decision-making and designing optimal strategies to enhance productivity while accounting for site-specific conditions.

1 | INTRODUCTION

Agriculture is vital for the economic and social well-being of most African economies and livelihoods. In Kenya, the agricultural sector accounts for approximately 26% of the gross domestic product (GDP) directly and 25% indirectly (World Bank Group, 2018). It also employs approximately 75% of Kenya's population, working part-time or full-time (CIA, 2022). Among the crops grown in Kenya, maize (*Zea mays* L.) is a widely cultivated cereal crop essential for alleviating food insecurity. The crop covers approximately 2 million ha with over 3 million metric tonnes of production based on recent statistics (FAO, 2020). It is grown by over 3 million smallholder farmers, accounting for 70% of the nation's output (D'Alessandro et al., 2015). In recent years, maize production has encountered many challenges, including the high cost of inputs, declining soil fertility, pest and disease invasions, and poor coordination of extension service delivery (Kinyanjui, 2019; Tittonell et al., 2008). The challenges faced by rainfed maize production are further exacerbated by climate change (Salami et al., 2010). The impacts of climate change are inherently heterogeneous, inducing varied effects on maize growth and yield across cultivated landscapes (Herrero et al., 2010).

Agricultural production is shaped by socio-economic, political, and technological factors and environmental conditions that vary in space and time. Farming systems are unique in different agroecologies, influenced by technological sets and environmental effects (Asante et al., 2019). Thus, to maximize production in a given environment, understanding the local variation of landscape characteristics and various crop requirements enables the optimization of production (Mujić & Ljuša, 2023). Agroecological zones (AEZs) have emerged as vital units for evaluating and assessing the physical and biological potential of natural resources for sustainable development planning (Greenland et al., 1997; Mkonda, 2021). Including the AEZ concept brings to attention the specific characteristics of a region and inherent production constraints that can be addressed using appropriate agricultural technologies.

Consequently, the Food and Agricultural Organization (FAO) has adopted the concept of AEZs in various regions to analyze solutions for sustainable agricultural development (FAO, 1996). Similarly, agricultural landscape characterization using agroclimatic zoning has been adopted to upscale crop yield by examining production heterogeneities within and between zones (van Wart et al., 2013). In analyzing these responsive differences, previous studies have established significant differences in agricultural productivity across various AEZs using statistical and process-based models (Asante et al., 2019; Kouame et al., 2023). The variability in production stems from differences in management practices, weather conditions, soil characteristics, and agricultural landscapes (Musafiri et al., 2022), and their influences vary across humid, semihumid, semiarid, and arid AEZs. In response to unpredictable weather patterns, recent studies have advocated optimizing agronomic practices to sustainably enhance production (Kogo et al., 2022; Rahut et al., 2021). Such agronomic practices are useful in the context of low-input production environments in sub-Saharan Africa (SSA). These practices include nutrient management, sowing window variation, water management, land preparation and conservation measures (Agoungbome et al., 2023; MacCarthy et al., 2018; Ten Berge et al., 2019). Agronomic practices can potentially enhance the resilience of cropping systems and moderate climate change effects, therefore, boosting social, economic, and environmental benefits such as net crop income, crop yield, soil fertility, and biodiversity richness (Jamil et al., 2021; Wekesa et al., 2018). Empirical evidence shows that contextualizing these practices based on biophysical and climatic conditions can help promote their adoption and deliver increased benefits (Autio et al., 2021; Nyang'au et al., 2021). Furthermore, understanding the impacts of these practices across various environmental contexts provides insights for scaling and promoting sustainable agriculture intensification.

Techniques such as field experiments and household surveys have been extensively used to assess the influence of agronomic practices at small scales (Chivenge et al., 2022; Rurinda et al., 2020; Tambo & Mockshell, 2018; Thierfelder & Mhlanga, 2022). Previous studies have utilized process-based crop models to assess technically feasible agronomic practices, estimate yield gaps, and evaluate maximum yield potential compared to conventional farmer practices. These studies, conducted in different regions, have explored tailored management practices and region-specific guidelines to sustain yields over time. Some agronomic practices explored include planting dates and cultivar maturity (Massigoge et al., 2023), nitrogen fertilization (Feleke et al., 2023), organic amendments (Lana et al., 2017), and supplemental irrigation (Volk et al., 2021), among other measures. Improved crop and soil management practices enhance agricultural production and contribute substantial yield gains in various parts of the world (Rizzo et al., 2022).

Furthermore, soil water conservation and enhancement practices such as minimum tillage and irrigation affect soil water balance and modify evapotranspiration, thus enhancing yields. Tillage practices also influence the yield of various crops. Although with varied influence across locations, tillage affects the structure of the soil, which in turn affects the capacity for water and nutrient conservation (Jug et al., 2021). On the contrary, barriers to yield increase emanate from suboptimal input use and a lack of improved technologies (Assefa et al., 2020). For instance, low fertilizer application and lack of improved seeds contribute to the largest technical and resource yield gaps in the SSA region (Assefa et al., 2020).

Although process-based crop models provide cost-effective approaches for assessing agronomic practices at large scales spanning diverse landscapes and environments, incorporating geospatial information on crop type coverage enables extensive scale assessments and trade-offs of various agronomic measures (Prestele & Verburg, 2020). Furthermore, crop models integrate biophysical factors, biochemical and physiological processes, and interactions between plant, atmosphere, and soil continuum to robustly model crop growth, development, and yield. Therefore, combining remote sensing (RS), geographical information systems (GIS), and crop modeling techniques provides insights into areas where certain agronomic practices can be targeted for enhanced crop productivity. Accurate data on crop type information provide an essential platform for assessing maize yield response to agronomic practices using crop modeling systems. Additionally, these data improve precision when targeting the allocation of resources. Eventually, the information is crucial for the national and county governments' extension officers in terms of the provision of services and knowledge transfer to farmers.

Core Ideas

- The influence of agronomic practices on maize production was analyzed using the CERES-Maize model (where CERES is Crop Environment Resource Synthesis).
- Crop type information was combined with the CERES-Maize model to analyze the trade-off of various agronomic measures.
- Sowing dates and cultivar type significantly influenced maize yield in the region.
- Average yield increase ranges between 81 and 202 kg ha^{-1}, considering optimal agronomic practices.
- The assessment indicates a potential of +5.7% in maize production from the current production in the study area.

This study seeks to address the aforementioned limitations by integrating on-farm experiments, RS, and crop modeling techniques to assess agronomic practices and to investigate their responses across various AEZs in two maize-growing counties in Kenya. The main research aim of the study is to assess whether the impacts of agronomic practices on maize production vary across AEZs. Furthermore, the study seeks to identify the optimal agronomic practices in each AEZ and determine the potential of the practices vis-à-vis alternative practices. Thus, the specific objectives of this study are to (i) simulate maize production under various agronomic practices in various AEZs, (ii) assess the optimal agronomic practices in various AEZs, and (iii) evaluate the trade-off of various agronomic practices at AEZs from simulated yields and maize cultivated areas. The study findings are of utmost importance to agricultural planning departments at both the county and national levels in responding to the location-specific needs of farmers. The results will further enhance the dissemination of routine extension services and increase farmer awareness about best management practice combinations that will improve productivity.

2 | MATERIALS AND METHODS

2.1 | Study area

The study covers Trans Nzoia and Uasin-Gishu Counties in the northwestern part of Kenya (Figure 1). Maize, wheat, sugarcane, tea, coffee, and horticultural crops are the primary agricultural products in these counties. AEZs I–III cover approximately 98% of the study area, while AEZ IV covers the

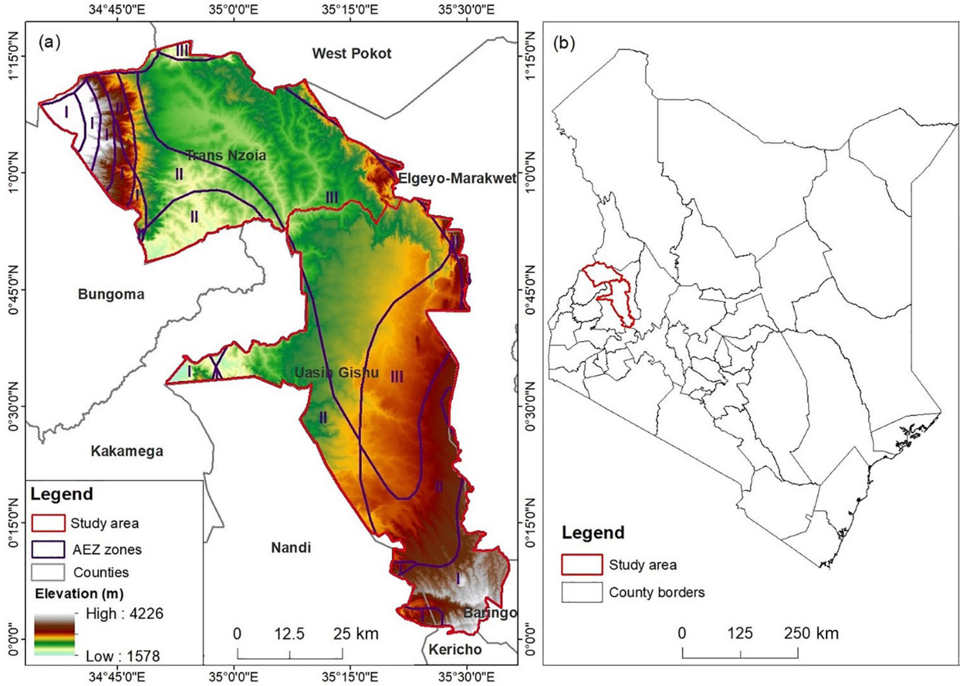

FIGURE 1 Map of the study area showing (a) the location of Trans Nzoia and Uasin Gishu Counties and bordering counties, the context of Trans Nzoia and Uasin Gishu Counties in Kenya. The agroecological zones (AEZs) are classified as I—humid, II—subhumid, III—semihumid, and IV—transitional zone. A 30 m horizontal resolution Shuttle Radar Transmission Mission (SRTM) digital elevation model (DEM) is superimposed on the study area to show elevation variation. The DEM is a global digital elevation product is freely available via the United States Geological Survey (USGS) earth resources observation and science archive.

TABLE 1 Agroecological zone characterization of the study area.

Agroecological zone	Moisture index (%)	Classification	Cultivated crops
I	>80	Humid	Tea (*Camellia sinensis*), coffee (*Coffea arabica*), sugarcane (*Saccharum officinarum*), wheat (*Triticum aestivum* L.), and maize (*Zea mays* L.)
II	65–80	Subhumid	Wheat, maize, beans (*Phaseolus vulgaris* L.), and potatoes (*Solanum tuberosum* L.)
III	50–65	Semihumid	Beans, maize, wheat, cotton (*Gossypium hirsutum* L.), and cassava (*Manihot esculenta* Crantz)
IV	40–50	Semihumid to semiarid	Beans, pigeon peas, *Cajanus cajan* (L.), sweet potatoes, *Ipomoea batatas* (L.), sorghum, *Sorghum bicolor* (L.) Moench, and millet, *Eleusine coracana* (L.) Gaertn

Source: Sombroek et al. (1982).

remaining portion. Consequently, the study was restricted to AEZs I–III. The AEZs are classified based on moisture index expressed as a percentage of annual rainfall to potential evaporation (Sombroek et al., 1982). The classification, biophysical characterization, and cropping systems of the AEZs covering the area are shown in Table 1.

2.2 | Climatic conditions

Climatically, Uasin Gishu County has an average annual rainfall of 900 mm. The temperature range is between 9˚C and 25˚C. The elevation ranges between 1500 and 2600 m above sea level (Murgor, 2021). Trans Nzoia has an annual rainfall between 900 and 1800 mm, with an average rainfall of approximately 1300 mm. The mean annual minimum and maximum temperatures are 12˚C and 26˚C, respectively. The elevation in the county varies from 1500 to 4226 m at the peak of Mount Elgon (Nyberg et al., 2020). The dominant soil types in Uasin Gishu County are Humic Nitisols and Haplic Ferralsols, while those in Trans Nzoia County are Humic Nitisols and Humic Ferralsols (Dijkshoorn, 2007). Agriculture is the main economic activity and source of livelihood for many smallholder farmers both counties.

2.3 | Sources of data

Various data sources were used to drive the DSSAT-CERES-Maize simulations (where CERES is Crop Environment Resource Synthesis and DSSAT is Decision Support System for Agrotechnology Transfer) across the study region. Standard local management practices, such as a sowing spacing of 25 × 75 cm and the recommended nitrogen level of 75 kg N ha^{-1}, were maintained. The soil profiles for the study region were obtained from the high-resolution global soil profile database for crop modeling applications (Han et al., 2015). The database was developed by synergistically combining soil data from the International Soil Reference and Information Centre (ISRIC) and the Africa Soil Information Service (AfSIS) projects. The soil properties (bulk density, organic carbon, percentage of clay and silt, soil pH, and cation exchange capacity) available from the original SoilGrids of ISRIC and AfSIS were directly used to develop DSSAT soil profiles at a spatial resolution of approximately 0.1° × 0.1° (∼10 km). Other soil properties from the database include soil hydraulic conductivity, saturation, drainage upper limit, and crop lower limit, estimated using pedo-transfer functions. Point data at the centroid of each grid were used to identify the individual soil profiles defining the study area. The weather data were derived from the National Aeronautics and Space Administration Prediction of Worldwide Energy Resource (NASA POWER; https://power.larc.nasa.gov/) and the Climate Hazards Group InfraRed Precipitation (CHIRPS; http://ftp.chg.ucsb.edu/pub/org/chg/products/CHIRPS-2.0/) (Funk et al., 2015). The NASA POWER data were obtained from the NASA Langley Research Center POWER Project funded through the NASA Earth Science Directorate Applied Science Program. The data derived included solar radiation (∼1° × 1° spatial resolution), maximum temperature, and minimum temperature (0.5° × 0.5°). The daily precipitation was mainly obtained from CHIRPS because of its high resolution (0.05° × 0.05°) (Ocampo-Marulanda et al., 2022).

Due to the extensive coverage of the study area, the weather variable retrieval and preparation of weather files into DSSAT weather file format were implemented using the *bestiapop* Python package (Ojeda et al., 2020). The program automatically extracts and processes Scientific Information for Land Owners and NASA POWER gridded climate data for crop modeling by converting the data to files that can be directly ingested into crop models. The precipitation columns of the prepared weather files for all locations were replaced with the values from the CHIRPS data, as the *bestiapop* package is based only on the NASA POWER data. The downloaded data and simulations were conducted for 2021, covering the period within which the on-farm experiments and RS data acquisition were conducted. The methodology adopted in the study is summarized in Figure 2.

2.4 | Crop-type classification

The crop-type classification and mapping followed a two-step process. First, a cropland mask for the study area was generated by combining land cover products from the FAO, the crop mapping initiative for GEOGLAM (Group on Earth Observations Global Agricultural Monitoring Initiative) Kenya country-level support, and a prior land use and land cover change analysis conducted by Kipkulei, Bellingrath-Kimura, Lana, Ghazaryan, Boitt et al. (2022). The second step involved identifying the dominant crops through crop type classification analysis. The crop mapping initiative for GEOGLAM Kenya country-level support developed a crop-type product for the larger agricultural region in Kenya, including our study area (ECJRC, 2021). Although most crop types in the study area were well represented compared with our reference data, we noted minor inconsistencies in mapped crops such as sorghum, maize, wheat, millet, and coffee. Therefore, we combined field reference data from the earlier project with detailed reference data collected in 2021 and generated a refined crop-type map for the study area.

We used Sentinel-2 satellite images to characterize different crop types in the study area. The images are acquired by the Multispectral Instrument on board S2A and S2B satellites with a total of 13 spectral bands having a spatial resolution between 10 and 60 m. For this study, we accessed level-2A surface reflectance products from the Google Earth Engine (GEE) platform corrected for radiometric and atmospheric artefacts. We used all available images with cloud cover below 80%, acquired between March 1, 2021, and September 31, 2021, corresponding to the long growing season in the region. We applied quality assurance bands to exclude low-quality pixels with clouds, cloud shadows, and cirrus, among other defects, from further analyses.

We performed supervised classification using the random forest (RF) classifier algorithm. RF consists of a collection of classifiers structured in trees $h\ (x, k)$, $k = 1, n\ldots$ where k values are identically distributed random vectors (Breiman, 2001). The ensemble learning algorithm combines decision trees, where each tree contributes a single vote to assign the most frequent class to the input vector (Rodriguez-Galiano et al., 2012). It uses the Gini index as a suitable attribute selection measure to maximize dissimilarity between classes and measures the impurity of an attribute in relation to the classes. The pixel is randomly selected and assigned to some class Ci in training. The Gini index can be written as shown in Equation 1:

$$\sum \sum_{j \neq i} \left(f\left(C_i, T\right) / |T| \right) \left(f\left(C_j, T\right) / |T| \right) \quad (1)$$

where $f\ (C_i, T)/|T|$ is the probability that the selected pixel belongs to class C. RF has several advantages, including a

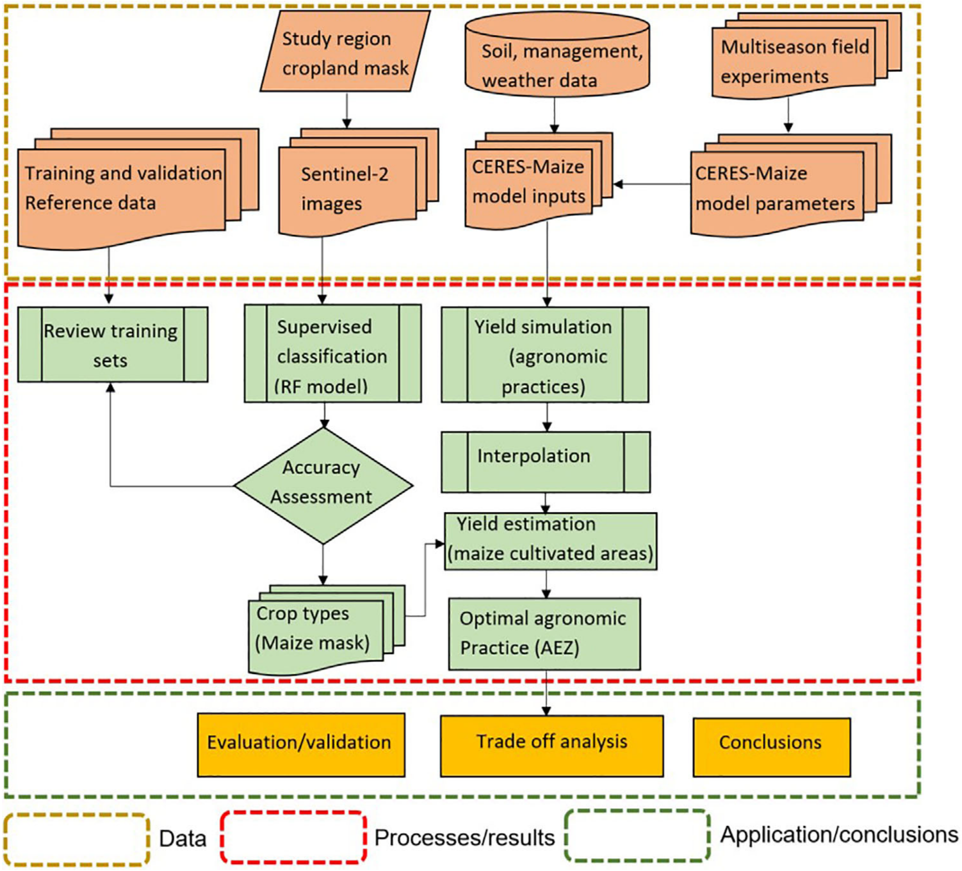

FIGURE 2 Methodology and approach utilized in the study. AEZ, agroecological zone; CERES, Crop Environment Resource Synthesis.

robust nature, lack of complex parameterization, the possibility of handling nonlinear effects of complex data, the ability to accommodate imbalanced data and few training samples, and the possibility of processing large amounts of data with high accuracy.

The reference data that aided the RS classification were acquired during a field study conducted between April 2021 and August 2021. During the study, major crop and noncrop types were mapped using a handheld Garmin geographical positioning system (Garmin etrex 10) with locational accuracy of around 3 meters. Additional reference data were supplemented by scanning and digitizing high-resolution imagery from the Google Earth application. We also relied on land use experts' knowledge to obtain crop types characterization in the region. We created a vector file of the reference data for import into the GEE for further analysis. The spectral bands of the Sentinel-2 satellite data used to build the RF model included blue, green, red, near-infrared, red edge, and shortwave infrared. Additionally, we calculated several vegetation indices and their temporal composites as inputs for the RF classification. The indices calculated included the normalized difference vegetation index (NDVI) (Rouse et al., 1974), normalized difference moisture index (Wilson & Sader, 2002), green chromatic coordinate (Reid et al., 2016), and enhanced vegetation index (Liu & Huete, 1995). These indices were used because they have been proven useful in vegetation condition monitoring, agricultural applications, land use classification, and land cover classification. We specified a 70/30 split of the reference data for model training (in-bag samples) and model testing out-of-bag samples.

2.5 | Accuracy assessment

The accuracy of the classification process was assessed using metrics calculated from the confusion matrix. The process involved evaluating the correspondence of the observed ground features with the classified map. Therefore, overall accuracy (OA), producer accuracy (PA), user accuracy (UA), and *F* score were used for the accuracy assessment (Congalton, 1991). The OA indicates the proportion of the correctly mapped classes. This value shows how much the classified map reflects the actual ground features. An OA of 1 indicates that the classification perfectly corresponds with actual ground features. Producer accuracy depicts how often actual features in the study area are correctly shown on the classification map, while user accuracy illustrates how often the class in the classification map is shown on the ground. The

F1 score (Equation 2) is a mean metric of precision (PA) and recall (UA). The metric is useful where the distribution of datasets across the sample training data is unequal (Sun et al., 2019), a characteristic of our reference samples. A value of 100% indicates perfect precision of the model and recall of all the test data, and a value close to 0 indicates the inverse.

$$F \text{ score} = 2 \times \frac{\text{PA} \times \text{UA}}{\text{UA} + \text{PA}} \quad (2)$$

2.6 | DSSAT-CERES-Maize model application

2.6.1 | On-farm experiments

The study used data from two seasons of on-farm experiments to parameterize and evaluate the DSSAT-CERES-Maize model version 4.7.5. The experiments were conducted in the 2015 and 2021 maize growing seasons in 42 field blocks across three major sites (Katuke, Sabwani, and Olngatongo) in Trans Nzoia County. The typical field sizes in the county range from 0.8 ha for small-scale farming to 22.6 ha for large scale farming, and the average farm size is approximately 4.7 ha (MoALFC, 2021). The H614 maize cultivar was parameterized and evaluated using the DSSAT-CERES-Maize model. The cultivar is popular among farmers given its suitability for growing conditions in the Kenyan highlands, high resistance to pest attacks, and high production potential (Almekinders et al., 2021; Smale & Olwande, 2014). Databases of weather, soil, cultivars, and crop management required to simulate crop growth and development were obtained. Weather variables, including solar radiation, precipitation, and maximum and minimum temperature, were collected from three weather stations across the study area. However, two weather stations had missing values, and thus complete weather coverage from one weather station was used as a representative station for the fields sampled in the region.

The crop management data (i.e., agronomic data) required by the model include land preparation, planting date, planting density, row spacing, planting depth, and fertilizer application dates and amounts. Land preparation across all sites was conducted between January and March, and planting was done in March/April in both seasons. The crop management information and records of key phenological stages across the sites are described in Table S1. Soil sampling was conducted to determine the soil's physical and chemical properties defining the soils in the study field sites. The sampling was conducted in both seasons before sowing to obtain the initial soil conditions before any fertilization enhancement. The analyzed data were used to design the soil files using the SBUILD program in the DSSAT program. More details of the experiments and cultivar information are described in Kipkulei, Bellingrath-Kimura, Lana, Ghazaryan, Baatz et al. (2022), including Supporting Information.

The data acquired in the 2021 and 2015 growing seasons were used to parameterize and evaluate the DSSAT-CERES-Maize model, respectively. Data collection was conducted based on the minimum dataset requirement recommended by Jones et al. (2003) for crop model application. The recommendations define variables such as soil physical and chemical properties, weather variables, plant biomass, leaf area index, and soil moisture as the necessary variables for model calibration and parameterization/evaluation. The experimental fields were optimally managed, and necessary measures, including weed control, fertilizer application, and pest and disease control, were applied based on standard agronomic practices. Fertilization was applied at a rate of 75 kg N ha^{-1} with a similar amount of top dressing 6 weeks after sowing. Maize spacing was based on the recommended practice of 25 cm between plants and 75 cm between rows, yielding an approximate population of 53,000 plants ha^{-1}.

2.6.2 | Model calibration and evaluation

The experimental fields, which showed minimum water and nitrogen stress, were used for model parameterization. Subsequently, 36 field blocks were used for DSSAT-CERES-Maize model parameterization in the 2021 maize growing season. The parameterization and evaluation process was necessary to ensure that the model accounted for the genetic, environmental, and management practice variability, affecting maize growth in the study region. This process results in cultivar coefficients that govern the accumulation of temperature heat units and plant development from emergence to physiological maturity. The parameters are divided into growth (G2, G3, and phyllochron interval) and development (P1, P2, and P5) (Chisanga et al., 2015; Chisanga et al., 2020). The parameterization was conducted using the Generalized Likelihood Estimator program in DSSAT software version 4.7.5. First, management data were entered using the XBuild module in DSSAT. The weather variables at all the experimental sites were formatted using the WeatherMan module in DSSAT and used to create the weather station data (Pickering et al., 1994). Soil variables at five depths (0–20, 20–40, 40–60, 60–80, and 80–100 cm) were entered into the SBuild module in DSSAT. The measured leaf area index and harvested dry mass yield for the sampled locations were input into the ATCreate module. The calibration began by specifying an arbitrary cultivar in the genotype file in DSSAT using a previously calibrated long-maturing cultivar adopted from the DSSAT genotype file.

In addition to the calibrated coefficients from the on-farm experiments, the study also assessed the H612 cultivar, for which the cultivar coefficients were calibrated and tested in the southern highlands of Tanzania, a region with comparable climatic and environmental conditions to those of our study area (Mfwango et al., 2018). The model's performance for the H614 and H612 cultivars has been evaluated by Kipkulei, Bellingrath-Kimura, Lana, Ghazaryan, Baatz et al. (2022) and Mfwango et al. (2018), respectively.

2.7 | Model application and spatial assessment

2.7.1 | Evaluation of agronomic practices

The study used the parameterized DSSAT-CERES-Maize model to evaluate various agronomic practices, namely, adjusting sowing dates (SDs) and cultivars, incorporating organic amendments with the recommended nitrogen fertilizer levels and tillage practices, and supplementing rainfed agriculture with varying levels of irrigation. Adjusting SDs is an inexpensive approach to adapting agriculture to changing climates. Farmers can ensure that key crop phenological stages are consistent with seasons of optimal weather conditions. One such critical stage is grain-filling, which requires sufficient moisture to ensure higher yields. Therefore, this study assessed six SDs at 15-day intervals from February 15, 2021 (SD1), to May 1, 2021 (SD6). The dates coincide with the onset of the rainy season and maize growing season in the study area.

Additionally, the study assessed the incorporation of organic amendments and the government's recommended nitrogen fertilization rate of 75 kg N ha^{-1}. The organic amendments evaluated in other studies include the use of farmyard manure, compost, leguminous trees, or the incorporation of organic inputs (Chebet et al., 2017; Nekesa et al., 2007). Therefore, the supply of organic inputs at a rate of 10 tonnes ha^{-1} was evaluated in the model in combination with 38 kg N ha^{-1} of the fertilizer for top dressing 6 weeks after sowing in the form of calcium ammonium nitrate as the usual practice in the study area (De Groote et al., 2007). Another practice evaluated in the study was the implementation of irrigation to increase the soil moisture content. The study assessed a single irrigation application of 100 mm. The model was configured to apply the irrigation amounts automatically when required by the crop. Such a configuration triggers water to be applied to crops when water stress is encountered or the water in the root zone falls below a certain threshold (Malik et al., 2019).

Tillage measures were also assessed in the DSSAT-CERES-Maize model. The minimum tillage practice was configured by specifying drilling without tillage to reduce soil disturbance and improve soil structure. The depth of the drill was estimated at 15 cm (Sijtsma et al., 1998). Conventional tillage involved a disc plough used to prepare the seedbed before sowing. The final agronomic practice evaluated was the adoption of an alternative hybrid cultivar in the region. The cultivar H612 was first released in Kenya and calibrated and evaluated using the DSSAT-CERES-Maize model in the southern highlands of Tanzania (Mfwango et al., 2018). The region has similar climatic characteristics to those in the area in this study, as it is tropical cool and sub humid to humid, according to Sebastian (2009). The temperature units indicated by the genotypic coefficients showed that the cultivar requires fewer temperature degree units to reach maturity compared to the H614 cultivar. The assessment of the practices was focused on the various AEZs that characterize the study region.

2.7.2 | Statistical analysis of agronomic practices

The simulations from the calibrated DSSAT-CERES-Maize model for the various agronomic practices were subjected to factorial analysis of variance (ANOVA). The hypothesis for the study was that maize yield is highly influenced by various agronomic practices across the AEZs. Therefore, factorial ANOVA was used to study the production impacts of agronomic practices and their interactions across the AEZs. A posteriori analysis was performed using the least significance difference test based on the hypothesis outcome to compare the mean yield under various agronomic practices. The test was performed for practices and interactions with significant differences at $p < 0.05$. The test was implemented using the *Agricolae* package in R statistical software (de Mendiburu & Simon, 2015).

2.7.3 | Mapping yield predictions

Maize yield distribution in the study region was characterized by interpolating the point-based simulations from the DSSAT-CERES-Maize model using the ordinary kriging (OK) spatial interpolation in ArcGIS (Equation 3).

$$[Z\ (S_o) = \sum_{i=1}^{N} \lambda_i\ Z\ (S_i)] \tag{3}$$

where $Z(S_o)$ is the predicted value at the unmeasured position S_o, $Z(S_i)$ is the measured value at S_i, λ_i is the unknown weight for the measured value at the location S_o, and n is the number of positions within the neighborhood searching. OK predicts new values at unsampled locations by calculating the weighted mean of the sampled locations (Lloyd, 2005). The weights depend on the distance to the location of the prediction and the spatial relationships among the measured values. Thus, OK does consider not only distance but also the

TABLE 2 Cultivar-specific parameters for H614 and H612 cultivars.

Cultivar	P1 (˚C day)	P2 (day)	P5 (˚C day)	G2 (No. of kernels per ear)	G3 (mg day^{-1})	PHINT (˚C day)
H614	290.8	0.471	921.2	796.8	5.26	39.74
H612	130.0	0.500	390.0	825.0	10.15	75.00

Note: 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^{-1}); PHINT, phyllochron interval, the interval in thermal time (degree days) between successive leaf tip appearances.

spatial distribution of the sampled locations to account for spatial dependence among the samples. A spherical semi-variogram model was fitted to obtain the variance of the weights at different distances to estimate model parameters, including the sill, nugget, and range. OK was implemented using the geostatistical package in ArcGIS software version 10.8.1. The yield prediction was performed for the combinations of the optimal agronomic measures. The surfaces were clipped using the Sentinel-2 derived maize mask to quantify modeled yield in the harvested areas. Subsequently, the obtained yield was aggregated to the AEZ level to generate the spatial explicit yield maps across the region. Finally, the aggregated surfaces of various measures were used for trade-off analysis.

3 | RESULTS

3.1 | RS-based classification

The RF classifier characterized the study area's crop types, and maize-cultivated areas were generated from the crop type map (Figure 3). The maize crop mask shows an even distribution of maize in AEZ II and III. However, maize coverage in AEZ I was less in both counties. Maize covered approximately 235,201 ha in the study region, 115,895 ha in Trans Nzoia, and 119,306 ha in Uasin Gishu County. The distribution of the main crop types across the study area is found in Figure S1.

Maize-cultivated areas were mapped with high accuracies. The producer accuracy was approximately 94%, and the user accuracy was 92%, showing the potential of the RF classifier in maize mapping in the region. Similarly, the classification of other crop types defining the study area indicated excellent user, producer, and overall accuracies and *F* scores (Table S2).

3.2 | Model calibration and evaluation

The DSSAT-CERES-Maize cultivar-specific parameters for the cultivars are shown in Table 2. The DSSAT-CERES-

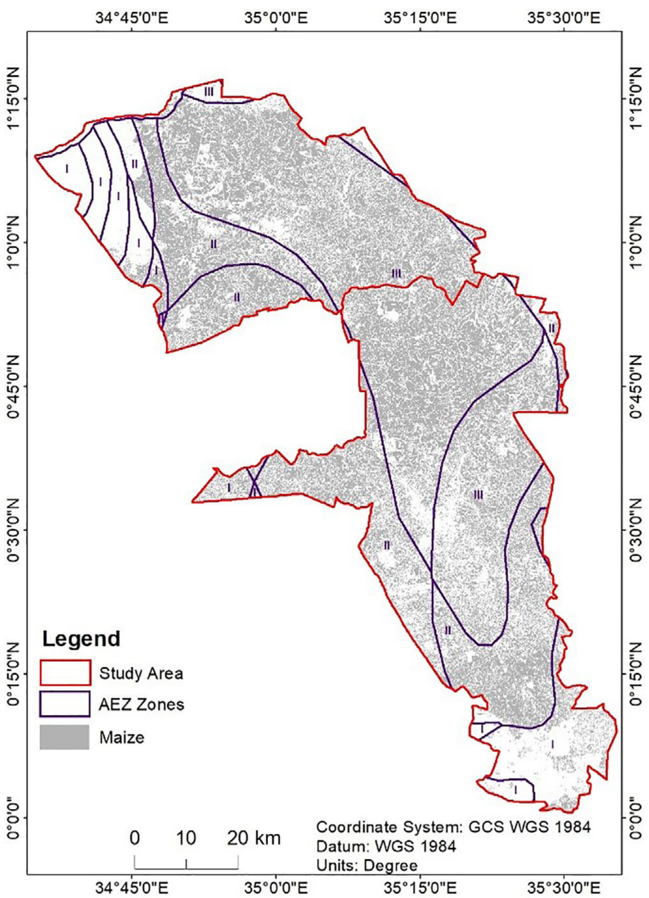

FIGURE 3 Maize-cultivated areas generated from the remote sensing classification. I, II, and III are the humid, subhumid, and semihumid agroecological zones, respectively.

Maize model calibration of the H614 cultivar showed good consistency between the simulated and observed yields. The mean calibrated grain yield was 4134 kg ha^{-1}, while the mean observed grain yield was 4150 kg ha^{-1}. The model also accurately estimated the observed dates for the other phenological variables, such as the number of days from sowing to anthesis and from sowing to physiological maturity. The deviation between the simulated and observed values was less than 10 days for each phenological variable, indicating the model's reliability in simulating maize growth and yield. Similarly,

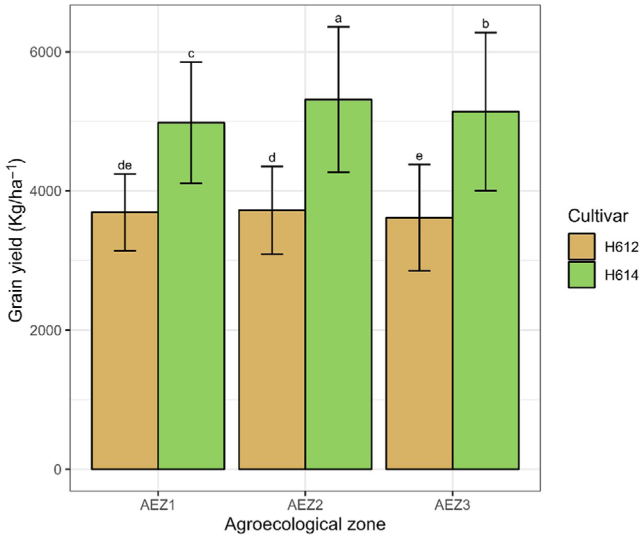

FIGURE 4 Maize yield variability as simulated by the DSSAT-CERES-Maize model (where DSSAT is Decision Support System for Agrotechnology Transfer and CERES is Crop Environment Resource Synthesis) across the various agroecological zones (AEZs) in response to different cultivars. Error bars indicate the standard deviation. Treatments sharing the same letter are not significantly different ($p < 0.05$).

the evaluation of the model using independent on-farm experiments conducted in the 2015 growing season showed good model performance for maize yield simulation with a coefficient of determination of 0.8 and root mean square error of 642 kg ha^{-1}.

3.3 | Influence of agronomic practices

The calibrated and evaluated DSSAT-CERES-Maize model simulations were used to assess the impacts of the agronomic practices across various AEZs in the study area. The simulations performed across 107 locations representing AEZs I–III revealed that AEZs largely shaped maize yields and that sowing and cultivar practices significantly influenced yield variability across the AEZs (Table S3). Other practices, such as tillage, organic amendments, and irrigation, significantly influenced maize yields independently, but their interactions with other factors were not statistically significant across the AEZs (Figures 4–5).

The results showed that maize yield was significantly higher for the H614 cultivar than for the H612 cultivar (Figure 4). Furthermore, the H614 cultivar yield significantly differed across the AEZs. AEZ II showed a higher average yield than AEZ I and III. The average yield in AEZ II was 5312 kg ha^{-1}, which was 3.4% and 7.6% higher than in AEZ III and AEZ I, respectively. However, the yield of the H612 cultivar was low across all the AEZs. Furthermore, the cultivar's production was not significantly different across the AEZs.

The interaction effect of the SDs and cultivars was significant across the AEZs, as shown in Figure 5. The H614 cultivar interaction with early SDs resulted in high grain yield across all the AEZs. The results further revealed that early and late sowing showed a more marked response on yield than mid-sowing. The optimal practices in AEZ II include sowing in early May and the H614 cultivar. However, the sowing window is not significantly different from sowing conducted in early March. A similar observation is noted in AEZ III, whereby sowing in early May and early March is preferable to sowing in mid-March, early April, and mid-April. However, in AEZ I, the sowing window is large, with sowing between early March and mid-March and early May preferable. For the H612 cultivar, sowing in mid-March demonstrated high yield potential in all the AEZs.

3.4 | Cumulative probability functions

Figure 6 illustrates the cumulative probability distributions (CPDs) of the simulated grain yield in response to various SDs. The plots demonstrate the likelihood of achieving maize yield below a certain threshold. As a reference, we used 5000 kg ha^{-1}, the potentially attainable yield in the study area. The frequency distribution shows that the probability of low yield increases away from the optimal SDs in all the AEZs. The results indicate that SD1, SD2, and SD6 are preferable SDs across the study area. SD4 and SD5 showed a higher probability (>75%) of obtaining a yield less than the 5000 kg ha^{-1} threshold in all the AEZs. SD6 favored AEZ I and AEZ II with a low probability of yield below the threshold compared to AEZ III. The early SDs (SD1 and SD2) and the delayed SD (SD6) resulted in a low probability that ranges between 50% and 60% of obtaining a yield of less than 5000 kg ha^{-1}. A medium SD between mid-February and early April yielded moderate effects on maize yield. In general, there was less variability in the yields for all SDs across the AEZs. The coefficient of variation was 22.4%, 25.9%, and 28.2% for AEZ I, AEZ II, and AEZ III, respectively.

Based on the cultivar type, cultivar H612 indicated a high probability of low production compared to the set threshold (Figure 7). The likelihood of yield below 5000 kg ha^{-1} was above 90% in all the AEZs. In contrast, the probability of obtaining the same quantity with the H614 cultivar was reduced by almost half in the three AEZs. The result indicates that the H614 cultivar had a reduced likelihood of yield decline in the study region. The CPD curves for the H612 cultivar flattened faster than those for the H614 cultivar, indicating higher probabilities of low yields. Overall, the H614 cultivar performed better than the H612 cultivar.

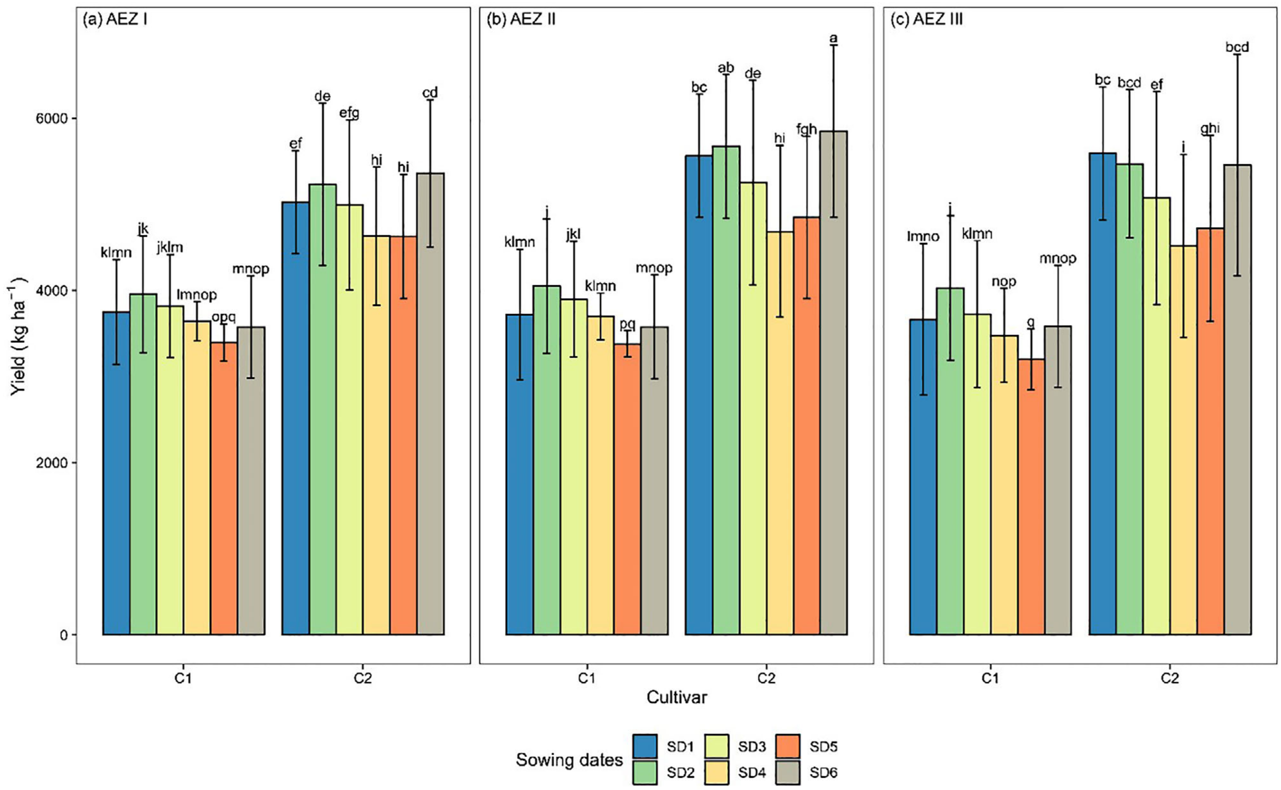

FIGURE 5 Interaction effect of sowing dates (SDs) and cultivars on maize yield response as simulated by the DSSAT-CERES-Maize model (where DSSAT is Decision Support System for Agrotechnology Transfer and CERES is Crop Environment Resource Synthesis) across the various agroecological zones (AEZs). C1 is the H612 cultivar, and C2 is the H614 cultivar. Error bars indicate the standard deviation. Treatments sharing the same letter are not significantly different ($p < 0.05$).

3.5 | Yield maps and domains across the AEZs

The optimal agronomic practices were evaluated for their responses across the study area. Therefore, the model simulations were used to derive spatial yield maps for the H614 cultivar and the optimal SDs. The analysis was restricted to the optimal agronomic practices evaluated based on their significant contribution to yield from the factorial ANOVA analysis. Therefore, we restricted our geographical analysis to cultivar H614 and SD1, SD2 and SD6, which displayed a higher impact on yield than other agronomic measures. The maize crop map generated from the crop-type mapping analysis was used to determine the trade-off between the optimal practices. The trade-off analysis of the optimal agronomic practices estimated the percentage increase in production in reference to an alternative strategy. The yield maps (Figure 8a–c) indicate that early sowing was most beneficial in most regions in the AEZ I. However, the model simulated low yields in this zone. In contrast, late sowing (SD6) was most beneficial in most parts of the AEZ II. However, the eastern and northwestern parts of AEZ II, especially in Uasin Gishu County, appeared to benefit more from early sowing than late sowing (Figure 8b,c).

Considering the 5000 kg ha^{-1} threshold, the yield maps indicate that most parts of the study area benefited from early sowing (Figure 8a,b) rather than late sowing. However, the effect is heterogeneous, as indicated by the variation in the yields across the study region. The observed pattern confirms that the factors driving maize production are spatial and vary from location to location. Thus, the maps show specific areas where production efforts need to be optimized for increased productivity.

The maize mask generated from the classified crop-type map of the study area was used to conduct agronomic measure trade-off analysis and assess each practice marginal effects. The mask was used to evaluate the yield increase/decrease rate resulting from an alternative practice. Therefore, three surfaces were created from the maize crop mask, which in this case represented the actual cultivated areas, allowing for an overall estimate of yield production.

The agronomic measures trade-off analysis of the assessed practices reveals varied trends, as shown in Figure 9a–c. Adopting SD1 as the reference, the assessment indicates that Trans Nzoia County benefits from early sowing (SD1). In contrast, the southern parts of Uasin Gishu County experience positive gains from SD2 and SD6. Furthermore, analysis

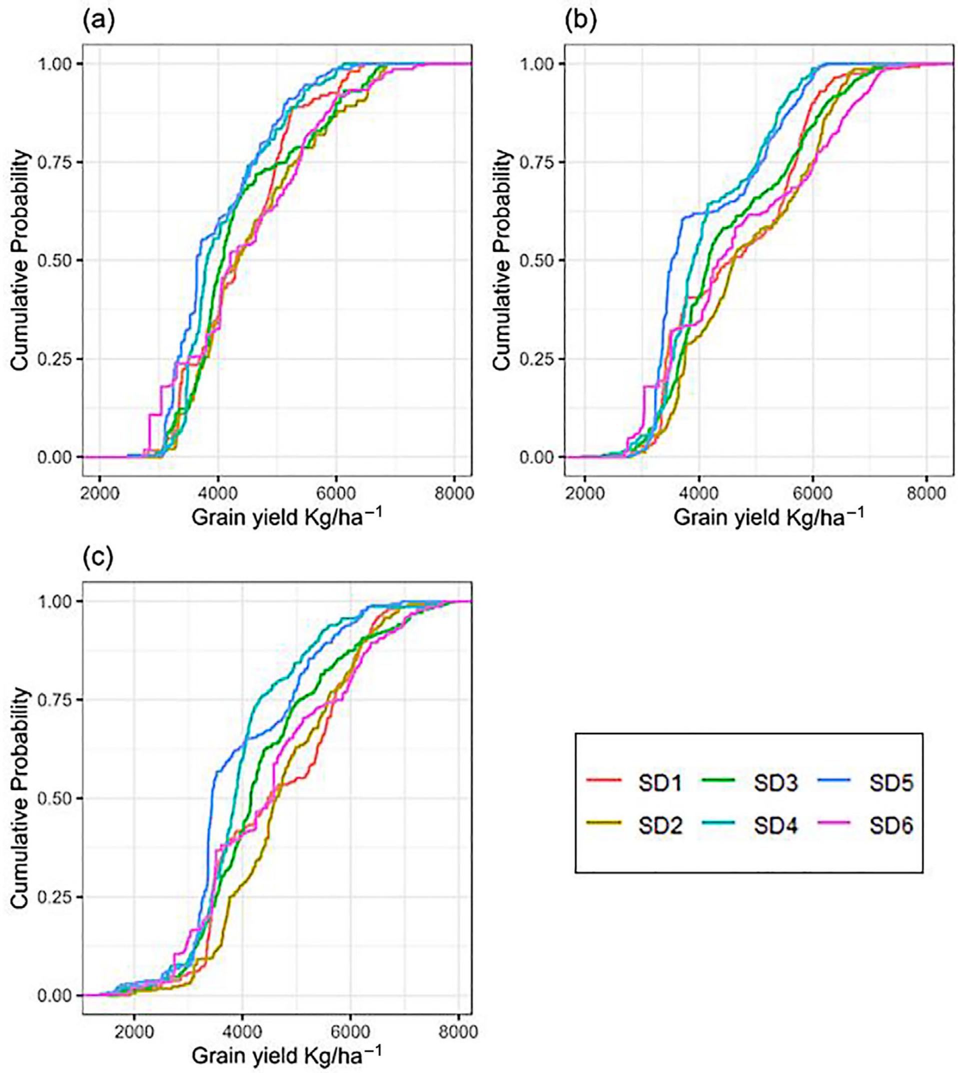

FIGURE 6 Cumulative probability distributions of maize grain yields as simulated by the DSSAT-CERES-Maize model (where DSSAT is Decision Support System for Agrotechnology Transfer and CERES is Crop Environment Resource Synthesis) across (a) agroecological zone (AEZ) I, (b) AEZ II, and (c) AEZ III in response to sowing dates (SDs).

indicates that SD6 can increase production by up to approximately 28% in some parts of AEZ II. Moreover, SD6 shows more positive effects than SD1 and SD2 in the western parts of Trans Nzoia County. A comparison of SD1 and SD2 indicates a minimal effect, as SD2 performs better in Uasin Gishu County (yield increase by up to 13%) (Figure 9a), whereas SD2 appears to result in yield decline in Trans Nzoia County. SD2 and SD6 are most beneficial in almost all parts of AEZ I, II, and III in Uasin Gishu County. SD1 is most beneficial in the northern parts of AEZ III of Uasin Gishu County. However, in the same region, SD2 also performs better than SD6. The mean spatial effect from the trade-off analysis shows that SD6 can increase yield by an average of 284 kg ha^{-1} in AEZ II. The results further show that relative to SD 1, SD 2 portrays a uniform effect on yield increase across all the AEZs. For SD2, the yield increase is, on average, 116, 115, and 86 kg ha^{-1} in the AEZ I, AEZ II, and AEZ III, respectively. The yield increase is also higher in the AEZ II and AEZ III for SD6. The southern parts of Uasin Gishu, mainly covering AEZ II and AEZ III, can record an average yield increase of 218 kg ha^{-1}. Considering these marginal benefits and the mapped area under maize crops, the study found that the potential yield increases in AEZ I, AEZ II, and AEZ III are 1120, 1148, and 35,658 tonnes, respectively. The total yield increase accounts for an approximately 5.7% increase from the current production of 0.67 Tg in the two counties.

4 | DISCUSSION

4.1 | Crop-type mapping

Crop-type maps provide useful inventories for decision-making regarding agricultural planning and production. One

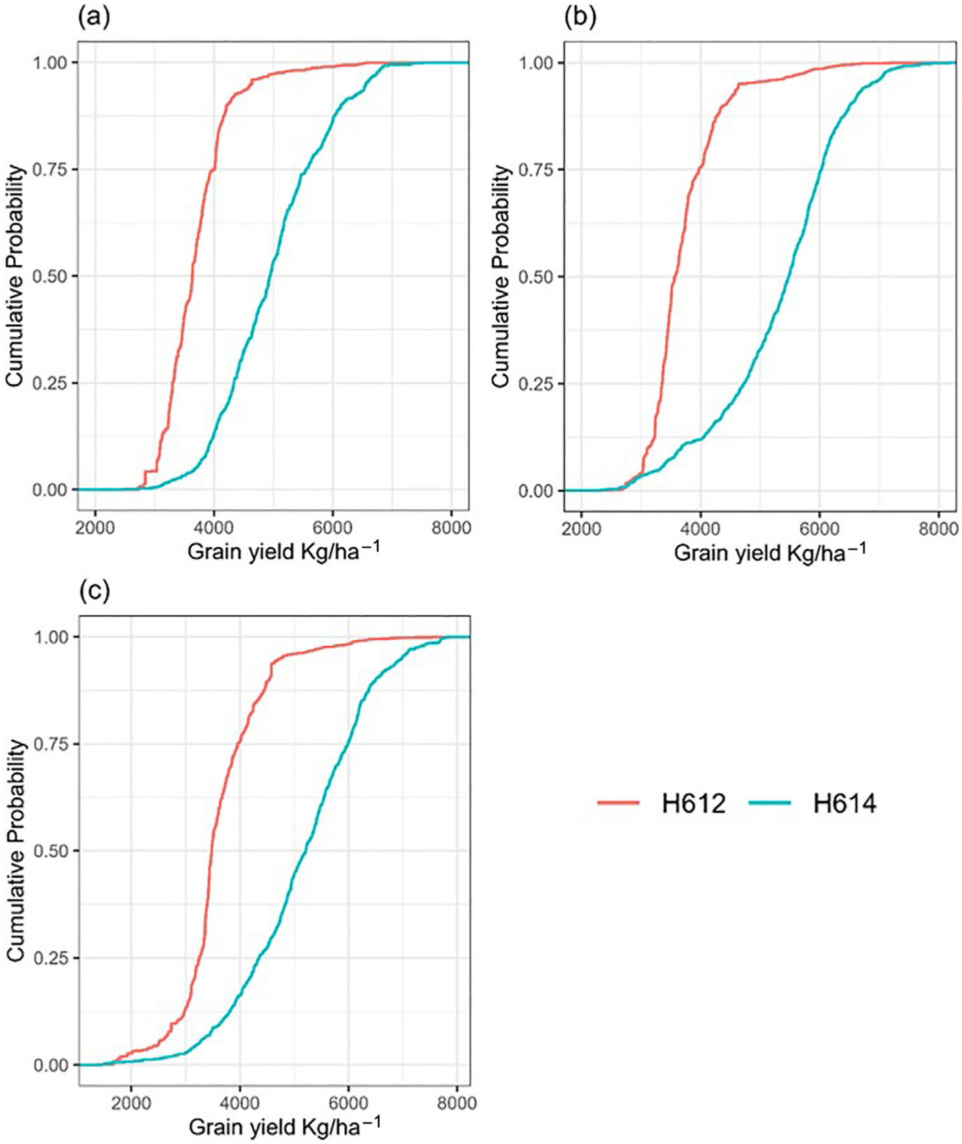

FIGURE 7 Cumulative probability distributions of maize grain yields as simulated by the DSSAT-CERES-Maize model (where DSSAT is Decision Support System for Agrotechnology Transfer and CERES is Crop Environment Resource Synthesis) across (a) agroecological zone (AEZ) I, (b) AEZ II, and (c) AEZ III in response to cultivar type.

major challenge in agricultural landscape monitoring is that these maps are not readily available, especially in the SSA region (Vancutsem et al., 2013). Another limitation is that the available crop-type maps in most countries are outdated (Waldner et al., 2017). Nonetheless, RS techniques have enabled the generation of crop-type maps and improved harvested area estimates for various agricultural applications (Mashaba-Munghemezulu et al., 2021). The results from the Sentinel-2-based classification showed that the crops that define the study region are well represented based on the high accuracies obtained. The spatial distribution patterns of various crops were mapped with accuracies comparable to those obtained by other related studies (Ibrahim et al., 2021; Zhang et al., 2020). The OA was excellent and corroborated other crop-type classifications involving regions with distinctive regional cropping patterns (Ibrahim et al., 2021; Maponya et al., 2020).

The RF model generally performed well in characterizing the various crop types in the region, as indicated by the model accuracy estimates. Our findings corroborate research conducted in other regions that used machine learning techniques to map various crop types (Kpienbaareh et al., 2021; Mashaba-Munghemezulu et al., 2021; Rao et al., 2021). Compared to other machine learning algorithms, the RF model is highly accurate in distinguishing between crop and noncrop cover types and retrieving maize-grown areas from Sentinel-2 images (Chen et al., 2021; Zhang et al., 2020).

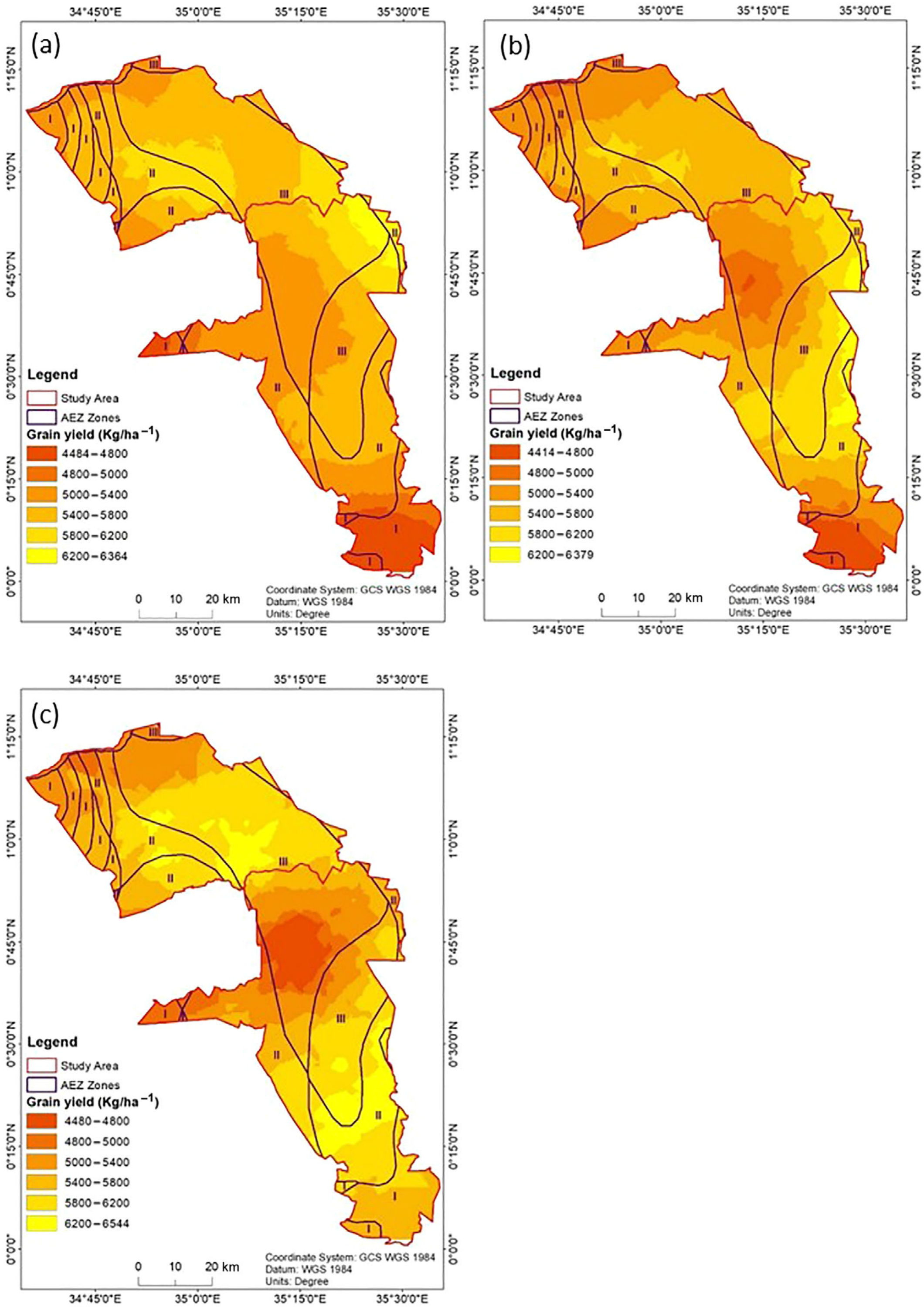

FIGURE 8 Yield maps of the H614 maize variety under optimal sowing dates (SDs): (a) SD1, (b) SD2, and (c) SD6 in the study area. I, II, and III are the humid, subhumid, and semihumid agroecological zones, respectively.

4.2 | Influence of agronomic practices

The simulated yield from the calibrated and evaluated DSSAT-CERES-MAIZE crop model revealed that various agronomic practices have varied influences on production across the AEZs. The results showed that SDs and cultivars are the main agronomic practices influencing the maize yield dynamics acting independently and in their interactions in the region. SDs and other farm management decisions determine the intersection of

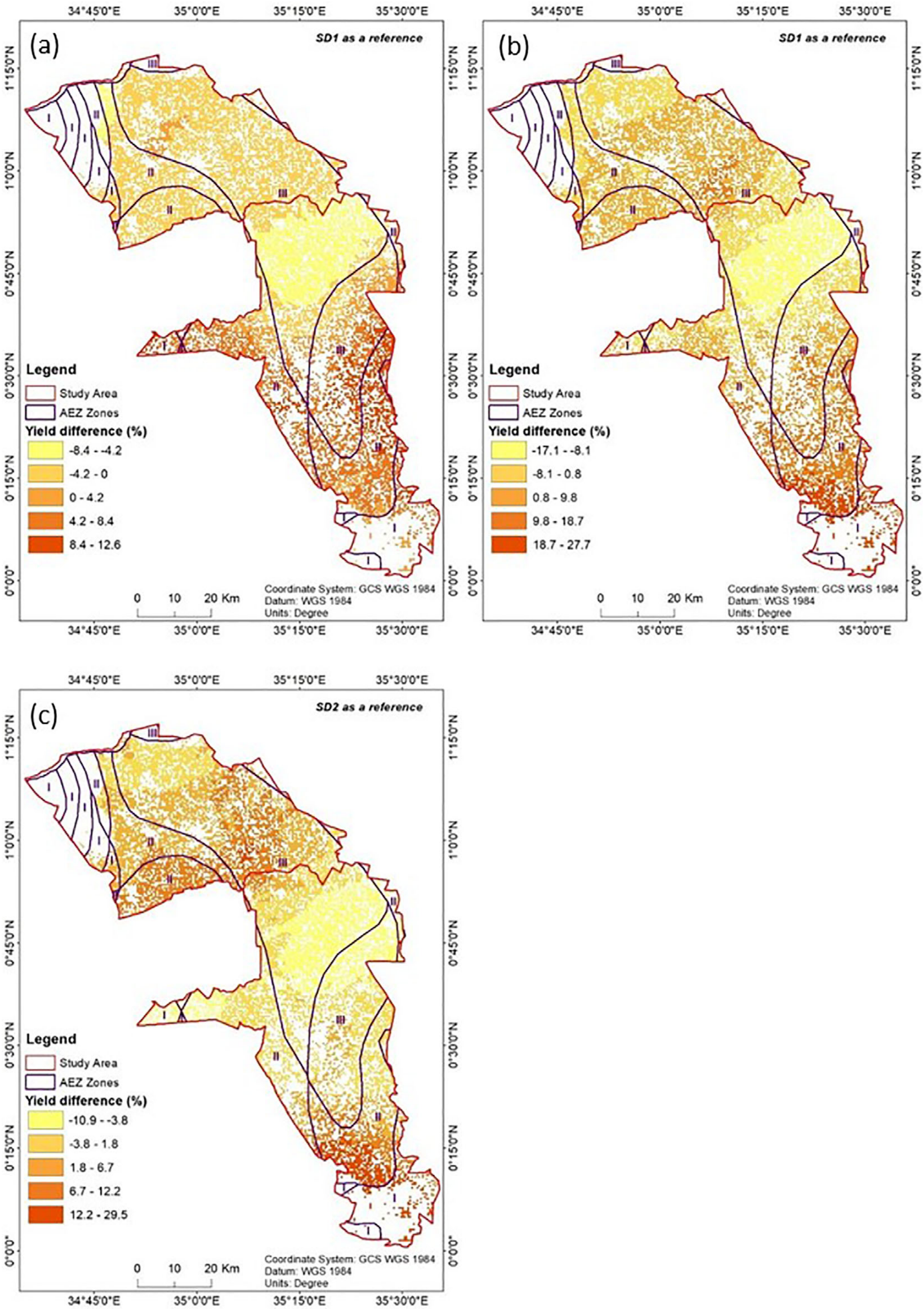

FIGURE 9 Percentage yield difference for H614 maize variety considering various sowing dates (SDs): (a) SD2 relative to SD1, (b) SD6 relative to SD1, and (c) SD6 relative to SD2. I, II, and III are the humid, subhumid, and semihumid agroecological zones, respectively.

critical phenological stages with favorable weather conditions (Feleke et al., 2023; Perondi et al., 2019). Maize requires sufficient precipitation during the tasseling, pollination, silking, and grain stages (Ramirez-Cabral et al., 2017). In addition, high temperatures during the same period induce thermal stress, limiting pollen viability and affecting silk receptivity (Waqas et al., 2021). Also, evidence of varied cultivar responses on maize production and stability was found in some studies, for instance, Lana et al. (2017) and Rezende et al. (2020). Despite the two cultivars being among the top cross hybrids in the East Africa region, the model calibration results indicated that H614 require more heat units to attain anthesis and reach physiological maturity. Longer growth duration in long-maturing varieties compounded by optimal weather conditions at critical crop phases increases dry matter accumulation and allocation to kernels, thus improving crop productivity (G. Liu et al., 2023; Zhiipao et al., 2023). The varied response of SDs and cultivars on maize yield aligns with other studies conducted in the African agricultural systems (Adnan et al., 2017; Tesfaye et al., 2017; Tofa et al., 2020).

The study found that yield can be enhanced beyond the current average production in all the AEZ zones in the study area by adjusting SDs and adopting the H614 cultivar. However, the increment is possible if the nutrient management aligns with the government-recommended nitrogen fertilization of 75 kg N ha^{-1} (Chebet et al., 2017). The H614 cultivar is one of the superior cultivars in the region and has been evaluated by Kipkulei, Bellingrath-Kimura, Lana, Ghazaryan, Baatz et al. (2022). The modeling results showed that the least feasible yield for the cultivar in the study area was 4400 kg ha^{-1}, an estimate slightly higher than the government statistics of 3700 kg ha^{-1} in Uasin Gishu County and 4000 kg ha^{-1} in Trans Nzoia County (MoA&LD, 2020). The slight discrepancy can be attributed to the low input application by the farmers with no consideration of site-specific conditions or government-recommended applications. For instance, Chebet et al. (2017) found that, on average, farmers apply 60 kg N ha^{-1} with no additional supplements such as manure.

Regarding the influence of AEZs, the study found varied effects of sowing and cultivars. A possible explanation for this variation is the different susceptibility of the zones to varying weather conditions. For instance, AEZ I is less sensitive to varying weather conditions, and the high and even distribution of precipitation in this zone is a catalyst for growth acceleration and yield stability. The findings corroborate the results of other studies in similar environments in SSA, which found that weather variability in different AEZs affects yield variability (Amikuzino & Donkoh, 2012; Mugandani et al., 2012). Furthermore, a high average yield was simulated for AEZ II compared to other zones. This result may be explained by the fact that climatic conditions in the zone are moderate compared to those in different zones. Despite AEZ I receiving high rainfall, the zone is characterized by poorly drained soils in most parts, which might result in yield decline. Another possible reason is that zone I lies in a low-temperature gradient bordering Mount Elgon in Trans Nzoia and a section of the Mau Forest complex in Uasin Gishu. This disadvantages maize performance, which usually requires temperatures above 20˚C for germination and rapid growth (Waqas et al., 2021). As for the zone, therefore, the seed germination and development rate may be suppressed, leading to a low plant population. Maize growth and development thrive under optimal temperatures beyond which a marked decline in yield occurs (Chemura et al., 2022). AEZ III, on the other hand, experiences low rainfall and is characterized by highly weathered, leached Ferralsols with poor water-holding capacity (Amikuzino & Donkoh, 2012). Low rainfall amounts and low soil fertility influence sowing and other agronomic practices in rainfed cropping systems (Rurinda et al., 2015).

The study revealed distinct impacts of early and late sowing practices across the AEZs, influenced by rainfall patterns characterized by onsets and cessation. In AEZ III, a delay in sowing led to decreased yield in comparison to AEZs I and II. Early sowing particularly benefited the eastern and northwestern parts of AEZ II, aligning with the observations of Kibii and Kipkorir (2018), who highlighted early precipitation onset in the region. The western parts of Trans Nzoia County, which mainly covers AEZ I and northern Uasin Gishu County, appeared to be affected by late sowing. A possible explanation for this trend might be in the prevailing weather conditions, including variable onset and cessation patterns in the region, causing diverse influences on the growth and development of maize (Mugalavai et al., 2008). On the other hand, the southern parts of both counties appeared to benefit from late sowing. The effect can be attributed to higher and relatively stable precipitation in the zones. The average rainfall in these zones is between 1200 and 1800 mm, with an even distribution across the growing season (Jaetzold et al., 2010). Moreover, these zones are characterized by nitisols and deep and productive soils typical of tropical environments (NAAIAP & KARI, 2014).

The influence of organic amendments, irrigation, and tillage practices did not significantly affect maize yield across the AEZs. A possible explanation for this result is that the additional nitrogen from organic amendments may not have been in sufficient quantities to contribute to yield increase. Other studies have found significant effects of organic amendments, especially when provided in larger quantities (Naderi et al., 2016). However, other research findings on the influence of tillage practices are consistent with our research (Khan et al., 2007; Naderi et al., 2016). Studies conducted in SSA, where agronomic practices are adjusted as measures against climate change effects, show that AEZs largely characterize maize yield.

4.3 | Yield maps and domains across the AEZs

This study found that agronomic practices had variable responses in maize production in the study area. The high response effect of AEZ I over a large range of SDs and stability in production in the zone can be attributed to high and stable annual precipitation compared to AEZs II and III (Kabubo-Mariara & Karanja, 2007). However, yield benefits were more pronounced in AEZ II than in the other zones. This finding may be due to the combined influence of temperature and precipitation, favoring a greater yield increase. AEZ I exhibits low minimum temperatures, sometimes falling below 10˚C, constraining maize germination and vegetative growth (Ramirez-Cabral et al., 2017).

4.4 | Limitations

One limitation of the study is that we used dual seasonal data to calibrate and evaluate the DSSAT-CERES-Maize model. Although two seasons present a minimum period for such assessments, future research will explore on-farm experiments spanning more seasons to obtain a better response of the model to diverse environmental and management scenarios. In addition, although the model has been found to perform well in representing crop growth, the DSSAT-CERES-Maize model cannot account for factors such as weed infestations, pests and diseases, and extreme weather conditions such as droughts and floods.

5 | CONCLUSIONS

The present study aimed to assess agronomic practices using the DSSAT-CERES Maize model and to assess the impact of these practices on maize yield across various AEZs in Uasin Gishu and Trans Nzoia Counties in Kenya. Our results indicate that the influence of agronomic practices varies with the AEZs. The study found that adopting the optimal SD and the H614 cultivar could increase yield by 1120 tonnes in AEZ I, 11,478 tonnes in AEZ II, and 35,658 tonnes in AEZ III. Cumulatively, the AEZs can account for a 5.7% increase in maize production from the current production. Although early sowing spanning to the end of March provides good potential for high yields, we established that some areas in the southern parts of Uasin Gishu could have significant yield increases if sowing is conducted in early May.

The outcome of this research offers an opportunity for farmers and the government to better understand the potential practices across the maize-cultivated areas. The study also helps to strengthen policies and improve resource allocation regarding agricultural planning at the county and national levels. Future research will focus on upscaling these measures and assessing a broad range of agronomic practices, including other cultivars that have not been calibrated and evaluated in the study area. The study provides a useful knowledge base to support sustainable crop production in rainfed cropping systems and under production constraints such as climate change.

AUTHOR CONTRIBUTIONS

Harison Kiplagat Kipkulei: Conceptualization; data curation; formal analysis; investigation; methodology; writing—original draft; writing—review and editing. **Sonoko Dorothea Bellingrath-Kimura**: Formal analysis; supervision; writing—review and editing. **Marcos Lana**: Formal analysis; supervision; methodology; writing—review and editing. **Gohar Ghazaryan**: Formal analysis; methodology; writing—review and editing. **Roland Baatz**: Formal analysis; methodology; writing—review and editing. **Custodio Matavel**: Formal analysis; writing—review and editing. **Mark Boitt**: Formal analysis; supervision; writing—review and editing. **Charles B. Chisanga**: Formal analysis; methodology; writing—review and editing. **Brian Rotich**: Formal analysis; writing—review and editing. **Rodrigo Martins Moreira**: Formal analysis; methodology; writing—review and editing. **Stefan Sieber**: Formal analysis; supervision; methodology; writing—review and editing.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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