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Evaluation of a regional crop model implementation for sub-national yield assessments in Kenya

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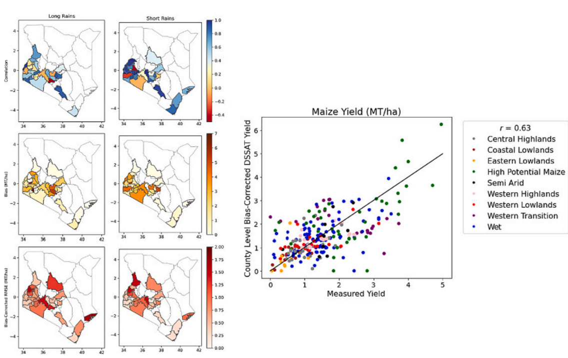
HIGHLIGHTS

- We use a coupled land surface and crop modeling framework (RHEAS) to simulate seasonal yield in Kenya.
- The modeling framework introduces an ensemble-based approach to characterize the uncertainty in a data limited region.
- Overall, the model simulated seasonal yield variations with a median correlation with reported yields of 0.66.
- The system shows skill at simulating extreme departures in anomalies.

GRAPHICAL ABSTRACT



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ABSTRACT

CONTEXT: Cropping system models can be used to both assess regional food security and to monitor and predict agricultural drought. Agriculture in Kenya is extremely important to both the economy and food security of the country.
OBJECTIVE: This study evaluated a regional implementation of a widely used crop model, the Decision Support System for Agrotechnology Transfer (DSSAT), within a coupled modeling framework, the Regional Hydrologic Extremes Assessment System (RHEAS), over Kenya. The goal of this study was to assess the ability of RHEAS to simulate the annual variability of maize yields at the county level and evaluate the uncertainty inherent in the model and inputs.
METHODS: The RHEAS system implements a stochastic ensemble approach to account for field scale variabilities in crop management practices and underlying soil and weather conditions. Satellite-derived datasets were used

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to evaluate the land surface component of the system and seasonally disaggregated yield for 5 years was used to assess the performance of the cropping system model.

RESULTS AND CONCLUSIONS: The median correlation between RHEAS and satellite-derived soil moisture and evapotranspiration estimates were 0.78, and 0.51, respectively, indicating that the model is able to capture the key drivers of the hydrological budget. Overall, RHEAS simulated yearly yield variations with a median correlation of 0.7 with reported yields, with the best performance in the short rains season. However, across both seasons, the RHEAS model was positively biased on the order of ~1.6 MT/ha. The overall median unbiased RMSE was 0.66 MT/ha. The RHEAS system shows skill at simulating extreme departures in anomalies, and a majority of the time (62.5%) the reported yields fall within the interquartile range of the simulations.

SIGNIFICANCE: One of the most important areas of improvement for the next generation of agricultural data and models is to better understand and communicate the inherent uncertainties. This is especially critical in data-limited regions. Here we present a modeling system and its implementation that begins to address these concerns. We demonstrate the ability to simulate broad trends in yields at the county level for sub-annual yields with skills that commensurate previous national/annual level studies.

1. Introduction

Agricultural simulation models can be a key component in addressing issues of sustainability and global food security (Boote et al., 1996; Godfray et al., 2010; Wheeler and Von Braun, 2013; Jones et al., 2017; Singh, 2019). These models can assist in the monitoring and prediction of agricultural drought and its impacts on yields (production) and water resources (Karthikeyan et al., 2020) while enhancing our understanding of the complex interconnections between different climatic conditions and soil characteristics on crop growth and development (Rosenzweig et al., 2014; Peng et al., 2020). These simulations can be crucial in developing national agriculture policies, analyzing trade and market balances, and planning effective adaptation strategies to mitigate climate change (Wheeler and Von Braun, 2013; Ruane et al., 2017). Additionally, these simulations are vital inputs to monitoring systems for early warning assessments of production anomalies (e.g. GEOGLAM, Becker-Reshef et al., 2019, 2020).

Crop modeling systems are constrained by inherent model errors that are compounded by inadequate inputs and implementation scales. Though the majority of the crop modeling systems are point-based, they can be configured to run in a gridded manner for national-level planning and large-scale applications (pyDSSAT, WOFOST, SIMS etc., Müller et al., 2019 Jägermeyr et al., 2021). Large scale implementation of such models necessitates a multitude of inputs related to weather and crop management practices. Sparse weather inputs (e.g. on average 1 climate station per 5000 km^2 globally, (Aghakouchak et al., 2015, Hooker et al., 2018), in combination with parameterized management options contribute towards the uncertainties in crop model simulations. Crop management information (e.g., crop type and cultivar, fertilizers amount/type, irrigation method and timing) can be particularly challenging to obtain and hence are often parameterized over large areas, sometimes even at the country level (e.g., crop calendars, Sacks et al., 2010). The inherent uncertainties in management strategies require the model results to be accepted with a wide array of assumptions at that scale (e.g., McNider et al., 2015; Müller et al., 2019).

Many studies have sought to mitigate these inherent model uncertainties by assimilating remotely sensed observations such as the soil moisture (SM); leaf area index (LAI); normalized difference vegetation difference index (NDVI) or evapotranspiration (ET) (Ines et al., 2013; Huang et al., 2019; Jin et al., 2018; Mishra et al., 2021) with some success. The basic assumption of these studies is that the remotely sensed observations are relatively more accurate than the parameterized inputs particularly at large spatial scales. However, the success of such an approach is highly dependent on the accuracy of remotely sensed observations that can often be spatially and temporally inconsistent and further limited by the spatial resolution of sensors (Jin et al., 2018; Huang et al., 2019).

Another approach to mitigate the limitations of the model is through coupling a cropping system model with other process-based models including the climate and/or land surface models (Tsakmakis et al., 2017; Casanova and Judge, 2008; Ingwersen et al., 2018; Maruyama and Kuwagata, 2010; Zhang et al., 2021; Zou et al., 2019). Coupling climate models with cropping system models can provide easy access to weather information and even offer opportunities to study the impact of vegetation change on climate change and vice-versa (Osborne et al., 2007; Tsakmakis et al., 2017). A coupled land surface-cropping model tends to better characterize the land-atmosphere interactions through a stronger feedback mechanism of energy fluxes (Casanova and Judge, 2008; Zhang et al., 2021; Tsarouchi et al., 2014). Although typically designed for more holistic agriculture-water management applications, linking crop models to a land surface or hydrologic model can also provide access to difficult to obtain inputs such as solar radiation or wind speed, where they can be resolved in more complex energy budget and boundary layer algorithms that are not typically included in crop models themselves (Kanda et al., 2018; Siad et al., 2019). Additionally, several widely used crop models have rather simplistic hydrologic parameterizations like that of the soil moisture routines (Eitzinger et al., 2004; Shelia et al., 2018; Siad et al., 2019), whereas a land surface model typically resolves soil moisture using process-based equations or explicit numerical solutions of the Richards equation (Chen and Dudhia, 2001; Gao et al., 2010). On the other hand, crop models tend to have more advanced root water uptake algorithms specific to the crop type, while most land surface models are parameterized based on broad (pixel level) characterizations of parameters like evapotranspiration, vegetation and land cover, (e.g. VIC: Liang et al., 1994 and NoahMP: Niu et al., 2011).

Most of these coupling studies were able to improve one or more parameters from either the climate/land surface model or the crop modeling systems, the implementation was essentially deterministic over a grid. In this study, we utilized a coupled hydrological and crop modeling system where the crop modeling component is implemented in a randomized ensemble mode to account for variations in soils, weather, and crop management over a region. The Regional Hydrologic Extremes Assessment System (RHEAS: Andreadis et al., 2017, Abhishek et al., 2021) is a framework that loosely couples a Variable Infiltration Capacity (VIC: Liang et al., 1994) hydrologic and Decision Support System for AgroTechnology Transfer (DSSAT: Jones et al., 2003; Hoogenboom et al., 2021) cropping system model. RHEAS is a modular framework that allows for seamless integration of multiple modeled and remotely sensed products across different components of the terrestrial water cycle. The RHEAS system allows a set of known crop management practices to be included as input since each farm/farmer will likely use a range of cultivars or have planting dates a week or more apart. The stochastic nature of RHEAS can represent a more realistic characterization of input variations (and their uncertainty) across an area. Understanding this uncertainty is one of the most important areas for improvement in the next generation of data, models and knowledge products (Jones et al., 2017).

The strength of the RHEAS system is particularly realized in data-limited regions. Here we apply RHEAS to estimate the annual variability of maize yield at the county level across Kenya. Agriculture in

Kenya is extremely important to both the economy and food security of the country. Dependence on rainfed agriculture in a highly variable climate renders crop and livestock production highly vulnerable to the impacts of climate shocks. It is estimated that 4.4 million people in Kenya are acutely food insecure (World Food Program, 2023), due to persistent drought since 2017 which was further exacerbated by COVID and locust outbreaks in recent years. Furthermore, Kenya's population has been increasing significantly, from 11 million in 1970 to over 48.5 million in 2020 (World Food Program, 2023), and as a result, farmers are pushed into less suitable land with poorer soils and less rainfall, where they are more vulnerable to climate shocks (FAO: Food and Agriculture Organization of the United Nations, 2023). The need for timely and actionable detailed early warning information on drought and its implications on crop productivity for decision-making has been explicitly expressed by food security stakeholders.

2. Material and methods

The RHEAS model was run over Kenya from 2015 to 2019. The gridded land surface variables for soil moisture and evapotranspiration were validated across the country. The m-DSSAT, a modified instance of the DSSAT, component was run over agricultural-ecological zones (AEZs) which represent the major agricultural producing areas. RHEAS yields were evaluated at the county and AEZ level using seasonal yield data from Kenya's Ministry of Agriculture, Livestock, Fisheries and Irrigation (MoALFI). Model vs actual yields were analyzed spatially and temporally to characterize the uncertainties in the model simulations.

2.1. Study area

The focus of this study is Kenya, with contrasting climatic conditions ranging from arid in the north to humid/sub-humid in the southwestern part of the country (Fig. 1). This study focused at the county administrative level. Though Kenya has 47 counties, this study covered just those counties with at least 10% of agricultural land which resulted in 31 counties. The counties were further classified into AEZ based on the FAO classifications (Vigani et al., 2019).The study area has a range of precipitation varying from about 2000 mm/year in the Wet AEZ to 700 mm/year in the driest Arid AEZ from 2012 to 2019 (Funk et al., 2015). Most rainfall occurs during the two rainy seasons, the long rains (March–June) and the short rains (October–December). Maize planting can range from February–April for long rains and August–October for short rains, and harvest can range from July–September for long rains and January–March for short rains, depending on the area, cultivar and the year. Maize agriculture in Kenya is concentrated in the Southwest, where the most area is cultivated and also has the most production.

2.2. Data description

RHEAS allows the user the flexibility to use data from multiple sources or bring in their own datasets as either forcing or for data assimilation (Andreadis et al., 2017; Abhishek et al., 2021). In this study, daily temperatures and wind speed forcing data was obtained from National Center for Environmental Prediction (NCEP) reanalysis (Kalnay et al., 1996). NCEP reanalysis data is a globally gridded dataset available at 1.875^{o} since 1981. In this study, coarse resolution weather data from NCEP was resampled to 0.05^{o} using nearest neighbor. Daily 0.05^{o} rainfall data was available for Climate Hazards Infrared Precipitation with Station data (CHIRPS) (Funk et al., 2015). CHIRPS is a gridded global satellite-driven rainfall dataset that has been corrected using ground stations and has been found to be fairly accurate over the eastern Africa region (Dinku et al., 2018; Ngoma et al., 2021; Shen et al., 2020).

Two satellite products were used for evaluating the model results. The surface soil moisture data from Soil Moisture Active Passive [SMAP; Entekhabi et al., 2010)] is used to evaluate the top layer (0–10 cm) soil moisture outputs. The derived Enhanced SMAP soil moisture product is from the original 36-km soil moisture product using L-band microwave sensors reprojected to 9-km grid. A 1000-km wide swath ensures a global coverage with 2–3-day revisit.

The Moderate Resolution Imaging Spectroradiometers (MODIS) Global Evapotranspiration (ET) product (MOD16; Mu et al., 2011) was used to quantify the atmospheric demand from the land surface. The MOD16 product uses an algorithm based on MODIS satellite imagery and global meteorology data to produce ET, latent energy (LE), potential ET and potential LE. The algorithm is constructed around the Penman-Monteith equation where the surface resistance is characterized by satellite-observed leaf area index (LAI). The output is summed 8-day,

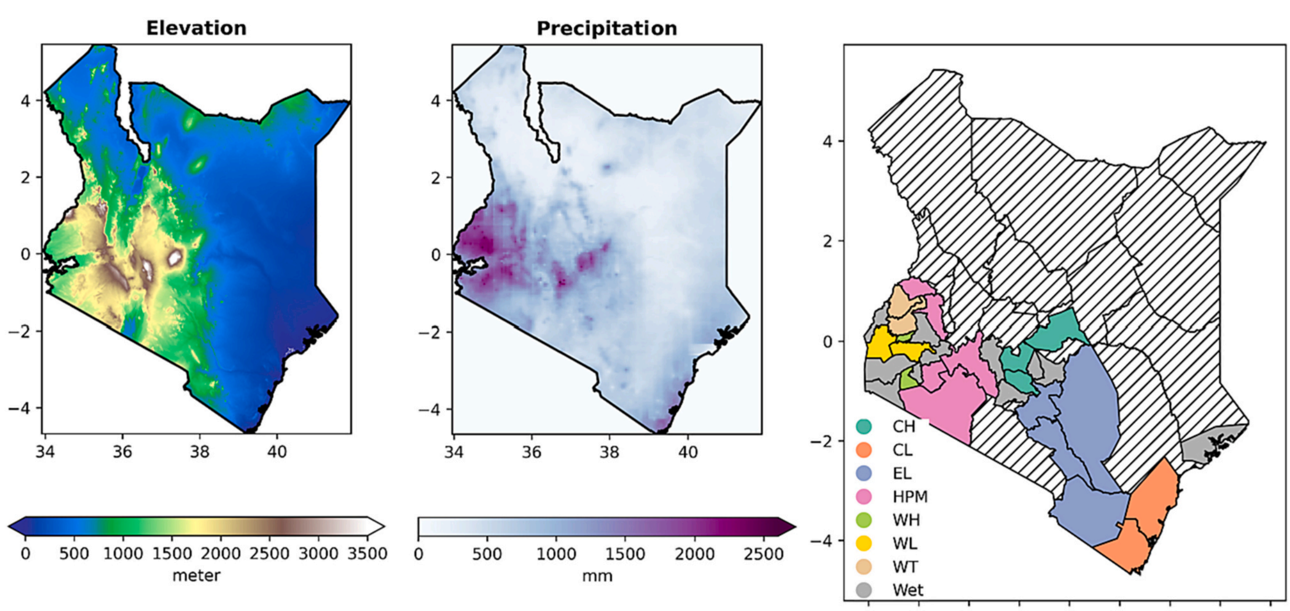

Fig. 1. Study area showcasing the (a) elevation based on Shuttle Radar Topography Mission digital elevation model (Farr and Kobrick, 2000) (b) total annual precipitation from Climate Hazards Infrared Precipitation with Station data (Funk et al., 2015) and (c) the county level administrative districts in Kenya. Colors denote the agricultural ecological zones and the hatched counties denote agricultural area < 10% and were excluded in this study.

monthly and annual ET at a 1 km^2 spatial resolution. Together, soil moisture and evapotranspiration can verify the surface water budget of the RHEAS land surface model.

Maize was simulated as a representative crop as it is a staple crop for Kenya, it is widely grown, and the country's production is regularly monitored and reported. Maize yield data was collected from the Kenya Ministry of Agriculture, Livestock, Fisheries and Irrigation's (MoALFI) online data portal and through personal communication with ministry officials. The yield data is disaggregated by county and by season (long/short rains) from 2015 to 2019 and are reported in tons per hectare. Data prior to 2015 were not available by season and thus excluded in this study. The yield is an average estimate based on production and harvested areas and includes both rainfed and irrigation fields, however, irrigation is not widespread in Kenya, particularly for small holder maize farmers by which over 75% of Kenyan maize is produced (Kanda and Lutta, 2022).

2.3. Model description

The main component of the RHEAS architecture hosts a spatially enabled relational (PostGIS) database that ingests a suite of earth science products (model datasets and satellite observations) which allows for automatic ingestion of datasets, forecasts, and climate projections from multiple sources and formats. Detailed information about the model design, architecture, installation, and operation is readily available at https://github.com/SERVIR/RHEAS/.

The hydrologic model used in RHEAS is the macroscale Variable Infiltration Capacity (VIC) model (Liang et al., 1994). VIC simulates the land-atmosphere fluxes and computes the energy (and water) balance at the land surface. Baseline VIC modeling parameters used in this study were calibrated using the method of Troy et al. (2008) as in Andreadis et al. (2017). The process-based Decision Support System for Agrotechnology Transfer (DSSAT: Jones et al., 2003, Hoogenboom et al., 2021) crop model is incorporated within RHEAS to simulate the crop growth, development, and yield under different management practices and soil properties. The crop model used in this study is a modified version of the baseline DSSAT (m-DSSAT) that enables data assimilation capabilities to allow for effective integration of leaf area index (LAI) and soil moisture during different phases of crop growth (Andreadis et al., 2017; Ines et al., 2013). The m-DSSAT is then sampled over a given area to better represent the variabilities in weather, soils, and crop cultivar within a region.

Since RHEAS is a regional implementation of an otherwise point-based model, some county level model inputs were parameterized to represent an AEZ as a whole. The crop model uses a wide scale global crop calendar (Sacks et al., 2010) for default planting date information based on location.

A specific fixed amount of fertilization (nitrogen) was made to apply twice in the model, first at the planting and then 30 days after planting. Amounts varied by AEZ, were derived from several reported sources in the literature from in-country assessments (Yamano and Arai, 2011; IFDC: International Fertilizer Development Center, 2012, One Acre Fund, 2016), and are provided in the supplemental data. Since the overwhelming majority of the agriculture is rainfed in the region (Kanda and Lutta, 2022), the model simulations were made assuming rainfed conditions only. DSSAT soil profiles are derived from the 5-km gridded dataset from Han et al. (2015).

Cultivar parameters are used to set genetic coefficients that control plant growth cycles such as sensitivity to daylight length, leaf appearance rate, and grain size and number. These parameters affect the timing of growth stages for maize, which have different water needs at different stages, and therefore the overall yield. A total of 29 cultivars from DSSAT v4.7 distribution and a comprehensive literature review were initially tested for general performance of season length and phenology (Müller et al., 2019). Most of these cultivars were calibrated in field specific trials in the region. Error statistics were calculated by comparing the simulated yield against the measured yields from MoALFI at a seasonal scale from 2015 to 2019. Similar to Müller et al. (2019), cultivar(s) were selected for each county that had average harvest dates that fit within the typical harvest time frame for the region, met general criteria for correlation (>0.8), and minimized unbiased RMSE. The goal was to select the top two or three cultivars that best represent the actual genomic diversity in the counties. However, if none of the cultivars met these specifications, the cultivar with the highest correlation was selected. On average, 2 cultivars were selected for each county with 5 counties having 3 or more selections. Of the 29 cultivars that were initially evaluated, 24 were used at least once. The cultivars used in this study are provided in the supplementary data.

3. Results

3.1. Hydrologic evaluation

The RHEAS model performance was evaluated using both hydrological and cropping system products. Surface soil moisture and ET are two critical components of the hydrological cycle that have significant impact on the hydrological budget. Therefore, these two components are evaluated with the assumption that other associated components will exhibit similar model error characteristics. Due to the general lack of independent data sources at such scale and to avoid model to model intercomparisons, available satellite products (surface soil moisture and ET) were used as proxies for reference datasets. The surface (0–10 cm) soil moisture data from the hydrological model are compared against the level-3 Soil Moisture Active Passive (SMAP) - Enhanced soil moisture product. Whereas, the ET data from the model was evaluated against the 8-day MODIS ET product. The SMAP evaluation was aggregated to 8 days for consistency and also ensured full coverage due to satellite swath paths. It should be noted that the comparison with satellite derived observation does not indicate that satellite observations are free from errors or systematic biases; instead, we are interested in the predictive abilities of the model to mimic general trends and spatio-temporal dynamics.

The results of hydrologic evaluation are shown in Figure 2. Overall, the median correlation between soil moisture from RHEAS-VIC and SMAP was 0.78 (the median daily correlation was slightly lower (r = 0.64) but with similar patterns across the country). This varied across elevation and climate zones. It can be seen that the better correlations were over the lower elevations, however, the biggest degradation in correlation was near and around Lake Turkana. The maximum correlation was 0.92 and the lowest was −0.04 (only 1 pixel had a correlation <0). It can be seen from the histogram in the lower right of the plot, that virtually all areas saw a correlation >0.5. The evaluation of RHEAS VIC-ET compared to MODIS ET was not as strong as the soil moisture comparisons, with a median correlation of 0.51. It can be seen that model and satellite product dissagreed the most over the higher elevations and high cloud cover regions. The maximum ET correlation was 0.84 with a minimum of −0.62. Combined the evaluation of these two variables give confidence in the model's ability to simulate the overall hydrologic budget.

3.2. Yield evaluation

The RHEAS DSSAT crop yields were compared with MoAFLI data for each county and for each growing season. It's important to note that the reported yields are an average of the total production vs harvested area in each county. Many 100's of fields are represented in each county under different soils, rainfall, and management practices. The RHEAS system attempts to simulate those scenarios and express the level of variance possible through its ensemble members.

Overall results show good comparisons with MoALFI yields, with a median correlation of 0.66. The short rains had better correlations (median r = 0.68) than the long rains (median r = 0.52). Both seasons

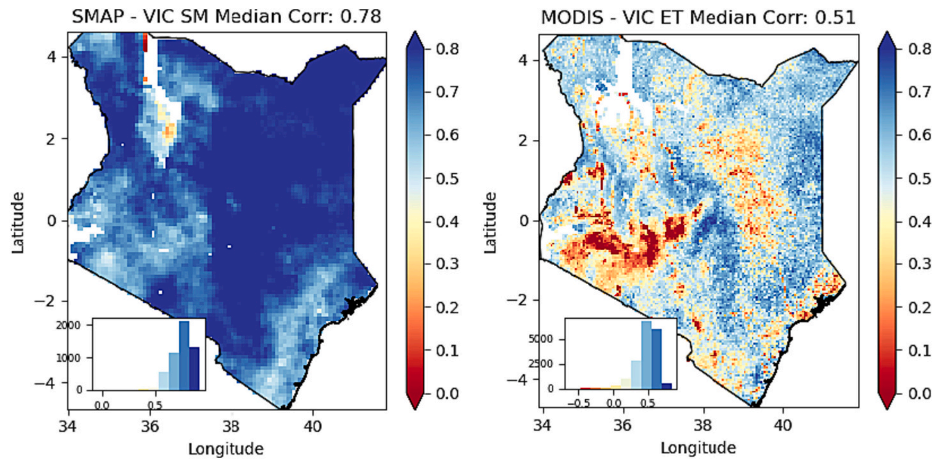

Fig. 2. Evaluation of the correlation between the Regional Hydrologic Extremes Assessment System's Variable Infiltration Capacity (VIC) hydrologic model -VIC as compared to (a) Soil Moisture Active Passive (SMAP) surface soil moisture and (b) Moderate Resolution Imaging Spectroradiometer (MODIS) Evapotranspiration.

exhibited high positive bias. Correlation, bias, and unbiased RMSE of selected cultivars are reported in Table 1.

Fig. 3 shows the performance of the model by county. The lowest correlation for the long rains was −0.68, with the majority of counties showing r > 0.5. Four counties (Kiambu, Nakuru, Nyeri, and Siaya, all from different AEZs) had negative correlations which brought down the overall average. The mean correlation improved nearly 20% (from 0.47 to 0.58) without those counties. For the short rains, the results were relatively more consistent with the lowest correlation of −0.50 in Nandi County, however the average was 0.67, again with most counties $r > 0.5$. Four counties (Nandi, Homa Bay, Mombossa, and Narok) were below 0. At the AEZ level, the long rains exhibited a wider range of correlations. Every AEZ in the short rains except the Arid region had a median correlation above 0.5.

Though RHEAS-DSSAT was able to capture the annual variation on the whole, the modeled yields did show bias and almost always overpredicted the final yields. Only three counties had a negative bias (Lamu, Samburu, and West Pokot) and it was for both seasons. The median bias was 1.62 MT/ha ranging from −1.67 to 7.52 MT/ha. Six counties had a bias of over 5MT/ha and were all in the Wet, Central, and Western Highlands (when these are removed the median bias lowered to 1.5 M/ha. Overall, the Central Highlands had the highest bias.

Figs. 4 and 5 show the performance of the model across time for each AEZ and each season, long rains and short rains, respectively. The box plots represent the anomalies of all the ensembles (40) that ran for each year (5) and county within the AEZ; thus, the number of simulations per AEZ would be the number of counties within the AEZ times 200. It can be seen that overall, the majority of the time (62.5%) the reported yields fall within the interquartile range of the ensembles indicating most of the ensemble's members are simulating the yield at a higher confidence interval. As with the overall performance, the short rains show the least uncertainty and best agreement.

Though the data doesn't exist at the sub county level, there are a wide range of soil, weather, and management decisions that contribute to the average reported county yields. The RHEAS system is in essence attempting to resolve these field scale variabilities through an ensemble approach at the aggregate level. In the AEZs with the lowest performance, the model shows the highest uncertainty (spread in ensembles). However, the model shows skill at simulating departures in anomalies, thus explaining the overall good correlations reported. For example, in

Table 1
RHEAS-DSSAT performance statistics for all counties over each growing season from 2015 to 2019 for each AEZ. Units are Metric Tons per hectare (MT/ha).

Season	AEZ	RMSE		Unbiased RMSE		Bias		Correlation	
Long Rains									
	Central_Highlands	4.3	(4.85)	0.56	(0.55)	4.16	(4.70)	0.31	(0.39)
	Coastal_Lowlands	1.01	(1.01)	0.56	(0.56)	0.17	(0.17)	0.45	(0.45)
	Eastern_Lowlands	1.72	(1.72)	0.68	(0.68)	0.99	(0.99)	0.89	(0.89)
	High_Potenital_Maize	2.46	(3.11)	1.07	(1.04)	1.88	(2.23)	0.36	(0.48)
	Semi_Arid	0.49	(0.49)	0.43	(0.43)	-0.33	(0.33)	0.73	(0.73)
	Western_Highlands	4.2	(4.20)	0.52	(0.52)	4.1	(4.10)	0.74	(0.74)
	Western_Lowlands	2	(2.00)	0.65	(0.65)	1.88	(1.88)	0.23	(0.23)
	Western_Transitional	0.56	(0.56)	1.38	(1.38)	-0.23	(0.23)	0.16	(0.16)
	Wet	2.52	(2.05)	0.68	(0.58)	1.96	(2.01)	0.56	(0.75)
	Mean	2.46	(1.72)	0.76	(0.70)	1.36	(1.39)	0.46	(0.52)
Short Rains									
	Arid	0.91	(0.91)	0.85	(0.85)	-0.71	(0.71)	0.39	(0.39)
	Central_Highlands	2.32	(1.96)	0.46	(0.51)	2.15	(1.93)	0.52	(0.57)
	Coastal_Lowlands	0.54	(0.54)	0.27	(0.27)	0.46	(0.46)	0.79	(0.79)
	Eastern_Lowlands	0.27	(0.27)	0.33	(0.33)	0.17	(0.17)	0.94	(0.94)
	High_Potenital_Maize	2.93	(3.33)	0.89	(0.94)	2.79	(3.22)	0.51	(0.54)
	Western_Highlands	3.8	(3.80)	0.28	(0.28)	3.79	(3.79)	0.55	(0.55)
	Western_Lowlands	1.5	(1.50)	0.31	(0.31)	1.5	(1.50)	0.96	(0.96)
	Western_Transitional	3	(3.00)	1.39	(1.39)	2.98	(2.98)	0.88	(0.88)
	Wet	2.4	(1.73)	0.7	(0.59)	1.97	(1.56)	0.49	(0.75)
	Mean	2.26	(1.83)	0.68	(0.59)	1.85	(1.73)	0.67	(0.68)
Mean		**2.33**	**(1.81)**	**0.73**	**(0.66)**	**1.86**	**(1.62)**	**0.53**	**(0.66)**

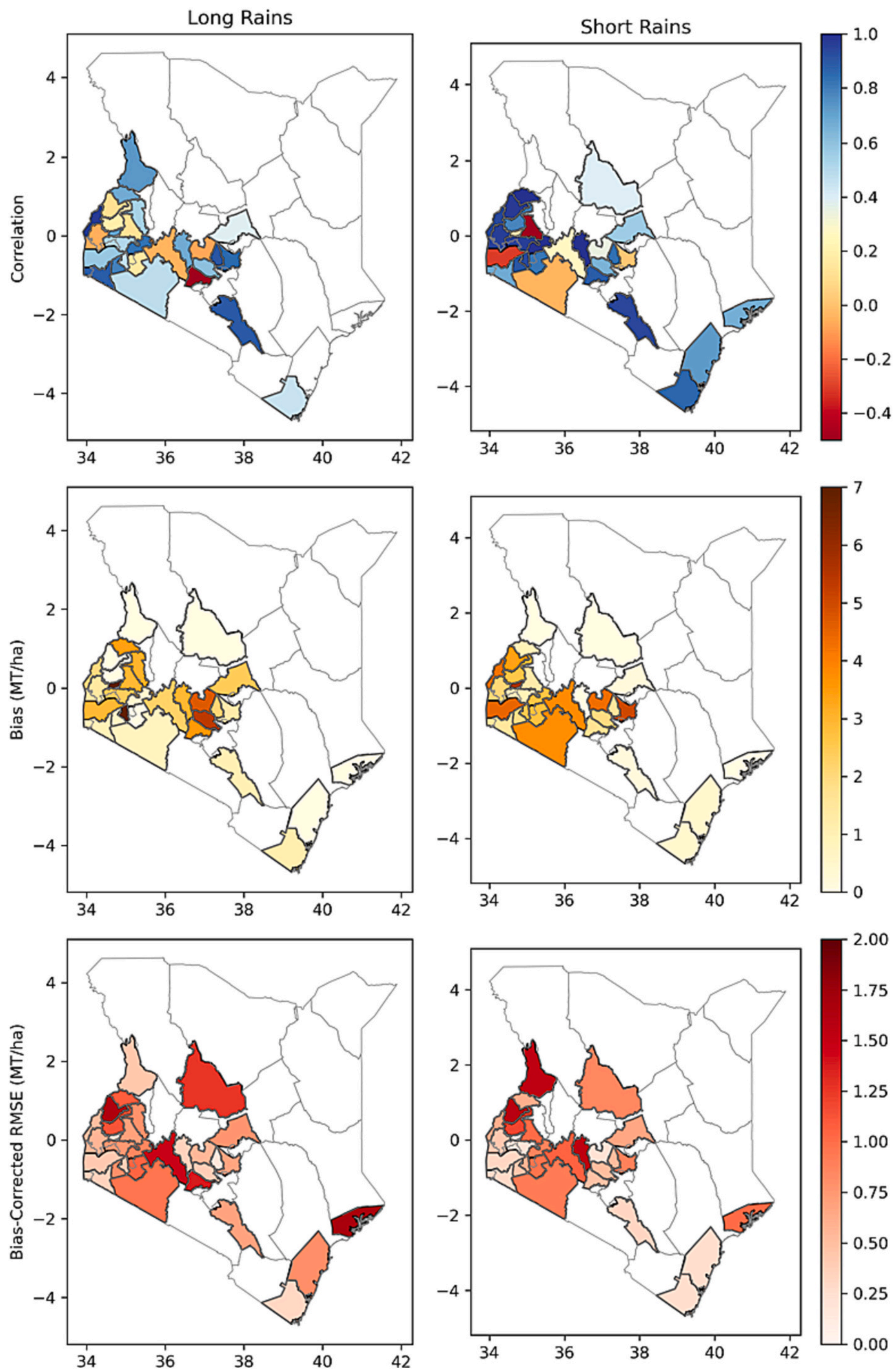

Fig. 3. Yearly performance of the Regional Hydrologic Extremes Assessment System's Decision Support Tool for Agrotechnology Transfer (DSSAT) agricultural model at each county before and after a county level bias correction was performed.

2016 there was severe drought during the short rain season which resulted in widespread famine across the country. A significant drop in yield anomalies exists across all AEZs in 2016, and the less spread (relatively) in the ensembles indicate a higher certainty of the event.

4. Discussion

4.1. Hydrological budget

The evaluation of the hydrologic model (VIC) shows good correlations with an independent satellite derived reference datasets. Performance was lowest over higher altitudes and near water. While certainly the model can struggle characterizing these regions, the reference datasets do as well. SMAP is known to perform poorly in wet areas near bodies of water, higher elevations and over thick vegetation (Entekhabi et al., 2010) and the correlations degrade in areas such as these (i.e. near Lake Turkana) and in higher elevations (>2000 m). The ET correlation significantly degraded in higher elevations near mount Kenya and in the coastal regions in the southeast. This contributes to the overall lower correlation and can be attributed, in part, due to lack of cloud free days in this region (Miller et al., 2020). The overall correlations suggest that there is confidence that the model is able to capture

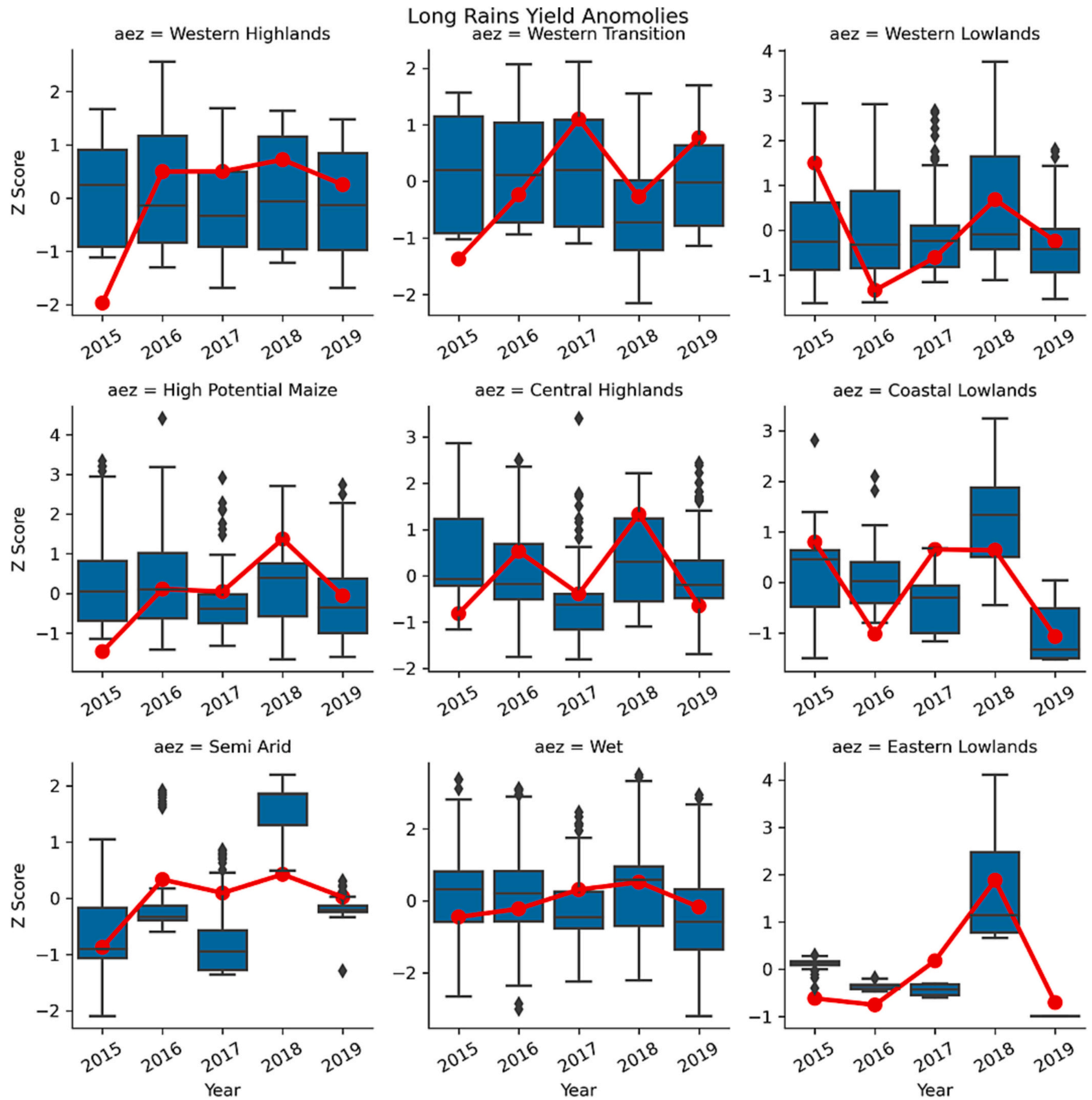

Fig. 4. Time series evaluation of the Regional Hydrologic Extremes Assessment System's Decision Support Tool for Agrotechnology Transfer (DSSAT) agricultural model performance across time for each agricultural ecological zone (AEZ) for the long rains season. The box plots represent the anomalies of all the ensembles that ran for each year and county within the AEZ. The red line is the reported average yield anomalies for each AEZ. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the key drivers of the total hydrological budget and match or exceed the performance of other modeling studies in the region (Pervez et al., 2021; Shukla et al., 2014; Srivastava et al., 2017).

4.2. Comparison of yield estimates with other studies

In terms of overall performance of RHEAS-DSSAT, the modeling system was able to simulate seasonal yields that captured most of the variance in the reported MoALFI data. A median correlation coefficient of 0.66 is among the better results when compared with previous process-based modeling studies (Abbaspour et al., 2015; Choruma et al., 2021; Folberth et al., 2012; Kamali et al., 2018) in the region. It's important to note, however, these were all done at a continental or national scale evaluating yearly data. This current study models sub-national (county-level) yields at the seasonal scale, where in the case of Kenya, two distinct growing seasons exist.

Previous studies based on statistical or machine learning models using satellite remote sensing data are often modeled at the field scale using crop cut or sampled yield information (as opposed to national assessments used here), which make it difficult to draw similar conclusions on performance. However, in review of the literature, the results generally align with results reported here (Guo et al., 2023; Jin et al.,

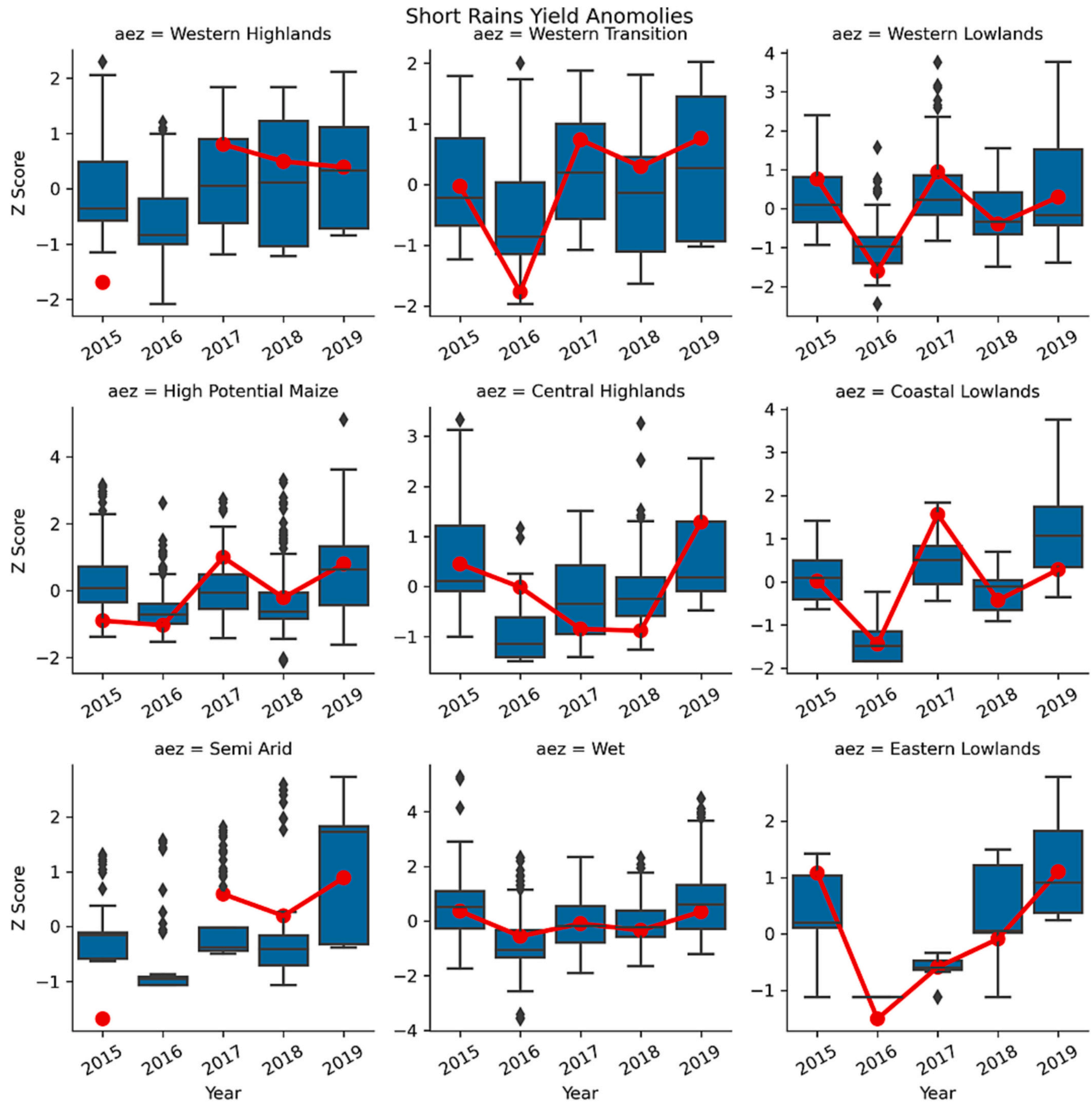

Fig. 5. Time series evaluation of the Regional Hydrologic Extremes Assessment System's Decision Support Tool for Agrotechnology Transfer (DSSAT) agricultural model performance across time for each agricultural ecological zone (AEZ) for the short rains season. The box plots represent the anomalies of all the ensembles that ran for each year and county within the AEZ. The red line is the reported average yield anomalies for each AEZ. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

2017, 2019; Luciani et al., 2019), with average correlations of ~0.5.

4.3. Model bias

Though the model was demonstrated to capture the overall variabilitly of reported yields, their model was almost always positively biased, on the order of 1.6MT/ha. When comparing to previous studies, this level of bias is high. Folberth et al. (2012) showed an average annual bias of 0.17 for Kenya, at the national scale, over 7 years. Choruma et al. (2019) found a pre-calibration bias of 0.321 MT/ha, however, they were evaluating the model at a field scale using agricultural field trials, which have significantly more localized data to force the models with. It's interesting that the counties with low correlations or high bias appear to be independent of each other or any spatial relationship, indicating that the reasoning is likely due in part to mischaracterized cultivars, reported yields, or other parameters not related to geography. Folberth et al. (2012) noted that overestimations are common in processed-based modeling studies in areas with reported yields <1.5 MT/ha. For this study, counties with reported yield <1.5 MT/ha had a positive bias of 2.43 MT/ha, while those counties with reported yield >1.5 MT/ha had a significantly lower positive bias of 1.51 MT/ha.

The bias reported here is likely explained in the models input characterizations as well as the reference dataset. In addition to the inherent model uncertainties, the characterization of environmental processes at regional scales often introduces errors and uncertainties both from inputs and parametrization. The model uses rather coarse resolution weather inputs from NCEP as forcings in this study and though CHIRPS at 5-km is a widely used dataset, especially in East Africa, it is not without error (Macharia et al., 2020; Macharia et al., 2022). CHIRPS typically has the most error in the agricultural areas and is mostly positively bias in the Kenyan region (Funk et al., 2015). Additionally, soil inputs are critical to crop simulations and systematic bias in crop models (particularly DSSAT) can be seen in low nutrient soils (Attia et al., 2021) and in low input systems. In limited agricultural management systems like Kenya, soil fertility can outweigh the effect of other factors, including weather, soil physical properties, crop genetics, and initial conditions (Asai et al., 2021; Correndo et al., 2021; Dokoohaki et al., 2021; Folberth et al., 2016; Huang et al., 2017; Jones et al., 2012; Mueller et al., 2012; Teixeira et al., 2017). Here we used a high resolution soils database, however, it is most suited to areas of intensive agricultural production (Han et al., 2019), therefore, this could result in higher uncertainties over relatively infertile and highly degraded soils. These uncertainties chiefly lie within the base models themselves and can be amplified when trying to model at the field scale. Though the RHEAS system is implemented at a county level, the model is trying to resolve field scale variations in anthropogenic decisions (i.e. planting dates, the timing and amount of fertilizer, cultivar selections, etc.).

With this understanding, when the bias is accounted for at the county level, the overall RMSE is 0.51 MT/ha, or approximately 30% of the mean yield in Kenya. Using the bias corrected yields a combined spatio-temporal correlation accross all AEZs, seasons, and years shows (Fig. 6) a correlation of 0.63, consistent with the temporal correlations of 0.70. The counties with the highest overall reported yields, typically those in the High Potential Maize and Wet AEZs, also showed the lowest bias. In only 6 of the 278 season/county/year combinations (~2%), the RHEAS-DSSAT model failed to bring a crop to maturity. This can be seen in the bottom of Fig. 6 where the bias corrected yields are 0 (more visible points are in high production zones where the reported yields were high). Given the amount of different input datasets used (management practices, weather, soils etc.), it is not possible to attribute this to one specific source of error, however, this is likely due to the mismatch of management practices and weather inputs.

4.4. Exogenous errors and uncertainties

There were some limits to the RHEAS-Modeling system in general that must be taken into account, beyond what is discussed above. Pest infestations that may affect the yield in the model were not considered. For example, fall armyworm has become an important pest for maize. In 2017, fall armyworm infestation resulted in a 37% loss in maize across the country (de Groote et al., 2020).

As has been often reported, there are challenges with respect to the availability and accuracy of the measured yield data for the region and there is a lack of long-term seasonally disaggregated yield data at county or sub-county level. Currently, most yield data available are aggregated to country level on a yearly, not seasonal, scale. A recent study by Grassini et al. (2015) compared yield data for Kenya from the Ministry of Agriculture and the Tegemeo Institute and shows a significant mismatch (~45%) between the two data sources in the mean yields (Grassini et al., 2015). Because of this mismatch in different yield datasets the Ministry of Agriculture was chosen for this study, as that had yield from the most recent seasons available for both the long and short rains. However, this did limit the number of years that could be considered. Only 5 years of seasonally disaggregated data were available over the region for both long and short rains. Therefore, a detailed cultivar calibration process could not be performed and may have also negatively impacted the quality of the cultivar selection process.

5. Conclusions

Estimates and prediction of agriculture production can be crucial in developing national agriculture policies and planning effective adaptation and mitigation strategies to climate change. However, it is also important to be able to quantify the uncertainties inherent to the models. In a comprehensive review of the cropping system modeling field, Jones et al. (2017) state that one of the most important areas of improvement for the next generation of data and models is to better understand and communicate that uncertainty. Here we provide a modeling system and its implementation that begins to address these concerns while also simulating broad trends in yields at the county level. To the best of our ability, this appears to be the first modeling study that simulates both short-rains and long-rains seasons separately at the county level for Kenya. We also discuss the challenges and limitations of inherent and implementation errors associated with data-scarce and

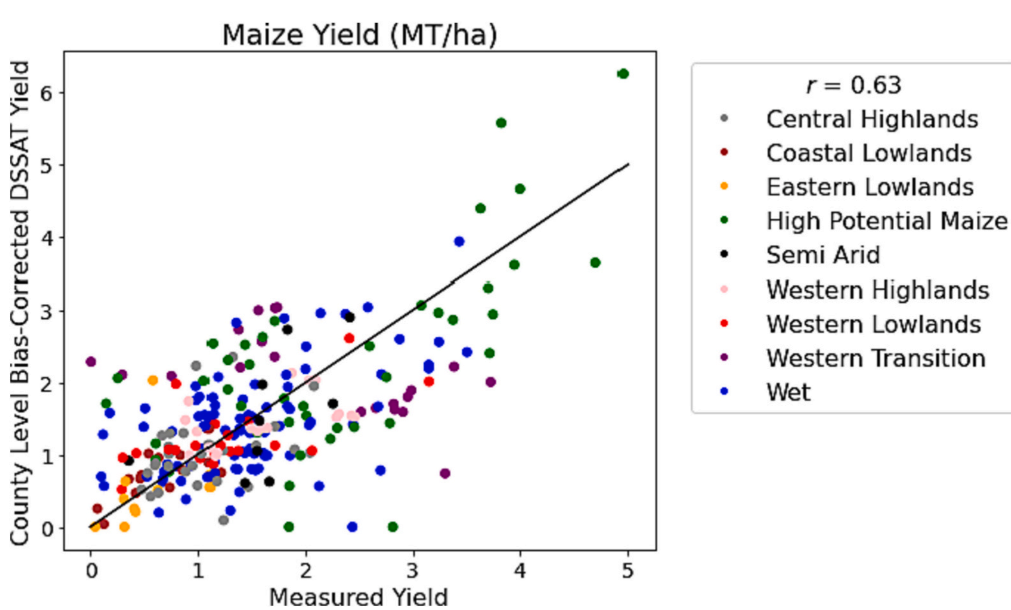

Fig. 6. The combined spatio-temporal correlation. Each point represents a county, year, and season. Simulated yields are bias corrected at the county level.

large-scale crop model simulations in the hopes that future studies can improve upon them.

The RHEAS system implements a stochastic ensemble approach to account for field scale variabilities in crop management practices and underlying soil and weather conditions. Together, the RHEAS system allows for a more realistic characterization of input variations (and their uncertainty) across an area. The performance of the system across both seasons shows good correlation, however, several counties with low or negative correlation degrade the overall performance, potentially due to mischaracterizing cultivars, reported yields or other variables that are parameterized within the model. Though the model currently produces high bias, the ability of the system shows skill in predicting annual variations, with yield anomalies falling within the interquartile range of the simulations the majority of the time, suggesting this system could provide valuable and timely information to stakeholders.

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CRediT authorship contribution statement

W. Lee Ellenburg: Conceptualization, Data curation, Formal analysis, Methodology, Writing – original draft, Writing – review & editing. **Sara E. Miller:** Data curation, Formal analysis, Writing – original draft, Writing – review & editing. **Vikalp Mishra:** Conceptualization, Methodology, Supervision, Writing – review & editing. **Lilian Ndungu:** Conceptualization, Methodology, Writing – review & editing. **Emily Adams:** Conceptualization, Methodology, Writing – review & editing. **Narendra Das:** Conceptualization, Methodology, Software. **Konstantinos M. Andreadis:** Conceptualization, Methodology, Writing – review & editing. **Ashutosh Limaye:** Conceptualization, Methodology, Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.agsy.2023.103819.

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