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Original research article

High spatial resolution seasonal crop yield forecasting for heterogeneous maize environments in Oromia, Ethiopia

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HIGHLIGHTS

- A functional and granular spatial yield forecasting system is demonstrated.
- Spatial-temporal variability of soil, weather, and management was considered.
- Combination of crop modeling with statistical approach insured good performance.
- Forecast captured the mean yield at the sub-regional level.
- Forecast uncertainty decreased as the growing season progressed.

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ABSTRACT

Seasonal climate variability determines crop productivity in Ethiopia, where rainfed smallholder farming systems dominate in the agriculture production. Under such conditions, a functional and granular spatial yield forecasting system could provide risk management options for farmers and agricultural and policy experts, leading to greater economic and social benefits under highly variable environmental conditions. Yet, there are currently only a few forecasting systems to support early decision making for smallholder agriculture in developing countries such as Ethiopia. To address this challenge, a study was conducted to evaluate a seasonal crop yield forecast methodology implemented in the CCAFS Regional Agricultural Forecasting Toolbox (CRAFT). CRAFT is a software platform that can run pre-installed crop models and use the Climate Predictability Tool (CPT) to produce probabilistic crop yield forecasts with various lead times. Here we present data inputs, model calibration, evaluation, and yield forecast results, as well as limitations and assumptions made during forecasting maize yield. Simulations were conducted on a 0.083° or ∼ 10 km resolution grid using spatially variable soil, weather, maize hybrids, and crop management data as inputs for the Cropping System Model (CSM) of the Decision Support System for Agrotechnology Transfer (DSSAT). CRAFT combines gridded crop simulations and a multivariate statistical model to integrate the seasonal climate forecast for the crop yield forecasting. A statistical model was trained using 29 years (1991–2019) data on the Nino-3.4 Sea surface temperature anomalies (SSTA) as gridded predictors field and simulated maize yields as the predictand. After model calibration the regional aggregated hindcast simulation from 2015 to 2019 performed well (RMSE = 164 kg/ha). The yield forecasts in both the absolute and relative to the normal yield values were conducted for the 2020 season using different predictor fields and lead times from a grid cell to the national level. Yield forecast uncertainties were presented in terms of cumulative probability distributions. With reliable data and rigorous calibration, the study successfully demonstrated CRAFT's ability and applicability in forecasting maize yield for smallholder farming systems. Future studies should re-evaluate and address the importance of the size of agricultural areas while comparing aggregated simulated yields with yield data collected from a fraction of the target area.

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Introduction

Seasonal climate variability determines crop productivity in Ethiopia, where rainfed smallholder farming systems dominate in the agriculture production. The highly variable nature of the climate in the country, particularly rainfall and temperature changes, increased frequency, and magnitude of droughts (Korecha and Barnston, 2007; Tesfaye et al., 2015a) poses many challenges for farmers and agricultural communities. Under such conditions, farmers, agricultural experts, and policy makers are lacking the information on the likelihood of achieving the optimal crop production level and making decisions. In such circumstances, reliable and timely issued crop yield forecast can play a vital role for pre-season and in-season planning of crop production. Therefore, forecasts must have a reasonable lead-time and accuracy, which is required for operational preparation and then implementation of suitable strategies (Troccoli,et al., 2008).

Nowadays, state-of-the-art seasonal climate forecasts are providing relatively accurate, location and time specific products and can be linked to various systems, including process-oriented crop simulation models (Cabrera et al., 2009; Jones et al., 2000; Basso and Liu, 2019). Liu and Basso (2020) developed a new method to forecast maize yield across smallholder farmers' fields by integrating field-based survey with a crop simulation model. The yield forecasting algorithm used historical weather to select years in which temperature and precipitation matched the reported in-season temperature and precipitation characteristics. Years were then categorized as colder, normal, and hotter than normal. They were also grouped into drier than normal, normal, and wetter than normal categories. The algorithm then selected weather series where the temperature and precipitation categories matched with the reported in-season weather characteristics to conduct simulations. The method has shown to provide acceptable forecasts 14–77 days prior to maize crop harvest across the three districts in Tanzania.

Detailed process-based crop models' suite, such as the Decision Support System for Agrotechnology Transfer (DSSAT), is designed to simulate the response of crop to weather conditions among other factors affecting crop production (Jones et al., 2003; Hoogenboom et al., 2019). Recent studies (Kirthiga, 2013; Shelia et al., 2019; Shin et al., 2010; Tesfaye et al., 2015b) have demonstrated the use of the DSSAT suite of crop models to understand causes of spatial yield variability and conduct yield gap analysis for factors that limit yield. To facilitate the use of DSSAT for decision support on a spatial scale and to conduct regional yield forecast, automated procedures and related tools are needed to implement crop growth simulations spatially (Elliott et al., 2014; Shelia et al., 2019; Thorp et al., 2008).

Recently, Ogutu et al. (2018) provided probabilistic maize yield prediction over East Africa using the European Centre for Medium-Range Weather Forecasts (ECMWF) system-4 ensemble seasonal climate hindcasts and the World Food Studies (WOFOST) model. In their study, the authors predicted annual maize yield anomalies 2-months prior to planting and found that the prediction had good probabilistic skill at above-average and below-average yield categories.

Various regional and national institutions provide operational seasonal climate forecasts. In Eastern Africa, the Greater Horn of Africa Climate Outlook Forum (GHACOF) organized by the Climate Prediction and Applications Centre (ICPAC) of the Intergovernmental Authority for Development (IGAD), the World Meteorological Organization (WMO), and other partners issues such forecasts. The forum tries to give a consensus estimate of the likely impacts of the forecast on-climate sensitive sectors such as agriculture and water resources, among others (Hansen et al., 2011). However, the impact assessments of the forecast are based on expert knowledge and thus, to a certain extent they are subjective. Additionally, use of impact models that can translate climate forecast into output forecasts such as crop yield are also limited.

Integrated modern seasonal climate forecast and crop modeling for crop production forecasts can support those who are engaged in climate risk management in agriculture (Ordonez et al., 2022; Troccoli et al., 2008). The use of crop simulation models along with climate predictors of yield and climate forecasts allows decision makers to make early planning of contingency options. Preparation and effective planning for the coming season and proper management helps reduce risks associated with weather uncertainty. Such tools could be employed by the GHACOF process to enhance the effectiveness of seasonal climate forecasts by translating them into yield forecast using crop models to provide an estimation of direct impacts of climate drivers on crop production (Ogutu et al., 2018).

A detailed overview of the eight main global and regional scale agricultural monitoring systems currently in operation and their comparison based on the input data and models used, the outputs produced and other characteristics such as the role of the analyst, their interaction with other systems and the geographical scale at which they operate was provided by Fritz et al. (2019). One example is the Famine EWS Network (FEWS-NET) that provides decision support to food assistance programs and relief agencies (Funk and Verdin, 2010) based on data from various sources, but especially agroclimatology data and by building monthly scenarios for further analysis (Brown et al., 2007; Senay et al., 2015). Similarly, the Global Information and Early Warning Systems (GIEWS) is monitoring the condition of major food crops across the globe to assess production prospects by utilizing remote sensing data on water availability and vegetation health during the cropping seasons (Rojas, 2015). Another example is GEOGLAM (GEO GLobal Agricultural Monitoring) that brings together key players in the global agricultural monitoring community to provide an assessment of crop growing conditions, crop status, and agroclimatic conditions that could have an impact on the global production of wheat, maize, rice, and soybean (Justice et al., 2015).

Such crop monitoring systems largely focus on soil water availability by crops without considering the complex interactions between weather variables, crop physiology and management practices (Ogutu et al., 2018). They are tailored to meet the needs of different stakeholders and, hence, they differ in the importance they place on inputs to the system as well as how they disseminate their results. Additionally, these systems mainly depend on data recorded by remote sensing satellites and reanalysis products, which assist with the assessment of crop condition anomalies that can then be used to infer information on yield, area, and production reductions. However, this approach is unable to provide a production forecast that ideally is needed for strategic and tactical crop production and food security interventions.

An operational real-time crop yield forecast system is the MARS-Crop Yield Forecasting System (MCYFS) (Lecerf et al., 2019). MCYFS is based on 25 km resolution gridded runs of WOFOST model (Boogaard et al., 2014). A team of experts together with the Consortium partners operates and maintains the system and provides crop yield forecasts to the public. Several decades ago, its earlier version was used in East Africa (Rojas et al., 2005). MCYFS is focused on Europe and neighboring countries. There are only a few examples of its use in Northern Africa.

There are various approaches currently being used or developed to produce seasonal and in-seasonal crop yield forecasts. They cover a broad range of approaches from data-driven statistical techniques to more physically based model-driven approaches (Basso and Liu, 2019; Schauberger et al., 2020). In data-driven approaches, the Machine Learning (ML) algorithms play major role to achieve accurate yield prediction for different crops (Chlingaryan et al., 2018; Liu et al., 2017). The most successful ML techniques have been Artificial Neural Networks (Emamgholizadeh et al., 2015; Gonzalez-Sanchez et al., 2014) or in some cases its combination with Multiple Linear Regression (MLR) (Maya Gopal and Bhargavi, 2019). Data-driven approaches have several limitations. They strongly depend on the data quality, model representativeness and the dependencies between the input and target variables (Chlingaryan et al., 2018).

Yield forecasting approaches that rely on crop models generally are combined with seasonal climate or weather forecasts. Crop models operate at a daily time step and require daily weather as one of the inputs. In their approach for linking seasonal climate forecasts with crop models Capa-Morocho et al. (2016) disaggregated seasonal climate data into daily weather data. In another approach, Togliatti et al. (2017) used combination of short-term daily weather forecasts from the Weather Research and Forecasting Model (WRF) along with the current and historic weather data to drive crop model. There is an example of using ensemble of yield predictions based on seasonal climate predictions in eastern Africa (Ogutu et al., 2018). Crop growth-based yield forecasting models are data intensive and are currently applied only for the USA by the USDA and for Europe by the MCYFS (Fritz et al., 2019). If agricultural communities are to benefit from crop production forecasts in managing climate risks, the information must be presented in terms of production outcomes at a scale relevant to their decisions, with uncertainties expressed in transparent terms (Hansen et al., 2006). In addition, such information can contribute to enhancing index insurance quality through better detection of adverse conditions. As yield estimation techniques improve, index insurance programs will ensure that they deliver on their promise of detecting and protecting against large-scale, community-wide shocks (Benami et al., 2021).

One way of achieving crop yield forecasts is using a lightweight desktop application compared to other systems such as the CCAFS Regional Agricultural Forecasting Toolbox (CRAFT) (Shelia et al., 2019). CRAFT is a flexible and adaptable software platform that is based on a crop engine that can run pre-installed crop models and is linked to the Climate Predictability Tool (CPT) (Mason and Tippett, 2016) for seasonal climate predictions to produce a crop yield forecast. In developing countries where smallholder agriculture is the dominant livelihood and the economic sector the forecasting system similar to CRAFT has not been widely used to support early decision making and in-season tactical interventions. A functional, granular (0.083° or ~ 10 km resolution grid) spatial yield forecasting system such as CRAFT could provide agricultural risk management options leading to greater economic and social benefits for highly variable environments. CRAFT has been successfully applied for in-season yield forecasting of wheat and rice cropping systems in Nepal and Bangladesh and is currently being evaluated for yield forecasting and climate change applications in West Africa in collaboration with Agrhymet, and the CASCAID Project of ICRISAT (NeKSAP, 2017).

This study aims to evaluate a methodology implemented in CRAFT that links seasonal climate forecasts with gridded crop simulations for in-season yield forecasting for East Africa. Specific objectives of the study were a) to calibrate and evaluate spatial simulations of CRAFT and b) to determine CRAFT's ability and applicability in forecasting maize yield of smallholder farming systems at a fine spatial resolution at the region of Oromia State in Ethiopia.

Materials and methods

Study area

The study area covered the Oromia regional state in Ethiopia (Fig. 1a), which consists of 17 administrative zones (CSA, 2016). Oromia regional state is the most populous subnational entity in all of Africa (Aynalem Adugna, 2021; Geremew, 2020) and the world's 42nd most populous subnational entity. Oromia is the major agricultural production region accounting for 50 % of major food crops production in Ethiopia (CSA, 2020). Out of the 5.86 million ha covered by grain crops in Oromia, 1.2 million ha (21 %) is covered by maize, which is grown by 72 % of the smallholder farmers (CSA, 2019).

Yield forecasting tool and data requirements

In this study, we have used CRAFT version of 3.4 for yield forecasting (https://craft.dssat.net/). CRAFT is a Windows desktop application with a graphical user interface. It is an integrated modeling framework for gridded crop simulations at two spatial resolutions (0.083° and 0.5°) and within-season yield forecasting, risk analysis, and climate change impact studies (Shelia et al., 2019). It runs pre-installed ensemble of crop models although the default crop engine is DSSAT. Gridded simulations can be conducted for any region and for up to three levels, but only for one level at a time. The levels could be for example, a country / state/ district if the administrative area is the region of interest or any other customized levels, represented with corresponding GIS shape files.

A crop engine, such as DSSAT, in CRAFT, requires daily weather data, comprehensive soil profile data used in the soil water and nutrient simulations by the crop model, crop and cultivar genetics, and management data. Accordingly, data required for gridded simulations are weather data, soil profile (s) data, and masked data for crop and management (inorganic and organic fertilizers, etc.) for each grid cell. They can be prepared based on provided templates and uploaded in CRAFT's MySQL database. The toolbox allows creation of projects such as calibration, yield forecast, climate change, and risk assessment. The conducted spatial simulation's results then can be viewed in thematic maps and summarized in tables with various statistics for the entire region and for each grid cell in the region.

Prior to yield forecasting, the observed yield data can be detrended.

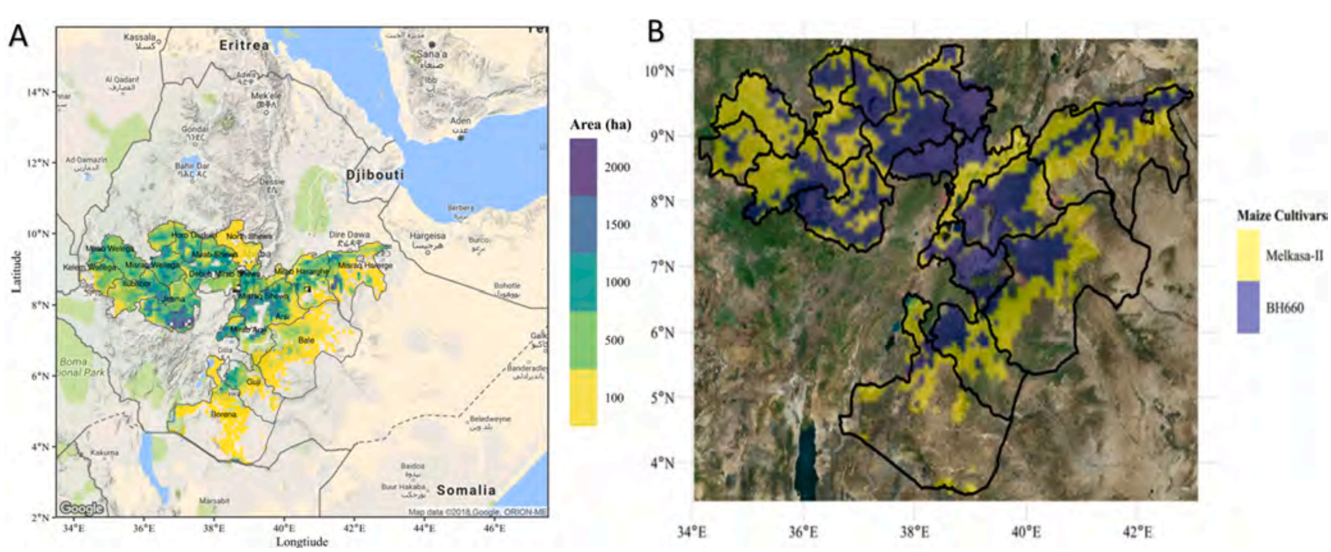

Fig. 1. The state of Oromia and sub-regional administrative zones overlaid with the total maize harvested area (A), and the planting area for two maize hybrids (BH660 and Melkasa-II) used for simulations (B).

After the optional detrending procedure, a yield correction factor for calibration can be applied to the regional yield aggregated from the simulated yield on a cell scale in order to minimize the root mean square error (RMSE) with observed regional yield (Challinor et al., 2005; Hansen and Jones, 2000). CRAFT combines crop simulations and a statistical approach to integrate the seasonal climate forecast with the crop yield forecast (Shelia et al., 2019). Preparation of a forecast for a certain date during the crop growing season in the current year can be described in four steps: (1) yield is simulated first with observed antecedent weather data for the current year up to the forecast date and then with weather data from available historic years one by one until final harvest is simulated (Hansen et al., 2004). (2) The resulting time series of simulated yields are treated as the predictand and used with a time series of appropriate seasonal climate predictor fields (e.g., fields of sea-surface temperatures (SSTs)), to train a multivariate statistical model using the Climate Predictability Tool (CPT) (Mason and Tippett, 2016). (3) The forecast yield value for the current season is a forecast produced from current seasonal climate predictor observations fitted in the multivariate statistical model. (4) The yield forecast distribution is then obtained from cross-validated hindcast residuals, centered on the expected value of the yield forecast (Hansen et al., 2004; 2006).

Datasets

Weather data

The daily precipitation data of the Climate Hazards Group Infrared Precipitations (CHIRPS), satellite data combined with gauge observations, at 5 km resolution were obtained from the data library of International Research Institute (IRI) for Climate and Society of the Columbia University (IRI Data Library). Dinku et al., (2013, 2018) evaluated CHIRPS with rain gauge data over Ethiopia and found that it performed well for all spatial and temporal scales with the most significant improvement in reducing biases. The daily maximum and minimum air temperature data of the AgERA5 historic and near real time forcing data at a 0.1° horizontal resolution were obtained from the Copernicus data portal (Boogaard and van der Grijn, 2019). The AgERA5 dataset provides daily surface meteorological data, tailored for agriculture, for the period from 1979 to present. The service is based on the fifth generation of ECMWF atmospheric reanalysis of the global climate (ERA5). Daily solar radiation data were obtained from NASA's POWER (Prediction Of Worldwide Energy Resource) data (Stackhouse et al., 2018), which is freely available for download at a spatial grid resolution of 0.5° (https://power.larc.nasa.gov/). Weather datasets were re-gridded to 0.083° resolution on which CRAFT operates, using nearest-neighbor remapping.

Soil data

The high-resolution soil profile data required by DSSAT were directly extracted from SoilGrids (https://soilgrids.org/), a system for digital soil mapping based on a global compilation of soil profile data (WoSIS) and environmental layers by the International Soil Reference and Information Centre (ISRIC). Several essential soil physical and chemical properties such as bulk density, silt, and clay content, and organic carbon were obtained from Harvestchoice data portal (IFPRI, 2020). Then, pedo-transfer functions were used to derive soil hydraulic properties (Rawls and Brakensiek, 1985; Saxton et al., 1986). Other soil parameters not available from SoilGrids were estimated from the Harvest Choice generic soil profiles (HC27) (Han et al., 2019). A single soil profile represents dominant soil properties for each 10 km grid-cell and the data are stored in the DSSAT soil database using the *.SOL file format. A soil mask containing a CellID, Soil Profile ID and percentage share of the soil profile within the grid-cell were used for the simulation area.

Crop mask

Maize production shows an expansion in area during the last decade in the regional state and maize has relatively better technologies compared to other crops. The region benefits from enough supply of improved hybrid seeds, better agronomic practices, and supply of synthetic fertilizers because of its proximity to the national fertilizer distribution centers through well-organized farmer unions and cooperatives. There is also a tendency of an increase in the use of improved hybrids over time. Popular maize hybrids BH660 and Melkasa-II are the most dominant varieties in the Oromia region. The maize annual total harvested area data at a 0.083° resolution (Fig. 1A) was obtained from the Spatial Production Allocation Model (SPAM) product, a spatially disaggregated crop production statistics data in sub-Saharan Africa for 2017 (IFPRI, 2020). The maize crop mask, the fraction of a grid cell covered by maize, was created by computing the ratio of the SPAM maize area in a grid cell to the total area of that particular grid cell. Maize crop mask was staying the same over the years during simulations. Dominant in the region and calibrated for maize mega environments (Tesfaye et al., 2015b) two varieties BH660 and Melkasa-II (Table 1) were assigned to entire maize crop area (Fig. 1B) and were used for the gridded simulations.

Crop management and observed yield

In the Oromia Regional State, the planting window for maize is from April to June with a harvesting period ranging from September to January. Almost all farmers in the region grow maize for food (MoA, 2020). Most importantly, a significant portion of the maize area increased with improved hybrids et.al. A rule-based automatic planting was used with a 120-day planting window starting from 1 April for the model runs over the 1991–2019 period. The maize hybrid BH660 was sown at a population of 4.44 plants/m^2 over areas having an elevation above 1800 m, whereas Melkasa-II was sown at a population of 5.33 plants/m^2 over areas with an elevation below 1800 m (Fig. 1a). As smallholder farmers in Ethiopia generally use crop residues from the prior harvest as animal feed, the soil was initialized with 100 kg/ha of root weight from previous crop and 50 kg/ha of fully incorporated crop residue at a depth of 10 cm with a 0.8 % nitrogen content (Tesfaye et al., 2015b).

Although fertilizer application rates have increased over time, the amount still falls short of the national recommendation of about 110–130 kg/ha of urea and di-ammonium phosphate (DAP) (MoA, 2020). Approximately 60 % of maize growers use 100–150 DAP kg/ ha (18–27 kg N/ha, 20–30 kg P/ha) and about 56 % used 150–200 urea kg/ ha (70–93 kg N/ha) in 2020, depending on the hybrid, as higher rates are recommended for hybrids (CSA, 2020). The Ethiopian Ministry of Agriculture (MoA) provided sub-regional levels of fertilizer types, application rates, timing, and frequency of application (Fig. 2).

As CRAFT operates on up to three levels, regional (level 1: Oromia)

Table 1
Description of the benchmark maize hybrids (BH660 and Melkasa-II) used in the study.

Maize hybrids	BH660	Melkasa-II
Type	Hybrid	Open pollinated
Year of release	1993	2003
Country/region of release	Ethiopia	Ethiopia
Maturity Group	Late maturing (160 days)	Intermediate maturing (130 days)
Maize mega environment	Highland (1600 – 2400 m)	Wet lower mid-altitude/dry mid-altitude/wet and dry lowland (1000 – 1700 m) 4500–5500
	6000–8000	
Average reported on-farmyield (kg/ha)		

Source: Tesfaye et al., 2015b.

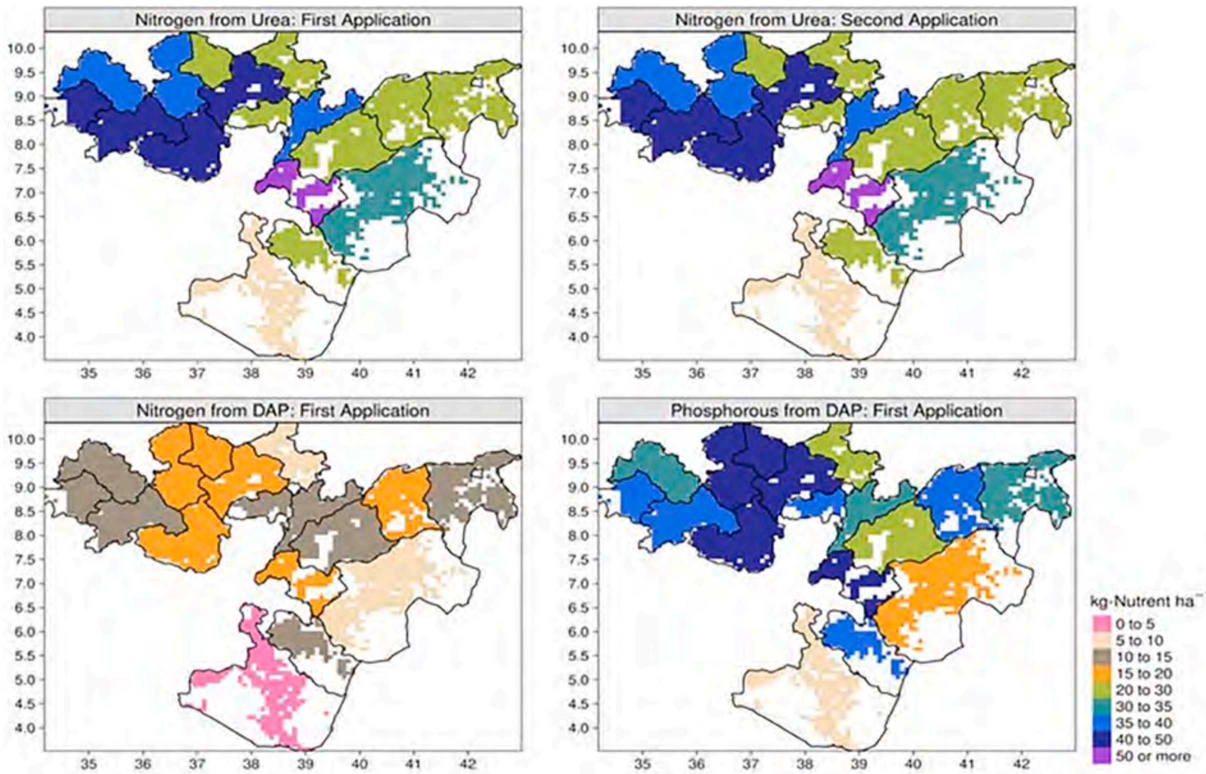

Fig. 2. Sub-regional fertilizer application rates in Oromia, Ethiopia.

and sub-regional (level 2: its sub-regional administrative zones) levels, observed maize yield data from 2004 to 2019 were obtained from the annual agricultural sample survey database (AgSS, https://www.statsethiopia.gov.et/our-survey-reports/) of the Central Statistical Agency (CSA) of Ethiopia. CSA provides national level area planted, production and yield data since 1980 for over 26 crops and a regional level area planted, production and yield dataset since 1999 (CSA, 2015). The agency's agricultural production survey typically evaluates over 500,000 agricultural plots, 38,000 households in 1,850 Enumeration Areas (EAs). While the CSA takes area measurements for all sampled agricultural plots, they do not measure yield estimates from each plot, instead five crop cuts at most ultimately determine the productivity for an entire woreda for any given year (Warner et al., 2015).

Predictor for yield forecast

The seasonal climate for Ethiopia has a significant inter-annual variability. One of the important mechanisms that control this variability is the El Niño-Southern Oscillation (ENSO). The ENSO is now understood to be among the dominant modes of variability dictating climate and yield anomalies, besides the primary source of predictability so far in Ethiopia (Clarke, 2008; Diro et al., 2010; Tesfaye and Assefa, 2010). The National Meteorological Agency (NMA) of Ethiopia uses the pre-season ENSO state and the associated equatorial pacific Sea Surface Temperature Anomaly (SSTA) to provide an operational outlook for the coming season and its expected impact on the crop production (Korecha and Sorteberg, 2013). The ENSO phases provide a rough categorization of underlying climatic variables and can be associated with crop yield (Rosenzweig and Hillel, 2008). In addition to SST, Lee et al. (2022) used precipitation, temperature, evapotranspiration, and vegetation index as a predictor field and demonstrated a potential for predicting maize yield over sub-Saharan Africa using machine learning approach. Similarly, Laudien et al. (2020) showed the potential of using SST of the Indian Ocean Dipole (IOD) and weather variables as predictors in robust statistical models to predict maize yield over Tanzania.

The Nino-3.4 SSTA was used as a gridded predictor field for the maize yield forecasts in this study. The 3-month running average SSTA of Nino-3.4 from the Extended Reconstructed Sea Surface Temperature version 5 (ERSSTv5) (Smith and Reynolds, 2003) for the domain located in the Pacific ocean (between 5° North and 5° South, and between 120° West and 170° West) were obtained from the IRI data library of the Columbia University.

Methods of analysis

Composite analysis

This study investigated the linkage of the anomaly pattern and the strength of the linear relationship between the regional (Oromia) aggregated simulated maize yield and the pre-season Niño-3.4 SSTA index using correlation and composite analyses (Boschat et al., 2016). Composite analysis is a sampling technique based on the conditional probability of a given event that will occur (maize yield anomaly) if it is certain that another event has taken place or will take place (SSTA). Thus, the composite analysis will provide information on the probability of the maize yield being in the above-average, near-average, or below-average category based on the state of ENSO episodes, i.e., El Niño, Neutral, or La Niña.

The National Oceanic and Atmospheric Administration (NOAA) operational definition of El Niño, La Niña and Neutral was used to determine the historical distribution of the ENSO episodes. Accordingly, the phases are categorized as El Niño when the SSTA departure is greater than or equal to $+ 0.5$ °C, La Niña when the SSTA departure is less than or equal to -0.5 °C and neutral when the SSTA departure is between -0.5 and $+ 0.5$ °C. In the composite analysis, the simulated maize yield data is converted to categorical data, e.g., above, near, and below average maize yield categories, using tercile cut points. Then, for each El Niño, Neutral, and La Niña event, the number of each above, near, and below values of average maize yield were counted. These category counts were recorded, and the probability of occurrence were calculated. This probability represents the historical event distribution or probability of the simulated maize yield being in the above, near, or below average category given the occurrence of El Niño, Neutral, and La Niña episodes (Fig. 3).

Crop simulation settings

The maize crop simulations were conducted on the 0.083° or ~ 10 km resolution spatial grid by the CRAFT toolbox using the DSSAT crop model as a crop engine and data for 1991 – 2019. The crop model simulation requires input data, such as weather, soil properties and management, and other data that varies in space and time. The model needs initial values to resolve daily changes in some aspects of the soil process, particularly, soil water and nutrient balance. However, acquiring initial values to initialize the soil water and nutrient balance every season on regional gridded simulation is difficult. One way to initialize the model is to 'spin-up' (initialize with the model simulation itself), so that the run will establish values for these state variables. The spin-up period is the time of adjustment it takes for the model to reach a state of equilibrium in soil water, carbon, and nitrogen conditions. When spinning up, the model should be run as a dynamic system to simulate carbon and nitrogen process fully to allow the soil profile to adapt, evolve and respond to the seasonal and inter-annual cycles of water redistribution in the system and soil organic matter pools. The maize simulations were initialized on the first day of each year (Jan-01) to allow for a 3 to 5-month spin-up period to equilibrate the soil water and nutrient balance.

Calibration and evaluation of the crop simulation outputs

Yield often shows an increasing trend over time, which can be attributed to technological improvements such as new varieties or enhanced crop management. Therefore, prior to calibrating simulated yield, time series of the observed yield data should be detrended (Lu et al., 2017). Time trend analysis is one of the most common methods used to detect the impacts of changes in yields over time. This is based on the hypothesis that the time trend may reflect the improvement of production techniques by crop yield observations (Chen, 2011). The observed maize yield will be regressed against time, and correlation between these two variables, i.e., the maize yield and time itself, will be tested. Some other factors that impact the maize yield may also correlate with time trend, which could be simplified by using time trend alone to detrend the yield. We assume the time trend is chosen as the main factor to detrend the yield over time, since maize production technology improvement may be the major impact. Thus, the observed regional yields (2004 – 2019) were detrended by CRAFT's detrending functionality using linear regression prior to their use.

When using dynamic cropping system models for spatial analysis, their ability to extrapolate the temporal patterns of crop growth and yield beyond a single experimental site is crucial. Thus, the quality and strength of crop models is related to the quality of scientific data used in model development, calibration, and evaluation (Bellocchi et al., 2009; Thorp et al., 2008). When a model is applied in a new environment, the calibration and evaluation steps are crucial to link model outputs to real world situations. Crop models are usually calibrated and evaluated using measured yield and yield components trial data from field plots for their use for field-level applications (Timsina, 2007). However, it is not always appropriate to extrapolate field-level model evaluations to large-scale conditions indicating the need to evaluation models at a higher scale to avoid the problem of extrapolating results from a plot level to a regional level in spatial modeling.

In CRAFT, the calibration process is based on long-term regional observed yield data after the cultivar parameters for a model are calibrated for a set of cells. As part of this empirical calibration process, yield is simulated from 2004 to 2019 and then by fitting a linear regression between the simulated and observed yield by conditioning that the regression line goes close to the X and Y axes intersection, i.e. (0,0) point, a value for the modification factor is determined. Thus, the empirical calibration was done using a yield modification factor, which was then applied to the simulated yield per cell aggregated to the regional level. As a result, the calibrated simulations will have the same yield levels as the observed yield at the aggregated regional level, since the simulated yield is scaled by a modification factor.

Yield forecast

The 3-month running average of Nino-3.4 SSTA indexes, January to March (JFM), February to April (FMA) and March to May (MAM), were used as gridded predictor fields to produce the pre-season and in-season maize yield forecast at the grid cell and at the regional level. CRAFT uses the Climate Predictability Tool (CPT) as an external engine to derive multivariate statistical model between the predictor (SSTA) and predictand (yield). In this study, the training period for the statistical model was a 29-year time span (1991–2019) with the crop model simulated yield data. The yield forecast was conducted at different dates in 2020. Each yield forecast update was initialized on the first day of each month until maturity using the presiding 3-month average Nino-3.4 SSTA index

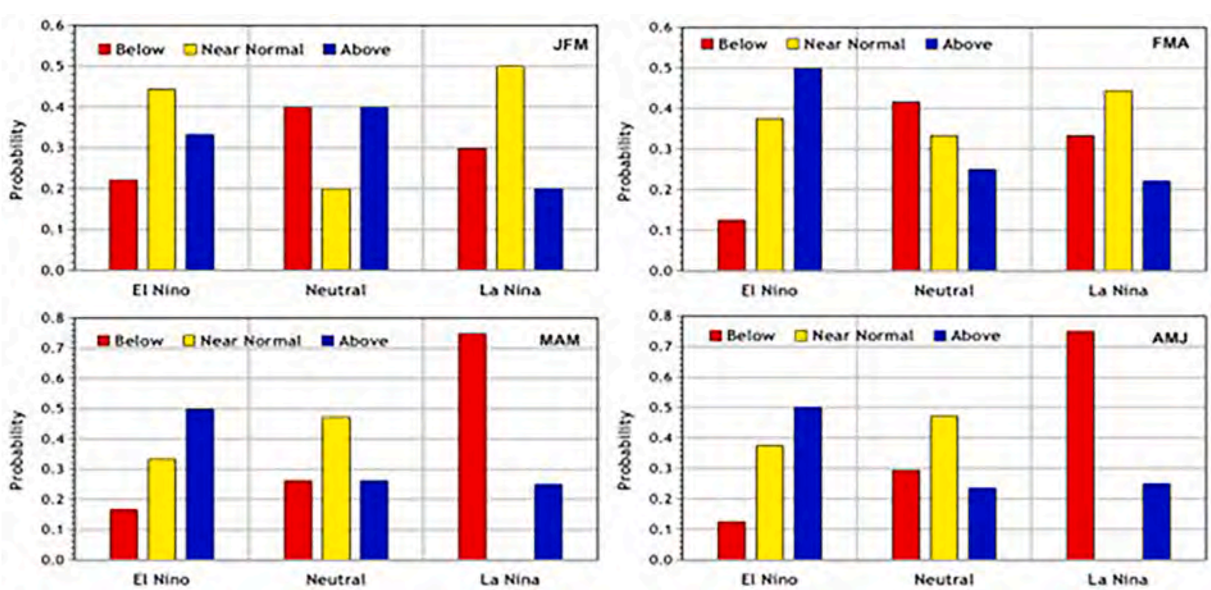

Fig. 3. Simulated yield composites (1991 – 2019) showing the ENSO episode probabilities. JFM-January, February, March; FMA-February, March, April; MAM-March, April, May; AMJ - April, May, June.

as a predictor. The maize yield forecast uncertainty is presented as cumulative probability distributions at the grid cell or aggregated regional level.

Evaluation of yield simulations and forecast verification

The crop simulation results were evaluated using sub-regionally aggregated observed yields. Visualizing tools such as a frequency histogram and a boxplot were used to display the evaluation metrics. The yield forecast was verified using a hindcast simulation initialized on April 1 from 2015 to 2019 and 5 years observed yield data (2015–2019) that were not used during the calibration process. In case of the yield forecast verification, a 2 x 2 contingency table (Table 2), that counts the frequency of occurrence of each combination of hindcast and observed yield category was constructed from dichotomous (Below-Above) of hindcasts. Then the well-known forecast quality measures were derived from it. The sub-regional aggregated yields were converted to binary events, i.e., below-average yield corresponds to a value of 0 and above-average yield corresponds to a value of 1.

By using a forecast quality measure derived from the contingency table, a performance diagram (Roebber, 2009) is produced. Through the performance diagram, the accuracy, bias, reliability, and skill of the hindcast yields can be simultaneously visualized and the underlying relationship can be easily understood. The key forecast quality measures in the performance diagram are the probability of detection or a hit rate (POD), false alarm ratio (FAR), bias, and critical success index (CSI), also known as the threat score, are then defined:

$$POD = \frac{A}{\mathrm{A} + \mathrm{C}} \tag{1}$$

$$FAR = \frac{B}{\mathrm{A} + \mathrm{B}} \tag{2}$$

$$CSI = \frac{A}{\mathrm{A} + \mathrm{B} + \mathrm{C}} \tag{3}$$

where *A* and *D,* are the number of correct hindcasts; *B* and *C* are is the number of false alarms. With some algebraic transformation, POD, FAR or its equivalent, a success ratio (SR = 1 - FAR), bias, and CSI can be related as presented in the following formula:

$$CSI = \frac{1}{\left[\left(\frac{1}{SR} + \frac{1}{POD}\right) - 1\right]} \tag{4}$$

Table 2
A contingency table for the hindcast and observed yield categories.

		Observed Yield Above Average	Below Average	Metrics
Hindcast Yield				
	Above Average	True positive (A) Hit	False positive (B) False alarm	Precision A/(A + B)
	Below Average	False negative (C) Misses	True negatives (D) Correct negatives	Negative predictive value D/(C + D)
Metrics		Sensitivity (POD) A/(A + C) Range: 0—1; Optimal value: 1	Specificity D/(B + D)	Accuracy (A + D)/(A + B + C + D) Range: 0—1; Optimal value: 1

Note: POD - probability of detection or a hit rate.

Results and discussion

Relations between sea surface temperature and maize yield

Inter-annual yield anomalies are often linked to variations in systems that control the regional climate with quasi-periodic fluctuations, such as ENSO and Nino-3.4 SSTA. The existence of ENSO signals in the maize yield anomaly could have a potential to drive the inter-annual variations in maize yields. Recent studies also suggest strong potentials for predicting crop yield using the pre-season and in-season ENSO state in eastern and western Africa (MacCarthy et al., 2017; Ogutu et al., 2018; Rojas et al., 2014; Rosenzweig and Hillel, 2008). The Nino 3.4 region provides a good measure of Sea Surface Temperature Anomaly (SSTA) gradients that result in changing the pattern of deep tropical convection and atmospheric circulation. It influences the local rainfall distribution and maize crop production sensitivity at varying magnitude over different spaces and times (Haile et al., 2021). The results from this study showed a positive correlation between Nino-3.4 index and the maize yield anomaly (Table 3).

The regional aggregated maize yield anomaly tends to increase as the Nino-3.4 SSTA index increases and vice-versa. The existence of this lag relationship raises the possibility of using the pre-season and in-season Nino-3.4 SSTA index to predict the performance of the expected maize production. This positive relationship was particularly observed in the temporal pattern of maize yield anomaly (Fig. 4). Few years are under the influence of only one specific El Niño phase while most years are characterized by a transition phase. For instance, the years from 1999 to 2009 were dominantly under the influence of La Niña episode, where we observe frequent negative yield anomalies. On the other hand, frequent positive yield anomalies are observed during the years from 1991 to 1994, in which the El Niño phase was dominant.

The historical (1991 – 2019) maize yield composite probabilities during the ENSO episode event distributions are presented in Fig. 3. The composite analysis suggests that the cycles associated with El Niño episodes are dominated by normal to above normal yield whereas La Niña episode are dominated by normal to below normal yield is more or less equal chance of getting normal, above normal or below normal yield during neutral years.

Empirical calibration by CRAFT

The empirical calibration was applied to simulated regional aggregated yields from 2004 to 2019 using a modification factor (0.98) calculated by CRAFT. After the calibration process the RMSE decreased from 267.9 to 254.5 kg/ha (Fig. 5).

Evaluation of the model performance

The mean spatial patterns of sub-regional level observed, and simulated yield are shown in Fig. 6. On average, observed spatial variability of yield across sub-regions agreed well with the simulated yield. The model overestimated the observed yield in Bale, Arsi, and east and west Harargie zones. The simulation captured the mean spatial maxima of observed yield in the western part of Oromia.

Table 3
Correlation between maize yield anomaly, and the pre-season and the in-season 3-month running average of Nino-3.4 SSTA.

	Yield	JFM	FMA	MAM	AMJ
Yield	1				
JFM	0.18	1			
FMA	0.21	0.99	1		
MAM	0.26	0.9	0.95	1	
AMJ	0.26	0.65	0.74	0.9	1

Note: JFM - January, February, March; FMA - February, March, April; MAM - March, April, May; AMJ - April, May, June.

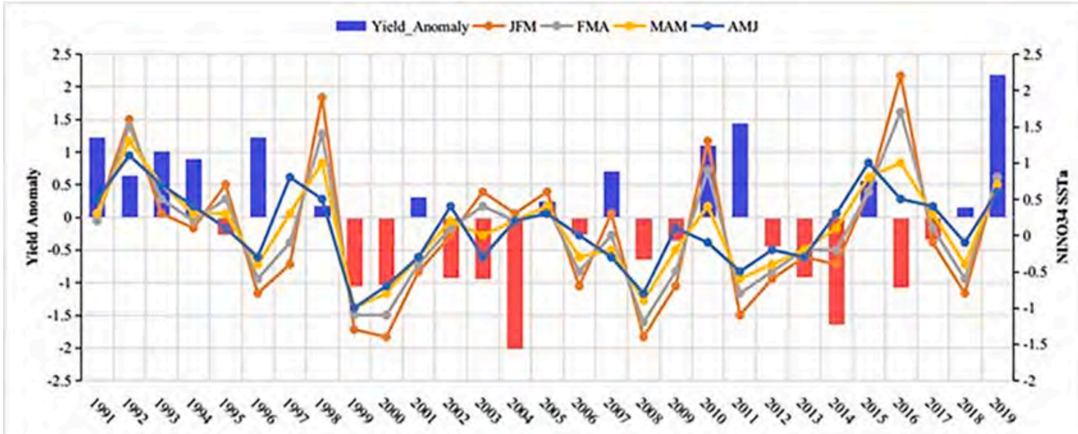

Fig. 4. Year to year variation of maize yield anomaly (stacked bars) and the pre-season NINO-3.4 SSTA index (marked lines).

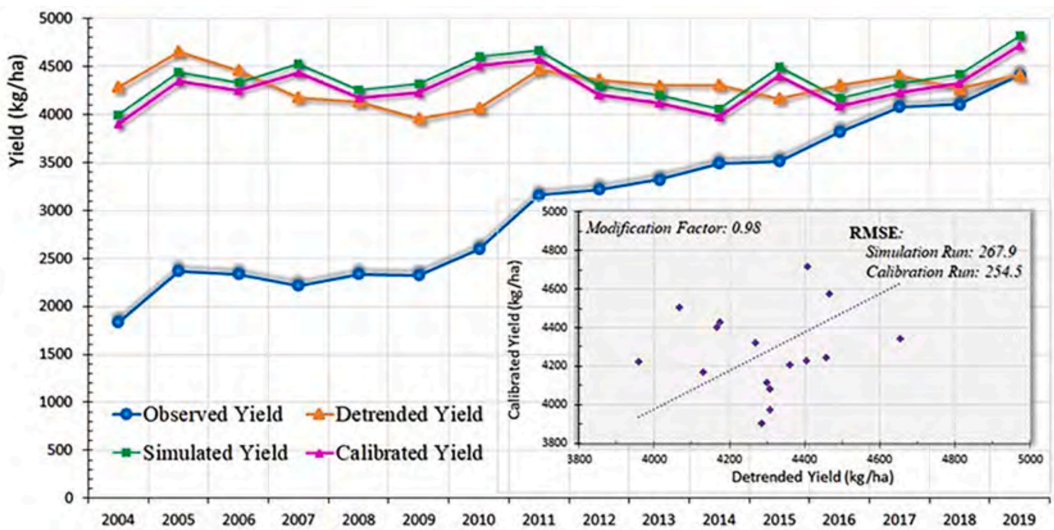

Fig. 5. Regional aggregated observed, detrended, simulated, and calibrated maize yields (kg/ha) in Oromia.

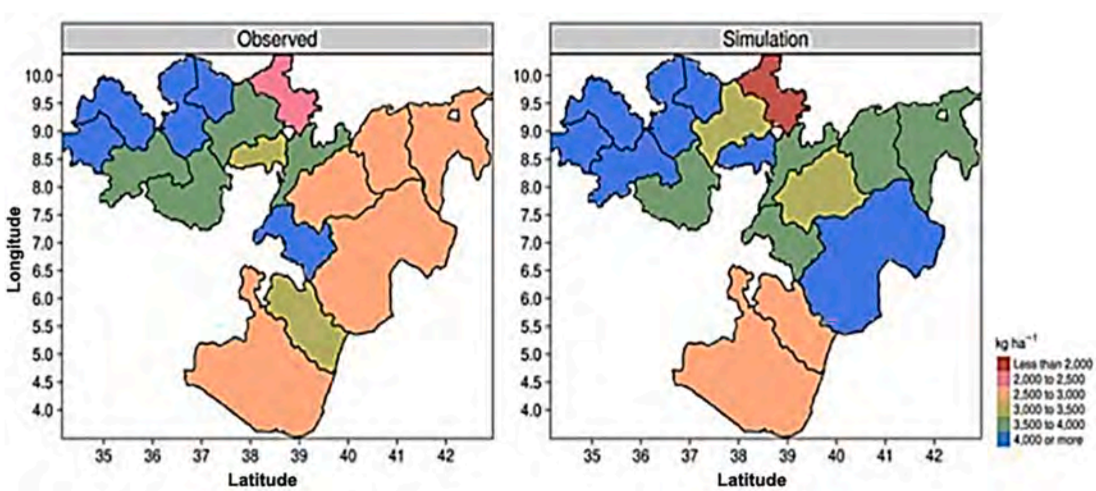

Fig. 6. Sub-region level average observed yields (CSA data, left panel) and simulated yields (right panel).

The frequency and cumulative frequency distribution of the aggregated observed and simulated yields at sub-region level is presented in Fig. 7. The simulation underestimated the observed distribution for lower (<3500 kg/ha) yield and overestimated the observed distribution at relatively moderate (3500——4500 kg/ha) yield levels. On the other hand, the simulation accurately reproduced the observed yield above

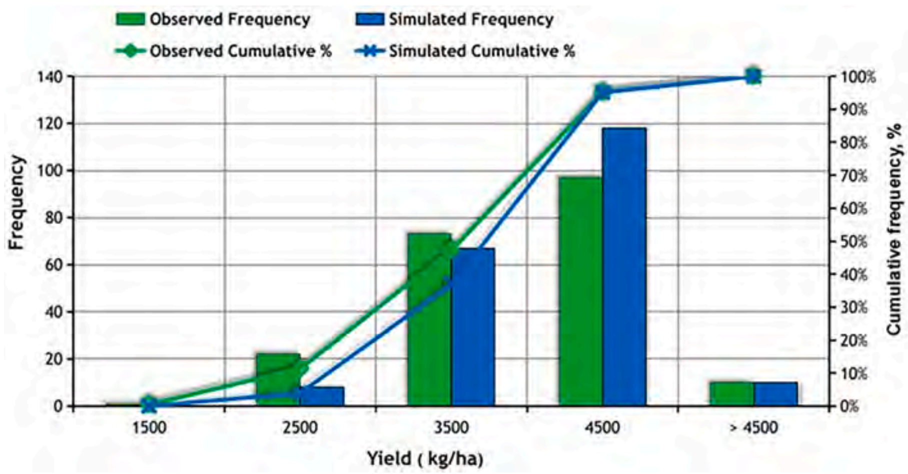

Fig. 7. Frequency and cumulative distribution of observed and simulated yield.

4500 kg/ha.

The temporal pattern of the spatial variability of observed and simulated yield across sub-regions as a box plot (which includes minimum and maximum values, lower and upper quartiles, average, median and outliers) is presented in Fig. 8. Accordingly, Fig. 8 shows more variability in the observed than in the simulated dataset. Nevertheless, the simulation performed relatively well in producing the year-to-year fluctuations of the observed yield across sub-regions having around 6 % bias (PBIAS) and 955 kg/ha of error (RMSE). Yet, the simulation slightly overestimated the observed yield in 2007 and 2010.

Yield forecast verification

The hindcast aggregated yield was assessed against the observed regional and sub-regional yields. The regional aggregated hindcast simulation from 2015 to 2019 was evaluated against detrended yield (Fig. 9). The hindcast simulations performed well with a RMSE of 164 kg/ha.

The quality of yield hindcast was assessed using aggregated sub-regional yields (Fig. 10). The comparison statistics show level of accuracy of the forecast with CSI value of 0.31 and SR value of 0.5. As SR increases, the POD decreases indicating that the slope of the contours remain negative.

Regional maize yield forecast for the 2020 growing season

The cumulative distributions of the regional yield forecast made on April 1, May 1, and June 1 are shown in Fig. 11. As expected, the interval of the forecast uncertainty decreased as the season progress. For the April 1 forecast, the predicted regional yield distribution ranged from 3900 to 4800 kg/ha while it ranged from 4150 kg/ha to 4600 kg/ha for the June 1 forecast.

We assumed that the mean simulated regional yield from 1991 to 2019 can be considered as Normal yield. Then, the percentage deviation of predicted sub-region yield from the normal yield was calculated for the April 1, May 1, and June 1 forecast dates. In general, a normal yield (-5% to 5 % of the mean) was predicted for all the forecast dates that were considered (Fig. 12). The April 1 forecast prediction showed 5 % to 15 % increase in yield relative to the normal over North Showa zone, Borena zone, and over adjacent areas of eastern and southeastern highlands. Those areas are considered marginally suitable for maize and hence the crop less cultivated in those areas. Surprisingly, the yield for May 1 prediction showed a −5% to −15 % deficit yield over the southeastern highlands, a complete reversal from the previous one. For June 1 forecast, most of the areas showed a close to normal yield prediction.

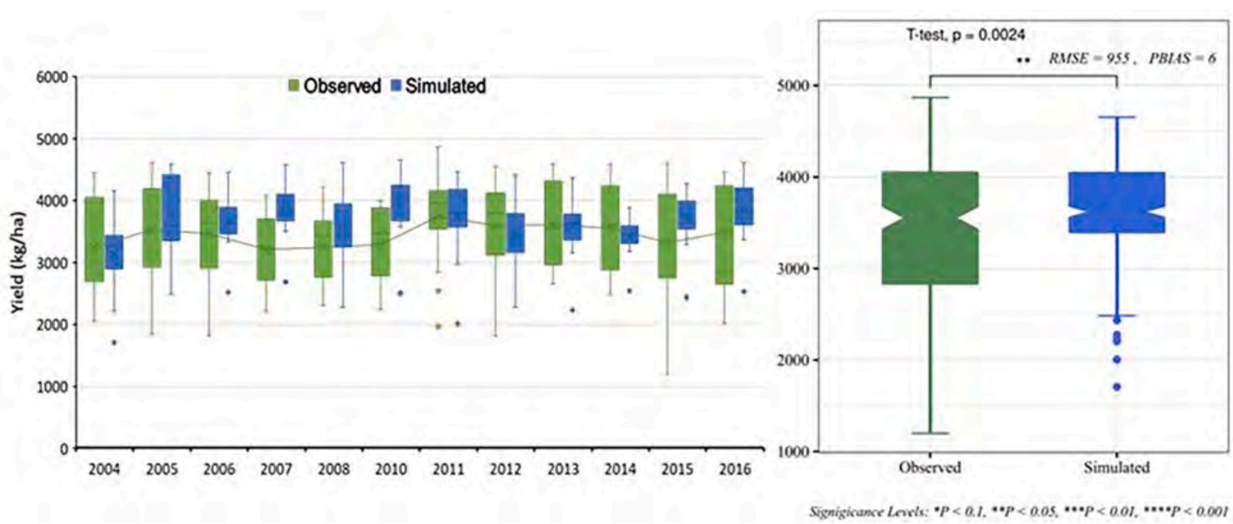

Fig. 8. Temporal pattern of yield variations across sub-regions.

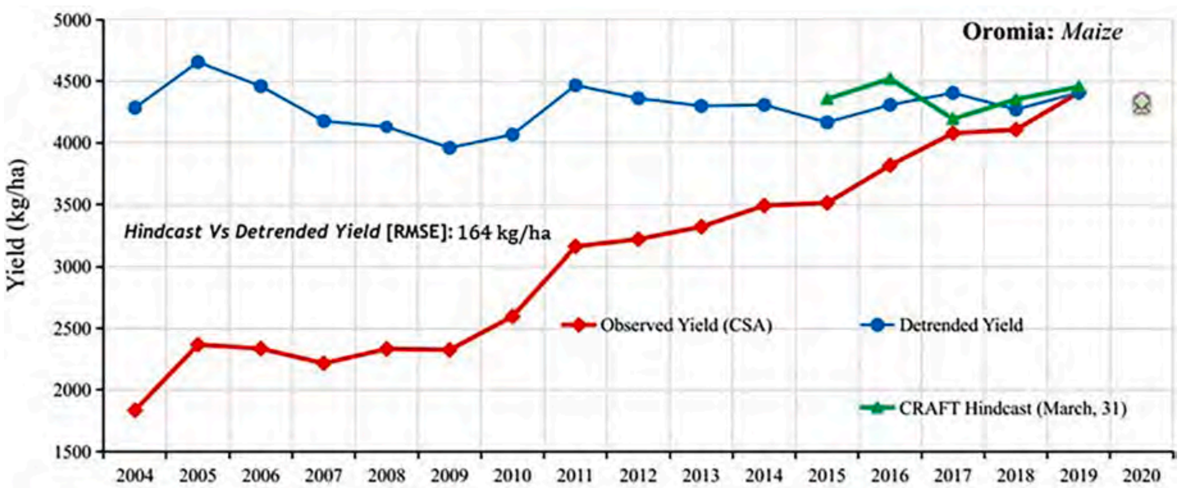

Fig. 9. Temporal pattern of regional aggregated observed, detrended and hindcast yields.

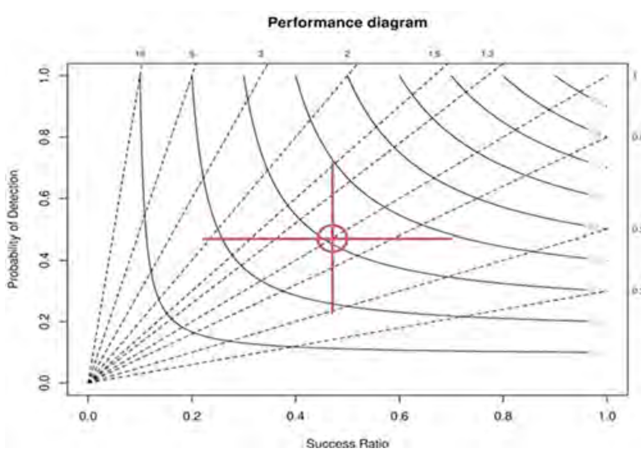

Fig. 10. Performance diagram summarizing success ratio (SR), probability of detection (POD), bias, and critical success index (CSI). Dashed lines represent bias scores with labels on the outward extension of the line, while labeled solid contours are CSI.

Maize yield forecast on a granular (grid cell) level for the 2020 growing season

High-resolution gridded crop yield forecasts that can adequately capture spatial variability of factors such as soil, weather, and management affecting growth and development and ultimately yield, are highly important for decision makers to advise smallholder farmers. The CRAFT toolbox can provide such forecasts. For demonstration, a maize yield forecast at a granular level is presented in Fig. 13, for a grid cell near Bako (9.12°N, 37.06°E) of the Oromia Regional State. The predicted values for this location ranges from 3200 kg/ha to 4100 kg/ha and there is 80 % chance that the location could produce up to 3900 kg/ha of maize yield.

The maize yield prediction by CRAFT presents a skillful forecast at aggregated level and a reasonable forecast at a granular level. The maize prediction also captures the spatial variability (heterogeneous nature) of the maize production in the regional state. The forecast shows poor performance over areas that are less suitable for maize production (over districts where maize production was fewer or scarce). Such limitations can be improved when management data such as fertilizer input, dominant cultivar type and planting window can be provided at finer spatial scale (district level). Because of the uncertainty associated with CSA's yield estimation and data scarcity, the calibration and evaluation

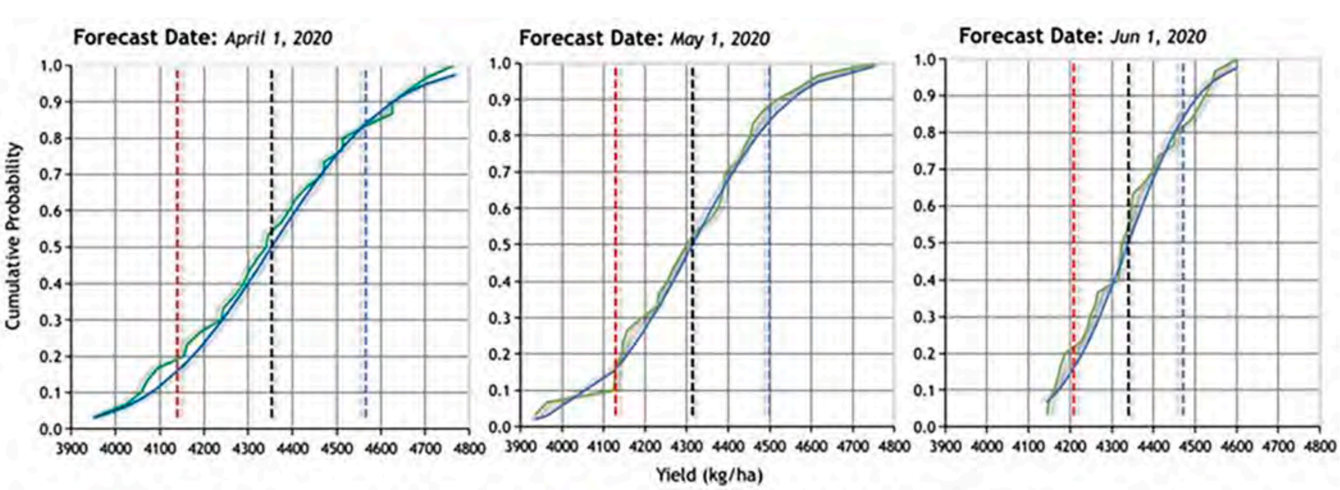

Fig. 11. Distribution of forecasted yield for the forecast dates of April 1, May 1 and June 1. Standard normal cumulative distribution (blue curve) and Empirical Cumulative distribution (green curve) with mean (black dash line) minus standard deviation (red broken line) and mean plus standard deviation (blue broken line). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

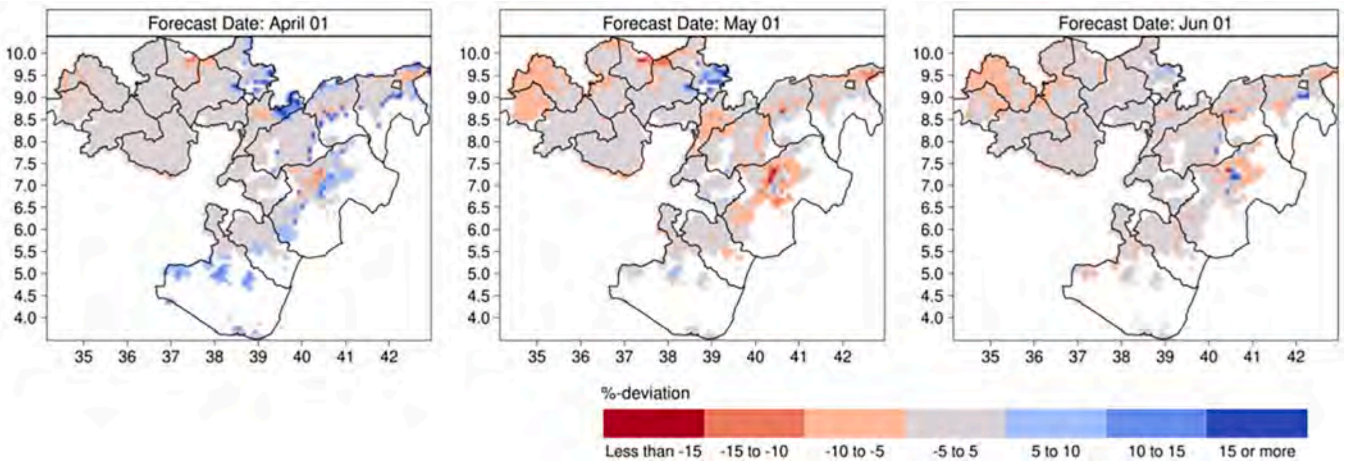

Fig. 12. Maize yield outlook for the 2020 growing season for the Oromia Regional Sate. Values are presented as percentage deviation from the normal yield.

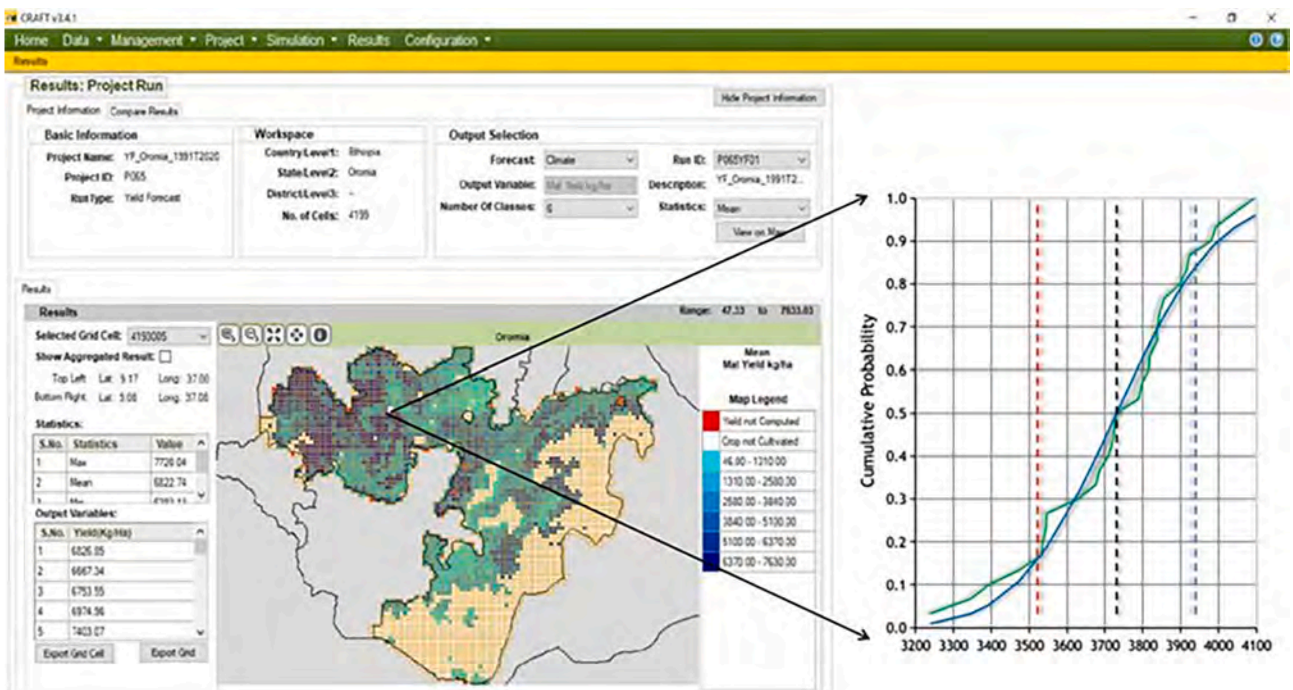

Fig. 13. Distribution of the yield forecast for April 1, at the grid-cell level. Standard normal cumulative distribution (blue curve) and Empirical Cumulative distribution (green curve) with mean (black line) minus standard deviation (red broken line) and mean plus standard deviation (blue broken line). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

of the maize simulation was only performed at a course scale (regional and sub-regional) using aggregated values, which could introduce additional sources of uncertainty. There was no indication that the area of planted maize in a sub-regional and regional level influenced the relationship between aggregated modeled yield and CSA regional yield estimates. The range of maize prediction values can also be improved with better representation of the spatial variability if the empirical calibration of the crop simulation is performed at a sub-regional or even district level. In this study, we were not able to analyze different maize cultivars effect on yield forecast. The reason for this is that CSA has provided yield estimations as aggregated values, not the disaggregated observed yield by varieties. Accordingly, we did not have comparable yield values with forecast.

Our study shows that functionality implemented in CRAFT has potential to contribute addressing pre-seasonal and in-season crop production strategic planning, through procedures related to maize management technology, particularly, variety selection, sowing (timing, areas, etc.), fertilizer applications (timing, rates). Because crop management related parameters are crop model inputs, and this allows developing various scenarios of those inputs. Our study also demonstrates effectiveness of seasonal climate forecasts, in this case SSTs, that are translated into granular maize yield forecasts, 10 km Cell level in CRAFT, that more useful for farmers. Derived maize production forecast can be used for strategic and tactical interventions for food security at district or country level.

The difficulties of adopting a dynamic crop simulation model, such as DSSAT, in CRAFT is associated with the intensive data requirement for the model simulation and evaluation. Data limitation was often a heavy burden on this study in order to provide detailed information at a finer spatial scale. Despite these challenges, CRAFT provides the capability of using crop models that can be run at a local or district scale with less demand on required data inputs. However, this can be improved if sufficient data on the local cultivar, crop management practices, and observations such as phenology and crop yield are available. This will provide the opportunity for calibration at a local scale of the cultivar coefficients and will allow for capturing the spatial variation of the local cultivar to variability in the seasonal climate for different locations.

Conclusions

In this study, we have shown the potential of CRAFT for yield forecasting and its ability and applicability in forecasting maize yield for smallholder farming systems. Normal-to-above normal maize production was forecasted for the 2020 growing season over the Oromia regional State of Ethiopia. Assessment of the potential predictability of maize production in Oromia indicates a relatively good performance of the forecast model in capturing the mean yield level at administrative level and its spatial and temporal variability. However, the forecast was not accurate in all cases; poor performance was observed in the marginal maize environments, which affected forecast accuracy.

The study indicated that CRAFT can be used to study the mesoscale nature of spatial and temporal crop yield variability, as well as it can be used as a decision support system for early yield estimation of major food security crops at the national level by institutions that oversee Agriculture. In addition, it also opens a pathway to ICPAC and AGRHYMET to consider the CRAFT toolbox as a regional crop yield forecasting system in East and West Africa, respectively. Future studies should re-evaluate and address the importance of the size of agricultural areas while comparing aggregated simulated yields with yield data collected from a fraction of the target area.

Practical implications.

The study evaluates a methodology implemented in the CCAFS Regional Agricultural Forecasting Toolbox (CRAFT) (Shelia et al., 2019) for spatial yield forecast for maize hybrids across Oromia region in Ethiopia, where maize is one of the most important staple crops for food security and a source of smallholder farmer incomes. CRAFT as a climate service links seasonal climate forecasts with gridded crop simulations for in-season probabilistic yield forecasting in the spatial scale. For spatial yield forecasting it requires gridded data sets on weather, soil, crop and crop management. In this study calibration was conducted using regional level observed maize yield data (2004–2014) and the yield hindcast was evaluated against sub-regional (2015–2019) aggregated observed yields. The results showed that the hindcast simulations were performed well (RMSE of 164 kg/ha).

A functional, granular (0.083° or $\sim$ 10 km resolution grid) spatial yield forecasting system such as CRAFT could provide probabilistic yield forecast with various lead time and thus, can serve as an early warning system. It can also provide agricultural risk management options for greater economic and social benefits for highly variable environments. Functionality implemented in CRAFT has potential to contribute addressing pre-seasonal and in-season crop production planning. Crop management related parameters are inputs for the Cropping System Model (CSM) of the Decision Support System for Agrotechnology Transfer (DSSAT) (Hoogenboom et al., 2019), and thus, it allows us to develop various scenarios of those inputs, particularly for selection of maize hybrids, sowing (timing, areas, etc.), and fertilizer applications (type, timing, rates) characteristics for decision making on the optimal management.

CRediT authorship contribution statement

Kindie Tesfaye: Conceptualization, Methodology, Writing – original draft. **Robel Takele:** Formal analysis, Writing – original draft. **Vakhtang Shelia:** Formal analysis, Writing – review & editing. **Esayas Lemma:** Writing – review & editing. **Addisu Dabale:** Formal analysis. **Pierre C. Sibiry Traore:** Conceptualization, Methodology, Writing – review & editing. **Dawit Solomon:** Conceptualization, Methodology. **Gerrit Hoogenboom:** Conceptualization, Methodology, 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 data that has been used is confidential.

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