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# A multi-scale and multi-model gridded framework for forecasting crop production, risk analysis, and climate change impact studies

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A R T I C L E  I N F O

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A B S T R A C T

Regional crop production forecasting is growing in importance in both, the public and private sectors to ensure food security, optimize agricultural management practices and use of resources, and anticipate market fluctuations. Thus, a model and data driven, easy-to-use forecasting and a risk assessment system can be an essential tool for end-users at different levels. This paper provides an overview of the approaches, algorithms, design, and capabilities of the CCAFS Regional Agricultural Forecasting Toolbox (CRAFT) for gridded crop modeling and yield forecasting along with risk analysis and climate impact studies. CRAFT is a flexible and adaptable software platform designed with a user-friendly interface to produce multiple simulation scenarios, maps, and interactive visualizations using a crop engine that can run the pre-installed crop models DSSAT, APSIM, and SARRA-H, in concert with the Climate Predictability Tool (CPT) for seasonal climate forecasts. Its integrated and modular design allows for easy adaptation of the system to different regional and scientific domains. CRAFT requires gridded input data to run the crop simulations on spatial scales of 5 and 30 arc-minutes. Case studies for South Asia for two crops, including wheat and rice, shows its potential application for risk assessment and in-season yield forecasting.

## 1. Introduction

The ability to predict agricultural production losses associated with extreme natural events through monitoring and forecasting creates an opportunity for governments, international aid organizations, NGOs, and donors to provide targeted assistance for replacing lost food income and maintaining some level of food security. Timely assistance stabilizes consumption, allowing households and communities to move towards economic security and sustainability. However, any delay in identifying and initiating a response to emerging food crises will greatly increase the long-term impacts on livelihoods and the cost of aid (Cabot Venton et al., 2012; Clarke and Hill, 2013; Haile, 2005). When a crisis requires external food aid, it can take up to several months before aid reaches affected populations. As a result, populations in crisis may already have suffered adverse health effects, divested productive resources, or migrated. In food-insecure regions, such as in Africa or Southeast Asia, early warning systems based on remote sensing of vegetation and monitoring of local commodity markets can provide an early indication of likely food shortfalls (Hallegatte, 2012; Verdin and Klaver, 2002). Thus, food aid organizations in developing countries are increasingly interested in seasonal agricultural forecasts to provide lead-time in response to extreme weather events that affect current agricultural production.

Operational crop forecasting and early warning systems for food security exist in many regions to help support market and policy decisions (Cantelaube and Terres, 2005; Motha, 2011; Verdin and Klaver, 2002; Vossen and Rijks, 1995). Often, they are based on monitoring weather and crop conditions during the growing season and incorporate regionally calibrated crop models to estimate yield uncertainty. Crop models are computerized representations of crop growth and

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development, and predict yield through mathematical equations as functions of soil properties, weather conditions, and management practices (Hoogenboom, 2000). There has been significant progress in the application of crop models to define strategies for more efficient crop production, improved risk management, sustainable cropping systems, and to study the impact of climate change on agricultural systems (Holzworth et al., 2015). Crop-model integrated decision-support tools as a computer-based technology to support complex decision-making have long been used to assess climate risk in agriculture. Risk refers to a likelihood that can be assessed using prior information, but when the likelihood cannot be estimated then uncertainty applies. Both risk and uncertainty are contributing factors in the choice of appropriate management practices for decision-makers (Han et al., 2017; Selvaraju, 2013). In addition to risk analysis and assessment, crop models have also been used for yield forecasting (Bannayan et al., 2003; Yun, 2003). Crop yield forecasts can be conducted prior to planting or during the actual growing season, and the results produced by the models can be used to make appropriate management decisions and to provide farmers and others with alternative options for their farming system (Hoogenboom, 2000). Skillful seasonal forecasts provide additional information that can increase the accuracy of within-season production forecasts based on monitoring and simulation alone, particularly early during the growing season (Cantelaube and Terres, 2005; Hansen et al., 2004; Stephens et al., 2000).

One of the main approaches for spatial crop simulations (Müller et al., 2017) is based on field scale crop models and various degree of GIS integration (Hartkamp et al., 1999). Current well-known spatial crop modeling systems include AEGIS, MARS/BioMA, GEPIC, pSIMS, MINK, SIMPLACE, and GeoSIM. For geostatistical and spatial analysis of crop modeling, the Agricultural and Environmental Geographic Information System (AEGIS; AEGIS/WIN) was created, linking the Decision Support System for Agrotechnology Transfer (DSSAT v3) with the geographic mapping tools ArcInfo and ArcView using an object-oriented macro programming language (Lal et al., 1993; Engel et al., 1997). In the 1990s the European crop growth monitoring system (EU-CGMS) and yield forecasting system was developed by the MARS Project coordinated by the Joint Research Centre (JRC) (Vossen and Rijks, 1995; Supit, 1997). To simulate the impacts of climate change on agriculture and to evaluate adaptation strategies, the JRC uses the Biophysical Models Applications (BioMA) framework (Donatelli et al., 2012). A GIS-based EPIC model (GEPIC) is another spatial tool that integrates a bio-physical EPIC (Environmental Policy Integrated Climate) model with a GIS to simulate the spatial and temporal dynamics of the major processes of the soil–crop–atmosphere-management system (Liu et al., 2007). Within the IMPETUS research project of the Global Change and Hydrological Cycle (GLOWA) program of the German Government, the SMILE (Scientific Model Integration pipeLine Engine) framework (Enders et al., 2010) and its improved version called SIMPLACE (http://www.simplace.net) were developed.

To facilitate climate impact modeling, Elliott et al. (2014) developed the parallel System for Integrating Impacts Models and Sectors (pSIMS) that is designed to support integration of site-based applications and allow researchers to use high-performance computing to run simulations over large spatial extents. At the International Food Policy Research Institute (IFPRI), a global-scale crop modeling system using a gridded approach, known as “Mink” (Robertson, 2017), was created to provide gridded simulated crop data for the International Model for Policy Analysis of Agricultural Commodities and Trade (IMPACT) (Robinson et al., 2015). Thorp and Bronson (2013) developed the Geospatial Simulation (GeoSim) tool as a plug-in for Quantum GIS to manage point-based model simulations at multiple locations.

These spatial crop modeling systems have been designed for specific applications and, accordingly, have certain requirements and limitations that could restrict the implementation in developing countries. Some of these tools are now obsolete (AEGIS); others are very robust, use scripting languages, and must be run on clusters or on high-performance computers (pSIMS, Mink), while some have associated implementation and maintenance issues (MARS) that might be costly, or they lack functionality such as yield forecast (GeoSIM).

In order to increase the capacity of developing regions for within-season forecasting of the impacts of climate fluctuations on crop production, the CGIAR research program on Climate Change, Agriculture and Food Security Program (CCAFS) convened a workshop on “Seasonal Weather Forecasts Linked Pre-Harvest Estimates of Crop Production: Methodological Approaches” (Negombo, Sri Lanka, 16–18 April, 2012). Following a participatory approach (Voinov et al., 2016) the intention was to bring together various stakeholders, scientists with expertise in problem domains (crop modeling, yield forecast and monitoring systems, climate) and other actors to jointly assess and identify key challenges of existing yield forecasting tools for research and operational use in the CCAFS focus regions. The identified challenges were to recognize the need for convenient and easy-to-use software platform to facilitate crop yield forecasting for researchers and operational institutions and to develop such a platform that could be accessible, cost-free and adaptable to support multiple crop models. As a result, CCAFS initiated the development of the CCAFS Regional Agricultural Forecasting Toolbox (CRAFT) to support within-season forecasting of crop production, and, secondarily, risk analysis and climate change impacts studies.

The main research questions to be explored and then implement in the software included management of spatial data and crop simulations, integration of seasonal forecasts, hindcast, spatial aggregation, probabilistic analysis, post-simulation calibration, risk analysis, climate change impact and visualization. The objectives of this paper are to (a) provide the basic concepts of gridded simulations and algorithms used for yield forecasting in CRAFT, (b) describe the toolbox architecture and its main components, (c) present the current version and its main functionality, and (d) demonstrate risk assessment and yield forecasting case studies.

## 2. Algorithms for crop production forecasts in CRAFT

### 2.1. Gridded crop simulation and empirical calibration

Process-oriented crop models predict crop growth, development, and yield for a variety of environmental conditions and management options at a point or field scale. In order to run point-based models at a regional scale, first the region is divided into grid cells that are considered as points, and then a crop model is run for each individual grid cell of the region. Finally, the results of the point-based simulations are aggregated to a region to determine spatial crop production. A similar approach has been implemented in CRAFT.

The reference grids in CRAFT are world grids (WGS84 projection) with two different spatial resolutions of 5 and 30 arc-minutes (Fig. 1a). Each grid cell of the reference grid can be assigned a unique ID (Identification Number) starting from one at the top-left corner and moving from west to east ($-180^{\circ}$ to $+180^{\circ}$ Long.) and from north to south ($+90^{\circ}$ to $-90^{\circ}$ Lat.). The process of generating a cell ID for each cell of the grid using the shape file of the region is considered the schematization process, and schema generation is one of CRAFT's functionalities. It should be noted that the boundary of the shape could be arbitrary and not necessarily coincide with an administrative boundary. As an example, Fig. 1c is a grid that comprises 112 cells within administrative boundaries in a 5 arc-minutes resolution grid; cell IDs were defined during schema generation and exported in text format (Fig. 1b). The corresponding cell IDs are used for preparation of the input files, for creating relations between the tables of the underlying database, and for processing, storing and retrieving data from the database.

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

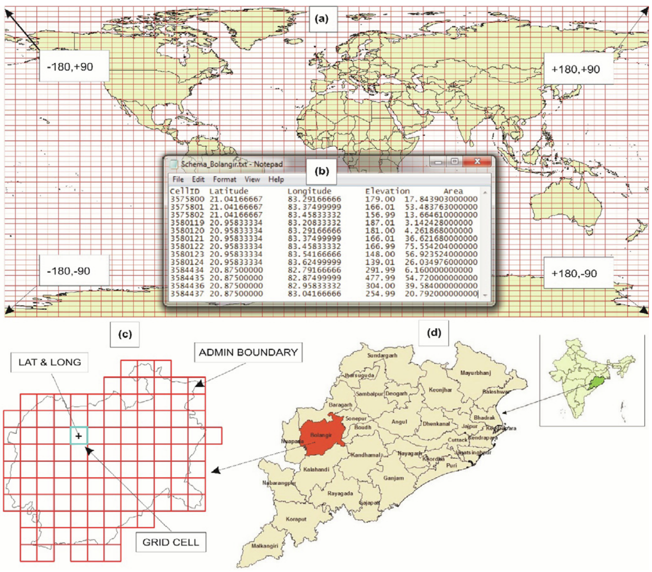


**Fig. 1.** Visualization of the basic concepts for gridded simulations at the 5 arc-minutes resolution such as the world grid(a), a schema file(b), a grid, and associated grid cells(c) for the Bolangir District of Orissa State, India (d).

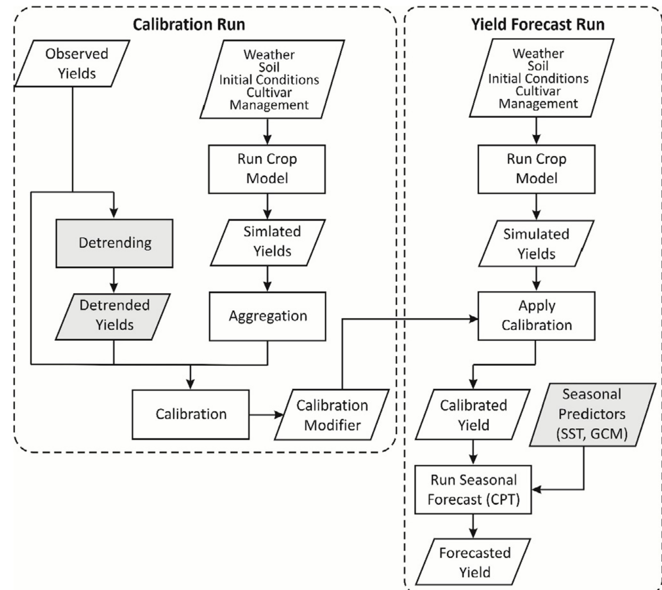


**Fig. 2.** The flowchart of the yield forecast and related calibration process with optional detrending procedure for observed yield as implemented in CRAFT. CPT - Climate Predictability Tool, SST - Sea-Surface Temperature, GCM - General Circulation Model.

yield, time series of the observed yield data optionally should be detrended. In CRAFT, two different methods for detrending the observed yield time series, namely, linear and quadratic detrending algorithms have been implemented. Various studies (Lu et al., 2017) have used these methods for detrending crop yield time-series data. Both regression models can be fitted over time using the least squares method. After simulating the trend with the appropriate statistical model, a decomposition model is applied to remove the simulated trend.

After the observed yield with optional detrending procedure is overlaid on the region, the calibration process is applied to the simulated yield in CRAFT. Most of the crop model calibration methods are applicable to deterministic simulations and crop model parameters are adjusted in order that simulated phenology, yield, and yield components values better match their corresponding observed values. Such a detailed calibration is generally not performed in gridded applications due to a lack of available reference data. Instead, cultivar parameters of models are typically calibrated at a set of points, and then the key parameters are extrapolated with relatively simple algorithms (Elliott and Müller, 2015). Alternatively, a yield correction factor can be applied to the regional yield aggregated from the simulated yield on a field scale in order to minimize the root mean square error (*RMSE*) with observed regional yield (Challinor et al., 2005; Hansen and Jones, 2000). Using the latter approach, the calibration process in CRAFT is based on long-term regional observed yield data after cultivar parameters of models are optionally calibrated for a set of cells. As part of this empirical calibration process, yield is simulated for all years for which observed yield is available; and then by fitting a linear regression between the observed and the simulated yield, a value for the calibration modification factor is determined.

### 2.2. Integration of seasonal climate forecasts with CPT

CRAFT uses a statistical approach to integrate the seasonal climate forecast with the crop yield forecast. This method was evaluated in a proof-of-concept study in Queensland, Australia, for operational wheat production forecasting (Hansen et al., 2004). The same method was later employed to improve sorghum yield forecasts (Mishra et al., 2008).

To prepare a forecast for a certain date during the growing season for the current year, yield is simulated first with observed antecedent weather data for the current year up to the forecast date and then complemented with weather data from available historic years until final harvest. The resulting time series of simulated yield 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 fit a multivariate statistical model. The expected yield value for the current season is forecast from current seasonal climate predictor observations and the fitted statistical model. The yield forecast distribution is obtained from cross-validated hindcast residuals, centered on the expected value of the forecast. Because the proportion of total uncertainty due to climate decreases during the growing season, the potential improvement in accuracy from incorporating seasonal forecasts is expected to be greatest early during the growing season (Hansen et al., 2004, 2006). A flowchart for the process of yield forecasting is provided in Fig. 2.

CRAFT uses the Climate Predictability Tool (CPT) developed by the International Research Institute for Climate and Society (IRI) (Mason and Tippett, 2016), which is widely used by national meteorological services and researchers throughout the world as a statistical forecast package. CPT was designed for producing seasonal climate forecasts using gridded outputs from GCMs and SSTs as predictors. It uses principal components (PCs) or empirical orthogonal functions (EOFs) to interact efficiently with gridded data as predictors, thereby reducing problems associated with multiplicity and collinearity. Finally, the tool performs rigorous cross-validation to avoid artificial skill. The statistical modeling component of CRAFT is implemented by running CPT in batch mode. Canonical correlation analysis (CCA) or principal components regression (PCR) settings are used for yield forecasting. It is recommended that the appropriateness and skill of a seasonal forecast system first be established before seasonal predictors are used.

### 2.3. Probability distribution of the forecast and transformation of non-normal data

Methods that have been developed for deriving and evaluating probabilistic climate forecasts are generally relevant to forecasts of agricultural impacts, including forecast distributions from hindcast residuals, historical analogs, and forecast distributions from dynamic climate model ensembles (Hansen and Indeje, 2004; Hansen et al., 2006). In CRAFT, the first approach was implemented, i.e. estimating a forecast probability distribution as the distribution of hindcast residuals, centered on the expected value of the current forecast (Hansen et al., 2006). The following are the steps for deriving a probabilistic forecast from hindcast residuals. A time series of hindcast residuals ($\varepsilon_i$) is calculated as follows:

$$\varepsilon_i = y_i - \hat{y}_i \tag{1}$$

where $y_i$ is yield time series simulated with current year of weather data through forecast date and complemented with the $i$th year weather data through harvest from available historic weather data for $n$ years; $\hat{y}_i$ are hindcasts calibrated to observations, for example, by PCR or CCA, and $i$ is an index for the year in the time series. $\varepsilon_i$ is then sorted to derive a residual distribution and cumulative density function (CDF) of residuals. The forecast distribution for a given forecast year is obtained by adding its expected value ($\hat{y}$) to each $\varepsilon_i$. The method accounts for the overall prediction error of the forecast system and is generally applicable to statistical or dynamic forecast models.

Artificial forecast skill and systematic underestimation of the dispersion of probabilistic forecasts are inherent risks in statistical forecasting, as the error of statistical forecast models tends to be smaller for the period used to calibrate the model than for predictions outside the calibration data (Hansen et al., 2006). To reduce the risk of artificial skill, the forecast distribution in a given year is derived from cross-validated regression residuals.

Methods for deriving probabilistic forecasts differ in their ability to handle changes in predictability from year to year. One source of apparent variation in predictability between years is the skewness of the underlying distributions. For strongly skewed variables, the magnitude of forecast residuals, and, therefore, the spread of forecast distribution, tends to increase in the direction of skewness. Several studies have shown that after applying a normalizing power series transformation (Box and Cox, 1964) to reduce the positive skewness of the rainfall series, the mean separation remains but variances were constant (Kruskal and Wallis, 1952; Levene, 1960). In CRAFT, a normalizing transformation to the predictand time series is used so that hindcast residuals can account for the effects of skewness on forecast dispersion; a forecast distribution in transformed space is derived and then applied as an inverse transformation to convert the forecast distributions into the original yield units (Hansen et al., 2004).

### 2.4. Spatial aggregation from yield to production

The simulated output of crop models can be scaled up at aggregate levels to account for the heterogeneity of environment and management of spatial data sets (Hansen and Jones, 2000). In CRAFT the level of aggregation ranges from point to a grid-cell, and from grid-cell to a region. Because the toolbox simulates on a grid-cell base, two aggregation steps are applied. The first step simulates multiple treatments within a grid cell and then, after calculating yield and other outputs weighted by the share of the area under different soils for a given cell, it aggregates yield to obtain an average value at a grid cell level. In the second step, average yield and cell area account for crop production on a grid cell level, and then production by grid cells is aggregated to polygons, thus resulting in regional level production.

Uncertainties in yield forecasting at a regional level are represented in terms of probability distributions on the aggregated level. The aggregation of the forecast probability distribution is derived from cross-validated regression residuals based on the simulated ($y_{ij}$) and the hindcast ($\hat{y}_{ij}$) yields for $i$th year and $j$th grid cell aggregated to a polygon level by taking their weighted linear combination according to the following equations:

$$Y_i = \sum_{j=1}^{m} w_j y_{ij} \tag{2}$$

$$\hat{Y}_i = \sum_{j=1}^{m} w_j \hat{y}_{ij} \tag{3}$$

where $Y_i$ and $\hat{Y}_i$ are aggregated to the area simulated and hindcast yields, $w_j = \frac{s_j}{S}$ is the share of the cell area ($s_j$) over the area of the region (S) and $m$ is the total number of cells in the area of aggregation. The weights ($w_j$) are non-negative and their total is one.

Then a time series of hindcast residuals ($\varepsilon_i$) is calculated similar to eq. (1), but applied to the aggregated values of the simulated and hindcast yields:

$$\varepsilon_i = Y_i - \hat{Y}_i, \qquad i = 1,2, \ \dots n \tag{4}$$

where $n$ is a number of years.

Finally, a time series of hindcast residuals ($\varepsilon_i$) is sorted to derive a CDF of residuals. The forecast distribution for a given forecast year is then obtained by adding its expected value ($\hat{Y}$) to each hindcast residual ($\varepsilon_i$). Thus, the aggregated probability distribution summarizes the accumulated information on yield by grid cells over the area.

## 3. Software architecture

### 3.1. Overview

The CRAFT application is based on the Microsoft .NET Windows platform and includes a user-friendly client application developed in C# that provides the interface with crop models and a MySQL database implementation. The database contains all input and output data for the crop models, including crop management, soil, weather, and climate data, as well as crop model related information. The toolbox is integrated with two external engines, namely, a crop model engine for linking and executing the crop models, and the CPT engine for running CPT as a statistical package. The application architecture follows Object Oriented Programming (OOP) paradigms, uses software design patterns (Gamma et al., 1995), and is designed as a multi-tiered system to allow for modularity and scalability. The overall system uses a Model - View - View Model (MVVM) design pattern and Windows Presentation Foundation (WPF) concepts since the View is part of the Graphical User Interface (GUI) of the application. The modules and components that are part of CRAFT are shown in Fig. 3. The integrated design and structure of the toolbox allows for easy adaptation of the system to other spatial domains and crop models.

The three main tiers of the system are Presentation, Business, and Data. The Presentation tier contains the components that implement and display the user interface, and it manages interaction with .NET base Windows forms. It also acquires and validates data input. The Business tier implements the logic for the system functionality and treats data as objects not considering how the data are stored or displayed. It manages a client's requests on information as well. The Business tier is designed to address scalability of the application, and it contains three entities: Interface, Factory Class and Implementation Class. The Interface separates the implementation and defines the structure. The Factory Class contains the methods that encapsulate the creation of objects. The Implementation Class inherits the interface and stores the logic to implement the Interface method. In the Data tier, the data access layer is designed to abstract the logic necessary to access the database. Using a separate data layer makes the application easier to configure and maintain, and it hides the details of the database from other layers of the application. Data transfer objects (DTOs) are used when interacting with other layers and to pass the data between layers.

### 3.2. Input data and storage

Gridded simulations by CRAFT can be conducted for any region for up to three scale levels, which, for example, could be a country, a state/province, and a district if the administrative area is the region of interest. The toolbox is built with a schema generation feature which

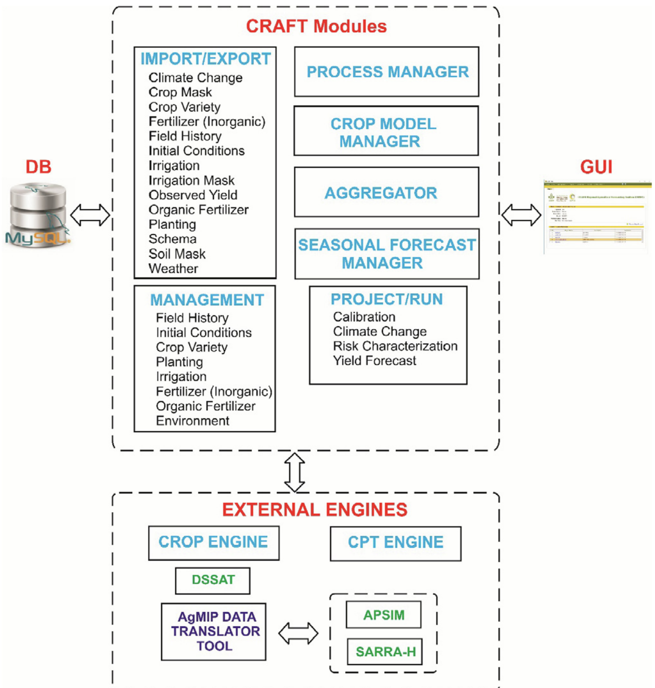


**Fig. 3.** The various modules and components of CRAFT.

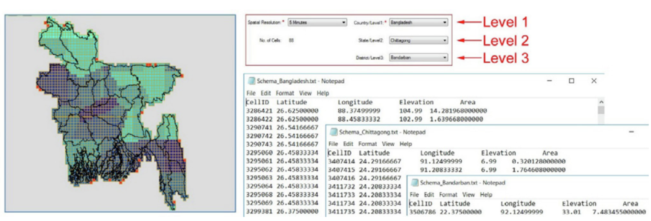


**Fig. 4.** Administrative boundaries and schematization at three levels.

allows for the generation of schema files through user-specified shape files that correspond to up to three spatial scales for the region. After completing the schema generating process, a schema folder will contain the respective schema files by the administrative or other specified boundaries (Fig. 4). The schema files then can be uploaded in the database using the data upload module.

CRAFT works on a gridded region with each grid cell representing an area along with its attributes. Therefore, gridded input data are required. The input data include information necessary to run the crop models, such as daily weather, soil properties, initial conditions, cultivar or varieties, and crop management. Downloadable templates are available to facilitate data preparation in the specific formats required by the toolbox. ArcGIS shape files are used for data associated with aerial mappings, including soil and crop coverage, and crop management (Fig. 5).

The data loader module is designed to manage uploading and downloading various datasets. It enforces rules to ensure the completeness of the data and adherence of the data to the defined data structures. The MySQL database is used as a Central Database to store all input and output data of the simulations (Fig. 3). The Central Database contains the configuration data, location-specific information, such as the coordinates and properties of each grid cell, the dynamic time series data, etc. The dynamic series data can either be imported from external sources or produced through internal data manipulation methods and crop model simulations.

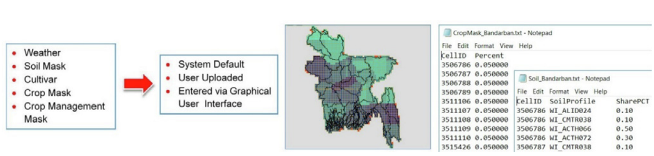


**Fig. 5.** Data inputs as gridded data sets and examples of soil and crop masks files.

### 3.3. Linkage between CRAFT and external modules

The crop simulation models and CPT have been kept independent from CRAFT as external modules. Hence, the data should be passed from the database to the external modules and from the external modules back to the database. The toolbox has two engines for linking to them. One is the Crop Engine for spatial crop simulations and the other is the CPT Engine for seasonal climate forecasting. Functionalities of the engines are to translate the internal database into a format that can be recognized by the external modules and to transfer the output data from the external modules into CRAFT's specific format. The engines also handle any errors that might occur during the operation of the external modules.

Because CRAFT works on a grid model and inputs are set at the time of model run creation, the grid cells are processed one by one and the data for each individual grid cell are provided to the Crop Engine as objects. The Crop Engine uses these objects to execute the crop model and returns the crop model run results to the application for further processing and storage in the database (Fig. 6). The Crop Engine uses the DSSAT Cropping System Model (CSM) as a crop model (Jones et al., 2003; Hoogenboom et al., 2017). The data formats of crop models vary widely and in order to extend the operational capabilities of the toolbox to additional crop models, the AgMIP Data Translator Tool (Porter et al., 2014) that comprises various formats and utilities has been implemented. Using this tool, CRAFT currently includes APSIM (Agricultural Production Systems sIMulator) (Holzworth et al., 2014) and SARRA-H (Baron et al., 2003) as two additional crop simulation models.

### 3.4. Output module: report generation and mapping integration

The output module is designed to optimize retrieval and

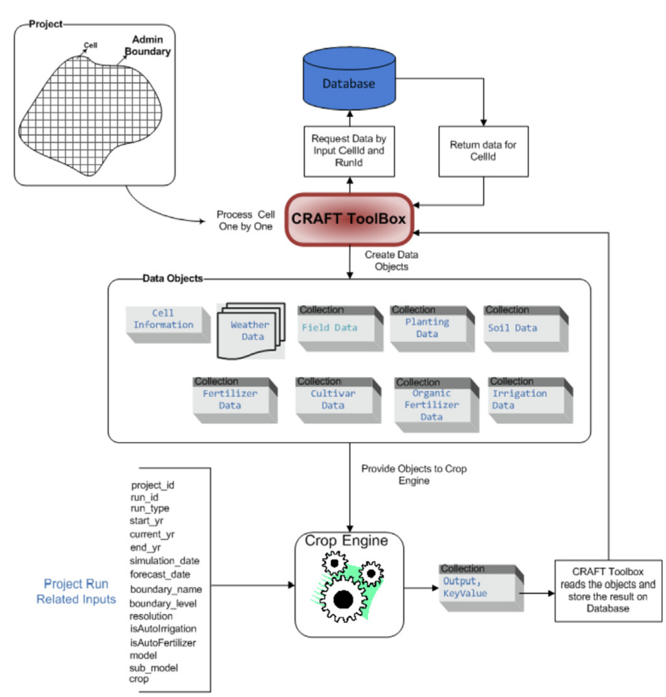


**Fig. 6.** Process flow of the Crop Engine in CRAFT.

**Table 1**
The main features of the CRAFT Graphical User Interface.

| Data | Crop management data | Project & run setup | Project Execution | Results |
|---|---|---|---|---|
| Import default data sets – ADMIN ONLY | Define crop/variety | Create a project | Run crop model | ***Single Project Run*** |
| Import gridded user data sets | Define planting dates | Search and select project & run | Run detrending module | Select project |
| Export default data sets | Define irrigation applications | Create run(s) | Run calibration module | Select outputs to view |
| Export gridded user data sets | Define fertilizer applications | Identify data sources | Run seasonal forecast module | View/Export results |
| Load cultivars | Define field history | Apply UI based inputs | Run hindcast module | ***Compare Project Runs*** |
| Load soils | Define initial conditions | | | Select two projects |
| | | | | Select outputs to compare |
| | | | | View/Export Results |

visualization of the result datasets. The final report generation is available in two types of forms. The first report option is a series of tables that can be exported in CSV file format, and the second report option is a map. MapWinGIS, a geographic information system programming ActiveX Control and application programming interface (API) (Ames et al., 2007) is used to provide CRAFT with the mapping functionality. Using the GIS shape files, maps along with the grid cells can be displayed and the various output variables from the crop model simulations can be depicted in thematic maps.

## 4. Use of CRAFT

### 4.1. Graphical User Interface

The CRAFT application provides .NET base Windows forms for various inputs and outputs. A summary of the main features of its GUI is described in Table 1. The “Home” window (Fig. 7) provides a summary of the most recently used projects, a link to create a new project, basic information for the last selected project, and the run that has been executed. The Project Name link allows navigation to the current state of the workflow. The toolbox can be configured via “Configuration” with the desired database and schema generation functionality that allows generation of schema files compatible with an application through user-specified shape files.

### 4.2. Input module: data loader and configuration

The Data Loader GUI is a tabular interface for the data Import/Export option (e.g., Fig. 8). It enables uploading various data sets that are required by the modeling engines into the Central MySQL Database after checks that reject incomplete or erroneous data during the upload process. The input module provides support for spatial input data through the use of 5 and 30 arc-minutes resolution grids. Input data should adhere to the data structure of the grid and be consistent with


**Fig. 7.** The user interface of the CRAFT application.

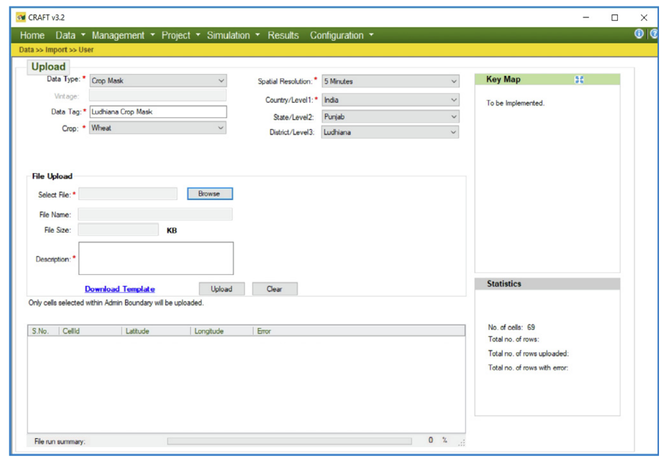


**Fig. 8.** Example of the “Data Upload” window when a crop mask is selected as data type.

the cell resolution. The datasets that can be uploaded are weather data for climate change, crop mask, soil mask, irrigation mask, etc. in Text (.txt) format file (Fig. 3). The Data Loader also provides an “Export/Delete” option to download data files and schema from the database or to delete uploaded data based on selection criteria.

The Management options that can be selected or entered as levels through the interface are the following: detailed information related to field, initial conditions, crop/variety, planting dates, irrigation, fertilizer (inorganic and organic), and environment (Fig. 3). These inputs need to be applied to the project run and the highest resolution for the application is the district level or level 3. All grid cells that fall within a district inherit the data applied for that particular district. The Configuration module also provides additional functionalities for dataset input in the Central Database, such as uploading varieties/cultivars for different crops and crop models and uploading new or updating existing soil profiles.

### 4.3. Projects

A project is defined by its spatial domain based on the selected boundary level, the spatial resolution, the project type, crop, and the crop model. There are four types of projects that can be created and executed: calibration, yield forecast, risk characterization, and climate change.

The calibration type project allows for the calculation of the modification factor and the equation for transforming simulated yield to the regional-level yield based on observed regional yield. The yield forecast type project runs the crop model, uses the calibration modifier to determine the calibrated yield, and executes CPT resulting in the in-season yield forecast. The risk characterization type project runs the crop model for various environmental and management scenarios and estimates the associated risk. The climate change type project assesses future climate risk for crop production and determines high climate-risk areas for crop yield. In this case the weather datasets should be associated with baseline and various future weather projections by General Circulation Models (GCMs) for four emissions scenarios (Representative Concentration Pathways (RCPs) adopted by the IPCC for its 5th assessment) and reflect changes in atmospheric conditions, particularly in temperatures or/and precipitation. Additionally, as the elevated atmospheric $CO_2$ concentrations have a direct impact on crop growth and yield, either current or future $CO_2$ concentration level can also be included in a project. During the climate change project run, adaptation measures can be considered using different management scenarios as input. The climate change study is only restricted by soil and climate characteristics and is independent of present or future land use patterns. For each project type different simulation settings and scenarios can be created by changing the data source, the crop model, and the date span.

### 4.4. Summary statistics and visualization

The final step of the gridded simulation process is the generation of information that can then be disseminated for decision support. Upon successful completion of simulations and after saving the results, final information can be viewed or exported to a file. Based on the selection criteria, various output variables (yield at harvest maturity, aboveground biomass at maturity, pod or grain weight, harvest index, the maximum leaf area index, total seasonal transpiration, soil evaporation and evapotranspiration, and total precipitation, runoff, and drainage) are displayed. The selected output variables are supported with summary statistics (mean, standard deviation, median, percentiles, coefficient of variance, and maximum and minimum values) that can be used for improved analysis of the results or regional summaries.

The toolbox also has two options for comparing the simulations results for the given parameter: a calculation of the differences and a calculation of the deviation (%) between the simulations. The final step in the workflow is to visualize the underlying information. CRAFT generates interactive thematic maps representing up to ten different classes for all output variables, their summary statistics, and the results of comparing simulations.

## 5. Case studies

We conducted and discuss three cases to illustrate the application of the toolbox; two are for risk characterization (Cases 1 and 2) and one is for yield forecast (Case 3). The primary steps for setting up the simulations were selecting the weather and soil data, and defining the levels for field history, crop/variety, and details for planting, fertilizer, and irrigation. Daily weather data included solar radiation, maximum and minimum temperatures, and rain obtained from the NASA Prediction Of Worldwide Energy Resource (POWER) data base (https://power.larc.nasa.gov/cgi-bin/cgiwrap/solar/agro.cgi) with a data resolution $1^{\circ} \times 1^{\circ}$ sliced to 5 arc-minutes. Details of the physical and hydraulic soil properties of the soil layer profiles were provided in the WISE database.

### 5.1. Case study 1: the impact of transplanting date on rice production

The Barisal District of Bangladesh is among the major rice growing regions of Bangladesh. The study region consists of 82 cells at a 5 arc-minute resolution grid. The impact of transplanting date on rice production was simulated with the DSSAT crop engine using the CSM-CERES-Rice module for 26 years (1984–2009). Local crop management details were adopted from Basak et al. (2010) (Table 2). The cultivar coefficients for the rice variety BR14 were obtained from a local calibration conducted by Basak (2012). The transplanting dates that were evaluated included January 1, 5, 10, 15, and 25. Rice growth, development, and yield were simulated for each grid cell, year, and transplanting date. Yield was summarized for each grid cell, aggregated for the region, and summarized by planting date (Fig. 9, top). After completion of the simulations, the results were exported in MS Excel and visualized. In general, the simulations showed the lowest yield (2000 kg $ha^{-1}$) for the early planting date (January 1) and the highest yield for the January 25 planting date (5490 kg $ha^{-1}$) (Fig. 9, bottom). The simulated yield also showed seasonal variation due to annual weather variability. The standard deviation for yield over the selected planting dates ranged from 552 kg $ha^{-1}$ (January 1 planting) to 671 kg $ha^{-1}$ (January 25 planting).

### 5.2. Case study 2: the effect of sowing dates on wheat yield

The Ludhiana District is among the major wheat growing regions of India. The study region consists of 69 cells at a 5 arc-minute resolution grid. The CSM-CERES-Wheat module of the DSSAT crop engine was used to estimate the long-term (1984–2008) mean yield and variability for the wheat variety PBW175. The cultivar coefficients for the wheat variety PBW175 were obtained from a local calibration conducted by Vashisht et al. (2013). Local crop management details were adopted from Timsina et al. (2008) (Table 2). Five sowing dates in fortnightly intervals, ranging from early October to early December, were evaluated (Table 2). Weeds, pests, and diseases were considered to be well controlled. Wheat growth, development, and yield were simulated for each grid cell, year, and sowing date. Yield was summarized for each grid cell, aggregated for the region, and summarized by sowing date (Fig. 10, top). After completion of the simulations, the data were exported into MS Excel and graphed. Potential yield varied across years and sowing dates (Fig. 10, bottom), with mean yield ranging from 1870 kg $ha^{-1}$ (October 10 sowing) to 2180 kg $ha^{-1}$ (October 25 sowing). Yield was highest for the sowings between October 25 and November 25, and smallest for the December 10 sowing date. Yield variability due to seasonal weather variability was greater than the variation across sowing dates. For example, for the October 25 sowing, the yield ranged from 1260 to 3240 kg $ha^{-1}$. The standard deviation for yield over the selected sowing dates ranged from 533 kg $ha^{-1}$ (October 25 sowing) to 753 kg $ha^{-1}$ (December 10 sowing). The crop model underestimated yield for all years and all sowing dates, which remains a concern and needs to be addressed by adjusting the management input.

### 5.3. Case study 3: yield forecast for rice

The CSM-CERES-Rice module of the DSSAT crop engine was used to forecast yield for the rice variety PR114. The study region of the Ludhiana District of Punjab State of India consists of 69 cells in a 5 arc-minute resolution grid. The genetic coefficients for the rice variety PR114 were obtained from the cultivar information distributed with DSSAT v4.7 (Hoogenboom et al., 2017). The crop management data that were used in the simulations (Table 2) were adapted from Basak et al. (2010). Soil and crop masks were provided by CRAFT. The observed rice yield (1998–2009) for the region was first detrended prior to the calibration run to determine the modification factor. A yield forecast type project was then created for the Ludhiana district, the crop model was run, and the simulated results were calibrated with the modification factor. The simulation start date was selected as June 10 and the yield forecast date as July 25, 2010. The yield forecast mode was run using CPT. CCA was selected for the forecast statistical method and *SST* for the gridded predictor file. The training period for the statistical model was 24 years (1986–2009) and the yield forecast was conducted for each year using the predictor file containing *SST* fields for January 16 and for the forecasting year of 2010 (Fig. 11, top) for each grid cell.

The rice yield forecast for 2010, $\hat{y}_{2010}$ was 4431 kg $ha^{-1}$ with lead time of 2 months (Fig. 11, bottom). Standard descriptive measures of goodness-of-fit and forecast accuracy were applied to evaluate the accuracy of rice yield predictions, including *RMSE* of prediction, mean absolute error (*MAE*), mean bias error (*MBE*), and mean absolute

**Table 2**
Crop management details for the rice (Basak et al., 2010) and wheat (Timsina et al., 2008) varieties used in the case studies.

| Parameter | Input data | | |
|---|---|---|---|
| | Rice variety BR14 | Wheat variety PBW175 | Rice variety PR114 |
| Planting method | Transplant | Dry seed | Transplant |
| Planting date | | 10 Oct, 25 Oct, 10 Nov, 25 Nov, 10 Dec | |
| Transplanting date | 1, 5, 10, 15 and 25 January | | 20 June |
| Planting distribution | Hill | Rows | Hill |
| At seedling, plants $m^{-2}$ | 75 | 150 | 75 |
| At emergence, plants $m^{-2}$ | 33 | | 33 |
| Row spacing, cm | 20 | 22.5 | 20 |
| Planting depth, cm | 3 | 8 | 3 |
| Transplant age, day | 35 | | 28 |
| Plants per Hill | 2 | | 2 |
| **Fertilizer application** | 18 days after transplanting 30 kg $ha^{-1}$ N<br>38 days after transplanting 70 kg $ha^{-1}$ N | Basal dose of Urea 50 kg $ha^{-1}$<br>25 days after planting Urea 50 kg $ha^{-1}$, 30 kg $ha^{-1}$ P, 25 kg $ha^{-1}$ K<br>56 days after transplanting 30 kg $ha^{-1}$ N | At transplanting Urea 30 kg $ha^{-1}$ N<br>21 days after transplanting Urea 30 kg $ha^{-1}$ N<br>42 days after transplanting Urea 30 kg $ha^{-1}$ N |
| **Irrigation** | 855 mm in 14 applications | at 25, 53, 72 DAP[a] 75 mm furrow | |

[a] DAP – Days After Planting.

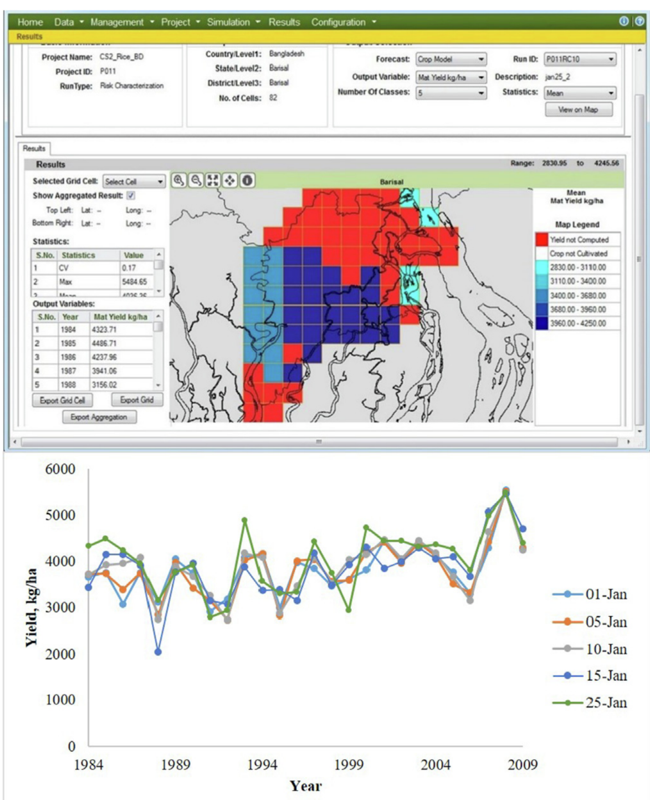


**Fig. 9.** Aggregated yield for the Barisal District of Bangladesh for the rice variety BR14 (top) and the effect of transplanting date on simulated regional yield (bottom).

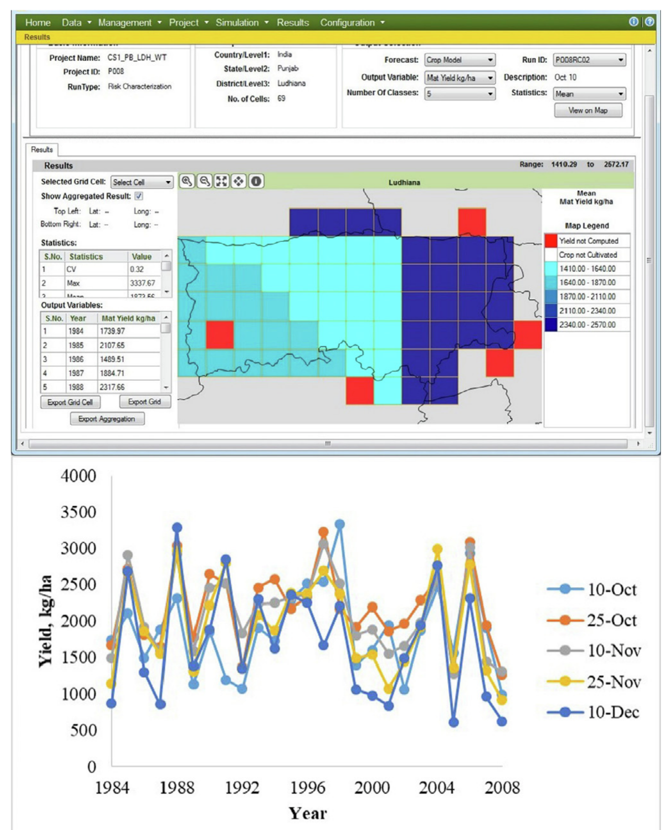


**Fig. 10.** Aggregated yield for the Ludhiana District of India for the wheat variety PBW175 (top) and the effect of sowing date on simulated regional yield (bottom).

percentage error (*MAPE*). We evaluated the accuracy of rice yield predictions against available (1998–2009) observed yield. The aggregated forecasted yield varied across years with a mean yield of 4435 kg $ha^{-1}$. The errors associated with rice yield forecasts were occasionally very large, such as 1998 and 1999 when residuals ($\varepsilon_i$) were 1316 kg $ha^{-1}$ and 1144 kg $ha^{-1}$, respectively, and absolute percentage errors of 41.8% and 34.2%. The most accurate predictions were obtained for 2002 through 2006 with residuals of less than 150 kg $ha^{-1}$ and forecast errors less than 3.4%. The overall forecast accuracy measures such as *RMSE, MAE, MBE,* and *MAPE* were 617 kg $ha^{-1}$, 439 kg $ha^{-1}$, 376 kg $ha^{-1}$, and 12.3%, respectively.

## 6. Discussion

There has been an increased interest in spatial crop simulations in the past decade and, at the same time, greater availability of various global geospatial data sets from a wide variety of data collection platforms. Therefore, there is a growing need for spatial crop simulation that employ tools and frameworks of different complexity and

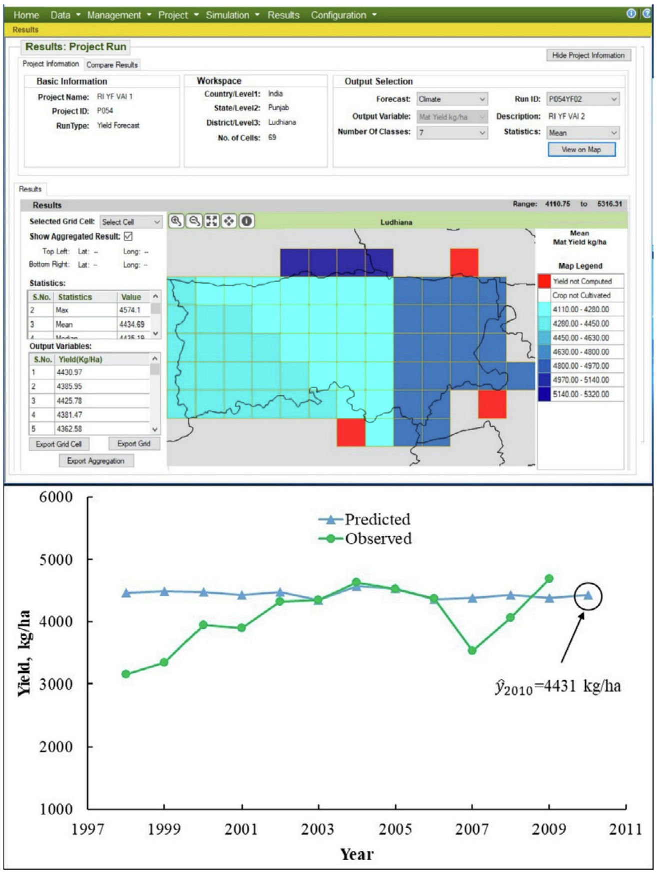


**Fig. 11.** Yield forecast (top) and time series of observations ($y_i$) and calibrated predictions ($\hat{y}_i$) (bottom) for the rice variety PR114 for the Ludhiana District of India.

approaches, including approaches that allow running existing field scale crop models on a spatial scale (Holzworth et al., 2015). Geographic information systems are often a logical part of such systems, as they can effectively support with functionality related to shapes, polygons, etc. Geospatial data from diverse sources, including soil, management application, and crop maps, can be provided within the CRAFT database as masks. Data are summarized in a format that permits realizations of the crop model simulations for each grid cell and then the toolbox provides functionality for easily performing the necessary geospatial data processing tasks and conducting spatial simulations.

Statistical seasonal climate forecasts have successfully supported agricultural applications using various approaches. These include historic analogs (De Jager et al., 1998; Hammer et al., 2001) and combining GCM-based seasonal rainfall forecasts with a crop model (Hansen et al., 2004; Mishra et al., 2008). Seasonal clime forecasts are somewhat constrained since the accuracy of statistical models is primarily limited by the length and quality of the historical observational record, and by assumption on the stationarity of the climate system (Hansen et al., 2004). A detailed review of advances in seasonal climate forecasting with a focus on agriculture is provided by Klemm and McPherson (2017). CRAFT is integrated with seasonal climate forecasts, along with historic and monitored weather data and other gridded data sets, to produce probabilistic forecasts of crop yields and area-aggregated production. It incorporates multivariate statistical forecast using CPT to connect the predictable components of seasonal climate with the crop simulation. Instead of developing the downscaled seasonal forecast model on historic weather data, it is developed from crop yields simulated with historic weather data. Therefore, various methods of climate science and crop production forecasting are built into the toolbox.

The presented case studies demonstrate the main functionalities of CRAFT. As DSSAT has already been evaluated extensively for the study region, it was selected as a crop model. Additionally, varieties and cultivar coefficients in the case studies are taken from sources that already calibrated and evaluated DSSAT for their respective regions. Most importantly, a lack of observed data limited our capacity to evaluate the simulations. It is the user's responsibility to prepare detailed inputs for cases that are more comprehensive, and such tasks are beyond of the scope of the current paper. It is worth noting that several case studies have shown that the toolbox can help institutional stakeholders by providing useful and reliable information on the spatial and temporal variability of crop production and yield forecasts (IWMI, 2014; NeKSAP, 2016–17).

Stakeholder interaction and potential user involvement is crucial for development and future success of such system (Voinov et al., 2016; Volk et al., 2010). Therefore, a wide range of stakeholders was involved to help develop the variety of objectives that are covered by the toolbox. The feedback-oriented development procedure ensured engagement with stakeholders during the entire project. Stakeholders gave feedback on the system structure, the models, and objectives as well on the design of the user interface. Training workshops with the potential users of the system gave additional insights in design improvements.

CRAFT's main advantage over other systems is its integration of seasonal forecast with CPT by inclusion of historic, monitored and forecast weather information, SST fields, and GCM outputs for regional forecasts made at any point in the growing season by using an ensemble of crop models (DSSAT, APSIM, SARRA-H) and corresponding GIS shape files on two spatial resolutions for any region. The majority of the spatial simulations were carried out for 0.5° resolution grids. The toolbox can also conduct simulations at a finer resolution of 0.083°. Operation of the system requires basic knowledge of GIS type software. Visualization of the results considerably improves stakeholder interaction with the system.

The toolbox is not reliant upon a specific crop model and assumes that any supported crop models can be pre-installed on the computer system. This approach permits the software to be extended to different crop models. For integration into CRAFT, a crop model should be able to communicate via ASCII files to its Input/Output and must be able to be called from the command line. If these conditions are satisfied, it takes advantage of the AgMIP data translator tool for crop model interoperability, or the crop engine can be extended to this particular crop model. To demonstrate this feature, it was used to run an ensemble of crop models for the same geospatial data sets at a field site. Although the models had somewhat different data input requirements, the toolbox was able to manipulate the input data to conform to the model requirements and conduct simulations across the region with each model (Shelia et al., 2018).

CRAFT is a freely accessible Windows desktop application that can be easily deployed using the installation tool. Its flexibility permits modelers and researchers with diverse objectives to combine geospatial data processing with their modeling analyses. The software description and case studies provided herein demonstrate possible applications that include risk assessment related to crop production and yield forecast, as well as the impact of climate change projections on yield and the potential for adaptation using different crop management scenarios.

The main shortcoming of the toolbox is its inability to run multithreaded simulations. As a result, time to run multiple simulations may vary significantly depending upon the area of interest. Therefore, CRAFT is best recommended for country- and/or regional-level scale that are relevant to food security early warning and market applications. The functionalities to generate and upload schema require the ESRI ArcGIS Version 10.1 or higher, which can be considered as a limitation. The current database already contains schemas at three administrative levels for several Asian countries; for future releases the number of supported countries will be increased, and additionally alternate options working with a schema will be provided via R (https://www.r-project.org/) and GDAL (https://www.gdal.org/) spatial libraries.

Future development plans include extending the number of crop models, incorporating an additional crop model such as InfoCrop (Aggarwal et al., 2006). To make the toolbox a cross-platform system, we intend to use Mono, an open source implementation of Microsoft's .NET Framework by Xamarin/Microsoft (http://www.mono-project.com/). In the future we are also planning to establish a repository for open-source development of CRAFT.

## 7. Summary and conclusions

CRAFT offers an integrated modeling framework for within-season yield forecasting, risk analysis, and climate change impact studies. The core of the system is based on three tiers: the user interface, computation modules, and the database. The toolbox provides support for spatial data through the use of 5 and 30 arc-minutes resolution grids. In the current version of CRAFT, the crop simulations are based on DSSAT, APSIM, and SARRA-H. However, any crop model for which an AgMIP data translator has been developed can be used. The toolbox integrates seasonal climate forecasts using the CPT engine. Crop model calibration uses historic agricultural statistics for regional yield. CRAFT provides spatial aggregation and probabilistic analysis of the forecast uncertainty and visualization of the results using thematic maps. Although the toolbox can be used for simulations on the global scale, its primary use is at the country or regional scale.

CRAFT has been designed to address the needs of planners and policy makers by offering improved access to a platform that simulates crop production systems using an ensemble of models. The case studies show that it can help a diverse range of stakeholders: regional policy makers, government agencies, and researchers by providing reliable information on the spatial and temporal variability of crop production, thus enabling improved risk management for agriculture associated with increasing climate variability.

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## Software availability

Name of the software: CRAFT – CCAFS Regional Agricultural Forecasting Toolbox.

Developer: University of Florida in cooperation with IRI and CCAFS.

Contact Address: Department of Agricultural and Biological Engineering, University of Florida, Gainesville, Florida 32611, USA.

Phone: +1 352-392-1864.

E-Mail: vakhtang.shelia@ufl.edu.

Year first available: 2014.

Hardware required: Desktop/Laptop with 2.5 GHz CPU, 6 GB RAM, HDD with 70 GB or more free space.

Software required: ArcGIS version 10.1 or higher.

Program Languages and Database: C#, Java, MySQL.

Platform: MS Windows 7/8/10.

Program size with the sample DB: 3.63 GB.

Availability and cost: freely available https://dssat.net/?s=craft&submit.x=0&submit.y=0.

## Appendix A. List of abbreviations

| | |
|---|---|
| AEGIS | Agricultural and Environmental Geographic Information System |
| AgMIP | The Agricultural Model Intercomparison and Improvement Project |
| API | Application Programming Interface |
| APSIM | The Agricultural Production Systems sIMulator |
| BioMA | Biophysical Models Applications framework |
| CCA | Canonical Correlation Analysis |
| CCAFS | CGIAR Research Program on Climate Change, Agriculture and Food Security |
| CDF | Cumulative Density Function |
| CGIAR | Consultative Group for International Agricultural Research |
| CRAFT | CCAFS Regional Agricultural Forecasting Toolbox |
| CPT | Climate Predictability Tool |
| CSM | Cropping System Model |
| DSSAT | Decision Support System for Agrotechnology Transfer |
| DTO | Data transfer object |
| EOF | Empirical Orthogonal Functions |
| EU | European Union |
| GCM | General Circulation Model |
| GIS | Geographic Information System |
| GUI | Graphical User Interface |
| ID | Identification Number |
| IFPRI | International Food Policy Research Institute |
| IRI | International Research Institute for Climate and Society |
| JRC | Joint Research Centre |
| MVVM | Model - View - ViewModel |
| NGO | Non-governmental organization |
| PC | Principal Component |
| PCR | Principal Components Regression |
| pSIMS | parallel System for Integrating Impacts Models and Sectors |
| RMSE | Root Mean Square Error |
| SARRA-H | System for Regional Analysis of Agro-Climatic Risks |
| SST | Sea-Surface Temperature |
| WPF | Windows Presentation Foundation |

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