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RESEARCH ARTICLE

Yield Forecasting of Spring Maize Using Remote Sensing and Crop Modeling in Faisalabad-Punjab Pakistan

Ishfaq Ahmad[1] · Umer Saeed[1] · Muhammad Fahad[1] · Asmat Ullah[2] · M. Habib ur Rahman[3] · Ashfaq Ahmad[1] · Jasmeet Judge[4]

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Abstract

Real time, accurate and reliable estimation of maize yield is valuable to policy makers in decision making. The current study was planned for yield estimation of spring maize using remote sensing and crop modeling. In crop modeling, the CERES-Maize model was calibrated and evaluated with the field experiment data and after calibration and evaluation, this model was used to forecast maize yield. A Field survey of 64 farm was also conducted in Faisalabad to collect data on initial field conditions and crop management data. These data were used to forecast maize yield using crop model at farmers' field. While in remote sensing, peak season Landsat 8 images were classified for landcover classification using machine learning algorithm. After classification, time series normalized difference vegetation index (NDVI) and land surface temperature (LST) of the surveyed 64 farms were calculated. Principle component analysis were run to correlate the indicators with maize yield. The selected LSTs and NDVIs were used to develop yield forecasting equations using least absolute shrinkage and selection operator (LASSO) regression. Calibrated and evaluated results of CERES-Maize showed the mean absolute % error (MAPE) of 0.35–6.71% for all recorded variables. In remote sensing all machine learning algorithms showed the accuracy greater the 90%, however support vector machine (SVM-radial basis) showed the higher accuracy of 97%, that was used for classification of maize area. The accuracy of area estimated through SVM-radial basis was 91%, when validated with crop reporting service. Yield forecasting results of crop model were precise with RMSE of 255 kg ha^{-1}, while remote sensing showed the RMSE of 397 kg ha^{-1}. Overall strength of relationship between estimated and actual grain yields were good with R^2 of 0.94 in both techniques. For regional yield forecasting remote sensing could be used due greater advantages of less input dataset and if focus is to assess specific stress, and interaction of plant genetics to soil and environmental conditions than crop model is very useful tool.

Keywords Crop model · Remote sensing · Landcover classification · Regional yield forecasting

✉ Ishfaq Ahmad
ishfaq.ahmad@uaf.edu.pk

Umer Saeed
usagrarian@yahoo.comay

Muhammad Fahad
fahadagr@outlook.com

Asmat Ullah
aumalik.aari@gmail.com

M. Habib ur Rahman
habib.rahman@mnsuam.edu.pk

Ashfaq Ahmad
ashfaqchattha@uaf.edu.pk

Jasmeet Judge
jasmeet@ufl.edu

[1] Agro-climatology Lab, Department of Agronomy, University of Agriculture Faisalabad, Faisalabad, Pakistan

[2] Agronomic Research Station, Karor-Layyah, Punjab, Pakistan

[3] Department of Agronomy, MNS-University of Agriculture, Multan, Pakistan

[4] Center for Remote Sensing, Agricultural and Biological Engineering Department, University of Florida, Gainesville, USA

Introduction

Accurate and real time crop yield forecasting is very important for policy makers and grain agencies in decision making (Mkhabela and Mkhabela 2000). Population of Pakistan is increasing, and future scenarios showed that it would be 271 million by 2050, but food production is not increasing at same rate (Schafer and Victor 2000). Severe drought and floods due to climate change also affect the availability of food. Access of policy makers and planners to real time crop condition and yield estimates is very important to sustain food availability for ever growing population of Pakistan (Briscoe and Qamar 2006).

Maize is the third most important crop by area after wheat and rice. It is the highest yielding crop of world and has significant importance in many countries including Pakistan. Early and accurate crop yield estimation help the decision maker in import and export policy (Dorosh and Salam 2008). For this, remote sensing and crop models are becoming important tools that help in yield forecasting. Remote sensing is also used to monitor the vegetation stress though different satellite observations like normalized difference vegetation index (NDVI) and Land surface temperature (LST) (Friedl et al. 2002). Crop models are used to understand the interaction of plant with soil, water and environmental factors. Crop models are crop specific and generally simulate water and nitrogen balance in soil and plant. Most of the crop models cannot simulate micronutrients; pest and diseases. On these basis, one can say that currently there is no comprehensive crop model (Boote et al. 1996).

Decision support system for agro-technology transfer (DSSAT) has been used in yield forecasting of many crops at different growth stages (Yun 2003). CERES-maize model, under the shell of (DSSAT), is comprehensive and process based model that has been evaluated to study the effect of different management practices in maize (Jones et al. 1986). Many researchers used this to evaluate the potential response of maize to farmers' management practices (Gaiser et al. 2010). Erda et al. (2005) used CERES-Maize for yield forecasting of maize in china. Fontana et al. (2000) reported that yield forecasting in Brazil was done after crop harvest. CERES-Maize model simulate the crop growth and development on daily basis from planting to maturity and describe the interaction of soil and environmental conditions (Fraisse et al. 2001). This shows that CERES-Maize can be used to forecast maize yield for different farmers' management practices.

Vegetation indices calculated from remotely sensed data during crop peak growth season has strong relationship with crop yield. Crop growth can be monitored continuously using time series indices like NDVI. NDVI during the crop season can help in yield forecasting. Crop growth profile can be formed by calculating statistical average of NDVI in certain regions (Zhang et al. 2004). Use of LST and NDVI in regional yield forecasting gave good index of agreement with observed yield (Johnson 2014).

Crop simulation models and statistical approaches like regression models are the two main approaches used to forecast yield using weather data (Lee et al. 2013; Dumont et al. 2015). Johnson (2014) developed regression tree-based models to study the relationship of remotely sensed pre- and within-season NDVI, land surface temperature, and rainfall with crop yield to forecast the yield of corn and soybeans. Crop simulation models need a lot of input data such as crop phenology, soil characteristics, cultivar coefficients, weather data, and cultural practices data for calibration and simulations (Van Wart et al. 2013). Linear multiple regression models use less input data, but higher numbers of independent variables and the results might not be as good because it assumes that all independent variables are linearly correlated with dependent variables (Osborne and Waters 2002), which is not always the case. Different forecasting models account for single source of variability in crop yield, which could be explained by combined effects of remotely sensed indices and climatic conditions. Crop models that use crop management practices, soil and weather data fail to include information from remote sensing and also do not take into account the spatial variability (Batchelor et al. 2002). The forecasting models that are based on remote sensing indices alone cannot explain yield variability due to climatic factors (Singh et al. 2003).

Combined use of remote sensing and crop models for accurate and real-time yield forecasting of maize could be very useful. Yield forecasting models, based on satellite derived indices, use less input data as compared to crop models. Crop models need large amount of input data (soil, weather, yield and yield components) for calibration and evaluation and simulate crop growth on daily basis. Crop models are also very helpful to explain different mechanism in crop growth but yield forecasting models (regression) based on remotely sensed data cannot help to explain growth mechanisms. The study was planned with specific objective to forecast crop yield by using both remote sensing and crop modeling. Instead of relying on one technique, researchers could use different yield forecasting tools to get reliable production estimates.

Materials and Methods

Site of Study Area

Study was conducted at Faisalabad district in Central Punjab Pakistan. The latitude 31.25 N, Longitude 73.06 E and the elevation from the seas level is 184.5 m It has semi-arid climate characteristic. The annual temperature and rainfall is 24.2 °C and 346 mm. Mainly summer season has more rainfall than the winter. The mean maximum and minimum temperature gradually start to decrease from November to January and then rise. The soil of Faisalabad is silt loam or very fine sandy loam. Faisalabad has mixed cropping zone, in which wheat, rice, maize and sugarcane etc. are cultivated.

Survey Data Collection

Comprehensive survey was conducted in Faisalabad district to collect the crop management data from the farmers. Stratified random sampling technique were used for the selection of farms. A total of 64 farm were surveyed during 2015 as shown in Fig. 1. Mobile Agricultural Geotagging Information System (MAGIS) system were used to collect data. It is mobile based application which allows to collect the digital and georeferenced field data. It is based on GeoODK platform. MAGIS form was created in the Microsoft excel sheet and uploaded on database (https://ona.io/). The developed form was excess using GeoODK Collect app by cell phone. The farmers interview were conducted at their farms. Survey data includes crop management data (sowing time, irrigation and fertilizer date and amount, tillage operation, pesticide applications and harvest operations etc.) and initial conditions (previous crop etc.).

Application of Crop Model at Regional Scale

Before application of crop model at regional scale, first calibration and evaluation of model is done with experimental data set. A complete set of experiment on spring maize was conducted during the year 2015 and 2016. Experiment include four Maize hybrids (Pioneer-1543, Mosanto-DK6103, Syngenta-NK8711) of different companies and four sowing dates (27 January, 16 February, 08 March, and 28 March). Calibration (adjustment of genetic coefficients) of CERES-Maize model V4.6.1 was done with the best sowing date of 27 January 2015 and evaluation (testing with independent data set) was done with remaining sowing date of 2015 and with data of 2016. The performance of model was checked using Mean Absolute Error (MAE) and Mean Absolute Percent error.

$$\mathrm{MAE} = \frac{1}{\mathrm{n}}\sum_{i=1}^{\mathrm{n}}|\mathrm{Y}_{\mathrm{S}_i} - \mathrm{Y}_{\mathrm{O}_i}| \quad (1)$$

$$\mathrm{MAPE} = \frac{1}{\mathrm{n}}\sum_{i=1}^{n}\frac{|Y_{S_i} - Y_{O_i}|}{Y_{O_i}} * 100 \quad (2)$$

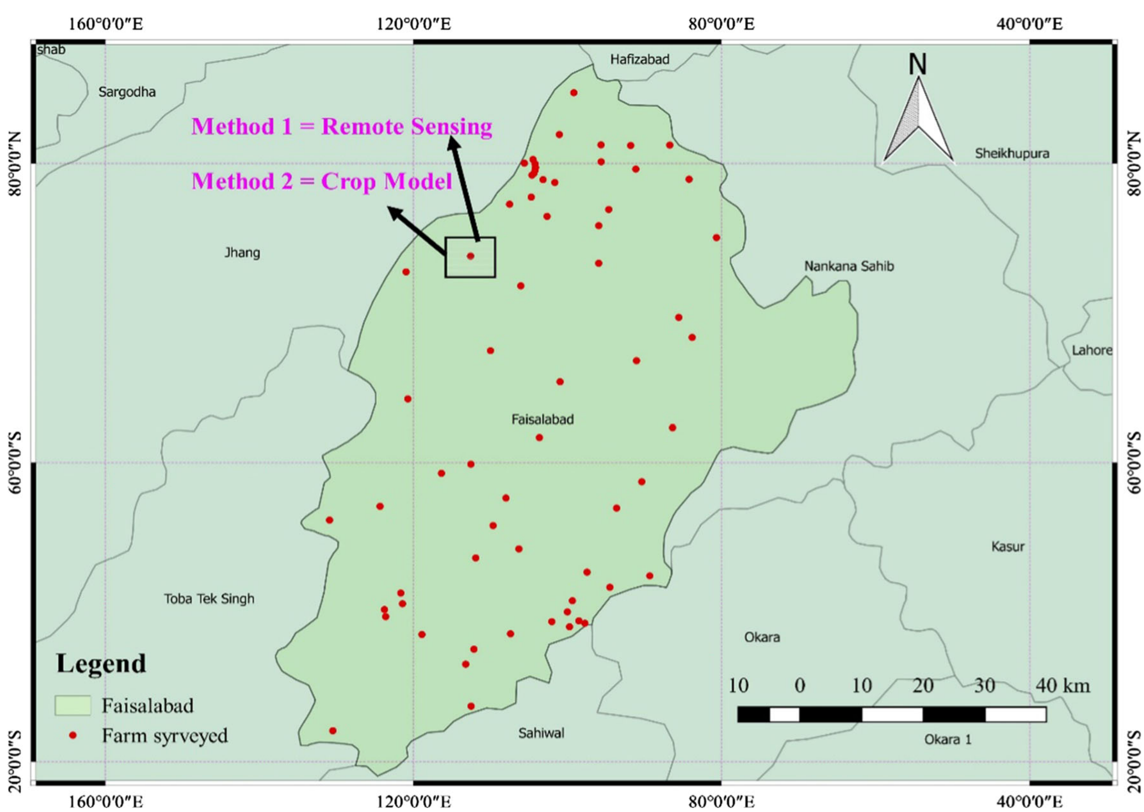

Fig. 1 Farm surveyed in Faisalabad district during 2015

where S*i* and O*i* are the simulated and observed value, n is the number of parameter to be compared and *i* each value of comparison. MAE measure the manganite of error in observed and simulated values, while MAPE showed the relative term of mistake made in predicted values.

After calibration model was applied at regional scale. For this translation tools (ADA, QuadUI, and ACMO UI) were used to create model file and to get arranged output. The collected survey data of 64 farms was put in the .xlsx sheet, which have some variables for the conversion into model files. The weather data of 2015 was collected from the weather observatory, which includes maximum and minimum temperature, precipitation, wind speed. Solar radiation were calculated from the temperatures using the formula describe by (Allen et al. 1998). Soil series data was collected form the Soil Survey of Pakistan (SSOP). Lyallpur soil series of Faisalabad was used. Soil layers (0–190 cm) wise data were used which include silt%, Clay%, organic carbon%, total nitrogen and cation exchange capacity (meq/100gm). The drainage upper limit, lower limit, saturation%, bulk density and saturation hydraulic conductivity were calculated from the model.

Crop management, soil and weather data was feed into survey sheet and data regarding cultivar information like row spacing, number of plant m^{-2} etc. were used in field overlay sheet. The linkage file was created to link these files. These three files of .xlsx format were converted into .CSV format using AgMIP data assistant (ADA), then QuadUI was used to convert the .CSV file into model file having one batch file. By using this batch file model was run and output was taken using agricultural crop model output (ACMO-UI)

Satellite Remote Sensing for Regional Yield Forecasting

For regional yield forecasting, first landcover classification for spatial distribution maize were done using machine learning algorithm. Three Landsat-8 images taken in second week of May which correspond spatially and temporally to the local, peak growing season for maize were gathered. By sampling the second, third, and fourth bands of the Landsat-8 imagery at these reference locations, training data was constructed for a variety of machine learning algorithms. Cross validation was used for parameter tuning as well as estimating the generalized performances.

After classification, the time series NDVI and LST for growing season of spring maize were calculated for 64 farms that were surveyed. NDVI and LST were calculated with 16 days interval, which starts from end week of January to second week of June. Principle component analysis (PCA) were run to see which NDVI and LST were closely related to yield. Then closely related NDVI and LST were used to get co-efficient by using Least Absolute Shrinkage and Selection Operator (LASSO) Analysis. The developed coefficients were used to predict the yield of each farm. Detail methodology is given in flow diagram of Fig. 2.

Results and Discussion

Model Calibration and Evaluation Results of CERES-Maize Model

Data presented in Table 1 showed the calibration of three maize hybrid with 27 January planting date and evaluation with remaining planting dates and 2016 data. Results indicate that the performance of model to the recorded parameters during experiment was good. In calibration (3 number of pairs) model showed a close match between observed and simulated values of phenology (days to anthesis and maturity), with MAE of 1.66. The value of MAE was little high of about 718 in case of grain yield. The LAI and biomass has values of MAPE are 0.35 and 4.39.

Model evaluation results showed the accuracy of calibrated model. The anthesis and maturity days were evaluated well, with MAPE values 2.22 and 3.92. Similar results were recorded for grain yield and LAI maximum. The high values of MAE were recorded in simulation of final grain yield (Table 1).

Our results are similar to Saseendran et al. (2005) who found that CERES-maize indicate a good accuracy in simulation of planting on grain yield of three maize hybrids. The CERES-Maize was calibrated and evaluated by Lin et al. (2015) who reported that model showed a good root mean square error (RMSE) of 8.44 kg ha^{-1} in simulating the grain yield. CERES-maize model was calibrated and evaluated using planting and nitrogen fertilizer. Model prediction in days to anthesis and maturity showed 2–3 days difference between observed and simulated. Model is useful tool and can accurately simulate the phenology, growth, grain yield and biomass (Chisanga et al. 2015). Calibrated the CERES-model by adjusting the genetic co-efficients and evaluated with independent data set. Results showed a good agreement with observed values and reported that CERES-maize model is useful tool in yield prediction of maize (Liu et al. 2012). (Mubeen et al. 2016) reported that CERES-maize model has ability to predict the biomass and grain yield accurately. During model calibration and evaluation, the simulated LAI, grain yield and biomass are within 10% error. Model is useful tool in decision making and can help in yield estimation at farm level (Table 1).

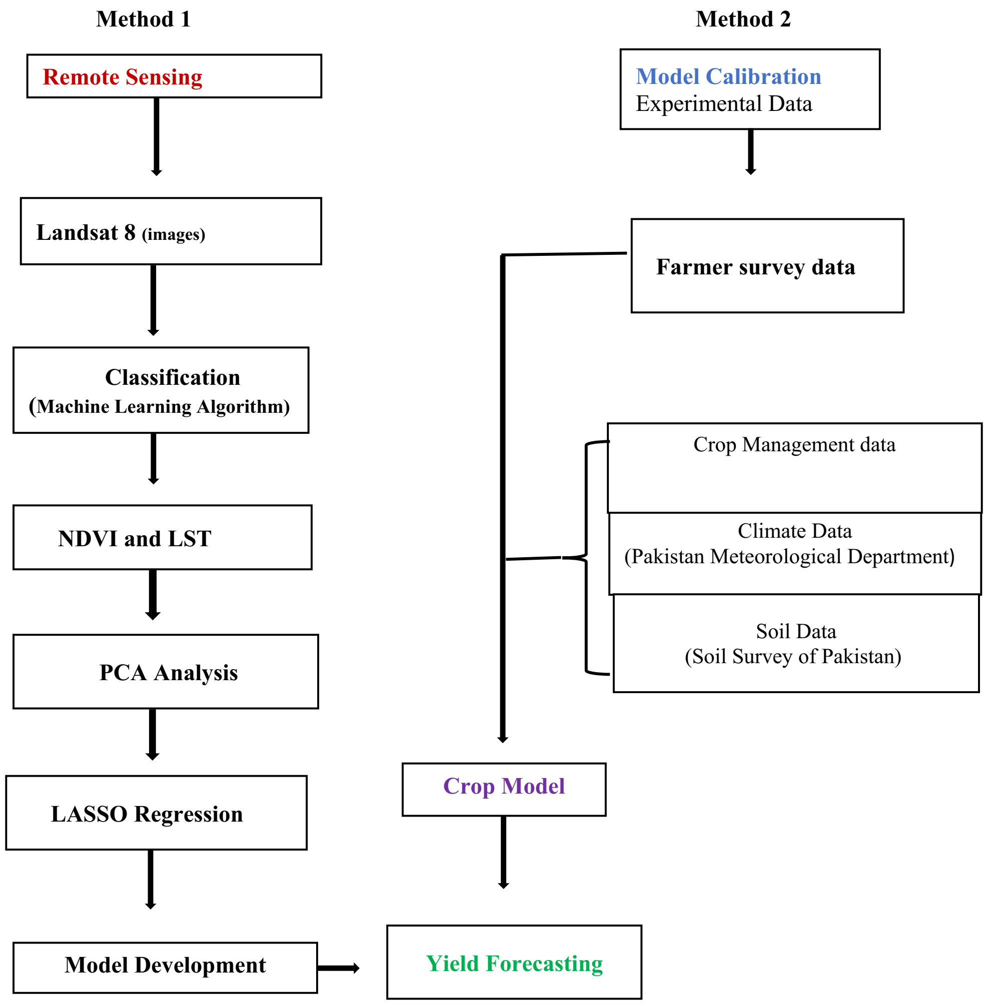

Fig. 2 Flow diagram methodology for yield forecasting using remote sensing and crop modeling

Table 1 Calibration and evaluation of CERES-maize model with experimental data set

Paramters	No. of paired	Observed range	MAE	MAPE
Anthesis day (DAP)	3	71–76	1.66	2.26
Physiological maturity day (DAP)	3	107–114	1.66	1.52
LAI maximum	3	7990–9380	33	0.35
Yield at harvest maturity (kg ha^{-1})	3	19,051–22,850	718	3.51
Tops weight at maturity (kg ha^{-1})	3	5.75–6.27	0.26	4.39
Anthesis day (DAP)	21	45–72	2.42	3.92
Physiological maturity day (DAP)	21	88–111	2.33	2.22
LAI maximum	21	5118–9203	454.9	6.71
Yield at harvest maturity (kg ha^{-1})	21	16,471–22,265	878.6	4.74
Tops weight at maturity (kg ha^{-1})	21	3.86–6.24	0.22	4.16

Yield Estimation from Crop Model

Farm survey data were used to create crop management file, initial condition, soil characteristic and observed weather data were used as input into model. After calibration and evaluation model was run with for the year 2015. Simulated yield was compared with the observed yield of each farm as shown in Fig. 3. Results indicated that there is good agreement between the simulated and observed 64 farmer yields of maize with value of coefficient of regression and RMSE were 0.99 and 255 (Fig. 4). The performance of the model differed for good and poor

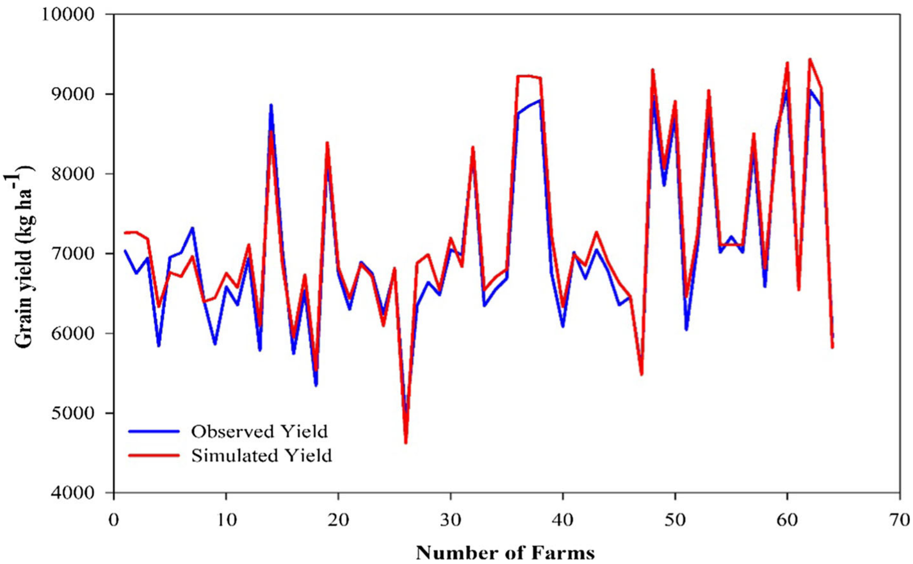

Fig. 3 Comparison of observed and simulated yield of 64 farms

management practices of the farmers. The difference between simulated and observed yield was less for those farmers whose management practices were according to recommendations. Planting time, plant population, number of irrigation, irrigation at critical stages, fertilizer application dates, application at crop critical stages, weed management and disease control were better in case of progressive farmers field and model also simulated almost same yield as observed (Fig. 3).

CERES-wheat model was applied at 150 farms in rice–wheat cropping system of Punjab Pakistan. The performance of model was well in simulation of grain yield of wheat with observed having RMSE of 749 kg ha^{-1} (Ahmad et al. 2015). CERES maize model has been used at regional scale for yield estimation under different climate scenarios. The performance of model was asses through closeness of observed and simulated grain yield, Root mean square difference was 1098 kg ha^{-1}. Xiong et al. (2007) reported that model is very sensitive to management practices and environmental variable. If there is any stress or excess of management practices model under or over-stimulated the results (Jagtap and Jones 2002). Study was conducted for regional yield estimation of maize. Different scenarios of planting, soil combination were incorporating into the model. Model showed the very high accuracy with the actual. Model estimated the yield by interaction of plant to soil, climate and other management factors (Moen et al. 1994).

Yield Estimation Using Remote Sensing

Image Classification

The tuned models of Machine Learning algorithms were used to determine the spatial distribution of maize fields for growing seasons in the Faisalabad district using parallel

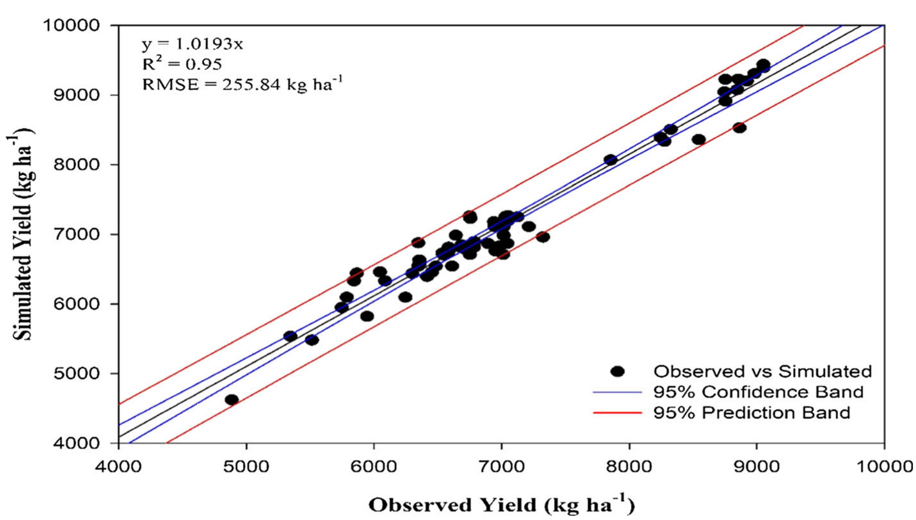

Fig. 4 Relationship of observed and simulated yield of 64 farm

Table 2 Accuracy of machine learning algorithm used for spatial distribution of maize

Classifier	Accuracy %
Support vector machine (SVM)-radial basis	0.97
SVM-linear	0.92
Quadratic discriminant analysis (QDA)	0.95
Linear discriminant analysis (LDA)	0.90
Random forests	0.94
Decision trees	0.93
k-nearest neighbor (KNN)	0.92
Boosting	0.90

processing to improve computation time as shown in Table 2. All classifiers of machine learning showed the accuracy greater then 90%, however support vector machine with radial basis showed higher accuracy of 97%. The best classifier (SVM-radial basis) were used for the classification of maize. The accuracy of estimated area using machine learning algorithm was 91%, compared with Crop Reporting Service (CRS) of Punjab Pakistan (Fig. 5). CRS reported the spring maize area of 6400 acres, while our model predicted the area of 5824 acres.

Johnson et al. (2012) used the machine learning algorithms for the classification of forest with accuracy of 85.9%. LST and NDVI has been for the monitoring of drought in Turkey, results showed a good agreement between real time ground and satellite data with R^2 of 0.90. (Orhan et al. 2014). An empirical relationship of NDVI and LST was developed by Anbazhagan and Paramasivam (2016), which indicated the crop health with respect to land surface temperature.

Analysis of Time Series NDVI and LST

Figure 6 represents the principle component analysis of time series NDVI (Fig. 6a) and LST (Fig. 6b). The results of NDVI (a) showed that that NDVI before peak season (X5) ~ 60–62 days after planting (DAP), peak season NDVI (X6) ~ 76–78 DAP and after peak season NDVI (X7) ~ 90–92 DAP, are highly correlate to the grain yield. Results of LST showed that LST (X3) which is surface temperature ~ 10–13 days after recommended planting date and LST (X4) which is ~ 28–30 DAP are highly correlated to yield. PCA is multivariate techniques which can be used with time series observations and correlate dependent variables (Algur et al. 2002). Time series NDVI and LST correlation was carried out by PCA to develop the yield estimation model (Ramachandra et al. 2016).

The correlated variable were used to develop the yield prediction model. LASSO regression was applied to get the

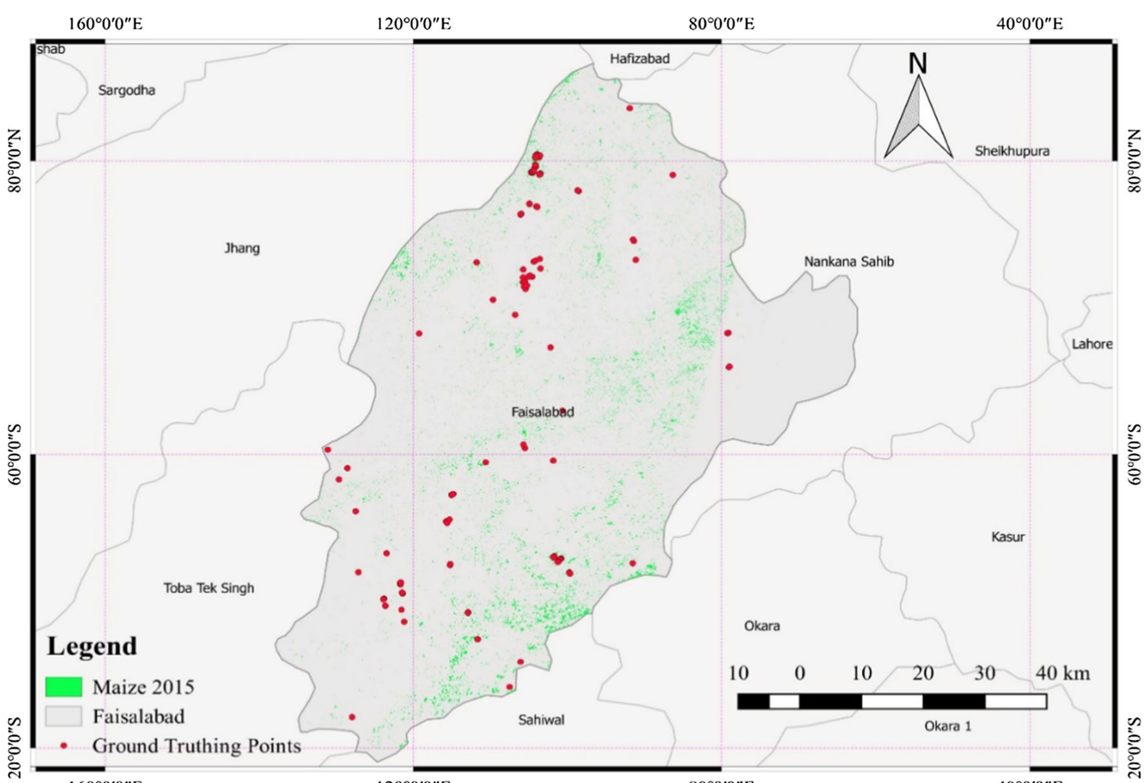

Fig. 5 Classified map of maize for Faisalabad district during 2015

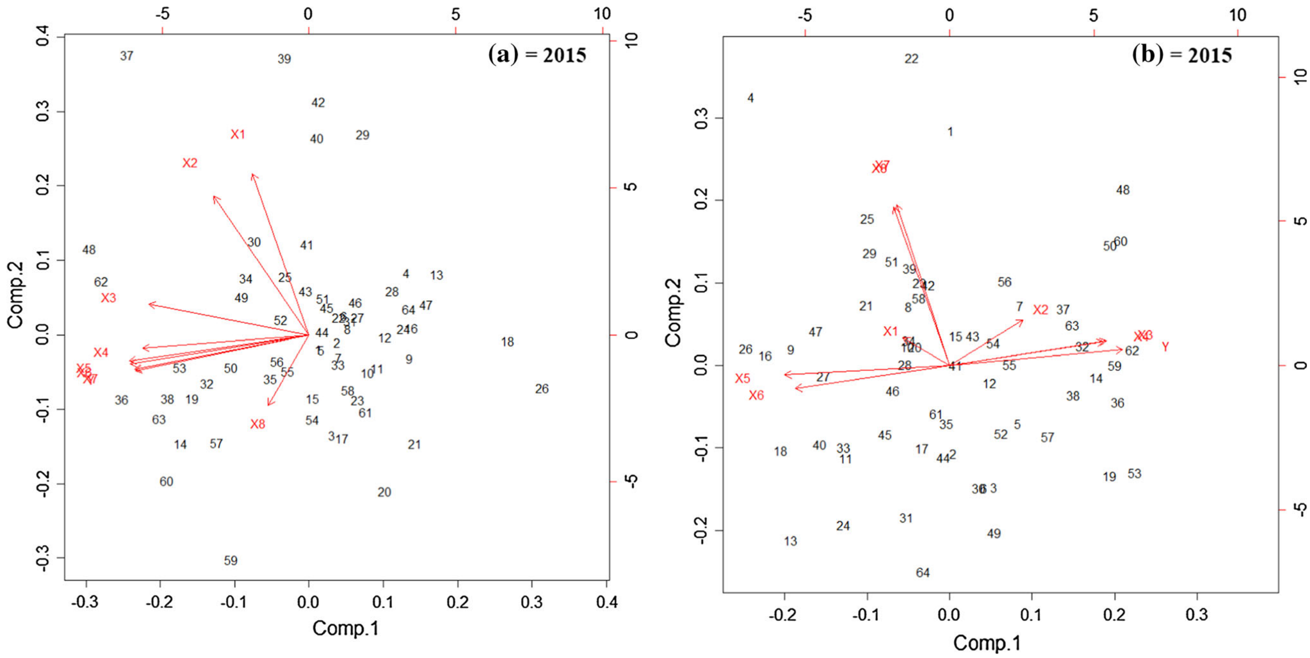

Fig. 6 Principle component analysis of NDVI (**a**) and LST (**b**) of 64 farms during 2015

coefficient for model. The final developed with coefficients are given below

$$\begin{aligned} Yield = & -5020.26 + 200.80 \times LST_1 + 25.65 \times LST_2 \\ & - 518.04 \times NDVI_1 + 12561.22 \times NDVI_2 \\ & - 1154.30 \times NDVI_3 \end{aligned}$$

LST_1 = Land surface temperature (10–13 days after recommended sowing date); LST_2 = Land surface temperature (28–30 days after recommended sowing date); $NDVI_1$ = Values of NDVI before peak season (60–62 days after sowing); $NDVI_2$ = Values of NDVI at peak crop growth season (76–78 days after sowing); $NDVI_3$ = Values of NDVI after peak crop growth season (90–92 days after sowing)

Results of this model are presented in Figs. 7 and 8. There was a close relation between observed and predicted yield with R^2 of 0.94 (Fig. 8). However, few of the farms have large variation in from the observed yield which higher RMSE of 397.4 kg ha^{-1}. The 95% prediction and confidence interval showed that there is variation in observe and simulated values. The variation in yield of few farms might be due to high temperature at later productive stage of maize causes the reduction in yield. In our case we have taken the LST at vegetative growth stages and NDVI at peak season. High temperature at reproductive stage reduces the time for grain filling duration that lead to decrease the yield. Panda et al. (2010) reported that NDVI has been widely used for vegetation health monitoring, NDVI value is high over high biomass due to saturation of signal, but its relationship with yield may not good.

Comparison of Crop Model and Remote Sensing

The inter-comparison of crop model and remote sensing are mainly based on the forecasting error like RMSE. This error was calculated from the predicted yield of 64 farm with their observed yield. RMSE results showed that model results are more precise then the remote sensing. While overall strength of relationship between predicted and observed was good. The indicator like NDVI performed well during early season of crop but remote sensing indicator some time did not if there is any stress in later stage of crop. Based on the performance the remote sensing indicator perform batter in some situation as shown in Fig. 7. If long term time series observation are available for regional yield estimation then remote sensing has greater advantages (Genovese et al. 2006) then model. Crop model predict the yield by interacting soil, water, plant and environmental conditions and it gave us simulation on daily basis. But for crop model we need lot of data set of soil parameters, weather conditions, crop management data, which is labor intensive. So, in regional yield forecasting we can get good results with remote sensing, without collection of intensive survey, but if we want to assess the specific stress like temperature, water, nutrient at specific stage then crop model are useful tools.

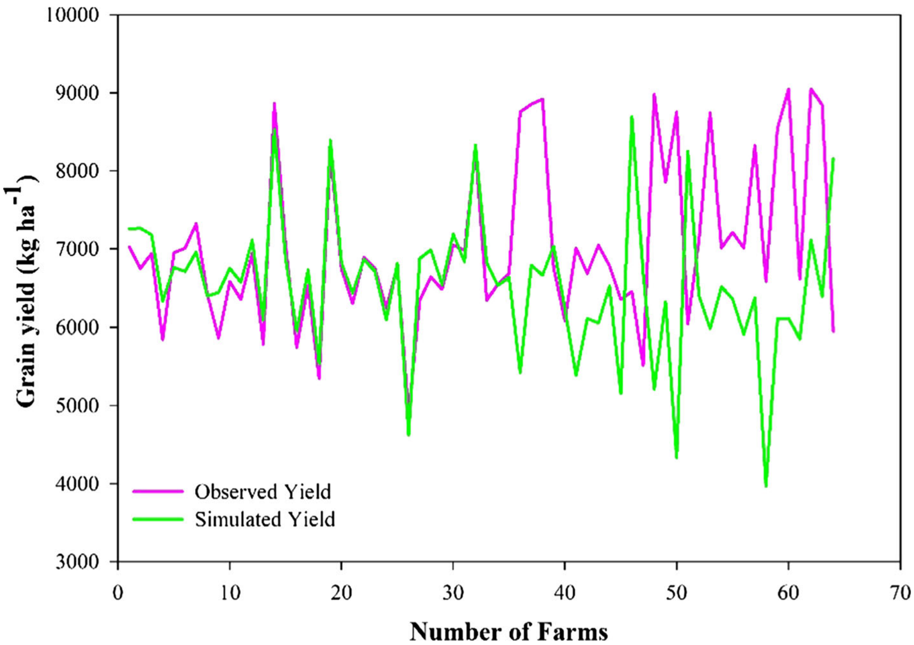

Fig. 7 Comparison of observed and simulated yield of 64 farms

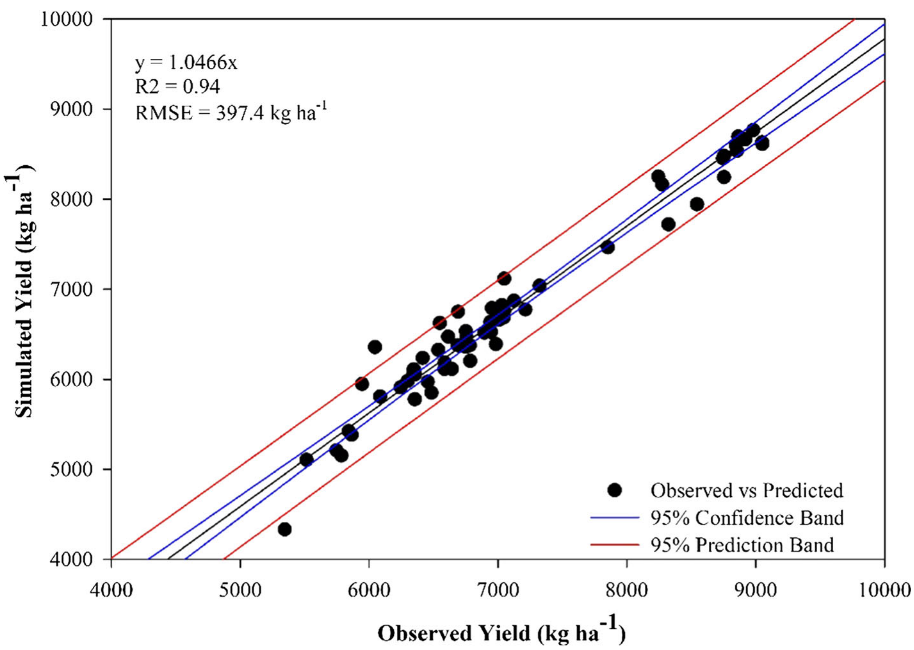

Fig. 8 Relationship of observed and simulated yield of 64 farms

Conclusion

Accurate and timely yield forecasting is becoming more important in decision making. In this study remote sensing and crop model were used for yield forecasting of maize. CERES-Maize model was calibrated and evaluated using field experimental data, which showed the mean absolute percent error ranged from 0.35 to 6.71 for recorded parameters. While in Remote sensing, machine learning algorithm were used for image classification that showed the accuracy greater than 97%. The best classifier was used for land cover classification of maize that showed the accuracy of 92%, as compared with the area estimated by crop reporting service (CRS) Punjab-Pakistan. Yield forecasting results of crop model were precise with RMSE of 255 kg ha^{-1} then the remote sensing, having RMSE of 397 kg ha^{-1}. But overall strength of relationship between predicted and actual grain yield was good with R^2 of 0.94 in both techniques. So, it can be concluded for yield forecasting remote sensing could be used due to greater advantages of less input dataset and if focus is to assess specific stress and interaction of plant genetics to soil and environmental conditions than crop model is very useful tool.

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