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SEASONAL CROP YIELD FORECASTING-METHODS, ACCURACIES AND LIMITATIONS: A REVIEW

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ABSTRACT
Accurate crop yield forecasting helps the government to formulate sound policies related to import and exports, allocation of food grains and price setting. Similarly, the traders and industries can make decisions regarding business activities like wages, purchase of raw materials and working hours. Crop management practices can be standardized to get maximum yield to reduce the pre and post harvest losses of produce. The impact of climate change on the crops can also be known. This forecasting can be done using different techniques like statistical models and crop simulation models. The information of weather, plant characters, environment, remote sensors *etc.* can be used as input data for forecasting. It can be concluded that forecasting the crop yield near the harvest is more accurate, with $r2 = 0.7\text{-}0.8$ being predominant than at the early stages ($r2 = 0.5\text{-}0.6$). Further improvement in the accuracy in forecasting is possible with the use of artificial intelligence and machine learning.

INTRODUCTION

Agriculture is the backbone of the Indian economy. It is gifted with varied soil and climatic resources, which enables the production of different crops. India is one of the major producing countries of various crops. Therefore, forecasting the yield has many benefits. Predicting the yield of the crop within the season prior before its harvest is known as yield forecasting. The top 10 countries where yield forecast is implemented are the United States, India, Canada, China, Spain, Germany, Australia, United Kingdom, Italy and France (Fig. 1). Thompson (1969) was the first to forecast the yield of corn by regressing the average regional yields with the weather to generate a general trend in the former Soviet Union. The biotic and abiotic factors like pests and genetics of the crop, soils and climate (temperature, relative humidity, wind, rainfall and solar radiation) affect the yield of the crops (Hanumanthappa *et al.*, 2016a). These factors are taken as input parameters in yield forecasting models. Weather data is recorded according to the standard meteorological weeks (SMW) *i.e.* first week of crop season to last week of crop season. All the weather data used in the models are weekly average. In contrast, the rainfall is taken as a weekly summation.

India stands second in the forecasting of yield. Forecasting provides ample time for policymakers to formulate suitable policies. By comparing the forecasted supply with the demand, import and export related decisions can be made. With the help of a demand-supply schedule, prices of the grains can be fixed. Allocation of food grains to the public distribution system, disaster relief, and storage can be planned better. Traders can decide the purchase of crop yield; fix the laborers' working hours, and their wages and the sales. The impact of climate change and different crop management practices can be assessed by changing the weather parameters, date of sowing, fertilizers, spacing, irrigation and so on (Hanumanthappa *et al.*, 2016a). Suitability of varieties to different locations can be tested, thereby reducing the time and resources involved in multi location trails. Overall, the food security of the nation and the price fluctuation can be managed.

Many scientists have used different methods of forecasting in various crops to date. The review is done to summarize some of those and know the possible future works.

MATERIALS AND METHODS

Methods of crop yield forecasting

Basso and Liu (2018) classified the forecasting methods region wise (Fig. 2). It can be seen that globally, remote sensing data is used in more than 50 percent of the papers. Agrometeorological data follow this. A similar trend is observed

Table 1: Methods of yield forecasting.

Method of forecasting	Selected references
1.Statistical models using	
a)Meteorological inputs.	Murata (1975); Sreenivasan and Banerjee (1978).
b)Sensor based inputs.	Erdle *et al.* (2011); Bannari *et al.* (1995).
2.Crop simulation models	Asseng *et al.* (2014); Basso *et al.* (2016).

in Asia, Africa and Americas. In Oceania, there is the use of agro-meteorological data in many of the papers, followed by remote sensing. In Europe, both the data are used equally.

Use of Sensors in crop yield forecasting

Each crop has a specific heat signature and this signature is detected by using sensors. Satellites like SPOT Vegetation, AVHRR, LANDSAT, MODIS, Radar satellite, and handheld sensors like Green seekers, N-tester, Spadometer, Crop Circle and Field Spec can be used to detect these signatures. Since forecasting is done before the harvest of the crop, the weather data that we deal with are of two types- known data recorded till the day of forecasting and the unknown data, between the forecasting day and the harvest. Different scientists have used various methods, mainly- Historical data, mean of historical data, weather generator models, climate forecast models and satellite derived climate variables.

Yield forecasting using statistical models-

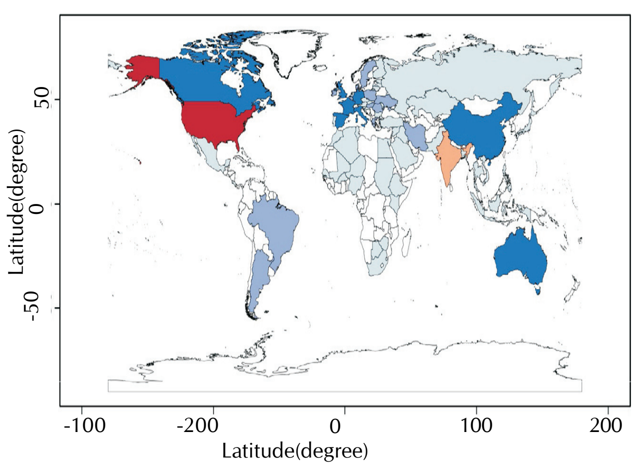


Figure 1: Country wise crop yield forecasting

Citation-Baso and Liu(2018)

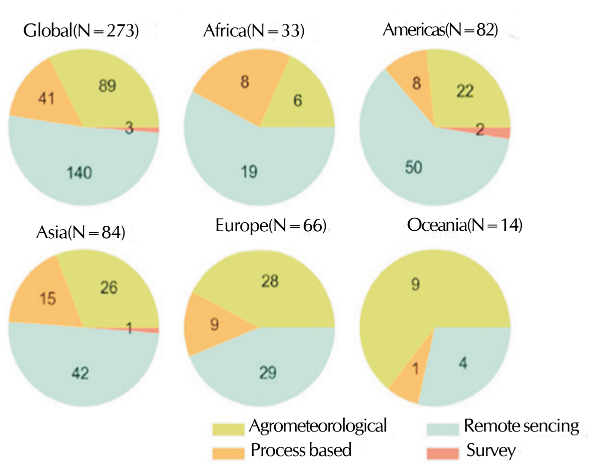
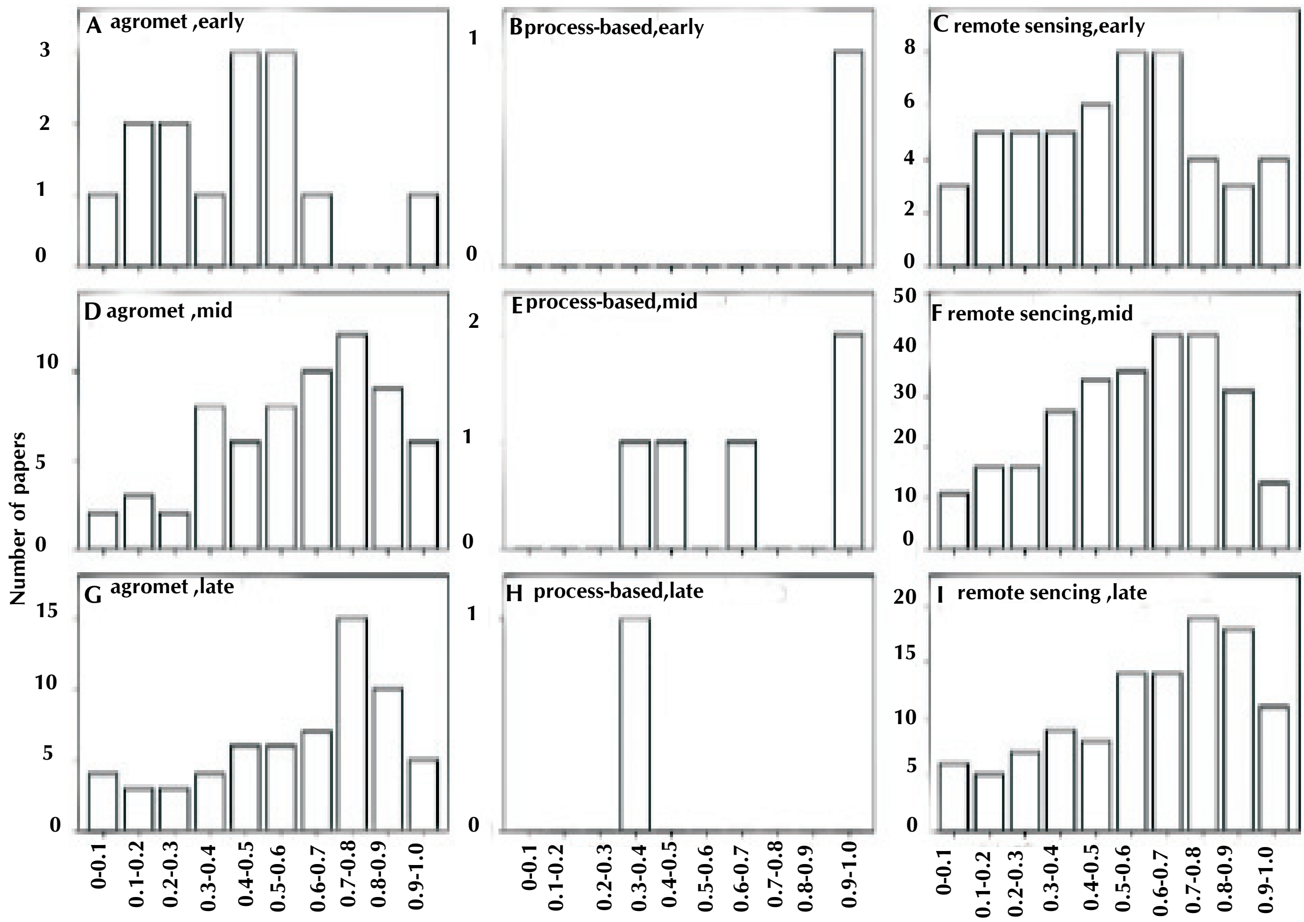


Figure 2: Region wise distribution of various crop yield forecasting methods.

These are mathematical equations (empirical models), by using independent variables like temperature, plant morphology, remote sensor data etc forecasting of the dependent variable (crop yield) is done. Ranjan *et al*. (2012) developed regression equations for yield prediction of Wheat using remote sensing and meteorological data. Dharmaraja *et al*. (2019) forecasted the yield of Bajra by linear regression and time series models. Gupta *et al*. (2018) developed different statistical models using weather variables for different U.P. districts to forecast mustard yield. Sawa and Ibrahim (2011) studied the impact of different dry spell parameters on the yield of millet and sorghum in Nigeria and they correlated 21 dry spell parameters with the yield. Poonam *et al*. (2017) developed three models using weather parameters (artificial variables generated from weekly weather values) as input data to forecast the yield of wheat in Hisar, Harayana. Annu *et al*. (2018) forecasted rice yield by discriminant function analysis of yield and related it to its biometrical characters in U.P., India. Kour *et al*. (2018) forecasted rice yield in Gujarat using the time series model. Rice yield data and historical weather data were used as inputs for the model. Dry matter production, Agro-meterological Indices of Rice as influenced by methods of establishment and transplanting dates (Chandrashekar *et al*. 2010). Patil *et al*. (2012) developed three different statistical models to predict the yield of wheat using remote sensing and vegetative parameter in Dharwad. Yadav *et al*. (2018) made a pre harvest forecast of pigeonpea by regression analysis of weather variables in U.P. Mahapatra and Dash (2019) forecasted the production of green gram in Odisha by time series model using the best fit ARIMA (2,1,0) model. Sarvesh *et al*. (2019) forecasted rapeseed and mustard yield for different years in the Sultanpur district of U.P. using a discriminate functional analysis of weather data. Girma *et al*. (2006) used the NDVI, leaf color, and chlorophyll content measured by the SPAD meter in the multiple linear regression to forecast wheat yield under nutrient application treatments at the Feekes 7 stage (second node appearance). Gero *et al*. (2017) used the proximally sensed reflectance data of 34 cultivars to develop vegetation indices and to calibrate PLSR models. They concluded that PLSR and REIP gave superior predictions of grain yield of spring barley. Raja *et al*. (2014) used the time series rainfall data of 25 years to derive the 1- and 3-month Standardized Precipitation Index of different wet season months and related the meteorological drought and its impact on rice productivity in Odisha. Patel *et al*. (2006) used the remotely sensed estimates of the fraction of absorbed photosynthetically active radiation (fAPAR) and daily temperature as input to a simple model based on light-use efficiency to estimate wheat yields at the pixel level in Harayana. Ayyoob and Krishnadas (2013) developed the linear correlation coefficient and multiple linear regression models among yield with various weather factors of 13 years observed during the stage of 50 per cent flowering of groundnut crop. Sarika *et al*. (2011) used time series model to forecast the pigeonpea yield by using the production data of 38 years. Verma *et al*. (2015) recommend using of linear mixed models for pre-harvest yield forecasting of the mustard crop in Haryana. Pritam and Deepak (2018) correlated the transplanting data and biomass derived from remote sensing data for its yield prediction in Shivamogga. Gupta *et al*. (2009) made a forecast and compared the forecasting methods using parametric models like polynomial, logarithmic, inverse, and exponential, with those of Box-Jenkins techniques like ARMA,



Citation-Basso and Liu (2018)

Figure. 3: Accuracy or r-squared values of crop yield forecasting

ARIMA using 41 years data in West Bengal. . Sellam and Poovammal (2016) used Regression Analysis to predict rice crop yield in Tamil Nadu. Barmeier *et al*. (2017) and Christenson *et al*. (2016) forecasted barley yield at anthesis and soybean at yield early-to-mid reproductive stages using a PLS model with hyper-spectra reflectance. Sandeep *et al*. (2018) compared different efficiencies of different models in predicting the yields of sugarcane using LANDSAT data. Prity *et al*. (2016) forecasted the yields of pigeonpea using different linear and non-linear statistical models. Amrender and Lalmohan (2005) developed multiple linear regression models to forecast the yield of Indian mustard using weather parameters. Sandeep *et al*. (2015) forecasted rice yield and jute over Bihar using weather parameters and technological trends. Dubey *et al*. (2018) developed empirical models between VCI and historical yield of sugarcane over 52 major sugarcane-growing districts in five states of India by stepwise regression technique to forecast its yield. Mkhabela *et al*. (2011) reported that MODIS-NDVI could be used effectively to predict crop yields across the Canadian Prairies one to two months before harvest. Farai *et al*. (2014) predicted the maize yield throughout Zimbabwe by regressing the number of dry dekads derived from VCI against official ground-based maize yield estimates to generate simple linear regression models. Bu *et al*. (2017) developed linear regressions and compared the satellite imagery and ground-based active optical sensors to predict the yields in Sugar Beet, Spring Wheat, Corn, and Sunflower. Toshichika *et al*. (2018) used statistical models to seasonal temperature and precipitation hindcast data, which were derived from a multi model ensemble (MME) in crops like maize, rice, wheat and sorghum. The analysis was performed for five individual atmosphere-ocean coupled general circulation model (GCM) and two MME datasets generated from average methods and the mosaic method. Sharma *et al*. (2018) forecasted Soybean and wheat crop yield based on the statistical model in Malwa agroclimatic zone using weather variables and historical crop yield. Anup *et al*. (2006) predicted the corn and soybean crop yield for Iowa using remote sensing and surface parameters by piecewise linear regression method with breakpoint and a non-linear Quasi-Newton multi-variate optimization method. Ajit Sharma *et al*. (2016) used different time series modeling techniques like a straight line, second degree parabola, exponential, modified exponential, Gompertz and logistic using the secondary data from 1980-2010 to forecast the production of apple in H.P, India. Vijaya *et al*. (2005) predicted the yield of castor and found that the canopy air-temperature differentials using infrared thermometer and yield were inversely related. Kogan *et al*. (2013) forecasted the wheat yield in Ukraine by using NDVI values from the MODIS, at 250 m spatial resolution.

Prity Kumara *et al*. (2014) developed different Autoregressive Integrated Moving Average (ARIMA) models by using time series data of sixty two years (1950-2012) to forecast the rice yield in India and concluded that ARIMA (1, 1, 1) is the best fitted model.

Crop simulation models (CSM)-

These are computer software packages that are readily available to plot the data and fit the model. They are alternative and less time consuming means of determining the optimum crop yield. The Decision Support System for Agrotechnology Transfer (DSSAT) is a software application program comprising crop simulation models for over 42 crops (Version 4.7) and tools to facilitate effective use of the models. It was developed by the International Benchmark Sites Network for Agro-technological Transfer (IBSNAT) in the 1980s, with the first official release in 1989. The development has continued in affiliation with the International Consortium for Agricultural Systems Applications (ICASA). DSSAT is like a shell storing different CSM. The main advantage of using CSM is that it mimics daily plant growth. Mojarad *et al*. (2018) in Iran forecasted the yield of safflower under different saline irrigation strategies using the Aqua Crop model, version 4.0. Pal *et al*. (2013) forecasted the wheat yield in Palampur, H.P. using the CERES Wheat model for which stochastic weather generator was used to get the unknown weather data. Nain et al. (2004) forecasted the yield of wheat using the CERES wheat model and two different technology trends in central IGP of India. Sarvesh *et al*. (2019) forecasted the yield of several chickpea cultivars under different sowing dates using DSSAT software version 4.6. Walikar *et al*. (2018) studied the impact of climate change by forecasting the yield of soybean variety JS20-29 at different locations of Madhya Pradesh, India, using the CROPGRO model. Vimal *et al*. (2019) forecasted the yield of different chickpea varieties for finding out the suitable date of sowing using the DSSAT model in U.P. Kamal *et al*. (2018) used DSSAT-CERES-Rice model to forecast the yield under different nitrogen levels in Meghalaya. Debjyoti and Lalu (2018) forecast rice yield under different nitrogen and irrigation management levels in West Bengal using ORYZA2000. Mumtaz *et al*. (2018) predicted the cotton yield with a new hybrid copula driven approach that combined the Markov Chain Monte Carlo-based simulation model with genetic programming algorithm. Machakaire *et al*. (2016) forecasted the yield and tuber size of potato eight weeks before the final harvest by LINTUL-Potato-DSS model which used the linear relationship between radiation intercepted by the crop and radiation-use efficiency, long-term and actual weather and crop data. Julien *et al*. (2014) forecasted the yield of sugarcane by an empirical relationship method, the Kumar-Monteith efficiency model, and a forced-coupling method of a sugarcane crop model (MOSICAS) and the satellite-derived fraction of absorbed photosynthetically active radiation. Abdul Haris *et al*. (2020) used the Info Crop model to forecast the crop yield and duration of the potato crop in Bihar due to climate change. Gang Li *et al*. (2011) used Hyper spectral remote sensing combined with important biophysical parameters like CCD and LAI successfully in castor growth assessment and yield prediction on China's coastal saline land using OSAVI model. Rojalin *et al*. (2013) forecasted the wheat yield in Punjab state of India by incorporating biophysical parameters like LAI and management parameters like planting date, derived from satellite data in crop simulation model WOFOST. (Hanumanthappa *et al*., 2010) recorded the pattern of annual and seasonal rainfall variability in coastal district of Karnataka. Rohit *et al*. (2020) used Agriculture Production Systems Simulator (APSIM) model to know the impact of climate change (change in temperature and rainfall patterns) on the productivity of maize in the state Madhya Pradesh by using 74 soil profiles from thirty districts. Jia *et al*. (2011) observed that the WOFOST model could simulate wheat yield with a difference of less than five percent while validating the WOFOST model in North China. Ghosh *et al*. (2014) developed a rice yield prediction system for Bhubaneswar, India, by combining the extended range forecast and CERES-rice model. Kulapramote *et al*. (2018) used the Aqua Crop model and moderate-resolution satellite images to simulate the rice yield for small-scale farmers. Gowtham *et al*. (2020) studied the impact of global warming (temperature increase of 1.5ºC) on the productivity of C3 and C4 crops like rice and maize in the year 2035 and 2053 in Tamil Nadu using DSSAT. Dua *et al*. (2020) studied the impact of climate change on the productivity of three potato varieties in Madhya Pradesh using the WOFOST crop growth simulation model in 38 locations.

Accuracies

The accuracy of the methods was represented as the r-squared values between the forecasted yield and the observed grain yields. Basso and Liu (2018) grouped the reported r-squared value based on the forecasting methods (statistical, process based and remote sensing) and forecasting time (early, mid and late crop stage) (Fig. 3). It is observed that when the forecasting time progressed, the accuracy also increased (fig. 3 A, D, G and fig. 3 C, F, I). Forecasting at early stages in all the techniques has a predominant r2 value of 0.5-0.6. Similarly, forecasting during later stages has a predominant r2 value of 0.7-0.8 (fig. 3 A, C and fig. 3 G, I). The process based models (CSM) are evaluated using different methods like frequency distribution, probability distribution and measure of central tendency rather than r2 value. The forecasting of the yield at later stages, *i.e.*, one month before harvest, gives a satisfactory forecasting result.

Limitations of models in crop yield forecasting

Most of the model needs to be calibrated to represent the genetics of the crops and such information is often not available. Lack of/improper crop model calibration causes inaccurate yield forecasts (Kolotii *et al*., 2015). Long-term good quality datasets of yield, agro meteorological conditions, crop genetics and sensor data are required to develop efficient yield-forecasting models which are difficult in some countries. Getting good quality remotely-sensed data and the post data-acquisition process is a significant challenge. Yield-forecasting statistical models are specific to crops, users and regions and cannot be worked outside the range of parameterized conditions. Unforeseen events that occur between the forecasting day and the harvest day reduce the precision of the forecasting.

RESULTS AND DISCUSSION

Depending on scientist, the models are calibrated and validated using recent 10 to 25 years field and experimental data.Statistical models to forecast yield is relatively simple as it establishes a relation between the yield and input variables like temperature, rainfall, historical data, *etc.* It is simple to use and less parameter-intensive. Incorporating the remotely sensed information to the statistical models can improve the forecasting accuracy, particularly for large-scale yield forecasts (Manjunath *et al.*, 2002). The number of parameters used in the process-based simulation models is larger. It results in the interaction effects between weather, soil, crop, and management on the grain and biomass yield. There must be proper long-term good quality datasets of yield, agrometeorological conditions, remotely sensed data, and genetics of the crop to get higher accuracy. The skill in operating software, generating remote sensing data, processing, interpretation and storage must be developed in the individuals. There is a possibility of using AI and machine learning in forecasting the crop yield to reduce human errors and get higher accuracy.

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