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Research Article

District-wise Statistical Yield Modelling of Wheat using Weather and Remote Sensing Inputs

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ABSTRACT

Accurate yield estimation has always been a matter of challenge to the scientific community especially so in the recent times due to the heightened risk of climatic variability. This study explored the statistical technique of fixed effect panel regression for estimation of the district-wise wheat yield using weather as well as satellite remote sensing indices. As wheat crop is sensitive to heat, extreme temperature during the reproductive stage was used for modelling. Along with that trend adjusted vegetation condition index (VCI_{Tadj}), temperature condition index (TCI) and vegetation health index (VHI) during the thermo-sensitive reproductive phase (TSP) was also used for modelling of wheat yield. The results show that, models developed with extreme temperature and remote sensing indices could capture the broad variation in district-wise wheat yield. The error was higher for extreme temperature based model as compared to the remote sensing based models. Among the remote sensing based models, VHI based one outperformed both the TCI and VCI_{Tadj} based models which may be due to the reason that VHI combines both the information about greenness as well as temperature stress in it. The error in estimated yield varied based on the model but it was below 10% for all the districts for VHI based model. Further, it was seen that the accuracy was good for first year of prediction but it decreases for the second year. It indicates that the model should be used in a rolling mode, updating the parameters in each year before using it for next year.

Key words: Wheat yield modelling, Extreme temperature, Trend adjusted vegetation condition index, Vegetation heath index

Introduction

The accurate estimation of yield is essential for many purposes starting from planning at the country or regional scale to loss estimation at very local scales. Though Indian agriculture is very prone to the factors ranging from weak rural infrastructure, uncertainties in yields and prices but recently climate variability and change has aggravated the risk. It is reported that, globally, almost one third of the observed yield variability is governed by climate variability which even goes up to 60% for major breadbaskets of the world (Ray *et al.*, 2015). Climate change effects have become widespread and even getting strongly felt due to the impacts of the extremes resulted from climatic variability (Klein Tank *et al.*, 2006). Temperature is undoubtedly the most important weather variable but its extremes have much larger ramifications due to its widespread

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impact on different sectors starting from environment, agriculture, livestock and above all, the lives of human being (Azhar *et al*., 2014). Extreme temperatures often influence the physiological mechanisms of plants through influencing their transpiration rate, stomata opening and closing mechanisms, photosynthesis, respiration rate (Ayeneh *et al*., 2002) and if coincided with the reproductive phase, may lead to severe damage of reproductive organs like pollen grains (Saini and Aspinall, 1982) hampering grain setting and its filling (Wardlaw and Moncur, 1995), leading to early senescence (Lobell *et al*., 2012; Duncan *et al*., 2015), ultimately incurring economic losses to farmers. Klein Tank *et al*. (2006) has shown that the warm days are increasing at a very sharper rate over the central and southern Asia, including India.

Though all crops are affected by the climatic variability but there remains a large variation in their specific sensitivity. Ray *et al*. (2015) found that yield variability of 79% of wheat harvesting region was explained by climate variability while it was 70%, 67% and 53% for maize, soybean and rice respectively indicating wheat is more vulnerable crop compared to others. Wheat, the most important support to the food security over the globe, which is harvested in more than 220 M ha of land and with over 700 Mt of production (FAO), also remains at the centre of the discussion due to its sensitivity to the heat (Duncan *et al*., 2015; Lobell *et al*., 2012). Wheat is a cool temperature loving crop and it is sensitive to heat especially during its reproductive growth stage (Tashiro and Wardlaw 1989). It has become quite common world over where the crop is grown being affected by extreme high temperature events incurring penalty in the form of yield loss (Asseng *et al*., 2015; Liu *et al*., 2016; Lobell *et al*., 2012).

Considering the importance of climatic variables on crop yield, it becomes imperative to understand the quantitative relationship between the two. These relationships are usually explored in two ways, statistical models based on regression (Lobell and Burke, 2009; Lobell *et al*., 2012; Duncan *et al*., 2015) and using process based crop simulation models (Asseng *et al*., 2015). The statistical models are developed using the statistical relationship between historical data of crop production and weather parameters. There are three common types of techniques for statistical modelling in the literature: solely based on time series data of a single point or area (time series methods), based on time and space variations (panel methods), and based only on variations in space (cross-section methods). Time-series models are having advantages for capturing the behaviour of a specific area. In case of panel and cross-section methods common parameter values are assumed for all locations. But particularly the cross-section methods are prone to errors from omitted variables such as soil parameters, fertilizer inputs etc. which have large spatial variability. On the other hand, time-series models are often data limited whereas panel and cross-section methods can aggregate data from multiple sites (Lobell and Burke, 2009). There are several advantages of the statistical models like limited dependence on data for field calibration, and assessment of model uncertainties in a transparent manner (Lobell and Burke, 2009). As for example, if a model is unable to properly represent crop yield responses to climate, it will be reflected by the low value of coefficient of determination (R^2) between the modelled and observed variables, as well as the confidence interval around model coefficients and predictions will be large. Although process-based models could in theory be accompanied with similar statistics, in practice they rarely are.

On the other hand, now a days, satellite image is increasingly being used for different applications in the agricultural sector. The change in green biomass of the crops within the duration of crop growth cycle has been successfully investigated using Normalized Difference Vegetation Index (NDVI). The satellite-based vegetation health (VH) indices, which include the vegetation condition index (VCI), the temperature condition index (TCI) and the vegetation health index (VHI) (Kogan, 1990; Unganai and Kogan, 1998; Kogan *et al*., 2016), have been developed which not only overcome the limitations of NDVI for large area spatial applications but also segregates the effect of weather and ecosystem in it. The VCI concept was designed to extract the weather component from NDVI values (Kogan, 1990). Hence, this study was structured with two main objectives firstly, to model the district-wise wheat yield based on extreme temperature and secondly, models were developed using different satellite remote sensing based vegetation health indices. Further the developed models were compared using different statistical techniques.

Material and Methods

Datasets

The high resolution daily gridded temperature data developed by India Meteorological Department (IMD) was used for the analysis. Maximum (day) and minimum (night) temperature from 395 quality controlled station was used by IMD for developing the data set (Srivastava *et al*., 2009). Interpolation of the station temperature data into 1° latitude × 1° longitude grids was carried out using a modified version of the Shepard's angular distance weighting algorithm. The developers of the dataset have compared it with high resolution datasets before successfully applying it for deriving temperature related parameters such as cold and heat waves, temperature anomalies over India (Srivastava *et al*., 2009; Ratnam *et al*., 2016).

National Oceanic and Atmospheric Administration's (NOAA) Centre for Satellite Applications and Research (STAR) have developed Global and Regional Vegetation Health (VH) which is a NOAA/NESDIS system estimating vegetation health, moisture condition, thermal condition and their products. It contains Vegetation Health Indices (VHI) derived from the radiance observed by the Advanced Very High Resolution Radiometer (AVHRR) onboard afternoon polar-orbiting satellites: the NOAA-7, 9, 11, 14, 16, 18 and 19 and VIIRS from Soumi-NPP satellite. Jiang *et al*. (2008) have employed the adjusted cumulative distribution function (ACDF) method based algorithm to rectify the discontinuities and biases in the time series of global smoothed NDVI (SMN) due to sensor degradation, orbital drift [equator crossing time (ECT)], and differences from instrument to instrument in band response functions. The System contains the following vegetation health indices and products: No noise Normalized Difference Vegetation Index (SMN), No noise Brightness Temperature (SMT), Vegetation Condition index (VCI), Temperature Condition index (TCI), Vegetation Health index (VHI), Soil Saturation index (SSI), Fire risk index (FRI); products - Drought, Malaria, Vegetation health, Ecosystems, Land sensitivity to ENSO.

This study utilized the district level area, production and yield data of wheat crop from three major wheat growing districts of Rajasthan namely Ganganagar, Hanuamagarh and Alwar. The datasets available at the website of Directorate of Economics and Statistics, Department of Agriculture, Cooperation and Farmers Welfare, Ministry of Agriculture and Farmers Welfare, Government of India is used. In case of Ganganagar and Alwar districts, the yield time series was of 33 years (1982-83 to 2015-16) while for Hanumangarh district it was of 21 years duration (1995-96 to 2015-16).

Processing of the datasets

Extreme day temperature was calculated from the time series of daily maximum temperatures for each gird. Extreme temperatures were regarded as the values which fall above the 90th percentile for a particular day and location/grid as described by the Expert Team for Climate Change Detection and Indices (Klein Tank *et al*., 2009; Sen Roy, 2009; Seneviratne *et al*., 2014). Extreme warm days (ExWD) were considered as those days which are above the 90th percentile threshold value of the reference period, i.e. 1961-1992.

The open source software TIMESAT was used to estimate the vegetation phenology for the study area using time series of NDVI (Jonsson and Eklundh 2002; Jönsson and Eklundh 2003, 2004). The NDVI time series of both the products was fitted with Savitzky- Golay (SG) (Sehgal *et al*., 2011; Chakraborty *et al*., 2014) to each time series on a pixel to pixel basis with an adaptive upper envelope to account for negatively biased noise such as cloud. The details can be found in Chakraborty *et al*., (2018). From the processed NDVI profile we defined start of the season (SOS) in each year as the point when the fitted curve reaches 10% of its maximum amplitude for that year (Lobell *et al*., 2012); end of the seasons (EOS) is defined as the equivalent point on the declining portion of the function. Length of the season (LOS) was computed for each year as the number of days between SOS and EOS.

The period of maximum NDVI/EVI has been shown to correspond to heading date in cereal crops (Sakamoto *et al*., 2005). In terms of the satellite derived phenology matrices it corresponds to the mid of the season (MOS). Teixeira *et al*. (2013) found that a 30 day period around the reproductive crop development phase represented the thermo-sensitive period (TSP) and captured extreme heat impacts on crop yield. A 30 day period post MOS was taken to represent the TSP (Duncan *et al*., 2015). A cumulative sum or integration of vegetation index (VI) values ($IntNDVI_{TSP}$) and maximum VI values are used commonly as surrogate measures of vegetation productivity and crop yield (Rembold *et al*., 2013; Duncan *et al*., 2015). The time integrated NDVI was computed for the duration of TSP in each pixel using the phenology derived MOS. The dominating MOS among the pixels of a district was considered as the district-wise MOS.

Trend adjusted VCI (VCI_{Tadj}) which is calculated after detrending/normalizing the NDVI time series i.e. removing the technology component, has been found to be more effective (Dhakar *et al*., 2013). In this study we have used VCI_{Tadj}, Temperature condition index (TCI) which is described by Unganai and Kogan (1998) and Vegetation Health Index (VHI) (Kogan *et al*., 2016). VHI was calculated as:

$$VHI = a \times VCI_{Tadj} + (1 - a) \times TCI \qquad \ldots(1)$$

where “a” is a coefficient quantifying a share of VCI_{Tadj} and TCI contribution in the VHI. Since this share is generally not known for a specific location and time of the year, it is assumed that VCI and TCI contributions are equal (a=0.5). But in this study we had the district-wise value of VCI, TCI and the de-trended yield time series. Hence, we have varied the value of “a” parameter of the above equation from 0.1 to 0.9 to generate different VHI value. These values were then correlated with the de-trended district yields. Based on the maximum coefficient of determination between the relationship of de-trended district level yield and VHI, the value of “a” parameter was found to be 0.7 for the Ganganagar and Hanumangarh districts and 0.6 for Alwar district.

Statistical modelling of yield

The identification of proper effects of weather in time series datasets of yield also needs to account for the impacts of other factors especially if they are not correlated to the weather variables (Lobell *et al*., 2011). As in the time series data of yield generally there is presence of positive trend which needs to be normalized before understanding impact of any factor on yield; otherwise the relation may be biased due to the common trends. But many a times it is also better to include the time trend in the model itself (Lobell and Burke, 2009). Here, in the regression we have included district-specific quadratic time trends. Hence the model estimates for weather effects rely on year-to-year variations in weather and yields, and not common trends. In some cases, districts do exhibited highly nonlinear trends, with sudden jumps in the data, which means that a quadratic time trend would poorly fit the data. We have used a model similar to that of Lobell *et al*. (2011) as given below:

$$Y_{i,t} = c_i + b_{1t} * year + b_{2t} * year^2 + d_{1i} * year + d_{2i} * year + \beta.X_{i,t} + \varepsilon_{i,t} \qquad \ldots(2)$$

Where, C_i is a district fixed effect, b_{1t} is the linear time trend, b_{2t} is the quadratic time trend, d_{1i} is the district -specific linear time trend, d_{2i} is the district specific quadratic time trend, ® is a vector of coefficients and X is a vector of variables. The fixed effects model has the advantage of accounting for time-invariant country differences (e.g. irrigation facility, soil quality, specific management practices etc.), thereby removing biases due to the omitted variables. The district-specific time trends also capture differential rates of progress among them. In panel models, fixed effects (i.e. district-wise dummy variables) were used to control those variables which are not included in the regression models and which can explain the differences among the locations. This is a crucial advantage over the cross-sectional regression models (Lobell *et al.*, 2011).

Software used

All the analysis and mapping was carried out using open source R software and it's IDE R-Studio (R Core Team, 2017; R Studio Team, 2015). We have used the "Raster" package for handling all the raster datasets of temperature, rainfall as well as satellite remote sensing datasets (Hijmans, 2015). The "plm" package was used for panel regression.

Results and Discussion

The district wise yield was modelled using panel regression with fixed effects. The fixed effect was assigned at district scale. The model was developed using extreme warm days as well as different remote sensing derived vegetation indices (VCI_{Tadj}, TCI and VHI) as independent variables. It can be seen that all the four variables could capture the broad variation in district level wheat yield over time (Table 1 and Figures 1, 2, 3). Though the value of coefficient of determination is very high and almost similar for all the four variables, but the value of residual standard error show the difference among the models for different districts. The residual standard error value for the model of extreme temperature is 0.30 while it is 0.23, 0.25 and 0.19 for VCI_{Tadj}, TCI and VHI based models, respectively. Though the F-statistic is significant for all the models indicating that all the selected variables could capture the yield variation, but its value also show the strength of the model. The results of root mean square error (RMSE) and normalized RMSE are also shown in table 1. The RMSE of wheat yield for Ganganagar, Hanumangarh and Alwar districts are 0.30 (nRMSE: 0.10), 0.19 (nRMSE: 0.06) and 0.31 (nRMSE: 0.10), respectively for extreme temperature based model. For VCI_{Tadj} based model the RMSE are 0.24 (nRMSE: 0.08), 0.17 (nRMSE: 0.05) and 0.21 (nRMSE: 0.07) corresponding to Ganganagar, Hanumangarh and Alwar districts. For VHI based model the RMSE are 0.21 (nRMSE: 0.07), 0.12 (nRMSE: 0.04) and 0.18 (nRMSE: 0.07) for the three districts. Almost in all the cases the RMSE and nRMSE was higher for TCI based models. If we consider all the districts together, the RMSE for different models are 0.28 (nRMSE: 0.094), 0.21 (nRMSE: 0.07), 0.23 (nRMSE: 0.08) and 0.18 (nRMSE: 0.06) for

Table 1. Statistical parameters of the panel regression model for wheat yield using different variables for three districts of Rajasthan

Parameters		Extreme temperature	VCI	TCI	VHI
Residual standard error		0.30	0.23	0.25	0.19
Multiple R-squared		0.9914	0.9952	0.994	0.9966
Adjusted R-squared		0.9903	0.9946	0.9933	0.9962
F-statistic		892***	1591***	1285***	2278***
Overall RMSE	RMSE	0.28	0.21	0.23	0.18
	nRMSE	0.094	0.07	0.08	0.06
Ganganagar	RMSE	0.30	0.24	0.30	0.21
	nRMSE	0.10	0.08	0.10	0.07
Hanumangarh	RMSE	0.19	0.17	0.19	0.12
	nRMSE	0.06	0.05	0.06	0.04
Alwar	RMSE	0.31	0.21	0.19	0.18
	nRMSE	0.10	0.07	0.06	0.07

*** indicates significant at $p<0.01$

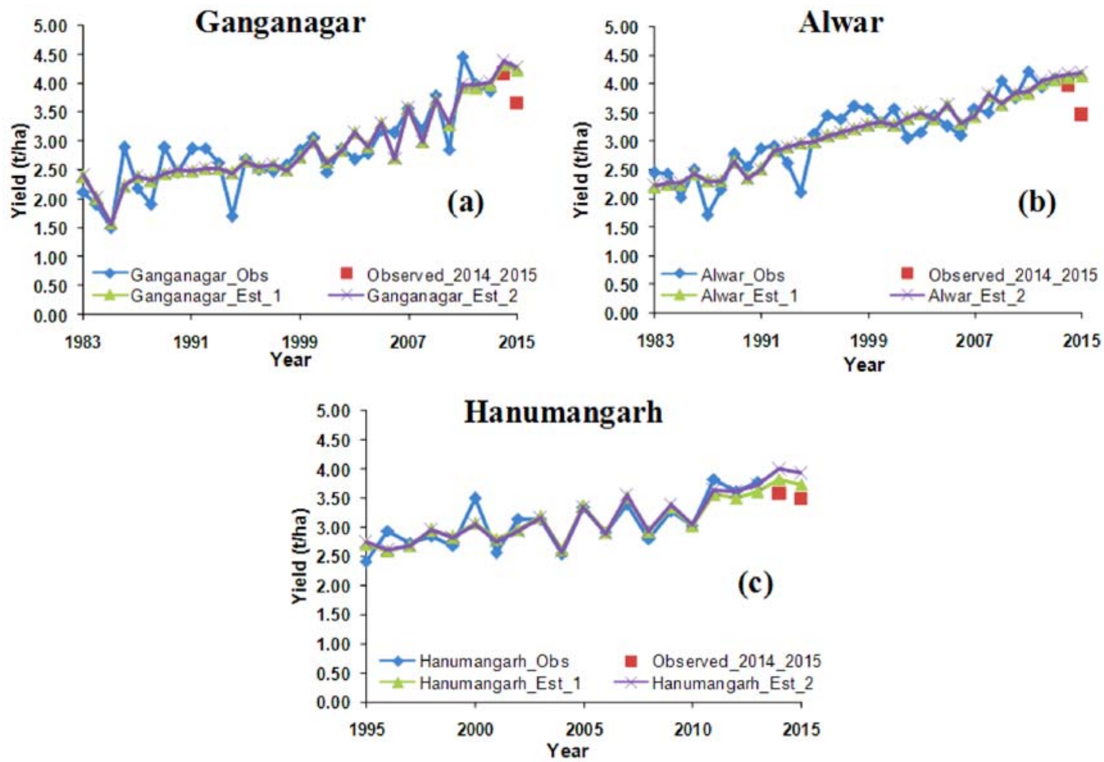

Fig. 1. Panel regression yield models for three districts of Rajasthan using extreme warm days as independent variable

extreme temperature, VCI_{Tadj}, TCI and VHI based model respectively. The residual standard error, RMSE and nRMSE values indicates that among the remote sensing derived vegetation indices based models, VCI_{Tadj} and VHI performed is better as compared to TCI. So, TCI was dropped from further analysis. The F-statistic supplemented the same results.

To test the performance of the models we estimated the yield using the models for two cases: a) yield was estimated for only the last year while rest of the time-series was used for model development, and b) yield was estimated for last two years while rest of the time-series was used for model development. The model fitting and estimation of yield using extreme warm days are presented in figure 1 and table 2. It can be seen from the figure that the model could capture broad variation of district-wise yield over time. But for Ganganagar and Alwar districts many a time the model was unable capture the observed changes in yield especially in the 1990s. Though for Hanumangarh district,

Table 2. Performance of the panel regression model for yield estimation for the last two years of the time series using the extreme warm days as independent variable

District	Year	Error (%)	
		Last one year	Last two years
Ganganagar	2014	–	4.8
	2015	15.6	16.9
Hanuamangarh	2014	–	11.7
	2015	7.5	12.6
Alwar	2014	–	5.1
	2015	19.1	20.8

the model captured the variability in a better way. The error (%) in yield estimation when only the last year was estimated were 15.6, 7.5 and 19.1 for Ganganagar, Hanumangarh and Alwar districts, respectively. When yield was estimated for last two years, for the first year of this two year, the error (%) were 4.8, 11.7 and 5.1 for Ganganagar, Hanumangarh and Alwar districts,

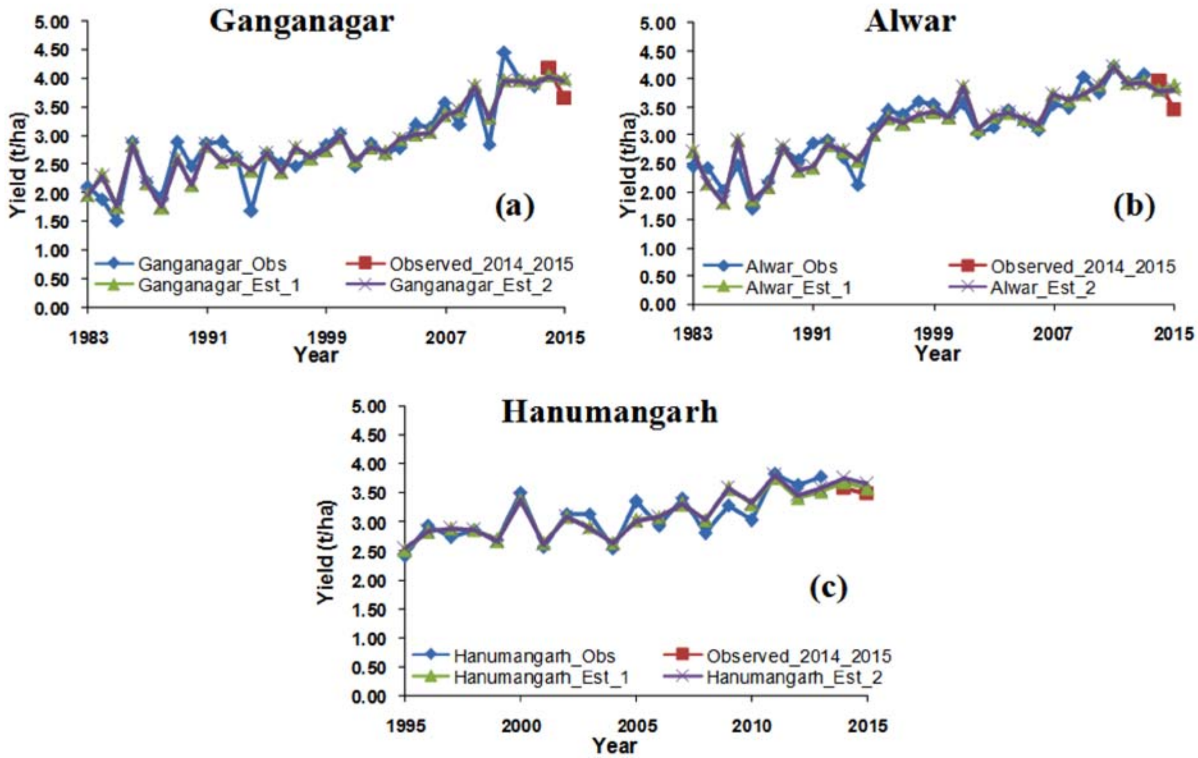

Fig. 2. Panel regression yield models for three districts of Rajasthan using VCI_{Tadj} as independent variable

respectively, which increased to 16.9, 12.6 and 20.8, respectively during the second year.

The models for estimation of yield using two remote sensing based indices i.e. VCI_{Tadj} and VHI are presented in figures 2 and 3 and tables 3 and 4, respectively. These models could also capture the broad variations in district yield over time. Both the models could capture the inter-year yield variability. These models even could clearly capture the large decrease in yield in years 1994 and 2010 for Ganganagar district, in 1987 and 1994 for Alwar and 2001 and 2004 for Hanumangarh district. It is clear from the figure 3 and table 4 that VHI could capture the variation in a much better way as compared to the VCI_{Tadj} for all the three selected districts. The error (%) in yield estimation using VCI_{Tadj} when only the last year was estimated were 9.3, 2.9 and 11.8 for Ganganagar, Hanumangarh and Alwar districts, respectively which were 7.4, 0.9, 6.4 for VHI index based model. For VCI_{Tadj} based model, when yield was estimated for last two years, for the first year of this two year, the error (%) were 4.1, 5.0 and 4.8 for Ganganagar, Hanumangarh and Alwar districts, respectively, which increased to 8.2, 5.2 and 10.4, respectively.

Table 3. Performance of the panel regression model for yield estimation for the last two years of the time series using VCI as independent variable

District	Year	Error (%)	
		Last one year	Last two years
Ganganagar	2014	–	4.1
	2015	9.3	8.2
Hanuamangarh	2014	–	5.0
	2015	2.9	5.2
Alwar	2014	–	4.8
	2015	11.8	10.4

The accurate estimation of yield loss is essential for many purposes. Here, statistical modelling approach was implemented to estimate the crop yield using panel regression for district scale. District-wise fixed effect panel regression model was used for estimation of wheat crop yield. Both the weather (extreme warm days) and

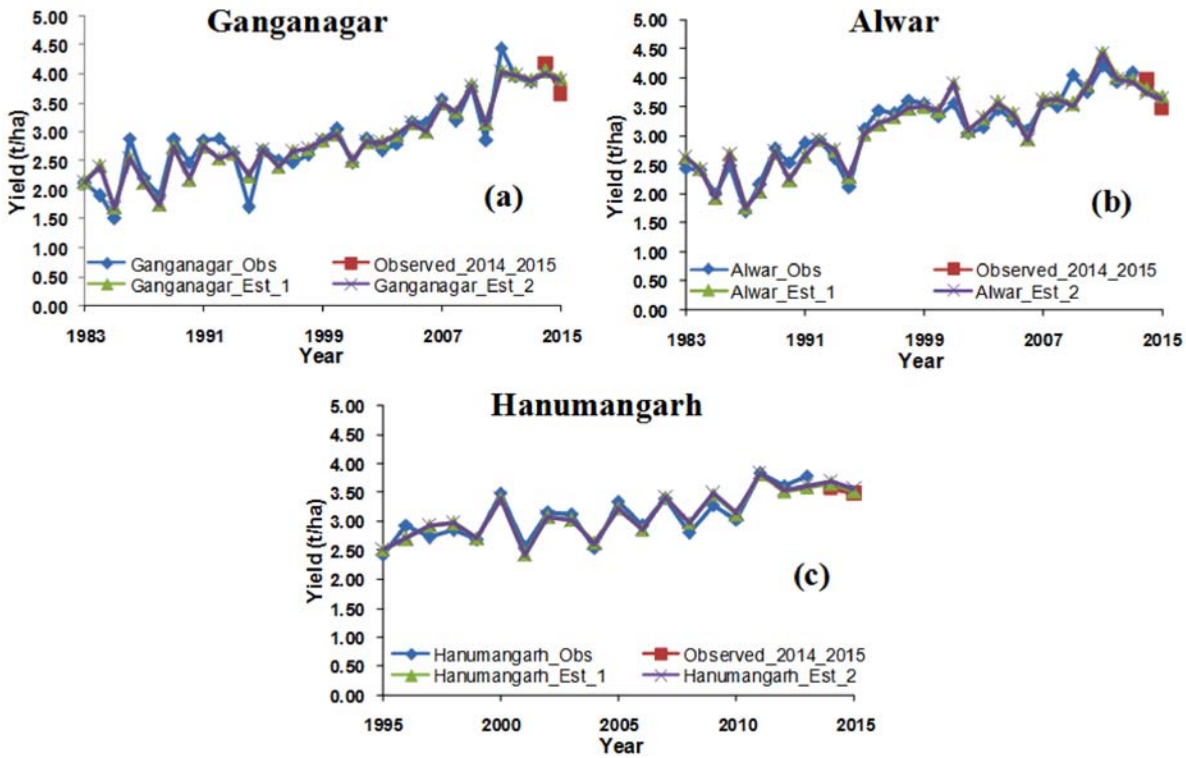

Fig. 3. Panel regression yield models for three districts of Rajasthan using VHI as independent variable

Table 4. Performance of the panel regression model for yield estimation for the last two years of the time series using VHI as independent variable

District	Year	Error (%)	
		Last one year	Last two years
Ganganagar	2014	–	4.3
	2015	7.4	6.0
Hanuamangarh	2014	–	3.4
	2015	0.9	2.3
Alwar	2014	–	5.8
	2015	6.4	4.3

remote sensing variables (VCI_{Tadj}, TCI and VHI) could capture the broad variation in crop yield from year to year. As the time series of yield is having trend, indicating increase in yield over time, the incorporation of linear as well as quadratic time trend factor in the model improved the performance of the model (Lobell *et al.*, 2011). Even though all the models using the weather as well as the remote sensing variables show high coefficient of determination for explaining the district-wise wheat yield time series, but based on F-statistic and residual standard error, remote sensing variables were found to be more effective as compared to the weather variable. Further the RMSE and normalized RMSE values for these models established closeness of their predicted yield with the reported yield. Though among the remote sensing derived indices, there were variations, the performance of VHI based model was much better as compared to the VCI_{Tadj} and TCI based models. It may be due to the fact that the VHI index is a combined index designed from VCI_{Tadj} and TCI thus encompassing both information about the crop growth (NDVI) and temperature, making it more holistic. Singh *et al*. (2004) used RVI and NDVI index individually as well as in combination to estimate the Rohtak district wheat yield for 1997-98 using linear regression model. They have reported significant improvement in the performance of the model when both the indices were used in the one model. Though both these indices are only related to the crop growth still there was substantial improvement in yield model. The indices used in this study (VCI_{Tadj} and TCI) were especially designed to capture the effect of weather component in the crop growth (Kogan, 1990). The error in estimated yield varied based on the model but it was below 10% for all the districts for VHI based model. Further, it was seen that the accuracy was good for first year of prediction but it decreases for the second year. It indicates that the model should be used in a rolling mode, updating the parameters in each year before using it for next year.

Conclusions

This study explains statistical yield models for wheat crop in three districts of Rajasthan using different weather and remote sensing variables. As wheat is a heat sensitive crop especially during the reproductive stage, the models were developed considering this period using the extreme warm days and remote sensing based indices (VCI_{Tadj}, TCI and VHI). The district-wise fixed effect panel regression based model developed using the extreme warm days as well as remote sensing indices could capture the broad variation in the district wise wheat yield. The error was higher for extreme warm days based model, followed by TCI, VCI_{Tadj} and it was minimum for VHI based model. As VHI combines the information from VCI_{Tadj} and TCI i.e. both the crop growth/ greenness (NDVI) as well as temperature, hence it could capture the condition in a better way. Overall for VHI based index the error in estimated yield was less than 10%. Further updating of the model parameters in each year was found to yield better results for prediction in the next year.

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