

Chapter 13

Application of Remote Sensing and GIS in Crop Yield Forecasting and Water Productivity



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Abstract Sugarcane is one of India's most important cash crops and one of the major crops of Uttarakhand state. Accurate crop yield forecasting is essential for making appropriate government policies. Statistical regression method using meteorological parameters is one of the most widely used crop yield forecasting methods. With the help of statistical regression, it is possible to forecast the sugarcane yield a few months before the harvest. But there is no direct cause–effect relationship between meteorological parameters and crop yield, so uses of other independent parameters can increase the crop yield accuracy. Evapotranspiration is one of the most crucial independent parameters, which can be easily estimated using remote sensing. The benefit of remote sensing over other fields and empirical methods for evapotranspiration is the easy availability of data over a large area as data availability becomes critical in other methods. Crop water efficiency can be easily found by crop water productivity. The developed Sugarcane yield actual evapotranspiration (AET) model using regression techniques for the F2 stage and both with and without AET model for F3 stage except 2019–20 in Haridwar district and the developed sugarcane yield model with and without AET using regression techniques for the F2 and F3 stage in Dehradun district showed a good relationship between predicted and observed values of yield which is below 5% deviation. From the study of crop water productivity, we can easily mark the areas with low water productivity and used different planning to increase the water efficiency to fulfill the need of people in reducing water availability.

13.1 Introduction

Sugarcane (*Saccharum officinarum* L.) is one of India's most important economic beneficial crops, which plays a vital role in the country's agriculture and industrial development (Natarajan et al. 2016). Global production of sugarcane in 2018

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was 1.90 billion tons over an area of 26.26 million hectares which are continuously increasing over the years (FAO 2018; Naseri et al. 2021). India produces 18.17% (341.20 million tons) of the world's total production, whereas basil holds the second position, i.e., 39.38% (739.27 million tons). The production of sugarcane in Uttarakhand is 71.42 lakh tons (Department of Agriculture and Farmers Welfare Report 2017–2018). Sugarcane has a large cropping season, so it undergoes all seasons, i.e., summer, rainy, and winter. The major weather components which control the crop yield are rainfall, temperature, and humidity (Bhatla et al. 2018). Ministry of agriculture in 2006 estimated the sugarcane yield as 283.4 million, which is further revised to 355.5 million tons due to which there is a ban on sugarcane exports at the time of high international sugarcane market rate for which farmers suffered a huge loss (Suresh and Krishna Priya 2009), so it is necessary to forecast accurate crop yield.

Crop yield is defined as the crop produced per unit area, basically taken in kg/Ha. The crop yield forecast is an important parameter to make the policy and to import and export the crop for food security (Verma et al. 2021). Crop yield forecasting needs historical yield data and weather parameters in which the relationship is made by different models (Jayakumar et al. 2016). Previous studies show that very less notable work is done on sugarcane in India as compared to any other cereal crops. For crop yield forecasting, the regression model is a simple yet effective technique to make the relationship between weather parameters and actual crop yield (Wisioł 1987).

The regression method is quite simple and powerful, which is mostly used in crop yield forecasting, but in most cases, the accuracy from these simple regression models is not satisfactory. So for better accuracy, we need to use the statistical regression model with other different independent parameters other than the basic meteorological parameters. Different remote sensing parameters can be used for advancements in crop yield forecasting. Many worldwide researchers have stated that various remote sensing-based products can be used for crop yield forecasting (Mulianga et al. 2013; Morel et al. 2014). For the Indian condition, Rao et al. 2002 used NDVI for sugarcane yield forecasting. Recent agricultural studies focused on MODIS data (Doraiswamy et al. 2004; Potgieter et al. 2011; Mkhabela et al. 2011; Kouadio et al. 2012; Vintrou et al. 2012; Johnson 2014; Mosleh and Hassan 2014; Whitcraft et al. 2014), because of its high temporal resolution and free availability (Potgieter et al. 2011).

Evapotranspiration (ET) is the exchange of water and energy between the atmosphere, land surface, and soil by the processes of transpiration (from plants) and evaporation (Liu et al. 2019; Gunawardhana et al. 2021). It can be used as an independent parameter in the regression models. Nowadays, there are a number of remote sensing-based evapotranspiration product which is freely available and can be used to estimate spatially distributed region-scale evapotranspiration (Mu et al. 2011).

As we know that agriculture accounts for the largest share (85%) of global freshwater consumption. The availability of freshwater is continuously decreasing with an increase in industrialization and urbanization (Seckler et al. 1998; Toung and Bhuiyan 1994; Brar et al. 2012). So it is need of the hour to know the crop water

productivity of different crops. Crop water productivity is the ratio of actual crop yield and actual evapotranspiration. Recent development in land and water management improves water use efficiency (Zwart and Bastiaanssen 2004). When water is limited, it is essential to know the crop water use efficiency (Brauman et al. 2013). The study of crop yield with crop water productivity is beneficial to know the relationship between these two components (Rockstorm et al. 2007; Monfreda et al. 2008; Speelman et al. 2008).

Keeping in mind the above points, the objectives of the study are

- To develop the sugarcane yield forecast model using the statistical regression method.
- To compare the accuracy of the sugarcane yield forecasting model with and without actual evapotranspiration as independent parameters.
- To study the changes of crop water productivity of sugarcane in the study area.

13.2 Materials and Methods

13.2.1 Study Area

The study area is shown in Fig. 13.1, which lies between 77° 20' E—79° 00' E Longitudes and 29° 30' N—30° 20' N Latitudes. It covers Haridwar and Dehradun districts of Uttarakhand. The rainfall in the Haridwar and Dehradun districts ranges from 1500–2000 mm. The temperature is varying from below 5 to above 40 °C. The Tarai area's soils are deep, well-drained, a small amount of alkaline, and a mixture of coarse and fine loamy soils. At places, the problems of wetness, overflow, and erosion are also observed. Tarai soils are one of the most productive soils in the country (Pareek et al. 2019). Sugarcane is one of the dominant crops in the districts of Haridwar and Dehradun, which is the study area.

13.2.2 Data Collection and Preprocessing

13.2.2.1 Weather Data

Historical weather data (rainfall, maximum and minimum temperatures, maximum and minimum relative humidity) at a daily scale was collected from AMFU Roorkee for Haridwar district, whereas the gridded data (rainfall, maximum and minimum temperatures at a spatial resolution of 0.25×0.25 and 1×1 degree, respectively) for Dehradun district data were downloaded from Indian Meteorological Department (IMD) Web site for the period of 2001–20.

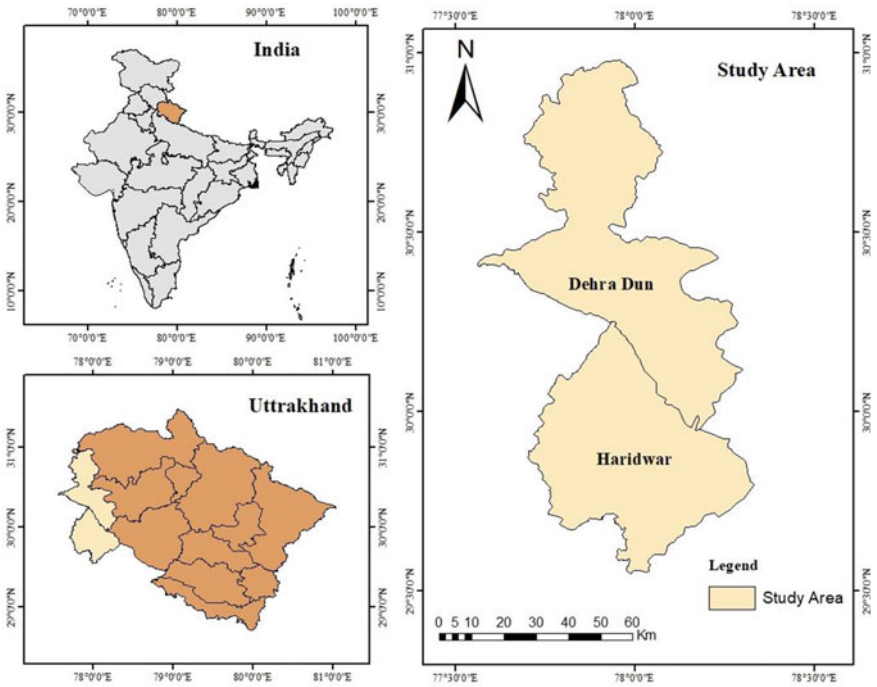


Fig. 13.1 Location map of the study area

13.2.2.2 Crop Yield Data

District-level sugarcane yield data for Haridwar and Dehradun districts were obtained from the Directorate of Agriculture, Uttarakhand, for the period of 2001–19. Figure 13.2 shows the officially reported crop yield statistics of Haridwar and Dehradun districts for the past 19 years. It represents the trend and changes in sugarcane productivity over the years. It is quite clear from Fig. 13.2 that sugarcane productivity shows an increasing trend for both the district, which may be probably due to recent scientific advancements, proper agriculture management, and crop pattern improvement.

13.2.2.3 Land Use Land Cover (LULC) Map

LULC map of the Haridwar and Dehradun districts was taken from the <https://livingatlas.arcgis.com/landcover/> Web site for the year 2020. This map was developed by Impact Observatory for Esri. © 2021 Esri. This dataset is produced by the National Geographic Society in partnership with Google and the World Resources Institute for the Dynamic World Project using ESA Sentinel-2 imagery at 10 m spatial resolution.

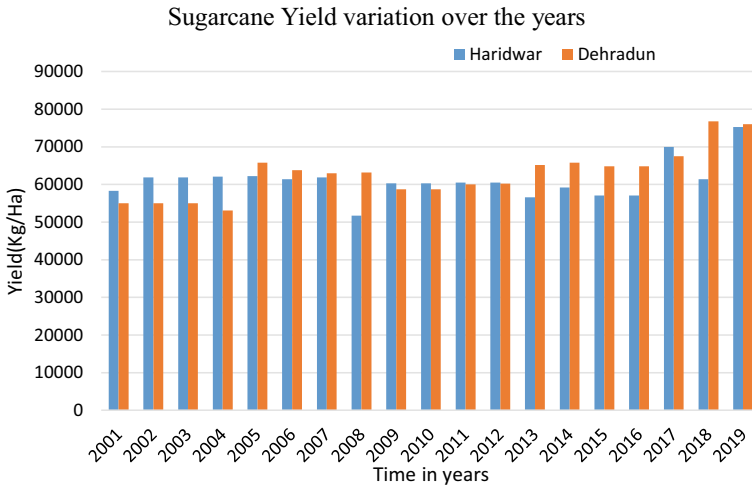


Fig. 13.2 Sugarcane productivity of Haridwar and Dehradun districts (2001–19)

There is 40.75% and 5.78% of the total geographical area which is an agricultural area in Haridwar and Dehradun districts, respectively, which is shown in Fig. 13.3.

13.2.2.4 Evapotranspiration Dataset

MODIS MOD16A2 V6 8 day interval at 500 m resolution evapotranspiration data is downloaded for the period of 2001–20 from <https://lpdaac.usgs.gov/>. The MOD16 evapotranspiration data is based on the Penmen–Monteith equation (Monteith 1965) where the inputs such as land cover, vegetation property, and albedo are taken from MODIS remotely sensed products and other daily inputs taken from meteorological reanalysis. These images are firstly preprocessed in the QGIS platform and then 0.1 is multiplied to MOD16 data in order to get the actual evapotranspiration in mm/8 day.

13.2.3 Methodology

13.2.3.1 Statistical Regression Models

Statistical regression techniques are one of the widely used crop yield forecasting techniques in which regression equations are made between crop yield and one or more meteorological variables. This is a straightforward method, and also the requirement of data is less as compared to other methods. The limitation of this method lies in that the long-range of historical yield and weather data are needed for accurate crop yield forecasting. Care is needed to give priority to agronomic

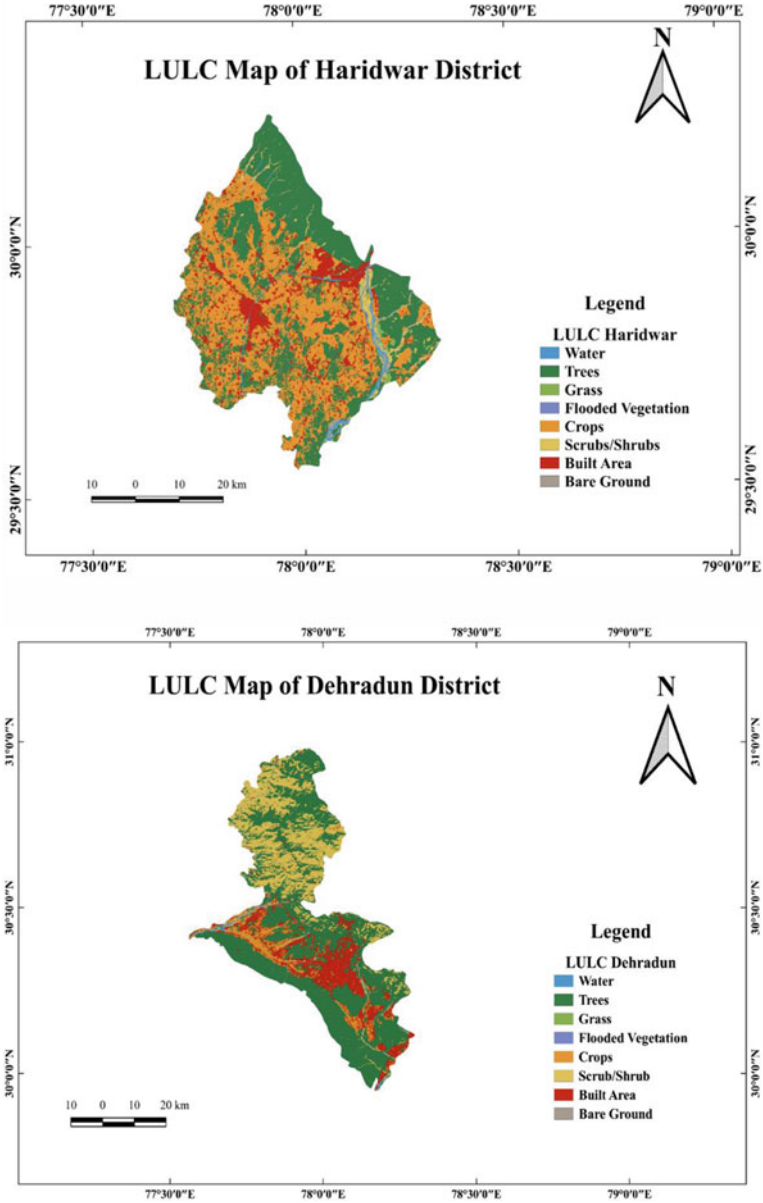


Fig. 13.3 Land use and land cover (LULC) map of Haridwar and Dehradun districts

significance as compared to statistical significance; otherwise, they will provide unrealistic forecasted values.

In statistical regression models, different independent parameters are used other than the meteorological parameters to increase the accuracy of the model, which are generally used in statistical regression models. In this study, actual evapotranspiration was used as independent parameters to improve the accuracy of the crop model for sugarcane.

This model using weighted and unweighted averages for stepwise regression analysis, which are going in the model one by one. This method requires at least 15 years of actual yield data and weekly meteorological data during the cropping period of the individual years (Verma et al. 2021). In this study, 20 years' historical yield data and the weekly meteorological data during the crop period of the individual years are used, in which two years are used for validation of the model. The method involves few steps laid down in a flowchart.

Figure 13.4 presents a flowchart showing yield forecasting of sugarcane using a simple regression model. The regression analysis used weekly weather data for the

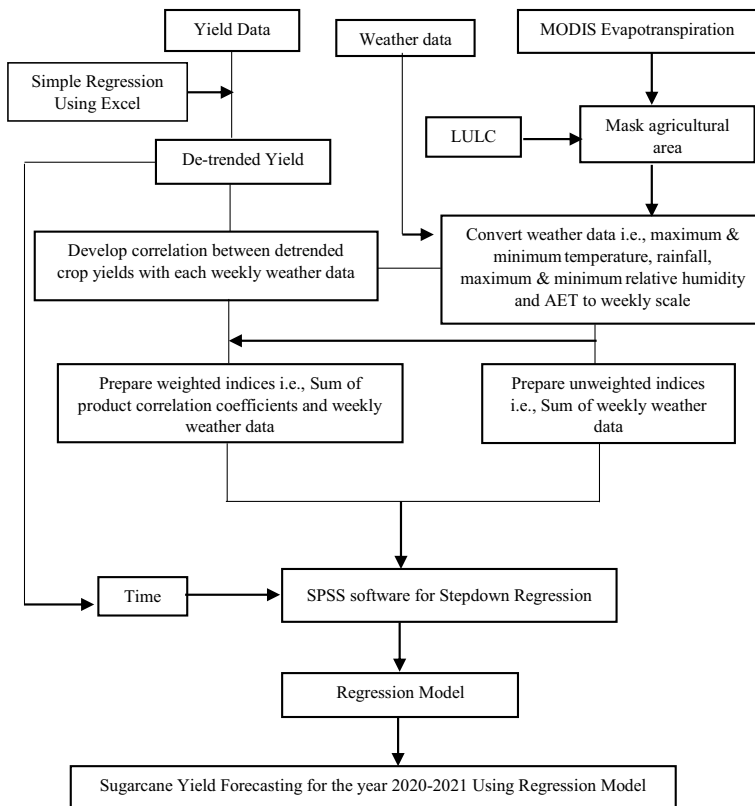


Fig. 13.4 Sugarcane crop yield forecasting using simple regression model

historical period (2001–20) followed by detrended yield data for the same period. Evapotranspiration for the respective crop period was evaluated from the MODIS dataset, whereas humidity (max, min) values of Haridwar district were used due to the unavailability of data at Dehradun district. After correcting crop yield data, weighted and unweighted indices were obtained and fed into SPSS software so as to develop the regression equations. Eventually, the indices of the current years were substituted in the developed equations so as to forecast crop yield.

13.3 Crop water Productivity

Crop water productivity of sugarcane is defined as the ratio of actual crop yield and actual crop evapotranspiration. Generally, the unit of water productivity is in kg/m^3 . High crop water productivity shows high crop water efficiency. It is calculated by the formula (Zwart and Bastiaanssen 2004), which is described below-

$$\text{Crop Water productivity} = \frac{\text{Actual Crop Yield}}{\text{Actual Crop Evapotranspiration}}$$

13.4 Results and Discussions

13.4.1 Sugarcane Statistical Forecast Model

The sugarcane crop yield forecasting was divided into two stages: F2 and F3. For sugarcane, the F2 stage was taken from the first week of February to the second week of July, whereas the F3 stage was from the first week of February to the third week of December. The crop yield forecasting was done by SPSS Software using stepwise regression both with and without AET as an independent parameter which is given in Table 13.1. The correlation between various meteorological parameters and yield was computed, and its significance was tested using a t-test at F2 and F3 stages for the Haridwar district. Various statistical parameters are given in Table 13.2.

Table 13.1 Sugarcane forecast model summary for F3 stage

Crop	Districts	AET	R	R square	Adjusted R square	Std. error
Sugarcane	Haridwar	Without	0.819 ^b	0.670	0.629	3166.837
		With	0.819 ^b	0.670	0.629	3166.837
	Dehardun	Without	0.972 ^d	0.945	0.929	1717.232
		With	0.964 ^d	0.930	0.910	1939.315

Table 13.2 t-test and regression coefficients for Haridwar district

Stage	AET	Model	Unstandardized coefficients		t	sig
			B	SE		
F2	Without	Constant	4597.942	15788.850	0.291	0.775
		Z120	0.988	0.297	3.330	0.004
		Z11	447.624	161.389	2.774	0.014
	With	Constant	44476.682	2688.295	16.545	0.000
		Z361	0.679	0.108	6.287	0.000
		Z240	0.621	0.102	6.119	0.000
	Z30	-6.075	2.787	-2.180	0.048	
F3	Without	Constant	26187.088	8930.439	2.932	0.010
		Z451	0.708	0.224	3.162	0.006
		Z41	47.182	15.531	3.038	0.008
	With	Constant	26187.088	8930.439	2.932	0.010
		Z451	0.708	0.224	3.162	0.006
		Z41	47.182	15.531	3.038	0.008

Similarly, the correlation between various meteorological and yield was computed, and its significance is given in Table 13.3 for the Dehradun district.

From Table 13.4, it is quite clear that in the F2 stage, with AET model was performing better than the without AET model based upon different statistical indicators (R^2 and standard error), whereas for the F3 stage, the performance of both the models is almost similar, which is given in Table 13.1.

It was observed that in both with and without AET cases, the percentage deviation is varying within $\pm 5\%$, and some cases lie within $\pm 10\%$, which was under the permissible limit (Fig. 13.5). Overall, considering all the statistical parameters, i.e., coefficient of determination, standard error, and percentage deviation regression model, with AET model is performing comparatively better than without the AET model, which is given in Tables 13.1 and 13.4.

Using the collected data, regression models were developed and validated for sugarcane for Haridwar and Dehradun districts. Several regression models with and without AET considered an independent variable for the Haridwar and Dehradun districts are generated using SPSS, and the best model is shown below.

For F2 stage, with AET for Haridwar ($R^2 = 0.906$ and Std. error = 1268.29) and Dehradun ($R^2 = 0.903$ and Std. error = 2203.86) performed well as compared to without AET models for Haridwar ($R^2 = 0.675$ and Std. error = 3145.10) and same for Dehradun ($R^2 = 0.903$ and Std. error = 2203.86) district.

For F3 stage, with AET for Haridwar ($R^2 = 0.728$ and Std. error = 2734.45) and Dehradun ($R^2 = 0.930$ and Std. error = 1939.31) performed well as compared to without AET models for Haridwar ($R^2 = 0.670$ and Std. error = 3166.83) slightly less for Dehradun ($R^2 = 0.945$ and Std. error = 1717.23) district.

Table 13.3 t-test and regression coefficients for Dehradun district

Stage	AET	Model	Unstandardized coefficients		t	sig
			B	SE		
F2	Without	Constant	64178.445	3012.418	21.305	0.000
		Time	632.483	106.457	5.941	0.000
		Z31	46.800	9.794	4.779	0.000
		Z151	1.930	0.530	3.639	0.002
	With	Constant	64178.445	3012.418	21.305	0.000
		Time	632.483	106.457	5.941	0.000
		Z31	46.800	9.794	4.779	0.000
		Z151	1.930	0.530	3.639	0.002
F3	Without	Constant	58400.269	6753.432	8.647	0.000
		Time	912.031	84.320	10.816	0.000
		Z351	0.443	0.072	6.176	0.000
		Z41	179.757	38.648	4.651	0.000
		Z40	-39.766	9.587	-4.148	0.001
	With	Constant	57058.580	6563.376	8.693	0.000
		Time	988.133	93.490	10.569	0.000
		Z61	157.411	25.884	6.081	0.000
		Z51	19.633	6.260	3.136	0.007
		Z60	8.403	3.148	2.670	0.018

Table 13.4 Sugarcane forecast model summary for F2 stage

Crop	Districts	AET	R	R square	Adjusted R square	Std. error
Sugarcane	Haridwar	Without	0.821 ^b	0.675	0.634	3145.100
		With	0.952 ^c	0.906	0.885	1268.292
	Dehradun	Without	0.950 ^c	0.903	0.883	2203.867
		With	0.950 ^c	0.903	0.883	2203.867

From this, it was evident that the F2 stage model for sugarcane was better performing as compared to the F3 stage. AET model was better than without AET model, except in the F3 stage without the AET model, which was slightly better (Tables 13.5 and 13.6).

The validation model shows that, therefore, Haridwar district was good with AET on 2018–2019, and on 2019–2020, AET model is slightly underperformed. In Dehradun district, the percentage deviation was very less for both AET and without the AET model. Without AET model is slightly better in Dehradun. Overall performance of the AET model is acceptable (-3.27% to -0.33%) except in Haridwar district's sugarcane yield forecasting on 2019–2020 (-17.94% and -10.3852%) (Table 13.7).

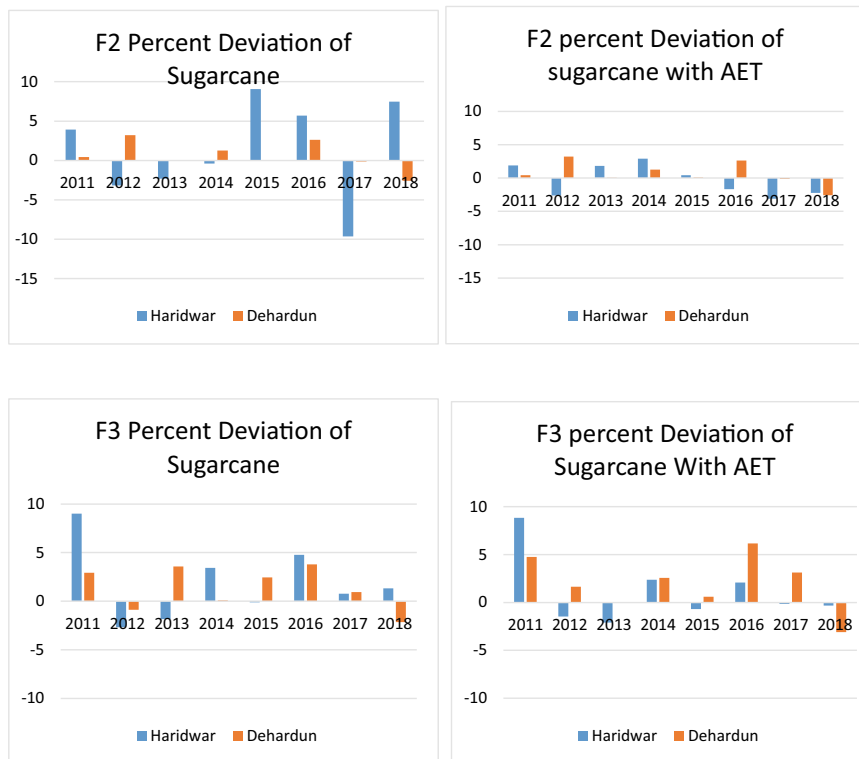


Fig. 13.5 Sugarcane forecasted yield deviation from actual yield for F2 and F3 stages

Table 13.5 Validation of statistical regression model of sugarcane yield forecasting

Districts	Year	Actual yield (kg/ha)	F2 stage		F3 stage	
			Without AET	With AET	Without AET	With AET
Haridwar	2018–19	70,000	73,182.44	66,579.14	62,213.78	61,193.5
	2019–20	68,100	62,956.23	61,786.25	67,479.93	67,479.93
Dehradun	2018–19	67,500	74,810.87	74,810.87	75,138.35	74,422.23
	2019–20	76,800	75,234.6	75,234.6	73,492.93	73,514.54

Table 13.6 Deviation percentage in the validation of statistical regression model of sugarcane yield

Districts	Year	F2 stage		F3 stage	
		Without AET	With AET	Without AET	With AET
Haridwar	2018–19	7.4632	-2.23328	1.325383	-0.33633
	2019–20	-16.3928	-17.9466	-10.3852	-10.3852
Dehradun	2018–19	-2.59001	-2.59001	-2.16361	-3.09606
	2019–20	-1.0071	-1.0071	-3.29878	-3.27034

Table 13.7 Forecasted yield for sugarcane for the year 2020–21

Districts	Yield (Kg/ha) from regression model without AET		Yield (Kg/ha) from regression model with AET	
	F2	F3	F2	F3
Haridwar	61,788.82	68,821.9	81,990.18	85,751.89
Dehradun	65,301.82	71,094.0	65,301.82	74,008.8

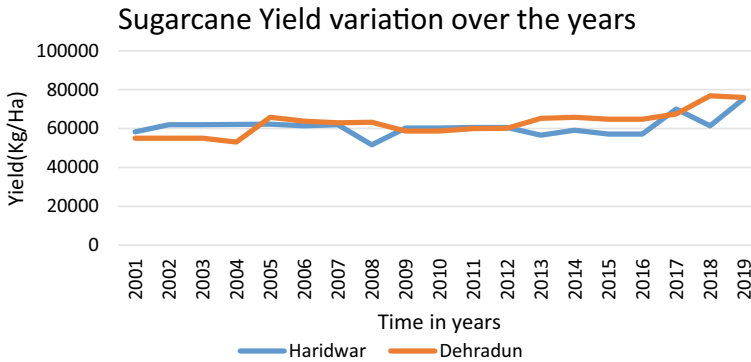


Fig. 13.6 Yield trend of sugarcane in Haridwar and Dehradun districts (2001–2019)

13.4.2 Crop Water Productivity

From the crop water productivity, we can see that crop water productivity is increased in the past several years in the study area. Dehradun’s crop water productivity for sugarcane crops is slightly better than Haridwar district. The continuous decrease in water has had a significant impact on the agricultural sector. India’s water use efficiency is significantly less for the agricultural sector, so we need to increase crop water productivity, especially for sugarcane which is a water-intensive crop. Though from this, we can see that the crop water productivity of Sugarcane for Haridwar and Dehradun district is increasing, we have to increase it more. With the use of advanced methods and equipment, the yield of the study area is increasing, which also increases the water requirement. It is need of the hour to improve the crop water productivity of the crop. By using remote sensing, we can easily get the data for large areas for our study, which can be used for this type of study (Figs. 13.6 and 13.7).

13.5 Conclusion

Remote sensing uses in crop yield forecasting at the regional scale are continuously increasing. This study shows that remote sensing-based MODIS evapotranspiration

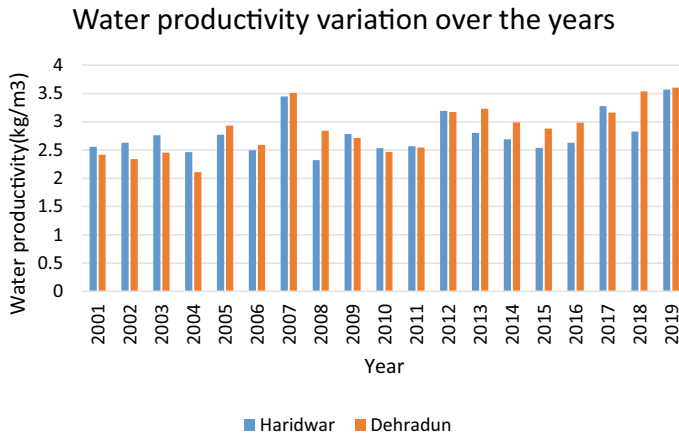


Fig. 13.7 Crop water productivity variation of sugarcane in Haridwar and Dehradun districts

data can be utilized for sugarcane yield forecasting. From this, we conclude that step-wise regression with AET as an independent parameter can be successfully applied for sugarcane yield forecasting, and in F2 stage, it gives good result for Haridwar and Dehradun districts. For the F3 stage, other remote sensing parameters can be used for improving the forecasting accuracy. The model discussed in this paper reasonably reduces the error in yield forecasting, giving a high R^2 value and less standard error. This model developed using remote sensing-derived evapotranspiration gives promising result which can be used for yield forecasting of other crops like wheat and rice. The use of remote sensing-based evapotranspiration is used for finding the crop water productivity of sugarcane. The variation of sugarcane water productivity from 2.2 kg/m^3 to 3.5 kg/m^3 shows an enormous scope for an increase in water productivity. This paper successfully shows the integration of remote sensing data in crop yield forecasting and calculation of crop water productivity.

Acknowledgements The authors wish to acknowledge the Ministry of Earth Science (MoES) for providing the funds and to the Directorate of Agriculture, Uttarakhand, for providing historical crop yield data. We are also grateful to AMFU Roorkee, IIT Roorkee, and Indian Meteorological Department (IMD) for providing weather data.

Appendix 1

Weather Indices

Weather variable	Weather indices	
	Unweighted weather indices	Weighted weather indices
Tmax	Z10	Z11
Tmin	Z20	Z21
Rain	Z30	Z31
RHmax	Z40	Z41
RHmin	Z50	Z51
AET	Z60	Z61
Tmax_Tmin	Z120	Z121
Tmax_Rain	Z130	Z131
Tmax_RHmax	Z140	Z141
Tmax_RHmin	Z150	Z151
Tmax_AET	Z160	Z161
Tmin_Rain	Z230	Z231
Tmin_RHmax	Z240	Z241
Tmin_Rhmin	Z250	Z251
Tmin_AET	Z260	Z261
Rain_RHmax	Z340	Z341
Rain_RHmin	Z350	Z351
Rain_AET	Z360	Z361
RHmax_Rhmin	Z450	Z451
RHmax_AET	Z460	Z461
RHmin_AET	Z560	Z561

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