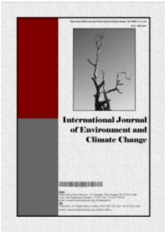

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Remote Sensing and GIS Based Crop Acreage Estimation of the Rabi Season Growing Crop of the Middle Gujarat (India)

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Authors' contributions

This work was carried out in collaboration among all authors. Author SHP designed the study, performed the statistical analysis, wrote the protocol and wrote the first draft of the manuscript. Authors GRP and MMT managed the data interpretation and manuscript preparation analyses of the study. Authors MMT and SHP managed the literature searches. All authors read and approved the final manuscript.

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ABSTRACT

Accurate and precise information about crop type, crop stage, and crop acreage is essential for sustainable utilization of available water resources. The present study is concerned with the estimation of Rabi season growing crops in the Panchmahal district of Gujarat state, India. In these study generation of spectral profiles and crop acreage estimation, Sentinel-2 satellite images were classified using unsupervised classification with ISODATA clustering classification techniques. The satellite image of the study area was classified into 52 classes and overlaid with a ground truth point shape file on the classified image. Total twelve date NDVI based signature derived from sentinel – 2 data during rabi season 2020 - 2021. NDVI based data set is used to classify the study area's major crops, which are maize, wheat, castor, chilli, cotton, pigeon pea, sorghum, and tobacco. The total

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research area's growing crops was estimated as 34472.59 ha, 16517.09 ha, 2186.92 ha, 250.59 ha, 8005.56 ha, 1130.93 ha, 1719.38 ha and 1468.52 ha for maize, wheat, castor, chilli, cotton, pigeon pea, sorghum and tobacco, respectively. The overall accuracy and kappa coefficient for crop acreage estimation were calculated to be 90.71% and 0.78%, respectively. The resulted acreage estimation will help to understand the cropping pattern and their interaction with spatial and temporal variability for present and future estimation of crop water requirement and proper resource availability in this selected region.

Keywords: Sentinel-2, ISODATA unsupervised classification; kappa coefficient; cropping pattern; accuracy.

1. INTRODUCTION

Agriculture is the foundation for social and economic development [1], food security [2,3] and land resource management [4,5]. Crop type mapping can assist us in determining the geographical distribution patterns and proportions of cultivated areas for various crop types, and it serves as the foundation for yield estimation [6,7], water resources management [8], and disaster assessment [9]. Traditional methods of acquiring and updating crop type and planting area information, on the other hand, are mostly based on sampling surveys and statistical reports. Which have problems such as strong subjectivity, time-consuming, labour-intensive, delayed updating, and the lack of spatial distribution information [9]. Remote sensing technology, on the other hand, provides broad coverage, timely data collecting, and fast and dynamic updating, making it an increasingly useful tool for crop type mapping [10,11].

To quantify the crop acreage during the kharif and rabi seasons the field visit, farmers' review, and use of government officials are commonly applicable procedures. This standard approach to crop mapping is carried out primarily through seasonal sample surveys based on a number of sample clusters that are composed of samples from across the nation to measure crop area during the growing season. Regional statistics officers further check the region and sample clusters that field staff have recorded during multiple visits. However, this technique of enumeration is highly tedious, labour-intensive, expensive, comparatively less accurate, time-consuming, and inconsistent, with its invaluable capacity to understand historical trends in the region.

Remote sensing techniques have demonstrated their potential to provide information on the characteristics and spatial distribution of natural resources, including agricultural resources, because of their unique advantages of providing multi-spectral, multi-temporal, and multi-spatial resolutions. Crop type distribution maps that are up to date and accurate could give valuable information for crop monitoring and yield prediction. This early-season information could supply a variety of decision-making and private-sector applications, such as crop insurance and land renting decisions [12,13,14,15].

Various researchers have conducted numerous studies for acreage estimation for various crops [16]. used IRS LISS-III data to estimate crop acreage at the village level using a maximum likelihood classification approach. In the kharif season of 2007, soyabean acreage and crop production were estimated using MODIS satellite data and a GIS database for some districts in Madhyapradesh [17]. For the assessment of cropped area in central Ethiopia, [18] used a hybrid high-medium resolution approach [19]. used IRS P6 LISS-III data to calculate the minimum and maximum sugarcane concentrations using the Bhatia concentration index for all tehsils in Maharashtra's Solapur district. On a regional scale, the MOD16 ET product was compared to validated ET maps with the same spatial and temporal resolution, and it was found to be useful for irrigation scheduling and crop water management in the study area [20]. The current study used remote sensing and GIS techniques to estimate major crop acreage in Gujarat's Panchmahal region.

Accurate and timely data on spatial crop acreage would be helpful for stakeholders (cultivators, manufacturers of fertilizers and pesticides, and organizations for agricultural extension) to plan product supply, market activities effectively, and also help agencies formulate policies related to food security. Besides, crop area would be helpful as an input to estimate crop health and water demand. From the point of view of crop insurance, mapped areas of crop are useful for determining the remote extent of prevented, delayed, or affected sowing to facilitate the appropriate assessment of insurance cover.

In the current study Sentinel-2 satellite data was used. Fortunately, with the operation of the Sentinel-2 series of satellites, the spatial resolution of medium-resolution images can reach 10 m, which can more accurately represent the spatial distribution patterns of different crop types. Meanwhile, the return cycle of Sentinel-2 is just five days, which is excellent for recording the phenological information of crops throughout the growing season. This type of bi-directionally enhanced data provides us with a new opportunity for precise crop type mapping [21,22].

2. MATERIALS AND METHODOLOGY

2.1 Study Area

The area selected for the present study is located in Panchmahal district (sub-district) of Gujarat, India. Panchmahal is located in between 22^{0} 30' N to 23^{0} 30' N latitudes and 73^{0} 15' E to 74^{0} 30' E covering an area of 3314.56 km². It is secured under tropical region of middle Gujarat, location map of study area shown in Fig. 1. The climate of area is tropical and semi-arid with an average annual rainfall of 650- 750 mm and average annual pan evaporation of 6.8 mm/day. About 80% of the rainfall occurs during the month of July and August. The wind speed is varying between 7 to 25 km/h. Maximum humidity ranges from 98.2 % to 79.6 % while minimum range is from 28 to 83.5 %. The monsoon commences early i.e. around 15^{th} June and withdraws by 1^{st} week of September. Temperature varies from 22°C to 44°C in summer and 10°C to 35°C in winter. The major crops grown in the study area are Maize, Wheat, Paddy, Millet, Pulses, and Castor.

2.2 Ground Data Collection

Ground truth data represents the position of an earth feature with respect to the whole world. The exact location of the earth feature was collected using global positioning system (GPS) devices and the SW Maps mobile application. In this study, ground truth data was taken from the Panchmahal district of Gujarat. This ground truth data was collected during the Rabi season of 2020–21, the period for which the image was acquired. Maize and wheat are the major crops grown during the Rabi season (crops associated with the Rabi season are mostly sown in November-December and harvested by March-April). In this research, all the growing crops in the rabi season of the study area were selected for acreage estimation. An ideal sowing time for Rabi season maize and wheat crops is from the last week of October to the mid-week of November, with harvest taking place during March-April. The ground truth sites for the collection of the observational data required for the current investigation were selected from the seven talukas of Panchmahal district. The areas where the maize crop was predominant and occupied more areas were selected as ground truth sites. For easy and better identification of the fields in the satellite imagery, fields with a greater number of locations of growing crops are identified. A total of 700 ground truth locations were collected from the seven talukas (Fig. 2).

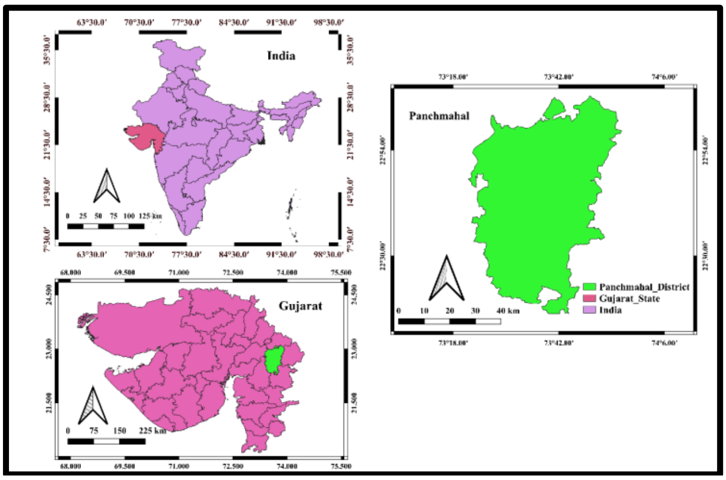


Fig. 1. Location map of study area

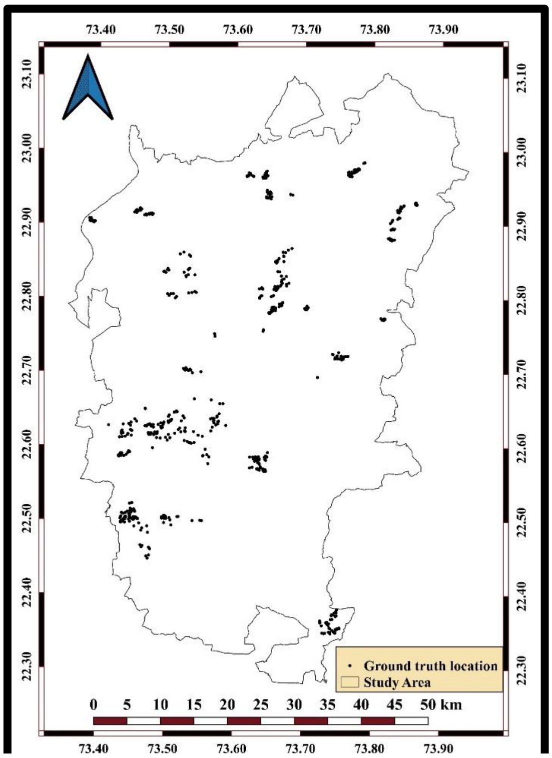


Fig. 2. Spatial distribution map of ground truth locations

2.2.1 Satellite data collection

Sentinel-2 multispectral data was used in this study. The Sentinel-2 satellite mission was developed by the European space agency (ESA). Sentinal-2 images were acquired from November 2020 to April 2021. The entire study area is covered by two scenes of Sentinel-2 data. Rabi season selected for current research, so all season covered with 34 images with two scenes with five-day sensing interval therefore 68 images downloaded for further investigation as per requirement. Because the sky is mostly clear during the Rabi season, satellite image accuracy for acreage estimation is unaffected. So, these seasons give higher accuracy compared to the monsoon season. The current study made use of a total of twelve clear sky images.

2.3 Methodology

Our research consisted of four aspects: Unsupervised classification with ISODATA approach, generation of spectral profile, estimation of crop acreage and accuracy assessment. The classification precision was evaluated using a confusion matrix of the classification results. In the following section, specifics on some aspects will be provided:

2.3.1 Generation of spectral profile and crop acreage estimation

Acreage estimation of Rabi season growing crops was carried out in the Panchmahal region of Gujarat state. In this research, a spectral pattern profile based on remote sensing was employed to identify all growing crops in the Rabi season in the study area. The spectral profiles of all crops were different because each crop has different characteristics and profiles. During the first stage of classification, unsupervised classification with the ISODATA clustering technique was applied. GPS-based ground truth data was used to validate the temporal profile of all growing crops. Then, in the second stage, the class with ground truth was recoded and the second iteration of the ISODATA clustering technique with appropriate classes was applied. The detailed flowchart of the methodology is shown in Fig. 3 for crop acreage estimation.

2.3.1.1 Unsupervised classification with ISODATA approach

Unsupervised classification refers to pixel-based classification that is primarily computer-assisted. The number of classes is determined by the user, and the spectrum classes are formed exclusively on the basis of numerical data in the data (i.e. the pixel values for each of the bands or indices). To establish the natural, statistical grouping of the data, clustering techniques are used. Based on their spectral similarity, the pixels are grouped together. The computer analyses and groups the data into classes using feature space. While the process is generally automated, the user does have control over certain inputs. This includes the number of classes, the maximum iterations, (how many times the classification algorithm runs) and the change threshold, which specifies when to end the classification procedure. After the data has been classified, the user must interpret it, name it, and colour code it according to the classes.

Unsupervised approaches are suitable for large areas with a diverse range of vegetation types and where landscape variation makes finding homogeneous training sites difficult [23,24]. In this study, the ISODATA (Iterative Self-Organizing Data Analysis Technique) clustering algorithm was utilized to perform unsupervised image pixel classification into spectral clusters. Each cluster is a group of pixels in the input bands with similar spectral characteristics. ISODATA was used as an unsupervised classifier by recognizing multi-temporal patterns in the dataset [25]. On a multi-date NDVI stack layer image, the ISODATA clustering algorithm was used. Initially, certain unsupervised classification classes were clustered together based on spectral similarity and closeness to a similar signature. Then, for each group of classes, the ideal spectral signature of ground truth data was matched, and a class name was assigned.

The NDVI stack layer 12 date sentinel-2 image was chosen for classification in unsupervised classification using the ISODATA technique as an input file. In the current investigation, more precise categorization is required, therefore the ISODATA unsupervised technique is given 52 to 60 clustering classes. For this study area, unsupervised classification using the ISODATA technique was performed with a maximum iteration of 20 and a convergence threshold of 0.999.

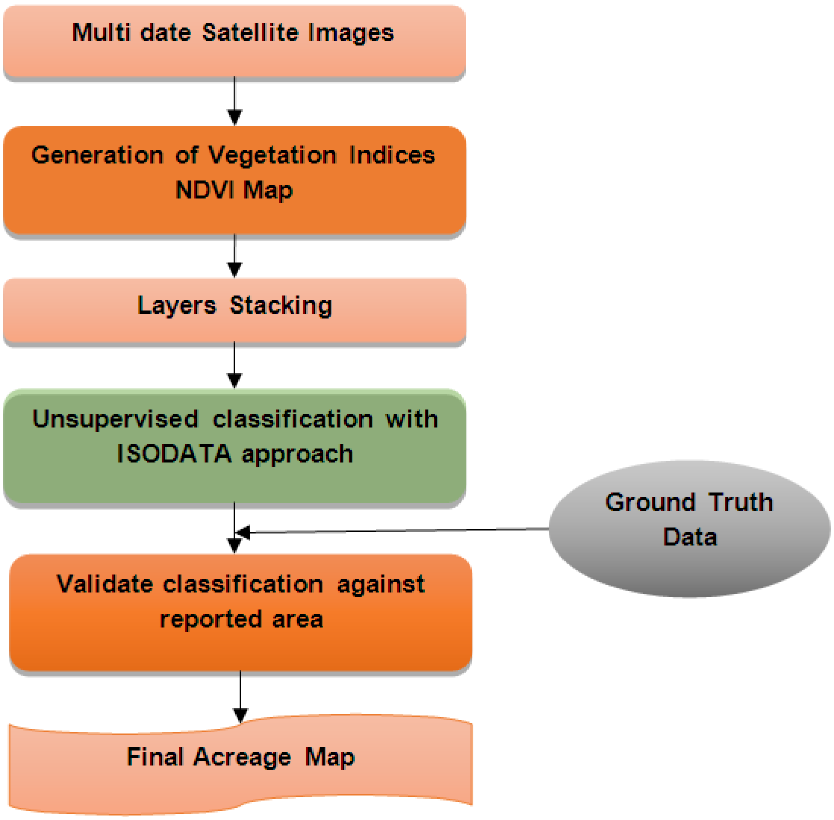


Fig. 3. Flow chart of acreage estimation

2.3.1.2 Generation of spectral profile

The variation of a material's reflectance or emittance with respect to wavelengths (i.e., reflectance/emittance as a function of wavelength) is referred to as its spectral signature (ESA- Eduspace). The spectral characteristics of stars indicate the stellar atmosphere's makeup. The incidental EM wavelength and material interaction with that region of the electromagnetic spectrum determine an object's spectral signature. The spectral profiles represent the average phenological behaviour of all growing crops in the Rabi season of Panchmahal district. Based on the dates of image acquisition of the 12 Sentinel-2 images collected and further determined the spectral profile of growing crop. These processes were done by using classified unsupervised ISODATA classification output image and overlap with ground trothing shape file. Spectral profile of the Rabi season crop of study area was generated by using spatial analysis of ERDAS imagine software. Unsupervised classified image was open in ERDAS imagine software and overlay ground truth point shape file on classified image. Subsequently, the GT shape file was imported by right-clicking on the window and clicking on open vector layer. Then signature editor (Raster -> Supervised signature editor) is the opened and added to the mean of all classified classes. The resultant outcome is exported to excel and to project or present the different classes.

2.3.1.3 Estimation of crop acreage

Previously, only survey methods were used for crop area estimation. These techniques were time consuming and labour intensive. Development in science and technology gives new tools such as remote sensing for quick view of a specific object in a short period of time. A land use and landcover map can be prepared by using remote sensing. The area estimate can be obtained from classified satellite data. For image classification, discrimination of crop types is an important task. The area estimate from the survey may be further improved by using satellite data as an auxiliary variable along with the survey data. It can be used at both the design level and the estimation level. At design level, it is used for area frame construction and stratification. At the estimation level, it is generally used as an auxiliary variable for improvement of previously developed estimators. Crop acreage estimation was done using an unsupervised classification method using the ISODATA technique in this study. ERDAS Imagine software was used to estimate the crop acreage of the overall defined signature of the classified image. In the ERDAS imagine software, open the unsupervised classified image and GT point shape file. Then, open the attribute of the classified image and modify the colour of the class where the GT point has fallen. Examine the profiles of several classes. Match the same profile and use the same colour for the required crop. Merge different classes and open the raster menu. Open thematic record and select the classified file as the input. Click the setup record button and enter a new value of 1 for the needed class and 0 for the not required class. The process is repeated for all the all classes to estimate total acreage.

2.4 Accuracy Assessment of Classified Crop Acreage

For evaluating the performance of various classifiers, accuracy measurements need to be identified [26]. Overall accuracy and the kappa coefficient were used in this study for accuracy assessment. By observing overall accuracy, one can directly interpret the proportion of correctly classified pixels [27,28]. The Kappa coefficient is a statistical test for examining the divergence between two algorithms [29]. Accuracy assessment was done in terms of the confusion matrix. Accuracy was calculated in terms of the kappa coefficient and overall accuracy. The evaluation of accuracy is a crucial aspect of any classification. Accuracy assessment was performed using ENVI software, choosing error matrix method.

2.4.1 Error matrix

An error matrix is a square array of values in rows and columns that expresses the number of sample units (pixels) assigned to a particular category relative to the actual category as verified by the test data set. The following equations were used to estimate overall accuracy, user accuracy, and producer accuracy.

$$\text{Overall accuracy} = \frac{\sum_{i=1}^{m} n_{ii}}{N} \quad (1)$$

$$\text{User's accuracy} = \frac{n_{ii}}{n_{i.}} \quad (2)$$

$$\text{Produser's accuracy} = \frac{n_{ii}}{n_{\cdot i}} \quad (3)$$

Where, n_{ii} = correctly classified pixels.
$n_{i}\cdot$ = Marginal totals of classification categories.
$n_{.i}$ = Marginal totals of reference categories.
N = Total number of pixels.

$$\text{Kappa coefficient} = \frac{\text{Observed accuracy} - \text{chance agreement}}{1 - \text{chance agreement}} \quad (4)$$

$$\widehat{K} = \frac{P_0 - P_c}{1 - P_c} \quad (5)$$

Where, $P_0 = \frac{\sum_{i=1}^{m} n_{i\,i}}{N}$

$P_c = \frac{\sum_{i=j\ j=1}^{j} n_{i}\, n_{j}}{N}$

2.4.2 Kappa coefficients (K)

The Kappa index of agreement for categorical data was developed by Cohen and associates in the context of psychology and psychiatric diagnosis. Kappa was subsequently adopted by the remote sensing community as a useful measure of classification accuracy. Kappa coefficient values greater than 0.80 are said to indicate good categorization performance. Kappa coefficient values of between 0.40 and 0.80 indicate moderate classification performance, and Kappa coefficient values of less than 0.40 indicate poor classification performance [30]. Kappa statistics calculates the proportion of agreement after chance agreement is removed, and it was calculated as follows:

3. RESULTS

3.1 Spectral Profile

Crop identification and discrimination using remote sensed data is based on the fact that each crop has a unique spectral signature. Multidate data analysis is based on the concept of using the differences in the phenology (growing patterns) of different crops grown in the same area. There is a total of twelve date NDVI products, derived from Sentinel-2 data, for the Panchmahal region during the rabi (winter) season (November-December to March-April). This data set is used to classify its major crops, which are maize, wheat, castor, chilly, cotton, pigeon pea, sorghum, and tobacco. Spectral NDVI profiles for all of these crops are shown in Fig. 4. For maize, the NDVI increases sharply and peaks at the end of January and decreases towards the end of March. For wheat, NDVI gradually increases from the end of December and decreases towards the end of February. It was observed that the spectral signatures of maize and wheat go parallel up to the end of January and then they separate in February. The spectral profile for castor and chilli shows an increase in the NDVI from November to February which continues throughout the growing period, which is down from March. The spectral profile for cotton and pigeon pea shows a higher NDVI value from the start of November and continues to decrease throughout the growing period. For sorghum, the NDVI increases sharply and peaks at the end of January and decreases towards the end of March. The spectral profile for tobacco shows an increase in the NDVI from November to the end of January which continues throughout the growing period, which is down from the end of February. The spectral characteristics of maize and wheat, along with other crops, are presented in Fig. 4 [31]. For each of the 12 dates, each of these crops has a unique spectral response. Maize shows the highest NDVI value compared to other agriculture crops. Maize crop has high biomass; open cover canopy high chlorophyll content per unit area gives higher reflectance in NIR band and absorption RED band.

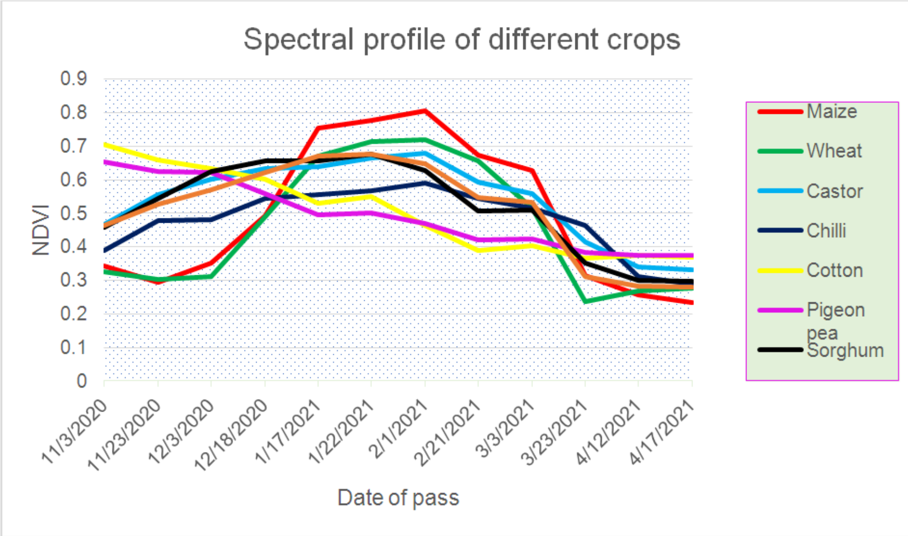


Fig. 4. Spectral profile of different crops

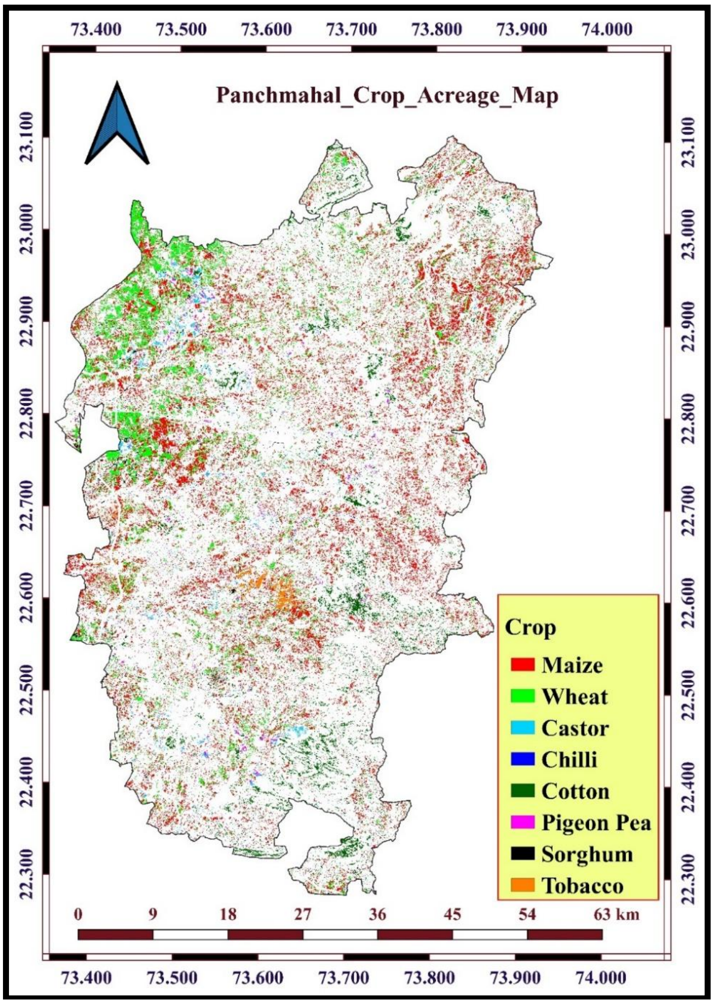


Fig. 5. Crop acreage map of Panchmahal

3.2 Crop Acreage Estimation

Previously only survey methods were used for crop area estimation. However, it is a time-consuming and labour-intensive process. Development in science and technology gives new tools such as remote sensing for quick view of a specific object in a short period of time. A land-use and land-cover map can be prepared by using remote sensing. The area estimate can be obtained from classified satellite data. For image classification discrimination of crop types is an important task. The area estimate from the survey may be further improved by using satellite data as an auxiliary variable along with the survey data. It can be used at both the design level and the estimation level. At design level, it is used for area frame construction and stratification.

The classification results presented in this section were obtained via ISODATA unsupervised classification. Fig. 5 intuitively presents the spatial distribution patterns and proportions of the cultivated areas of the different crops in the study area. In detail, maize has the largest growing area in the study area, with a uniform and continuous distribution and a relatively large plot area. The planting area of wheat ranks second, and its spatial distribution is relatively concentrated, along with Shehra and Godhra talukas, which have a higher growing area. The crop with the third-largest planting area is cotton, whose spatial distribution is discrete, and the largest planting area of cotton in the study area is covered by Ghodhamba. The planting area of castor ranks fourth. The distribution of castor is concentrated in the middle part of the study area. Sorghum has the fifth rank of planting areas in the study area. The crops with the sixth, seventh, and eighth planting areas are tobacco, pigeon pea, and chilli.

3.2.1 Study area's taluka wise crop acreage estimation

As shown in Fig. 3.3 maize, wheat, castor, chilli, cotton, pigeon pea, sorghum and tobacco crops account for 53%, 25%, 3%, 0.38%, 12%, 7%, 2%, 3% and 2% of the total agriculture area. Mainly in the middle Gujarat region maize and wheat are the dominant crops because the soil and atmosphere of this area are highly suitable for them. That's why maize and wheat planting area is higher than other crops.

According to the satellite-based ISODATA unsupervised classification of growing crops in the study area, like maize, wheat, castor, chilli, cotton, pigeon pea, sorghum and tobacco acreage map. The total area was estimated at 34472.59 ha, 16517.09 ha, 2186.92 ha, 250.59 ha, 8005.56 ha, 1130.93 ha, 1719.38 ha and 1468.52 ha for maize, wheat, castor, chilli, cotton, pigeon pea, sorghum and tobacco, respectively for the years 2020–2021 (Rabi season) (Table 1).

The largest maize cultivation was found in Godhra taluka, while the lowest cultivation was recorded in Jambughoda taluka. It was also observed that maize cultivation was found to be high in the area, where irrigation facilities were easily available.

3.3 Accuracy Assessment of Crop Acreage Estimation

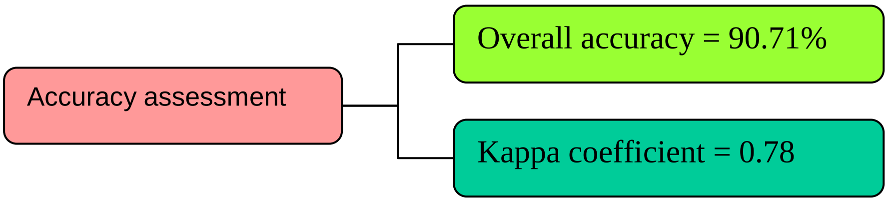
Table 2 represents the error matrix for ISODATA unsupervised classification using ERDAS and ENVI software. In this case, a total of 700 pixels were resampled and an error matrix was generated. From the table it is obvious that out of 174 pixels of maize 158 pixels are correctly classified and 7, 3, 1, 1, 2, 1, and 1 pixel are wrongly classified as wheat, castor, chilli, cotton, Pigeon Pea, sorghum and Tobacco. From 176 pixels of wheat 163 pixels are correctly classified and 13 pixels are classified into maize. Out of 80 pixels of castor 72 were correctly classified whereas 6 pixels were misclassified into cotton and 2 pixels were misclassified into pigeon pea. From 63 pixels of Chilli 56 pixels were correctly classified, 6 pixels were misclassified as pigeon pea and 1 pixel was misclassified as sorghum. From 98 pixels of cotton 89 pixels were correctly classified, 2 pixels were misclassified into maize, 1 pixel was misclassified into wheat and 6 pixels were misclassified into castor. Out of 63 pixels of pigeon pea 57 were correctly classified whereas 2 pixels were misclassified into cotton and 4 pixels were misclassified into chilli. From 28 pixels of sorghum 24 pixels were correctly classified and 4 pixels were misclassified as maize. From 18 pixels of tobacco 16 pixels were correctly classified and 2 pixels were misclassified as castor.

Table 1. Taluka wise crop acreage with respect to its planting area in hectare

	Godhra	Kalol	Halol	Ghodhamba	Jambughoda	Shehra	Morava	Total	Percentage
Maize	9463.96	4326.64	3543.03	5368.24	595.27	6277.16	4898.29	34472.59	53
Wheat	5138.51	1652.38	1762.33	966.03	242.06	5492.21	1263.57	16517.09	25
Castor	597.02	363.76	480.8	72.75	61.02	541.07	70.5	2186.92	3
Chilli	68.21	67.9	41.8	32.14	6.19	22.65	11.7	250.59	0.20
Cotton	1079.8	350.36	1583.77	2188.79	772.79	1278.26	751.79	8005.56	12
Pigeon Pea	286.11	156.32	303.44	83.55	18.41	252.86	30.24	1130.93	1.80
Sorghum	426.99	283.63	381.96	146.21	287.26	159.73	33.6	1719.38	3
Tobacco	126.7	649.4	99.62	453.61	45.4	85.37	8.42	1468.52	2

Table 2. Error matrix of ISODATA unsupervised classification

Categories	**Reference Categories**								
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**Total**
Maize	158	7	3	1	1	2	1	1	174
Wheat	13	163	0	0	0	0	0	0	176
Castor	0	0	72	0	6	2	0	0	80
Chilli	0	0	0	56	0	6	1	0	63
Cotton	2	1	6	0	89	0	0	0	98
Pigeon Pea	0	0	2	4	0	57	0	0	63
Sorghum	4	0	0	0	0	0	24	0	28
Tobacco	0	0	2	0	0	0	0	16	18
Total	177	171	85	61	96	67	26	17	700



3.3.1 Overall accuracy and Kappa coefficient

An accuracy assessment was performed using the ground-based GPS points of individual features (Table 2). Due to the importance of accuracy assessment in digital image processing, it is critical to recommend the precision of classified images. With the use of GPS-based growing crop plots, the confusion matrix was created. These samples were used in the post-classification technique for the accuracy assessment of classified images. For ISODATA unsupervised classification techniques overall accuracy and kappa coefficient were computed. The detailed methodology was explained in section 2.4.1. Overall accuracy along with a kappa coefficient was computed using the formula given in section 2.4.2. For crop acreage estimation using ISODATA unsupervised classification techniques overall accuracy and kappa coefficient are summarized.

4. CONCLUSION

The integration of remote sensing and GIS technology may not only help in reducing the workload of field survey but also provide a technique of improving the quality of information in this sector by integrating both sources of information. Remote sensing which has proven to be efficient and useful with the advantage of large area coverage, synoptic view, receptivity of the satellite is capable of providing information pertaining to large areas in much lesser time. The resulted acreage estimation will help to understand the cropping pattern and their interaction with spatial and temporal variability for present and future estimation of crop water requirement and proper resource availability in this selected region. Based on results, we concluded that the used strategy with the ISODATA classification technique gives accurate identification of growing crop. A simple and highly accurate method for growing crop identification will be useful in early forecasts of supply and demand. This study is also used for planning and managing demand and supply of selected crop in the country. Further study is also needed to assess site suitability from the full range of geographical information of current planning areas in relation to the specific biological/ agro ecological requirements of selected growing crop.

APPLICATION OF RESEARCH

Understand the cropping pattern and their interaction with spatial and temporal variability for present and future estimation of crop water requirement and proper resource availability.

DISCLAIMAR

The products used for this research are commonly and predominantly use products in our area of research and country. There is absolutely no conflict of interest between the authors and producers of the products because we do not intend to use these products as an avenue for any litigation but for the advancement of knowledge. Also, the research was not funded by the producing company.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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