

REMOTE SENSING AND GIS BASED CROP ACREAGE ESTIMATION OF THE RABI SEASON GROWING CROP OF THE MIDDLE GUJARAT (INDIA)

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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 20 iterations with the use of ISODATA unsupervised classification and overlay 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 ~~tebceetobacco~~ tobacco. The total 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. Maize has the largest growing area in the study area, with a uniform and continuous distribution and a relatively large plot area. Crop acreage estimation using ISODATA unsupervised classification techniques overall accuracy and kappa coefficient was computed 90.71 % and 0.78 respectively. 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.

Comment [K1]: Abstract:

-The wording, specifically lines 15-26 could be reduced to ensure brevity and conciseness in the abstract. Repetitive phrases or lines like ... ISODATA unsupervised classification techniques... could be paraphrased as it has been used three times in the abstract. Authors can keep the abstract within a threshold of 200-250 words.

Keywords: Sentinel-2, Crop acreage, NDVI, ISODATA unsupervised classification, Overall accuracy, Kappa coefficient

1. INTRODUCTION

Agriculture is the foundation for social and economic development [1], food security [7,14] and land resource management [8,12]. 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 [4,23,23], water resources management [28], and disaster assessment [33]. 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 [33]. 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 [29,32].

Comment [K2]: Keywords:

-Authors can state or include keywords which haven't been included or stated in the study's title. This would enhance readability and availability of the study in a database or search. Words/phrases like: crop acreage, overall accuracy could be omitted or replaced.

Comment [K3]: Introduction:

-The authors can briefly integrate some underlying theories linked to some SDGs, livelihood frameworks among other green based approaches to enrich the literature.

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

48 Remote sensing techniques have demonstrated their potential to provide information on the
49 characteristics and spatial distribution of natural resources, including agricultural resources, because
50 of their unique advantages of providing multi-spectral, multi-temporal, and multi-spatial resolutions.
51 Crop type distribution maps that are up to date and accurate could give valuable information for crop
52 monitoring and yield prediction. This early-season information could supply a variety of decision-
53 making and private-sector applications, such as crop insurance and land renting decisions
54 [17,18,25,27].

55 Various researchers have conducted numerous studies for acreage estimation for various
56 crops. [22] used IRS LISS-III data to estimate crop acreage at the village level using a maximum
57 likelihood classification approach. In the kharif season of 2007, soyabean acreage and crop
58 production were estimated using MODIS satellite data and a GIS database for some districts in
59 Madhyapradesh [16]. For the assessment of cropped area in central Ethiopia, [9] used a hybrid high-
60 medium resolution approach. [30] used IRS P6 LISS-III data to calculate the minimum and maximum
61 sugarcane concentrations using the Bhatia concentration index for all tehsils in Maharashtra's Solapur
62 district. On a regional scale, the MOD16 ET product was compared to validated ET maps with the
63 same spatial and temporal resolution, and it was found to be useful for irrigation scheduling and crop
64 water management in the study area [21]. The current study used remote sensing and GIS
65 techniques to estimate major crop acreage in Gujarat's Panchmahal region.

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

73 In [the current study, studies](#) Sentinel-2 satellite data was used. Fortunately, with the operation
74 of the Sentinel-2 series of satellites, the spatial resolution of medium-resolution images can reach 10
75 m, which can more accurately represent the spatial distribution patterns of different crop types.
76 Meanwhile, the return cycle of Sentinel-2 is just five days, which is excellent for recording the
77 phenological information of crops throughout the growing season. This type of bi-directionally
78 enhanced data provides us with a new opportunity for precise crop type mapping [11,15].

79 2. MATERIALS AND METHODOLOGY

80 2.1. Study area

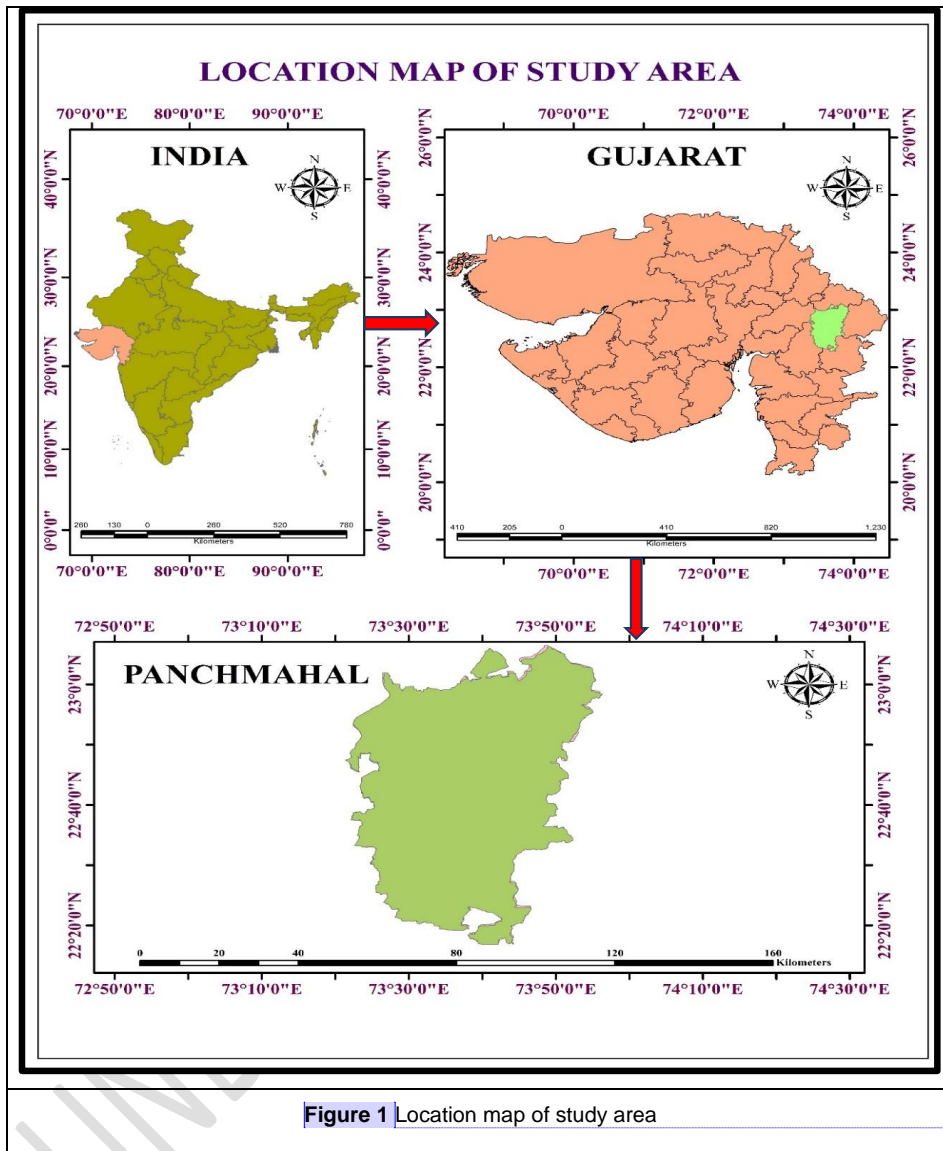
81 | The area selected for the present study is located in Panchmahal district (sub-district) of
82 Gujarat, India. Panchmahal is located in between 22° 30' N to 23° 30' N latitudes and 73° 15' E to 74°
83 30' E covering an area of 3314.56 km². It is secured under tropical region of middle Gujarat, location
84 map of study area shown in figure 1. The climate of area is tropical and semi-arid with an average
85 annual rainfall of 650- 750 mm and average annual pan evaporation of 6.8 mm/day. About 80% of the
86 rainfall occurs during the month of July and August. The wind speed is varying between 7 to 25 km/h.
87 Maximum humidity ranges from 98.2 % to 79.6 % while minimum range is from 28 to 83.5 %. The
88 monsoon commences early i.e. around 15th June and withdraws by 1st week of September.
89 Temperature varies from 22°C to 44°C in summer and 10°C to 35°C in winter. The major crops grown
90 | in the study area are Maize, Wheat, Paddy, Millet, Pulses, and so onete.

91 2.2. Ground data collection

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

Comment [K4]: Materials and Methods:
-Line 94: Kindly write SW in full before subsequently using the abbreviated form.

Comment [K5]: -Line 105: Technical procedures like accuracy assessments or ground truthing exercises require spatial representation or proof to depict such exercise. Therefore, authors are required to include a map to depict ground truthing sample points either in the methodology of the main text or as a supplementary file.



Comment [K6]: -Figure 1: Authors should consider adding administrative towns as a legend/feature to the study area map, specifically the map for "Panchmahal".

-Again, the **vertical grids** (i.e., the coordinates around the figures) for **India and Gujarat maps** could be reduced to just 3 to enhance readability and presentation of images (i.e., prevent images from being clumsy). The **horizontal grids** for the map of "Panchmahal" is too much. It could be reduced further using the grid classification to 3 or 4 for better representation of Fig. 1.

Comment [K7]: Lines 107-112:

-Authors need to integrate a justification for the period satellite imagery were acquired. References to existing literature could be made. The relevance of this is that periods are critical in affecting results generated. The season or period could influence the variables acreage fair representation considering NDVI being sensitive. Harmattan or dry seasons, rainy or wet seasons, or perhaps, fall, winter, spring and summer are influential in selecting best images that wouldn't affect the study's results or data analysis.

106 2.3. Satellite data collection

107 Sentinel-2 multispectral data was used in this study. The Sentinel-2 satellite mission was
 108 developed by the European space agency (ESA). Sentinel-2 images were acquired from **November**
 109 **2020 to April 2021**. The entire study area is covered by two scenes of Sentinel-2 data. Rabi season
 110 selected for current research, so all season covered with 34 images with two scenes with five-day
 111 sensing interval therefore 68 images downloaded for further investigation as per requirement. The
 112 current study made use of a total of twelve clear sky images.

113 2.3. Methodology

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

118 **2.3.1 Generation of spectral profile and crop acreage estimation**

119 Acreage estimation of Rabi season growing crops was carried out in the Panchmahal region
120 of Gujarat state. In this research, a spectral pattern profile based on remote sensing was employed to
121 identify all growing crops in the Rabi season in the study area. The spectral profiles of all crops were
122 different because each crop has different characteristics and profiles. During the first stage of
123 classification, unsupervised classification with the ISODATA clustering technique was applied. GPS-
124 based ground truth data was used to validate the temporal profile of all growing crops. Then, in the
125 second stage, the class with ground truth was recoded and the second iteration of the ISODATA
126 clustering technique with appropriate classes was applied. The detailed flowchart of the methodology
127 is shown in figure 2 for crop acreage estimation.

128 **2.3.1.1 Unsupervised classification with ISODATA approach**

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

139 Unsupervised approaches are suitable for large areas with a diverse range of vegetation
140 types and where landscape variation makes finding homogeneous training sites difficult [3,5]. In this
141 study, the ISODATA (Iterative Self-Organizing Data Analysis Technique) clustering algorithm was
142 utilized to perform unsupervised image pixel classification into spectral clusters. Each cluster is a
143 group of pixels in the input bands with similar spectral characteristics. ISODATA was used as an
144 unsupervised classifier by recognizing multi-temporal patterns in the dataset [2]. On a multi-date NDVI
145 stack layer image, the ISODATA clustering algorithm was used. Initially, certain unsupervised
146 classification classes were clustered together based on spectral similarity and closeness to a similar
147 signature. Then, for each group of classes, the ideal spectral signature of ground truth data was
148 matched, and a class name was assigned.

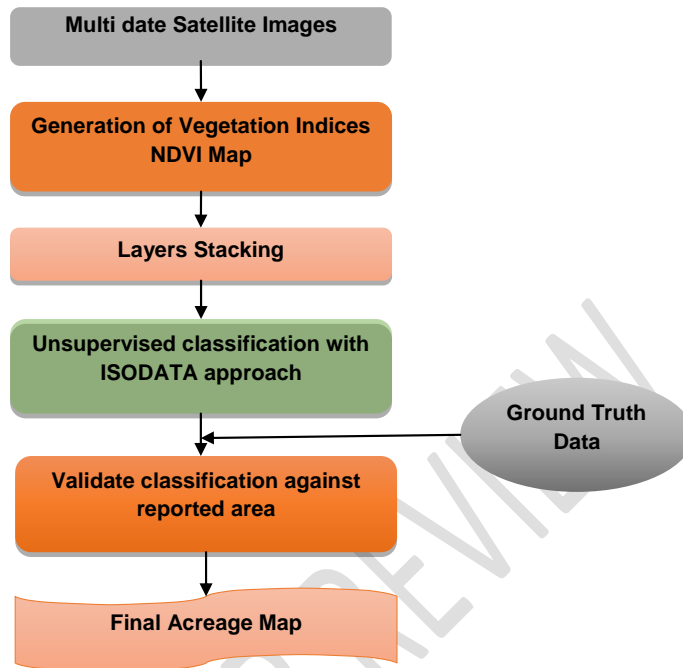


Figure 2 Flow chart of acreage estimation

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

154 2.3.1.2 Generation of spectral profile

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

signature editor) is then opened, and added to the mean of all classified classes. The resultant outcome is exported ~~Open statistics and apply the mean and copy all class wise mean~~ to excel and to project or present the ~~see the profiles of~~ different classes.

171 2.3.1.3 Estimation of Crop Acreage

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

190 2.4 Accuracy Assessment of classified crop acreage

191 For evaluating the performance of various classifiers, accuracy measurements need to be
192 identified [20]. Overall accuracy and the kappa coefficient were used in this study for accuracy
193 assessment. By observing overall accuracy, one can directly interpret the proportion of correctly
194 classified pixels [10,24]. The Kappa coefficient is a statistical test for examining the divergence
195 between two algorithms [6]. Accuracy assessment was done in terms of the confusion matrix.
196 Accuracy was calculated in terms of the kappa coefficient and overall accuracy. The evaluation of
197 accuracy is a crucial aspect of any classification. Accuracy assessment was performed using ENVI
198 software, choosing error matrix method.

199 2.4.1 Error Matrix

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

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

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

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

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

204 2.4.2 Kappa Coefficients (K)

205 The Kappa index of agreement for categorical data was developed by Cohen and associates
 206 in the context of psychology and psychiatric diagnosis. Kappa was subsequently adopted by the
 207 remote sensing community as a useful measure of classification accuracy. Kappa coefficient values
 208 greater than 0.80 are said to indicate good categorization performance. Kappa coefficient values of
 209 between 0.40 and 0.80 indicate moderate classification performance, and Kappa coefficient values of
 210 less than 0.40 indicate poor classification performance [13]. Kappa statistics calculates the proportion
 211 of agreement after chance agreement is removed, and it was calculated as follows:

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

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

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

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

212

213

214 3. RESULTS AND DISCUSSION

215 3.1 Spectral Profile

Comment [K8]: Results and Discussion:

-I did not see any in-depth discussion pertaining to the explanation of the study results against early studies or existing literature. Authors need to compare or show how the study results tally/agree or refute/disagree with other studies with similar scope either domestically or elsewhere across the globe with reasons.

-Are there policies, plans, programs and projects (agroforestry, technology, among other food or economic driven initiatives or strategies) or interventions (i.e., incentives, subsidies, and so on) coupled with external factors (international market prices of some crops or commodities, support etc) driving the extensiveness of some specific crops

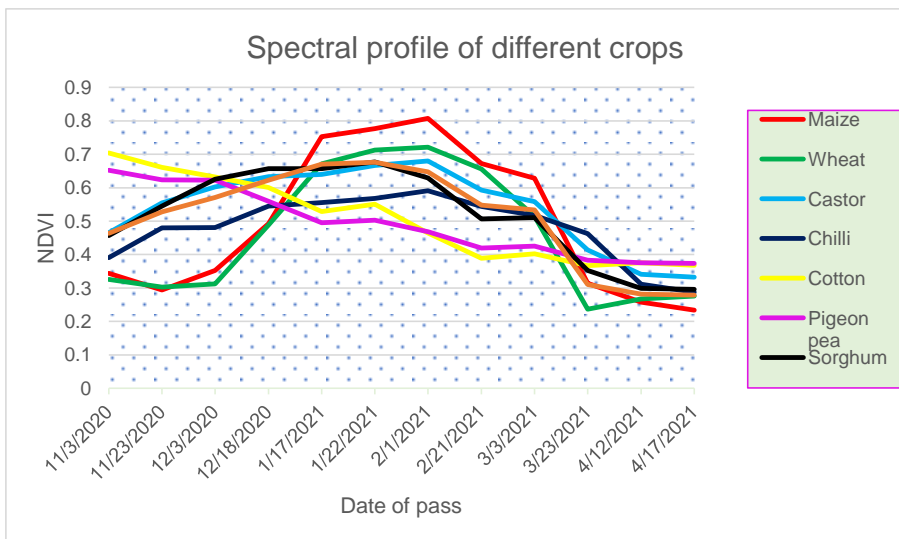


Figure 3 Spectral profile of different crops

Comment [K9]: Fig.3: It is highly inappropriate for authors to present a figure or an image directly after a major section. There must be a preceding or introductory section that introduces the section or figure before presenting the figure.

216 Crop identification and discrimination using remote sensed data is based on the fact that each
 217 crop has a unique spectral signature. Multidate data analysis is based on the concept of using the
 218 differences in the phenology (growing patterns) of different crops grown in the same area. There is a
 219 total of twelve date NDVI products, derived from Sentinel-2 data, for the Panchmahal region during
 220 the rabi (winter) season (November-December to March-April). This data set is used to classify its
 221 major crops, which are maize, wheat, castor, chilly, cotton, pigeon pea, sorghum, and tobacco.
 222 Spectral NDVI profiles for all of these crops are shown in figure 3. For maize, the NDVI increases
 223 sharply and peaks at the end of January and decreases towards the end of March. For wheat, NDVI
 224 gradually increases from the end of December and decreases towards the end of February. It was
 225 observed that the spectral signatures of maize and wheat go parallel up to the end of January and
 226 then they separate in February. The spectral profile for castor and chilli shows an increase in the
 227 NDVI from November to February which continues throughout the growing period, which is down from
 228 March. The spectral profile for cotton and pigeon pea shows a higher NDVI value from the start of
 229 November and continues to decrease throughout the growing period. For sorghum, the NDVI
 230 increases sharply and peaks at the end of January and decreases towards the end of March. The
 231 spectral profile for tobacco shows an increase in the NDVI from November to the end of January
 232 which continues throughout the growing period, which is down from the end of February. The spectral
 233 characteristics of maize and wheat, along with other crops, are presented in figure 3. For each of the
 234 12 dates, each of these crops has a unique spectral response. Maize shows the highest NDVI value
 235 compared to other agriculture crops. Maize crop has high biomass; open cover canopy high
 236 chlorophyll content per unit area gives higher reflectance in NIR band and absorption RED band.

237 3.2 Crop Acreage Estimation

238 Previously only survey methods were used for crop area estimation. However, it is a time-
 239 consuming and labour-intensive process. Development in science and technology gives new tools

240 such as remote sensing for quick view of a specific object in a short period of time. A land-use and
241 land-cover map can be prepared by using remote sensing. The area estimate can be obtained from
242 classified satellite data. For image classification discrimination of crop types is an important task. The
243 area estimate from the survey may be further improved by using satellite data as an auxiliary variable
244 along with the survey data. It can be used at both the design level and the estimation level. At design
245 level, it is used for area frame construction and stratification.

246 The classification results presented in this section were obtained via ISODATA unsupervised
247 classification. Figure 4 intuitively presents the spatial distribution patterns and proportions of the
248 cultivated areas of the different crops in the study area. In detail, maize has the largest growing area
249 in the study area, with a uniform and continuous distribution and a relatively large plot area. The
250 planting area of wheat ranks second, and its spatial distribution is relatively concentrated, along with
251 Shehra and Godhra talukas, which have a higher growing area. The crop with the third-largest
252 planting area is cotton, whose spatial distribution is discrete, and the largest planting area of cotton in
253 the study area is covered by Ghodhamba. The planting area of castor ranks fourth. The distribution of
254 castor is concentrated in the middle part of the study area. Sorghum has the fifth rank of planting
255 areas in the study area. The crops with the sixth, seventh, and eighth planting areas are tobacco,
256 pigeon pea, and chilli.

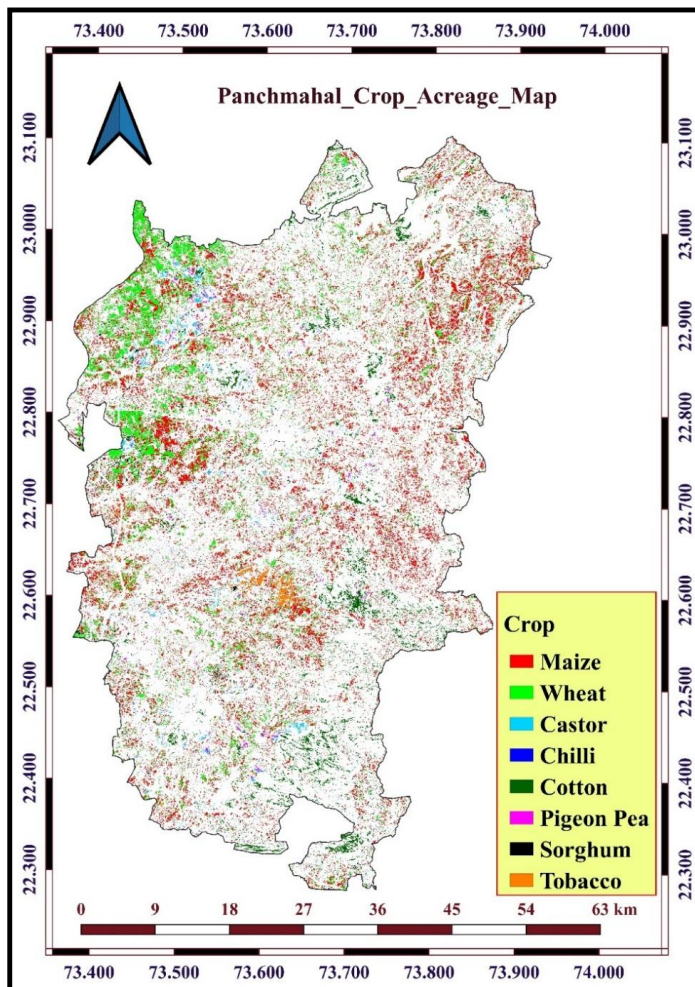


Figure 4 Crop acreage map of Panchmahal

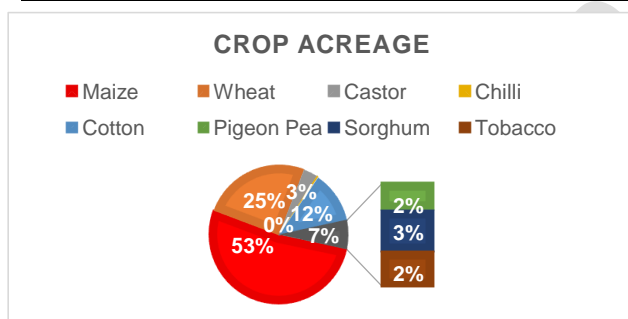
257 3.2.1 Study Area's Taluka Wise Crop Acreage Estimation

258 As shown in figure 5 maize, wheat, castor, chilli, cotton, pigeon pea, sorghum and tobacco
 259 crops account for 53%, 25%, 3%, 0.38%, 12%, 7%, 2%, 3% and 2% of the total agriculture area.
 260 Mainly in the middle Gujarat region maize and wheat are the dominant crops because the soil and
 261 atmosphere of this area are highly suitable for them. That's why maize and wheat planting area is
 262 higher than other crops.

263 According to the satellite-based ISODATA unsupervised classification of growing crops in the
 264 study area, like maize, wheat, castor, chilli, cotton, pigeon pea, sorghum and tobacco acreage map.
 265 The total area was estimated at 34472.59 ha, 16517.09 ha, 2186.92 ha, 250.59 ha, 8005.56 ha,
 266 1130.93 ha, 1719.38 ha and 1468.52 ha for maize, wheat, castor, chilli, cotton, pigeon pea, sorghum
 267 and tobacco, respectively for the years 2020–2021 (Rabi season) (Table 1).

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

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



Maize	34472.59
Wheat	16517.09
Castor	2186.92
Chilli	250.59
Cotton	8005.56
Pigeon Pea	1130.93
Sorghum	1719.38
Tobacco	1468.52

Figure 5 Taluka wise crop acreage with respect to its planting area in hectare

Comment [K10]: Table 1:

-The mini or summarized table below table one is similar to the total acreage for each crop. Authors need to delete the mini-table beneath table 1 since they present the same information.

-Again, I find it strange observing similar information presented in Table 1 in the form of a pie-chart. It is unacceptable for scientific reasons and academic papers to create such doublets. I suggest authors add a new column after the "Total" column with the title or caption Percentages. Fig. 5 needs to be removed in that regard.

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 Error matrix of ISODATA unsupervised classification

Categories	Reference Categories								Total
	1	2	3	4	5	6	7	8	
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

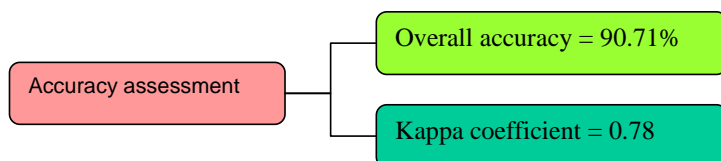
Table 2 represents the error matrix for ISODATA unsupervised classification using ERDAS and ENVI software. In this case, a total of 700 pixels were resampled and an error matrix was generated. From the table it is obvious that out of 174 pixels of maize 158 pixels are correctly classified and 7, 3, 1, 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.

3.3.1 Overall accuracy and Kappa coefficient

An accuracy assessment ~~was has been~~ performed using the ground-based GPS points of individual features (Table 2). ~~Due to Because of~~ 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

Comment [K11]: -Kindly refer to my comments above (in the methodology section) on integrating a spatial map to depict areas where samples were taken.

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 below.



4. Conclusion

Area estimate through survey involves large amount of field data collection and it is also a time-consuming process. With the advancement in space science the use of modern technologies like Remote Sensing and GIS proved to be potential tools for estimation of area of major crops of study area like maize and wheat. Thus, it is quite possible to integrate RS and GIS technology with ground survey and estimate area of growing crops using the integrated methodology. 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.

COMPETING INTERESTS DISCLAIMER:

Authors have declared that no competing interests exist. 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 rather it was funded by personal efforts of the authors.

Comment [K12]: Conclusion:

- The first two lines in the conclusion have been repeated severally in other sections.
- The main findings should be made clear and summarised in the conclusion without repetition or ambiguity.
- Authors could integrate briefly some study limitations or challenges, coupled with possible areas for further research.

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