

## ESTIMATION OF WHEAT CROP ACREAGE, HEALTH AND YIELD USING REMOTE SENSING AND GIS TECHNIQUES IN ALWAR DISTRICT OF RAJASTHAN

Gaurav Tripathi<sup>1</sup>, Rahul Saini<sup>2</sup>, Shruti Kanga<sup>3</sup>, Suraj Kumar Singh<sup>4</sup> and Priyanka Roy<sup>5</sup>

### ABSTRACT

Majority of the nations around world focus mostly on agriculture. However, wheat is the principal cereal crops in our country. An accurate prediction of agricultural production and acreage well before harvest is crucial for planners and policymakers. When creating plans for supply and demand, stock and inventory, pricing, export and import, etc. in the case of a shortfall or surplus, crop data are helpful. The focus of the current investigation is the Tehsil-level wheat crop for the *rabi* season in 2021–2022. Wheat is the primary crop grown in the Alwar district of Rajasthan, India, hence the study looked at whether crop area and productivity estimates could be made using remote sensing. Results exhibited that total 1930 km<sup>2</sup> were categorized under fallow land followed by Dense Forest (726.77 km<sup>2</sup>), Urban area (94.4 km<sup>2</sup>), Rural area (132.67 km<sup>2</sup>) and Crop Land (327.65 km<sup>2</sup>), majorly. Results also exhibited that wheat crop covers 11,929.1 km<sup>2</sup> of the geographical land. Wheat crop acreage was estimated and found that at Bansur district (228.63 km<sup>2</sup>) it was highest followed by Mandawar (212.95 km<sup>2</sup>), Alwar (173.27 km<sup>2</sup>) and Ramgarh (168.51 km<sup>2</sup>). Monitoring wheat acreage and growth enables researchers to assess studies and forecast regional and national productivity as well as food security. Crop health is determined by yet another important factor i.e., soil, water, and nutrients. Crop health is assessed using the remote sensing-based Normalized Crop Index (NCI). By separating the red band with high absorptivity from the near infrared with high reflectivity, the plant model NDVI image-transformation evaluates vegetation. By using the amount of chlorophyll, NDVI gauges crop health. Using the health slicing model, the NDVI values were categorised from Excellent to Poor to indicate the health of the wheat crop in the study area. Accurate crop output projections are essential for government authorities, farmers, scientists, and commercial sectors.

(Key words: Crop acreage production, yield assessment, supervised classification, water stress, NDVI, LSWI)

### INTRODUCTION

India is reliant on agriculture for food, employment, and income stability. It employs 66% of Indians and contributes 14% of GDP (Doraiswamy *et al.*, 2003; Dubey *et al.*, 2020). Rice-wheat farming dominates the Indo-Gangetic plains, covering 13.5 mha (IGP). India produces half the world's food grain and feeds 40% of its population. India produces 12% of global wheat. According to ITC Trade Map, 2021, wheat exports rose to \$ 243 million in 2020 from \$50 million in 2016 (Bele *et al.*, 2021; Panigrahy and Sharma, 1997). As our environment has changed gradually due to climate change, forcing us to adjust our planting and agronomic practices. Land use changes can harm the ecosystem. Fertilizers, pesticides, soil capping, compacting, and changed hydrologic, nutritional, and climatic cycles

may diminish biodiversity, soil deterioration and water, soil and air pollution. Land use affects economic processes by attracting labour and commerce. Biophysical and economical factors oppose land-use decisions. South Asia would produce 22 million tonnes less food grain by 2030. This rice-wheat cropping system is experiencing diminishing marginal yields, groundwater depletion, soil degradation, and heat stress (Bele *et al.*, 2021). "Heat stress"—short bursts of extremely high temperatures—will affect agricultural output more in the future. Since the last decade, India's wheat yields have suffered (Bairagi and Hassan, 2002; Tangle *et al.*, 2022; Tikadar and Kamble, 2021). Researchers have long acknowledged the significance to map soil and land use databases for sustainable natural resource management at the local, regional, and national levels (Baruah *et al.*, 2021; Metternicht, 2018; Pereira *et al.*, 2017). Irrigation, drainage, fertiliser, and other crop

1 & 5. Asstt. Professors, Centre for Climate Change and Water Research, Suresh Gyan Vihar University, Jaipur, Rajasthan

2. M.Tech Student, Centre for Climate Change and Water Research, Suresh Gyan Vihar University, Jaipur, Rajasthan

3. Assoc. Professor, School of Environment and Earth Sciences, Department of Geography, Central University of Punjab, Bhatinda (Corresponding Author)

4. Assoc. Professor, Centre for Sustainable Development, Suresh Gyan Vihar University, Jaipur, Rajasthan

management strategies, which are essential to PA, need understanding soil physical, biological, and chemical properties. Land use mapping can help evaluate regional to national management and policy. Remote sensing was utilised in agriculture before 1958 (Nellis, *et al.*, 2009).

Several studies have assessed agricultural remote sensing technology. While some research centred on specific application areas such as evaluating soil properties, measuring evapotranspiration, and managing disease and pests, others addressed more than one application area. (Courault *et al.*, 2005; Ge *et al.*, 2011; Maes and Steppe, 2012; Weiss, *et al.*, 2020). Most satellite data investigation depicts single-type acreage during the wet season (paddy) or winter (wheat or mustard). Due to weak remote sensing satellite data, limited agricultural variables, and significant heterogeneity crop patterns, little research has focused on distinguishing numerous crop types during crop seasons. This setting offers immense potential for mapping diverse crop types with a spatial precision of 10 metres using higher-resolution Sentinel-2B satellite data. An investigation will leverage Sentinel-2B satellite data to map winter crop types like wheat, mustard, and *rabi* crops (Parida *et al.*, 2021). Because of its consistency, the normalised difference vegetation index (NDVI) is one of the most widely used remote sensing indexes for measuring plant quality, including health, growth, and production. The Land Surface Water Index (LSWI) and Enhanced Vegetation Index (EVI) are also used to assess crop health and land cover (EVI). Since it is estimated from spectral bands sensitive to plant, soil moisture, and water properties, the LSWI is more specific to equal water thicknesses. (Felegari *et al.*, 2021).

Remotely sensed data is most useful for estimating acreage and yield. Farmed production before harvest helps to develop and implement successful agriculture management and export/import pricing. Several international researchers have used remote sensing data for crop inventory. The first regional satellite-based winter wheat projection study was the Large Area Crop Inventory Experiment (LACIE). Other nations have undertaken comparable investigations. Crop genetics, soil conditions, cultural practices (e.g., irrigation, fertiliser), temperature fluctuations, and biological impacts like plants, viruses, and pests affect yield. All of these factors affect a crop's spectrum analysis (Bairagi and Hassan, 2002; Rawat *et al.*, 2021; Tangle *et al.*, 2022; Tikadar and Kamble, 2021). The nation's main crops' output is measured by crop area and yield unit<sup>-1</sup> area. Complete enumeration estimates district agricultural acreage. However, the old method of assessing agricultural productivity has several drawbacks, including slow information distribution, doubts about patwari records, high capital and labour costs, and labor-intensive estimate methods. Better remote sensing equipment has replaced most surveying (Hunt *et al.*, 2019; Jha, *et al.*, 2013).

The study's primary objectives were, (1) To determine total crop area, (2) To estimate crop acreage and crop classification, (3) To predict crop yield unit<sup>-1</sup> area by

examining crop health, (4) To forecast and estimate crop yield early in the season or late in the season, and (5) To assess crop health using the Health Slicing and NDVI model.

### Study area

Alwar city serves as the district's administrative hub and is located in the state of Rajasthan in northern India. There are 8,380 km<sup>2</sup> in the district. The elevation of Alwar is 276 meters above sea level. Average temperature in Alwar is 24.9 °C, or 76.9 °F. Each year, this location receives about approximately 672 mm (26.5 inches) of precipitation (Tikadar and Kamble, 2021). According to 2011 Census figures, it is Rajasthan's third-most populous district (out of 33) after Jaipur and Jodhpur (Figure 1).

### Topography and drainage

The whole region is characterized by ridges of steep and precipitous hills that are, for the most part, parallel. The Aravalli Range is the district's most notable feature. From south to north and west to east, the hills are reported to get smaller in height and width.

### Geomorphology and soil type

The Aravalli ranges are often parallel and take the shape of ridges of stony hills. These first come in the district from the northeast in the Tijara division and extend south for roughly 24 km until coming to an end close to Naugaon. In the far southwest of the area next to Jaipur district, between Jindoli and Alwar, is Mandawar, another notable hill range. Nearly the whole Thanagaji and Rajgarh tehsils as well as nearly one-third of the Alwar tehsil 4 are covered by the low hills, which are also a notable feature of the Bansur, Kishangarh, and Tijara tehsils.

### Agriculture

The perspectives, effects, and adaptation tactics of disadvantaged farmers who grow wheat, mustard, and barley in Alwar and Jhunjhunu districts of Rajasthan. One significant agricultural practice linked to climate change is burning crop leftovers (Tikadar and Kamble, 2021). The crops for *rabi* include wheat, jou, gram, mustard, etc.; the crops for Jayad are fruits, vegetables, fodder, barseem, etc. Rajasthan's food crops include maize, wheat, jau, jawar, bajra, and pulses. Most observers are surprised by rural Rajasthan's highly diverse agricultural output. In addition to producing nearly 70% of the nation's guar, the state is India's largest producer of coarse grains, bajra, coriander, cumin, and other seed spices, including mustard and rapeseed. Large regions are dedicated to the cultivation of pulses, sugarcane, oilseeds, wheat, and barley. India's second-largest producer of oil seeds and one of the nation's top producers of edible oils is Rajasthan.

### Ground water level

Alwar district is largely underlain by Delhi Super Group rocks, with minor outcrops of Bhilwara Super Group and Post Delhi Intrusive at areas overlain by Quaternary alluvium. The presence of ground water in the district is mostly determined by geographic factors, physical traits, and structural features found in geological formations.

Ground water in the area occurs in confined conditions in phreatic zones, semi-confined conditions in deeper zones, and worn and fractured hard rock. The Central Ground Water Board monitors Alwar's National Hydrograph Network Stations (NHNS) four times a year: January, May (pre-monsoon), August, and November (Post-monsoon). The water level's depth depends on geography, drainage, bed rock, geology, and other factors. During the pre-monsoon season, Rajgarh, Tijara, and Laxmangarh (Govindgarh) blocks had shallow water levels of less than 10 metres, while Behror and Nimrana blocks had deepest water levels of more than 40 metres. The majority of the district's water depth is 10–40 m bgl. Behror and Neemrana blocks had the deepest water level, more than 40 m, while Rajgarh and Laxmangarh (Govindgarh) blocks had the shallowest, less than 10 m. Most of the region had 10–40 m bgl water depth. In 2019, the Alwar District's groundwater level rose 2.06% to 32.76 metres below ground level in 2019.

## MATERIALS AND METHODS

High-resolution Sentinel-2B data have been utilized to distinguish the wheat from other related *rabi* crops. Sentinel-2B data was acquired from the Copernicus Centerton to estimate the area, anticipate the production, and assess the health of the wheat in the Alwar District of Rajasthan. Satellite images were stacked and overlaid with certain bands to aid in the study. Using a supervised technique and the maximum likelihood algorithm, the crop categorization was finalized.

### Methods

The adopted methodology to pre-process satellite data has been discussed here as follows:

#### Resampling

Resampling performed to correct the original distorted image. The technique of assigning new pixel values to an original digital pixel was considered as resampling. In the current study, the SWIR band number 11 was downsampled from 20 m to 10 m using the nearest neighbour method.

#### Layer Stack

In the current study, we stacked blue, green, red, NIR, and SWIR bands to provide appropriate visibility of crops and other land use and cover features. The Sentinel 2 satellite picture layers bands 2, 3, 4, 8, and 11.

#### Mosaicing

A large-scale seamless high-resolution image was created using the image mosaic technique, which merges numerous overlapping satellite images.

#### Subsetting

Subsetting is the process of extracting a discrete chunk from a larger file. Spatial subsetting was done using region of interest shapefile.

#### Unsupervised classification

Without the assistance of labeled training examples, unsupervised classification is a method by which

every image in a dataset was determined to belong to one of the innate categories contained in the data acquisition.

#### Masking

The method of masking involves removing a certain land cover or land use trait for examination. The crop from remotely sensed data was identified by the pixel in a crop mask. Through ground truth points and supervised classification, crop mask was found in the current study.

#### Clump

The dispersion or gathering of leaves was described by the clumping index (CI), a canopy structural parameter. Prior to now, it was calculated using the multi-angle remote sensing data's normalized difference between hotspot and dark spot (NDHD).

#### Acreage and estimation

The crop acreage was used to compute the yields unit<sup>-1</sup> area. We computed agricultural acreage using remote sensing and geographic information system techniques. To estimate agricultural production, producers regularly count the quantity of a certain crop harvested in a sample region. The harvested crop was then weighed, and the sample crop production was extrapolated to reflect the total crop yield of the field.

When tracking how natural resources are being affected by the effects of climate change and human activity, reliable NDVI time series information was essential (Van Leeuwen *et al.*, 2006). Formula for NDVI calculation:

$$NDVI = (NIR - RED) / (NIR + RED) \dots \dots \dots \text{Equ. (1)}$$

Where,

NIR = Near-Infrared portion of the electromagnetic spectrum

RED = Red portion of the electromagnetic spectrum

To calculate LSWI following formulae has been used (Chandrasekar *et al.*, 2010):

$$LSWI = (NIR - SWIR) / (NIR + SWIR) \dots \dots \dots \text{Equ. (2)}$$

#### Crop yield

Crop yield represents the average quantity of produce realised agricultural<sup>-1</sup> area. The three major concepts of yield are biological yield, harvested yield, and economic output.

#### Yield estimation

This work provides a unique example of estimating within-field wheat production variability over a single year using openly accessible Sentinel-2 data (Hunt *et al.*, 2019). To do this, Sentinel-2 data were merged with environmental information collected at various stages throughout the growing season, including meteorological, topographical, and soil moisture data. To estimate yield, Random Forest (RF) regression models were utilised. According to the findings, Sentinel-2 data may be utilised to build exact maps of within-field yield variation at a resolution of 10 m.

#### Field validation

In the winter of 2020, a purposeful sample of 50 marginal farmers was taken. The information was acquired

from the respondent using a carefully created, tested, and produced questionnaire. All farmers in the identified sample respondents cultivate rainfed crops, followed by raising cattle (76 %). Farmers have a clear understanding of how the climate is changing, and they cite high temperatures (98%) and changing rain patterns (100%) as major concerns. Respondents reported crop loss due to climate change (98%) and a decline in soil moisture (100%) respectively.

## RESULTS AND DISCUSSION

### Landuse landcover

Successful land management requires LULC mapping. LULC modifications and environmental assessments guide optimal planning (Tripathi *et al.*, 2022). Satellite image classification uses several methods. Pixel-based picture categorization is common. These algorithms consider each image pixel's brightness and neighbourhood. Pixel-based and object-based image analysis are used nowadays. Object-based approaches may reliably create relevant image segments using structural or textural information and increase spectral information structure (Forkuor *et al.*, 2018).

Ten classifications in the Alwar district were taken. These categories included Urban Area (94.4 km<sup>2</sup>), Rural (132.67 km<sup>2</sup>), Crop Land (3272.65 km<sup>2</sup>), Fallow Land (1930 km<sup>2</sup>), Dense Forest (726.77 km<sup>2</sup>), Low Vegetation (181.67 km<sup>2</sup>), Waterbody (5.32 km<sup>2</sup>), Open Land (1920 km<sup>2</sup>), Road (48.25 km<sup>2</sup>), and Railways (6.70 km<sup>2</sup>), respectively. Total area cover is 8319.5807 km<sup>2</sup> as depicted in Figure 2 and the respective statistics were given in Table 1.

### Crop classification

Crop mapping is crucial for implementing sustainable farming practises and addressing environmental issues brought on by climate change and other factors. Crop classification gives crucial information that may be used to make a variety of decisions *viz.*, managing agricultural resource, management procedures etc. Satellite image processing can deliver accurate and fast information after employing information on crop type and dependable crop production based on modern categorization methods (Jiang *et al.*, 2020; Saini and Ghosh, 2018). In this work, decision trees were used to create crop categorization models based on remote sensing for certain cropping systems, and Sentinel-2 satellites (10 m) were used to track the distribution of the main crop species in 2017. Total Standing crop was mapped as it is the overall biomass of above-ground plants present at the location at a specific moment. The yield from this year and prior years were combined to form the standing crop. Based on seasonal circumstances and use by grazing cattle, the standing crop at a location varied both within and between years. The study area presents 4608.06 km<sup>2</sup> of Standing Crop, 702.175 km<sup>2</sup> of Fallow land, and 3004.07 km<sup>2</sup> of Other (Open, Tree, Built-up, etc.) as shown in Table 2.

The study presents *rabi* crop acreage where wheat crop covers 1929.10 km<sup>2</sup>, mustard crop and gram crop 2622.57

km<sup>2</sup>, other crops 56.4 km<sup>2</sup>, fallow land 702.18 km<sup>2</sup> and others 3004.07 km<sup>2</sup>, as shown in Table 3 and Figure 3.

### Wheat crop acreagemap of Alwar district

The recently deployed Sentinel-2 satellite is a strong option for mapping vegetation because it has thirteen spectral bands. This study used Sentinel-2 photos from a single date to categorise crop in the Indian state of Madhya Pradesh's Jabalpur. Unsupervised classification was used to perform the classification. Sentinel-2's Near Infrared, Red, Green, and Blue spectral bands were stacked in this study for the classification. According to the findings, there was an 83.07 % wheat crop, 14.64 % gram/pulses, and other crops (Rawat *et al.*, 2021).

As depicted in Table 4 and figure 4, tehsil-wise wheat crop acreage statistics of Alwar district showed wheat sown, other crops and fallow land in hectare of sixteen tehsils of the district. The wheat acreage for Alwar was 17327.41 ha, Behror 11558.1 ha, Bansur 22863.71 ha, Govindghar 3130.11 ha, Kathumar 4450.83 ha, Kishangarh Bas 10426.43 ha, Kotkasim 17341.14 ha, Lachhmangarh 10956.79 ha, Rajgarh 2742.13 ha, Malakhera 4929.69 ha, Mandawar 21295.16 ha, Neemrana 12191.77 ha, Ramgarh 16850.76 ha, Thanagazi 7205.78 ha, Tijara 25064.1 ha and Reni 4627.01 ha, while for other crops sown in the respective areas were Alwar 1270.36 ha, Behror 182.66 ha, Bansur 416.78 ha, Govindghar 46.06 ha, Kathumar 153.45 ha, Kishangarh Bas 293.09 ha, Kotkasim 127.39 ha, Lachhmangarh 322.4 ha, Rajgarh 591.68 ha, Malakhera 394.99 ha, Mandawar 260.56 ha, Neemrana 0.78 ha, Ramgarh 303.37 ha, Thanagazi 577.15 ha, Tijara 174.74 ha, and Reni 526.64 ha. Total area under fallow land was 70232.98 ha. The tehsil constituting largest area under fallow land was Bansur 9457.26 ha, Thanagazi 8243.35 ha, Reni 7865.15 ha, Ramgarh 5884.53 ha, Tijara 5739.66 ha, while the tehsil covering least area under fallow land were Govindghar 363.02 ha, Malakhera 774.44 ha, Kathumar 1778.75 ha, Neemrana 2936.92 and Behror 2964.32 ha.

### Alwar district wheat crop healthmap

Monitoring wheat's growth and acreage is helpful for assessing prior research and forecasting future productivity and food security at the national and regional levels. The crop's health depends on another crucial factor in determining the same. On the area's water and nutrient resources and soil. Based on remote sensing, the Normalized Crop Index (NCI) is a tool for assessing the health of crops. The image-transformation method known as NDVI measures vegetation by determining the distinction between Near Infrared with high reflectivity and high absorptivity red band. NDVI aids in assessing the health of the crop determined by the amount of chlorophyll in the crop. The data regarding wheat crop health in the research region are presented by categorising the NDVI values, from excellent to poor, using the health slicing model.

Based on the NDVI and LSWI values are shown in Table 5 for the years 2021 and 2022. The data were gathered on 21 October 2021, 10 November 2021, 10 December and 20 December 2021, with the maximum value

recorded for NDVI being 0.58, 0.68, 0.73, and 0.82, respectively, with the mean value recorded being 0.14, 0.19, 0.34, and 0.44. The maximum LSWI value recorded for 21 October 2021, 10 November 2021, 10 December and 20 December 2021, respectively, was 0.73, 0.61, 0.73, 0.86, while the mean value recorded was 0.02, 0.02, 0.1, 0.13. NDVI maximum values for 29 January 2022, 18 February 2022, 20 March 2022, 30 March 2022, 9 April 2022, and 19 April 2022 were 0.61, 0.56, 0.63, 0.51, 0.49, 0.47, and 0.37, respectively, while the mean value recorded was 0.32, 0.3, 0.32, 0.24, 0.23, 0.11, and 0.17. While, the maximum LSWI values were 0.49, 0.45, 0.48, 0.37, 0.33, 0.27, 0.24, while the mean values were 0.16, 0.15, 0.13, 0.06, 0.05, 0.08, 0.09, respectively. Results based on the data from 2021 to 19 April 2022 (Figure 5) the wheat crop health for the district is classified into four classes: Excellent ( $>0.6$ ), Good ( $=0.6$  to  $>0.5$ ), Average ( $=0.50$  to  $>0.3$ ), and Poor ( $=0.3$  to  $0.1$ ).

#### Area estimation

Crop area estimation and yield evaluation are the two primary factors in the production projection. Crop area estimation is useful and significant for a variety of policymakers and planners for the development of agriculture and policy decisions about procurement, price fixation, storage, buffer stock, public distribution, and other related issues.

For the purpose of area estimation, the crop was first classified using a supervised classification-based method, and then a maximum likelihood classifier was used with the ground truth points. The area of the wheat was calculated after creating the wheat crop mask by multiplying the quantity of pixels by the sum of the individual pixel areas. The Alwar district had a total wheat crop area of 192910 area (in hectares). The classified wheat crop is shown in closer detail in the Figure 5 when compared to sentinel 2 FCC satellite data from the Alwar district on March 20, 2022. The satellite image has the Ground Truth (GT) point overlaid on it. Visual interpretation of the optical data reveals that the wheat fields hidden in bright red spots. In healthy crops, the electromagnetic spectrum's NIR region reflected more light.

#### Yield estimation

The weight multiplied by the overall production area yields the total yield. Farmers are questioned about their estimates of the overall amount of crop collected. To calculate yield, divide this amount by the area of land that was planted. The FAO describes "crop yield" as "Harvested production unit<sup>-1</sup> of harvested area for crop items." Most of the time, yield data are calculated rather than documented by dividing production data by harvested area data.

#### Accuracy assessment by field validation

For the vast majority of the research region where

the place could be accessed, observations and verifications of the ground characteristics were gathered. The data were gathered in February. Assisted by the Excel Geomatics By 56 training locations several types of earth coverings were chosen as training grounds. On the ground, notable landmarks included GPS coordinates were also noted. On-site observations were also created for the principal waterways and logyards. Ground using area frame sampling, unaligned systematic random sampling, and the assistance of printable satellite images and topographic maps displaying the place and surroundings were observed. The sample location was landmarks were found to corroborate its arrival once it was precise location. A number was assigned to each observation station.

The present study has demonstrated the utility of multi-temporal remote sensing satellite data in wheat crop acreage and the crop yield mapping at the tehsil level of Alwar district, Rajasthan for *rabi* season crops during 2021-2022. Sentinel-2 satellite data were used to prepare a land use land cover map of Alwar district. A supervised classification technique followed by the maximum likelihood classifier was applied to achieve better accuracy in land use land cover mapping. The results exhibited that majority of the geographical area were covered by cropland (39.34%) followed by fallow land (23.2%), open land (23.08%), and dense forest (8.74%), across the district. It has also shown a very good correlation with field survey points. Remote Sensing data were effectively used for the discrimination, classification, and mapping of different types of crops with their different phenological stages. Satellite datasets were utilized in *rabi* crop acreage mapping, where the results showed that for Bansur tehsil, it was estimated as highest, i.e., 228.64 km<sup>2</sup>. Crop health was assessed based on the NCI tool by incorporating NDVI and LSWI values. Finally, crop yield data were calculated by dividing production data by harvested area data, further validated based on ground survey points.

Based on the study, it can be concluded that remote sensing can be used as a better stand alone tool in crop acreage and yield estimation. Satellite images can be used to map land use land cover of any region. It can also be used in crop type mapping very effectively. Crop acreage, crop health, and crop yield can also be estimated by using several remote sensing based indices. In the present study, we have shown the potential of remote sensing and GIS based technology for generating crop statistics at tehsil level. The availability of timely area and production forecast of crops is crucial for the planners and the policymakers for export, import, storage etc. Crop acreage, crop health, and crop yield statistics will help decision makers for the government funded schemes like Pradhan Mantri Fasal Bima Yojana (PMFBY).

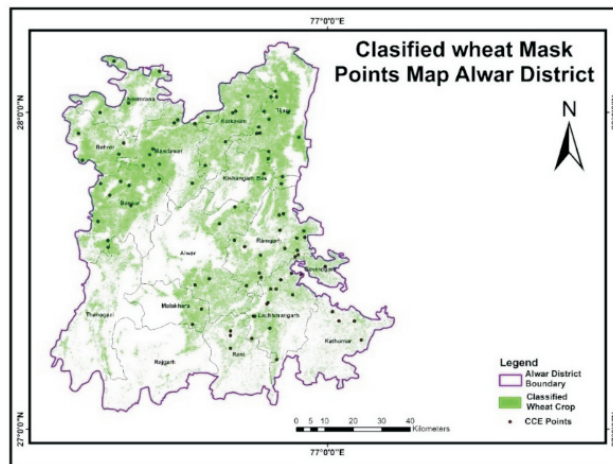
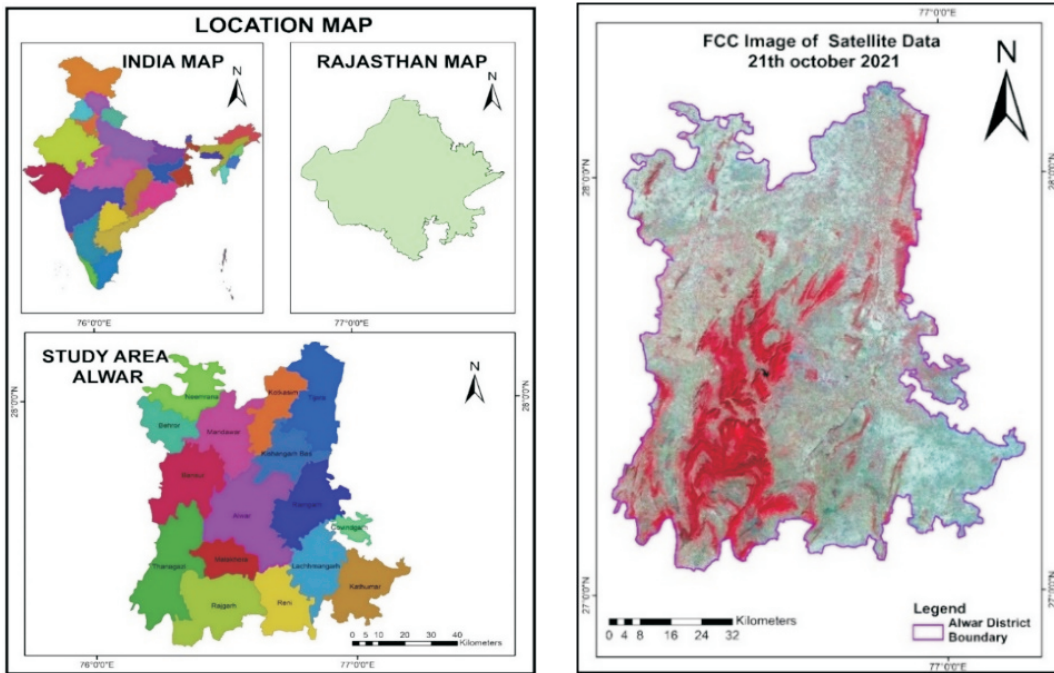


Figure 1. Study area map

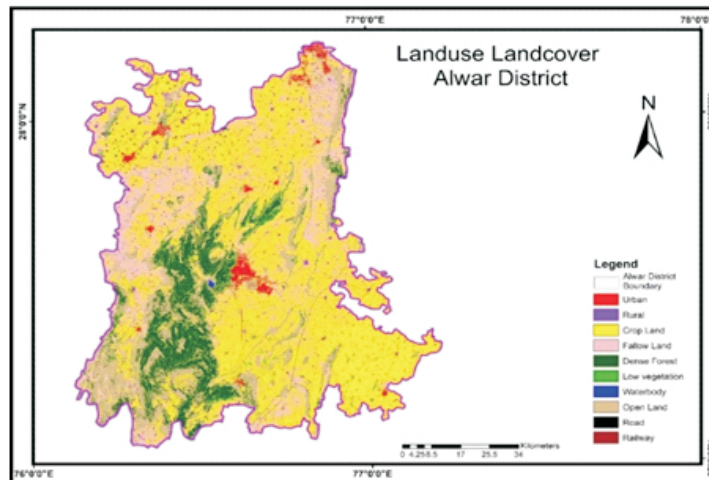


Figure 2. Land Use Land Cover map of Alwar district

**Table 1. Showing LULC area statistics of Alwar district**

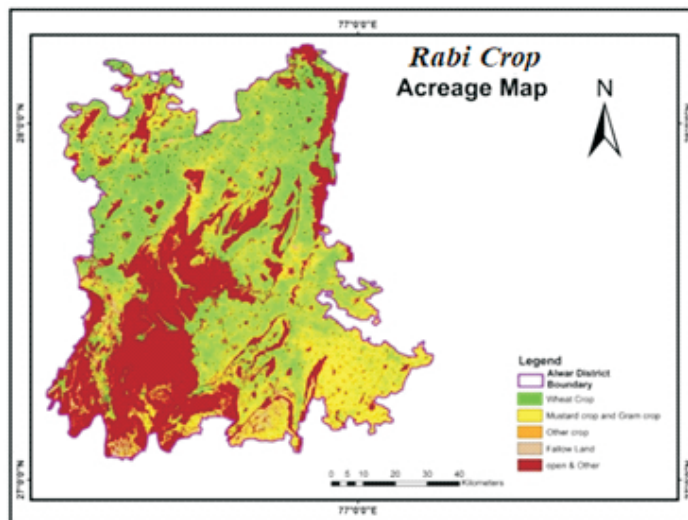
Sl. No.	Class Name	Histogram	Area (ha)	Area (km <sup>2</sup> )
1	Urban	944082	9440.82	94.4082
2	Rural	1326713	13267.13	132.6713
3	Crop Land	32726597	327265.97	3272.6597
4	Fallow Land	19304478	193044.78	1930.4478
5	Dense Forest	7267741	72677.41	726.7741
6	Low vegetation	1816782	18167.82	181.6782
7	Waterbody	53213	532.13	5.3213
8	Open Land	19206563	192065.63	1920.6563
9	Road	482591	4825.91	48.2591
10	Railway	67047	670.47	6.7047
<b>Total Area</b>		<b>8319.5807</b>		

**Table 2. Total standing crop statistics of Alwar district**

Crops	Area (km <sup>2</sup> )
Standing Crop	46219698
Fallow land	7060745
Other (Open, Tree, Built- Up, etc.)	29862685

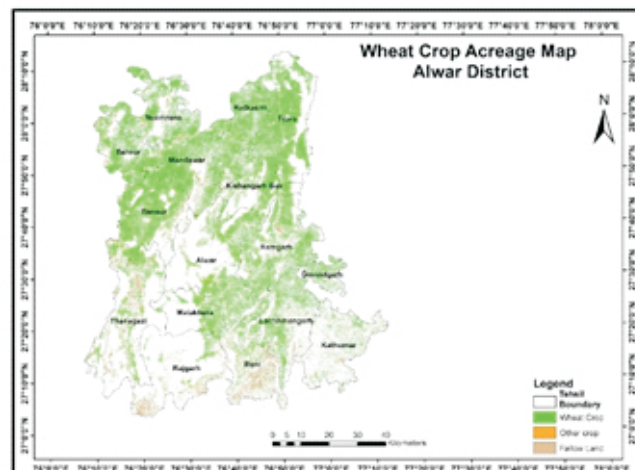
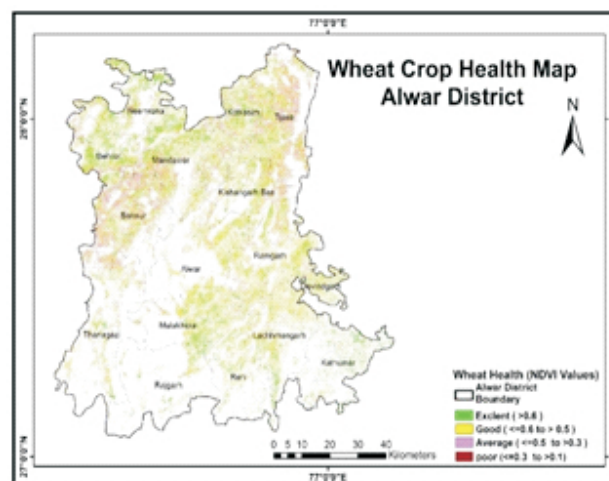
**Table 3. Rabi crop statistics of Alwar district**

Sl. No.	Class name	Histogram	Area (ha)	Area (km <sup>2</sup> )
1	Wheat Crop	19291027	192910	1929.1
2	Mustard crop and Gram crop	26225712	262257	2622.57
3	Other crop	563946	5639.46	56.3946
4	Fallow Land	7021749	70217.5	702.175
5	Others	30040694	300407	3004.07

**Figure 3. Rabi season crop acreage map**

**Table 4. Tehsil-wise wheat crop acreage statistics of Alwar district**

Sr. No.	Name of Tehsil	Wheat (ha)	Other Crop (ha)	Fallow Land (ha)
1	Alwar	17327.41	1270.36	4718.06
2	Behror	11558.1	182.66	2964.32
3	Bansur	22863.71	416.78	9457.26
4	Govindghar	3130.11	46.06	363.02
5	Kathumar	4450.83	153.45	1778.75
6	Kishangarh Bas	10426.43	293.09	3170.48
7	Kotkasim	17341.14	127.39	3131.45
8	Lachhmangarh	10956.79	322.4	3359.19
9	Rajgarh	2742.13	591.68	4209.75
10	Malakhera	4929.69	394.99	774.44
11	Mandawar	21295.16	260.56	5636.65
12	Neemrana	12191.77	0.78	2936.92
13	Ramgarh	16850.76	303.37	5884.53
14	Thanagazi	7205.78	577.15	8243.35
15	Tijara	25064.1	174.74	5739.66
16	Reni	4627.01	526.64	7865.15

**Figure 4. Wheat crop acreage map of Alwar district****Figure 5. Wheat crop health map of Alwar district**



**Table 5. NDVI and LSWI Values**

Date	NDVI		LSWI	
	max value	mean value	max value	mean value
21-Oct-21	0.58	0.14	0.72	0.02
10-Nov-21	0.68	0.19	0.61	0.02
10-Dec-21	0.73	0.34	0.73	0.1
20-Dec-21	0.82	0.44	0.86	0.13
29-Jan-22	0.61	0.32	0.49	0.16
18-Feb-22	0.56	0.3	0.45	0.15
28-Feb-22	0.63	0.31	0.48	0.13
20-Mar-22	0.51	0.24	0.37	0.06
30-Mar-22	0.49	0.23	0.33	0.05
09-Apr-22	0.47	0.11	0.27	0.08
19-Apr-22	0.37	0.17	0.24	0.09

## REFERENCES

- Bairagi, G. D. and Zia-Ul Hassan, 2002. "Wheat Crop Production Estimation Using Satellite Data." *J. Indian Soc. Remote Sens.* **30**(4):213–19. doi: 10.1007/BF03000364.
- Baruah, Nikhillesh, Ratna Kinkor Goswami, and Shobha Dutta Deka, 2021. "Influence of Land Configuration and Residue Management in *rabi* Crops under Rainfed Ecosystem of Assam." *J. Soils and Crops*, **31**(2):204–12.
- Bele, Krunal N., Gautam R. Shamkuwar, Rajesh D. Deotale, and Aditi S. Deshmukh, 2021. "Screening of White and Pigmented Rice Cultivars for Biochemical and Yield and Yield Contributing Characters." *J. Soils and Crops*, **31**(2): 355–59.
- Chandrasekar, K., M. V. R. Sessa Sai, P. S. Roy, and R. S. Dwevedi, 2010. "Land Surface Water Index (LSWI) Response to Rainfall and NDVI Using the MODIS Vegetation Index Product." *Int. J. Remote Sens.* **31**(15):3987–4005. doi: 10.1080/01431160802575653.
- Courault, Dominique, Bernard Seguin, and Albert Olioso, 2005. "Review on Estimation of Evapotranspiration from Remote Sensing Data: From Empirical to Numerical Modeling Approaches." *Irrig. Drain. Syst.*, **19**(3–4):223–49. doi: 10.1007/s10795-005-5186-0.
- Doraiswamy, Paul C., Sophie Moulin, Paul W. Cook, and Alan Stern, 2003. "Crop Yield Assessment from Remote Sensing." *Photogramm. Eng.* **69** (6):665–74. doi: 10.14358/PERS.69.6.665.
- Dubey, Rachana, Himanshu Pathak, Bidisha Chakrabarti, Shivdhar Singh, Dipak Kumar Gupta, and R. C. Harit, 2020. "Impact of Terminal Heat Stress on Wheat Yield in India and Options for Adaptation." *Agric. Syst.* **181**:102826. doi: 10.1016/j.agsy.2020.102826.
- Felegari, Shilan, Alireza Sharifi, Kamran Moravej, Muhammad Amin, Ahmad Golchin, Anselme Muzirafuti, Aqil Tariq, and Na Zhao, 2021. "Integration of Sentinel 1 and Sentinel 2 Satellite Images for Crop Mapping." *Appl. Sci.* **11**(21):10104. doi: 10.3390/app112110104.
- Forkuor, Gerald, Kangbeni Dimobe, Idriss Serme, and Jerome Ebagnerin Tondoh, 2018. "Landsat-8 vs. Sentinel-2: Examining the Added Value of Sentinel-2's Red-Edge Bands to Land-Use and Land-Cover Mapping in Burkina Faso." *GIsci Remote Sens.* **55**(3):331–54. doi: 10.1080/15481603.2017.1370169.
- Ge, Yufeng, J. Alex Thomasson, and Ruixiu Sui, 2011. "Remote Sensing of Soil Properties in Precision Agriculture: A Review." *Front. Earth Sci.* **5**:229–238. doi: 10.1007/s11707-011-0175-0.
- Hunt, Merryn L., George Alan Blackburn, Luis Carrasco, John W. Redhead, and Clare S. Rowland, 2019. "High Resolution Wheat Yield Mapping Using Sentinel-2." *Remote Sens. Environ.* **233**:111410. doi: 10.1016/j.rse.2019.111410.
- Jha, Ankita, A. S. Nain, and Rajeev Ranjan, 2013. "Wheat Acreage Estimation Using Remote Sensing in Tarai Region of Uttarakhand." *Vegetos- An Inter. Jour. of Plnt. Rese.* **26**(2):105. doi: 10.5958/j.2229-4473.26.2.061.
- Jiang, Yulin, Zhou Lu, Shuo Li, Yongdeng Lei, Qingquan Chu, Xiaogang Yin, and Fu Chen, 2020. "Large-Scale and High-Resolution Crop Mapping in China Using Sentinel-2 Satellite Imagery." *Agriculture*. **10**(10):433. doi: 10.3390/agriculture10100433.
- Maes, W. H., and K. Steppe, 2012. "Estimating Evapotranspiration and Drought Stress with Ground-Based Thermal Remote Sensing in Agriculture: A Review." *J. Exp. Bot.* **63**(13):4671–4712. doi: 10.1093/jxb/ers165.
- Metternicht, Graciela, 2018. *Land Use and Spatial Planning*. **1**(XVII, 116). doi: https://doi.org/10.1007/978-3-319-71861-3.
- Nellis, M., Kevin Price, and Donald Rundquist, 2009. "Remote Sensing of Cropland Agriculture." *The SAGE Handbook of Remote Sensing*. **1**. doi: 10.4135/978-1-8570-2105-9.n26.
- Panigrahy, S., and S. A. Sharma, 1997. "Mapping of Crop Rotation Using Multidate Indian Remote Sensing Satellite Digital Data." *ISPRS J. Photogramm. Remote Sens.* **52**(2):85–91. doi: 10.1016/S0924-2716(97)83003-1.
- Parida, Bikash Ranjan, Amritesh Kumar, and Avinash Kumar Ranjan, 2021. "Crop Types Discrimination and Yield Prediction Using Sentinel-2 Data and AquaCrop Model in Hazaribagh District, Jharkhand." *KN - J. Cartogr. Geogr. Inf.* 1-13. doi: 10.1007/s42489-021-00073-4.
- Pereira, Paulo, Erik Brevik, Miriam Munoz-Rojas, and Bradley Miller, 2017. *Soil Mapping and Process Modeling for Sustainable Land Use Management*. 1st ed. Elsevier.
- Rawat, Umakant, Ankit Yadav, P. S. Pawar, Aniket Rajput, Devendra Vasht, and S. Nema, 2021. "Determining Wheat Crop Acreage Based on Remote Sensing and GIS Technique in Jabalpur, India." Pp. 63–69 in *Current Topics in Agricultural Sciences Vol. 3*, edited by Dr. R. Teodor. Book Publisher International (a part of SCIENCEDOMAIN International).

- Saini, R., and S. K. Ghosh, 2018. "Crop Classification on Single Date Sentinel-2 Imagery Using Random Forest and Support Vector Machine." *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XLII-5, **683**(88). doi: 10.5194/isprs-archives-XLII-5-683-2018.
- Tangle, Ajay F., G. R. Shamkuwar, R. D. Deotale, and S. G. Shamkuwar, 2022. "Evaluation of Rice Genotypes for Bio Chemical and Yield and Yield Contributing Factors." *J. Soils and Crops*, **32**(1):123–26.
- Tikadar, K. S., and R. K. Kamble, 2021. "Wheat, Mustard and Barley cultivating marginalized farmers' climate change perceptions, impacts and adaptation strategies in Alwar and Jhunjhun districts, Rajasthan, India." *EJESM*. **14**(5):629–44.
- Tripathi, Gaurav, Arvind Chandra Pandey, and Bikash Ranjan Parida, 2022. "Flood Hazard and Risk Zonation in North Bihar Using Satellite-Derived Historical Flood Events and Socio-Economic Data." *Sustainability*. **14**(3):1472. doi: 10.3390/su14031472.
- Van Leeuwen, Willem J. D., Barron J. Orr, Stuart E. Marsh, and Stefanie M. Herrmann, 2006. "Multi-Sensor NDVI Data Continuity: Uncertainties and Implications for Vegetation Monitoring Applications." *Remote Sens. Environ.* **100**(1):67–81. doi: 10.1016/j.rse.2005.10.002.
- Weiss, M., F. Jacob, and G. Duveiller, 2020. "Remote Sensing for Agricultural Applications: A Meta-Review." *Remote Sens. Environ.* **236**:111402. doi: 10.1016/j.rse.2019.111402.

**Rec. on 23.11.2022 & Acc. on 07.12.2022**