



International Journal of Research in Agronomy

E-ISSN: 2618-0618

P-ISSN: 2618-060X

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www.agronomyjournals.com

2024; 7(12): 475-483

Received: 15-10-2024

Accepted: 22-11-2024

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Estimation of chickpea yield in the dediapada taluka using remote sensing and GIS

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DOI: <https://doi.org/10.33545/2618060X.2024.v7.i12f.2199>

Abstract

This study aims to evaluate the agricultural productivity of the Dediapada taluka using remote sensing and GIS technologies, focusing on NDVI and fAPAR data to estimate chickpea yield. The research spans two growing seasons, 2022-2023 and 2023-2024, utilizing satellite imagery from MODIS and Sentinel-2 combined with ground data collected from local sources. NDVI and fAPAR analyses reveal significant variations in vegetation health and productivity across the study area. The NDVI maps indicate high values during peak greenness periods, suggesting healthy crop growth. The fAPAR maps, derived from NDVI values, highlight regions with high photo synthetically active radiation absorption, correlating with higher productivity zones. Yield estimation models, incorporating APAR and other crop parameters, provide accurate predictions of chickpea yield. For the 2022-2023 season, the highest yield areas contributed 43.51% and 41.42% of the total area, with yields between 1.2-1.5 t/ha and 1.5-2.0 t/ha, respectively. The total estimated yield was approximately 1.59 t/ha. In the 2023-2024 season, the high-yield areas increased to 47.19% and 37.55%, with similar yield ranges. The total estimated yield improved to approximately 1.74 t/ha. The study underscores the importance of remote sensing data in providing timely and accurate yield estimates, which are crucial for effective agricultural planning and decision-making. The integration of NDVI and fAPAR indices with GIS tools presents a robust framework for monitoring and enhancing crop productivity in the Dediapada Taluka.

Keywords: Dediapada talukas, chickpea, GIS, agricultural

1. Introduction

Crop yield estimation in various countries is based on traditional data collection techniques for crop and yield estimation, which include on-the-ground field visits and reports. These reports are frequently subjective and take more time and money to complete. They are prone to large errors due to insufficient ground observations, which leads to inaccurate crop yield and production estimates [Bhattacharyay *et al.*, 2020; Gummadi *et al.*, 2022] ^[3, 9]. Crop yield estimation also can be done by using remote sensing data. Yield estimation using remote sensing is done by using statistical methods, like regression analysis and modelling in GIS and excels, including classification and estimation. With the advent of remote sensing and GIS technologies, it has come possible to estimate crop yields using various methodologies. In tropical regions, chickpea is cultivated as a winter crop and in temperature clines, as a spring or summer crop [Frimpong *et al.*, 2009] ^[7]. Chickpeas are grown across 59 nations in an area of 14.8 Mha, producing 15.1 million tons annually [FAOSATAT Crops. 2021]. In India, chickpea has played a significant role in the 'Pulse Revolution', making the country self-sufficient in pulses. From a level of seven 75.9 lakh tonnes in 2014-15, chickpea production rose to an all-time high of 126.1 lakh tones during 2020-21. Main food grain crops cultivated in Dediapada are Wheat, Jowar and Maize, Paddy while major oil seeds grown in the district are Groundnut and Castor, whereas the main crop cultivated in Dediapada are cotton and Gram.

In this aspect to the crop yield for asses the crop yield for the interior areas where no more data are available to assess the crop yield using Remote Sensing and GIS is very useful.

2. Materials and Methods

2.1 Data Collection

The data of crop yield was collected KVK, NAU, Dediapada for the year 2023 to 2024.

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The satellite image of MODIS was downloaded from USGS (United States Geological Survey) Earth explorer official website and sentinel-2 was downloaded from Copernicus Open Access Hub official website and other data were air temperature, relative humidity and solar azimuth calculate from NOAA (National Oceanic and Atmospheric Administration).

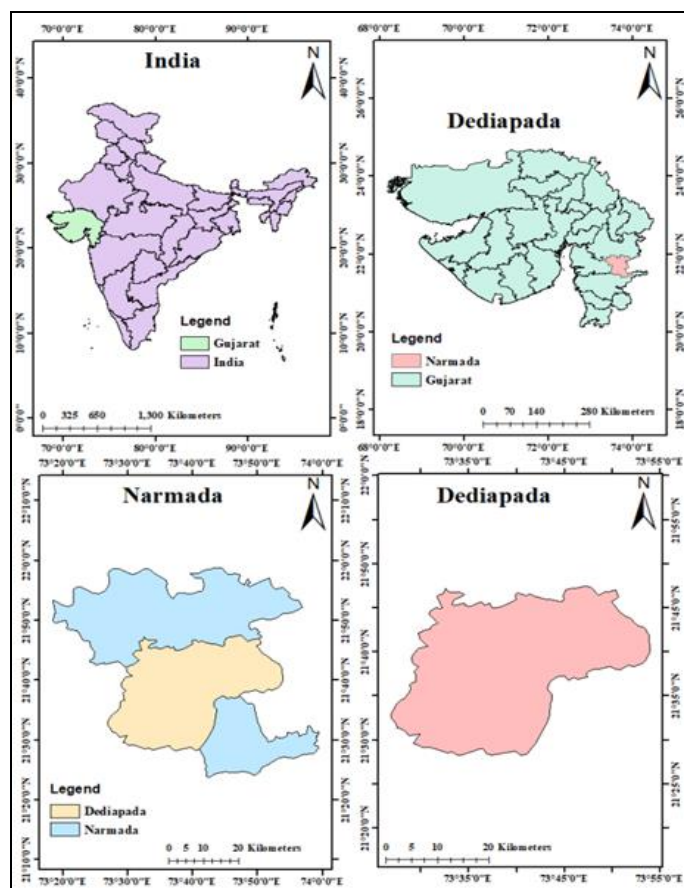


Fig 1: Location map of the study area

2.2 Study Area

Dediapada is a town in the Southern most region of Gujarat. It's a part of the Narmada District, Gujarat, India was selected as study area. The region is surrounded by forest and is abundant with diverse flora and fauna. Dediapada bounded by Umapada taluka towards South, Sagabara taluka towards East, Nandod and Rajpipala taluka towards North. Dediapada lies between 21° 37' 35" N (North Latitude) and 73° 35' 20" E (East Longitude) with an elevation of 169m above mean sea level covering an area of 1026.84 km².

The taluka has 168 Villages. It is biggest taluka of Narmada. The total population of Dediapada Taluka is 174,449 out of which urban population is 9,026 while rural is 165,423. Check out important data about Dediapada Taluka as per Census 2011. The climatic condition of the area is Semi-arid to dry sub-humid. The average minimum and maximum temperature of the year varying from 22.5°C to 30.75°C. The monsoon commenced by third week of June. The annual rainfall is 1205 mm. The soil is deep black clayey Soils with high moisture retention capacity which is poor in nitrogen medium in phosphorous and high in potash. Most of the area cultivated, some area non-cultivated under fallow and pasture forest.

2.3 Satellite Data Used

2.3.1 Sentinel Satellite Data

The Sentinels are a constellation of satellites developed by ESA

to operationalize the Copernicus program, which include all-weather radar images from Sentinel-1A and 1B, high-resolution optical images from Sentinel-2A and 2B, ocean and land data suitable for environmental and climate monitoring from Sentinel-3, as well as air quality data from Sentinel-5P.

Sentinel imagery supports precision agriculture by providing information on crop health, vegetation vigor, soil moisture content, and crop yield estimation. Farmers can use this data for better decision-making regarding irrigation, fertilization, and pest management [Source: European Space Agency (ESA)-Copernicus Programme].

2.3.2 Sentinel-2 satellite Data

SENTINEL-2, launched as part of the European Commission's Copernicus program on June 23, 2015, was designed specifically to deliver a wealth of data and imagery. The satellite is equipped with an opto-electronic multispectral sensor for surveying with a sentinel-2 resolution of 10 to 60 m in the visible, near infrared (VNIR), and short-wave infrared (SWIR) spectral zones, including 13 spectral channels, which ensures the capture of differences in vegetation state, including temporal changes, and also minimizes impact on the quality of atmospheric photography. The orbit is an average height of 785 km and the presence of two satellites in the mission allows repeated surveys every 5 days at the equator and every 2-3 days at middle latitudes.

The Sentinel-2 data provides GMES (Global Monitoring for Environment and Security) program, jointly implemented by the EC (European Commission) and ESA (European Space Agency) services related, for example, to land management, agricultural production and forestry, and monitoring of natural disasters and humanitarian operations. (Source: Sentinel-2: Satellite Imagery, Overview, And Characteristics (eos.com))

2.3.3 Derivation of NDVI and fAPAR from satellite image

A. NDVI

NDVI or Normalized Difference Vegetation Index is a remote sensing method that uses the reflectance of light in the visible and near-infrared (NIR) wavelengths to determine the amount and health of vegetation in an area. NDVI is widely used in agriculture, forestry, and ecology to monitor the growth and health of vegetation and to identify areas of stress or damage. NDVI values can also be used to map and classify vegetation types, and to detect changes in vegetation cover over time.

NDVI (Normalized Difference Vegetation Index) is a remote sensing method that was first developed in the 1970s. The concept of using the reflectance of light in the visible and near-infrared (NIR) wavelengths to determine the amount and health of vegetation was first proposed by a scientist named Rouse, in 1973. He used two filters, one to detect the red light and one to detect the near-infrared light. He calculated NDVI by subtracting the reflectance of the NIR band from the reflectance of the red band and then dividing that value by the sum of the reflectance of the NIR and red bands.

The formula below for the evaluation of NDVI

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)}$$

NDVI values range from -1 to 1, with -1 indicating no vegetation, 0 indicating bare soil or water, and values closer to 1 indicating greater amounts and healthier vegetation.

Table 1: NDVI Value

Sr. No.	NDVI Value	Descriptions
1.	-1 to 0	Dead plant or inanimate object
2.	0 to 0.33	Unhealthy plant
3.	0.33 to 0.66	Moderately healthy plant
4.	0.66 to 1	Very healthy plant

Source: [https://www.cropin.com/blogs/ndvi-normalized-difference-vegetation index#](https://www.cropin.com/blogs/ndvi-normalized-difference-vegetation-index#):

B. Modis LAI/FPAR

The MCD15A3H Version 6.1 Moderate Resolution Imaging Spectroradiometer (MODIS) Level 4, Combined Fraction of Photo Synthetically Active Radiation (FPAR), and Leaf Area Index (LAI) product is a 4-day composite data set with 500-meter pixel size. The algorithm chooses the best pixel available from all the acquisitions of both MODIS sensors located on NASA's Terra and Aqua satellites from within the 4-day period. FPAR is defined as the fraction of incident photosynthetically active radiation (400-700 nm) absorbed by the green elements of a vegetation canopy.

fPAR

fPAR is the fraction of Photosynthetically active radiation (400-700 nm) absorbed by green vegetation. fPAR data is derived from remote sensing observations, often obtained via satellite sensors like MODIS or VIIRS, which measure the reflectance of vegetation across different wavelengths. This information facilitates the monitoring of vegetation dynamics over time, including changes in growth patterns and seasonal variations. Moreover, fPAR serves as a crucial input for estimating vegetation productivity, carbon uptake through photosynthesis, and simulating land surface processes in Earth system models. Its applications extend to crop monitoring, where it aids in assessing crop growth and predicting yields, thus informing agricultural practices and food security strategies. Ultimately, fPAR data contributes significantly to our understanding of ecosystem functioning, ecosystem health, and the broader implications for land management and environmental policy decisions.

fPAR quantifies the fraction of sunlight that plants utilize for photosynthesis, which is crucial for their growth, biomass production, and overall health. It provides valuable information about the efficiency of light interception and utilization by vegetation.

fPAR is a key parameter in studies related to vegetation dynamics, ecosystem productivity, and carbon cycling. It is often used in conjunction with remote sensing techniques to monitor changes in vegetation cover, assess vegetation health, and estimate primary productivity at regional and global scales.

2.4 Yield Estimation by Satellite Image

During crop growing period of Dediapada Taluka, sentinel 2 image from Copernicus Open Access Hub was chosen for this study. The satellite image was registered and polyconic projection was applied uniformly to all the datasets with latitude/longitude information in degrees. A block level map of Dediapada Taluka was extracted from the shape file of India and boundary of this map was used to extract Dediapada Taluka from the satellite imageries. Dediapada block level map was digitized and polygons of these blocks were converted into Area of Interests (AOI) to use further to extract block level subsets. Utilizing remote sensing images, this approach estimates chickpea yield. Remote sensing provides precise information, allowing for accurate yield estimation.

Yield estimation refers to the process of predicting the amount of agricultural produce, typically crops, that will be harvested from a given area or field. It's an essential aspect of agricultural management and decision-making, providing valuable insights into crop productivity, resource allocation, and food security. Yield was estimated using a simple model derived from [Monteith *et al.*, 1972, 1977]^[15].

$$Yield = \frac{APAR \times \epsilon \times HI}{(1 - m_{oi})}$$

Where,

ϵ is light use efficiency in units of g biomass (MJ PAR⁻¹),

HI is the harvest index,

m_{oi} is moisture content

Light Use Efficiency (ϵ)

Light Use Efficiency (ϵ) is the efficiency with which the absorbed light is converted into biomass. It is usually measured in grams of biomass per mega joule of PAR. ϵ is a key factor in determining the overall productivity of a plant. Higher light use efficiency means that the plant is more effective at converting light energy into chemical energy (biomass). In models that estimate crop yield, ϵ helps in predicting the potential biomass production based on the amount of light absorbed by the crop canopy.

Harvest Index (HI)

Harvest Index (HI) is the ratio of the economic yield (grain yield) to the total above-ground biomass. A higher harvest index means a greater proportion of the plant's biomass is allocated to the harvestable part. The Harvest Index (HI) is a measure used in agriculture to quantify the efficiency of a crop in converting the total biomass produced into the economic yield, such as grain, tuber, or fruit.

Moisture content (m_{oi})

The ratio of the mass of water in the crop to the total mass of the crop, usually expressed as a percentage. Accurate moisture content measurement is essential for standardizing crop yield data. Yield is often reported at standardized moisture content to ensure consistency and comparability across different studies and regions. Moisture content can be measured using portable moisture meters, which provide quick and accurate readings. These devices work by measuring the electrical resistance or capacitance of the crop, which changes with moisture content. Advances in remote sensing technology allow for the estimation of moisture content over large areas. This involves using satellite data to monitor crop conditions and estimate moisture levels.

In this case, as in most studies, HI and ϵ refers only to above ground biomass and does not include roots. m_{oi} is the moisture content of product during harvest. The ϵ was taken as 2.5 and Harvest index at HI=0.237 and moisture content (m_{oi}) as 10%.

2.4.1 APAR Calculation

APAR quantifies the amount of solar energy absorbed by plants and used for the process of photosynthesis, which is crucial for their growth, development, and productivity. It serves as a key indicator of the photosynthetic activity and health of vegetation. APAR is an important metric in various fields, including agriculture, ecology, and environmental science. It helps researchers and practitioners assess plant productivity, monitor

changes in vegetation health, and understand ecosystem dynamics. By measuring APAR, scientists can gain insights into the functioning of ecosystems, carbon sequestration processes, and the impacts of environmental factors on vegetation. Measurements of APAR (MJ from 400-700 nm) estimated as the product of incident photo synthetically active radiation (IPAR) and the fraction of PAR absorbed by the canopy (fAPAR), summed over the growing season.

$$\text{APAR} = \sum (\text{IPAR} * \text{fAPAR}) \Delta t$$

$$\text{APAR} = G * E_c * \text{fAPAR}$$

$$\text{APAR} = G * \text{fAPAR} * (E_{c, \text{dif}} + E_{c, \text{dir}})$$

Where,

G= Global incident short wave radiation ($\text{MJ m}^{-2} \text{ day}^{-1}$);

E_c =Climatic efficiency: $E_{c, \text{dif}}$ -Diffuse and $E_{c, \text{dir}}$ -Direct) (400-700 nm) in the short wave radiation (300-3000 nm)

Where G and E_c are daily values, the total in case of G and average in case of E_c and fAPAR.

A. IPAR (Incident Photosynthetically Active Radiation)

The amount of PAR that reaches the plant canopy. Measured using PAR sensors or estimated from satellite data.

B. Time Interval (Δt)

The time period over which the measurements are taken. Typically defined based on the study or observation period.

C. Global Incident Short Wave Radiation (G)

The total solar radiation received at the Earth's surface. Measured using pyranometers or estimated from satellite data.

D. Conversion Efficiency (E_c)

The efficiency with which global radiation is converted into PAR. Derived from empirical models or field measurements.

E. Diffuse Conversion Efficiency ($E_{c, \text{dif}}$)

The efficiency with which diffuse radiation is converted into PAR. Derived from empirical models or field measurements.

F. Direct Conversion Efficiency ($E_{c, \text{dir}}$)

The efficiency with which direct radiation is converted into PAR. Derived from empirical models or field measurements. Climatic efficiency varies mainly with atmospheric conditions, [Blackburn *et al.*, 1983] but also with the solar elevation, geographical location and the time (hour, day or month) [Oliso *et al.*, 1987]. These values were obtained from the model.

2.4.2 fAPAR Calculation

Extract the Fraction of Absorbed Photosynthetically Active Radiation (fAPAR) values from the MODIS imagery. Fraction of absorbed photosynthetically active radiation (fAPAR) was calculated from the NDVI image by the following model [Sellers *et al.*, 1996].

$$\text{fAPAR} = \frac{(\text{NDVI} - \text{NDVI}_{\min})(\text{fAPAR}_{\max} - \text{fAPAR}_{\min})}{(\text{NDVI}_{\max} - \text{NDVI}_{\min})} + \text{fAPAR}_{\min}$$

Where,

$\text{NDVI}_{\min}$ and $\text{NDVI}_{\max}$ are the minimum and maximum NDVI values for the entire region of interest.

$\text{fAPAR}_{\min}$ and $\text{fAPAR}_{\max}$ are the defined minimum and maximum values of fAPAR

A. $\text{NDVI}_{\min}$ and $\text{NDVI}_{\max}$

The minimum NDVI value observed in the study area or for a specific vegetation type. It represents the baseline NDVI value, often corresponding to bare soil or non-vegetated surfaces.

The maximum NDVI value observed in the study area or for a specific vegetation type. It represents the peak NDVI value, often corresponding to the densest and healthiest vegetation.

B. $\text{fAPAR}_{\min}$ and $\text{fAPAR}_{\max}$

The minimum fAPAR value observed, often corresponding to non-vegetated surfaces or very sparse vegetation. It sets the lower bound for fAPAR values in the study area.

The maximum fAPAR value observed, often corresponding to the densest and healthiest vegetation. It sets the upper bound for fAPAR values in the study area.

3. Results and Discussion

3.1 NDVI Map of the study area

NDVI is considered a useful way to model crop yield assessment using a variety of approaches, from simple integration to more complex transformations. NDVI reflects the greenness of vegetation, thus indicating the level of healthiness of vegetation growth. Although vegetation growth of crop fields may differ from natural vegetation due to human influences such as irrigation, fertilizer and pesticide use, NDVI is considered a valuable source of information for crop condition [Prasad *et al.*, 2006] [17]. The NDVI data have been used extensively in vegetation monitoring, crop yield assessment and forecasting [Hayes, *et al.*, 1982; Rasmussen, *et al.*, 1992; Benedetti, *et al.*, 1993; Quarmby *et al.*, 1993] [10, 19, 2, 18].

In the case of the Sentinel 2 images, NDVI was calculated for both NIR bands (B8 and B8A) in order to establish which band results are better for NDVI calculation [Jelinek *et al.*, 2020] [11]. Generally, the Chickpea season in Gujarat continues from the month of October/November to February/March. Consequently, the maximum NDVI values can be found during peak greenness period of crop life cycle, which is around the month of March. All month NDVI map for 2022-23 and 2023-24 is as shown in Figure (2 & 3).

3.2 fAPAR Map of the study area

The Fraction of Absorbed Photosynthetically Active Radiation (fAPAR) is a critical parameter in remote sensing and vegetation studies. It quantifies the amount of incoming solar radiation that is absorbed by green vegetation for photosynthesis. The Fraction of Absorbed Photosynthetically Active Radiation (fAPAR) plays a crucial role in accurate estimation of crop yield. When combined with NDVI, it provides a more comprehensive understanding of vegetation health and productivity. Remember that fAPAR considers the actual radiation absorbed by the canopy during photosynthesis, making it an essential factor for yield models. fAPAR, derived from NDVI, quantifies the fraction of Photosynthetically Active Radiation absorbed by plants. It serves as a direct indicator of vegetation productivity and biomass accumulation [Chen *et al.*, 2019]. The fAPAR map of the study area is shown in Figure (4 & 5) for 2022-23 and 2023-24.

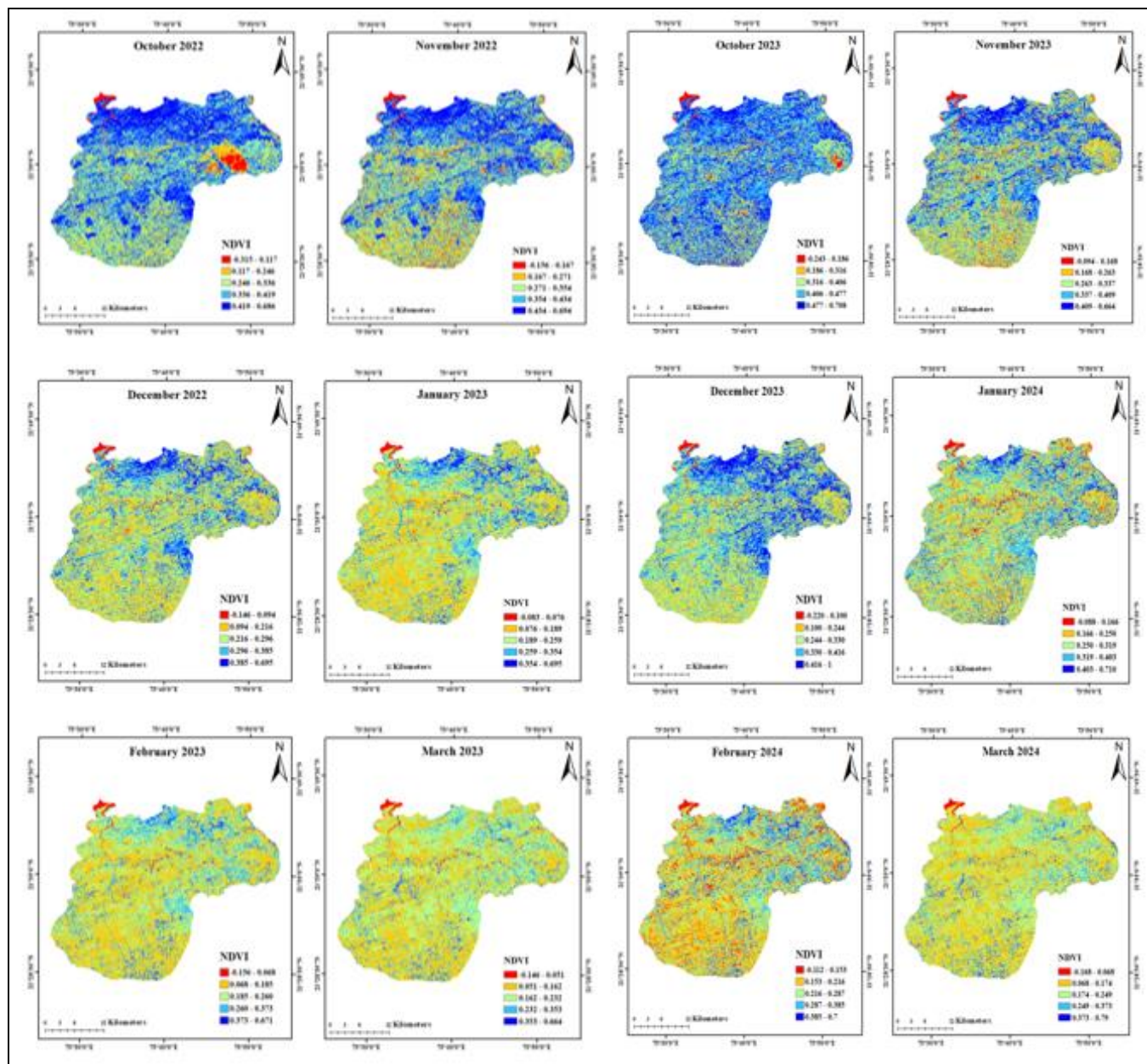
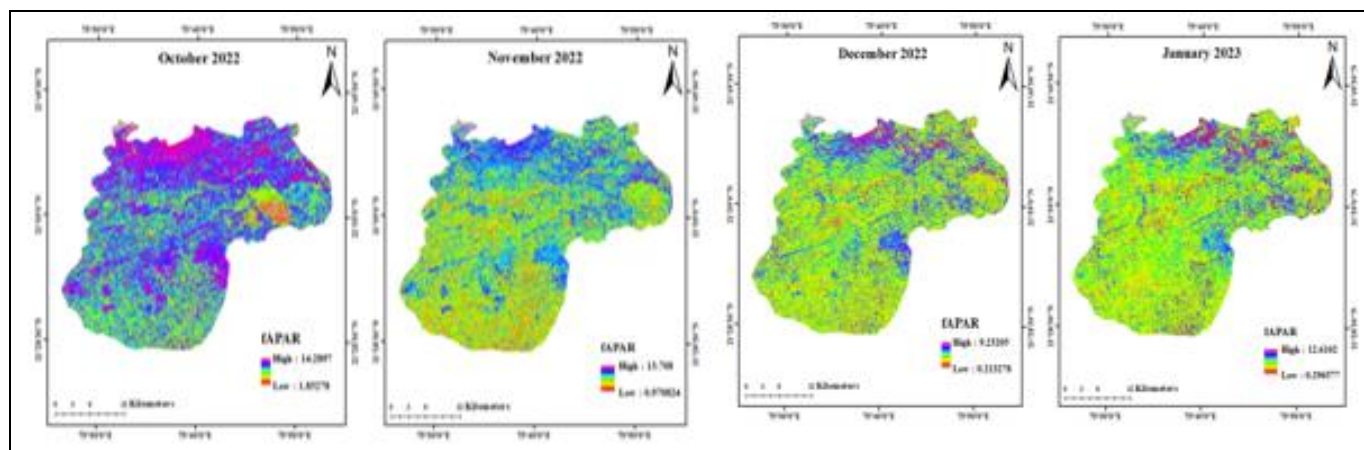


Fig 2: NDVI Map of October 2022 to March 2023

Fig 3: NDVI Map of October 2023 to March 2024



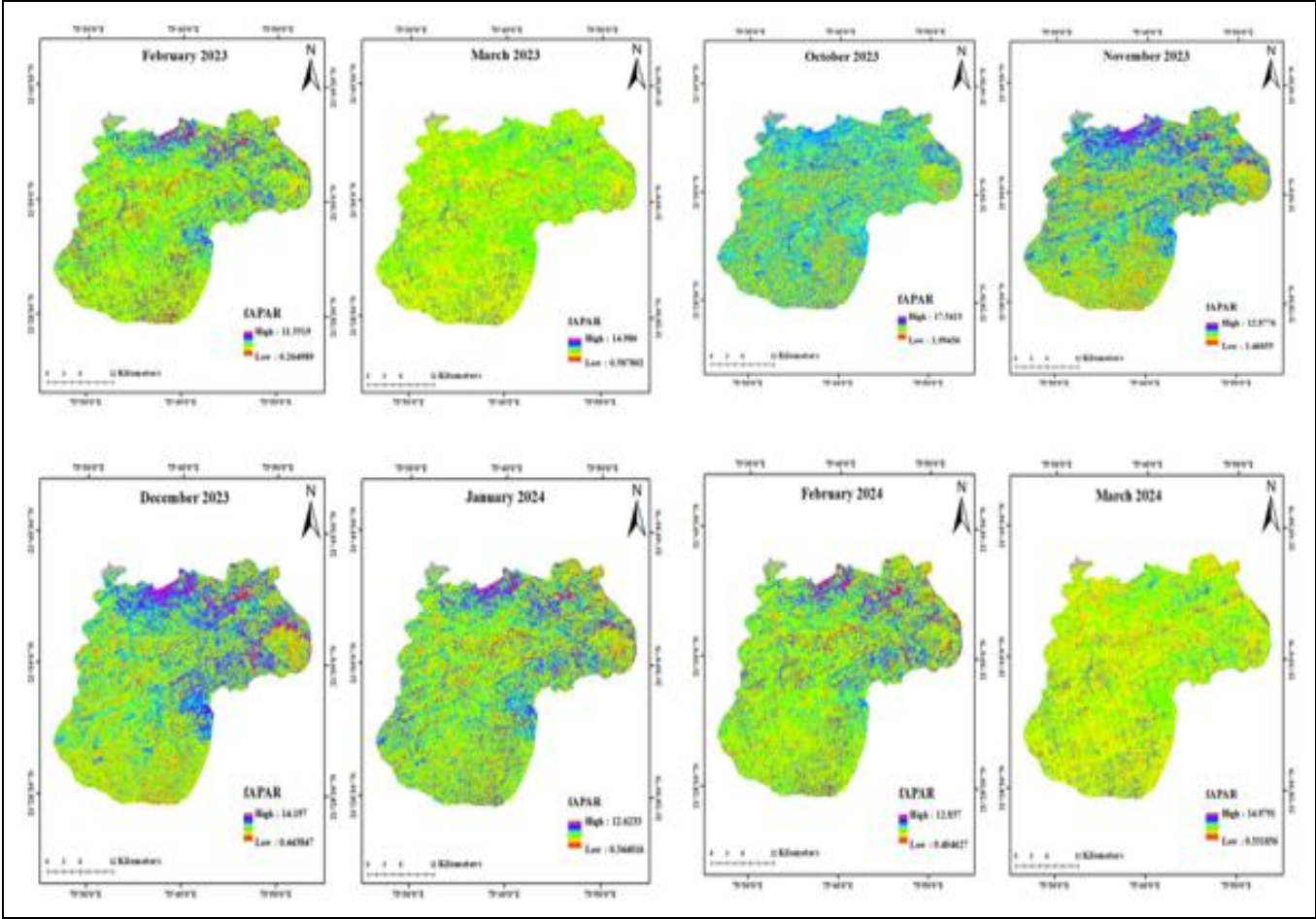


Fig 4: fAPAR Map of October 2022 to March 2023

Fig 5: fAPAR Map of October 2023 to March 2024

3.3 Yield

The most accurate estimates of yield were reported by using fAPAR-NDVI [Asrar *et. al.*, 1984; Gallo, *et. al.*, 1993] [1, 8]. NDVI and fAPAR maps derived from Sentinel-2 imagery provide detailed spatial information on vegetation health and productivity across the agricultural landscape. Higher NDVI values indicate denser and healthier vegetation, while fAPAR maps show areas of higher PAR absorption, indicating more productive regions [Jin *et. al.*, 2020; Diao *et. al.*, 2017] [12, 5]. Integrating NDVI and fAPAR maps facilitates precise and timely yield estimation, supporting informed decision-making in agriculture. These maps enable farmers to optimize resource allocation, such as irrigation and fertilizer application, based on real-time vegetation health indicators [Mkhabela *et al.*, 2021] [13]. Crop yield estimates are obtained through remote sensing, NDVI, fAPAR and ground-based crop statistics. Generally, the Chickpea season in Gujarat continues from the month of October/November to February/March. Consequently, the maximum NDVI values can be found during peak greenness period of crop life cycle, which is around the month of March. The yield estimated during 2022 to 2024 from NDVI is t/ha

which is close to the reported yield of the Narmada District (Table 4.1).

Table 2: Yield Estimation by satellite image and comparison with reported yield

Year	Estimated Yield (T/Ha)	Reported yield of Narmada District (T/Ha)
2022-23	1.59	1.7
2023-24	1.74	1.75
Average	1.67	1.73

It was observed that more chickpea yield was observed in high area (43.51%) and also (41.42%) followed by low yield level (0.79%), (3.19%) and (11.11%) during period of 2022-23 and in 2023-24 was observed that more chickpea yield was observed in high area (47.19%) and also (37.55%) followed by low yield level (0.91%), (3.38%) and (10.97%). The majority of the area is allocated to yield categories between 1.0-1.5 t/ha, with a significant portion achieving yields between 1.2-1.5 t/ha (Figure 6 & 7).

Table 3: Chickpea Yield of 2022-23

% of the Total Area	Yield (T/Ha)	Yield (T/Ha)
0.78	0.776	<0.5
43.50	1.151	1.0-1.2
41.42	1.387	1.2-1.5
11.11	1.794	1.5-1.6
3.19	2.845	>2.0
	1.5906	

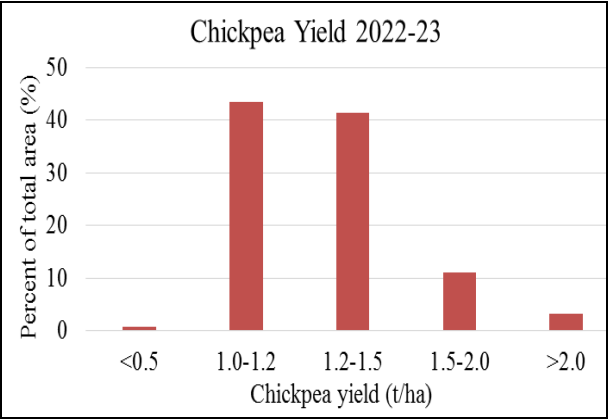


Fig 6: Chickpea Yield 2022-23

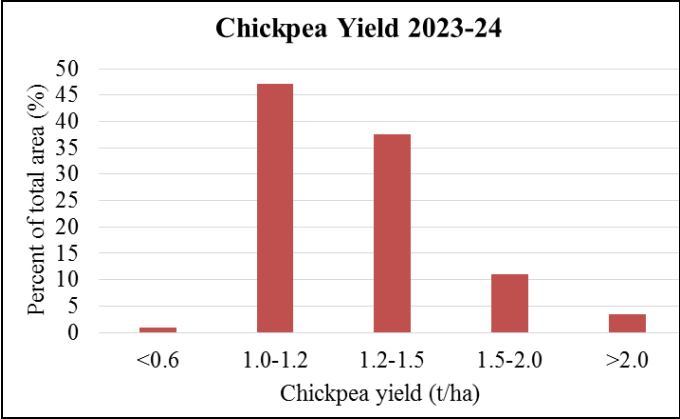


Fig 7: Chickpea Yield of 2023-24

Table 4: Chickpea Yield of 2023-24

% of the Total Area	Yield (T/Ha)	Yield (T/Ha)
0.78	0.776	<0.5
43.50	1.151	1.0-1.2
41.42	1.387	1.2-1.5
11.11	1.794	1.5-1.6
3.19	2.845	>2.0
	1.5906	

In the present study chickpea yields were calculated for NDVI method for each polygon and the estimated yields were grouped into (<0.6 t/ha), (1.0-1.2 t/ha), (1.2-1.5 t/ha), (1.5-2.0 t/ha) and (>2.0 t/ha) levels (Figure 8).

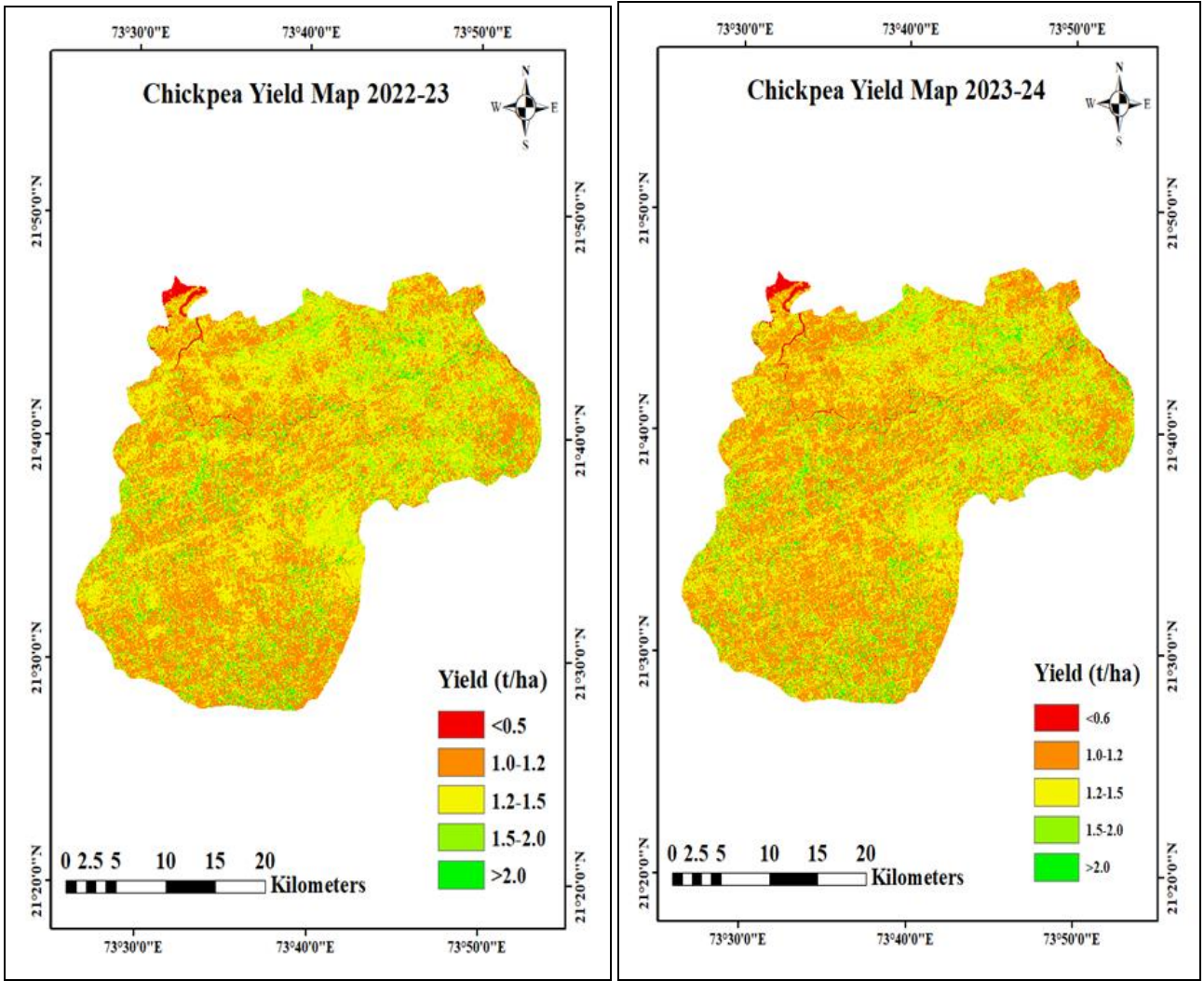


Fig 8: Yield map of Dediapada Taluka for year 2022-23 and 2023-24

Ground Truth Data

The ground truth points were collected for mapping chickpea areas using supervised classification in Google Earth. Ground truth data collection is crucial to validate and refine these classifications. Field surveys are conducted across Gajar Gota, Vedchha, Khokhra Umar, and Nighat to confirm the presence of

chickpea fields and to collect specific information about crop health and growth stages. This data is used to validate the accuracy of the satellite-derived classifications and to further improve the estimation of chickpea yield using remote sensing techniques.



Latitude: 21°41'8.599"N
Longitude: 73°31'11.974"E
Date: February 2024



Latitude: 21°40'18.001"N
Longitude: 73°42'15.285"E
Date: March 2024



Latitude: 21°37'1.004"N
Longitude: 73°35'58.37"E
Duration: March 2024



Latitude: 21°36'49.59"N
Longitude: 73°33'34.734"E
Duration: March 2024

Plate 1: Image of Visited Villages

The results of the yield estimation study provide valuable insights into spatial patterns of vegetation vigor, productivity, and predicted crop yield across the study area. By integrating remote sensing data (NDVI, fPAR, APAR) with GIS tools and applying the yield estimation formula, the study enhances understanding of agricultural productivity dynamics and supports decision-making for precision farming practices. Further research may focus on refining model parameters, incorporating additional data sources, and expanding the approach to different crop types or regions for broader applicability.

4. Conclusion

The yield estimation model, integrating APAR and other crop parameters, provided accurate predictions of chickpea yield. The 2022-2023 season showed the highest yield areas contributing 43.51% and 41.42% of the total area, with yields between 1.2-1.5 t/ha and 1.5-2.0 t/ha, respectively. The total estimated yield was approximately 1.59 t/ha. For the 2023-2024 seasons, the high-yield areas increased to 47.19% and 37.55%, with similar yield ranges.

This study successfully demonstrated the application of remote sensing and GIS technologies in estimating chickpea yield in the

Dediapada taluka. The integration of NDVI and fAPAR indices facilitated precise assessment of vegetation health and productivity, providing valuable insights for agricultural management.

Significant yield variations were observed across different areas, with high-yield zones contributing a substantial portion of the total chickpea production. The yield estimation model accurately predicted yields, aligning closely with reported values for the Narmada District.

The findings underscore the potential of remote sensing technologies to optimize resource allocation, improve crop management practices, and enhance overall agricultural productivity. Farmers and policymakers can leverage these insights to make informed decisions, ensuring better yield outcomes and sustainable agricultural practices.

The study relied on cloud-free satellite images, which could be a limiting factor in areas with frequent cloud cover. The accuracy of yield predictions could be further improved with more granular ground data for validation.

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