Original Research Article

Validation of the Sentinel-2 biophysical parameters derived from the SNAP toolbox with in-situ measurements in Anand district for accuracy assessment

ABSTRACT

In this study, the validation of SNAP-derived Leaf Area Index (LAI) and Chlorophyll content from Sentinel-2 was conducted to assess their consistency with in situ measured biophysical parameters.The accuracy and consistency of SL2B plugins were evaluated through validation and spatial variation comparison.For Leaf Area Index (LAI), the SNAP processor demonstrated strong correlations in the first year, with notable effectiveness in some selected fields. In the second year, acceptable accuracy was maintained for the different fields. The results showed moderate R^2, i.e., ~0.5 to ~0.7 between SNAP-derived LAI and *in-situ* LAI, but with high errors. Regarding chlorophyll estimation, SL2P-derived values showed an average estimate of 20-90 µg/cm², surpassing the field-based mean of 40-50 µg/cm². Despite some variability, the standard deviation for SL2P-derived chlorophyll was moderate at 22.68 µg/cm². The scatter plots highlighted a close alignment between retrieved and measured values, reinforcing the reliability of the data.Retrievals of LAI and chlorophyll were accurate for Anand district. It highlights the potential of Sentinel 2 data for precise retrieval of biophysical parameters of wheat.

Key words: Biophysical parameters, SNAP, Sentinel-2, Sen2Cor, LAI, CCC,

1. Introduction

The accurate mapping of crop biophysical variables is indispensable for diverse applications such as precision agriculture, land surface monitoring, natural resource management, and hydrological modeling. An integral component of these variables is the leaf area index (LAI), which provides valuable insights into both the function and structure of the canopy. Additionally, chlorophyll content emerges as a key player, being closely associated with leaf nitrogen content and serving as an effective indicator of stress, particularly nitrogen deficiency (Houlès *et al*., 2001).Quantifying and monitoring various biophysical parameters allow for the detection of crops photosynthetic capacity (Gitelson*et al*., 2007Boegh*et al*., 2002). Additionally, it aids in identifying nutrient stress (Gianquinto*et al*., 2011 Houlès *et al*., 2007)and assessing the developmental stage of crops (Solari *et al*., 2008,Sakamoto *et al*., 2012).

Conventional field assessments of crop biophysical characteristics are often laborious and time-intensive, typically confined to localized areas. An encouraging alternative involves

Comment [sz1]: Some things that need to be added, are research objectives, data, and data analysis techniques.

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Comment [sz3]: The references are not up to date employing earth observation techniques to map these parameters on a larger scale with high temporal resolution. Various approaches have been developed for retrieving crop biophysical variables from remote sensing data, generally categorized into two groups.Firstly, there are empirical approaches that establish statistical regression models correlating remote sensing data with field measurements, as demonstrated by studies such as Kira *et al*. (2016) and Pu and Cheng (2015).Secondly, physical modeling approaches utilize Radiative Transfer Models (RTMs) to simulate canopy spectral reflectance. Subsequently, the RTMs are inverted to obtain the desired parameters, as exemplified by research conducted by Campos-Taberner *et al.* (2016) and Féret *et al.* (2017). It is crucial to monitor the growth of agricultural crops throughout the entire growing season to enhance crop yields and reduce costs and input resources in the agricultural sector. The Leaf Area Index (LAI) is defined as one half of the total leaf area per unit horizontal ground surface area (m^2 leaf/m^2 ground surface or dimensionless). The Canopy Chlorophyll Content (CCC) parameter represents the total leaf chlorophyll content per ground surface (g leaf chlorophyll/m^2 ground surface). Typically, CCC is obtained as the product of Leaf Chlorophyll Content (LCC - g leaf chlorophyll/m^2 leaf area) and LAI (Gitelson *et al.*, 2005). Chlorophyll content assessment can be carried out at the leaf level (leaf chlorophyll content, LCC). Furthermore, it can be extended to the canopy level (canopy chlorophyll content, CCC) by multiplying the LCC and LAI. Noteworthy are studies that highlight the substantial interest in these chlorophyll products within primary production models, given their ability to indicate photosynthetic efficiency (Green *et al*., 2003).

For effective agricultural monitoring through remote sensing, it is imperative to achieve a spatial resolution of at least 20 m and a revisit period of less than 15 days to enable site-specific management (Mulla*et al*., 2003).The Sentinel-2 mission, facilitated by the European Space Agency (ESA), meets these requirements by delivering pixel sizes of 10 m and 20 m with a temporal resolution of 10 days. Comprising twin polar-orbiting satellites, Sentinel-2A and 2B, the mission primarily aims to furnish high-quality information for agricultural and forestry practices, contributing to enhanced food security (Drusch*et al*., 2012). While the launch of Sentinel-2A in June 2015 provided valuable data, the temporal resolution was initially insufficient for practical applications at the individual farmer's level. However, the subsequent launch of Sentinel-2B in March 2017 significantly improved the revisit period to five days under cloud-free conditions. To systematically retrieve vegetation biophysical variables from Sentinel-2 data, the Simplified Level 2 Product Prototype Processor (SL2P) algorithm was developed (Weiss, M& Baret, F 2016). Integrated into the Sentinel Application Platform (SNAP) biophysical processor, SL2P employs a collection of backpropagation Artificial Neural Networks (ANN) trained with globally representative simulations from the canopy radiative transfer model (PROSAIL: PROSPECT (Jacquemoud, S.; Baret, F 1990) + SAIL (Verhoef, W.1984). The ANN algorithm necessitates inputs such as top-of-canopy reflectance from the eight Sentinel-2 spectral bands, along with geometrical configuration parameters derived from satellite orbit characteristics and swath. Quality indicators are appended to the resulting biophysical products, ensuring the provision of operational parameters, including Leaf Area Index (LAI) and Canopy Chlorophyll Content (CCC), each accompanied by an associated quality indicator.

The study aims to evaluate the estimation of Leaf Area Index (LAI), Canopy Chlorophyll Content (CCC), and Fractional Vegetation Cover through the assessment of both in-situ measured biophysical parameters and automatic methods utilizing Sentinel-2 Land Products (SL2P). Real data from Sentinel-2 and in-situ field data collected from a wheat field in Anand district, Gujarat, are used for this evaluation. The primary focus is on validating the accuracy of LAI and CCC SL2P products.

2. MATERIAL AND METHODS

2.1 Field Campaign

The study utilized data from satellite acquisitions and in situ measurements conducted in Anand District, Gujarat, India (22.3299° N, 72.6151° E) (Fig. 1). Field data were recorded from wheat field, and the selected field coordinates of the study sites are listed in Table 1. The data collection period spanned from 15 November to 20 March for both the years 2019-20 and 2021-22.

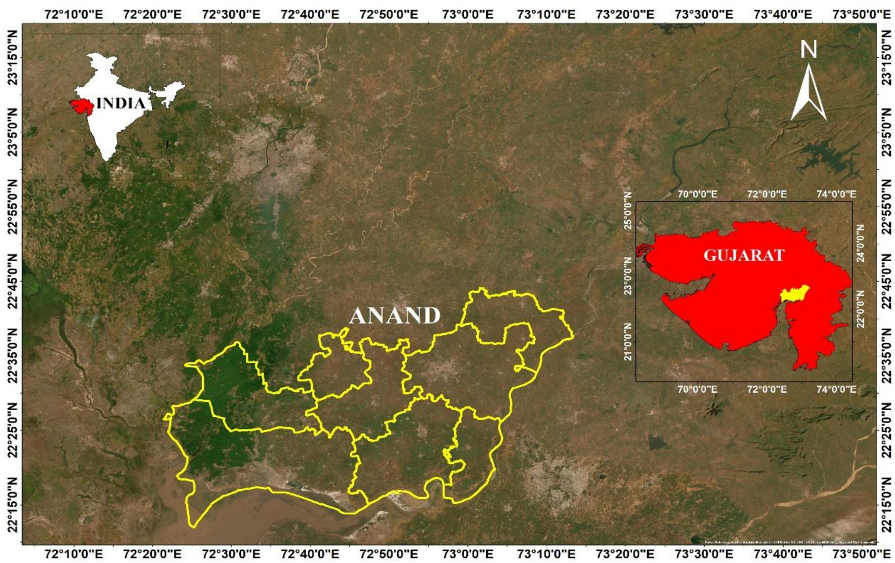

Figure 1. Test site location in Anand District, Gujarat from the Sentinel-2 image.

Table 1:Coordinates of selected Farmers' field for *rabi* wheat in Anand Region

Sr. No.	Year	Site Name	Latitude, Longitude
1	2019-20 (1st Season)	Experimental plot	22°32'14.42"N, 72°58'50.95"E
3		Navli Field 2	22°31'8.06"N, 72°57'52.06"E
4		Lambhvel tower field	22°35'24.57"N, 72°56'53.88"E
5		Lambhvel Field 2	22°35'11.01"N, 72°56'39.99"E
1	2020-21 (2nd Season)	Experimental plot	22°32'14.42"N, 72°58'50.95"E
4		Navli farm	22°31'8.06"N, 72°57'52.06"E

6		Lambhvel tower field	22°31'43.27"N, 72°58'9.79"E
7		Lambhvel Field 2	22°35'21.58"N, 72°56'55.84"E

Spectral reflectance in visible near-infrared (VNIR) bands weremeasured using the Spectroradiometer (UniSPec-DC). Throughout the study, observations were consistently recorded above the crop canopy level during every satellite pass in both experimental seasons. In the process of Radiance Spectrum Collection, a systematic approach was followed. Initial baseline measurements were conducted for dark current and white reference. Subsequently, the crop were targeted for precise measurements. To ensure the accuracy of the data, a cosine receptor was connected to the first channel, allowing for real-time correction of variations in irradiance. This comprehensive methodology in radiance spectrum collection was employed to capture the nuanced details of spectral reflectance, contributing to a thorough understanding of the study area and enhancing the overall quality of the research findings.

LAI was calculated based on green leaf area measurements obtained using the LI-3100 instrument (LI-COR Inc., USA). Measurements were taken at every satellite pass, starting 15 days after emergence until physiological maturity. The measurements were conducted in both season of experimentation.Chlorophyll values were calculated using Equation (1) as a validation relationship. Measurements were performed on randomly selected plants during both experimental seasons. To estimate chlorophyll concentration, the SPAD values were converted to micrograms per square centimeter ($\mu g cm^{-2}$) using the conversion formula (Lunagaria*etal*.,2015), expressed as:

$$Chla + b = 1.7838 + SPAD - 1.5333 \qquad (1)$$

2.2 Sentinel-2 imagery and SL2P

The Sentinel-2 satellite is equipped with a Multi-Spectral Imager (MSI) instrument/sensor featuring a swath of 290 km. The MSI have versatile set of 13 spectral bands covering the visible and near-infrared (NIR) to the shortwave infrared (SWIR) spectrum (443–2190 nm). This includes four bands at 10 m resolution (visible and NIR bands), six bands at 20 m resolution (red-edge and SWIR), and three bands at 60 m spatial resolution for atmospheric correction (refer to Table 2).

Table 2: Sentinel-2B MSI bands profile

Band	**Spectral Region**	**Band center(nm)**	**Band width (nm)**	**Spatial resolution (m)**
B1	Coastal Aerosol	443	20	60
B2	Blue	490	65	10
B3	Green peak	560	35	10
B4	Red	665	30	10
B5	Red edge	705	15	20
B6	Red edge	740	15	20
B7	Red edge	783	20	20

B8	NIR	842	115	10
B8 A	NIR narrow	865	20	20
B9	Water vapour	945	20	60
B10	Shortwave infrared	1375	30	60
B11	Shortwave infrared	1610	90	20
B12	Shortwave infrared	2190	180	20

The field campaign was carried out on days close to the overpass dates of Sentinel-2 over the study area. The Level-1C images for the two experimental seasons (2019-20 and 2020-21) were acquired from the European Space Agency (ESA) platform. These images were atmospherically corrected using the Sen2cor procedure, resulting in the corrected reflectance (Level-2A) for the selected fields.Additionally, the SNAP toolbox was used to obtain Leaf Area Index (LAI) Canopy Chlorophyll Content (CCC) automatic products for each field unit along with the corresponding product quality indicator.

Sentinel-2 satellite carries a Multi-Spectral Imager (MSI) instrument/sensor with a swath of 290 km on board. The MSI provides a versatile set of 13 spectral bands spanning from the visible and NIR to the shortwave infrared (SWIR) (443– 2190 nm), featuring four bands at 10 m (VIS and NIR bands), six bands at 20 m (red-edge and SWIR) and three bands at 60 m spatial resolution for atmospheric correction (Table 2). The field campaign was carried out on days close to overpass dates of Sentinel-2 over the study area. The images Level-1C of the two seasons of experimentation (2019-20 and 2020-21) were downloaded from the European space agency (ESA) platform and atmospherically corrected with Sen2cor procedure, obtaining the corrected reflectance (Level-2A) from the selected fields. The bands of the Sentinel images were also resampled to 10 m pixel size with all selected pixels falling entirely inside the corresponding field. In addition, we used the SNAP toolbox to obtain LAI and CCC automatic products of each ESU accompanied by the corresponding product quality indicator.

2.3 SNAP Biophysical processor

The biophysical processor, used in SNAP software (version 8.0), focuses on the retrieval of key vegetation parameters, including Leaf Area Index (LAI), Canopy Chlorophyll Content (CCC), canopy water content, fraction of Photosynthetically Active Radiation (PAR) absorbed by green elements of the canopy, and fraction of vegetation cover (FVC). the retrieval of these parameters from instantaneous observations captured by Sentinel-2, employing an Artificial Neural Network (ANN) approach. Utilizing a pre-trained neural network, the relevant biophysical variables can be promptly extracted for every pixel in the designated Sentinel-2 image (Figure 2).

The training data for the neural network is generated using a Radiative Transfer Model (RTM), ensuring accurate simulation of canopy reflectance within Sentinel-2 bands and geometry across diverse vegetation types and environmental conditions. The SNAP biophysical processor incorporates quantitative and qualitative quality indicators to assess the reliability of the generated product. These indicators enable users to assess the confidence level of the data and appropriately weigh its application.

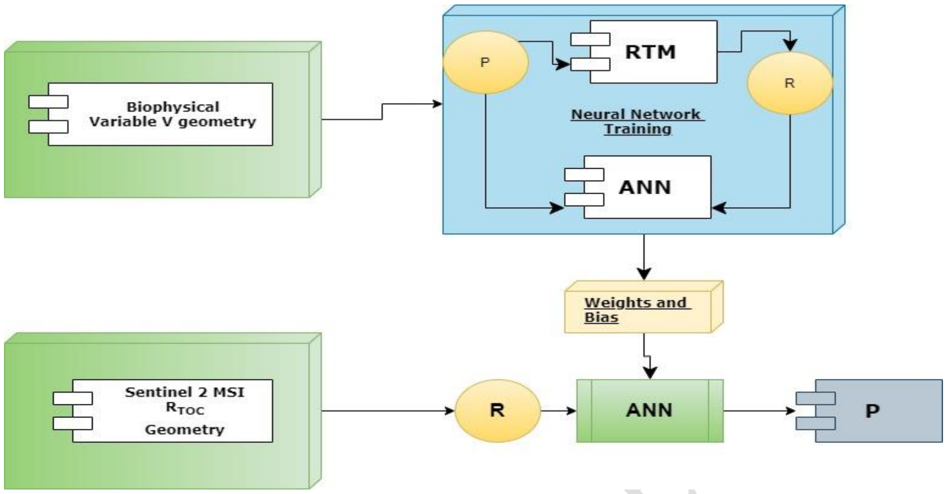

Figure 2: Flowchart for the retrieval of satellite-based biophysical parameters using SL2B algorithm in SNAP

Preprocessing steps on S2-MSI images were performed prior to biophysical parameter retrieval:

- Resampling S2-MSI spatial resolution bands (Table 3) to match the 20m grid using the nearest method integrated in the Sentinel application platform (SNAP) using S2 resampling operator.
- Use the SL2B algorithm, which is a part of the SNAP software, to process the satellite images. The algorithm extracts biophysical parameters such as leaf area index, and chlorophyll content.
- Use the extracted parameters to simulate the Sentinel-2 Top of Canopy (TOC) Reflectance (RTOC) and geometry, which are used as input to the Artificial Neural Network (ANN).
- Train the ANN using the simulated Sentinel-2 TOC reflectance and geometry data, along with the corresponding biophysical variables (P) as the target. The ANN is trained to learn the relationship between the simulated data and the biophysical variables by adjusting its coefficients (synaptic weights and bias)
- Validation of estimating biophysical parameters using remote sensing techniques. It was performed comparing the estimated values of various parameters (viz; LAI, FVC, CWC etc.) with ground-based measurements. The purpose of this comparison is to assess the accuracy and reliability of the estimated parameters and identify any discrepancies or biases that may exist. This process has been accomplished through the use of statistical methods. which allow to quantify degree of agreement between the estimated and measured data.

3.RESULT AND DISCUSSION

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3.1 Biophysical Parameters of Retrieved *vs* Measured

3.1.1Spatial distributionmap of Leaf area index

High-resolution (20 m) LAI data for Anand district in 2019-20 and 2020-21 reveal spatial variations, highlighting significant differences within the study region. Figures 3depict LAI maps, illustrating progression during growth stages, notably an increase from January to February. High LAI regions are concentrated in the North-central and west parts, while low LAI areas prevail in the southwest. The retrieved LAI values suggest a healthy vegetation concentration of pigments, with most wheat areas falling within the range of 2.5 to 4.0. Sentinel 2A data for February shows a similar pattern, indicating improved crop health towards the end of February during flowering to milking phases. The LAI tends to rise from mid-December to January, peaks in February, and gradually decreases towards the end of the growing season.

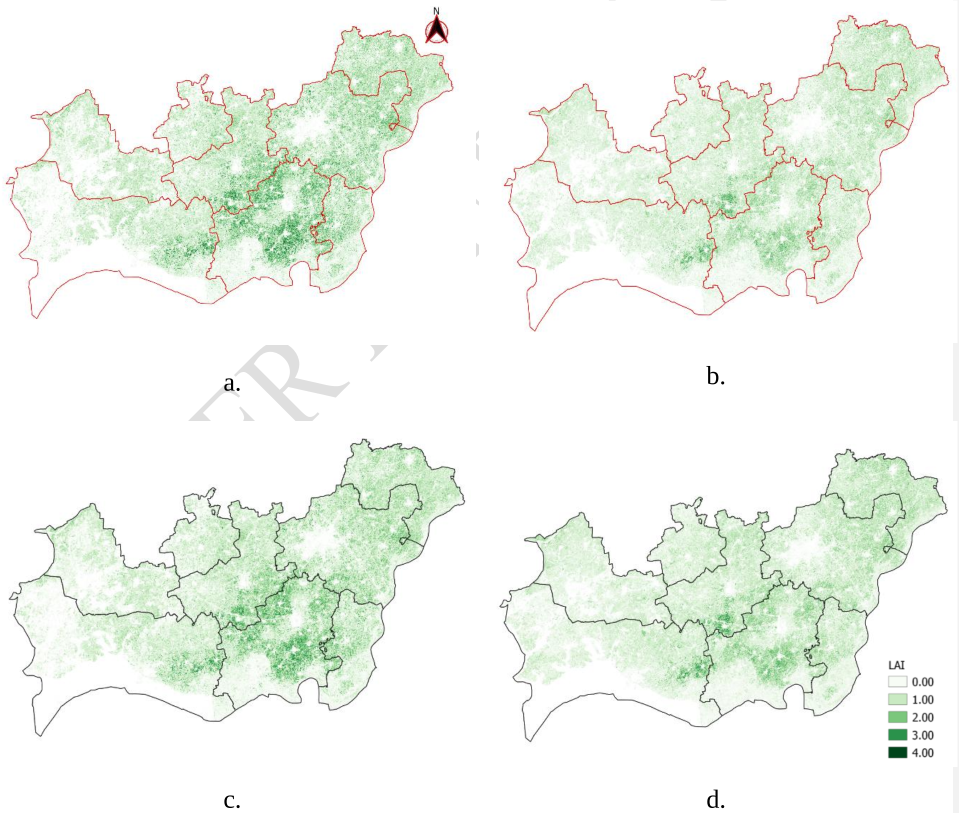


Figure 3: LAI retrieved (a) January 2020 (b) February 2020 (c) January 2021 (d) February 2021

3.1.2Spatial distribution map of Chlorophyll content

Figures 4depicted the spatial distribution of chlorophyll content, focusing on key growth stages (January and February). The maps revealed a gradual increase in chlorophyll from January to February followed by a steep decline from late February to March. This progression was consistent with findings by Djamai *et al.* (2019), affirming the utility of Sentinel-2 imagery for accurate canopy chlorophyll content estimation.

The presented result revealed a comprehensive overview of chlorophyll patterns during the two-month period, highlighting widespread spatial distribution. Specifically, Figure 4a and Figure 4c indicated chlorophyll levels predominantly exceeding 30 µg/cm², with most regions exhibiting content between 20 µg/cm² and 60 µg/cm². In February (Figure 4b and Figure 4b), the chlorophyll concentration was widespread, with values ranging from >40 µg/cm² to <90 µg/cm². Notably, the north-east region (Anand, Borsad, and some parts of Anklav block) showed chlorophyll content in the range of 40 µg/cm² to 60 µg/cm², while Tarapur, Khambhat, and some areas of Sojitra blocks displayed content ranging from 20 µg/cm² to 40 µg/cm².

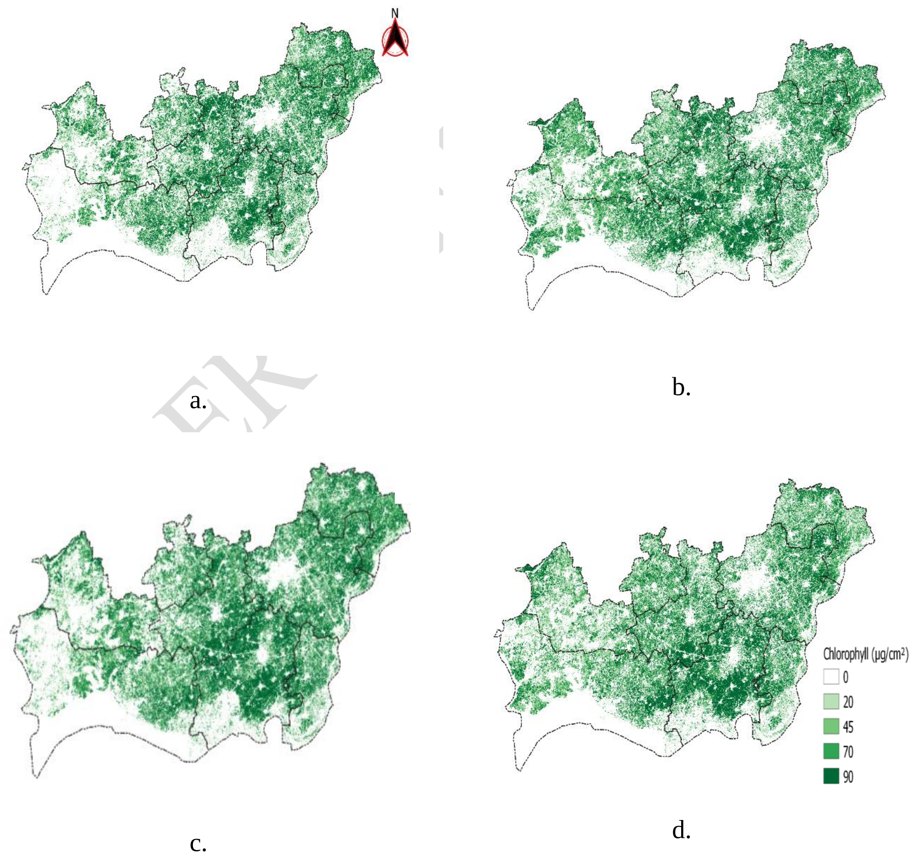


Figure 4: Chlorophyll retrieved for a. January, 2020 b. February 2020c. January, 2020 d. February 2020

3.1.3 Temporal Trends in Fractional Vegetation Cover (FVC)

Temporal FVC results for 2019 and 2020-21 in Anand district are presented in Figure 5, indicating an increasing trend during this period. The FVC was classified into six categories (0.0-0.2, 0.2-0.4, 0.4-0.6, and 0.6-0.8) to analyze the temporal dynamics. Figure 5 illustrates a rising FVC trend during both seasons. The early growth phase (November to December) showed FVC values of 0.0-0.2 and 0.2-0.4, representing sparse vegetation. The peak growing season (0.4-0.7) reflected the widest FVC range, aligning with the vegetation coverage in the study site. As the crop matured in March, FVC decreased, with few regions having values >0.6, attributed to wheat leaf and stem growth.

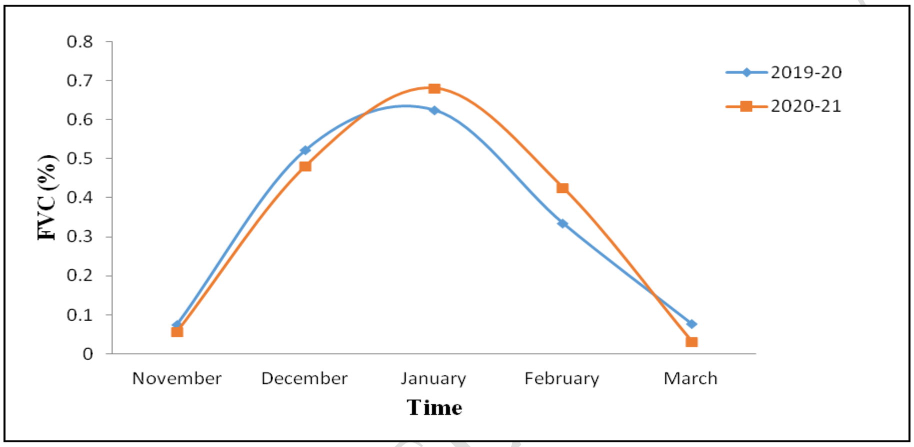


Figure 5: Temporal change in FVC during the growing seasons (November- March during years 2019-20 and 2020-21)

3.2 Validation of biophysical variables retrieved by the SNAP biophysical processor

3.2.1 Leaf area index retrieved versus measured

Ground measurements facilitated the evaluation of high-resolution LAI estimates generated by the SNAP biophysical processor. Correlation coefficient (r), root mean squared error (RMSE), mean absolute error (MAE), mean squared error (MSE), and goodness-of-fit were computed for accuracy assessment.

In the first year, the SNAP processor demonstrated a high correlation in the experimental plot (r=0.71) and Lambhvel tower field (r=0.85), indicating effective LAI estimation. Moderate correlations were observed for Navli research station field (r=0.49) and Livestock lambhvel farm (r=0.75). In the second year, the processor maintained acceptable accuracy for the Experimental field (r=0.79) and Lambhvel field (r=0.81), while showing lower accuracy for Navli field (r=0.36) and moderate accuracy for Lambhvel tower field (r=0.78).

Scatter plots in Figure 6 and Figure 7support the conclusion of good agreement between satellite-derived LAI data and ground measurements. Despite some poor estimations attributed to flagged input values, the SNAP algorithm achieved a 50-60% accuracy for good quality retrievals. Overestimations and underestimations observed in the validation may stem from an inadequate training database. However, it is noteworthy that the retrieved values remained within acceptable tolerance ranges.

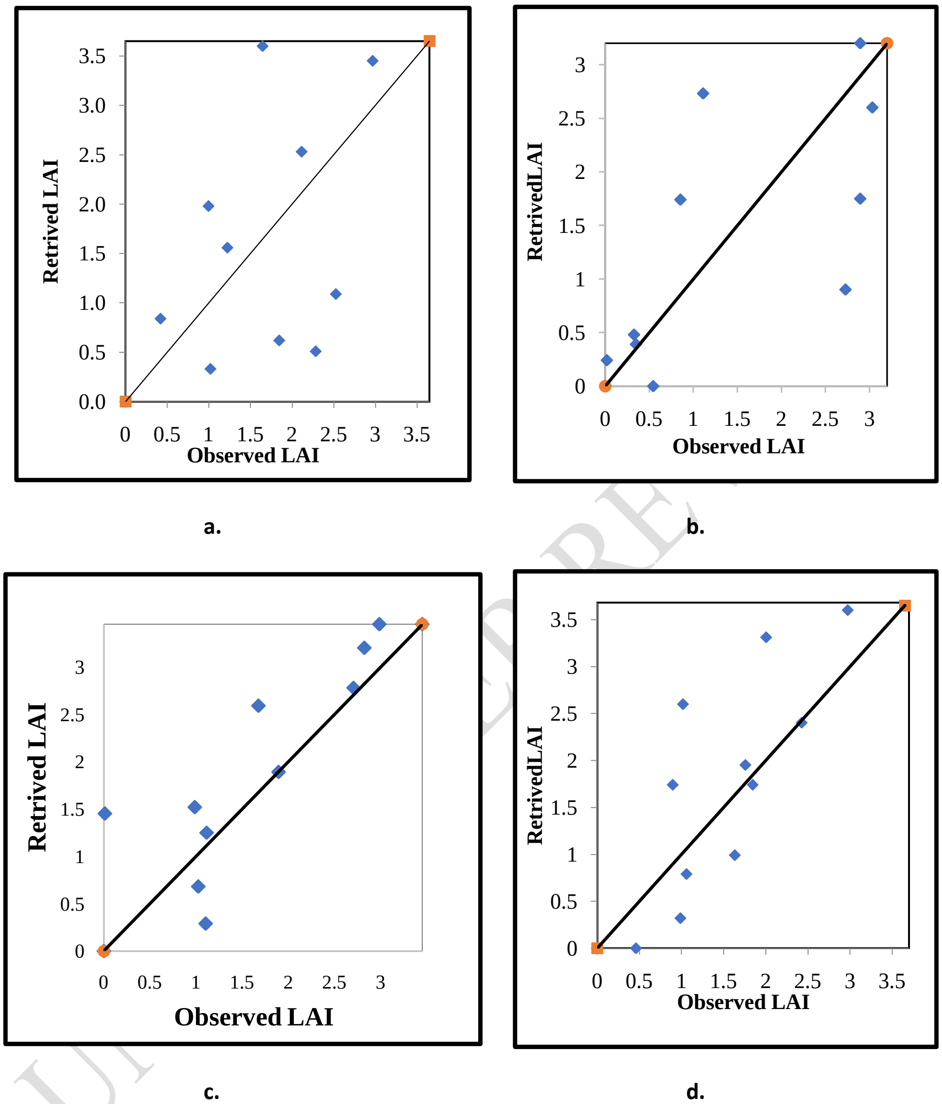
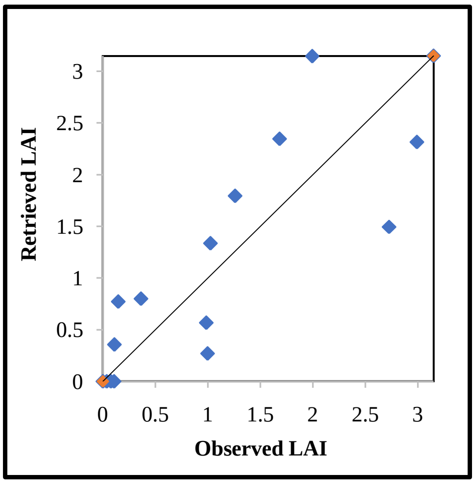


Figure 6: **Retrieved versus measured LAI during *rabi* year 2019-20;a. Experimental plot, b. Navli research station field, c. Lambhvel tower field, d. Livestock research station field.**



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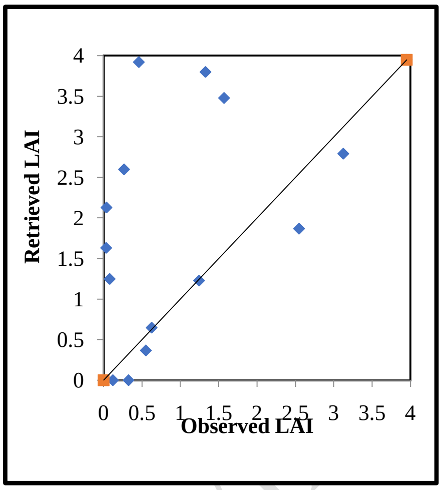

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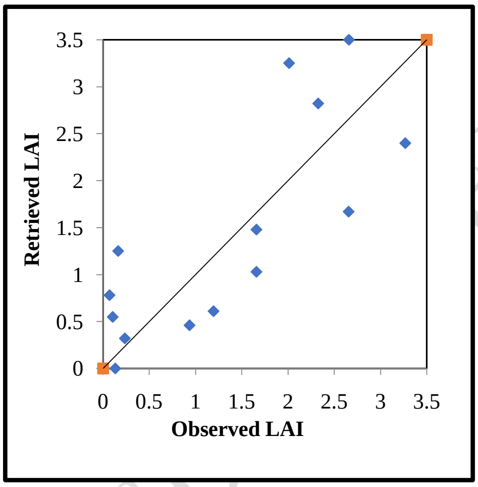

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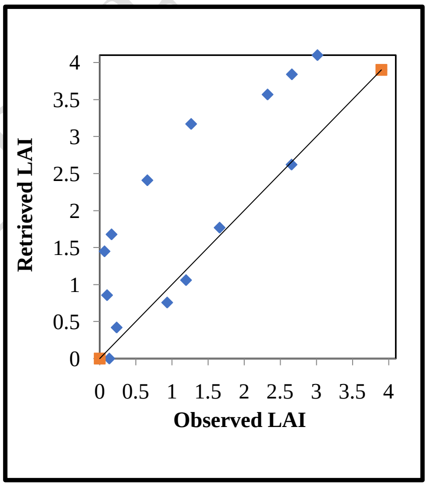


d.

Figure 7: **Retrieved versus measured LAI during *rabi* year 2020-21*;* a. Experimental plot, b. Navli research station field, c. Lambhvel tower field, d. Livestock research station field.**

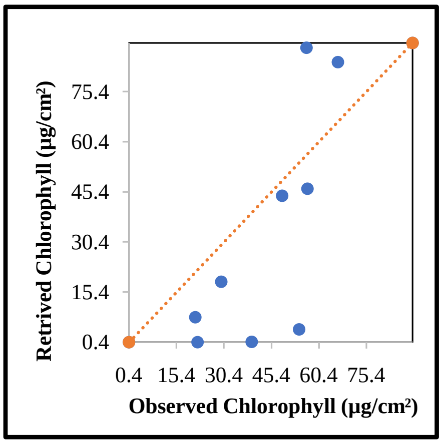
3.2.2Chlorophyll content retrieved versus measured

Retrieved canopy chlorophyll was validated using in situ measured data for both seasons (see Figure 8 and Figure 9). Scatter plots indicate a reasonable agreement between retrieved and measured leaf chlorophyll content. Table 3presents correlation coefficients for the Experimental plot, Lambhvel field, Navli field, and Lambhvel tower field. The results reveal acceptable correlation levels for the Experimental plot and Lambhvel field (coefficients of 0.74 and 0.68 for 2019-2020 and 2020-2021, respectively), while the correlation for Navli field and Lambhvel tower field was moderate (coefficients of 0.61 and 0.76 for 2019-2020, and 0.71 and 0.80 for 2020-2021).

The scatter plots demonstrate that retrieved versus measured values closely align with the 1:1 line. On average, SL2P-derived chlorophyll had a mean estimate of approximately 20-90 µg/cm², higher than the field-based mean estimate of 40-50 µg/cm². SL2P-derived chlorophyll exhibited moderate variability with a standard deviation of 22.68 µg/cm². Figures 8 and 9 scatter plots show that SL2P-estimated biophysical parameters closely follow the 1:1 line, albeit with significant underestimation.

Table 3:Statistical validation of retrieval of chlorophyll

Year	Sites	MAE	MSE	RMSE	r
2019-20	Experimental plot	42.94	685.40	76.15	0.74
	Navli Field 2	66.53	112.54	134.72	0.61
	Lambhvel tower field	24.9	579.13	64.34	0.71
	Lambhvel Field 2	51.88	420.01	46.66	0.72
2020-21	Experimental plot	30.12	175.57	19.50	0.68
	Navli farm	31.23	339.48	37.72	0.76
	Lambhvel tower field	23.66	259.65	28.85	0.80
	Lambhvel Field 2	29.28	633.50	70.38	0.71



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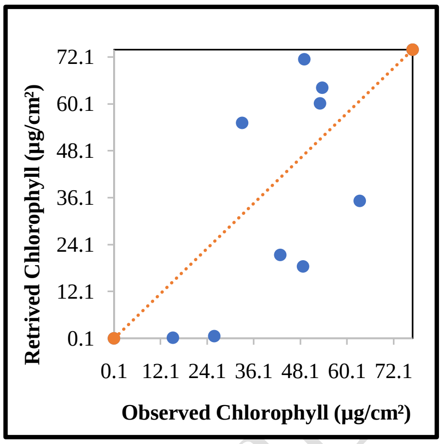

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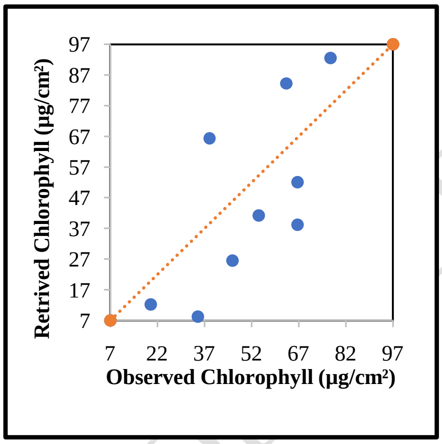

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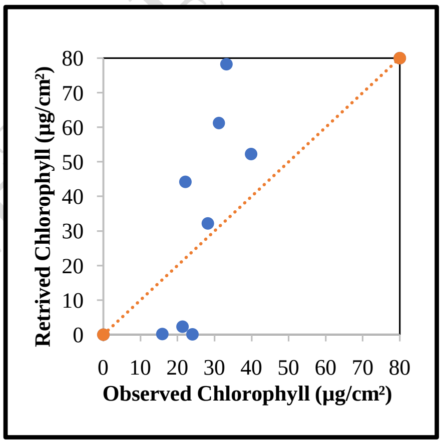

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Figure 8: Retrieved chlorophyll vs measurements during year 2019-20 *viz;*a. Experimental plot, b. Navli research station field, c. Lambhvel tower field, d. Livestock research station field.

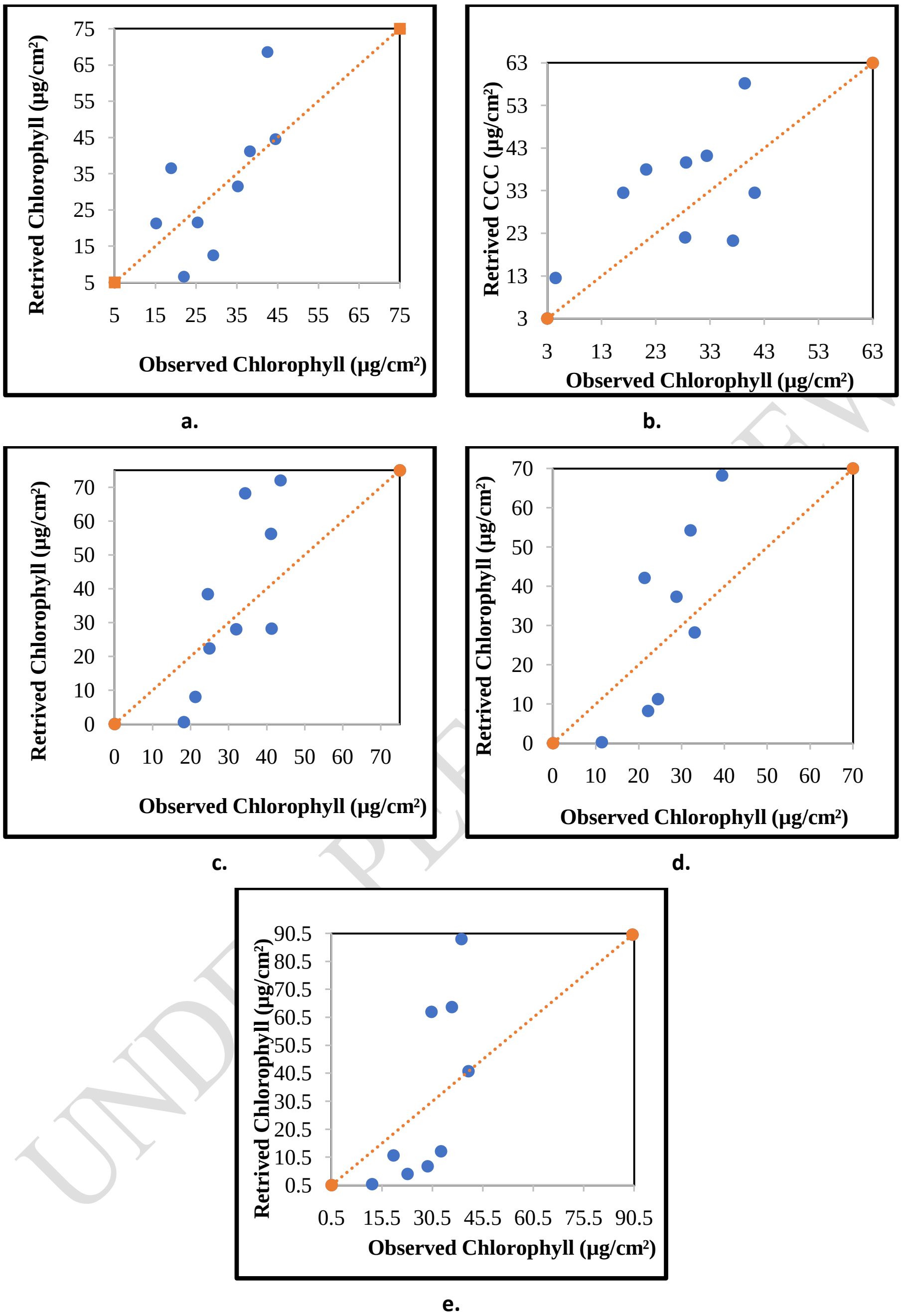

Figure 9: **Retrieved chlorophyll vs measurements during year 2020-21 *viz;* a. Experimental plot, b. RRS gate field, c. Navli research station field, d. Lambhvel tower field, e. Lambhvel field.**

CONCLUSION

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In conclusion, the effective assessment of wheat crop conditions through biophysical parameters, including leaf area index (LAI) and chlorophyll content, reveals a healthy vegetation pattern with optimal pigment concentration, as indicated by retrieved LAI values ranging from 2.5 to 4.0. Temporal variations in LAI, peaking in February and gradually decreasing thereafter, align with expected wheat crop growth phases. Spatially, Anand's North-west region exhibits a moderate LAI concentration, reflecting green and healthy vegetation, while the South and South-east regions display varying degrees of lower LAI values. The close correlation between LAI and chlorophyll concentration indicates a chlorophyll-dependent relationship, with spatial distribution maps showing widespread chlorophyll values exceeding 30 µg/cm², particularly during January and February. Despite the significant underestimation of chlorophyll parameters by the SL2P model, the agreement between satellite-derived LAI data and ground-measured data, as demonstrated by scatter plots aligning closely with the 1:1 line, underscores the reliability of remote sensing for wheat crop assessments. The overall consistency of LAI retrieval with ecological spatial patterns and the wheat status of Anand district reinforces the utility of biophysical parameters for comprehensive crop condition assessments, highlighting the need for continued refinement and validation of remote sensing models, particularly in chlorophyll estimation, to enhance the accuracy of future assessments.

References:

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