

Integration of Sentinel-2 Imagery and Field Spectroscopy for Vegetation Spectral Analysis

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Abstract

Remote sensing plays a key role in precision agriculture and vegetation monitoring due to its specifications to provide rapid and efficient large-scale observations. This field involves the analysis of reflection, absorption, and emission of radiation of different surface features in function of different wavelengths of electromagnetic spectrum. The aim of this study is to evaluate the consistency between spectral signature extracted from Sentinel-2 imagery and collected using a field spectrometer. For this purpose, a statistical comparison was executed using Pearson correlation coefficient (r), coefficient of determination (R^2) and Root Mean Square Error (RMSE) of a specific sampling points. The results indicate that it was an agreement between satellite and field measurements, showing a high values of R^2 (> 0.90) and a low value of RMSE. Overall, the findings confirm that compared to the spectrometer measurements, the sentinel-2 imagery could accurately differentiate the spectral characteristics of vegetation. On the other hand, the results demonstrate the reliability of Sentinel-2 imagery for vegetation monitoring and highlight its integration with field spectroscopy for improved calibration and validation.

Introduction

Precision agriculture and environmental management are founded on vegetation monitoring. This is ensured by several modern techniques available today. Remote sensing based on spectral signatures is the most effective technique for accomplishing this mission as a non-destructive, and non-invasive technique. Using a field spectrometer, a drone, or a satellite, the spectral signatures of any element can be collected remotely and non-contact, for the identification and characterization of the object in different scales.

While satellite sensors offer a wide spatial coverage, theirs output are often influenced by a lot of parameters witch may reduce their accuracy, as; atmospheric interference, sensor degradation, and spatial aggregation effects. Therefore, in-situ spectral measurements collected with field spectrometers are usually considered as the most appropriate for the calibration and validation of satellite data. In fact, a field spectrometer acquires detailed spectral measurements under different controlled conditions and at high spatial resolution (Milton et al., 2009). Consequently, the results present an accurate characterization of plant properties, so they are used as reference to validate satellite sensors (Thenkabail et al., 2012 Hyperspectral Remote Sensing of Vegetation).

However, while comparing spectral data resulting from field spectrometer and satellite, a differences was identified. These differences can be attributed to numerous causes witch complicate the comparison, as; variations in spatial resolution, sensor spectral response functions and atmospheric effects...(Gao et al., 2009).

In recent years, numerous researchers have used remote sensing methods to study crops. In fact, due to its high spectral and spatial resolution, previous studies demonstrated the dependability of Sentinel-2 data for monitoring crop (Delegido et al., 2013; Drusch et al., 2012). Also, Liu et al. (2025) combines multispectral technology using a VideometerLab4 instrument (Videometer A/S, Hørsholm, Denmark)

within a spectral wavelength range of 365–970 nm and machine learning to analyze the relationship between the spectral characteristics of *L. japonicus* leaves and their chemical composition. However, Taia et al. (2024) evaluates the feasibility of detecting changes in mint using UV–NIR spectroscopy with an ASD fieldSpec spectrometer under varying water and nitrogen conditions. With the same spectrometer, El Azizi et al. (2026) develops a spectral signature–based algorithm to identify crop species and cultivation conditions using remote sensing, matching unknown samples to reference signatures. On the other hand, there are studies who combine field spectrometer and satellite images to study crop. For example, JAZ EL-350 portable spectrometer and WorldView-2 (WV-2) with image were combined and used to measure and analyze mangrove spectral reflectance patterns and map the distribution of dominant species. This study also evaluates how field-based spectral data can be applied to remote sensing imagery and highlights key considerations for its use. (Kamal et al., 2018). Moreover, a study by Isnaen et al. (2019) evaluates the efficiency of radiometric correction on WorldView-2 imagery by comparing corrected reflectance with field spectrometer measurements, including mangroves, other vegetation, soil, and asphalt.

In this context, this study aims to explore the correlation between in spectral reflectance measured using an ASD fieldspec spectrometer and that extracted from sentinel-2 sensor. In fact, the use of statistical indicators such as Pearson correlation, coefficient of determination and RMSE is essential for evaluating the concordance between field spectrometer results and satellite results.

Materials and methods

In this section, the entire experimental design is shown and described from the data acquisition to statistical analysis. Figure 1 illustrate a summarize of our experimental design.

Sentinel-2 images acquisition

Sentinel-2 imagery was chosen to extract spectral signatures for our field. Level-2A (L2A) data were selected, as they are atmospherically corrected. Sentinel 2 acquires optical imagery at high spatial resolution (10 m to 60 m) over land. It is a Multi-Spectral Instrument, which has 13 spectral channels in the visible/near infrared (VNIR) and short wave infrared spectral range (SWIR). Spectral bands specification of these images is presented in Table 1 (Drusch et al., 2012).

Table 1
Spectral bands for the Sentinel-2A sensors

Sentinel-2 bands	Central wavelength (nm)	Spatial resolution (m)
Band 1 – Coastal aerosol	443	60
Band 2 – Blue	490	10
Band 3 – Green	560	10
Band 4 – Red	665	10
Band 5 – Vegetation red edge	705	20
Band 6 – Vegetation red edge	740	20
Band 7 – Vegetation red edge	783	20
Band 8 – NIR	842	10
Band 8A – Narrow NIR	865	20
Band 9 – Water vapour	945	60
Band 10 – SWIR – Cirrus	1380	60
Band 11 – SWIR	1610	20
Band 12 – SWIR	2190	20

The image was downloaded from the Copernicus Open Access Hub on July 4th, 2024 and processed in ESA SNAP software (version 10.0) to extract spectral signatures corresponding to the five sampling points.

Field Spectral Reflectance Measurement

Data acquisition

Spectral data were acquired using ASD FieldSpec HandHeld Spectrometer with a spectral range from 325 to 1075 nm. White reference was used for calibration before each acquisition. Dark current was subtracted from each spectrum to avoid noise by measuring the reflectance of dark reference by covering the collimating lens.

Spectral preprocessing

A number of factors, including instrumental noise and environmental heterogeneity can lead to errors in the raw spectral data. These errors may compromise the integrity of the analysis that follows.

Preprocessing the spectral data is therefore essential to guaranteeing the accuracy and consistency of

the analysis results. The data in this study was refined using two preprocessing methods Savitaky Golay (SG) and Standard Normal Variable transformation (SNV). While SG filter lowers noise maintaining the shape of spectral features, SNV corrects multiplicative scattering effects and baseline shifts by standardizing each spectrum. When these techniques are combined, the signal-to-noise ratio and spectrum comparability are improved.

All spectral preprocessing has been computed in Python (version 3.10) using the libraries *NumPy*, *Pandas*, *SciPy*, and *OpenPyXL*.

Spectral resampling

Field spectrometers collect hyperspectral data in a multiple band. To compare these with the results of Sentinel-2 and to correlate between spectral signature collected by a field spectrometer and extracted from sentinel-2 image, the field spectra must be processed with the sensor's Spectral Response Functions (SRF) (Richardson et al., 1980), in this situation, (Dkhala et al., 2020) demonstrated that spectral indices and reflectance values change in function of the spectral resolution of sensors. This approach ensures that the simulated band reflectance accounts for the specific spectral sensitivity and width of the satellite sensor (Jiang et al., 2022; Richardson et al., 1980).

$$R_{Pi_{Spec}}(B_j) = \frac{\sum_a^b R_{spec} * SRF}{\sum_a^b SRF}$$

With:

$\backslash \text{varvec}R \backslash \text{varvec}P \backslash \text{varvec}i_{\backslash \text{varvec}S \backslash \text{varvec}p \backslash \text{varvec}e \backslash \text{varvec}c} (\backslash \text{varvec}B \backslash \text{varvec}j)$: is the resampled spectral reflectance of sample point i for band B_j , with $1 \leq i \leq 5$ and $1 \leq j \leq 10$.

a

is the last wavelength in the band B_j

b : is the last wavelength in the band B_j

SRF : is the resampling coefficient.

Correlation and statistical analysis

The aim of this study is to evaluate the agreement between satellite and field measurements in a specific field in the same period. In this purpose, a statistical analysis using Pearson correlation, coefficient of determination and RMSE was applied.

Pearson correlation is a standard statistical method widely used in crop remote sensing. Little studies have calculated Pearson correlation to evaluate relationships between spectral variables and crop biophysical parameters, canopy structure or stress conditions (Aparicio et al., 2000; Othman et al., 2025; Thapa et al., 2019). In this study, Pearson correlation was computed to quantify the linear relationship between spectral signatures and identify Sentinel-2 bands most related to field measurements.

Also, the Root Mean Square Error (RMSE) was calculated as a statistical parameter to quantify the difference between spectral signature using field spectrometer and extracted from sentinel-2 image. RMSE provides a measure of the average magnitude of the error between observed and estimated values, with greater emphasis on larger deviations. Lower RMSE values indicate a better agreement between spectrometer and satellite data, reflecting higher accuracy of the satellite data (Willmott and Matsuura, 2005).

$$\text{RMSE} = \sqrt{\frac{\sum_1^n (R_{\text{spec}} - R_{\text{sat}})^2}{n}}$$

All statistical analyses were computed in Python (version 3.10) using the NumPy, SciPy, and scikit-learn libraries.

Application: “Yellow melon of “Guichar Variety” in a region in Northern Morocco

The region of interest is a field situated in northern Morocco, specifically in the Larache province (Fig. 2). This region climate is Mediterranean, characterized by hot, dry, and sunny summers, and mild, wet, and windy winters. The field is occupied by yellow melon of “Guichar Variety”. The melon was sown for 20 days in the nursery and then planted in this field at the beginning of May.

During the protocol, we took 120 measurements of five samples, for each sample 25 spectral measurements were averaged.

The spectral data have been taken under natural light on the 03rd of July 2024 (Fig. 3). The meteorological and time conditions of data acquisition are shown in Table 2.

Table 2

important parameter taking during the protocol The five sampling points are located at the edges of the plot and in the middle. Table 3 presents their Geographic coordinates:

Location	Rissana Janoubia, Tangier-Tetouan-Al hociema (Fig. 1)
Date	03/07/2024
Time	02:30 pm to 03:00 pm
Temperature	30°C
Humidity	54%
Wind	19km/h
Cloud cover	0%
Precipitation	0 mm

Point N°	Longitude	Latitude
1	447959.99	512519.91
2	447982.52	512531.14
3	448002.13	512498.61
4	447978.60	512484.88
5	447959.99	512519.91

Table 3: Geographic coordinates of sampling points

Results and discussion

Spectral reflectance of field spectrometer

Field spectrometers have high spectral resolution (on the order of a few nanometers), which allows them to capture very fine details specific to each wavelength.

Figure 4 shows the spectral signature of the samples using our field spectrometer. Observing the curves, we note that the shape of all curves is relatively similar and they all correspond to the spectra of healthy vegetation. The reflectance between 500 nm and 600 nm exhibits a peak of reflectance due to the absorption of these wavelengths by chlorophyll pigments. As for the NIR, the maximum values (740–1000 nm) show high reflectance, linked to the internal structure of the leaves, which strongly scatters light in this region, reflecting the health of the vegetation and leaf density.

Spectral reflectance of sentinel-2

After downloading the Sentinel-2 image, we import it on ESA SNAP and we extract the plots reflectance. The spectral reflectance of vegetation on image showed a similar pattern to the results of the field measurement on each band (Fig. 5). Besides, the spectral reflectance curve of vegetation objects increases sharply in the near-infrared band due to the reflectance of the internal structure of the leaves.

Spectral resampling

The spectral response functions (SRF) for Sentinel-2A sensor were downloaded from the official ESA documentation and used to convolve the spectral signatures measured in situ. Resampling result of spectral measurements obtained using field spectrometer is shown on Fig. 6.

Correlation analysis between spectral reflectance band per band

In general, the two signatures show similar trends, particularly the low reflectance in the visible bands and the peak in the near-infrared. This confirms that both measurements accurately capture the crop’s spectral properties. The discrepancies in the visible spectrum (particularly in the blue and red bands) could be due to imperfections in atmospheric corrections or differences in lighting conditions at the time of satellite acquisition. So, in order to compare the two sensors, we must test the correlation between results.

The results of Pearson correlation coefficient are shown in Table 4 and Fig. 7

Table 4
Pearson correlation between spectral data using field spectrometer and satellite

Samples	Pearson correlation (r)	Coefficient of determination (R ²)
P1	0.968	0.936
P2	0.986	0.971
P3	0.952	0.906
P4	0.973	0.946
P5	0.949	0.901

The Pearson correlation analysis performed band-by-band between field spectrometer measurements and Sentinel-2 reflectance revealed a strong linear relationship across all samples. Pearson correlation coefficients ranged from 0.949 to 0.986, indicating a very high degree of consistency between ground-based and satellite observations. Similarly, the coefficient of determination (R²) varied between 0.90 and 0.97, suggesting that more than 90% of the variability in satellite-derived reflectance can be explained by field measurements. Slight differences observed between samples may be attributed to spatial resolution effects, atmospheric influences, and heterogeneity within the sampled plots. Overall, these

results confirm the reliability of Sentinel-2 data for representing crop spectral behavior under the studied conditions. These findings are consistent with previous studies highlighting the capacity of Sentinel-2 to accurately capture vegetation spectral responses due to its high spatial and spectral resolution (Delegido et al., 2013; Drusch et al., 2012).

In addition to the coefficient of determination, we used root mean square error (RMSE) as evaluation criteria. When the R^2 value was larger, the RMSE was smaller, and the correlation was higher.

The RMSE values reveal generally low errors, confirming the reliability of satellite-derived reflectance. However, notable variability is observed among samples. In particular, Sample 5 exhibits a relatively high RMSE despite a strong correlation, suggesting the presence of systematic deviations or increased within-pixel heterogeneity. Conversely, Sample 3 shows the lowest RMSE, indicating the best agreement between in situ and satellite measurements. These results underline the influence of spatial resolution mismatch and local variability on the accuracy of satellite observations.

Previous studies focused on the combination or the comparison of field spectrometer measurements with satellite spectral data. For example, Richardson et al. (1980) demonstrated a strong correlation between the two sensors, through the comparison of LANDSAT-2 MSS data with spectroradiometer measurements over rangeland plant communities, confirming that atmospherically corrected satellite data can accurately reproduce spectral signatures measured in field. More recently, Isnaen et al. (2019) showed a good agreement between field spectral measurements and WorldView-2 imagery. Similarly, (Kamal et al., 2018; Wicaksono et al., 2017) highlighted that spectral resampling may reduce spectral precision and affect classification accuracy. Despite these reported limitations, the present study showed a strong correlation and good agreement between field spectrometer measurements and spectral data derived from sentinel-2, confirming the reliability of satellite observations for spectral analysis.

Conclusion

This study evaluated the consistency between field spectrometer measurements and Sentinel-2 derived reflectance for agricultural monitoring through band-based approaches. The results confirm that Sentinel-2 reflectance data provide a reliable representation of field spectral measurements. In fact, the combination of high correlation coefficients, strong determination coefficients ($R^2 > 0.90$), and generally low RMSE values confirm the reliability of Sentinel-2 data in capturing vegetation reflectance under the studied conditions and supports the use of this data for a wide range of agricultural applications, including crop condition monitoring, irrigation management, and nutrient assessment. The strong agreement between ground and satellite data reinforces the validity of integrating field spectroscopy for calibration and validation purposes in remote sensing studies.

Declarations

Funding

declaration

The authors declare that there are no financial interests, commercial affiliations, or other potential conflicts of interest that could have influenced the objectivity of this research or the writing of this paper.

Author Contribution

T.H. Conceptualization, methodology, data collection, field spectral measurements, data processing, statistical analysis, visualization, writing, original draft preparation
E.S. Conceptualization, methodology, data collection, data processing, statistical analysis, visualization, writing, original draft preparation
B.A. Methodology, data analysis, validation, review and editing
W.E. Scientific consultation, data interpretation, validation, review and editing
A.M. Supervision, validation and review

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Data Availability

All data supporting the findings of this study its Supplementary Information. And are available from the corresponding author upon reasonable request and can be provided.

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Figures

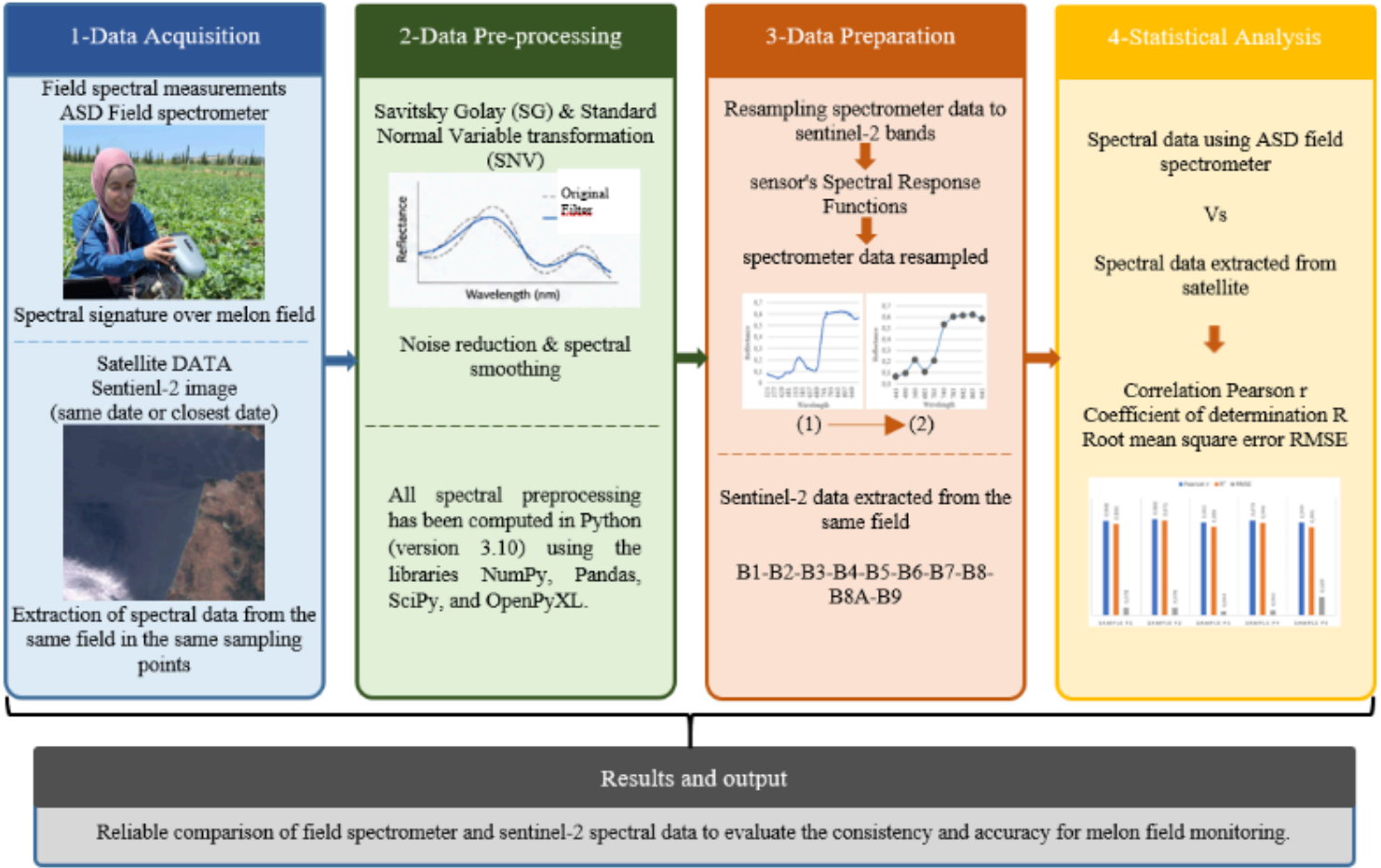


Figure 1

Experimental design overshaw



Figure 2

Study Area (Google Earth)



Figure 3

measurement site

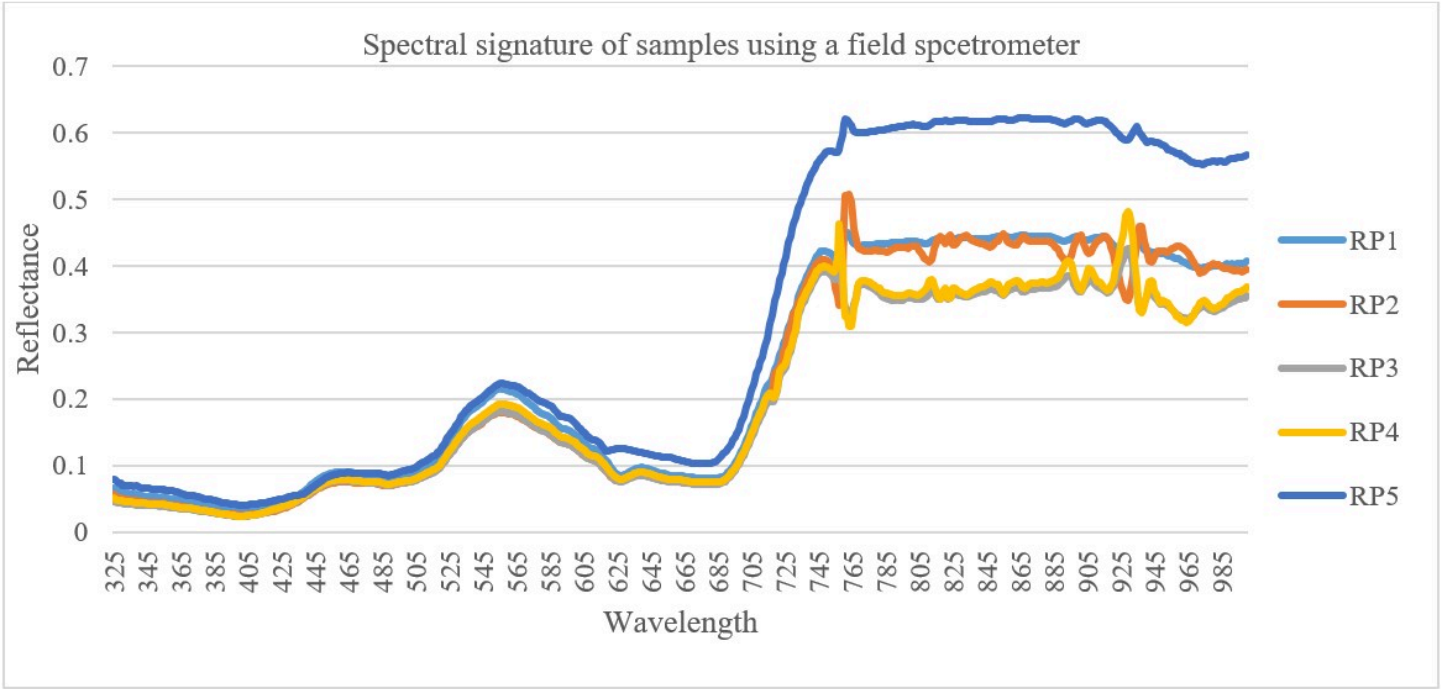


Figure 4
Melon spectral reflectance curves resulted from field measurement

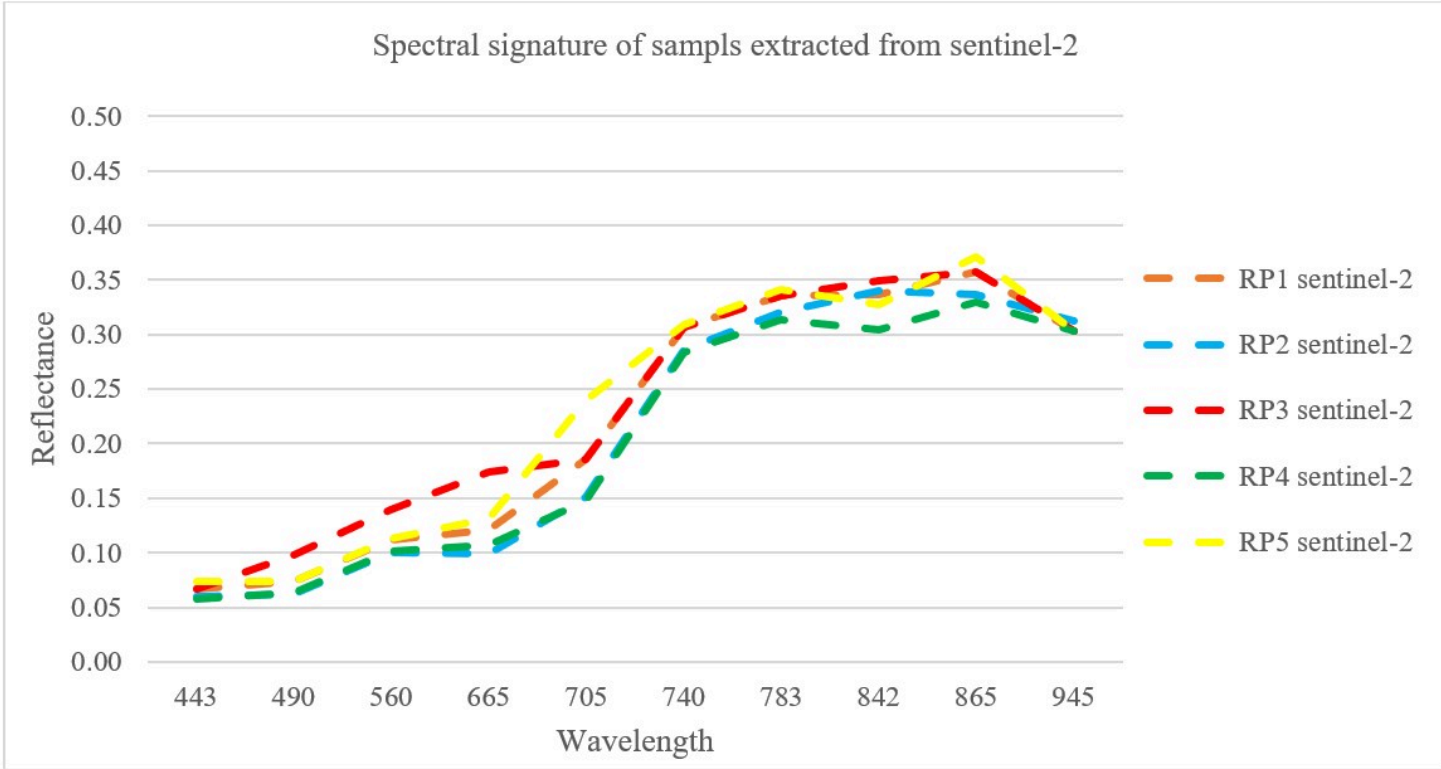


Figure 5

The spectral reflectance curve of vegetation from the Sentinel-2 image

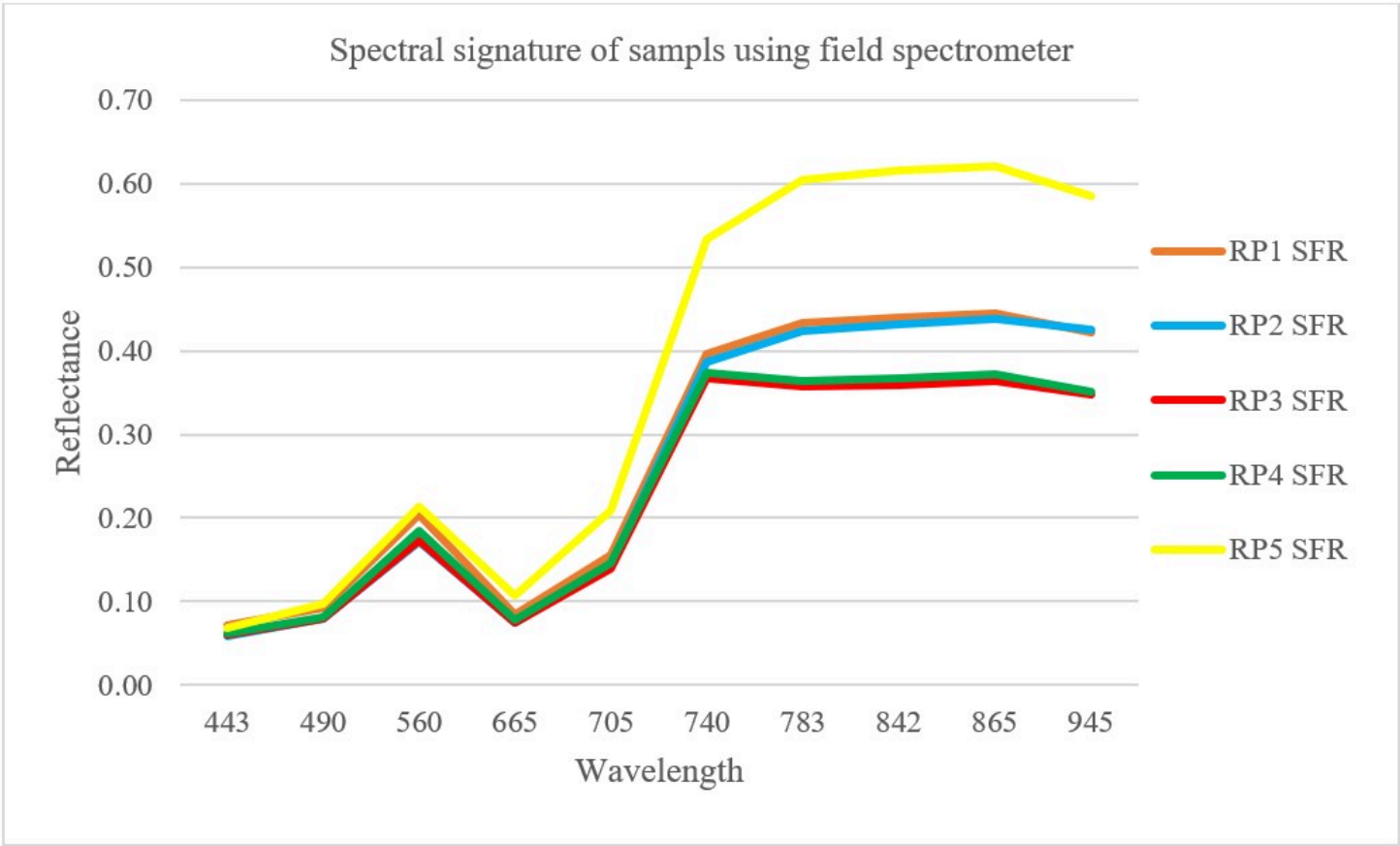


Figure 6

Resampling result of spectral measurements obtained using field spectrometer

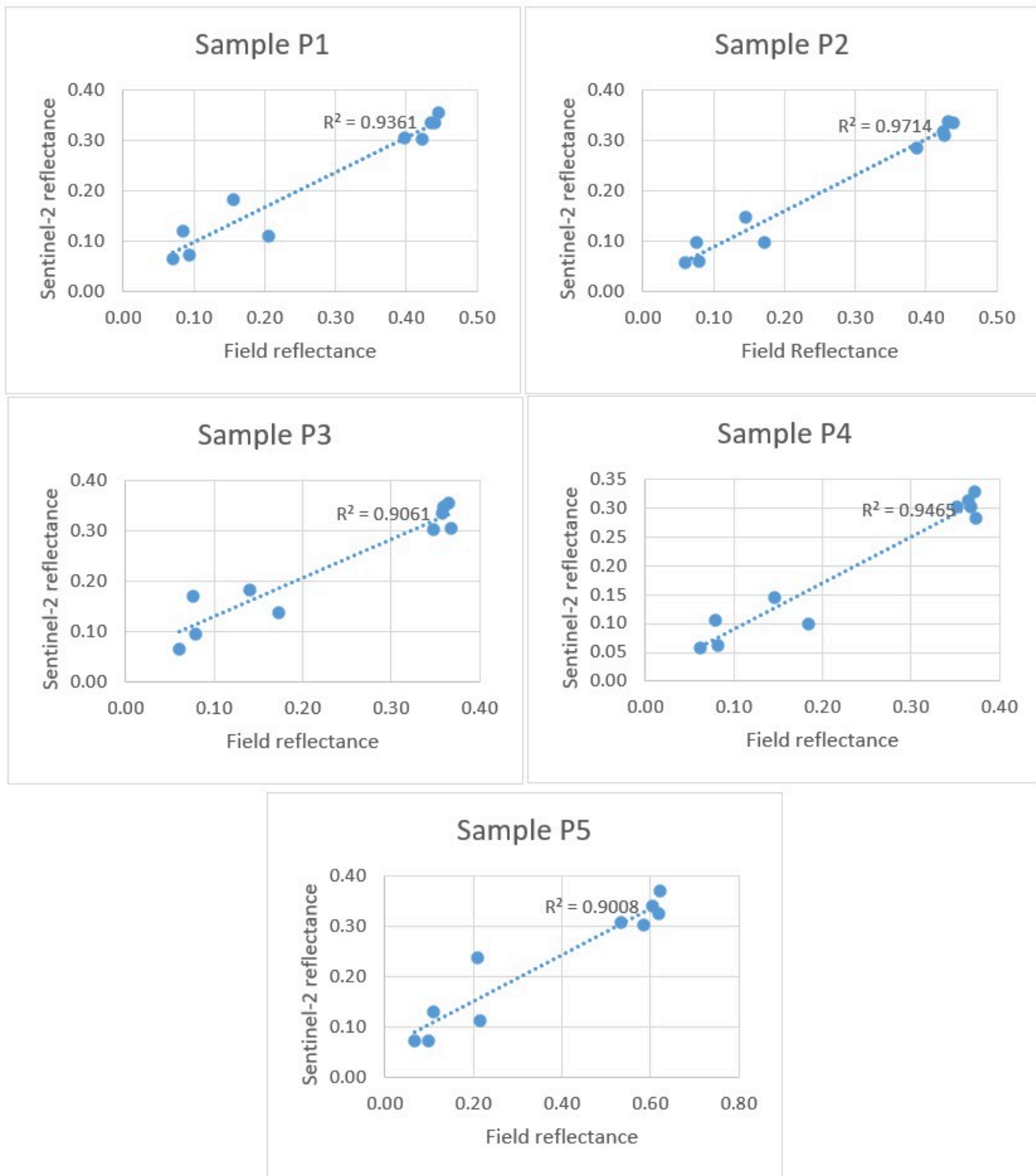


Figure 7

Correlation analysis between spectral data using spectrometer and satellite

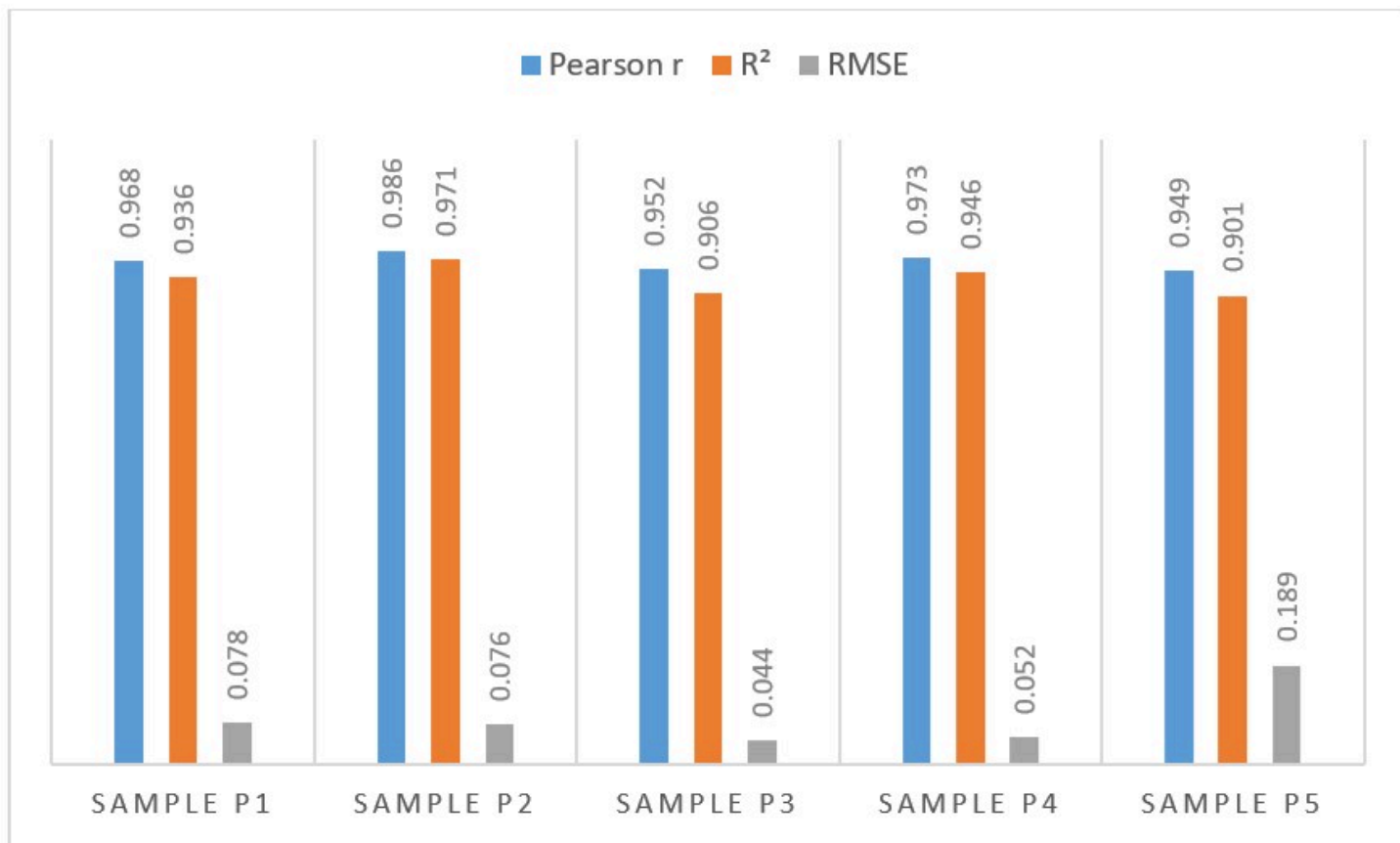


Figure 8

Pearson correlation, R^2 and RMSE analysis between reflectance using spectrometer and sentinel-2