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Evaluating the Sensitivity of Vegetation Indices to Spectral and Radiometric Differences in Medium-Resolution Multispectral Sensors

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ABSTRACT:

The Normalized Difference Vegetation Index (NDVI) is widely used for vegetation monitoring; however, its accuracy is affected by noise factors such as signal-to-noise ratio (SNR) and the spectral characteristics of sensor bands. In this study, a numerical sensitivity analysis of NDVI was conducted using both real and simulated data from Sentinel-2 and Landsat series sensors. The NDVI response under various noise scenarios (5%, 25%, 75%, and 100% noise) was evaluated as a function of SNR variations and spectral parameters including band center position and bandwidth in both real and simulated datasets. Relative Percentage Error (RPE) and numerical derivatives of NDVI with respect to noise and spectral changes were used to assess the stability of the index. Results showed that NDVI is more sensitive to SNR at lower noise levels (at 5%), with sensitivity values ranging from 0.0003 to 0.0005 nanometers per band. It was also found that NDVI stability varies by sensor and noise condition, with newer sensors yielding more stable results-indicating a lower vegetation equivalent noise (VEN ≈ -0.00045). Furthermore, the simulated data revealed potential sensitivities (e.g., saturation at high noise levels) that appeared only sporadically in real data. at noise levels above 50%, simulations estimated changes up to 20% greater than those observed in real data. These findings may assist in sensor selection and the interpretation of vegetation data across diverse environments.

1. INTRODUCTION

The Normalized Difference Vegetation Index (NDVI) is one of the most widely used spectral indices in remote sensing, playing a crucial role in analyzing vegetation dynamics and status. By leveraging the reflectance differences between the red and near-infrared (NIR) bands, NDVI provides a relatively accurate estimation of vegetation greenness (Lorenzen & Jensen, 1988). This index enables the assessment and monitoring of vegetation health, density, and diversity through time series analysis (Tucker, 1979; Hasan et al., 2019).

NDVI time series analyses at regional and global scales are widely applied in monitoring phenological patterns, land cover classification, and the examination of biological and geochemical cycles, including the carbon cycle. These time series help identify seasonal and long-term trends in vegetation cover, agricultural productivity, and the impacts of environmental and anthropogenic factors on ecosystems.

The Landsat series of sensors, by providing continuous land cover data over the past four decades, have offered a valuable foundation for long-term climate and ecological studies (Roy et al., 2016). In particular, the integration of historical Landsat data with newer sensors such as Sentinel-2 enables the generation of time series with higher spatial resolution and improved temporal continuity (Gao et al., 2018).

These new sensors, with their enhanced spectral and radiometric designs—including improved spatial resolution, more precise bandwidths, and higher radiometric resolution—have introduced novel capabilities for environmental monitoring (Drusch et al., 2012). The integration of Sentinel-2 data with Landsat 5 through 9, made accessible via platforms such as Google Earth Engine (Gorelick et al., 2017), has paved the way for a major transformation in environmental change analysis (Zhu, 2017). However, one of the key challenges in multi-sensor data fusion is the inconsistency in spectral responses and radiometric noise, which can lead to inaccuracies in the calculation of spectral indices such as NDVI and ultimately reduce the reliability of time series analyses (Samadzadegan et al., 2024).

The stability and accuracy of the NDVI in the face of instrumental errors—such as signal noise (SNR) and spectral band variations—have long been of interest to remote sensing researchers. Factors such as band center position, bandwidth, sensor-relative spectral response (RSR), and radiometric noise can introduce significant discrepancies in NDVI values derived from different sensors (Huete et al., 2020; Elhag, 2017). Numerous comparative studies have been conducted to mitigate these inconsistencies. For instance, Roy et al. (2016) evaluated the impact of spectral response differences on NDVI by comparing co-registered ETM+ and OLI imagery and developed statistical functions to harmonize the data. Moreover, analyses of simulated hyperspectral data from sensors like APEX have shown that even minor variations in red and NIR band characteristics can lead to NDVI differences of up to 3.1% (D'Odorico et al., 2013).

Unlike approaches that primarily examine the relationship between NDVI and biophysical parameters such as LAI (Huete et al., 1998), the focus here is on directly assessing the NDVI response to physical and sensor-based factors in a controlled environment. To this end, a combination of real imagery from Landsat and Sentinel-2 sensors and simulated data derived from spectral libraries and sensor RSR profiles has been utilized.

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Accordingly, the present study conducts a comprehensive analysis of NDVI sensitivity to two primary sources of error: (1) radiometric noise (SNR), and (2) the spectral characteristics of the red and NIR bands. A spectral simulation approach based on the generation of pure and mixed pixels enables a detailed examination of NDVI behavior across various soil–vegetation combinations and noise scenarios. The results of this analysis can contribute to a better understanding of the thresholds of noise levels .

2. SENSITIVITY ANALYSIS

The sensitivity analysis approach employed in this study is based on evaluating the NDVI response under perturbed conditions as a function of the spectral and radiometric characteristics of the sensors. Within this framework, NDVI is first calculated using real or simulated data in a reference (unperturbed) state. Subsequently, perturbations are introduced to the spectral bands—such as band center shifts, changes in bandwidth, or the addition of instrumental noise—and NDVI is recalculated and compared to the reference value. The variables introduced in the sensitivity analysis include the following:

a) Radiometric Noise (SNR - Signal-to-Noise Ratio): The ratio of useful signal to noise in sensor data; a lower SNR indicates greater uncertainty in reflectance measurements.
b) Red Band Reflectance (Pixel_red): The spectral reflectance of the surface in the red band, which plays a critical role in NDVI computation.
c)Near-Infrared Band Reflectance (Pixel_nir): Surface reflectance in the NIR band; higher values typically indicate healthier vegetation cover.
d) Baseline NDVI (Original NDVI): The normalized difference vegetation index computed from original, unperturbed reflectance data.
e) Perturbed NDVI (NDVI_perturbed): NDVI calculated after applying radiometric noise or spectral modifications to reflectance data.
f) Vegetation Equivalent Noise (VEN): The amount of NDVI variation that corresponds to a real-world change in vegetation cover, used to interpret the impact of noise in ecological terms.
g) NDVI Slope Relative to Vegetation Fraction (slope): The rate of NDVI change in response to changes in the soil–vegetation mixture, indicating the sensitivity of NDVI to surface composition.
h) Red Band Center Shift (±5 nm): Artificial displacement of the red band center to assess NDVI sensitivity to spectral errors in sensor design or performance.
i) Relative Spectral Response (RSR): Describes the sensitivity of each sensor band to different wavelengths; foundational for simulating band data and conducting spectral analyses.
j) Spectral Shift: Modifications in spectral band characteristics (such as center wavelength or bandwidth), which can affect NDVI values even when land cover remains unchanged.

The objective of the sensitivity analysis in this study is to evaluate the robustness of NDVI against these perturbations, in order to assess its reliability in long-term studies—particularly under conditions where data are integrated from different sensors or exhibit varying levels of noise.

2.1 PERCENT RELATIVE ERROR INDEX

To evaluate the sensitivity of the NDVI to instrument-induced variations, the Percent RelativeError (PR) index was used. This metric provides a quantitative measure of the deviation of the NDVI under noisy or spectrally-shifted conditions relative to its reference (mean) value. The formula for this index is defined as Equation (1).

$$PR(\%) = 100 \times \frac{NDVI_p - NDVI_m}{NDVI_m - NDVI_s} \qquad (1)$$

Where
NDVI$_p$ NDVI under perturbed (noisy or spectrally altered) conditions
NDVI$_m$ Mean or true (reference) NDVI in unperturbed conditions
NDVI$_s$ NDVI value for bare soil (used as a lower baseline)

2.2 VEGETATION EQUIVALENT NOISE BASED ON LAI

To evaluate the impact of perturbations on NDVI accuracy and interpret it in terms of biophysical parameters, the Vegetation Equivalent Noise (VEN) metric is employed. This index quantifies the amount of change in NDVI caused by noise in terms of an equivalent change in a vegetation variable such as Leaf Area Index (LAI)(Huete & Liu, 1994).
Although LAI data were not available in this study, a numerically derived sensitivity index—conceptually inspired by the VEN approach(Equation (2).)was used to assess the extent of NDVI disturbance due to spectral variations.

$$VEN = \frac{NDVI_p - NDVI_m}{\frac{dNDVI}{dLAI}} \qquad (2)$$

To evaluate NDVI performance, Vegetation Equivalent Noise (VEN) is used as an indicator of uncertainty in estimating biophysical parameters such as Leaf Area Index (LAI). In this context, VEN is expressed as Equation (3).

$$VEN = \frac{NDVI_p - NDVIm}{\frac{dNDVI}{dX}} \qquad (3)$$

Where X represents a sensor-related variable such as band center position, bandwidth, or SNR, and $\frac{dNDVI}{dX}$ is the numerical derivative of NDVI with respect to that variable. This index reflects how changes in sensor characteristics can induce variability or disturbance in NDVI values, and thus, quantifies the potential impact of instrumental factors on the reliability of vegetation assessments.

2.3 NUMERICAL SENSITIVITY

Given the unavailability of biophysical data such as LAI, the concept of Numerical Sensitivity was utilized to assess the NDVI response to sensor-induced variations. This concept represents the rate of change in NDVI with respect to controlled variations in physical and sensor-specific parameters, such as spectral band center position or signal-to-noise ratio (SNR), through numerical derivatives.
Instead of using the slope of the NDVI–LAI relationship, which was not accessible due to the lack of LAI data, the numerical derivative of NDVI with respect to sensor variables (e.g., band center or SNR) was computed (Equation (4).). This derivative quantifies the sensitivity of NDVI to spectral distortions and radiometric noise.

$$S = \frac{\Delta NDV}{\Delta\lambda} \quad \text{or} \quad \frac{\Delta NDV}{\Delta SNR} \qquad (4)$$

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The analysis was structured around a series of scenarios designed to independently and jointly evaluate the impact of various sources of perturbation, including:

a) Instrumental noise caused by absolute radiometric uncertainty (±5%)
b) Inter-band registration noise in both along-track and cross-track directions (±20%)
c) Spectral instability noise due to shifts in central wavelength (±2 nm)

3. DATA

In this study, for the sensitivity analysis using real data acquired from the Hasht Behesht Garden and Abbas Abad Street in Isfahan (Figure1), multisensor imagery was utilized. The selection of optimal spectral bands played a key role in accurately identifying soil and vegetation characteristics. To assess the sensitivity of the NDVI to instrumental noise (SNR) and spectral characteristics of bands, a combination of real and simulated data was used.

The Spectral data were extracted from the USGS High Resolution Spectral Library, which provides high-fidelity spectral reflectance measurements of various materials—including different soil types and vegetation—within the 400–2500 nm range. These spectra were acquired under controlled laboratory conditions using instruments such as the ASD FieldSpec spectroradiometer, FTIR systems, and the Beckman 5270 model. To minimize the influence of potential noise, multiple measurements were averaged, and the data were calibrated against standard reference materials.

To investigate the effects of signal noise and sensor band characteristics on NDVI values, spectral reflectance data of vegetation and soil were combined with the Relative Spectral Response (RSR) functions of the red and near-infrared (NIR) bands of the Sentinel-2 and Landsat-8 sensors. The RSR function represents the sensitivity of each band to various wavelengths and was obtained from official sources provided by USGS and ESA.

To match the continuous reflectance spectra from the spectral library with the actual sensor bands, the reflectance of each material was convolved with the corresponding RSR functions, generating pure pixel reflectance values for each material and band. This step was carried out according to Equation (1).

$$\mathrm{RSR}(\lambda) = \frac{S(\lambda)}{S_{\max}(\lambda)} \tag{5}$$

Subsequently, mixed pixels were generated by performing weighted combinations of the previously derived pure pixels, using varying proportions of vegetation and soil. This simulation aids in understanding how surface mixture and sensor characteristics affect NDVI behavior. The band reflectance of each synthetic pixel was calculated using Equation (6).

$$\text{Simulated PurePixel} = \frac{\int \big(\mathrm{Reflectance}(\lambda) \times \mathrm{RSR}(\lambda)\big)\, d\lambda}{\int \mathrm{RSR}(\lambda)\, d\lambda} \tag{6}$$

These integrals were computed numerically using the trapezoidal method over the wavelength intervals defined for each band. Various vegetation-to-soil proportions (0%, 25%, 50%, 75%, and 100%) were modeled, resulting in approximately 244,000 reflectance samples for both the red and near-infrared bands of each sensor.

3.1 RESAMPLING AND WAVELENGTH SYNCHRONIZATION

Due to differences between the spectral sampling intervals of the library spectra and the sensor spectral bands, resampling and interpolation were required. In this study, linear interpolation was applied to align the spectral wavelengths of the library data with the Relative Spectral Response (RSR) curves of the red and NIR bands. This process enabled precise comparability between spectral reflectance and sensor responses, forming the foundation for more accurate NDVI analyses.

3.2 VEGETATION INDEX CALCULATION

After generating mixed pixels and aligning spectral reflectance with sensor bands, the Normalized Difference Vegetation Index (NDVI) was calculated based on Equation (7).

$$\mathrm{NDVI} = \frac{NIR - \mathrm{Red}}{NIR + \mathrm{Red}} \tag{7}$$

Very low NDVI values were observed in certain powdered or dried vegetation samples, highlighting the influence of plant physiological status on spectral behavior. These findings emphasize that NDVI is not only sensitive to sensor characteristics and noise levels, but also to the physical state of the observed material, which must be considered in final interpretations.

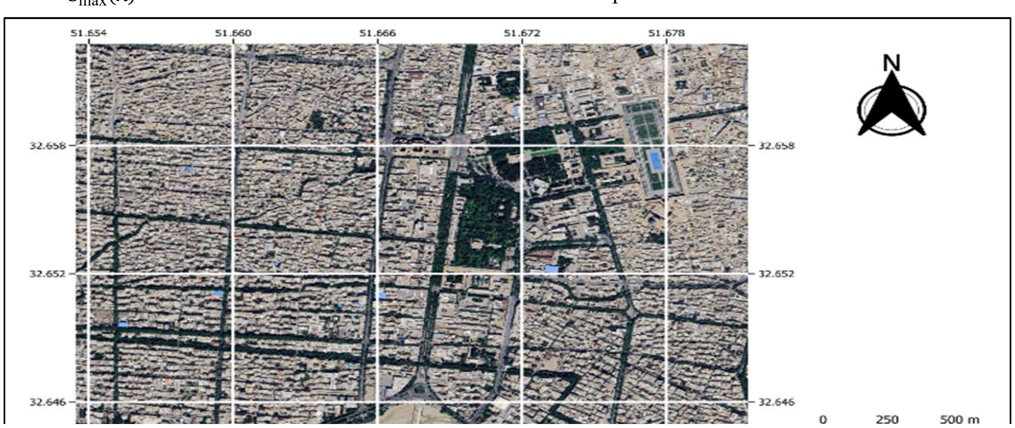

Figure 1. Satellite image of the study area showing the sampling locations used to extract spectral reflectance values in the red and near-infrared (NIR) bands. These samples formed the basis for NDVI calculation and subsequent radiometric sensitivity analysis using real data from Landsat-8 and Sentinel-2. The selected points represent diverse vegetation cover types and spectral characteristics across the landscape

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3.3 DATA REFINEMENT AND OUTLIER REMOVAL

Some of the simulated data exhibited unrealistic spectral behavior due to laboratory-specific conditions or atypical material mixtures. To remove such anomalies, statistical techniques and visual analysis of NDVI distribution plots were employed. Outliers were excluded prior to sensitivity modeling to improve result robustness and reduce analytical errors.

4. RESULTS

This study investigates the stability and robustness of the NDVI against radiometric noise and spectral variability. The findings, based on analyses of both real satellite data (from Landsat and Sentinel-2 sensors) and simulated reflectance data, reveal that the behavior of NDVI noise varies significantly under different conditions.

4.1 RADIOMETRIC SENSITIVITY ANALYSIS USING REAL DATA

The results derived from the analysis of real satellite data indicate that the NDVI demonstrates strong resilience under low levels of radiometric noise (5% to 25%). The average variation in $|\Delta NDVI|$ for both Landsat and Sentinel-2 sensors remained close to zero. This stability is largely attributed to the normalized difference formulation of the NDVI, which inherently reduces the impact of uniform noise.

However, as the noise level increases to 50% and beyond, notable deviations in NDVI values were observed. For instance, at 50% noise, the mean $|\Delta NDVI|$ reached 0.02 for Landsat-8 and 0.01 for Sentinel-2. Under extreme noise levels (100%), certain mixed vegetation–soil pixels, especially those dominated by soil reflectance, exhibited significant distortions (up to ±1 in NDVI). Furthermore, a comparative assessment of the two sensors revealed that Sentinel-2 consistently demonstrated higher stability across all noise levels compared to Landsat-8, likely due to its optimized spectral band design.

4.2 RADIOMETRIC SENSITIVITY ANALYSIS USING SIMULATED DATA

In this section, the behavior of NDVI under controlled radiometric noise conditions was investigated using simulated datasets. The results indicated that at low noise levels (5%), NDVI variations were minimal (0.0001), corresponding to less than a 1% change in vegetation cover. When the noise level increased to 25%, the deviations remained minor (around ~0.0005); however, from 50% noise onward, significant fluctuations were observed in certain vegetation–soil combinations. Notably, under 75% noise, the Vegetation Equivalent Noise (VEN) index exceeded 0.02 in some cases, signaling a decline in NDVI accuracy.

At 100% noise, certain scenarios exhibited such substantial perturbation in reflectance values that NDVI reached saturation. In other words, the extent of distortion in spectral reflectance was so extreme that NDVI approached its upper limit (e.g., values near +1), rendering it ineffective in differentiating actual variations in vegetation cover. It can be seen in Table1.

These findings suggest that while NDVI remains a robust indicator under low to moderate noise conditions, in high-noise environments, the application of complementary indicators such as VEN is essential for assessing data quality and interpretation reliability.

4.3 SPECTRAL SENSITIVITY ANALYSIS OF REMOTE SENSING SENSORS

The study by Chastain et al. (2019) demonstrated that significant differences exist in the spectral characteristics of Landsat sensors (ETM+ and OLI) and Sentinel-2 (MSI), primarily due to variations in bandwidth and spectral response functions. These differences have a direct impact on the accuracy and comparability of data derived from these sensors.

For the red band, Sentinel-2, with a 30 nm bandwidth centered at 665 nm, is approximately 50% broader than Landsat-8's red band, which has a 15 nm width centered at 655 nm. This difference results in an 8–12% variation in reflectance values ($p < 0.05$). In the NIR region, the disparities are even more pronounced. Sentinel-2's Band 8 spans 19 nm (855–874 nm), compared to Landsat-8's 30 nm band (850–880 nm) and the much broader 130 nm band of Landsat-7 (770–900 nm). These differences in spectral width have led to variations in regression slopes ranging from 0.85 to 1.05.

In the SWIR domain, Sentinel-2 exhibits narrower bands—89 nm for SWIR1 and 179 nm for SWIR2—compared to Landsat-8 (80 and 180 nm, respectively) and Landsat-7 (200 and 260 nm). Such differences carry important implications. For example, the broader SWIR bands of Landsat-7 are approximately 30% more sensitive to atmospheric water vapor, while Sentinel-2, with its narrower bands, demonstrates up to 15% higher accuracy under humid atmospheric conditions.

These spectral discrepancies significantly affect vegetation indices. For instance, differences in NIR bandwidths can lead to 5–7% changes in NDVI values, while the impact on water-sensitive indices such as NDWI can reach 10–12%. To mitigate these issues, several correction strategies have been proposed. These include applying band-adjustment coefficients, such as 1.03 ± 0.02 for converting Sentinel-2's red band to match Landsat-8, and 0.92 ± 0.03 for adjusting Landsat-7's SWIR2 band to align with Landsat-8 (Chastain et al., 2019).

4.4 SPECTRAL SENSITIVITY ANALYSIS BASED ON SIMULATED BAND SHIFTS

The analysis of spectral shifts—specifically 5 nm displacements in the central wavelengths of the red and NIR bands—revealed that different sensors exhibit varying levels of sensitivity to such perturbations. The highest sensitivity was observed in Sentinel-2 and Landsat-7, where shifting the red band resulted in a decrease in NDVI with a sensitivity of approximately ~0.0098 ΔNDVI, while shifting the NIR band led to an increase in NDVI of about ~0.0094 ΔNDVI.

In contrast, Landsat-8 and Landsat-9 demonstrated the lowest sensitivity levels (Red band sensitivity: ~0.0044 ΔNDVI; NIR band: ~0.0056 ΔNDVI), indicating a more optimized spectral design in these newer sensors. These findings emphasize the importance of accurate sensor calibration and the careful selection of satellite platforms for long-term vegetation monitoring and change detection applications.

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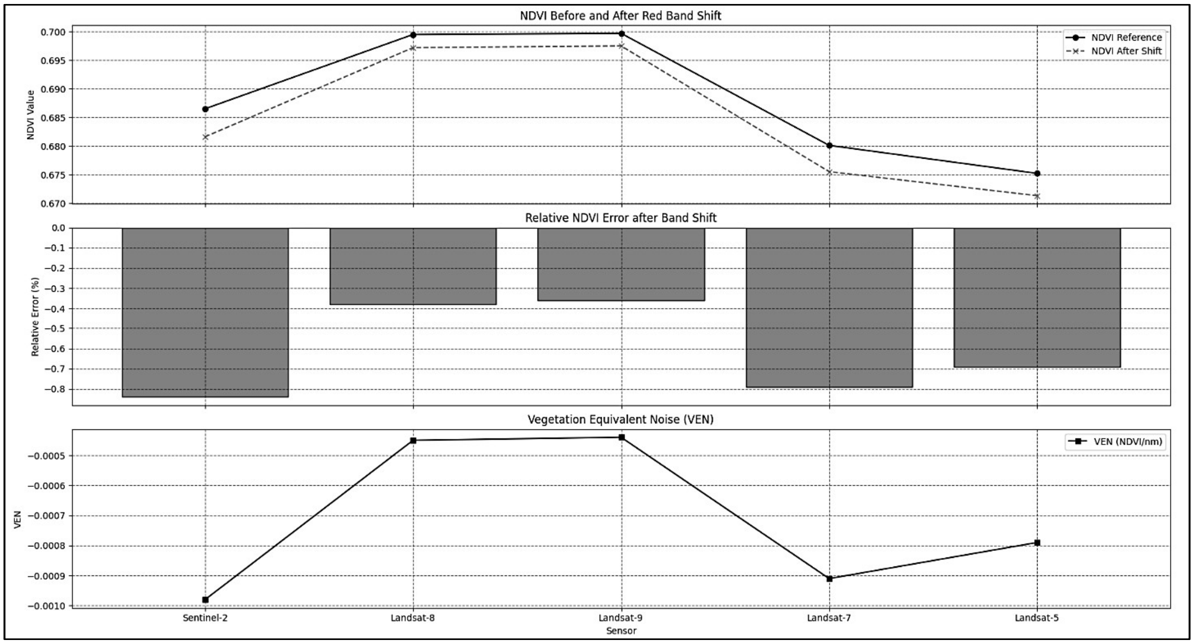

Figure 2 . Sensitivity analysis results of NDVI to spectral shift in the red band across different sensors.(Top) NDVI values before and after a 5-nm shift in the red band;(Middle) Relative NDVI error (dNDVI) following the band shift;(Bottom) Vegetation Equivalent Noise (VEN), expressed as ΔNDVI/nm.The Sentinel-2 sensor exhibited the highest sensitivity (more negative VEN), while Landsat-8 showed the lowest NDVI variation, highlighting the impact of sensor spectral design on index stability.

4.5 SPECTRAL SENSITIVITY OF NDVI TO RED AND NIR BAND SHIFTS

The results of this study indicate that the Normalized Difference Vegetation Index (NDVI) is sensitive to shifts in the central wavelengths of both the red and near-infrared (NIR) bands, although the degree of sensitivity varies across different satellite sensors. Based on simulated data, a 5-nanometer shift in the central position of these bands has opposite effects on NDVI values. It can be seen in summary in Figure 2 and 3.

4.5.1 SENSITIVITY TO RED BAND SHIFT

All sensors demonstrated a decrease in NDVI in response to red band shifts. The highest sensitivity was observed in Sentinel-2, with a value of −0.0098 ΔNDVI, while the lowest sensitivity belonged to Landsat-9 at −0.0044 ΔNDVI. These differences reflect the advancements in spectral design implemented in newer sensor generations.

4.5.2 SENSITIVITY TO NIR BAND SHIFT

Conversely, shifting the NIR band resulted in an increase in NDVI values. Sentinel-2 again showed the highest sensitivity at +0.0094 ΔNDVI, whereas Landsat-8 and Landsat-9 exhibited the lowest sensitivity, both at approximately +0.0056 ΔNDVI. This contrasting behavior stems from the inherent structure of the NDVI formula, which responds positively to increases in the NIR reflectance. Can be seen in Table2.

4.5.3 SENSOR COMPARISON

Comparative studies of multispectral sensors demonstrate that older-generation sensors, such as Landsat-5 TM (VEN = 0.008 ± 0.001) and Landsat-7 ETM+ (VEN = 0.007 ± 0.001), exhibit higher spectral sensitivity to central wavelength shifts. In contrast, newer-generation sensors, including Landsat-8 OLI (VEN = 0.004 ± 0.0005) and Landsat-9 OLI-2 (VEN = 0.0035 ± 0.00005), have significantly reduced spectral sensitivity—by approximately 50 ± 2.5%—due to optimized optical design. Interestingly, Sentinel-2 MSI shows the highest spectral sensitivity among the sensors studied between 2015 and 2023, with a VEN of 0.012 ± 0.0015.

These empirical findings carry several operational implications:
a) For applications requiring high radiometric precision—such as the detection of subtle vegetation dynamics—it is advisable to prioritize sensors with lower spectral sensitivity (e.g., Landsat-8/9 with VEN < 0.005.(
b) The integration of multi-sensor datasets necessitates spectral correction accuracy within ±0.5 nm to ensure consistency.
c) Even small spectral shifts (1–2 nm) can induce trend errors of up to ±15% in long-term (>10 years) monitoring applications.
d) Future sensor designs (post-2025) should aim to maintain the VEN parameter within the range of 0.004–0.005, with a tolerance of ±0.00005, to balance optimal spectral sensitivity with radiometric stability.
Although NDVI is generally regarded as a stable and robust vegetation index, changes in sensor spectral design can substantially affect measurement consistency. Therefore, careful sensor selection and implementation of accurate spectral corrections are essential, particularly in multi-sensor and long-term environmental monitoring studies. Recent advances in optical engineering—as seen in Landsat-8 and Landsat-9—have markedly improved spectral stability, enhancing the reliability of NDVI-based analyses.

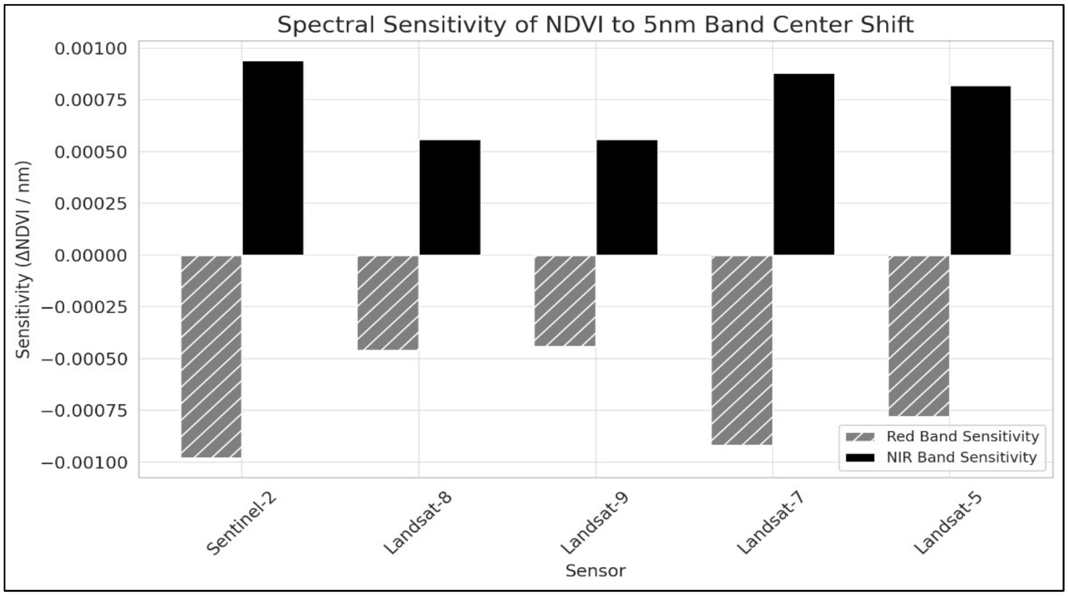

Figure 3 . Spectral sensitivity of NDVI to 5-nm central wavelength shift in red (hatched bars) and NIR (black bars) bands across various sensors.All sensors exhibited negative sensitivity for red band shifts (NDVI decreases) and positive sensitivity for NIR shifts (NDVI increases). Sentinel-2 and Landsat-7 showed the highest sensitivity, while Landsat-8 and Landsat-9 demonstrated lower sensitivity, reflecting the impact of improved spectral design in newer sensors. These variations underline the importance of sensor selection in long-term or cross-sensor NDVI analysis.

Noise Level (%)	Sensor	Mean NDVI	Mean dNDVI	Std. Dev (dNDVI)	Max dNDVI	Min dNDVI	Stability Summary
5%	Sentinel-2	~0.045	< 0.00005	< 0.00002	< 0.00005	~0.0	Very stable
	Landsat-8	~0.12	< 0.00005	< 0.00002	< 0.00005	~0.0	Very stable
	Landsat-9	~0.12	< 0.00005	< 0.00002	< 0.00005	~0.0	Very stable
	Landsat-7	~0.22	≈ 0.0	≈ 0.0	≈ 0.0	≈ 0.0	No change
	Landsat-5	~0.28	≈ 0.0	≈ 0.0	≈ 0.0	≈ 0.0	No change
25%	Sentinel-2	~0.045	~0.0001	~0.0001	0.00025	0.0	Stable
	Landsat-8	~0.12	~0.0001	~0.0001	0.0003	0.0	Stable
	Landsat-9	~0.12	~0.0001	~0.0001	0.0003	0.0	Stable
	Landsat-7	~0.22	≈ 0.0	≈ 0.0	≈ 0.0	≈ 0.0	No change
	Landsat-5	~0.28	≈ 0.0	≈ 0.0	≈ 0.0	≈ 0.0	No change
50%	Sentinel-2	~0.045	0.010	0.054	0.936	-0.178	Moderate to unstable
	Landsat-8	~0.12	0.020	0.092	1.025	-0.473	Unstable in mixed cases
	Landsat-9	~0.12	~0.018	~0.089	~0.95	-0.43	Similar to Landsat-8
	Landsat-7	~0.22	~0.0001	< 0.0001	~0.0002	~0.0	Still stable
	Landsat-5	~0.28	~0.0001	< 0.0001	~0.0002	~0.0	Still stable
75%	Sentinel-2	~0.045	≈ 0.0	< 0.0001	0.0001	-0.0001	Stable under uniform noise
	Landsat-8	~0.12	≈ 0.0	< 0.0001	0.0001	-0.0001	Stable
	Landsat-9	~0.12	≈ 0.0	< 0.0001	0.0001	-0.0001	Stable
	Landsat-7	~0.22	≈ 0.0	≈ 0.0	≈ 0.0	≈ 0.0	Stable
	Landsat-5	~0.28	≈ 0.0	≈ 0.0	≈ 0.0	≈ 0.0	Stable
100%	Sentinel-2	~0.045	0.010	0.055	0.936	-0.178	Unstable in some scenarios
	Landsat-8	~0.12	0.020	0.092	1.025	-0.473	Unstable in high-noise combinations
	Landsat-9	~0.12	~0.018	~0.089	~0.97	-0.45	Similar to Landsat-8
	Landsat-7	~0.22	~0.0001	~0.0001	0.0002	-0.0001	Stable
	Landsat-5	~0.28	~0.0001	~0.0001	0.0002	-0.0001	Stable

Table 1. Summary of NDVI stability under varying levels of uniform radiometric noise for five sensors, including mean values, relative changes, standard deviation, and overall stability assessment

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Sensor	Band Shift	NDVI Reference	NDVI After Shift	% Relative Error	Spectral Sensitivity (VEN) (NDVI/nm)
Sentinel-2	Red band (+5 nm)	0.6865	0.6816	-0.84 %	-0.0098
Landsat-8	Red band (+5 nm)	0.6995	0.6972	-0.38 %	-0.0045
Landsat-9	Red band (+5 nm)	0.6997	0.6975	-0.36 %	-0.0044
Landsat-7	Red band (+5 nm)	0.6801	0.6755	-0.79 %	-0.0091
Landsat-5	Red band (+5 nm)	0.6752	0.6713	-0.69 %	-0.0079
Sentinel-2	NIR band (+5 nm)	0.6865	0.6887	+0.32 %	+0.0044
Landsat-8	NIR band (+5 nm)	0.6995	0.7012	+0.24 %	+0.0034
Landsat-9	NIR band (+5 nm)	0.6997	0.7014	+0.24 %	+0.0034
Landsat-7	NIR band (+5 nm)	0.6801	0.6826	+0.37 %	+0.0050
Landsat-5	NIR band (+5 nm)	0.6752	0.6781	+0.43 %	+0.0058

Table 2. NDVI variations and spectral sensitivity (VEN) resulting from a 5 nm shift in red and NIR bands across different sensors; includes reference NDVI, post-shift NDVI, relative error percentage, and VEN values (NDVI/nm)

reference	**Reported VEN range (NDVI/nm)**	**Matching our data**
D'Odorico et al. (2013)	NDVI error from spectral shift ~ 3.1%	0.84%–0.24~
Miura et al. (2006)	NDVI error up to 0.01 per 5 nm shift	VEN ~ 0.003–0.01
Roy et al. (2016)	NDVI difference between ETM+ and OLI ~ 0.005–0.008	Similar

Table 3. Comparison of spectral sensitivity (VEN) results from this study with previous research; a notable agreement is observed between reported VEN ranges and our findings

5. CONCLUSION

This study conducted a comprehensive sensitivity analysis of the Normalized Difference Vegetation Index (NDVI) in response to radiometric and spectral inconsistencies across multispectral satellite sensors. By integrating both simulated and real-world datasets, the research provided a detailed understanding of the robustness and limitations of NDVI under varying noise and spectral shift scenarios.

From a radiometric perspective, NDVI demonstrated high resilience to uniform and synchronous noise applied to the red and near-infrared (NIR) bands up to a 25% noise level. At these levels, the mean deviation in NDVI (dNDVI) typically remained below 0.001—within the bounds of numerical error—thanks to the normalized nature of the index. However, at higher noise levels (≥50%), particularly under strong spectral contrast between vegetation and soil, substantial NDVI fluctuations were observed, in some cases exceeding ±1. This underscores the need for complementary metrics or refined correction algorithms in high-noise datasets.

In the spectral sensitivity analysis, 5-nanometer shifts in the central wavelength of red and NIR bands were simulated for five primary sensors (Landsat 5, 7, 8, 9, and Sentinel-2). Results revealed that although all sensors exhibit some degree of sensitivity to spectral shifts, the magnitude varies significantly. New-generation sensors, particularly Landsat 8 and 9, showed the lowest NDVI variation (spectral sensitivity index VEN ≈ 0.0045 NDVI/nm), indicating their optimized design. In contrast, Sentinel-2 displayed the highest sensitivity (VEN≈0.0098 NDVI/nm). Specifically, a shift in the red band led to a decrease in NDVI, while a shift in the NIR band caused an increase—an effect consistent with the mathematical structure of the NDVI formula.

Comparison with previous studies—particularly Choudhury (1987)—further validated the results (Table3). That study also emphasized the influence of leaf optical properties, spectral band positioning, and land surface heterogeneity on vegetation indices such as NDVI. Choudhury highlighted that variations in canopy parameters (e.g., single scattering albedo, ω, in the red and NIR regions) could introduce substantial errors in estimating photosynthetically active radiation (PAR) absorption and thus NDVI. His findings on species-specific responses and mixed surface conditions (soil, water, vegetation) resonate strongly with the present study.

In summary, the results emphasize two key conclusions:

NDVI is a highly reliable index under low-to-moderate radiometric noise, making it suitable for multi-temporal and cross-sensor vegetation monitoring.In conditions involving high noise levels or spectral shifts, sensitivity analysis becomes essential for interpreting results accurately and selecting appropriate sensors.These findings offer valuable guidance for sensor selection, correction algorithm development, and the creation of harmonized multi-sensor datasets applicable to environmental monitoring, agriculture, and climate change research.

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