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The Effect of Sensor Resolution (Landsat 9 and Pleiades) on Spectral Indices Information: Comparison and Analysis

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Abstract

Remote sensing images are key tools in environmental and urban studies, where precise natural resource monitoring is becoming increasingly important. However, using medium-resolution images, such as Landsat 9, frequently presents difficulties in delivering correct spatial data, such as the distribution of vegetation and other land coverings, due to the pressing need for improving remote sensing techniques to satisfy the needs and assess environmental changes in increasingly metropolitan regions. In this study, spectral and spatial information (vegetation indices and modified water index) driven from Landsat 9 images were compared to spectral information from high-resolution Pleiades images, which was evaluated using linear regression between the spectral information samples from Landsat and Pleiades indices. The results revealed a limited correlation between traditional Landsat 9 data and high-resolution Pleiades spectral indices. However, the NDVSI spectral index derivative from Landsat data showed efficiency and accuracy in estimating vegetation parameters, with a correlation coefficient (R^2 =0.5) with the Pleiades. Unlike the usual NDVI metric with a correlation coefficient (R^2 = 0.2). These findings highlight the necessity of enhancing medium-resolution remote sensing data in urban settings, as it adds to improving and estimating natural resources.

Keywords: Spectral Indices, Landsat9, Pleiades, NDVI, NDVSI, MNDWI, IDW

تأثير دقة المستشعر (*Landsat 9* و *Pleiades*) على معلومات المؤشرات الطيفية: مقارنة وتحليل

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الخلاصة

تُعَد صور الاستشعار عن بعد أدوات أساسية في الدراسات البيئية والحضرية، حيث تتزايد أهمية الرصد الدقيق للموارد الطبيعية. ومع ذلك، فإن استخدام الصور متوسطة الدقة، مثل ***Landsat 9***، غالبًا ما يواجه صعوبات في تقديم بيانات مكانية صحيحة، مثل توزيع الغطاء النباتي وغيره من الأغطية الأرضية. نظرًا للحاجة الملحة لتحسين تقنيات الاستشعار عن بعد لتلبية الاحتياجات وتقييم التغيرات البيئية في المناطق

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الحضرية المتزايدة. في هذه الدراسة، تمت مقارنة المعلومات الطيفية والمكانية (مؤشرات الغطاء النباتي ومؤشر المياه المعدل) المستمدة من صور ***Landsat 9*** بالمعلومات الطيفية من صور ***Pleiades*** عالية الدقة، والتي تم تقييمها باستخدام الانحدار الخطي بين عينات المعلومات الطيفية من مؤشرات ***Landsat*** ومؤشرات ***Pleiades***. كشفت النتائج عن وجود ارتباط محدود بين المؤشرات الطيفية التقليدية من بيانات ***Landsat 9*** وبيانات ***Pleiades*** عالية الدقة. ومع ذلك، أظهر مؤشر الطيف ***NDVSI*** المشتق من بيانات ***Landsat*** كفاءة ودقة في تقدير معلمات الغطاء النباتي، بمعامل ارتباط ($R^2 = 0.5$) مع ***Pleiades*** على عكس مقياس ***NDVI*** المعتاد مع معامل ارتباط ($R^2 = 0.2$). تسلط هذه النتائج الضوء على ضرورة تعزيز استخدام بيانات الاستشعار عن بعد متوسطة الدقة في المناطق الحضرية، لأنها تضيف إلى تحسين وتقدير الموارد الطبيعية.

1. Introduction

Accurate land use categorization is a critical technique for improving the efficacy of natural resource management and a key component of sustainable planning. Proper classification aids in understanding the complicated patterns of land use and the environmental distribution of resources, hence improving the capacity to monitor alterations in usage patterns caused by population increase and urban expansion. This categorization promotes environmental sustainability and helps mitigate negative consequences on biodiversity and resource distribution. Remote sensing data may provide precise insights into the distribution of land cover and land use, allowing us to make more informed decisions at the local, regional, and global levels [1].

In this perspective, the significance of our research rests in offering analytical approaches and information that help plan sustainably and manage their resources effectively. Remote sensing data gives an excellent chance to gather reliable information on the Earth's surface via satellites such as Sentinel-2, Landsat 8, and Landsat 9 [2]. However, because high-resolution data is expensive, underdeveloped nations confront economic barriers to its use. Obtaining medium-resolution data, such as free satellite images, is a viable alternative for these countries. These images give a valuable opportunity for academics in these places to examine and evaluate environmental trends without incurring significant expenses. Providing open-source data improves researchers' capacity to undertake in-depth studies and yield major environmental benefits, particularly in countries with diverse geographic variety. The main automatic classification methods currently available for remote sensing images include supervised classification and unsupervised classification [3]. Spectral indices-based classification is also commonly utilized for land cover classification because of its ability to recognize various surface characteristics or situations [4]. Most research on estimating vegetation cover from remote sensing data employs statistical models based on spectral data or contrast indices, such as linear regression, multiple linear regression, and so on [5]. The development of machine learning algorithms, including Landsat and Pleiades, is one of the most prominent methods currently used to process and classify data. However, atmospheric effects and noise pose a major challenge for researchers worldwide when classifying or reconstructing vegetation from medium-resolution data. Clouds, pollutants, and other atmospheric events can distort satellite images and cause inaccurate estimates of the vegetation index.

The study, conducted in a mixed environment (Mahmoudia, Baghdad), aims to compare vegetation indices derived from different sensor data, such as Pleiades high-resolution images and Landsat 9 images, taking into account that the spectral bands used to calculate the indices are comparable within both different types of data, hoping to provide a valuable contribution to the selection of appropriate data sources and reflectance index inversion models in future research and apps. Furthermore, the work promotes the creation of more precise spectral indices to increase the precision of environmental assessments. Landsat products span vast regions, with spatial resolution ranging from (30 meters) to Landsat and 15 meters for some Landsat 9 bands [6,7]. The visible, near-infrared (NIR), and short-wave infrared (SWIR) bands are used to calculate spectral indices like the Normalized Difference Vegetation Index (NDVI), the Normalized Difference Vegetation Shortwave Infrared Index (NDVSI), the Normalized Difference Built Index (NDBI), the Modified Normalized Difference Water Index (MNDWI), and the Bare Soil Index (BSI) [8,9]. However, VI models may not be transferable to other places since the empirical model developed in one region cannot represent the vegetative features of another.

2. Materials and Methods

2.1. Study area

Al-Mahmoudiya is a district located 30 km south of Iraq's capital, Baghdad, with geographical coordinates 33.05683°N 44.36509°E. Its area is around 1,400 km^2. The districts of Al-Yusufiyah, Al-Latifah, and Al-Rashid are part of it, and its variegated nature is defined by its agricultural land, government, and municipal facilities, as well as land transportation and transit lines. It is considered a gateway to Southern Baghdad. Figure 1 shows the Al-Mahmoudiyah study area.

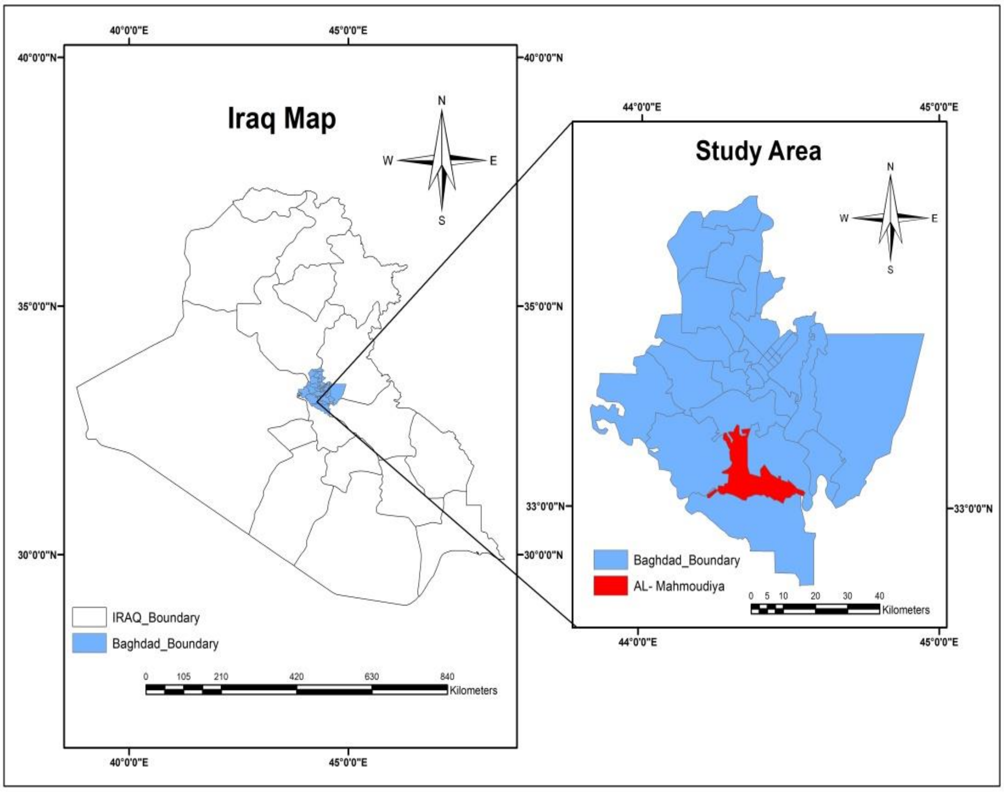

Figure 1: Study area, Al-Mahmoudiya

2.2. Dataset and Pre-processing

Two types of remote sensing data were used in this research, specifically middle-resolution Landsat 9 imagery, launched in 2021, which includes equipment identical to Landsat 8 but with an enhanced infrared thermal sensor and ten spectral bands [10]. All Landsat satellites provide valuable data products for various applications, including surface reflectance, upper atmospheric reflectance, and temperature, and the Landsat data repository is publicly available. The second kind, a very high-resolution Pleiades Imager, is a dataset of Pleiades-1A and 1B products. Raw, projected, and ortho Pleiades products are available in the following modes: (0.5 panchromatic image) Meter + 2-meter multispectral image obtained from the official agent, Al-Bayt Al-Iraqi Company [11]. Table 1 shows the spectral and spatial characteristics of the sensors [12].

Table 1: The spectral and spatial characteristics of the Landsat 9 and Pleiades satellites

Band	Landsat 9 Wavelength (μm)	Spatial Resolution(m)	Band	Pleiades Wavelength (µm)	Spatial Resolution (m)
Coastal/Aerosol	0.43-0.45	30	**Blue**	0.43-0.55	2
Blue	0.45-0.51	30	**Green**	0.50-0.62	2
Green	0.53-0.59	30	**Red**	0.59-0.71	2
Red	0.63-0.67	30	**NIR-Infrared**	**0.74-0.94**	2
NIR-Infrared	**0.85-0.87**	30	**Panchromatic**	**0.48-0.83**	0.5
Short Infrared1	1.56-1.65	30			
Short Infrared2	2.10-2.29	30			
Panchromatic	**0.50-0.67**	15			
Cirrus	1.36-1.38	30			
Thermal Infrared	10.60-11.19	100			
Thermal Infrared	11.50-12.51	100			

The data comprises multispectral images acquired by the Landsat 9 and Pleiades high-resolution satellites, which provide high-resolution surface observations. To increase image quality and usability, the data is preprocessed. Radiometric calibration, atmospheric correction, geometric correction, and noise reduction are all part of this. To measure particular land cover properties, indices such as The Normalized Difference Vegetation Index (NDVI), The Normalized Difference Vegetation Shortwave infrared index (NDVSI), and the Soil Adjusted Vegetation Index (SAVI). Normalized Difference Built Index (NDBI), Modified Normalized Difference Water Index (MNDWI), and Bare Soil Index (BSI) are typical spectral indices used in change detection analyses and were calculated as shown in Table (2).

Table 2: The spectral indices

Index	Formula	Definition	Reference
NDVI	$\frac{NIR - Red}{NIR + Red}$	The Normalized Difference Vegetation Index (NDVI) is determined as the difference between the spectral reflectance values in the near-infrared (NIR) and red bands, normalized to the range [-1, 1]. Vegetation cover levels between 0.2 and 1 are classified.	[13]
SAVI	$\frac{NIR - Red}{NIR + Red + L} * (1 + L)$	The Soil-Adjusted Vegetation Index (SAVI) reduces the soil effect on canopy spectra by introducing a soil adjustment factor (L) into the NDVI calculation. The constant L = 0.5 significantly reduces soil noise in plants. This index returns values between -1 and 1.	[14,15]
NDVSI	$\frac{(\mathrm{NIR})^3 - (\mathrm{SWIR2})^3}{(\mathrm{NIR})^3 + (\mathrm{SWIR2})^3}$	The modified index was defined as the Normalized Difference Vegetation Shortwave Index (NDVSI): this index uses radiances , or reflectance from a near-IR channel around a WSIR2 channel (i.e., around 2.1 μm). This index returns values between -1 and 1 with vegetation values between (0.5-1).	[16]
MNDWI	$\frac{\mathrm{Green} - \mathrm{NIR}}{\mathrm{Green} + \mathrm{NIR}}$	The Modified Normalized Difference Water Index (MNDWI) improves open water features by utilizing green and SWIR bands. It also reduces built-up area characteristics frequently associated with open water in other indexes. This index returns values between -1 and 1.	[17,18]
NDBI	$\frac{\mathrm{SWIR} - \mathrm{NIR}}{\mathrm{SWIR} + \mathrm{NIR}}$	The normalized difference The NIR and SWIR bands are used in the Built-up Index (NDBI) to highlight artificially constructed built-up regions. It is ratio-based to compensate for changes in landscape lighting and atmospheric influences. This index will produce values between -1 and one.	[19]
BSI	$\frac{(\mathrm{SWIR} + \mathrm{Red}) - (\mathrm{NIR} + \mathrm{Blue})}{(\mathrm{SWIR} + \mathrm{Red}) + (\mathrm{NIR} + \mathrm{Blue})}$	To extract exposed soil pixels, the bare soil index (BSI) is calculated by combining the NDVI and the Normalized Difference Built-up Index. The BSI is a spectral index that improves the identification of exposed soil surfaces and uncultivated regions using soil properties. The values range from -1 to 1, with a high value indicating the most barren soil.	[20]

2.3. Comparison and analysis:

Analysis of Variance (ANOVA) is a statistical approach for determining if a certain variable significantly affects an observed variable [21]. This is accomplished by analyzing the variance of the observed variable while adjusting for other factors. In this study, one-way ANOVA was utilized to assess whether there are significant differences in the simulation results of spectral indices. Spectral and spatial information was extracted from the spectral indices and modeled into data tables. Non-vegetation pixels were excluded [22]. Pearson correlation was used to assess the relationship between the spectral indices of both data types [23]. Pearson correlation is a correlation test that measures the strength of a linear relationship between two variables. Two variables are said to be correlated if a change follows a change in one variable in the other, and both move in the same direction or vice versa. Eq. 1 contains the formula for calculating correlation [24]. Pearson's correlation coefficients range from +1 to -1. Values around 1 indicate a strong linear association, whereas negative values near -1 or -1 indicate a negative linear relationship. Average values of 0.5 indicate a moderately linear association, whereas zero indicates no correlation [25].

$$R_{XY} = \frac{n\sum XY - (\sum X)(\sum Y)}{\sqrt{\{n\sum X^2 - (\sum X)^2\}\{n\sum y^2 - (\sum Y)^2\}}} \tag{1}$$

R_{XY} is the correlation value, ***X*** is the variable ***X axis***, and ***Y*** is the variable ***Y axis.***

2.4. The vegetation maps in the research region are created by interpolating the vegetation prediction findings with spectral and spatial information obtained from spectral indices using inverse distance weighting (IDW). Interpolation is a method for guessing values when no data is available. Interpolation predicts values beyond a certain sample point [26].

3. Results and Discussions

Reflectance spectra at various wavelengths can be combined to create spectral indices that aid in determining the relative abundance of specific qualities of interest. This research field includes buildings, plants, and bodies of water. Consequently, Landsat 9 data generated spectral indices such as NDBI for building information and BSI for bare soil. NDVI, NDVSI, and SAVI were used to extract vegetation information, while MNDWI was used to compare water body information. Figure 2 depicts the results of applying NDVI, NDVSI, SAVI, MNDWI, and BSI on Landsat 9. Based on Pleiades catalog entries, Figure 3 illustrates the results of applying NDVI, SAV, and MNDWI. This section presents the findings of the comparison and analysis.

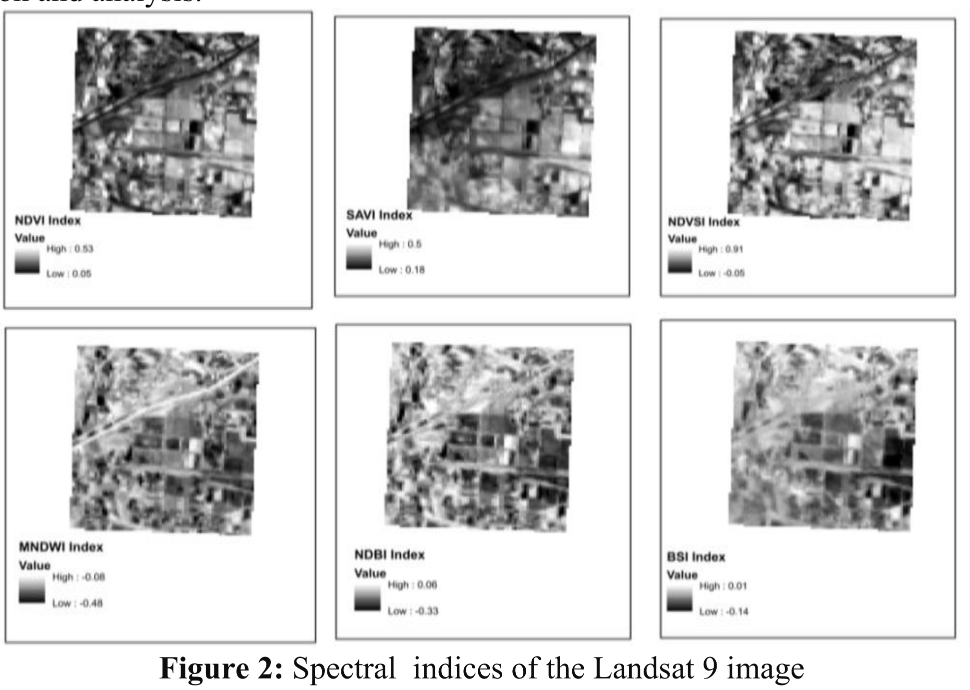

Figure 2: Spectral indices of the Landsat 9 image

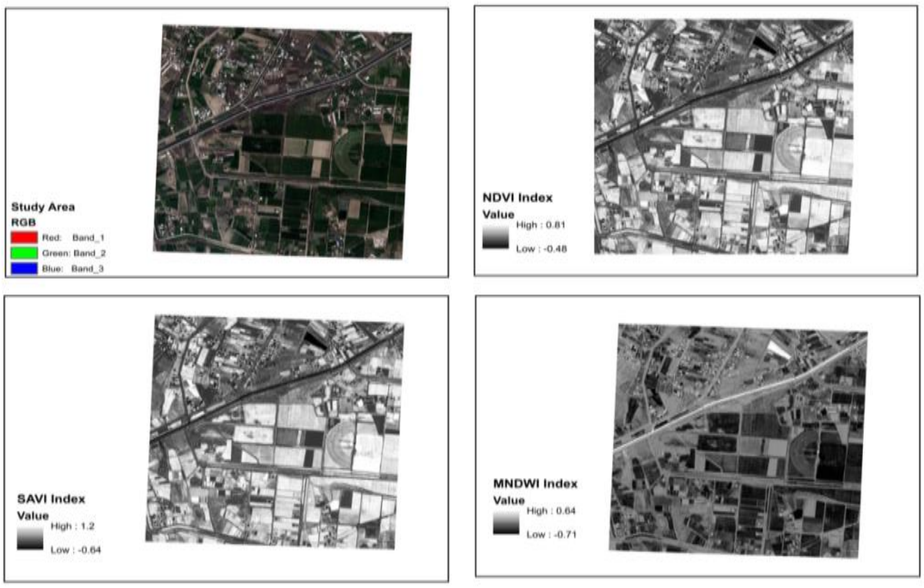

Figure 3: Spectral indices of the Pleiades image

3.1. Analysis of variance (ANOVA): A one-way analysis of variance was done with all indices' data treated as a single data set, Table 3. This study aims to determine how spectral resolution features affect the performance of vegetation cover indicators NDVSI_Landsat, resulting in a significant difference ($p < 0.001$) with an F value of 1.943. This shows that there are considerable disparities across the data sets. The variation within the sets was small ($p=0.021$). A substantial difference ($p<0.001$) was discovered with an F value of 1.619 for NDVI_Landsat, indicating that spectral resolution influences the NDVI's performance. The variation among the sets was equally small ($p = 0.005$). This suggests that spectral resolution differences impact the NDVI, with substantial effects indicating that data with high spectral resolution result in a considerable variation in performance, and the difference between medium-resolution and high-resolution indices is statistically significant and not attributable to chance. The results for SAVI_Landsat were confusing; there was no significant difference between groups ($p= 0$), which might imply that differences across indices (i.e., different resolutions) are not statistically significant. Although the data differs, there is no substantial variation in the SAVI index when using Landsat data. This might be due to data constraints or less apparent impacts. The findings reveal that spectral resolution considerably influences the performance of several vegetation cover indices, such as NDVSI and NDVI, mainly when Pleiades data is used instead of Landsat. The SAVI index does not demonstrate the same impact.

Table 3: The ANOVA analysis

Variables	Analysis	Sum of Squares	df	Mean Square	F	Sig.
NDVSI_Landsat	**Between Groups**	221.466	5465	.041	1.943	<.001
	Within Groups	2.545	122	.021		
	Total	224.011	5587			
NDVI_Landsat	**Between Groups**	44.777	5465	.008	1.619	<.001
	Within Groups	.617	122	.005		
	Total	45.395	5587			
SAVI_Landsat	**Between Groups**	21.052	5587	.004	.	.
	Within Groups	.000	0	.		
	Total	21.052	5587			

3.2. Statistical analysis: The statistical analyses are presented in Table 4. shows the results of a spectral index study utilizing data from two independent sources: Landsat 9 and Pleiades. The lowest (Min), maximum (Max), mean (Mean), and standard deviation (Std) of each index were computed. NDVI-Landsat 9 index values ranged from 0.05 to 0.53, with a mean of 0.24 and standard deviation of 0.08. The NDVI-Pleiades index ranged from -0.4 to 0.81, with a mean of 0.41 and a standard deviation of 0.21. Pleiades delivers a broader range of values than Landsat 9. This increased range might be attributed to improved resolution or sensitivity in capturing changes in plant cover. The Pleiades' mean NDVI is greater than that of Landsat 9, suggesting there is likely to be more plant cover in the areas investigated with the Pleiades. The Pleiades have a higher standard deviation than Landsat 9, suggesting more significant variability in recorded values. This might be due to higher resolution or a wider range of values. Landsat 9 measured SAVI index values between 0.1 and 0.50, with a mean of 0.31 and a standard deviation of 0.06. The Pleiades had readings ranging from -0.6 to 1.2, with an average of 0.62 and a standard deviation of 0.31. Results infer that the Pleiades have a broader range of values, which might imply more distinction between vegetated and non-vegetated regions. The NDVSI index ranged from -0.05 to 0.91, with a mean of 0.47 and a standard deviation 0.20. Landsat 9 has a broad range of readings, reaching a maximum of 0.91. This demonstrates a wide range of data that may be tied to soil and vegetation patterns in the study region.

Table 4: The Variance indicators

Data source	Index	Min	Max	Mean	Std
Landsat 9	NDVI	0.05	0.53	0.24	0.08
	SAVI	0.1	0.50	0.31	0.06
	NDVSI	-0.05	0.91	0.47	0.20
	MNDWI	-0.48	-0.08	-0.24	0.06
	NDBI	-0.33	0.06	-0.01	0.07
	BSI	-0.13	0.01	-0.05	0.02
Pleiades	NDVI	-0.4	0.81	0.41	0.21
	SAVI	-0.6	1.2	0.62	0.31
	MNDWI	-0.7	0.64	-0.35	0.16

3.3. Differences analysis: To demonstrate the differences between the indices, the difference findings for the research region are given using Landsat-9 vegetation indices, created from the corresponding Pleiades indices as a reference, Figure 4. The research area's vegetation exhibited spectral reflectance values exceeding 0.32 for the NDVI index and over 0.46 for the SAVI index. The vegetation threshold passed 0.65 in the NDVSI index.

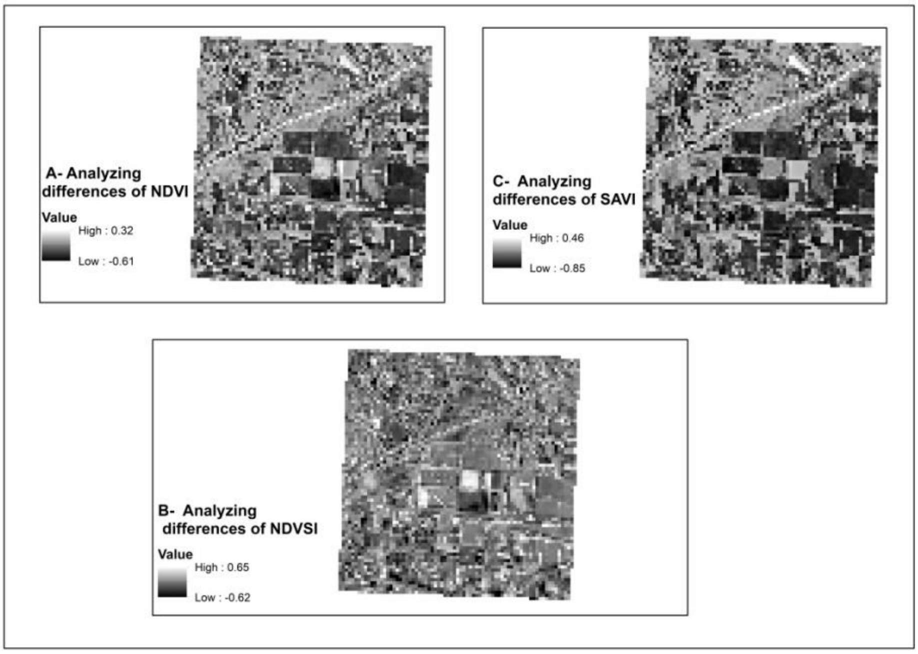

Figure 4: Difference analysis of Landsat indices

3.4. Visual analysis: Based on the variance analysis results, a preliminary visual comparison was done between Pleiades and medium-resolution Landsat data (Figures 5 and 6). Figure 5 illustrates how spatial resolution influences vegetation identification. These findings show the difference between high-resolution and medium-resolution data at 30 m. Most plant pixels are lost due to roughness and mixing inside the 30 m pixel. Despite having different spectral bands than traditional vegetation indices, the NDVSI performed better in recognizing vegetation and is comparable to Pleiades data.

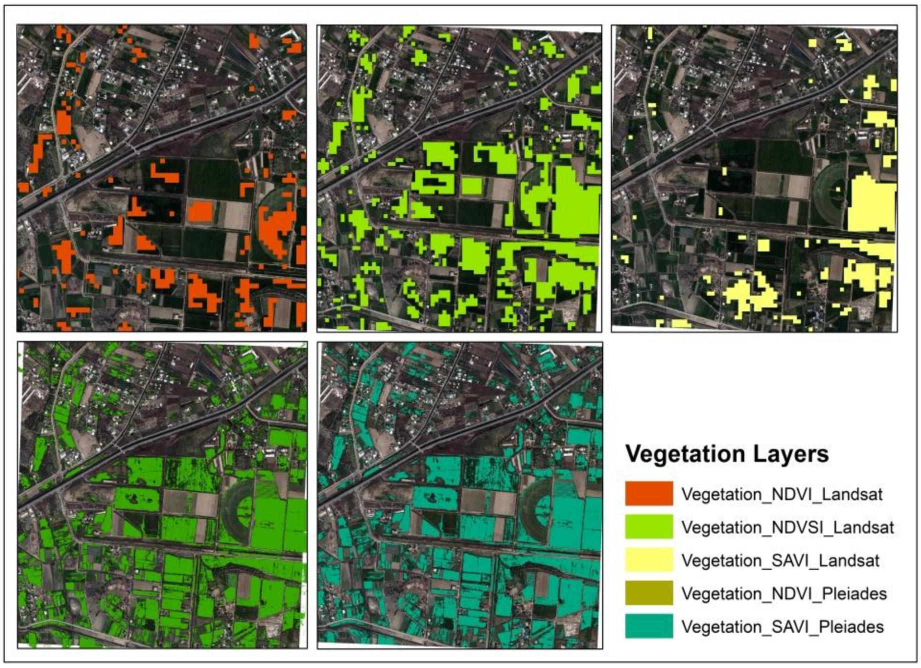

Figure 5: The boundaries and spatial variations of the vegetation cover in typical Landsat indices at vegetation layers.

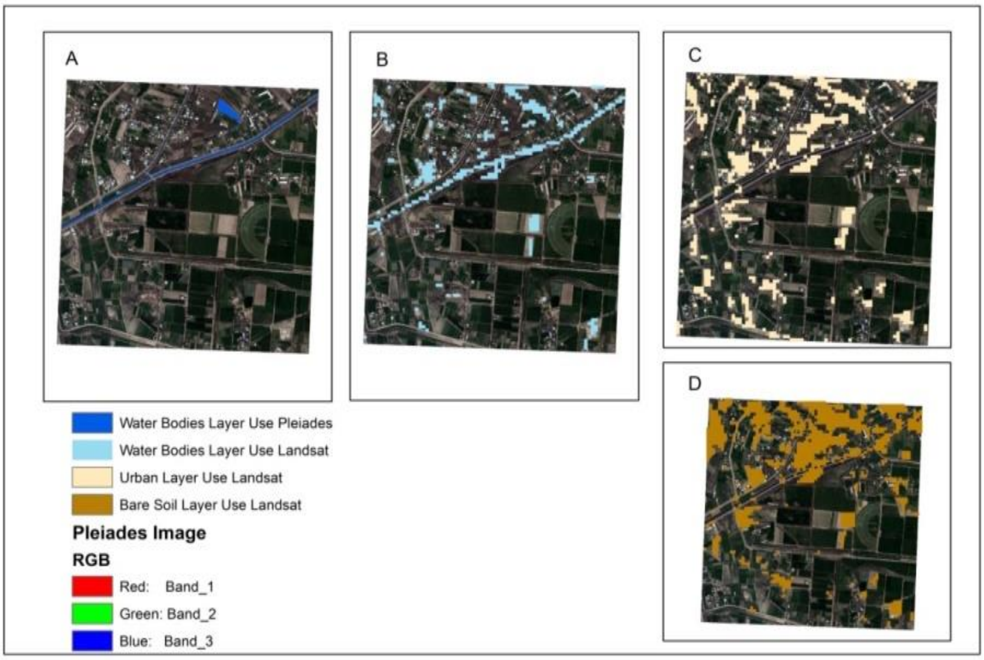

Figure 6: Spatial distribution of land cover layers: Spatial distribution of land cover layers: (A) the water bodies layer from Pleiades data, (B) the water bodies layer from Landsat data, (C) the estimated NDBI for building, and (D) the BSI predicted soil areas

The resolution of the spectral indices derived from the high-resolution Pleiades image was adjusted to be equivalent to the Landsat 9 indices, Figure (7). The results suggested that, despite being a resolution of 30*30, the Pleiades data excelled the Landsat data in knowing the extent of vegetation.

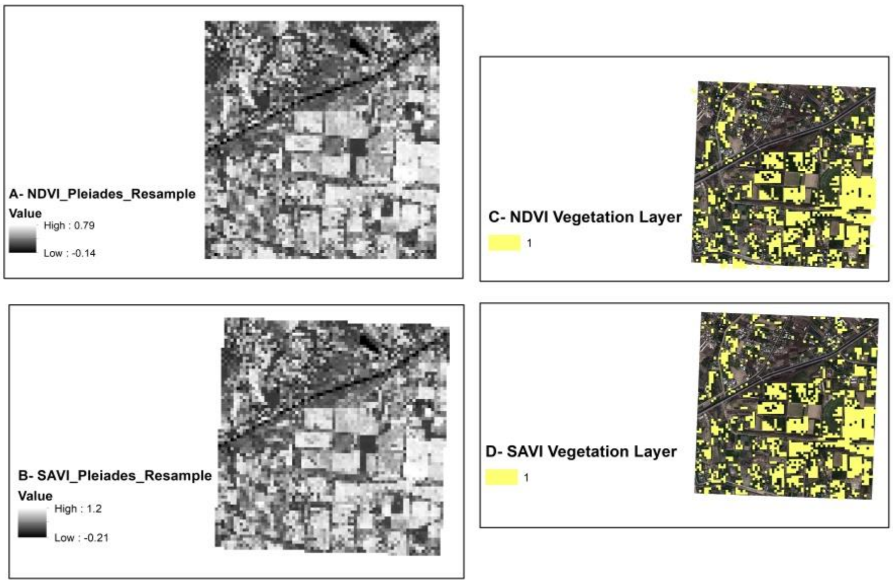

Figure 7: Pleiades indices samples

3.5. Distribution analysis: Landsat spectral and spatial data differ from Pleiades data in multiple respects, including pixel size, atmospheric influences, viewing angle, etc. The natural vegetation index (NDVI) is a valuable measure of changes in vegetation patterns.

Figure (8) depicts the spatial distribution of vegetation cover index values (NDVI Pleiades index) and NDVSI values (Landsat data) in the near-infrared and short-wave infrared ranges.

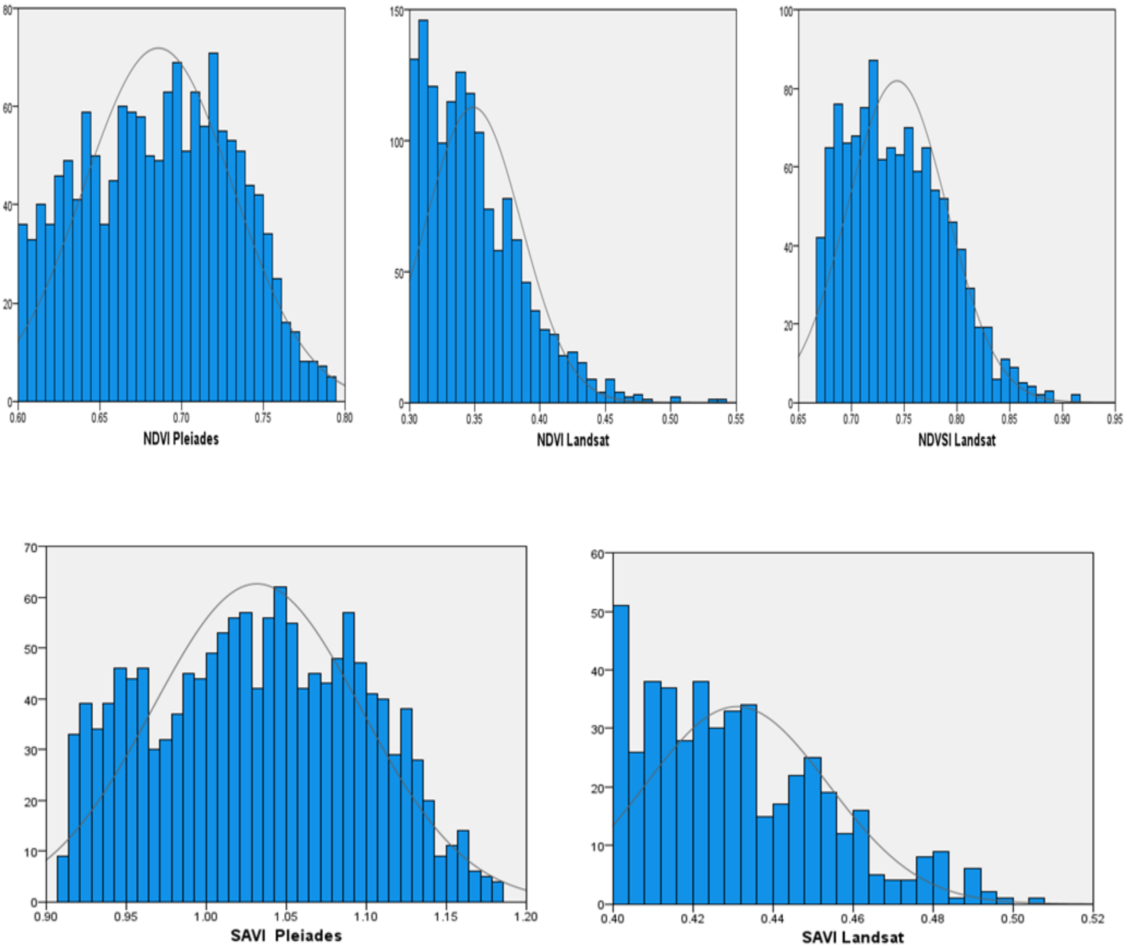

Figure 8: The histogram of vegetation reflectivity

3.6. Correlation analysis: VI metrics have been under development for more than five decades, and to date, hundreds of VI metrics have been reported to retrieve biophysical and biochemical variables of vegetation. VI metrics are a versatile, straightforward, and reliable way to establish a simple link between biological components and spectra by utilizing the selective absorption properties of specific biochemical components of incident sunlight. However, the scientific community has difficulty identifying the underlying processes that generate changes in VI measures. The vegetation spectral signal in a satellite image pixel is primarily contributed by pigmentation and structural information from the upper cover (i.e., visible signals) within the field of view and is influenced by the background soil coverage. A linear regression model was used to assess the spectral indices with Landsat 9 indices as the dependent variable and Pleiades indices as the independent variables, Figure 9. Pearson's correlation coefficient was utilized to determine the linear connection between the dependent and independent variables. R^2 values were derived using 5588 sample points for each scenario.

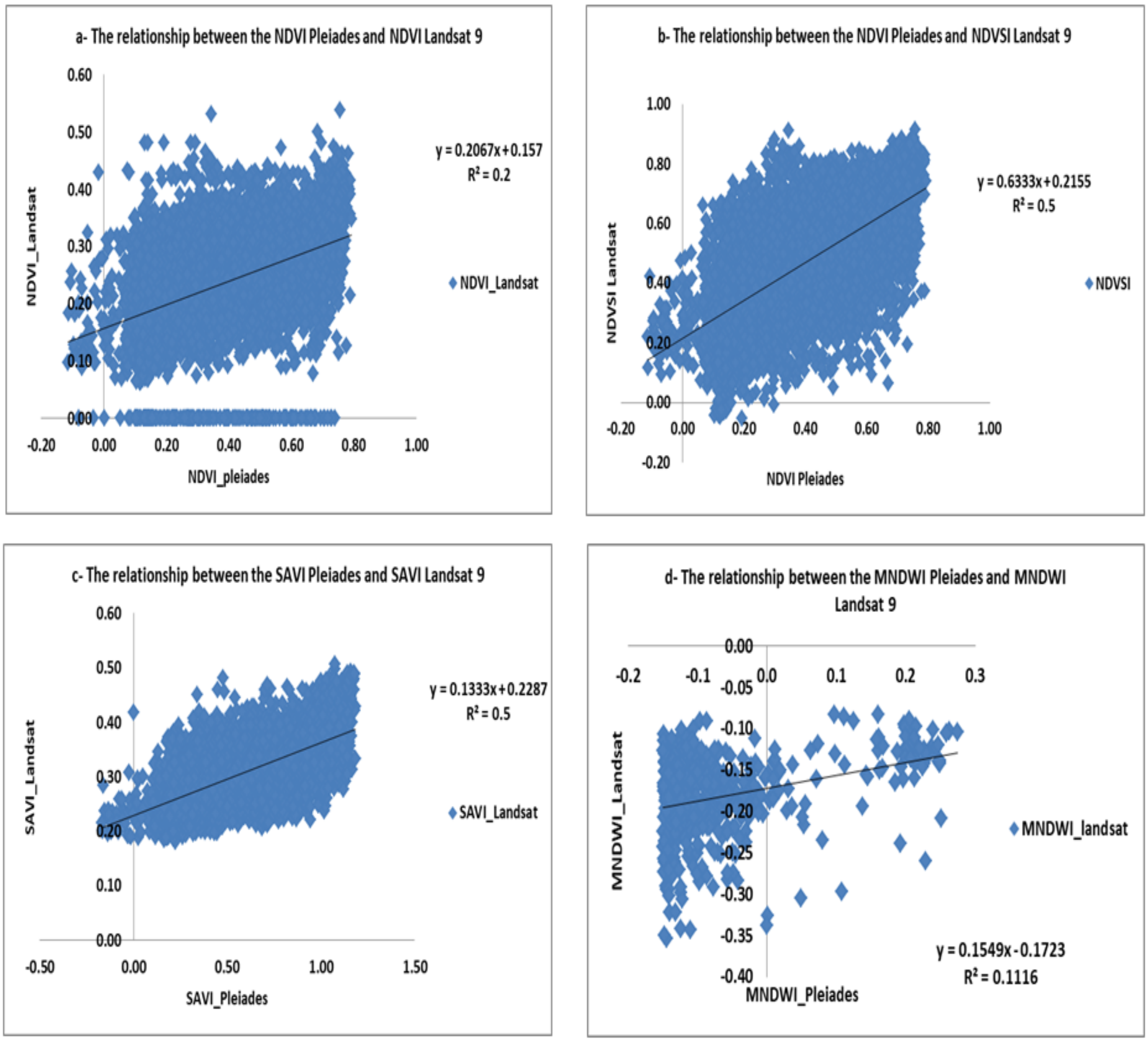

Figure 9. The relationship between the Pleiades indices and Landsat 9 indices: When the correlation value approaches one, it shows a linear link between the two variables, whereas a value of 0 indicates the lack of a linear relationship. Negative numbers show an inverse link between the two variables.

The results revealed that the coefficient between (NDVI_Landsat & NDVI_Pleiades) R^2 =0.2, showing poor consistency. The correlation coefficient between the MNDWI indicators was (0.1116). The SAVI soil-reduced indicators revealed a strong association, with a correlation value 0.5. Furthermore, when comparing the NDVSI_Landsat index to the standard NDVI vegetation index, a correlation value of 0.5 was observed. In investigating and comparing the accuracy of Landsat 9 and Pleiades sensors in different spectral bands based on spectral indices, Landsat-9 indices consistently demonstrated saturation ratios of 0.5 in the red and near-infrared bands compared to the Pleiades bands. At the same time, the Landsat-9 (NDVSI) index proves its better capacity to monitor vegetation in SWIR and NIR bands. Vegetation maps in the research region were created by interpolating vegetation prediction results using inverse distance weighting (IDW). Figure 10 shows a digital elevation model created using GPS visualization and vegetation points collected from Pleiades data.

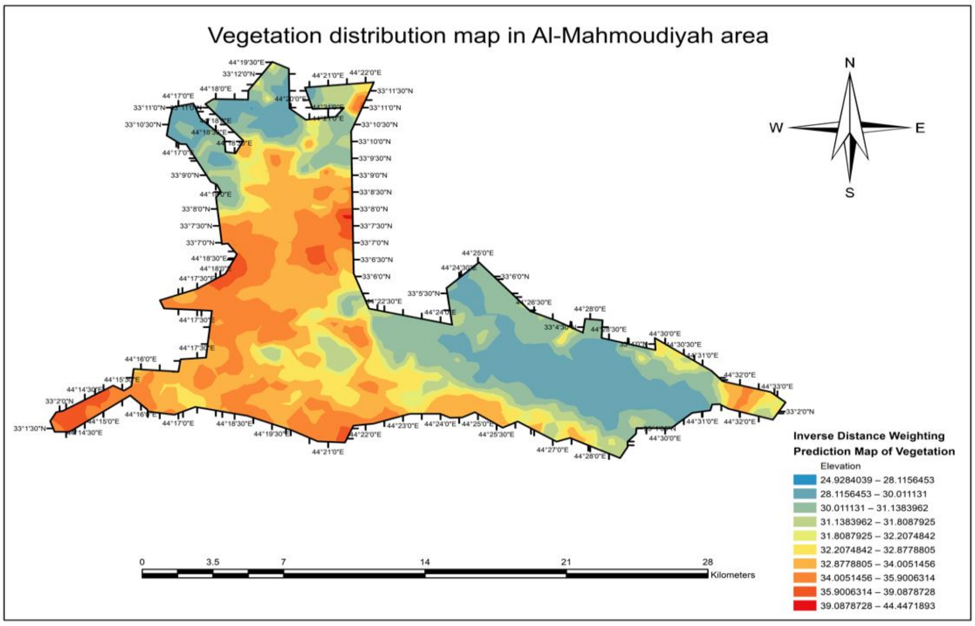

Figure 10: According to the vegetation map and the Pleiades spectral data, 24-30 m heights suggest sparse vegetation, 31-34 m indicate medium vegetation, and 34-44 m indicate extensive vegetation.

4. Conclusions

Based on our examination of vegetation indices utilizing satellite-band reflectance data in this study, results have highlighted the best indices for properly assessing vegetation. The statistical analyses show that Pleiades delivers a broader range of values than Landsat 9. This increased range might be attributed to improved resolution or sensitivity in capturing changes in plant cover.

Landsat 9 showed traditional indices, such as the NDVI and SAVI, performed less accurately than more specialized alternatives, such as the NDVSI derived using the SWIR 7 and NIR bands, which have a broad range of readings, reaching a high maximum of 0.91. This demonstrates a wide range of data that may be tied to soil and vegetation patterns in the study region.

A one-way analysis of variance shows that the difference between medium-resolution and high-resolution indices is statistically significant and not attributable to chance. Pleiades satellite indices data, on the other hand, demonstrated the highest overall performance for vegetation tracking because of their high-resolution imagery and capacity to detect minor spectral changes even at a resolution of 30 x 30 meters.

Comparison results using linear regression show that traditional Landsat 9 data are less suitable; however, new spectral indices such as NDVSI can potentially increase performance with a correlation coefficient of 0.5. These data can help to improve vegetation monitoring and research in greater detail and dependability. Traditional Landsat 9 data are less suited; however, new spectral indices like NDVSI can potentially increase performance. Satellite data provide a good foundation for researching environmental changes, urban expansion, and vegetation dynamics. These data may be used to examine temporal changes in plant cover and their effects on the environment and local ecosystems, providing a sound foundation for environmental decision-making and sustainable resource management.

Finally, this study emphasizes the need for combining high-resolution satellite images with sophisticated analytical approaches, which helps to provide data-driven solutions for monitoring environmental changes and attaining sustainable development.

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