Effectiveness of Normalized Difference Bult-Up Index in Mapping Built-up Features across Arid Rural Regions

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Abstract. The Normalized Difference Built-up Index (NDBI) is a widely used remote sensing method for detecting built-up areas. However, its effectiveness in distinguishing built-up land from open land in dry rural regions remains underexplored. This study aims to evaluate the performance of NDBI in identifying built-up areas in Bayat Sub-district, Klaten Regency, Central Java, which is a predominantly rural area characterized by semi-arid land conditions in October 2023. Landsat 8 OLI imagery acquired in 2023 was used in this study, and NDBI values were derived from the processed data. The resulting NDBI values were classified into four levels of built-up intensity using the Natural Breaks (Jenks) method: Very Low, Low, Medium, and High. Validation was carried out using 36 ground truth points representing various land cover types, including vegetation, built-up land, open land, and water bodies. Classification accuracy was assessed using a confusion matrix. The results showed a considerable degree of misclassification. NDBI is calculated based on the difference in reflectance between the Shortwave Infrared (SWIR) and Near Infrared (NIR) bands. Built-up areas typically exhibit high SWIR and low NIR reflectance. However, dry open lands such as bare soil or unvegetated areas often display similar spectral characteristics, with high SWIR reflectance due to dry surfaces and low NIR reflectance due to the absence of vegetation. This similarity results in elevated NDBI values in non-built-up areas, making it difficult to distinguish them from actual built-up regions. The confusion matrix yielded an overall accuracy of 75.00% and a Kappa coefficient of 0.628, indicating moderate agreement between the classification results and the ground reference data. These findings highlight the limitations of using NDBI alone to distinguish built-up areas from non-vegetated open lands in semi-arid rural environments..

Keywords: Bayat Sub-district; Built-Up Land; Landsat 8 Imagery; NDBI; Semi-Arid Rural Area.

I. INTRODUCTION

Land cover change, particularly the expansion of built-up areas, has become an increasingly prominent spatial phenomenon driven by population growth, accelerated urbanization, and economic transitions from primary to secondary and tertiary sectors. In developing countries like Indonesia, the expansion of built-up land frequently occurs without adequate spatial regulation or data-driven planning. This unregulated growth has various consequences, including environmental degradation, the loss of productive lands such as agricultural fields and forests, and increased pressure on ecological carrying capacity. These land transformations have triggered complex and multidimensional socio-ecological challenges, particularly in dry, rural environments such as Bayat Sub-district, Klaten Regency, Central Java, which is characterized by hilly terrain, seasonal vegetation, and scattered settlement patterns. Unlike large urban areas equipped with advanced spatial monitoring systems and comprehensive datasets, rural regions like Bayat often suffer from limited spatial data availability, coarse resolution, and inconsistent temporal coverage.

Although land cover change in Bayat occurs on a smaller scale and in a non-uniform manner, it remains critical to monitor due to its ecological and socio-economic implications. Remote sensing offers an efficient and scalable approach for tracking such changes in data-limited regions. Among the various remote sensing-based indices, the Normalized Difference Built-up Index (NDBI) [14] has become one of the most widely adopted methods for detecting built-up land. NDBI exploits the difference in spectral reflectance between the shortwave infrared (SWIR) and near-infrared (NIR) bands, producing positive values for built-up areas, which typically reflect more strongly in SWIR than in NIR.

Numerous studies have validated the effectiveness of NDBI in urban environments. For instance, Suparta and Hartono [11] applied NDBI to map built-up land expansion in Surabaya from 2002 to 2022 and found a 21% increase, emphasizing the index's utility in densely populated settings. Similarly, Yasin et al. [13] combined NDBI and NDVI to assess rapid urban expansion in the Iskandar region of Malaysia, successfully mapping fragmented built-up growth (leapfrog development) and supporting regional spatial planning. However, these studies were primarily conducted in large, well-mapped metropolitan areas. In contrast, rural and peri-urban regions, especially in semi-arid settings, have received far less attention in the application of NDBI. In such regions, land surfaces like dry bare soil can spectrally resemble built-up features, particularly under drought conditions. As a result, NDBI may overestimate built-up areas due to high SWIR and low NIR reflectance from non-built surfaces [14]. To address these challenges, several studies have proposed modifying or complementing NDBI. Integrating NDBI with vegetation indices such as NDVI has been shown to improve classification accuracy by reducing false positives in vegetated or mixed-use areas [13]. In dry-climate cities like Erbil, built-up areas have exhibited higher reflectance in the Blue band and lower reflectance in the TIR1 band compared to bare soil, and the exclusion of NDVI from composite indices, such as in DBI and DBSI, has enhanced classification reliability by minimizing confusion with vegetated land [7].

This study addresses that gap by evaluating the effectiveness of NDBI in detecting built-up land in Bayat, a semi-arid rural sub-district dominated by dry open areas and characterized by seasonal drought. This study employs Landsat 8 OLI imagery acquired in October 2023, during the dry season with minimal vegetation cover. Given Bayat's unique environmental characteristics and limited spatial infrastructure, it serves as a compelling case study to assess the applicability and limitations of NDBI in non-urban, water-scarce contexts. The results are expected to provide both methodological contributions to remote sensing-based land classification and practical insights for local spatial planning, land monitoring, and sustainable rural development.

II. METHODOLOGY

The overall methodological workflow of this study is summarized in **Fig. 1.**

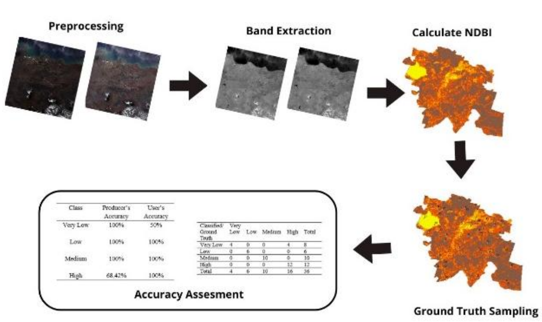

Figure 1. Methodological workflow used in this study, covering image preprocessing, NDBI computation, classification, validation, and interpretation stages.

2.1 Study Area

The study area is Bayat Sub-district, located in the southeastern part of Klaten Regency, Central Java. Geographically, Bayat borders Gunungkidul Regency to the south and functions as a transitional zone between the Klaten lowlands and the Sewu Mountains [2]. As a region characterized by dryland agriculture and high dependence on seasonal rainfall, Bayat is particularly vulnerable to declining agricultural productivity and reduced clean water availability during extended dry periods [3]. The peak dry season typically occurs between July and September, during which monthly rainfall can drop to zero, leading to climatic anomalies that affect food security [5]. The location of the study area in Bayat Sub-district, Klaten Regency, is shown in **Fig. 2.**

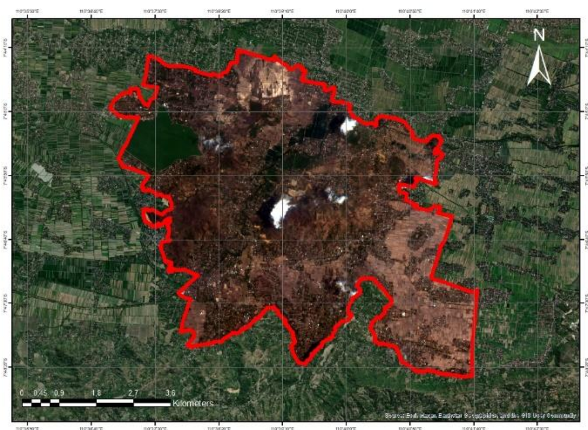

Figure 2. Location of the study area in Bayat Sub-district, Klaten Regency, Central Java.

Previous studies have identified the southern part of Klaten, including Bayat, as a drought-vulnerable zone based on remote sensing data and spatial analysis [5]. Additionally, annual reports from BMKG consistently indicate that Bayat is one of the four sub-districts most frequently affected by drought due to low rainfall intensity [3]. These findings highlight the importance of continuous spatial monitoring for land cover change and environmental vulnerability in Bayat.

2.2 Methodology

a) Data Source and Pre-Processing

A Landsat 8 image from October 2023 with a spatial resolution of 30 meters was used in this research. The image covers Bayat District and its surrounding areas, located within Path 120 Row 65, and was obtained from the official United States Geological Survey (USGS) through the EarthExplorer platform (https://earthexplorer.usgs.gov).

The Landsat 8 image used in this research was processed to the surface reflectance level through atmospheric correction to reduce atmospheric distortion. The image was projected using the Universal Transverse Mercator (UTM) coordinate system, Zone 49S. The selection of October 2023 was based on climatological data from BMKG, identifying it as the peak of the dry season in Klaten Regency [3]. The details of the spectral bands, spatial resolution, and acquisition time used in this study are presented in **Tab. 1.**

Table 1. The wavelengths, spatial resolution, and acquisition time of Landsat 8 images

Sensor	Band	Λ (µm)	Spatial Res.(m)	Acq. Time
Landsat-8 OLI	5–NIR	0.845–0.885	30	October 2023
	6-SWIR 1	1.560–1.660	30	

Atmospheric correction was performed using the Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) module in ENVI. This method converts radiance data to surface reflectance by accounting for atmospheric effects such as absorption and scattering, making the imagery more reliable for spectral index calculations. The corrected image was then projected to UTM Zone 49S (WGS 84 datum).

b) *Normalized Different Built-Up Index*

Normalized Difference Built-Up Index (NDBI) is an algorithmic method used to identify or indicate the density index of built-up areas by utilizing the spectral characteristics of the SWIR (Shortwave Infrared) and NIR (Near-Infrared) bands in satellite imagery. This index was introduced by Zha et al. [14] as an automated approach for mapping urban or built-up areas. The NDBI is calculated using **Eq. (1),** which is based on the reflectance values from those two bands.

$$NDBI = \frac{\rho_{SWIR}-\rho_{NIR}}{\rho_{SWIR}+\rho_{NIR}} \qquad (1)$$

ρ_{NIR} = *Reflectance at Near Infrared (Band 5)*

ρ_{SWIR} = *Reflectance at Shortwave Infrared (Band 6)*

. Positive NDBI values generally represent built-up regions such as buildings and other impervious surfaces, whereas negative values tend to indicate the presence of vegetation or water bodies. The index is considered effective for detecting and monitoring the spatial distribution of built-up areas, making it widely used in studies on land use change and urbanization. NDBI also enables the identification of high-density built-up zones that may be difficult to detect visually [10].

c) *Classification of NDBI*

NDBI values were classified into four levels using the Natural Breaks (Jenks) method to reflect built-up intensity:

- Very Low
- Low
- Medium
- High

The Natural Breaks (Jenks) method was selected because it identifies natural groupings within the data by minimizing within-class variance and maximizing between-class variance. This classification technique is particularly suitable for semi-arid rural areas such as Bayat, where the spectral values of land cover types, especially between dry bare soil and built-up surfaces, do not follow a uniform distribution. It is also effective for data distributions that are irregular but not extremely skewed toward one end, allowing more balanced class intervals [9]. Compared to equal interval or quantile methods, Jenks classification offers more data-driven boundaries that better represent the actual variation in NDBI values. This classification was performed in ArcGIS Pro, which provides advanced tools for maximizing between-class spectral differences while minimizing within-class variance. The resulting land cover classes were visualized as thematic maps.

d) *Ground Truth Collection and Accuracy Assesment*

To evaluate the accuracy of the classification results based on the NDBI, a total of 36 sample points were selected using a binomial probability approach. This method determines the minimum number of samples required for accuracy assessment based on a specified confidence level and acceptable margin of error. In this study, a 90% confidence level and a 10% margin of error were used as the basis for calculation, following the approach proposed by Congalton [4]. The number of ground truth samples was calculated using **Eq. (2**), which is a binomial probability formula.

$$N = \frac{Z^2(p)(q)}{E^2} \qquad (2)$$

Where N = Number of test sample points; Z = 2 (standard deviation for 95% confidence level); P = Expected accuracy level, and q is 100 – p; and E = Tolerated error percentage

To ensure proportional representation across land cover types, a stratified random sampling method was employed. In this method, the population is divided into distinct groups based on relevant characteristics. In this study, the groups were defined according to NDBI class levels, and random samples were then selected from each group. This approach enhances the precision of the sampling process and ensures that all land cover categories are adequately represented during the validation phase [12]. Based on the calculation, 36 sample points were selected, consisting of 11 vegetation samples, 11 bare land samples, 12 built-up area samples, and 2 water body samples. Each point represents a single pixel in the classified image and was compared aga7inst high-resolution satellite imagery from Google Earth Pro (October 2023) as the reference data. The sampling points were visually interpreted and verified using satellite imagery. To ensure spatial representativeness, the points were evenly distributed across the study area. The spatial distribution of these validation points is illustrated in **Fig. 3.**

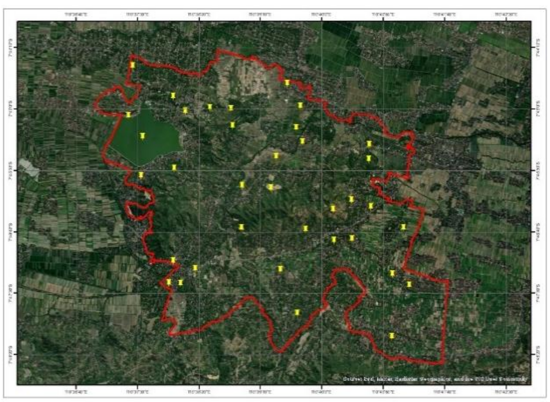

Figure 3. Spatial distribution of the 36 ground truth validation points across the study area.

In addition, **Fig. 4** presents visual examples of the land cover types used during the validation process. These land cover classes include vegetation, bare land, built-up areas, and water bodies. This visual reference is intended to clarify the classification categories used in validation and to support transparency in the applied validation approach.

An analysis was conducted using a confusion matrix to evaluate the Accuracy of the NDBI classification results. This matrix compares the classification values obtained from image processing with the reference data for each land cover class [6]. Based on the confusion matrix, several accuracy metrics were calculated, including Overall Accuracy (OA),

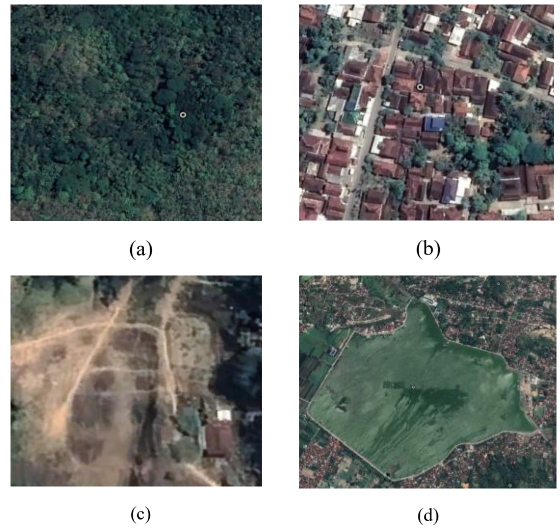

Figure 4. Samples of selected land covers in Bayat: (a) vegetation, (b) built-up area, (c) open land, and (d) water body.

Producer's Accuracy (PA), User's Accuracy (UA), and the Kappa Coefficient.

- Overall Accuracy (OA) represents the proportion of correctly classified pixels to the total number of reference samples, as calculated using **Eq. (3).**

$$\text{Overall Accuracy} = \frac{\sum_{i=1}^{k} x_{ii}}{N} \quad (3)$$

x_{ii} = number of correctly classified pixels for class i (the diagonal elements of the confusion matrix)
N = total number of reference samples
K = number of land cover classes

- Producer's Accuracy (PA), which shows how well a reference class is correctly identified, is given in **Eq. (4).**

$$\text{Producer's Accuracy} = \frac{x_{ii}}{\sum_{j=1}^{k} x_{ij}} \quad (4)$$

x_{ij} = number of pixels that belong to reference class i but were classified as class j by the model.

- User's Accuracy (UA), reflecting classification reliability from the user's perspective, is defined in **Eq. (5).**

$$\text{User's Accuracy} = \frac{x_{ii}}{\sum_{j=1}^{k} x_{ji}} \quad (5)$$

x_{ji} = number of pixels that were classified as class i but actually belong to reference class j.

- The Kappa Coefficient measures the agreement between the classification results and the reference data while accounting for the possibility of agreement occurring by chance [6], is calculated using **Eq. (6).**

$$\text{Kappa Coefficient} = \frac{P_0 - P_e}{1 - P_e} \qquad (6)$$

P_0 = observed agreement
P_e = expected agreement by chance

III. RESULT AND DISCUSSION

The atmospherically corrected NDBI image derived from Landsat 8 OLI (October 2023) was classified into four intensity levels using the Natural Breaks (Jenks) method. The NDBI values ranged from -0.621 to 0.244, with a mean value of -0.044 and a standard deviation of 0.136, indicating that most of the study area is dominated by pixels with low to moderate NDBI values. The classification scheme, including the NDBI value ranges and their corresponding map colors, is summarized in **Tab. 2.**

Table 2. Classification of NDBI values into built-up intensity categories and their corresponding map colors.

Class	NDBI Value Range	Map Color
Very Low	< -0.370	Yellow
Low	-0.370 - 0.135	Light Brown
Medium	0.135 - 0.010	Orange
High	0.010 - 0.244	Dark Brown

The NDBI value histogram (**Fig. 5**) indicates that the Low class (light brown, -0.370 to -0.135) and Medium class (orange, -0.135 to -0.010) dominate in terms of pixel frequency. This confirms that the Bayat Sub-district mainly comprises dry open land, sparse vegetation, and lightly built-up settlements. Meanwhile, the Very Low class (yellow, ≤ -0.370), typically representing dense vegetation or water bodies, and the High class (dark brown, > -0.010 to ≤ 0.244), indicating moderate to densely built-up areas, occupy relatively fewer pixels. This reflects the nature of the study area as a semi-arid rural region with limited urban development and predominance of non-vegetated drylands.

To provide a clearer spatial visualization, the classified NDBI was mapped and presented as a thematic map (**Fig. 5**), showing the spatial distribution of built-up intensity across the sub-district.

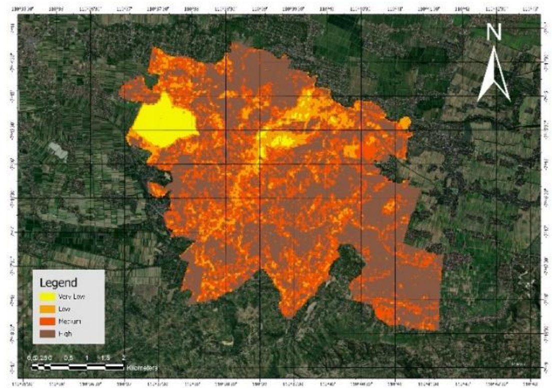

Figure 5. Spatial distribution of built-up intensity based on NDBI classification in Bayat Sub-district (October 2023).

Visual inspection of the map reveals that areas with high NDBI values (classified as "High" and "Medium") are distributed in a predominantly scattered pattern. These built-up zones appear as small, isolated patches, indicating the dispersed nature of rural settlements. However, there are also visible semi-linear clusters along what appear to be transportation corridors or village centers, especially in the central, northern, and southeastern parts of the study area. This suggests that while the built-up features are generally fragmented, they still show alignment with accessibility features such as roads, which is characteristic of rural land development patterns in semi-arid zones.

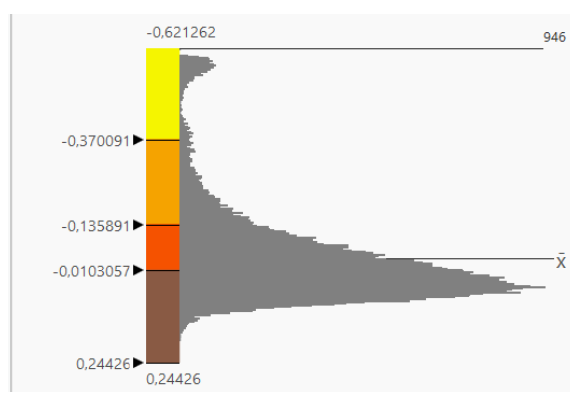

Figure 6. Histogram of NDBI values in Bayat Sub-district (October 2023), classified into four intensity levels using the Jenks natural breaks method. The distribution shows a left skew toward negative values.

As illustrated in **Fig. 6**, the histogram shows a clear left skew (toward negative values), suggesting that most pixels fall between -0.37 and 0.1, a spectral transition zone between bare soil and scattered built-up surfaces. The spectral similarity within this range often causes classification ambiguity between dry open land and built-up features, highlighting a significant limitation in relying solely on NDBI for land cover classification in non-urban and drought-prone environments.

A confusion matrix was constructed based on 36 ground truth samples, representing four land cover classes: Very Low, Low, Medium, and High. These validation points were interpreted using high-resolution satellite imagery from Google Earth Pro (October 2023). The classification results were compared with the reference data and are summarized in **Tab. 3**, which presents the confusion matrix for the NDBI classification in Bayat Sub-district.

Table 3. Confusion matrix comparing the NDBI classification results with reference land cover data for Bayat Sub-district

Classified/ Ground Truth	Very Low	Low	Medium	High	Total
Very Low	4	0	0	4	8
Low	0	6	0	0	6
Medium	0	0	10	0	10
High	0	0	0	12	12
Total	4	6	10	16	36

From this matrix, several accuracy metrics were calculated, including Overall Accuracy and the Kappa coefficient. The results are presented in the following table, along with the overall accuracy and Kappa coefficient summarized in **Tab. 4.**

Table 4. Summary of Overall Accuracy and Kappa Coefficient from the NDBI classification.

Overall Accuracy	75.00%
Kappa Coefficient	0.628

The Overall Accuracy reached 75.00%, indicating that 75% of the reference samples were correctly classified based on the NDBI results. While this value reflects a moderately good level of classification accuracy, it also suggests that the use of NDBI as a single index may not be sufficient to fully distinguish between built-up and non-built-up dry areas, particularly in semi-arid rural regions where spectral confusion with bare soil is common. The Kappa coefficient was calculated at 0.628, which indicates a substantial agreement between the classified data and the ground truth beyond what would be expected by chance. Although not considered a high agreement (typically above 0.8), a Kappa value above 0.6 still demonstrates acceptable reliability in land cover classification, especially when using medium-resolution imagery and a single spectral index under challenging environmental conditions.

Table 5. Producer's Accuracy and User's Accuracy for each land cover class based on the confusion matrix.

Class	Producer's Accuracy	User's Accuracy
Very Low	100%	50%
Low	100%	100%
Medium	100%	100%
High	68.42%	100%

The Producer's Accuracy and User's Accuracy for each land cover class are shown in **Tab. 5.** All four land cover classes achieved 100% Producer's Accuracy, indicating that all reference samples were correctly detected by the classification. However, User's Accuracy varied, particularly for the Very Low class, which only reached 50% due to a considerable number of misclassified pixels that were actually High in the reference. This spectral confusion is likely caused by the similarity between dry, sparsely vegetated areas and impervious surfaces in semi-arid regions.

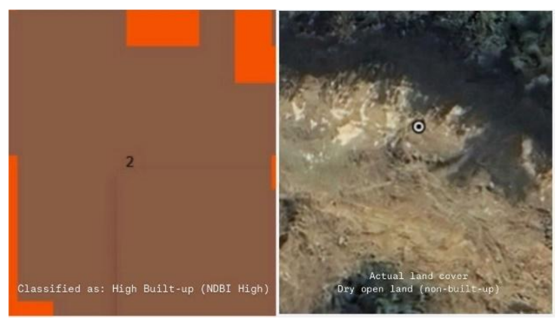

Figure 7. Visual comparison between classified built-up land (right) and true land cover from Google Earth (left) at location

To further validate the classification results, selected locations with high NDBI values were visually inspected using Google Earth imagery. Although classified as "High" built-up zones, several of these areas were actually dry open land or harvested fields, as illustrated in **Fig. 7**. This observation confirms the earlier issue of spectral confusion, where non-vegetated surfaces in semi-arid conditions exhibit high SWIR reflectance similar to that of impervious surfaces. Visual verification helps clarify the nature of misclassification, which may not be fully captured through the confusion matrix alone. These findings highlight the limitations of using NDBI alone to differentiate between bare, dry land and built-up areas, especially in non-urban, drought-prone environments. To improve classification performance, it is recommended to integrate NDBI with other spectral indices such as NDVI, or to apply supervised classification algorithms (e.g., Random Forest, SVM) that can account for more complex feature interactions.

The misclassification can be further explained by the spectral characteristics of built-up areas and dry bare soil. Both tend to exhibit similarly high reflectance in the visible and SWIR bands and low reflectance in the Near-Infrared (NIR) band due to the absence of moisture and vegetation. This similarity is illustrated in the spectral profile shown in **Fig. 8**, where the reflectance curves of built-up areas and dry open land closely overlap, especially in the SWIR and NIR regions.

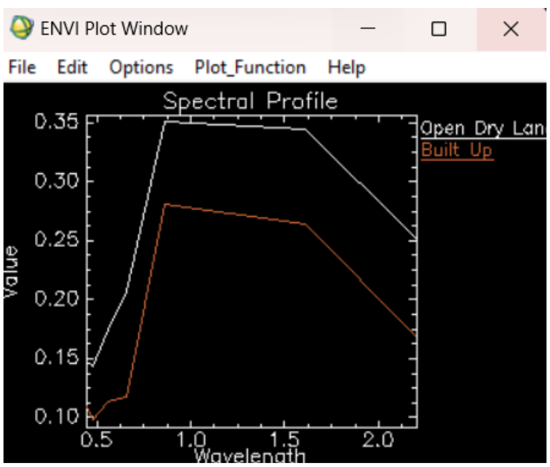

Figure 8. Spectral reflectance profile of built-up areas and dry open land extracted from Landsat 8 OLI imagery.

The lack of chlorophyll activity results in minimal NIR response, while a significant portion of incoming energy in the visible and SWIR wavelengths is reflected back to the sensor [8]. A similar phenomenon has been observed in dry-climate cities such as Erbil, where built-up areas showed higher reflectance in the Blue band and lower values in the TIR1 band compared to bare soil. In such cases, excluding NDVI from built-up indices like DBI and DBSI improved mapping accuracy by reducing confusion with vegetated areas [7]. These findings are consistent with the classification issues observed in Bayat and emphasize the importance of integrating thermal data or refined indices to reduce spectral confusion and enhance built-up detection in semi-arid rural environments.

Moreover, the timing of image acquisition may influence classification outcomes due to seasonal variation. The satellite imagery used in this study was captured in October 2023, a period marked by extremely dry conditions in the study area. According to rainfall data, Bayat Sub-district received 0 mm of precipitation during October 2023, indicating the absence of rainfall and very low environmental moisture [1]. These conditions likely resulted in reduced vegetation cover and increased spectral similarity between dry bare land and built-up surfaces, thereby increasing the risk of misclassification in the NDBI classification. Furthermore, this study relied on a single-date image and did not incorporate multi-year or seasonal comparisons. To address inter-annual variability and seasonal dynamics, future research is encouraged to use multi-temporal datasets to evaluate the consistency and accuracy of built-up land classification under varying climatic conditions.

Beyond its relevance for remote sensing analysis, the results of this study may serve as a preliminary reference for rural spatial planning, particularly in areas with limited mapping infrastructure. The findings may also contribute to cadastral data improvement by identifying informal or unregistered built-up areas not recorded in official land administration systems.

IV. CONCLUSION

This study assessed the effectiveness of the Normalized Difference Built-up Index (NDBI) in detecting built-up land within a semi-arid rural environment, specifically in Bayat Sub-district, Klaten Regency. The NDBI values derived from Landsat 8 imagery were classified into four built-up intensity levels using the Natural Breaks (Jenks) method. Validation using 36 ground truth points revealed an overall classification accuracy of 75.00% and a Kappa coefficient of 0.628, indicating a moderate agreement between the classification and reference data.

The results show that while NDBI can generally distinguish built-up areas from vegetated and water-covered regions, it encounters significant limitations in differentiating between built-up surfaces and dry bare land. This spectral confusion, common in semi-arid zones, leads to notable misclassification. Visual inspection using high-resolution imagery further confirmed that several areas with high NDBI values were not built-up, but rather dry, unvegetated fields.

In conclusion, NDBI alone is insufficient for accurate built-up land detection in semi-arid rural contexts due to spectral overlap with non-vegetated surfaces. To improve classification performance, future studies are recommended to integrate NDBI with other spectral indices such as NDVI or employ supervised classification algorithms (e.g., Random Forest or SVM). These methods may enhance feature discrimination and provide more reliable spatial information for land use monitoring and rural spatial planning.

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