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ABSTRACT

A comparative evaluation of built-up indices applied to high-resolution multispectral imagery from the WorldView-2 satellite is presented. Four urban regions are analyzed: Athens, Bucharest, Rome, and Torino. Each index is tested on different land covers, such as vegetation, water, bare soil, and built-up. A binarization strategy based on cumulative histograms of ground truth samples is implemented. The performance was assessed using the Spectral Discrimination Index (SDI). Results indicate that NBEI outperformed the other indices in separating impervious surfaces from spectrally similar bare soil. The findings confirm the potential of index-based approaches for built-up extraction in high-resolution imagery while also highlighting their limitations in heterogeneous urban environments.

Keywords: WorldView-2, Urban Segmentation, Spectral Indices, Urban Land Cover, Built-Up Index.

1. INTRODUCTION

Monitoring the spatial extent and growth of built-up areas is essential for sustainable urban planning, environmental management, and infrastructure development. High-resolution satellite imagery has become a valuable tool for mapping impervious surfaces, enabling timely assessments of land cover changes in rapidly urbanizing regions [1, 2]. Among the various techniques available for urban feature extraction, spectral index-based methods remain widely used due to their low computational cost, ease of implementation, and adaptability across sensors. These methods rely on algebraic combinations of multispectral bands to enhance the spectral contrast between artificial structures and other land cover types. Despite their simplicity, they often face limitations in accurately separating built-up surfaces from spectrally similar classes such as bare soil or dry vegetation, particularly in heterogeneous urban environments [3]. To address this challenge, several indices have been proposed that incorporate different spectral regions of high-resolution sensors like WorldView-2. Recent studies have demonstrated the utility of built-up indices in improving the mapping of impervious surfaces, particularly when combined with careful thresholding and statistical validation frameworks [4].

This study evaluates four index-based methods: the Built-up Area Index (BAI) [5], Built-up Spectral Index (BSI) [6], New Built-up Extraction Index (NBEI) [7], and Red Edge-Green Index (RGI) [8]. Each one is selected based on its relevance in recent literature and its compatibility with WorldView-2 spectral capabilities. A comparative performance in extracting impervious surfaces across four European cities (Athens, Bucharest, Rome, and Torino) using a consistent and quantitative evaluation framework is shown. The analysis includes accuracy metrics and spectral discrimination indicators to assess the ability of each index to distinguish between built-up that includes asphalted roads, buildings, concrete and other manmade impervious surfaces, and background surfaces, particularly bare soil, water and vegetation.

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2. MATERIALS AND METHODS

2.1 Satellite Data

The testing dataset is composed of high-resolution multispectral imagery acquired by the WorldView-2 (WV-2) satellite launched by DigitalGlobe in 2009. WV-2 was among the first high-resolution commercial satellites to provide eight-band multispectral data in the visible and near-infrared (VNIR) spectrum at a spatial resolution of 1.6 meters alongside a 0.46-meter panchromatic band. Its unique spectral configuration enhances the discrimination of urban features such as impervious surfaces, vegetation, and bare soil, which is critical for urban mapping applications [9, 10]. Table 1 summarizes the spectral bands and their wavelength ranges.

Table 1. Spectral bands from the WorldView-2 satellite.

Band	Name	Wavelength (nm)
B1	Coastal Blue	400–450
B2	Blue	450–510
B3	Green	510–580
B4	Yellow	585–625
B5	Red	630–690
B6	Red Edge	705–745
B7	NIR1	770–895
B8	NIR2	860–1040

The dataset contains urban scenes from four European cities: Athens, Bucharest, Rome, and Torino. For each city, a Region of Interest (RoI) of 939×939 pixels—corresponding to approximately 1.5×1.5 km of ground area was selected to secure spatial consistency across cities with diverse urban morphologies. These cities were chosen for their distinct architectural styles, land cover heterogeneity, and urban density gradients, which provide a comprehensive testbed for spectral index evaluation. All imagery was preprocessed through orthorectification and atmospheric correction to ensure geometric and radiometric consistency. Only the eight multispectral bands were used in this work. The panchromatic band was excluded. These multispectral subsets are particularly well-suited for evaluating built-up indices, as demonstrated in prior urban remote sensing studies [11, 12].

2.2 Index-Based Methods

Index-based methods are widely employed in remote sensing to extract impervious surfaces from multispectral imagery. These methods use mathematical combinations of spectral bands to emphasize specific land cover types, particularly built-up areas, by exploiting their distinct reflectance properties. Their simplicity, computational efficiency, and adaptability across different sensors and resolutions make them a common choice for large-scale and multi-temporal urban analysis [4, 13, 14]. However, a common problem of spectral indices for urban mapping is the spectral confusion between built-up areas and bare soil. Both surface types often exhibit similar reflectance in the visible and near-infrared ranges, particularly under dry conditions or in sparsely vegetated environments. This spectral overlap may result in the overestimation of urban extents, reducing classification accuracy [3, 15]. A comparative assessment of built-up index-based methods is conducted to evaluate their performance across multiple cities with varying urban morphologies.

2.2.1 Built-up Area Index (BAI)

The Built-up Area Index (BAI) is a simple yet effective spectral index designed to enhance the detection of artificial surfaces, particularly asphalt and concrete, in high-resolution imagery. It leverages the contrast in reflectance between the near-infrared and blue bands based on the characteristic reflectance of most built-up materials. The BAI was initially proposed to support the object-oriented classification of urban roads but has since demonstrated broader applicability in delineating impervious surfaces in dense urban fabrics [5]. Its mathematical formulation is given as:

$$\mathrm{BAI} = \frac{\mathrm{NIR} - \mathrm{Blue}}{\mathrm{NIR} + \mathrm{Blue}} \tag{1}$$

Figure 1 shows the cumulative histogram for BAI, and the maps of BAI values across the four cities.

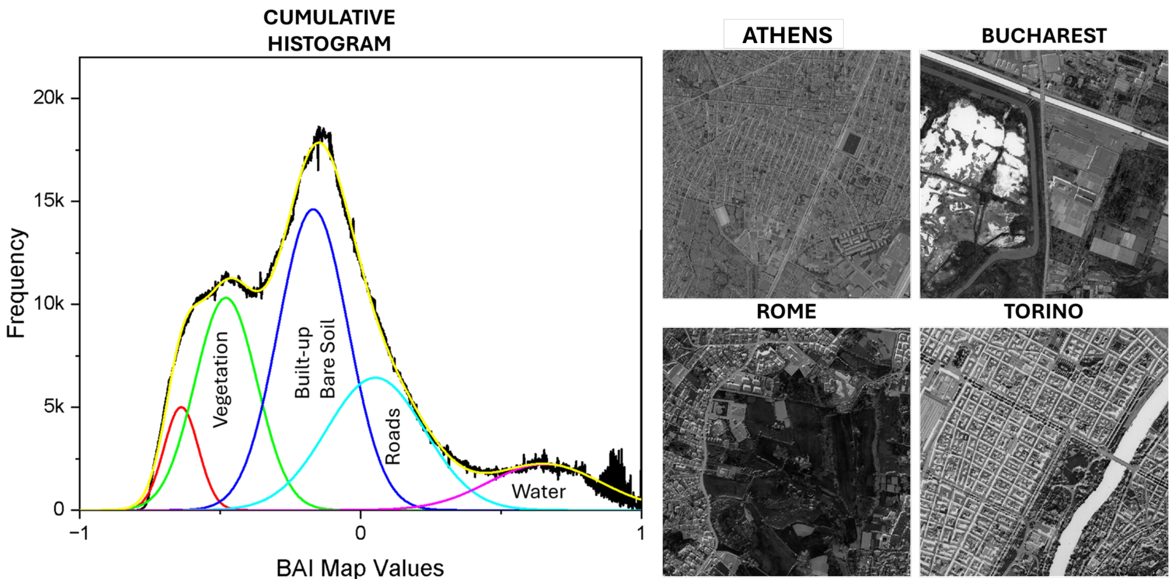

Figure 1. Cumulative histogram and spatial distribution of the **BAI** across the four urban scenes. The histogram shows most surfaces below values of zero, effectively separating water, but failing to distinguish completely vegetation from built-up areas and confusing built-up with bare soil and roads.

2.2.2 Built-up Spectral Index (BSI)

The Built-up Spectral Index (BSI) was designed to improve the extraction of impervious surfaces from WorldView-2 data. Unlike conventional indices derived from heuristic band combinations, BSI was developed using a multi-objective particle swarm optimization algorithm. This technique identified the most relevant spectral bands and their optimal weights to enhance spectral separability between built-up and non-built-up surfaces [6].

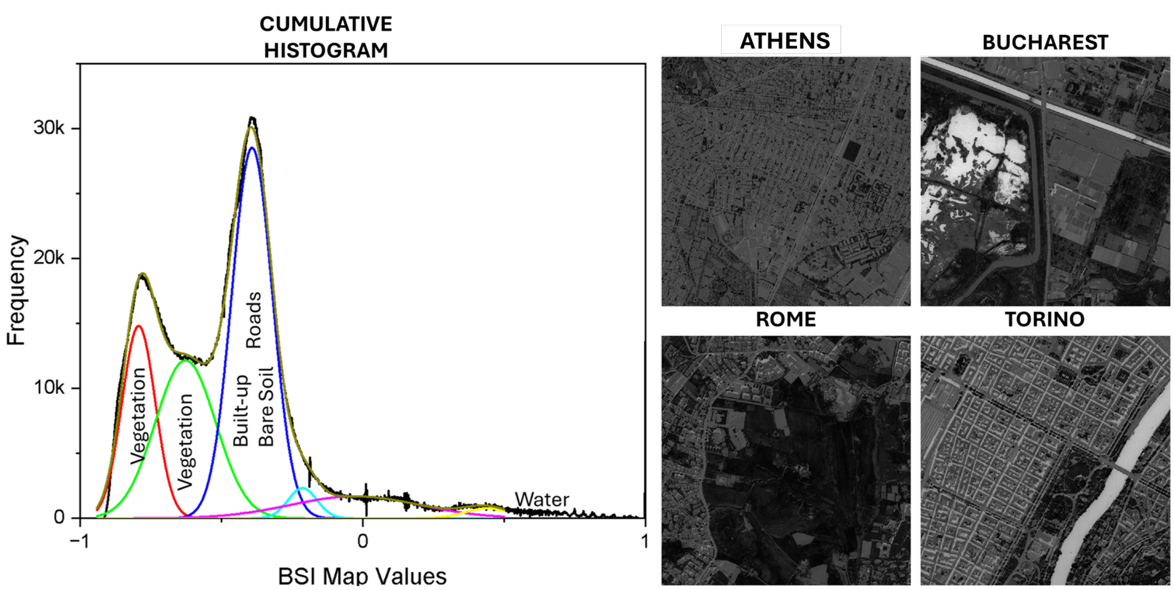

Figure 2. Cumulative histogram and spatial distribution of the **BSI** across the four urban scenes. Similar to BAI, the histogram displays most surfaces below zero, effectively isolating water. It offers improved separation between vegetation and built-up areas but still confuses built-up with bare soil and roads.

The final BSI formulation is expressed as:

$$\text{BSI} = \frac{\text{Yellow} - 2 \times \text{NIR1}}{\text{Yellow} + 2 \times \text{NIR1}} \tag{2}$$

Figure 2 shows the cumulative histogram for BSI, and the maps of BSI values across the four cities.

2.2.3 New Built-up Extraction Index (NBEI)

The New Built-up Extraction Index (NBEI) was developed to address the limitations of traditional spectral indices when applied to very high-resolution imagery such as WorldView-2. NBEI enhances the spectral contrast between impervious surfaces and surrounding land covers by combining the most discriminative bands identified through ReliefF feature selection: NIR2, NIR1, Green, and Red Edge. Its formulation is based on the normalized difference between the sum of the near-infrared (reflective) and visible-edge (absorptive) bands, which increases separability among heterogeneous urban materials [7]. The index is expressed as:

$$\text{NBEI} = \frac{(\text{NIR2} + \text{NIR1}) - (\text{Green} + \text{RedEdge})}{(\text{NIR2} + \text{NIR1}) + (\text{Green} + \text{RedEdge})} \tag{3}$$

Figure 3 shows the cumulative histogram for NBEI, and the maps of NBEI values across the four cities.

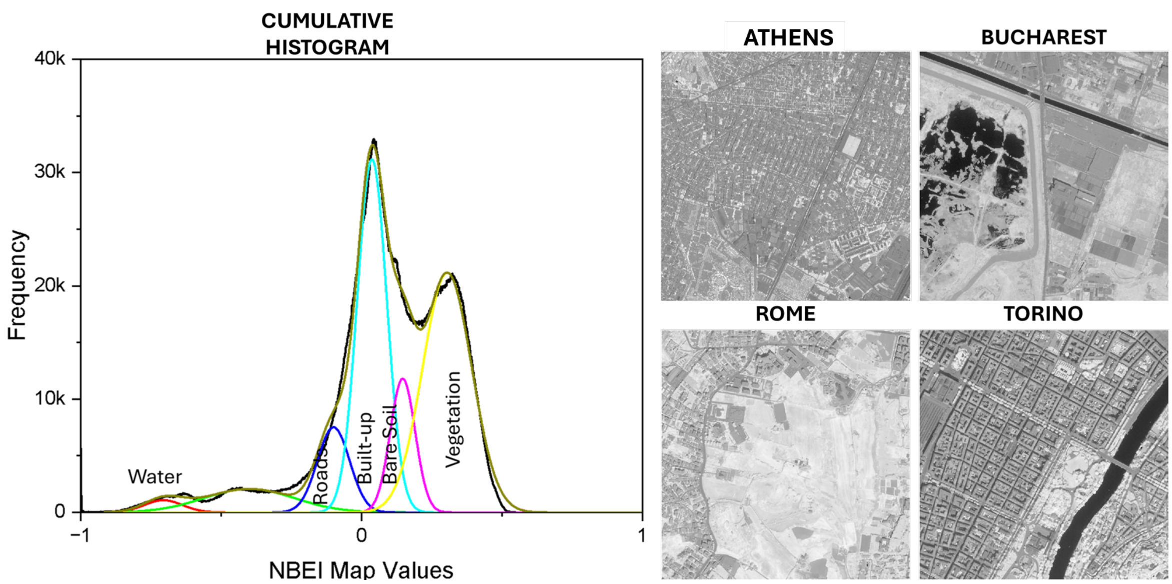

Figure 3. Cumulative histogram and spatial distribution of the **NBEI** across the four urban scenes. Built-up values cluster around zero, vegetation appears at higher values, and water near –1. Like other indices, built-up areas are often confused with bare soil.

2.2.4 Red Edge - Green Index (RGI)

The Red Edge-Green Index (RGI) is a spectral index designed to improve the discrimination between impervious surfaces and bare soil in urban and peri-urban environments. It uses the Red Edge and Green bands of the WorldView-2 sensor to capture subtle differences in surface reflectance [8]. The index is computed as the normalized difference between the Red Edge and Green bands:

$$\text{RGI} = \frac{\text{RedEdge} - \text{Green}}{\text{RedEdge} + \text{Green}} \tag{4}$$

Figure 4 shows the cumulative histogram of RGI and the maps of RGI values in the four cities.

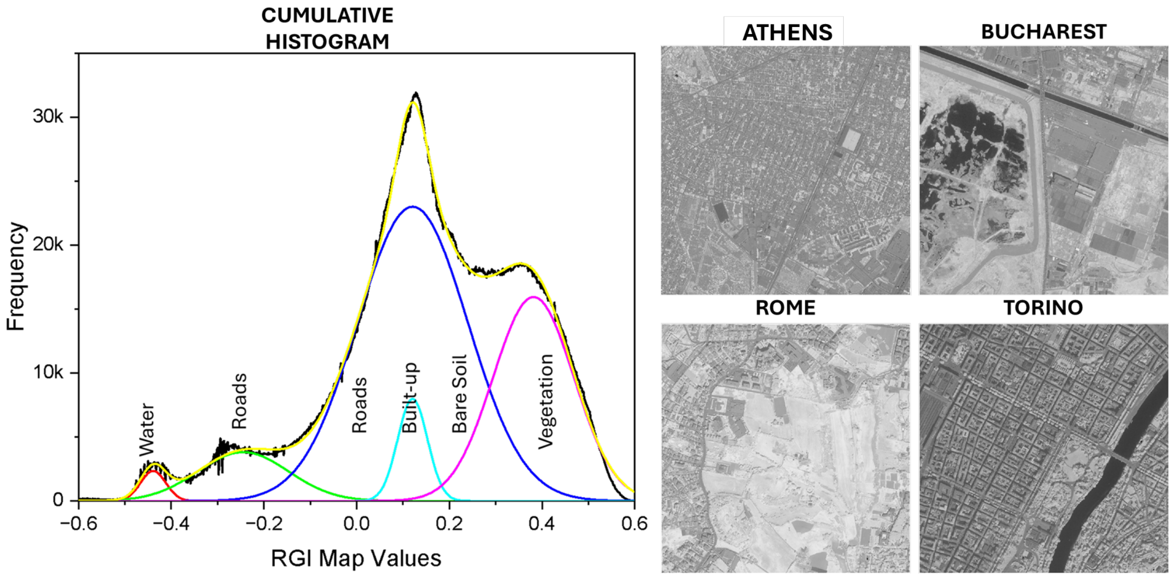

Figure 4. Cumulative histogram and spatial distribution of the **RGI** across the four urban scenes. Built-up values clusters between -0.2 and 0.4, vegetation appears between 0.2 and 0.6, and water below –0.4. Like other indices, built-up areas are often confused with bare soil.

3. BUILT-UP EXTRACTION RESULTS

The four spectral indices—**BAI** (Eq. 1), **BSI** (Eq. 2), **NBEI** (Eq. 3), and **RGI** (Eq. 4)—were applied independently to four urban scenes corresponding to Regions of Interest (RoIs) in **Torino**, **Rome**, **Athens**, and **Bucharest**. Each index was computed using its respective spectral formulation, as described in the previous sections. The resulting index maps were binarized using thresholds, optimized to extract built-up surfaces while minimizing the misclassification of bare soil.

A quantitative evaluation was conducted using manually selected **ground truth points** for four dominant surface classes: vegetation, water, bare soil, and construction. The high spatial resolution of the WorldView-2 imagery facilitated accurate identification and labeling of these reference points through visual interpretation. A total of 722 points were collected for background classes (water, vegetation, and bare soil), and 712 points for built-up surfaces. This balanced distribution ensures a fair comparison between built-up and non-built classes, reducing class bias and enhancing the reliability of the computed accuracy and spectral discrimination metrics. Table 2 lists the number of ground truth samples collected per surface class in each city.

Table 2. Number of ground truth points per surface type in each study area.

City	Vegetation	Water	Bare Soil	Construction
Athens	115	0	56	210
Bucharest	22	52	54	127
Rome	75	0	79	141
Torino	179	69	21	234
Total	391	121	210	712

Cumulative histograms were generated for each index, based on the ground truth samples of the four classes. For each index, an optimal **construction threshold range** was selected based on regions where the cumulative frequency of built-up samples was maximized, and bare soil was minimized. Figure 5 shows the cumulative histograms and determined built-up threshold for each index. Classification results across the four RoIs allow for a qualitative evaluation of the implemented built-up index-based methods.

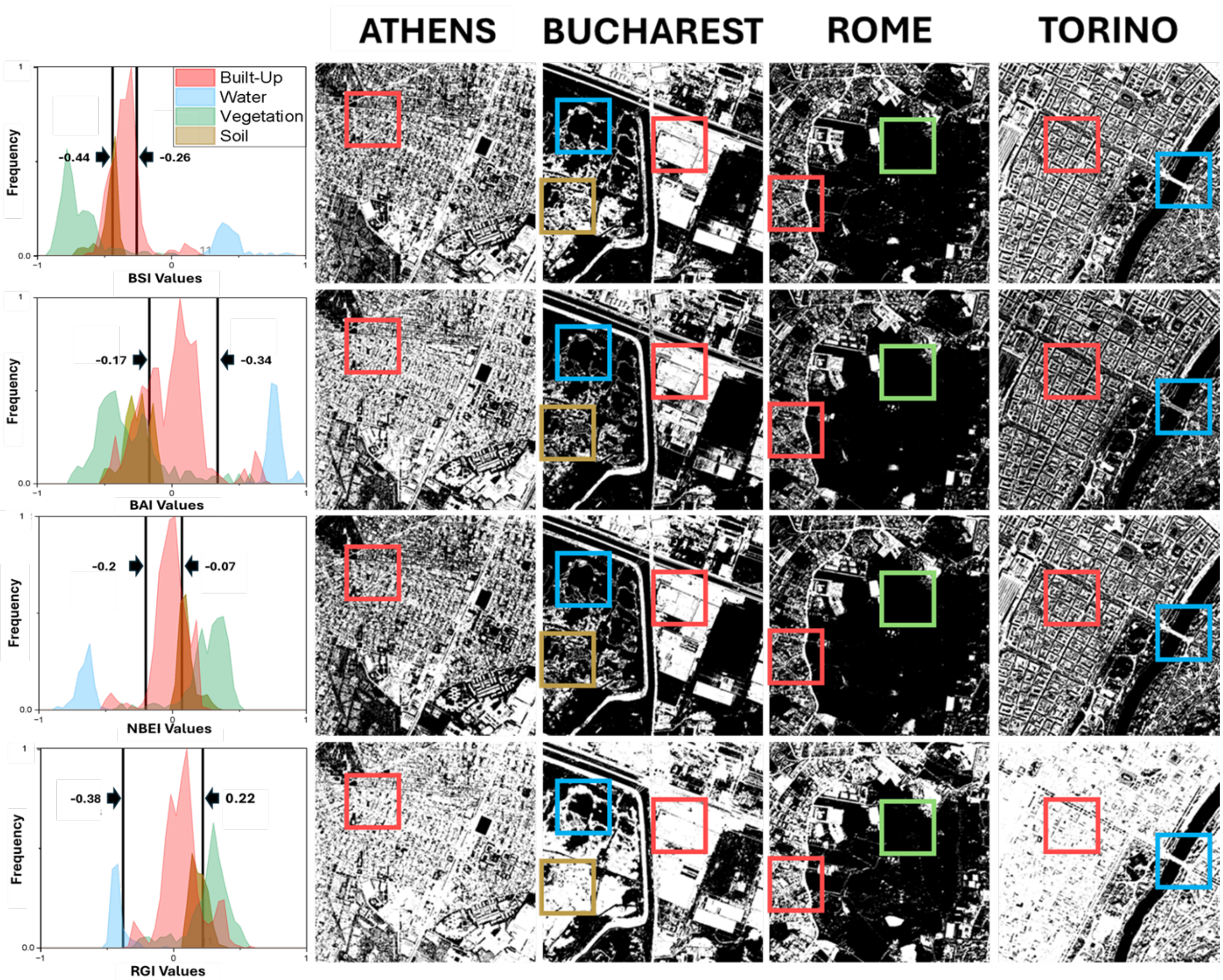

Figure 5. Binary built-up maps obtained from multispectral imagery corresponding to the four study areas: Torino, Rome, Athens, and Bucharest. White pixels indicate a built-up area; black pixels indicate a background. From top to down **BSI** map, **BAI** map, **NBEI** map, and **RGI** map.

To evaluate classification performance, the **accuracy (AC)** was computed for each index and RoI using the following expression:

$$AC = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

where TP, TN, FP, and FN denote the number of true positives, true negatives, false positives, and false negatives, respectively, based on the validation ground truth.

Additionally, to assess the spectral separability between **construction** and **bare soil**, the **Spectral Discrimination Index (SDI)** was calculated as:

$$SDI = \frac{|\mu_1 - \mu_2|}{\sigma_1 + \sigma_2} \tag{6}$$

where μ_1, μ_2 and σ_1, σ_2 are the means and standard deviations of the index values for construction and bare soil classes, respectively. A higher SDI indicates greater spectral separation, and therefore, a lower risk of misclassification between these two critical classes.

Table 3 summarizes the overall classification performance of each spectral index across all study areas. The results include both the binary classification accuracy and the Spectral Discrimination Index (SDI), which quantifies the spectral separability between construction and bare soil classes. Among the indices evaluated, the NBEI achieved the highest accuracy (63.40 %) and the best spectral discrimination (SDI = 4.40), reflecting its robustness in distinguishing impervious surfaces from spectrally similar materials. The BAI showed moderate performance in both metrics, while the BSI yielded a low SDI value (0.08), indicating a weak separation between built-up and bare soil features. The RGI demonstrated limited accuracy but a relatively high SDI (2.19), suggesting that although its classification output may lack precision, its spectral response to construction materials is distinct under certain conditions. These findings confirm the varying degrees of effectiveness of each index depending on their spectral formulation and sensitivity to urban surface heterogeneity.

Table 3. Overall Accuracy (%) and Spectral Discrimination Index (SDI) for each spectral index across all study areas.

Index	**Accuracy (%)**	**SDI**
BAI	61.43	0.97
BSI	60.91	0.08
NBEI	**63.40**	**4.40**
RGI	54.10	2.19

4. CONCLUSIONS

This study evaluated and compared four spectral indices—BAI, BSI, NBEI, and RGI—for the extraction of built-up areas using high-resolution multispectral imagery from WorldView-2. The indices were applied to four urban environments with varying spatial and spectral characteristics. Results indicate that index-based methods remain a practical and low-cost solution for impervious surface mapping, particularly when computational simplicity and interpretability are required. Among the evaluated indices, the NBEI demonstrated the highest overall accuracy and the strongest spectral separation between construction and bare soil classes. Its balanced use of near-infrared and visible-edge bands provided consistent performance across diverse urban forms. The BSI and BAI offered moderate accuracy but were more susceptible to confusion with bare soil, especially in areas with low vegetation cover. The RGI, although less accurate in classification, showed the potential to capture distinct spectral responses from specific construction materials. The analysis confirms that the spectral similarity between built-up and bare soil surfaces remains a key limitation in index-based extraction approaches. However, when appropriate thresholds and discrimination metrics such as SDI are applied, these methods can yield robust and transferable results. Future work may explore the integration of spatial features, texture, or machine learning classifiers to improve urban delineation accuracy further.

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