A new index for extracting built-up land features using Landsat satellite imagery

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Abstract. Land features mapping in urban regions are changing rapidly over time as a result of continuous urbanization. Spatial remote sensing allows continuous monitoring of this change using multi-date image data and providing a synoptic view. In light of this, a new spectral index based on pre-existing indices is suggested for the purpose of extracting built-up features in the Beni Mellal study area utilizing two Landsat-5 TM and Landsat-8 OLI images from 2013 and 2023. This time range of ten years enables the spatial and temporal monitoring of built-up surfaces. The accuracy of the results obtained is confirmed by using Pearson's correlation to land surface temperature and the two spectral indices, the Normalized Difference Moisture Index (NDMI) and Normalized Difference Vegetation Index (NDVI).

Keywords: Index; remote sensing; monitoring; built-up; Landsat.

1 Introduction

Earth observation includes all of the methodologies and techniques used to extract spectral, spatial, radiometric and temporal information from geospatial data images. Observing an area on a specific scale leads to the collection of any database and, most importantly, to the analysis and computation of correlations between all the components of the studied area [1], [2]. One of the most widely used techniques in earth observation is spatial remote sensing, given the availability of satellite images by an extensive variety of spectral, spatial and radiometric characteristics [3]. The ongoing development and optimization of image processing software is making it much easier to use and apply methods and algorithms for transforming, enhancing and classifying satellite images [4].

The continuous sprawl of urban areas has caused the substitution of vegetated areas with impervious surfaces including built-up lands and other man-made structures that prevents the infiltration of surface water into the soil. This transformation has resulted in several environmental impacts, such as the increase of the temperature of land surface [5]. These

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changes significantly exacerbate climate change and contribute to the degradation of the natural environment.

Mapping urban sprawl with Landsat imagery allows for a comprehensive quantitative evaluation of urban growth [6]. The method of computing spectral indices makes rapid use of multi-temporal datasets for identifying and evaluating spatio-temporal changes in urban sprawl [7]. Urban studies using geospatial data become more accurate, scalability is supported, and the reliability of the geoprocessing of geospatial data is improved, all of which speed up the process of evaluating and comprehending the dynamics of urban sprawl [8].

To map built-up areas from remote sensing data, several spectral indices were intended using the visible-near infrared (VNIR), shortwave infrared (SWIR), and thermal infrared (TIR) spectral regions. Bouhennache et al 2019 revealed the efficiency of visible and SWIR Landsat 8 OLI bands to calculate Built-up land features index [9]. Furthermore, The three spectral bands of RGB (spectral band 3), SWIR1 (spectral band 5), and SWIR2 (spectral band 7) of Landsat 7 ETM+ satellite imagery were used by Kaimaris and Patias et al. (2016) to map built-up regions [10]. All applied spectral indices using remote sensing data are well discussed in the review of kaur and pandey 2022 [7]. Therefore, the initial goal of this study is to map built-up areas by using Landsat data imagery by proposing a new built-up index and evaluating its performance. Additionally, determining change detection and Pearson's correlation between the built-up index, LST grayscale images, NDVI, and NDMI establishes the second step.

2 Study area

Beni Mellal is located in central Morocco, specifically at the coordinates of approximately 32.3361° N latitude and 6.3498° W longitude. It is the capital city of the Beni Mellal-Khenifra region, with an elevation of around 625 meters. The city exhibited significant urban sprawl in the last decade including new residential areas, roads network and infrastructure projects. This urban growth offers a case study to study urban sprawl using Landsat remote sensing data (Figure 1).

Fig. 1. location of the city of Beni Mellal.

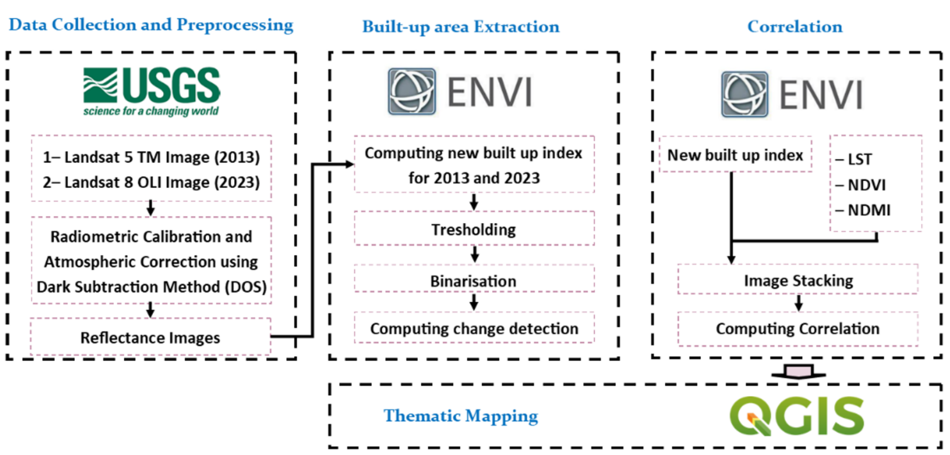
3 Data and Image Pre-processing

The present study employs two Landsat images to analyze the dynamic of urban sprawl over a decade (from 2013 to 2023) by applying the new developed index. The first image, captured by Landsat-5 (TM) on August 18, 2013, comprises seven spectral bands that span the VNIR, SWIR and TIR regions. Thus, the second image, acquired by the Landsat-8 OLI on June 11, 2023, offers better spectral and radiometric resolution (Table 1). Using the Dark Subtraction method (DOS), both scenes were atmospherically corrected and radiometrically calibrated after being downloaded in the GeoTIFF format from the USGS official website [11] (Figure 2).

Table 1. Technical specifications of Landsat sensors.

Sensor Name	Spectral Band (µm)	Wavelength (µm)	Spatial Resolution (m)
OLI	1- Coastal aerosol	0.43 - 0.45	30
	2- Blue	0.45 - 0.51	30
	3- Green	0.53 - 0.59	30
	4- Red	0.64 - 0.67	30
	5- Near Infrared	0.85 - 0.88	30
	6- SWIR 1	1.57 - 1.65	30
	7- SWIR 2	2.11 - 2.29	30
	8- Panchromatic	0.50 - 0.68	15
	9- Cirrus	1.36 - 1.38	30
TM	1- Blue	0.45 - 0.52	30
	2- Green	0.52 - 0.60	30
	3- Red	0.63 - 0.69	30
	4- Near infrared	0.76 - 0.90	30
	5- SWIR 1	1.55 - 1.75	30
	6- SWIR 2	2.08 - 2.35	30

Fig. 2. Methodological flowchart.



4 Methodology of developing built-up index

This study proposes a new spectral index to map built-up zones using Landsat satellite imagery. This index uses VNIR and SWIR bands. Thus, the new built-up index is written as follows (1):

$$\textit{New Built-up Index} = (\textit{Green} \times \textit{Red} \times \textit{SWIR1}) / (\textit{Blue} \times \textit{NIR}) \qquad (1)$$

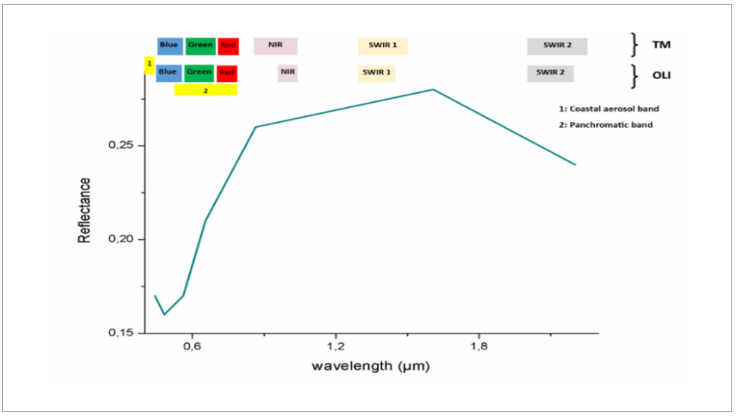


Fig. 3. Spectral signature of built-up surface for Landsat images.

The formula illustrates the usefulness of using the SWIR1 spectral band in developing indices by examining the image spectral signature of the built-up surface (Figure 3). This is because built-up surfaces show higher reflectance values in SWIR bands, especially in the SWIR 1 band. In contrast to the NIR spectral band, the built-up surface show a high reflectance value in the SWIR spectral band. it remains to be pointed out that the high values of the calculated index are bare land with very bright pixels. however, a thresholding value has been applied based on google earth pro basemap image to identify built-up areas and bare surfaces. The calculated correlation between the built-up index and NDVI (2), NDMI (3) and LST images, is key step to analyse the relations and impacts of urban sprawl on environmental factors.

$$NDVI = (NIR - Red) / (NIR + Red) \qquad (2)$$

$$NDMI = (NIR - SWIR1) / (NIR + SWIR1) \qquad (3)$$

The surface temperature image was calculated by calibrating the thermal band 10 of Landsat-8 OLI image and applying the thermal atmospheric correction to calculate the temperature and emissivity images.

5 Results and Discussions

5.1 Built-up area extraction and change detection

The change detection has been determined to calculate the overall surface area of built-up zones. The new index for each time period using the relevant formula has calculated for both dates of 2013 and 2023. Once the index graysclaes images are generated, we applied density

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slicing to categorize the index values into distinct ranges and subsequently we applied the thresholding value for extracting only the built-up zones and bare surfaces (Figure 4).

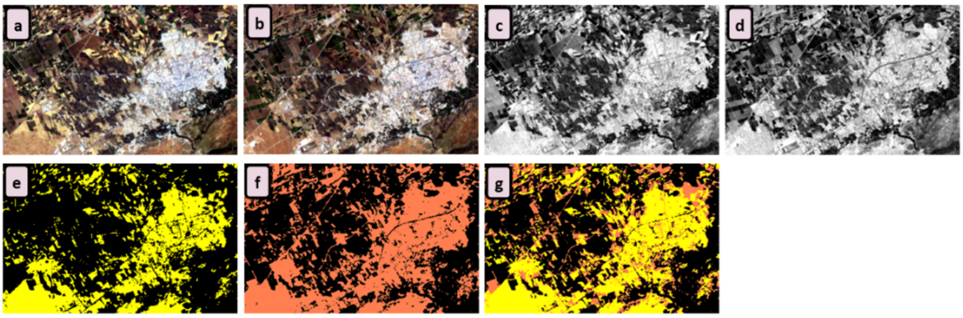

Fig. 4. (a) True color composite of TM image for 2013, (b) True color composite of OLI for 2023, (c) Calculated built up index for landsat-5 TM image, (d) Calculated built up index for landsat-8 OLI image, (e) Extracted built-up areas from TM image, (f) Extracted built-up areas from OLI image, (g) Overlay of the extracted built-up areas from the two images.

5.2 Correlation

Urban sprawl and other environmental indices such as NDVI, NDMI and LST, have spatial correlation which can be quantified to measure its strength and direction. The grayscales images of NDVI, NDMI and LST calculated from OLI image have been colored in order to exhibit suitable enhancement (Figure 5). The intensely negative correlation value of -0.89 between the built-up index and NDVI would indicate that urban sprawl is linked to reduction of vegetation cover. The positive correlation value of 0.47 between built up index and LST show that urban areas tend to have higher temperatures, indicative of the urban heat island effect phenomenon [12]. In addition, the built-up index shows negative correlation of -0.79 with NDMI similarly to NDVI (Figure 6).

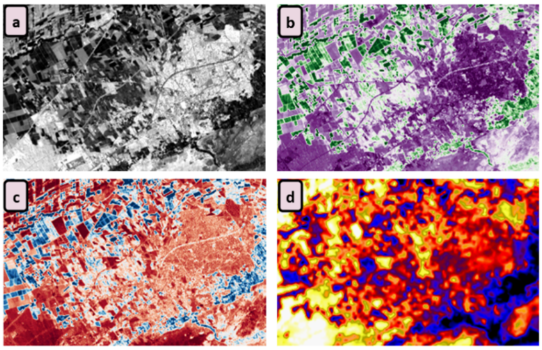

Fig. 5. (a) Calculated built up index for landsat 8 OLI image, (b) NDVI image with vegetation shown in green color, (c) NDMI image with moisture areas shown in blue color, (d) LST image with high temperature shown in yellow-red color.

	New Built up Index	LST	NDVI	NDMI
New Built up Index	1	0,47	-0,89	-0,79
LST	0,47	1	-0,46	-0,62
NDVI	-0,89	-0,46	1	0,88
NDMI	-0,79	-0,62	0,88	1

Fig. 6. Pearson's correlation between built-up index, LST, NDVI and NMDI indices.

6 Conclusion

The present study proposes a new built-up spectral index to map built-up zones in order to monitor the spatio-temporal variation in the study area. This index needs to be tested further in other geographic areas and validated accurately with more field data as it shows a spectral mixture with bare surfaces.

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Author contribution
All authors (Amine Jellouli, Mohcine Chakouri, Jaouad El Hachimi, Soufiane Hajaj, Abdessamad Jari & Zakaria Adiri) reviewed and approved the final manuscript. With Amine Jellouli contributing in study conceptualization, methodology, formal analysis, and writing, Mohcine Chakouri, Jaouad El Hachimi, Soufiane Hajaj, Abdessamad Jari and Zakaria Adiri contributing in reviewing, maps editing and interpreting the results.

Ethics approval and consent to participate
Not applicable.

Consent for publication
All the authors have agreed to publish this article.

Competing interests
The authors declare no competing interests.

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