Characterization and monitoring of urban sprawl using Landsat optical satellite imagery

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Abstract

Remote sensing images are of use when it comes to monitoring the growth of urban areas compared to other traditional approaches, as they can provide quick and synoptic views. One of the common approaches is to use spectral indices to extract built-up areas to track the phenomenon of urbanization and change in land use. Several built-up indices, that are derived from remote sensing measurements, are commonly used to characterize the urban growth pattern of cities. In this work, four built-up-indices were compared and analyzed to extract the urban areas in the city of Hassi-Bahbah (Province of Djelfa) from medium resolution remote sensing data (Landsat), namely: Band Ratio for Built-up Area (BRBA), Normalized Built-up Area Index (NBAI), New Built-up Index (NBI), Normalized Difference Built-up Index (NDBI). The reliability of the four indices was measured using confusion matrices and the Kappa coefficient through 50 validation zones mapped using field surveys and photo interpretation. The results showed that the BRBA index obtained the best performance for the extraction of built-up areas and better separation from to bare soil. The approach adopted can be used to assess the phenomenon of urbanization in areas with similar characteristics and to guide possible actions to control this phenomenon.

Keywords: index, urban sprawl, extraction, built-up areas, Hassi Bahbah.

I. Introduction :

Tracking urban expansion has always been the concern of geographers and planners, who have long preferred to bring together several old cartographic documents and compare them to trace the spatial extent of cities.

Today, remote sensing images are of use when it comes to monitoring the growth of urban areas compared to other traditional approaches, as they can provide quick and synoptic views (Zha, Gao, & Ni, 2003). One of the common approaches is to use spectral indices to extract built-up areas from bare soil in order to track the phenomenon of urbanization and change in land use.

A large number of built-up indices, derived from remote sensing measurements, are commonly used to characterize the urban growth pattern of cities (As-syakur, Adnyana, Arthana, Nuarsa, & others, 2012).

As part of this work, Landsat data were used to derive four indices namely: Band Ratio for Built-up Area (BRBA) (Waqar, Mirza, Mumtaz, & Hussain, 2012), Normalized Built-up Area Index (NBAI) (Waqar et al., 2012), New Built-up Index (NBI) (Chen, Li, Liu, Shen, & Hu, 2010), Normalized Difference Built-up Index (NDBI) (Zha et al., 2003)., for precise discrimination between bare soils and built-up areas in the agglomeration of Hassi-Bahbah (Province of Djelfa).

The objective of this study is to propose a method to map and quantify the urban growth between 1987 and 2018 of the agglomeration of Hassi-Bahbah using a series of medium-resolution Landsat images.

II. Material :

- **Study area :**

The agglomeration of Hassi Bahbah is located north of the Ouled Nail mountains that form the Saharan Atlas chain, a transition zone between the High Plains and the Saharan Atlas. It lies between 3.01 ° and 3.06 ° east longitude, and between 35.04 ° and 35.09 ° north latitude (Figure1). The relief of this area is generally not very rugged. The land is shallow and characterized by an accumulation of limestone (CNTC, 2014). In 2015, the town had a population of around 109,300 inhabitants. It recorded a growth rate that exceeded 3.41 between 1998 and 2008 (DPSB, 2014

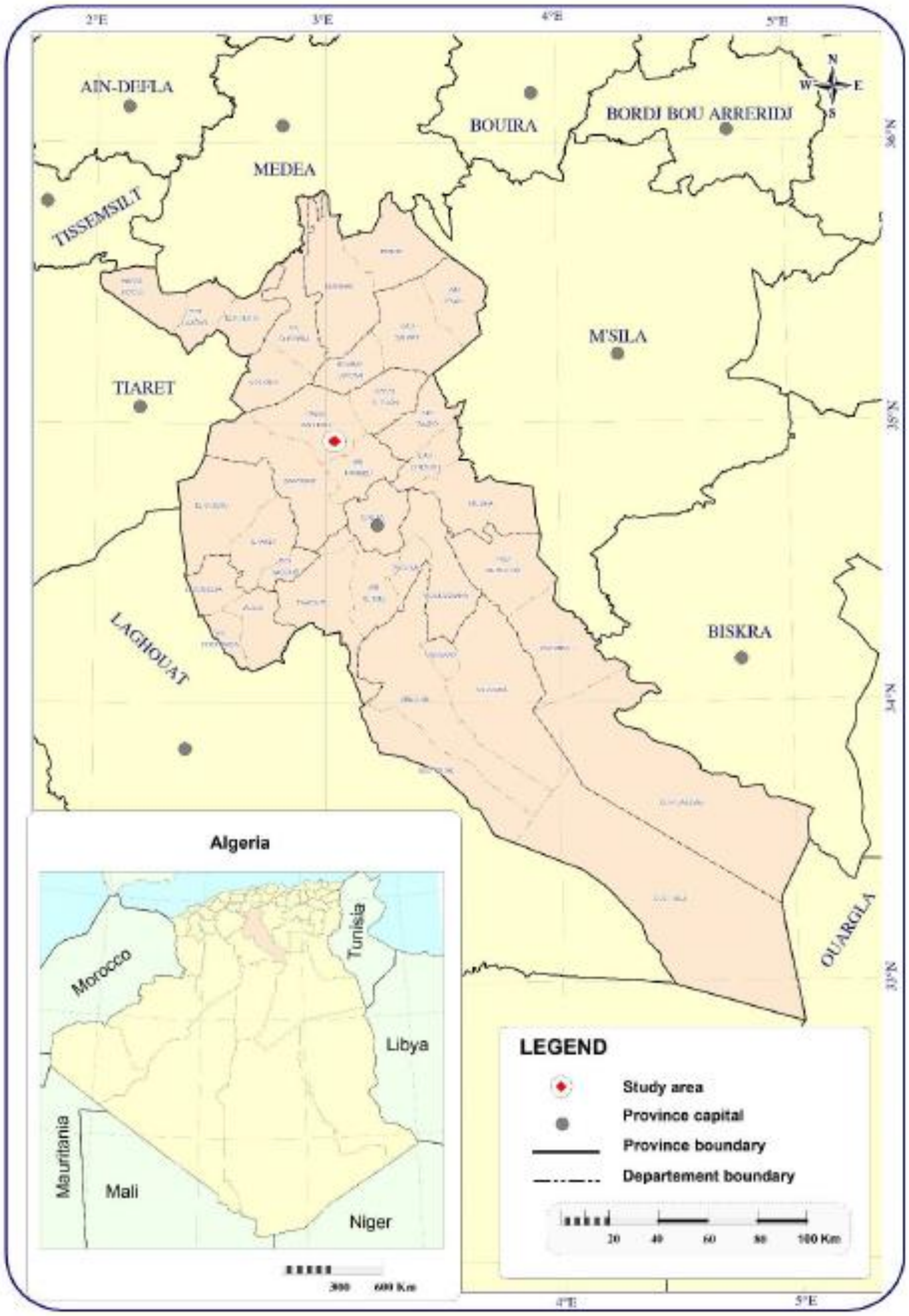

Figure 1 : Location of the study area

- **Data :**

For this study, we used the Landsat archive available through United States Geological Survey online platform (USGS Glovis data archive), for the period from 1987 to 2018. This dataset includes images acquired by Operational Land Imager (Landsat 8, OLI), Enhanced Thematic Mapper Plus (Landsat 7, ETM+), and Landsat Thematic Mapper (Landsat 5 TM).

We selected cloud-free images in one tile (path/row 195/036) covering the study area, with a spatial resolution of 30 m (Table 1).

Table 1 : Characteristics of images selected for processing

Images	**1987**	**2000**	**2009**	**2013**	**2018**
Satellite	Landsat 5 TM	Landsat 7 ETM^{+}	Landsat 5 TM	Landsat 8 OLI	Landsat 8 OLI
Sensor	Multi spectral	Multi spectral	Multi spectral	Multi spectral	Multi spectral
Bands (µm)	0.45-0.52 0.52-0.60 0.63-0.69 0.76-0.90 1.55-1.75 10.4-12.5 2.08-2.35	0.45-0.52 0.53-0.61 0.63-0.69 0.77-0.90 1.55-1.75 10.4-12.5 2.08-2.35	0.45-0.52 0.52-0.60 0.63-0.69 0.76-0.90 1.55-1.75 10.4-12.5 2.08-2.35	0.43-0.45 0.45-0.51 0.53-0.59 0.64-0.67 0.85-0.88 1.57-1.65 2.11-2.29	0.43-0.45 0.45-0.51 0.53-0.59 0.64-0.67 0.85-0.88 1.57-1.65 2.11-2.29
Spatial resolution	30 m	30 m	30 m	30 m	30 m
Scene time	9 :46 :11	10 :11 :10	10 :09 :34	10 :22 :06	10 :19 :34
Acquisition date	17/08/1987	12/08/2000	29/08/2009	08/08/2013	22/08/2018

III. Tools and methods :

- **Indices**

Spectral indices are mathematically combinations of radiometric values taken from several bands used to extract built-up areas efficiently. Various indices have been developed for extracting built-up areas using satellite images **(**As.syakur, Adnyana, Arthana, Nuarsa, & others, 2012; Bhatti & Tripathi, 2014; He, Shi, Xie, & Zhao, 2010; Waqar, Mirza, Mumtaz, & Hussain, 2012; Zha et al., 2003).

In the context of this study, we applied four spectral indices, namely: BRBA, NBAI, NBI and NDBI.

After radiometric calibration and atmospheric correction of the images (Figure 2), we calculated the four indexes according to the following equations (Elfadaly, Lasaponara, Murgante, & Qelichi, 2017; Waqar et al., 2012):

- BRBA = TM3 / TM5	(1)
- NBAI = (TM7 - TM5 / TM2) / (TM7 + TM5 / TM2)	(2)
- NBI = (TM3 x TM5) / TM4	(3)
- NDBI = (TM5 - TM 4) / (TM5 + TM4)	(4)

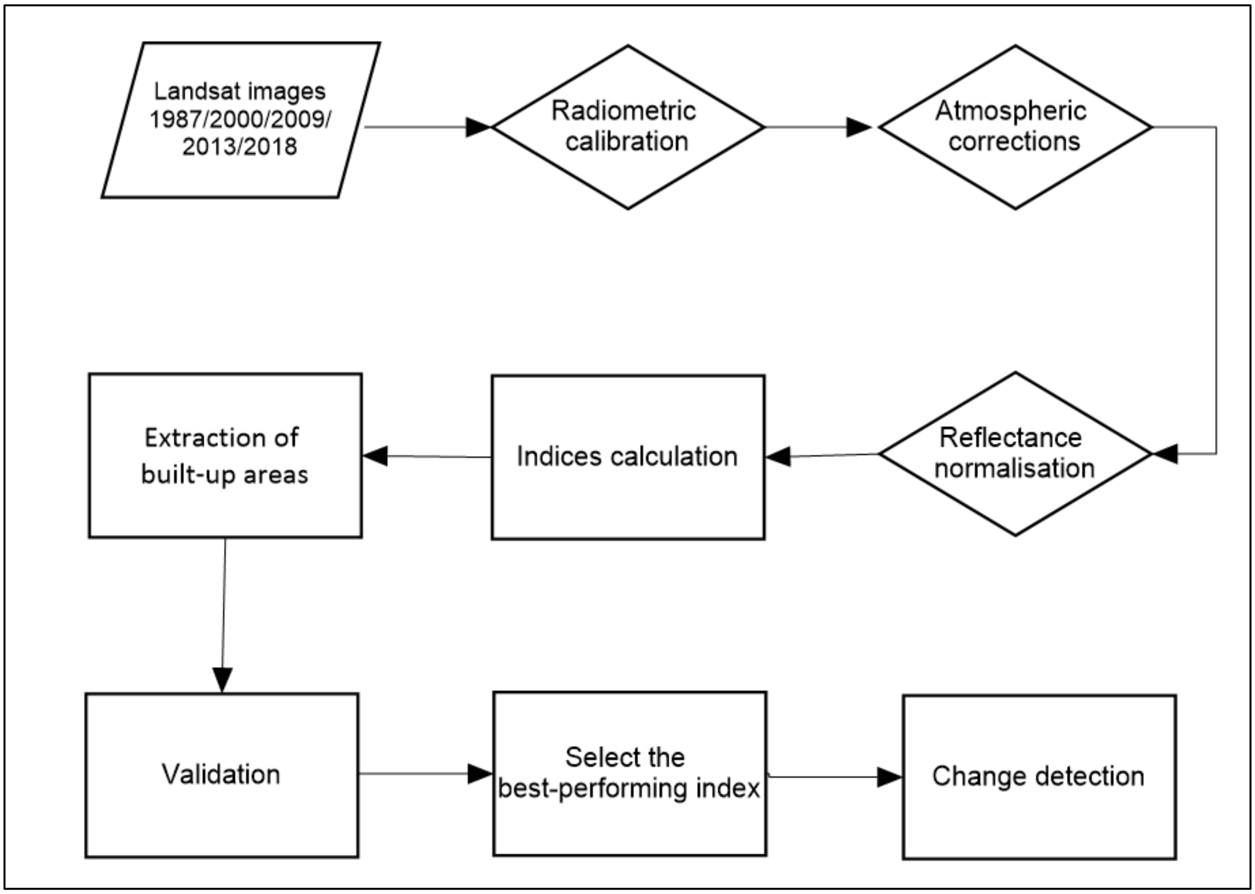

Figure 2 : Flow chart of the methodology used in the present work

- **Accuracy assessment**

Accuracy assessment is a crucial step in the classification process. The goal behind this step is to quantitatively assess the degree of efficiency with which pixels were sampled in the correct land cover classes **(Rwanga & Ndambuki, 2017)**.

To assess the accuracy of the results and identify the best index to trace the urbanization in the study area, we applied Kappa statistic and overall accuracy based on confusion matrix (Qian, Zhou, & Hou, 2007; Waqar et al., 2012).

Confusion matrix included two classes: built-up areas and bare soils, it makes it possible to assess the accuracy of the classification globally and for each class. It is calculated from the pixels correctly and incorrectly classified in the validation zones, these zones correspond to areas for which the land use is already known.

The confusion matrix using 50 validation zones for the built-up class and 50 validation zones for the bare soil class (each zone contains at least one pixel).

The overall accuracy is an important proportion metric that ensures the pixel is correctly classified to describe the accuracy classification, it is usually derived from the confusion matrix with the diagonal elements (Li et al., 2014).

Kappa gives a more precise estimate of the quality of the classification, which takes into account well-classified pixels. This coefficient is always between -1 and 1. Usually, the following scale is used to interpret the value obtained (McHugh, 2012): $K < 0$ no agreement, 0 to 0.20 none to slight, 0.21 to 0.60 moderate, 0.61 to 0.80 substantial, and $K \geq 0.81$ almost perfect agreement.

IV. Results and discussion

After the evaluation and interpretation of the built-up indices from the confusion matrix and the Kappa coefficient, the results showed that the BRBA index obtained the best performance for the extraction of built-up areas and better separation. compared to bare soils.

The precision assessment shows that the overall accuracy for built-up areas and bare soils using NBAI, NBI, and NDBI indices is lower than that of the BRBA index. The accuracy of these indices varies from 45.55% to 81.85% for built-up areas, or 05% to 13% less than the BRBA where its accuracy varies between 84.84% and 91.53% (Table 2, Figure 4).

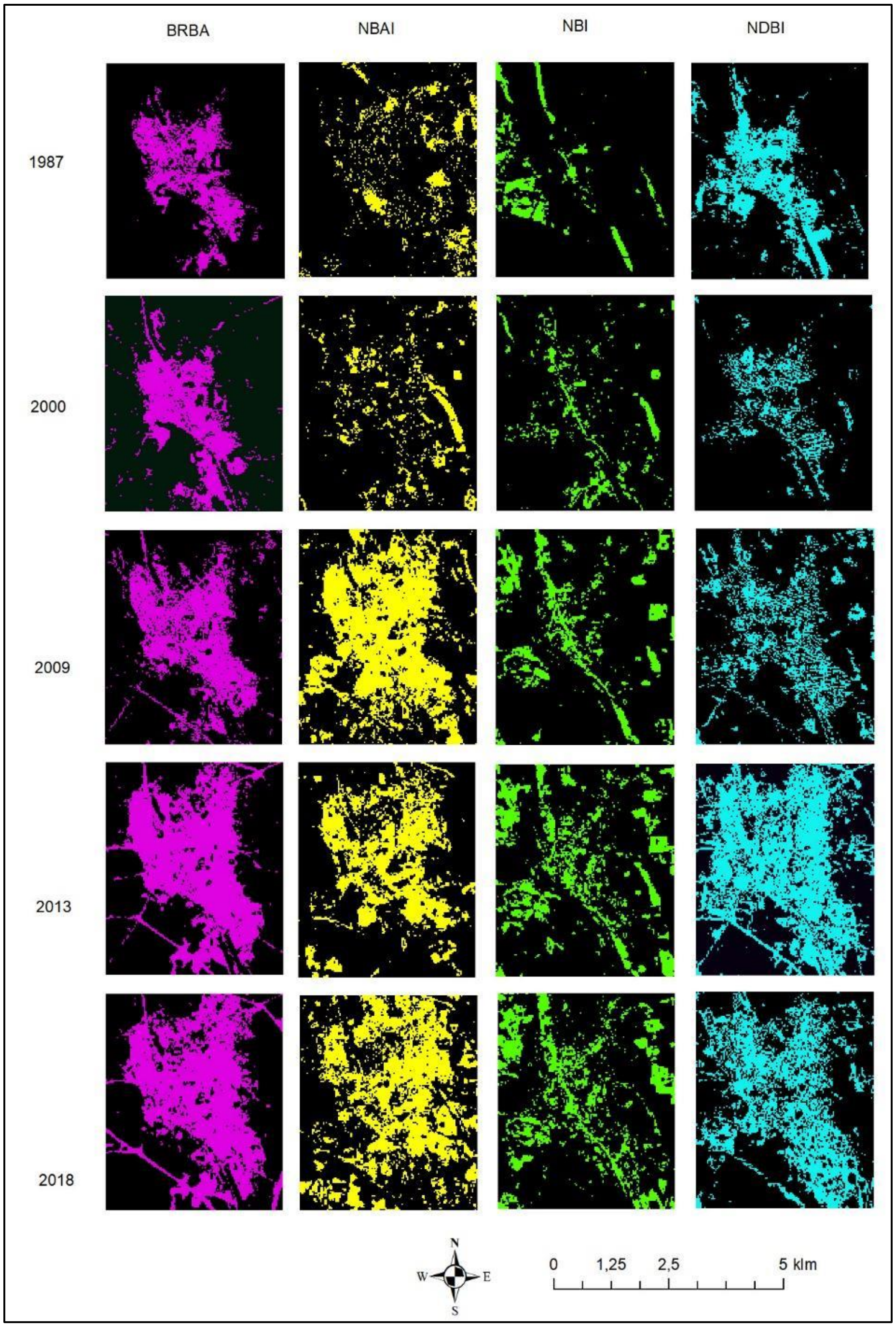

Figure 3: Result of the extraction of built-up areas using the BRAB, NBAI, NDBI and NBI indices for the agglomeration of Hassi-Bahbah.

The same results were observed for the Kappa coefficient. However, its results were more contrasted than those for the overall precision and there was less confusion between the NBAI and the BRBA. The values of the kappa coefficient for the BRBA are between 0.70 and 0.82, while, its values are almost low for the rest of the indices (NBI, NBAI and NDBI). Other minor differences were observed (Table 2).

Table 2: Summary of the accuracy assessment results

Images		BRBA	NDBI	NBAI	NBI
1987	Overall Accuracy	84.84%	73.86%	46.59%	46.96%
	Kappa coef.	0.70	0.48	~0	~0
2000	Overall Accuracy	85.01%	65.16%	48.68%	54.30%
	Kappa coef.	0.70	0.31	~0	0.10
2009	Overall Accuracy	88.80%	63.70%	79.53%	45.55%
	Kappa coef.	0.77	0.29	0.59	~0
2013	Overall Accuracy	91.53%	63.70%	81.85%	45.55%
	Kappa c coef.	0.83	0.29	0.64	~0
2018	Overall Accuracy	91.17%	70.58%	76.89%	46.21%
	Kappa coef.	0.82	0.42	0.54	~0

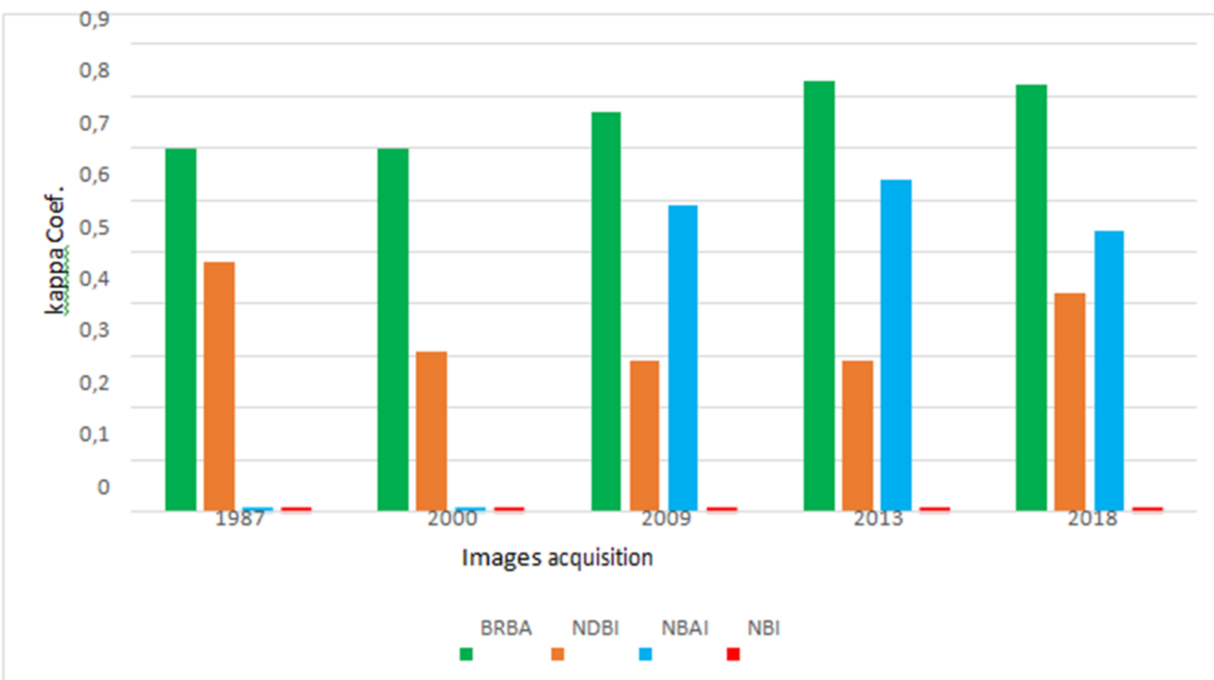

Figure 4: Summary of the accuracy assessment results (with the Kappa coefficient)

(Valdiviezo- N, Téllez-Quiñones, Salazar-Garibay, & López-Caloca, 2018; Waqar et al., 2012) , it presents a robust tool capable of extracting urban areas compared to other indices that were not able to effectively separate built-up areas from bare soils lands.

The best clue for detecting change is the BRBA, the latter is recommended for mapping and tracing the urban sprawl of the city of Hassi-Bahbah from 1987 to 2018.

V. Conclusion

Today, remote sensing provides quantitative information on the evolution of urban areas that provides almost-real monitoring. The extraction method we used in this study appears to be very effective in distinguishing between built-up areas and bare soils, precisely with the BRBA index. These results were verified using the confusion matrix and the Kappa coefficient. This method can be applied to other images of equivalent or finer spatial resolutions, to carry out studies of urban growth. The approach adopted can be used to assess the phenomenon of urbanization in areas with similar characteristics and to issue actions to control this phenomenon, to help all stakeholders in the field of planning to understand, control, and master the dynamics of our cities.

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