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Remote sensing of Land Use and Land Cover changes in semi-arid regions: a Google Earth Engine approach for urban planning in Djebel Ouahch (Constantine, Algeria)

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Abstract. This study provides a critical analysis of land use and land cover changes in the Djebel Ouahch region (Constantine, Algeria) across three significant time periods: 1984, 2004 and 2023. Using remote sensing data and spectral indices, the research reveals important trends in urban development and vegetation cover. The Normalised Difference Built-up Index (NDBI) showed notable variations: from minimal urban development (0.01) in 1984, to a significant decrease (to –0.06) in 2004 following shantytown eradication programmes, and a slight increase (to –0.03) by 2023 due to rural housing initiatives launched in 2008. Concurrently, the Normalised Difference Vegetation Index (NDVI) demonstrated an overall positive trend, increasing from 0.45 in 1984 to 0.55 in 2023, despite a temporary decline in 2004. This research contributes significantly to understanding urban-environmental dynamics in semi-arid regions and provides valuable insights for policymakers and urban planners. The findings are particularly relevant for developing sustainable urban development strategies that balance population needs with ecosystem preservation in rapidly evolving regions.

Key words:
NDVI,
NDBI,
BU,
Urbanisation,
Djebel Ouahch

Introduction

Rapid and uncontrolled urbanisation constitutes a major environmental challenge in sub-Saharan Africa, threatening forest and agricultural ecosystems. Recent research highlights its potentially dramatic consequences, including the disappearance of vast forest areas and ecosystem simplification (Mundo et al. 2023). With the world's highest urbanisation rate (~67%), Africa perfectly illustrates this territorial transformation (Abubakar and Ejaro 2013).

In Algeria, particularly in the northern Mediterranean regions, this phenomenon translates to an alarming decline in forest areas, confronted by multiple anthropogenic pressures such as overgrazing, illegal logging and wildfires (Bassene et al. 2020). The scientific community has extensively documented these dynamics through diachronic studies conducted in various Algerian regions, including El Kala National Park, the Tessala Mountains and the Tolga region (Rekis and Belhamra 2015).

To understand and quantify these transformations, researchers now mobilise advanced remote sensing and spatial analysis tools. Spectral indices such as NDVI (Normalised Difference Vegetation Index), NDBI (Normalised Difference Urban Index), and the BU (Building) index now allow for fine-grained examination of vegetation cover and urbanisation dynamics (Bouhennache 2018; Bouteraa et al. 2023). These methods offer an integrated approach to modeling complex interactions between urbanisation and forest ecosystems.

In this context, the Djebel Ouahch massif, located in the Numidian ranges of Constantine, represents a particularly significant study area. This unique phytogeographical ensemble, characterised by singular geographical, geological and climatic conditions (Tlidjane et al. 2019), is undergoing profound mutations. Peri-urban forests, essential for climate regulation, carbon storage and environmental security (Rufino et al. 2011; Kearse et al. 2012; Joël et al. 2018), are threatened by increasing land artificialisation.

The objective of this research is to evaluate the impact of urbanisation on the forest ecosystems of Djebel Ouahch over a 40-year period. By utilising the Google Earth Engine platform and integrating complex biogeographical factors, we seek to quantify and understand the transformation dynamics of this natural space. How does urbanisation modify forest cover? What are the consequences for biodiversity and ecosystem services? These are the central questions that will guide our analysis.

Materials and methods

Study area

The Djebel El Ouahch massif, located in the north-east of the Constantine region, covers an area of 66,535 hectares. Anchored by the seven municipalities of Zighoud Youcef, Didouche Mourad, Constantine, El Khroub, Ibn Badis, Aïn Abid and Ouled Rahmoune, it lies between 36°14'20.19" and 36°33'55.81" north latitude and between 6°38'0.82" and 6°58'37.65" east longitude.

This area offers a representative microcosm of land use dynamics in the Constantine region and, by extension, in Algeria's Tell. The study area is characterised by its geographical diversity, ranging from the sub-humid heights of the north (1,100–1,300 m) dominated by cork oak forests to the eroded agricultural plains of the south, thus capturing a significant urban–rural gradient. It perfectly illustrates the tensions between urban development, agricultural preservation and the conservation of natural ecosystems, reflecting the major challenges facing the region.

The representativeness of this area is evident through the dynamics of urban expansion, challenges in forest conservation, soil erosion issues, and land use conflicts, all emblematic of broader regional trends. This diversity and representativeness lend particular importance to the study's findings, allowing for cautious extrapolation of observations at the regional level. Thus, the conclusions drawn from the analysis of Djebel El Ouahch can effectively inform land use planning and environmental management policies, not only for the immediate area but also for a broader understanding of territorial dynamics in north-eastern Algeria (Fig. 1).

Data processing and analysis

Remote sensing approaches combined with mapping were adopted for the diachronic analysis of landscape dynamics using the Google Earth Engine (GEE) platform for the periods 1984, 2004 and 2023. For this study, images from two types of LANDSAT sensors were used:

– LANDSAT/LT05/CO2/T1 for the dates 1984 and 2004;

– LANDSAT/LC08/CO2/T1 and LANDSAT/LE07/C02/T1_L2 for the classification of the 2023 period.

A collection of scenes was produced, and the average was chosen for this study. Finally, the classified images were filtered with a cloud mask. Satellite images were processed using the same analytical methods used to produce the maps. Arcmap10.5 was used to process the images.

The main objective of this study was to examine the spatiotemporal dynamics of urbanisation and construction and their impact on the forest environment, using special indices: NDVI, NDBI and BU. We then carried out a supervised classification of the different types of land use and land cover (LULC). These indices were correlated using Minitab statistical software.

Urban development has led to an expansion of municipal territory, causing changes in land use. The study mainly aimed to identify, quantify

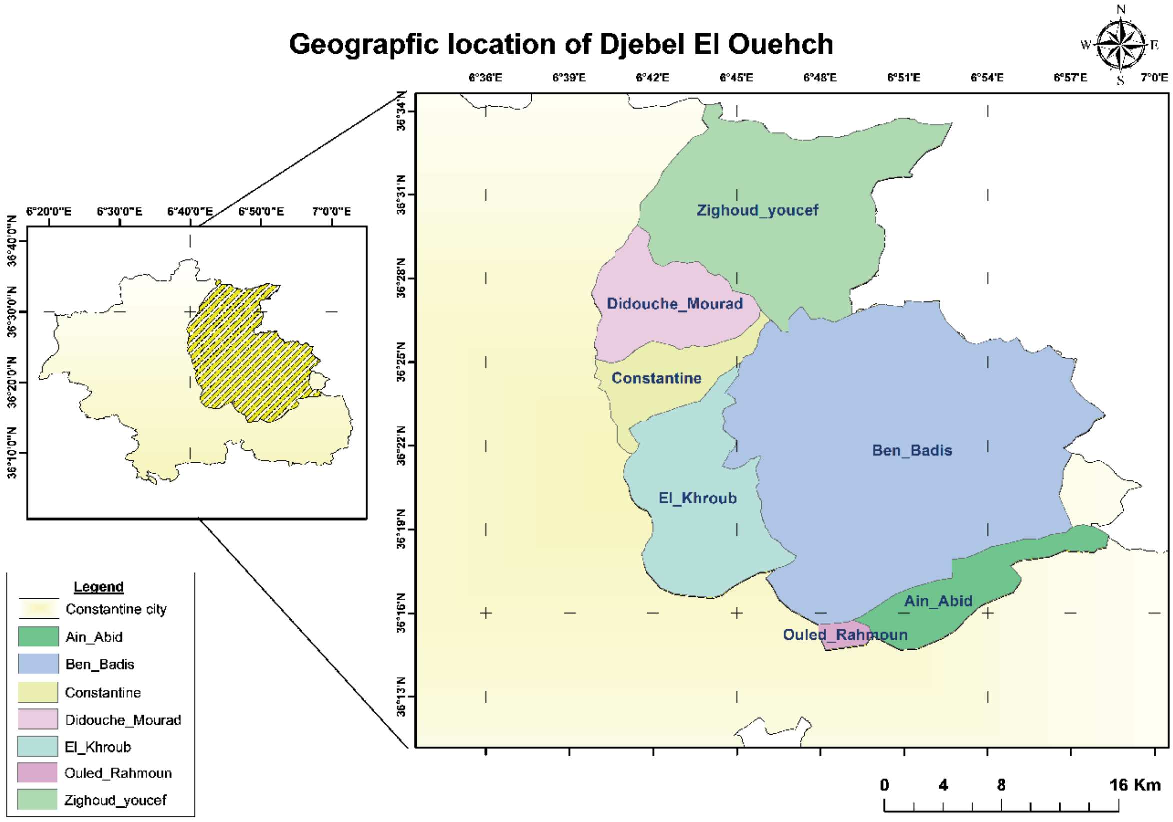

Fig. 1. Location of Djebel El Ouehch

and interpret the evolution of land use and urban growth based on data obtained from satellite imagery through the GEE platform.

Image processing stage

The main objective of the image processing was to accurately extract the built-up coverage of the study area for the years 1984, 2004 and 2023. The images were taken at different dates with minimal alteration to the geometric accuracy. Therefore, additional adjustment of the datasets was required, and all images were reprojected into the WGS 1984 UTM 32N coordinate system to eliminate image distortion. The images were processed through a series of operations, including georeferencing, spectral band composition, mosaicking and extraction of the area of interest for the study using appropriate formulae and scripts.

Supervised classification and land use

Classification has been carried out here to show a visualisation of urban spatial changes and extensions for the years 1984, 2004 and 2023. Supervised classification with the maximum likelihood algorithm method was applied here to measure land use changes over time, and this method has proved to be an effective classifier, among others (Aronoff 1982). The images were classified into five classes, namely built-up areas, bare land, vegetated areas (agricultural and vegetation), water bodies and forests. To study the spatial configuration of urban areas during the study period, the LULC classes were reclassified into built-up and unbuilt-up areas. In this study, the built-up area class was used to represent areas of urban expansion.

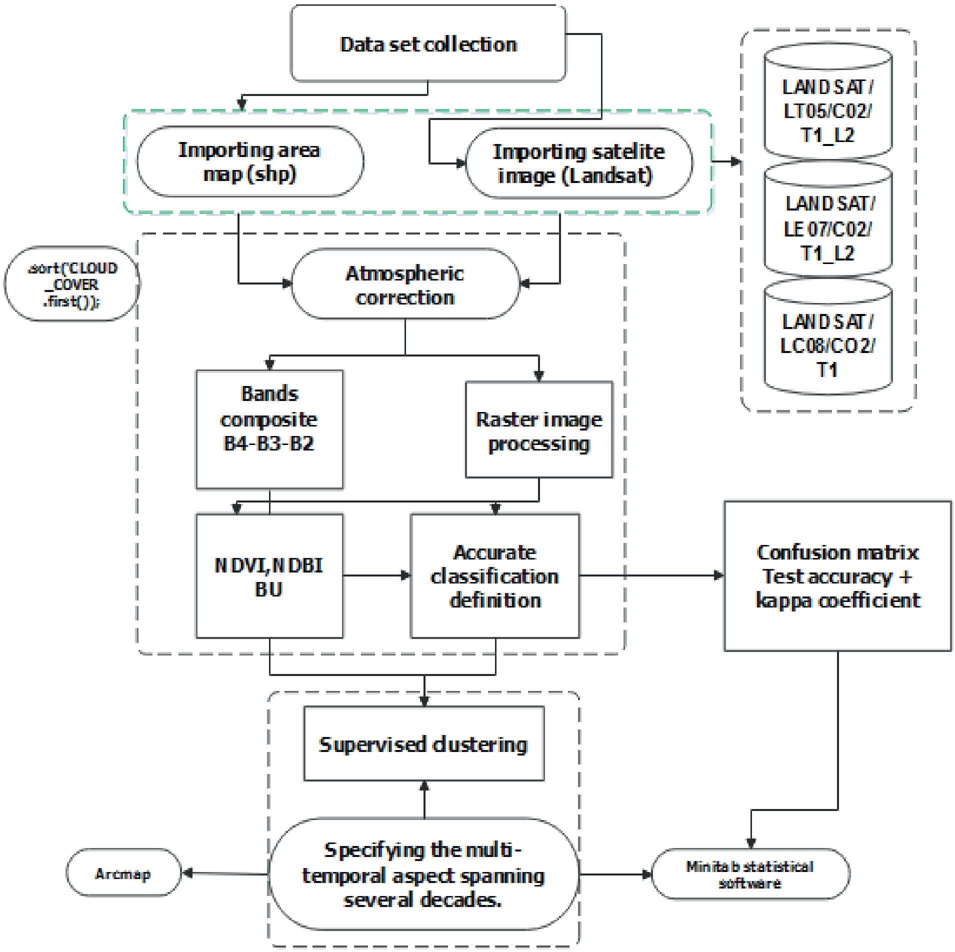

Fig. 2. Process flowchart

Accuracy assessment to minimise error during classification

Accuracy assessment is essential to minimise error when classifying satellite images (Rakotomala 2015). It was used to identify built-up areas, natural areas and other types of land cover in the study area. Several metrics are used for this purpose, such as the confusion matrix, Kappa coefficients, and omission and commission error rates. In this case, we opted for the confusion matrix method, which compares the classified pixels with reference data (ground truth), and the Kappa coefficient to confirm the accuracy of the classification in relation to a known ground truth. Researchers explain that 85% is the minimum acceptance accuracy value (Mosammam et al. 2017).

The accuracy values for the Djebel Ouahch zone are 0.98 in 1984 and 0.99 in 2004 and 2023 (Table 1). Consequently, the matrix confusion test is 0.96 in 1984 and 0.94 for 2004 and 2023. An in-depth analysis identified the classes most prone to errors and adjusted the classification parameters (training samples, algorithms, etc.) to improve overall accuracy. High accuracy is crucial for reliable land cover mapping and monitoring changes over time (Pelletier 2017).

Table 1. Accuracy assessment for LULC

Category	1984	2004	2023
Test accuracy	0.98	0.99	0.99
Test confusion matrix	0.96	0.94	0.94

Normalised difference vegetation index (NDVI)

The (Normalised Difference Vegetation Index) is the most widespread and widely used index for vegetation extraction (Guha et al. 2018). Its formula is as follows:

NDVI = (NIR – Red) / (NIR + Red)

For LANDSAT/LT05/C02/T1_L2

$$\mathrm{NDVI} = \frac{\mathrm{SR_{B4}} - \mathrm{SR_{B3}}}{\mathrm{SR_{B4}} + \mathrm{SR_{B3}}}$$

For LANDSAT/LE07/C02/T1_L2

$$\mathrm{NDVI} = \frac{\mathrm{SR_{B4}} - \mathrm{SR_{B3}}}{\mathrm{SR_{B4}} + \mathrm{SR_{B3}}}$$

Normalised difference built-up index (NDBI) Built-up Index (BU)

There are several indices for analysing built-up areas, but we chose the Normalised Difference Built-up Index (NDBI) and the Built-up Index (BU).

NDBI = (SWIR – NIR) / (SWIR + NIR)

For best results in mapping urban areas, (BU) combining NDBI (Liu et al. 2004) and NDVI is recommended. The BU produces a binary image in which only high positive values correspond to built-up areas and bare ground, making them easier to extract automatically.

BU = NDBI - NDVI

For LANDSAT/LE07/C02/T1_L2

$$\mathrm{NDBI} = \frac{\mathrm{SR_{B5}} - \mathrm{SR_{B4}}}{\mathrm{SR_{B5}} + \mathrm{SR_{B4}}}$$

The binary combination approach (NDVI-NDBI) of Zha et al. (2003) is based on the following hypothesis: a positive NDBI value indicates the presence of built-up areas, while a positive NDVI value indicates the presence of vegetation.

These two indices can be used to categorise different types of land cover on the basis of appropriate threshold values. In order to obtain a more accurate classification, a correlation between these indices was used to confirm our approach to supervised classification. For example, NDVI > 0.2 and NDBI < 0 allow vegetation to be extracted. Similarly, NDVI < 0 and NDBI < 0 are used to extract water bodies, while 0 < NDVI < 0.2 and NDBI > 0.1 are used to extract built-up areas and bare land. However, these threshold values may vary due to atmospheric conditions. They can also be used to classify land cover. The Kappa coefficient and overall accuracy were calculated at 0.97 and 0.98, respectively.

Results and discussion

Assessment of changes in land use and land cover

The Djebel Ouahch region is an important geographical unit, located to the east of the city of Constantine and made up of mutually interacting forest–agriculture–habitat interfaces. It is a fragile natural environment, profoundly disturbed by multiple use (Gana et al. 2017). Overall, the increase in built-up areas is due to various human activities, namely land

Table 2. NDVI value ranges and land cover

NDVI value	Represents
–1 to 0	Water bodies
–0.1 to 0.1	Barren rocks, sand, or snow
0.2 to 0.5	Shrubs and grasslands or senescing crops
0.6 to 1.0	Dense vegetation or tropical rainforest

use change, urbanisation, population growth and industrialisation. The distribution of the population across the landscape can affect the state of the environment in many ways. Population growth is often synonymous with increased urbanisation, including the conversion of forests, farms and other land for housing, transport and commerce, as confirmed by satellite images. The dynamics of land use and vegetation cover have had highly variable effects on vegetation indices and built-up areas. By calculating the NDVI-NDBI in the Djebel El Ouahch region between 1984 and 2023. For this reason, an attempt was made to discuss and compare the results of the two indices over three years (1984, 2004 and 2023).

For the three years studied (1984, 2004 and 2023), the bare land class largely dominates the landscape, occupying almost half of the total area, with a maximum value of 59.09% in 1984 (Table 3). Vegetation is the second class, with a maximum percentage of 42.46% in 2004, followed by forest (15.37%) in 2023. The dominance of bare land in the landscape can be attributed to several factors, including historical land use practices, urbanisation, and agricultural expansion. The maximum value of 59.09% in 1984 reflects this. The subsequent increase in vegetation cover to 42.46% in 2004 indicates a recovery thanks to reforestation efforts during that period. With the exception of 2023, when built-up areas increase to 2.5%, the remaining built-up areas and water bodies are relatively small, representing less than 1% of the combined area. This distribution suggests a predominantly natural or semi-natural landscape, with limited urban development and water bodies.

These results are in perfect agreement with those for all medium-sized towns in Algeria, and Guelma in particular, which has been affected by rapid and massive urban growth that has greatly disrupted space, generating profound spatial and environmental transformations (Benoumeldjadj et al. 2023). The distribution of built-up areas is linked to the socio-economic activity specific to this region, which is based essentially on livestock rearing and small-scale subsistence farming organised around farms and rural

Table 3. Spatial distribution of land cover types in years (1984, 2004 and 2023)

Year	1984		2004		2023	
Class	km²	%	km²	%	km²	%
Built-up area	1.62	0.24	2.69	0.40	17.13	2.57
Bare area	394.23	59.09	316.03	47.37	342.19	51.29
Water	0.42	0.06	0.76	0.12	0.47	0.07
Vegetation	197.12	29.55	283.26	42.46	204.81	30.70
Forest	73.76	11.06	64.40	9.65	102.55	15.37

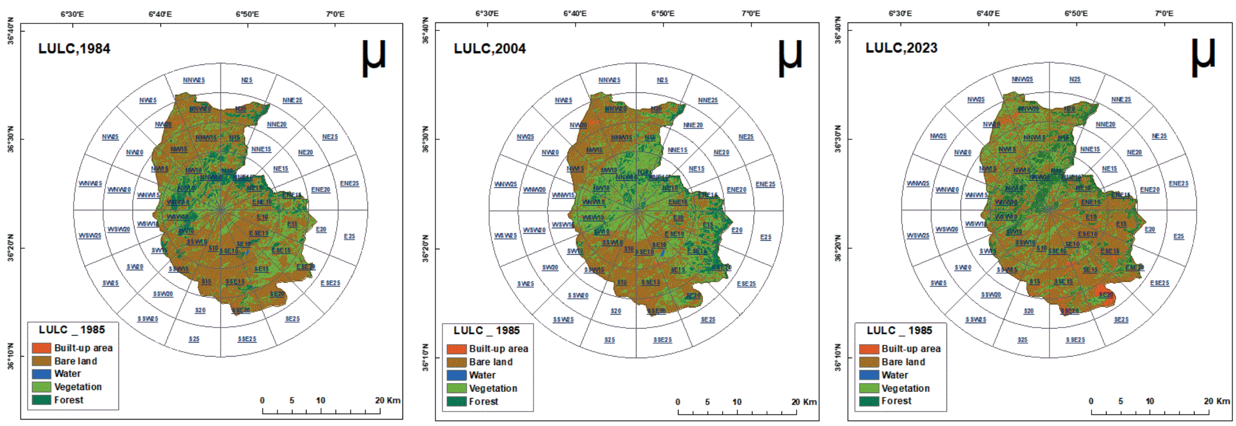

Fig. 3. LULC Djebel Ouahch, 1984, 2004 and 2023 in order

houses. This increase in built-up areas is due to the rapid economic, social and political changes that have occurred in Algeria over the last three decades, which have led to new urban and rural dynamics (Belguesmia et al. 2019), involving the emergence of a new spatial organisation that has resulted in growing competition for land use in peri-urban areas.

There was a clear increase in forest cover, from 64.40 km² (9.65%) in 2004 to 102.55 km² (15.37%) in 2023, most likely due to reforestation and forest conservation efforts in the region (Fig. 3).

The built-up area developed 20 km from the centre of Djebel Ouahch, extending in the NNW and NW directions, as well as in the SE and SSE directions. Forests are distributed within a 10 km radius of the selected centre, primarily in the N, NNE and NNW directions, and also extend 15 km to the E and ENE. Vegetation is found 10 km from the core, predominantly in the NW and NNW directions.

Spatial distribution of NDVI, NDBI and BU

NDVI increased from 0.35 in 1984 to 0.45 in 2004, suggesting an increase in vegetation cover during this period. It decreased from 0.45 in 2004 to 0.42 in 2023, indicating a slight decline in natural vegetation cover in recent years. This decline is attributed to a number of factors, including human activity, which remains the main cause of vegetation degradation in the Djebel Ouahch region. Between 1987 and 2014, the area of forest stands burnt amounted to 4,323.51 ha, i.e. an average of 160.13 ha/year (Bouzenzana 2015). Indeed, fire activity develops during the dry season when climatic factors favour vegetation flammability (Bond et al. 2003; Sharples et al. 2009). A comparison of remote sensing vegetation regression data and forest fire assessments reveals that the period 2002–09 is the most affected by fires, with an average burnt area of 340.21 ha/year (Bouzenzana 2015). Climatic factors such as temperature, air humidity, insolation, precipitation and wind speed have a strong influence on the ignition capacity of vegetation and the spread of fires. However it should be noted that these conditions are supported by the water content of the soil and the state of the vegetation. Thus, high temperatures, strong winds and a lack of water in the vegetation are highly conducive to fires breaking out and spreading.

Similarly, topography, with its slope and altitude, is capable of amplifying the extent of fires. These results are identical to those obtained by several authors who have incorporated the parameters studied into models for determining the risk of wildfire (Valea 2005; Carrega et al. 2007; Guettouche et al. 2011). It is important to note, however, that none of these parameters is sufficient on its own to influence the spread of fire. It takes a combination and complementarity of effects, and above all a trigger, generally of human origin, for the fire to be ignited (Hann and Bunnell 2001; Hardy et al. 2001).

On the other hand, the expansion of agricultural activities, which is not included in our vegetation class, has contributed to the reduction of areas of natural uncultivated vegetation. Indeed, land converted to agriculture is classified as bare land in this study, which would partly explain the observed decrease in NDVI between 2004 and 2023, a period during which interest in agriculture is likely to have increased in the region. Thus, the moderate decline in natural vegetation cover is potentially the result of a combination of environmental (climatic disturbances) and anthropogenic (agricultural expansion) factors, highlighting the pressures exerted on the natural ecosystems of the study area over recent decades (Kefifa and Benabdeli 2014).

The mapping of built-up areas is a key element in urban growth, development and expansion. Human population growth leads to increased demand for housing, schools, hospitals, transport, etc. The steady growth of urban areas consumes nearby cultivated land, resulting in a reduction in agricultural land. Given these dynamics of LULC and the detection of land surface changes, scientists are committed to working on a series of indicators such as BU and NDB to monitor and map built-up land (Zhao and Chen 2005; Xu 2008).

In 1984, a low soil construction index (NDBI) of 0.01 indicates limited urban development at that time. However, by 2004, this index had turned negative, reaching −0.06, which suggests an apparent decline in built-up areas compared to 1984. This setback can be attributed to the efforts made by Algerian local authorities to eradicate slums and illegal constructions, in accordance with urban planning laws aimed at eliminating precarious housing. These

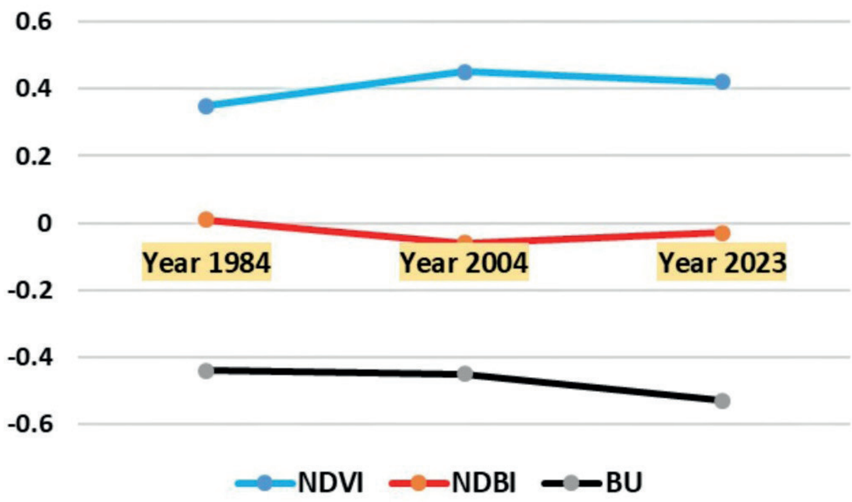

Fig. 4. Mean of NDVI, NDBI and BU in 1984, 2004 and 2023

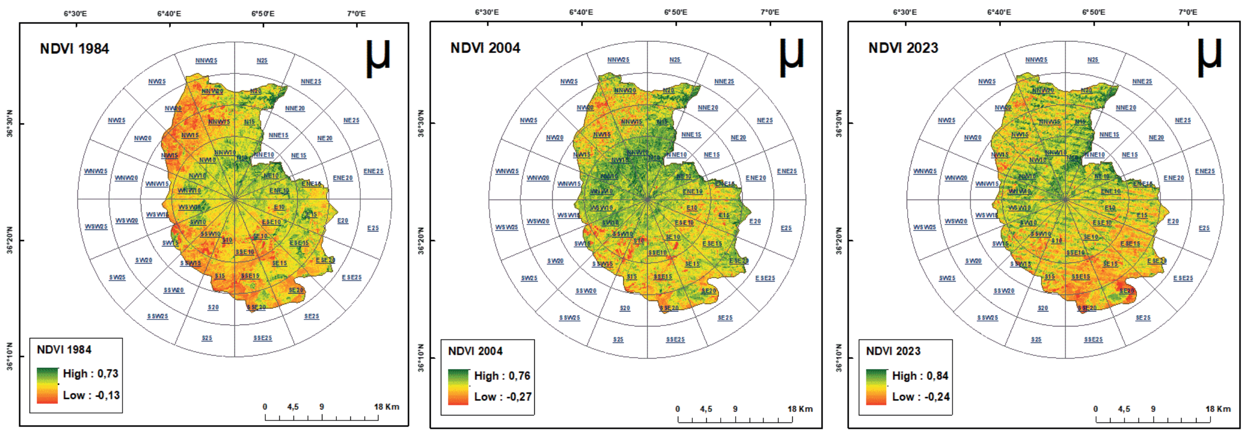

Fig. 5. NDVI map of Djebel Ouahch 1984, 2004 and 2023 in order

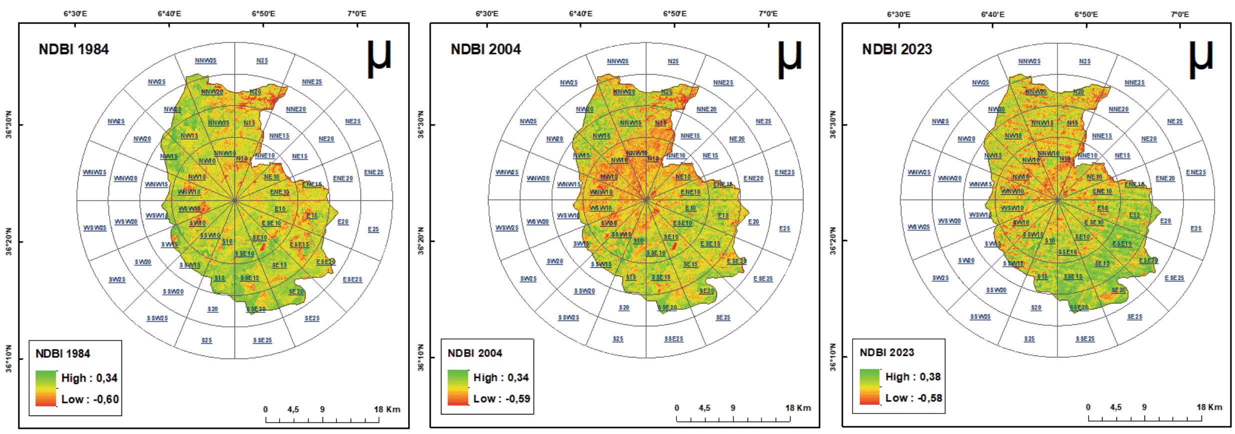

Fig. 6. NDBI map of Djebel Ouahch 1984, 2004 and 2023 in order

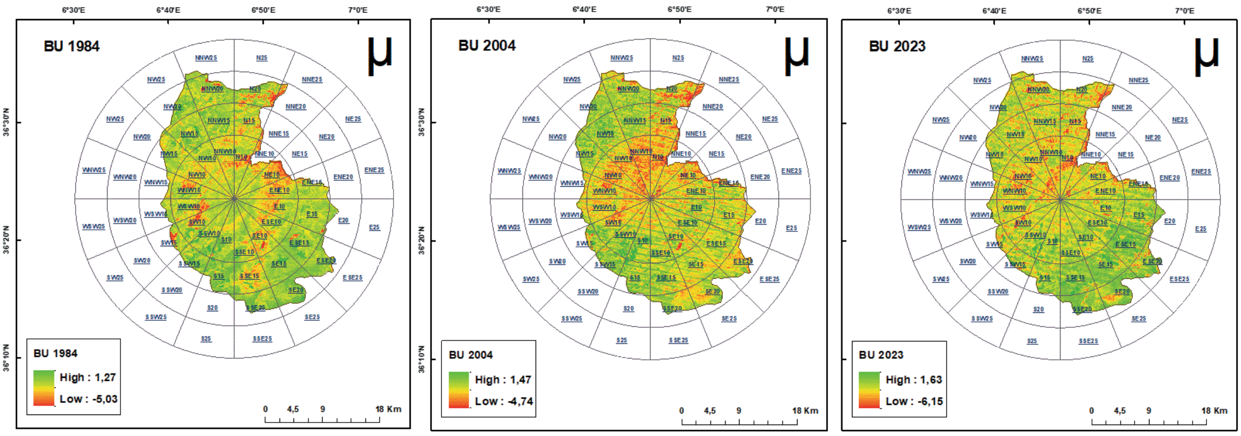

Fig. 7. BU map of Djebel Ouahch 1984, 2004 and 2023 in order

actions highlighted a strong commitment from the authorities towards planned and sustainable urbanisation, with the goal of improving citizens' living conditions and rebuilding healthier and more functional urban spaces.

The situation then changed, with an increase in the NDBI to –0.03 in 2023, suggesting a slight upturn in urban development compared with 2004. This can be attributed to the rural housing programme initiated in 2008, aimed at providing people with adequate housing. Nevertheless, the 2023 value is still lower than that of 1985, because, following the allocation of social housing and the eradication of illegal buildings, urban development has probably stabilised at a more controlled and planned level.

The fluctuations in the NDBI therefore reflect the efforts being made to eliminate substandard housing and provide decent housing solutions, while controlling urban sprawl in a more sustainable way in the region studied.

Correlation between indices

While positive values indicate agricultural land, crops and pasture and are positively correlated with green vegetation, NDVI is mainly used for vegetation and crop monitoring. It is accurate, reliable, simple to calculate and convenient for mapping crops and farmland. Vegetation index and building indices are the indices most widely applied remote sensing techniques in previous research works. The vegetation indicator NDVI is generally used to investigate the correlation of different indices, i.e. NDVI-NDBI, LST-NDVI and NDVI-NDWI. Therefore, this study focuses on examining the correlation between NDVI-NDBI in the Jebel El Ouahch region from 1984 to 2023.

Pearson's correlation coefficient is used to measure the strength and direction of this linear NDVI-NDBI relationship. A value close to –1 indicates a strong negative correlation, suggesting that the increase in NDBI (increased presence of built-up areas) is associated with a decrease in NDVI (loss of vegetation cover), and hence the assessment of statistical significance.

The overall trend of the scatterplot shows a strong negative linear relationship between NDVI and NDBI. The correlation coefficient (r) shown on the graph is –0.989 with a 95% confidence interval ranging from –0.988 to –0.990. This value, close to –1, indicates a very strong negative correlation between the two indices.

As for the dispersion of the points, there is some dispersion of the points around the linear trend line. This indicates that other factors, in addition to the inverse relationship between built-up areas and vegetation, may influence NDVI and NDBI values. NDBI values are mainly between –0.4 and 0.1, while NDVI values are between approximately 0.1 and 0.5. This indicates a predominance of areas with moderate to high vegetation cover (Chuvieco et al. 2010) and a relatively low presence of built-up areas in 1984 (Fig. 8).

The graph shows a strong positive linear correlation between the two indices. The Pearson correlation coefficient, r = 0.993 and CI = (0.992, 0.994) is very close to 1, confirming the strong

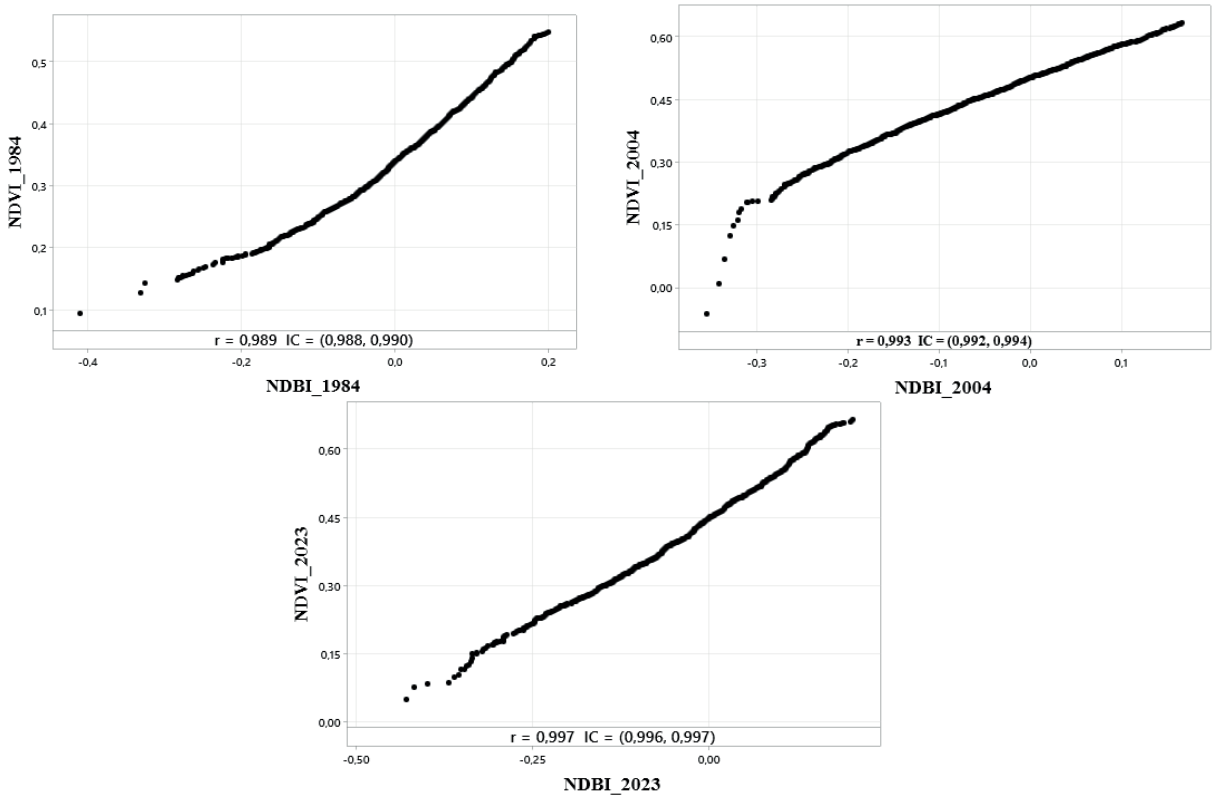

Fig. 8. Correlation between NDVI and NDBI in 1984, 2004 and 2023

Fig. 9. Built up area from 1984 to 2023

Legend: Red Color: Represents the built-up area, including urban and peri-urban development such as residential, commercial, industrial, and infrastructure zones. The increasing intensity and spread of red across the maps from 1984, 2004 and 2023 visually represent the expansion of human settlement and construction over time positive correlation observed (Chaabane et al. 2022). The narrow confidence interval indicates that the estimate of the correlation coefficient is very accurate (Fig. 8).

The data points are tightly clustered around the plotted regression line, indicating a strong linear relationship. As the NDBI value increases, the NDVI value also increases proportionally. The correlation coefficient r is 0.997, extremely close to 1, confirming the very strong positive correlation observed graphically. The narrow confidence interval (0.996, 0.997) indicates that the estimate of the correlation coefficient is very accurate (El-Hattab et al. 2018).

The distribution of the BU index has shifted towards higher values over the years, becoming increasingly spread-out and asymmetric towards the south-east and north-west. This indicates a marked trend towards the expansion of built-up areas between 1984 and 2023 (Fig. 9)

Conclusion

The assessment of land use and land cover changes in the Djebel Ouahch region from 1984 to 2023 reveals a complex dynamic of urbanisation, reforestation and agricultural conversion. While urban expansion continues, the study also shows a resurgence in forest cover, suggesting success in reforestation efforts. However, the conversion of land to agriculture, combined with population growth, has led to a slight decline in natural vegetation.

The fluctuations in the NDVI and NDBI indices reflect the need to balance socio-economic development and ecological conservation. To achieve this, the study advocates an integrated approach including urban planning to limit sprawl, promoting sustainable agriculture, establishing ecological corridors, enhancing reforestation, and improving water and land management. Implementing these recommendations through collaborative stakeholder engagement will be critical to ensuring sustainable development in the Djebel Ouahch region.

Disclosure statement

No potential conflict of interest was reported by the authors.

Author contributions

Study design: MB; data collection: MB; statistical analysis: MB, NB, MR-K; manuscript preparation: MB, MR, AB, MR-K; literature review: NB, MR, AB.

References

ABUBAKAR A and EJARO SP, 2013, *The Impact of Rapid Urbanization on Sustainable Development of Nyanya, Federal Capital Territory abuja, Nigeria*. University of Abuja, Nigeria.

ARONOFF S, 1982, Classification accuracy: a user approach. *Photogrammetric Engineering and Remote Sensing* 48(8): 1299–1307. DOI: https://doi.org/10.14358/PERS.48.8.1299.

BASSENE C, SAMBOU KS, DSIATTA AA and SAMBOU B, 2020, Étude floristique et ethnobotanique des plantes utilisées en Basse Casamance (Sénégal): Cas de la commune de Mlomp (Floristic and ethnobotanical study of plants used in Lower Casamance (Senegal): Case of the municipality of Mlomp – in French). Revue Marocaine Des Sciences Agronomiques et Vétérinaires 8(1): 42-49.

BELGUESMIA S, YOUSFI B and OTMAN T, 2019, Interface ville/campagne et dynamiques des espaces périurbains d'une ville intermédiaire sud-méditerranéenne. L'exemple de Mostaganem (Algérie) (City/countryside interface and dynamics of peri-urban spaces of a South Mediterranean intermediate city. The example of Mostaganem (Algeria) – in French). *Cahiers de géographie du Québec* 63(179-180): 259-279. DOI: https://doi.org/10.7202/1084236ar.

BENOUMELDJADJ M, BOUARROUDJ N and BOUCHAREB A, 2023, The effect of vegetation cover on dust concentration: Case study (Constantine, Algeria). *Indonesian Journal of Geography* 55(2): 311. DOI: https://doi.org/10.22146/ijg.79253.

BENOUMELDJADJ M, BOUGHOUAS S, RACHED-KANOUNI M and BOUCHAREB A, 2025, Analyzing urbanization and environmental change in Aïn Fakroun, Algeria using landsat imagery through Google Earth Engine. *Italian Journal of Engineering Geology and Environment* (1): 31–42. DOI: https://doi.org/10.4408/IJEGE.2025-01.O-03.

BOND WJ, MIDGLEY GF and WOODWARD FI, 2003, What controls South African vegetation - climate or fire? *South African Journal of Botany*

69(1): 79-91. DOI: https://doi.org/10.1016/S0254-6299(15)30362-8.

BOUHENNACHE R, 2018, Traitements des images satellitaires en vue d'une classification et/ou de détection des changements interimages (Satellite image processing for classification and/or inter-image change detection – in French). Theses-Algerie.

BOUTERAA A, ABID C and NEZZARI H, 2023, *Traitement d'images de Télédétection pour la détermination des changements inter-images dans les zones urbaines* (Remote sensing image processing for determining inter-image changes in urban areas – in French). Universite de Echahid Cheikh Larbi Tebessi.

BOUZENZANA L, 2015, *Etude diachronique de la régression de la végétation forestière par télédétection dans le massif de Djebel El Ouahch* (Constantine) (Diachronic study of forest vegetation regression by remote sensing in the Djebel El Ouahch massif (Constantine) – in French). Master en protection et conservation des écosystèmes. Université des Frères Mentouri Constantine 1, Algérie.

CARREGA P and JERONIMO N, 2007, *Risque météorologique d'incendie de forêt et méthodes de spatialisation pour une cartographie à fine échelle* (Meteorological forest fire risk and spatialization methods for fine-scale mapping – in French). Actes du XXeme colloque international de l'AIC. Tunis.

CHAABANE SB, HIJJI M, HARRABI R and SEDDIK H, 2022, Face recognition based on statistical features and SVM classifier. *Multimedia Tools and Applications* 81(6): 8767–8784. DOI: https://doi.org/10.1007/s11042-021-11816-5.

CHUVIECO E, LI J and YANG X, 2010, Advances in earth observation of global change. Dordrecht, The Netherlands: Springer. DOI: https://doi.org/10.1007/978-90-481-9085-0.

EL-HATTAB M, AMANY SM and LAMIA GE, 2018, Monitoring and assessment of urban heat islands over the Southern region of Cairo Governorate, Egypt. *The Egyptian Journal of Remote Sensing and Space Science* 21(3): 311–323. DOI: https://doi.org/10.1016/j.ejrs.2017.08.008.

GANA M, ARFA AMT, BENDERRADJI MEH and ALATOU D, 2017, Analysis of Vegetation Change and Mapping Tree Species in Mountainous Area Using Multi-Source Satellite Data: A Case Study of Djebel El Ouahch, Algerie. *American Journal of Environmental Protection* 5(2): 44-51. DOI: https://doi.org/10.12691/env-5-2-3.

GUETTOUCHE MS, DERIAS A, BOUTIBA M, BOUNIF MA, GUENDOUZ M and BOUDELLA M, 2011, A Fire Risk Modelling and Spatialization by GIS. Application on the Forest of Bouzareah Clump, Algiers (Algeria). *Journal of Geographic Information System* 3: 255-266. DOI: https://doi.org/10.4236/jgis.2011.33022.

GUHA S, GOVIL H, DEY A and GILL N, 2018, Analytical study of land surface temperature with NDVI and NDBI using Landsat 8 OLI and TIRS data in Florence and Naples city, Italy. *European Journal of Remote Sensing* 51(1): 667–678. DOI: https://doi.org/10.1080/22797254.2018.1474494.

HANN WJ and BUNNELL DL, 2001, Fire and land management planning and implementation across multiple scales. International Journal of Wildland Fire 10: 389-403. DOI: https://doi.org/10.1071/WF01036.

HARDY CC, SCHMIDT KM, MENAKIS JP and SAMPSON RN, 2001, Spatial data for national fire planning and fuel management. *International Journal of Wildland Fire* 10: 353-372. DOI: https://doi.org/10.1071/WF01034.

JOËL N, MARC N, PAUL H, FRANÇOIS H, FRÉDÉRIC B and TATIEN M, 2018, Effets potentiels de l'urbanisation sur l'écosystème de la Réserve Naturelle Forestière de Nkayamba (Commune Rumonge, Province de Rumonge, Burundi) (Potential effects of urbanization on the ecosystem of the Nkayamba Forest Nature Reserve (Rumonge Commune, Rumonge Province, Burundi) – in French). *Annales Des Sciences et Des Sciences Appliquées* 4(3/4): 107–128.

KEARSE M, MOIR R, WILSON A, STONES-HAVAS S, CHEUNG M, STURROCK S, BUXTON S, COOPER A, MARKOWITZ S and DURAN C, 2012, Geneious Basic: an integrated and extendable desktop software platform for the organization and analysis of sequence data. *Bioinformatics* 28(12): 1647–1649. DOI: https://doi.org/10.1093/bioinformatics/bts199.

KEFIFA A and BENABDELI K, 2014, Contribution to the Study of the Structure of the Main Ligneous Species in the Preservation of Forest Spaces in the Monts of Saida and Dhaya (Algerian West). *Ecologia Balkanica* 6(1): 11-18.

LIU Y, ZHA Y, GAO J and NI S, 2004, Assessment of grassland degradation near Lake Qinghai, West China, using Landsat TM and in situ reflectance spectra data. *International Journal of Remote Sensing* 25(20): 4177–4189. DOI: https://doi.org/10.1080/01431160410001680419.

MOSAMMAM HM, NIA JT, KHANI H, TEYMOURI A and KAZEMI M, 2017, Monitoring land use change and measuring urban sprawl based on its spatial forms: The case of Qom city. *The Egyptian Journal of Remote Sensing and Space Science* 20(1): 103–116. DOI: https://doi.org/10.1016/j.ejrs.2015.12.002.

MUNDO IA, ZAMORANO-ELGUETA C, SALOMÓN MES, VÉLEZ ML, SPEZIALE K, SHEPHERD JD, SKEWES O, RELVA MA, PUCHI P and PAUCHARD A, 2023, Relevant scientific information for management and conservation of the Pewen biocultural ecosystem in Chile and Argentina. *Revista Bosque* 44(1): 179–190. DOI: https://doi.org/10.4067/S0717-92002023000100179.

PELLETIER C, 2017, *Cartographie de l'occupation des sols à partir de séries temporelles d'images satellitaires à hautes résolutions : identification et traitement des données mal étiquetées* (Land cover mapping from high-resolution satellite image time series: identification and processing of mislabeled data – in French). Université de Toulouse, Université Toulouse III-Paul Sabatier.

RAKOTOMALA FA, 2015, Estimation de la déforestation des forêts humides à Madagascar utilisant une classification multidate d'images Landsat entre 2005, 2010 et 2013 (Estimation of deforestation of humid forests in Madagascar using multi-date classification of Landsat images between 2005, 2010 and 2013 – in French). *Revue Française de Photogrammétrie et de Télédétection* 1(211–212): 11–23. DOI: https://doi.org/10.52638/rfpt.2015.119.

REKIS A and BELHAMRA M, 2015, Etude diachronique du changement de la végétation par télédétection Cas de la région de Tolga en Algérie (Diachronic study of vegetation change by remote sensing Case of the Tolga region in Algeria – in French). *International Journal for Environment and Global Climate Change* 3: 49–60.

RUFINO MC, DURY J, TITTONELL P, VAN WIJK MT, HERRERO M, ZINGORE S, MAPFUMO P and GILLER KE, 2011, Competing use of organic resources, village-level interactions between farm types and climate variability in a communal area of NE Zimbabwe. *Agricultural Systems* 104(2): 175–190. DOI: https://doi.org/10.1016/j.agsy.2010.06.001.

SALOMON W, 2023, Urbanisation, agriculture et dynamique spatio-temporelle de l'anthropisation des écosystèmes forestiers en Haïti.

SHARPLES JJ, MCRAE RHD, WEBER RO and GILL AM, 2009, A simple index for assessing fire danger rating. *Environmental Modelling & Software* 24: 764-774. DOI: https://doi.org/10.1016/j.envsoft.2008.11.004.

TLIDJANE A, MENAA M, REBBAH AC, TELAILIA S, SEDDIK S, CHEFROUR A and MAAZI MC, 2019, La richesse et la distribution des Amphibiens dans la région de Souk Ahras (Nord-Est de l'Algérie) (The richness and distribution of Amphibians in the Souk Ahras region (North-East Algeria) – in French). *Bulletin de La Société Zoologique de France* 144(4).

VALEA F, 2005, *Élaboration d'une méthode de suivi et d'analyse spatio-temporelle des feux de brousse en Afrique de l'Ouest : cas du Sénégal et du Burkina Faso* (Development of a method for monitoring and spatio-temporal analysis of bushfires in West Africa: case of Senegal and Burkina Faso – in French). Guide méthodologique, Laboratoire d'Enseignement et de Recherche en Géomatique, Dakar, Sénégal.

XU H, 2008, A new index for delineating built-up land features in satellite imagery. *International Journal of Remote Sensing* 29: 4269-4276. DOI: https://doi.org/10.1080/01431160802039957.

ZHA Y, GAO J and NI S, 2003, Use of normalized difference built-up index in automatically mapping urban areas from TM imagery. *International Journal of Remote Sensing* 24(3): 583–594. DOI: https://doi.org/10.1080/01431160304987.

ZHAO HM and CHEN XL, 2005, Use of Normalized Difference Bareness Index in Quickly Mapping Bare Areas from TM/ETM+. In Proceedings of 2005 *IEEE International Geoscience and Remote Sensing Symposium, Seoul, Korea* 3: 25-29. DOI: https://doi.org/10.1109/IGARSS.2005.1526319.

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