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LAND USE MAPPING USING MAXIMUM LIKELIHOOD CLASSIFICATION AND REMOTE SENSING INDICES: CASE STUDY AIN-ABID CONSTANTINE (ALGERIA)

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ABSTRACT

Land use is an essential theme in monitoring environmental phenomena. The supervised maximum likelihood classification algorithm has been shown to provide the best results from remotely sensed data. This work is aimed at the application of a supervised classification (maximum likelihood) based on a priori knowledge of the terrain under study and information extracted from the two remote sensing indices NDVI (Normalized Difference Vegetation Index) and NDBI (Normalized Difference Built-up Index) for mapping land use of the area of Ain Abid Constantine (located in eastern Algeria) for the year 2020. The obtained result showed that this city is an agricultural area with a percentage of 68.49% of agricultural land and a low percentage of 2.02% of Buildings.

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Introduction.

Remote sensing is becoming an essential tool for the management, monitoring and surveillance of the territory by using information obtained remotely in the form of satellite or airborne images. This tool combined with geographic information systems (GIS) allows planners to opt for the best possible decision-making.

This technique includes the entire process of capturing and recording the energy of emitted or reflected electromagnetic radiation, processing and analyzing the information, and then applying this information. This method has widely used to prove and analyze the evolution of natural areas

(OUSSEDIK et al., 2003; ELBOUQDAOUI et al., 2005; BOUIADJRA et al., 2011; KOUMASSI et al., 2014; BELAL et al. 2014; LEULMI et al. 2023).

Among the applications of remote sensing, land cover and land use has been widely discussed in the literature and many methods have been used for land use mapping using remote sensing data either in spatially or in spatiotemporal terms (evolution of land use). Methods are based on remote sensing indices such as the Normalized Difference Vegetation Index NDVI or the Normalized Difference Built-up Index NDBI (WESSELS et al., 2004; SINGH et al., 2016; ANDRIANI et al., 2018) and others based on classification methods such as maximum likelihood classification (MESEV, 2001; ABD & ALNAJJAR, 2013; LIN et al., 2020).

Land use and land change maps are real planning and decision support tools, especially in terms of management and preservation of natural resources and ecosystems (DIEDHIOU et al., 2020). The objective of this work is the mapping of the land use by the use of the supervised classification Maximum Likelihood based on spectral indices and of course the knowledge of the terrain under study for the training stage.

Materials and Methods.

The city of Constantine is part of the North East of Algeria, it is limited to the North and the South respectively by the latitudes 36 ° 27" 35 "N and 36 ° 16" 30 " N, as to the East and the West by longitudes 6 ° 49'30 "E and 6 ° 37 "30" E. The city of Constantine is one of the most important cities in the country; it covers an area of about 2297.20 km².

Ain Abid is one of the municipalities of the city of Constantine located between longitudes 6°45', 7°50' East and latitudes 36°5', 36°25' North. It is located in the high plains to the south east of the city on the border of the city of Guelma to the east, the city of Oum El Bouaghi to the south with an area of 323 km². (Figure 1).

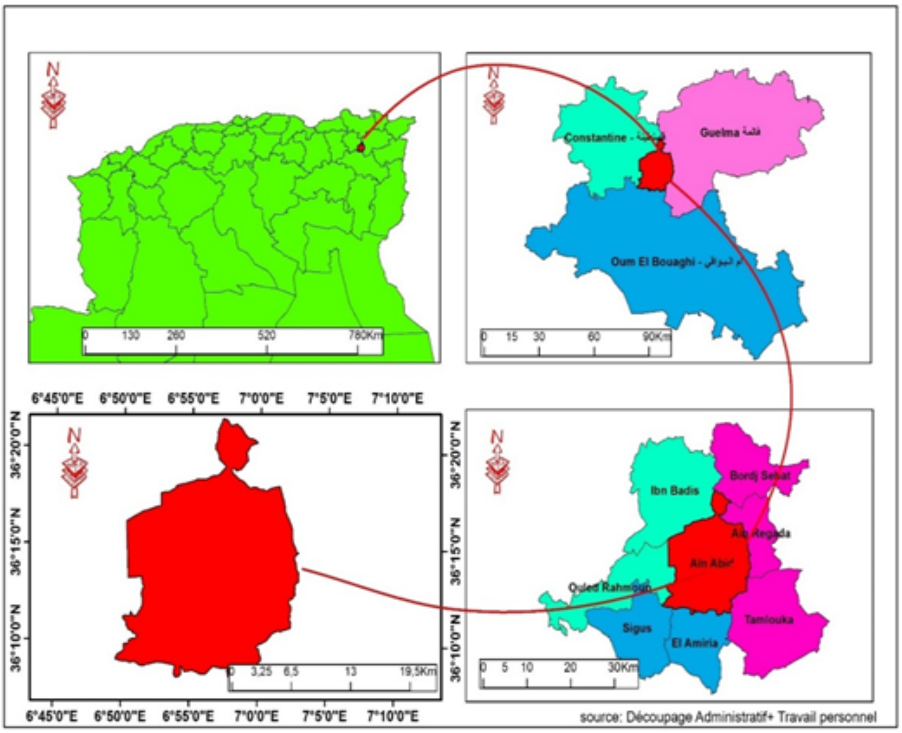

Fig. 1. Situation map of the Municipality of Ain Abid.

Our study is based on the processing and the analysis of two satellite images of the LANDSAT 8 program with the OLI/TIRS sensor (some characteristics are given in Table. 1). We have used two successive dates that can be free downloaded from the USGS site: the first acquired in April 2020 and the second acquired on the same date in 2021. Two software programs were used in this study; the ArcGis 10.3 software is used for the calculation of spectral indices, classification and cartography.

Google Earth Pro software is used for the validation and the confirmation of the result obtained by the classification method.

The supervised classification method used in this study is that of the maximum likelihood (BOLSTAD & LILLESAND, 1991). This method is based on a very important step which is the training step. This step allows the location and the identification of the representative samples of the themes on the basis of a priori knowledge of the observed area. These samples must respect certain criteria: the distribution on the image, the number of pixels per part of a class and the representativeness.

Table 1. Spectral Bands of Landsat 8 OLI / TIRS.

Spectral Bands	Wave length	Resolution
Band 1 - Coastal/aerosol	0,433 – 0,453 µm	30 m
Band 2 – Blue (B)	0,450 – 0,515 µm	30 m
Band 3 – Green (G)	0,525 – 0,600 µm	30 m
Band 4 – Red (R)	0,630 – 0,680 µm	30 m
Band 5 - Near Infrared (NIR)	0,845 – 0,885 µm	30 m
Band 6 – Middle Infrarouge (MIR)	1,560 – 1,660 µm	30 m
Band 7 - Middle Infrarouge (MIR)	2,100 – 2,300 µm	30 m
Band 8 – Panchromatic (PAN)	0,500 – 0,680 µm	15 m
Band 9 – Cirrus	1,360 – 1,390 µm	30 m
Band 10 - Thermal Infrared	10,30 – 11,30 µm	100 m
Band 11 - Thermal Infrared	11,50 – 12,50 µm	100 m

For a supervised maximum likelihood classification, samples chosen for each class are assumed to be distributed according to a Gaussian law and these distributions are assumed to be Gaussian for all classes under the condition of a sufficiently large number of pixels. In our work, the training step is based on knowledge of the terrain and information extracted using two spectral indices: the NDVI and the NDBI.

The normalized difference vegetation index NDVI (ROUSE et al., 1974) is a widely used tool in environmental fields because it provides information on the greenness and the state of the vegetation. This index uses both red (B4) and near infrared (B5) bands. The formula for calculating NDVI from Landsat 8 OLI spectral bands is given by:

$$NDVI=\frac{Band\ 5\text{-}Band\ 4}{Band\ 5\text{-}Band\ 4}$$

The NDVI values are between -1 and +1; positive values close to 1 indicate a plant formation rich in chlorophyll.

The normalized difference built-up index NDBI (ZHA et al., 2003) is used to indicate the building density of an area. This index uses both bands: near infrared (B5) and middle infrared (B6). The NDBI index takes its values between -1 and +1; a value closer to 1 indicates a high density of built-up land. This index is calculated from the Landsat 8 OLI spectral bands by:

$$NDBI=\frac{Band\ 6\text{-}Band\ 5}{Band\ 6\text{-}Band\ 5}$$

Result and Discussion.

In this section we present the results obtained for the different stages of the used classification method (training, classification and validation). In the training stage, the maps of the two spectral indices NDVI and NDBI are produced using the ArcGis software for the two years 2020 and 2021. The results obtained showed that the NDVI takes values between -0.024 and 0.57 in 2020 and between -0.0147 and 0.54 in 2021 (Figure 2 and Figure 3). The NDBI values are between -0.41 and 0.195 for the year 2020 and between -0.36 and 0.18 in 2021 (Figure 4 and Figure 5).

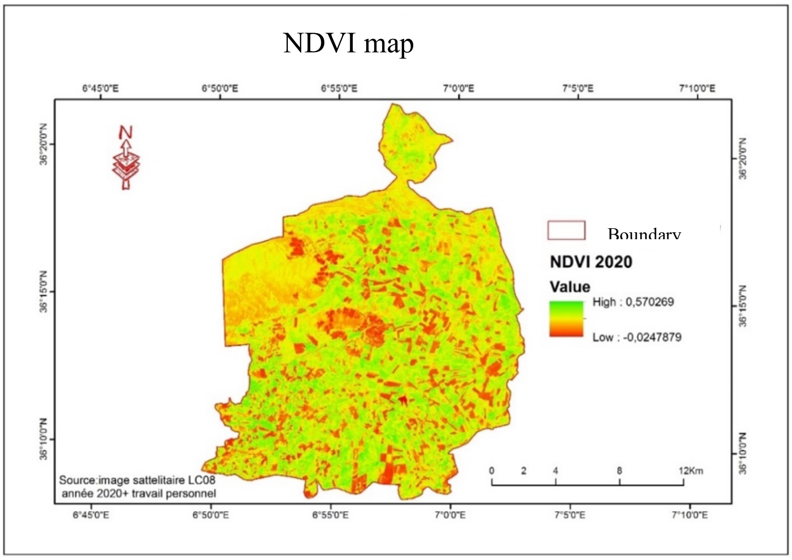

Fig. 2. NDVI map of the municipality of Ain Abid for the year 2020.

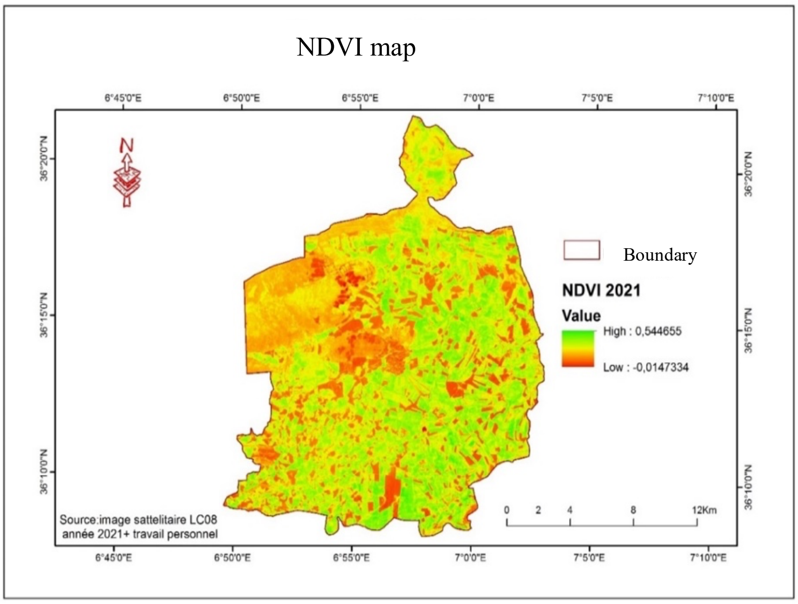

Fig. 3. NDVI map of the municipality of Ain Abid for the year 2021.

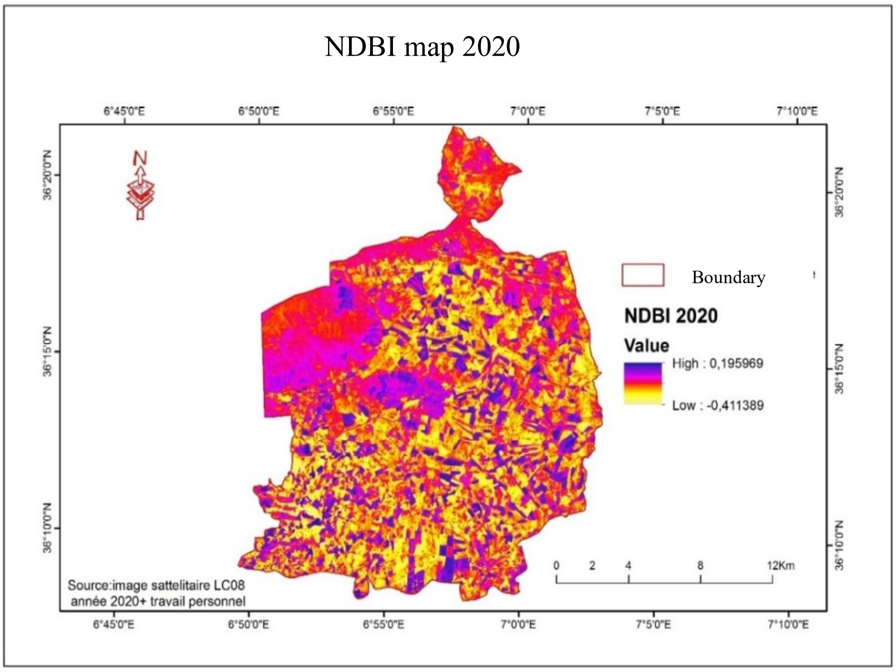

Fig. 4. NDBI map of the municipality of Ain Abid for the year 2020.

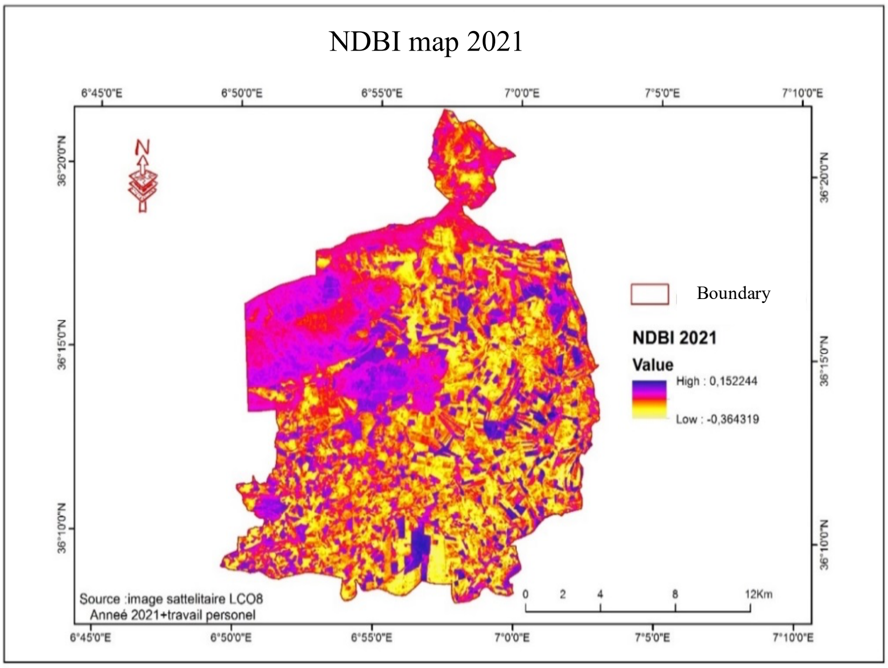

Fig. 5. NDBI map of the municipality of Ain Abid for the year 2021.

The obtained maps of the two indices are then used, with a priori knowledge of the study area, for the extraction of the samples of the thematic classes of the observed area. Six thematic classes were defined at the launch of the supervised classification using the maximum likelihood algorithm using the ArcGis software. This type of classification consists of assigning the pixels of the image to the closest samples according to a Bayesian distance based on the probability that a pixel has to belong to a given class. The two successive years 2020 and 2021 are used to discriminate between cultivated and plowed lands.

The evaluation and validation of the classification accuracy is generally done by comparing the results obtained with reference information. This comparison is based on a confusion matrix and the calculation of the Kappa index (LANDIS & KOCH, 1977). If the classification is not satisfactory (poor quality), we return to the training stage, otherwise the classification is acceptable or perfect depending on the value of the Kappa index (Table 2). To calculate the Kappa index we use the following equation:

$$Kappa=\frac{N\sum_{i=1}^{L}x_{ii}-\sum_{i=1}^{L}(x_{i+}*x_{+i})}{N^2-\sum_{i=1}^{L}(x_{i+}*x_{+i})}$$

Where N: total number of observations; L: number of rows and columns of the confusion matrix; x_{ii}: number of observations in row and column i; x_{i+}: the marginal sum of the row i; x_{+i}: the marginal sum of the column i.

Table 2. Interpretation of the Kappa index values (LANDIS & KOCH, 1977).

Kappa index values	Classification Accuracy Interpretation
0,81 - 1,00	Excellent
0,61 - 0,80	Good
0,41 - 0,60	Moderate
0,21 - 0,40	Poor
0,00 - 0,20	Bad
<0.0	Very Bad

To form the confusion matrix, we choose using Google Earth Pro a sample of 43 points spread over the entire territory of the municipality of Ain Abid: 13 points of agricultural areas (cultivated and plowed), 9 points of Bush and arboriculture, 10 course points, 9 building points and two (02) hillside restraint points (Table 3).

Table 3. Confusion matrix for the classification of the image of 2020.

	Agricultural areas	Bush and arboriculture	Course and bare land	Building	Hill reservoir	Total	Accuracy of use	Kappa
Agricultural areas	**13**	0	0	0	0	13	1	
Bush and arboriculture	6	**1**	2	0	0	9	0.1111	
Course and bare land	1	0	**9**	0	0	10	0.9	
Building	0	0	0	**9**	0	9	1	
Hill reservoir	0	0	0	0	**2**	2	1	
Total	20	1	11	9	2	**43**	0	
Production precision	0.65	1	0 .8181	1	1	0	**0.7906**	
Kappa								**0.7205**

According to the confusion matrix the percentage of the global precision is 79.06% and the value of the Kappa index is 72.05. The classification is therefore judged to be good and the result is represented by Figure 6.

The land use of the municipality of Ain Abid for the year 2020 is summarized in Table 4. From this table we can see that the municipality of Ain Abid is an agricultural municipality with a percentage of 68.49% occupied by the agricultural land class (combination of cultivated land and plowed land) and a very low percentage of 2.02% occupied by the Building class.

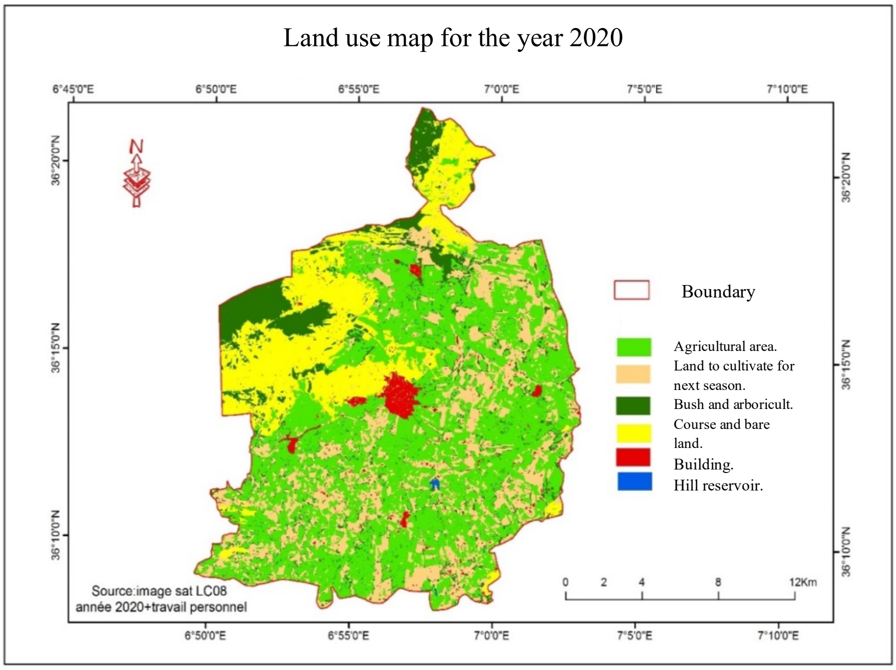

Fig. 6. Land use map of the municipality of Ain Abid for the year 2020.

Table 4. Land use of the different thematic classes.

Land use	Area (ha)	%
Cultivated land	14096,01	45,76
Land to cultivate for next season	7002,78	22,73
Building	622,74	2,02
Bush and arboriculture	3406,13	11,06
Course and bare land	5663,84	18,39
Hill reservoir	11,5	0,04
Total	30803	100

Conclusion.

In this study we have applied the maximum likelihood supervised classification method to map the land use in the municipality of Ain Abid, Constantine. Six thematic classes were obtained based on the information extracted by two spectral indices: the NDVI and the NDBI and a priori knowledge of the studied area. With an overall precision of 79.06% and a Kappa coefficient of 72.05% of the confusion matrix, the obtained result from the applied supervised classification has shown the following land use: 68.49% agricultural land, 18.39% course and bare land, 11.06 bush and arboriculture, 2.02% buildings and 0.04% hillside reservoir. We can conclude from this land use that this city is an agricultural area.

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