Extraction of urban land features from TM Landsat image using the land features index and Tasseled cap transformation

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Abstract— In this paper we propose a method to map the urban areas. The method uses an arithmetic calculation processed from the land features indexes and Tasseled cap transformation TC of multispectral Thematic Mapper Landsat TM image. For this purpose the derived indexes image from the original image such SAVI the soil adjusted vegetation index, UI the urban Index, and EBBI the enhanced built up and bareness index were staked to form a new image and the bands were uncorrelated, also the Spectral Angle Mapper (SAM) and Spectral Information Divergence (SID) supervised classification approaches were first applied on the new image TM data using the reference spectra of the spectral library and subsequently the four urban, vegetation, water and soil land cover categories were extracted with their accuracy assessment. The urban features were represented using a logic calculation applied to the brightness, UI-SAVI, NDBI-greenness and EBBI- brighteness datasets. The study applied to Blida and mentioned that the urban features can be mapped with an accuracy ranging from 92 % to 95%.

Keywords—EBBI, SAVI, Tasseled Cap Transformation, UI.

I. Introduction

The fast urbanization and urban expansion have significant impact on conditions of urban ecosystems. Updated information on the status and trends of urban ecosystems is needed to develop strategies for reasonable development and to improve the livelihood of cities. The necessity to monitor urban land-cover/land-use changes is highly desirable by the policy decision makers and regional planners. Remote sensing materials in the form of satellite images are usually converted into useful information such as land cover maps using software and hardware processing and allow the opportunity to accurate and actualize the specific mapping, besides the useful indexes of studying LC/LU can more helping interpretation of the evolution and the management of land features such as NDVI which has been widely used for mapping vegetation and NDBI for interpreting urban. [1] were used a technique of combining the NDBI and the NDVI with a specific processes calculation to extract the built-up areas and were retched an accuracy of 92.6%, [2] developed an approach to detect urban LC/LU changes by quantifying sub-pixel percent imperviousness using Landsat and high-resolution imagery and they have mentioned The satisfactory of method based on a comparison using independent reference data and that information on sub-pixel imperviousness allows the data user to quantify urban LC/LU based on their own threshold.[3] transformed a raw correlated image to a new uncorrelated dataset using the features land index NDBI, Soil Adjusted Vegetation index SAVI and Normalized Difference Water Index NDWI and Through a supervised classification, a principal components analysis, and a logic calculation on the new image, the urban built-up lands were finally extracted with an overall accuracy ranging from 91.5% to 98.5 %, many studies have combined the changes like [4] witch attempted to employ a quantitative approach in exploring the relationship LC/LU index to detect urban between temperature and several indices, including NDVI, NDWI and NDBI, they have proposed a new index, the Normalized Difference Bareness Index NDBaI to extract bare land from the satellite images, others studies were compiled and analyzed using the famous post classification comparison PCC like in [5,6]. In our previously study [7], we have followed the expansion of urban tissue using the method of difference soil adjusted vegetation index DSAVI, difference normalized difference built up index DNDBI and also the post classification of multispectral and multi-temporal L5 and L7 Landsat satellite using a MLC and we have mentioned the fast urban growth with a rate of 0.5% annually. In this study we attempt to extract the urban features using the proposed urban land features indexes combined with the Tasseled cap transformation, using only NDBI needed a complex processing and a various process calculation besides the not satisfactory of accuracy, however if the maximum likelihood supervised classification method cluster the image pixels into classes corresponding to the defined training classes [8], The SAM and SID supervised classifications are based on match pixels spectrum to the identified of reference spectra. SAM compares the angle between the reference spectrum vector and each pixel vector in n-D space where smaller angles represent closer matches to the reference spectrum [9]. SID uses a divergence measure to match pixels to reference spectra, the pixels will be cluster in the class if the divergence will be smaller [11]. This study used the SAM and SID classification methods because the LC/LU features extracted have known identified reference spectra. Besides The urban features were represented using a logic calculation applied to the brightness, UI-SAVI and EBBI- brightness and NDBI-greenness datasets.

II. Materials and Methods

A. Study area and data used

Situated at the north of Africa, Blida is a town near of Algiers the capital of Algeria as shown in Fig 1. Acquired at the 19 may 2010 the TM Landsat satellite image was georefferenced to UTM projection WGS 84 datum zone 31, the radiometric characteristics of TM Landsat is shown in tableI .

Fig.1 Location of Blida the study area

B. Data preprocessing

The principal visualization RGB is the composite 742 and it's available to distinguishing between vegetation (green), urban (magenta) and water (blue). To minimizing the effects of sensor a radiometric correction is involved using Lmin/Lmax calibration of radiance image as in Table II

Table I Acquisition of scene and radiometric characteristics sensors

Scene size =170×183 Km^2		Swatch = 185 KM	
Sensors	**Bands**	**spectral Resolution (µm)**	**spatial Resolution (m)**
TM5	Band1: blue	0,45 – 0,52	30
	Band2 : red	0,52 – 0,60	30
	Band3 : green	0,63 – 0,69	30
	Band4 :near IR	0,76 – 0,90	30
	Band5 : mid IR	1,55 – 1,75	30
	Band 6 : Thermal	10.4 – 12.5	120
	Band7 : mid IR	2,08 – 2,35	30

Table II the coefficients Lmin/Lmax used for calibration

Bands	Lmin	Lmax
Band1	-1.52	193.00
Band2	-2.84	365.00
Band3	-1.17	264.00
Band4	-1.51	221.00
Band5	-0.37	30.20
Band7	-0.15	16.50

C. Methodology

a. Derived indexes image

The UI index is used instead the normalized difference built up index NDBI because the urban and soil features are more distinguishable in UI rather than NDBI and more correct results were obtained when using band 7 instead band 5 like in [10] as in Fig 2, the SAVI is more sensitive to the vegetation and the EBBI is a remote sensing index that applies wavelengths ranged from 0.83 µm to 1.65 µm, and 11.45 µm (NIR, SWIR, and TIR, respectively) to Landsat ETM+ images. These wavelengths were selected based on the contrast reflection range and absorption in built-up and bare land areas.

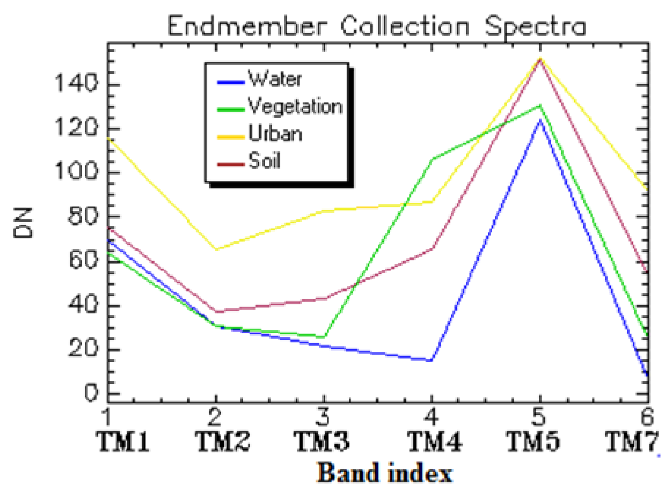

Fig. 2 Spectral response of the four land features in the six TM bands

The expression of land features indexes is

$$UI = \frac{TM7 - TM4}{TM7 + TM4} \quad (1)$$

$$NDBI = \frac{TM5 - TM4}{TM5 + TM4} \quad (2)$$

$$EBBI = \frac{TM5 - TM4}{10\sqrt{TM5 + TM6}} \qquad (3)$$

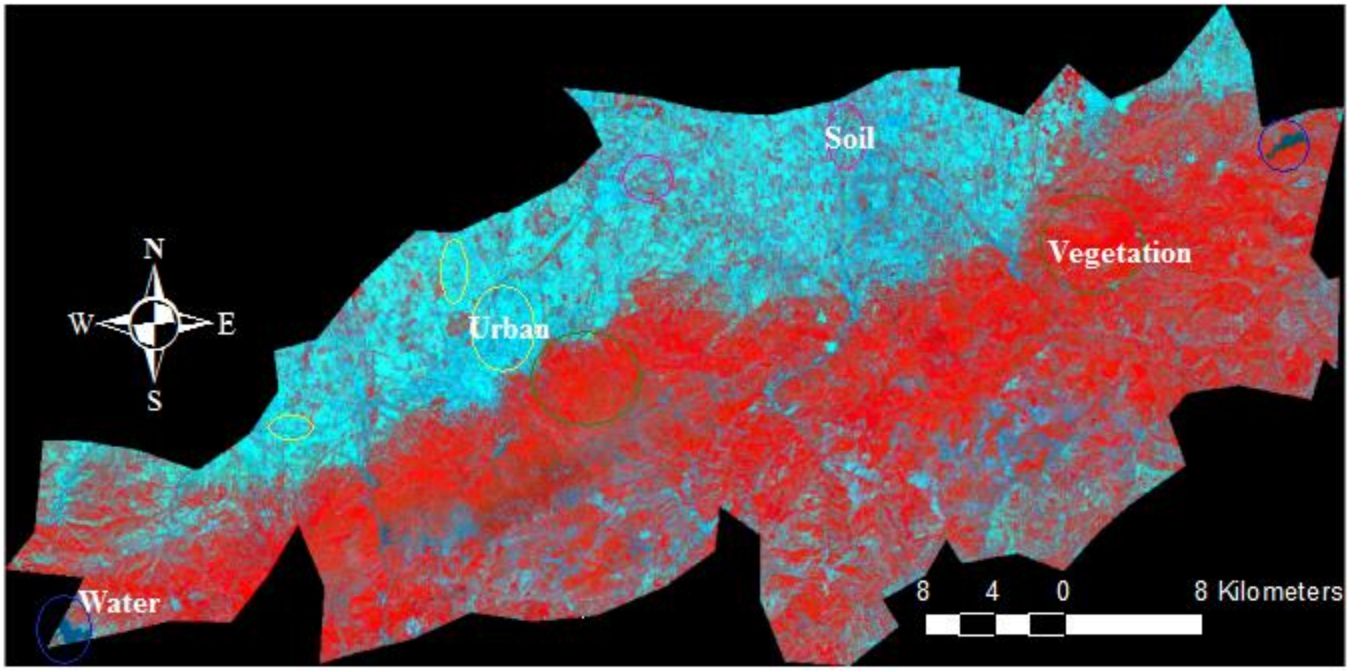

Fig 3 the false color RGB combination of derived indexes, SAVI is displayed as Blue, NDBAI as Green and UI as Red.

$$SAVI = \frac{(TM4 - TM3) \times 1.5}{TM4 + TM3 + 0.5} \qquad (4)$$

$$NDBAI = \frac{TM5 - TM6}{TM5 + TM6} \qquad (5)$$

b. Tasseled Cap transformation

The Tasseled Cap transformation is a practical vegetative index and spectral enhancement which transforms six TM bands [1-5] and 7 to basically three outputs bands named respectively brightness, greenness, and soil/vegetation wetness or third component [19], however to represent urban features the datasets outputs aren't used singly, the NDBI – greenness and EBBI-brightness were used to highlight the urban features.

c. Classification and accuracy assessment

To produce a single thematic map coming from all bands and reflecting the real ground land cover, theclustering pixels to classes is required and a spectral angle mapper SAM, spectral information divergence classification SID [12] were performed and subsequently the four urban, vegetation, water and soil land cover categories were extracted with their accuracy assessment and Kappa coefficient as in Table III and Fig 4. Accuracies assessment were carried out using ground truth data acquired from topographic map.

d. Extraction of urban features

The urban land cover was extracted from the binary

Table III Overall Accuracy, Kappa Coefficient of SAM and SID classification and the statistics of DNs of the four covers in the six spectral TM bands.

		SAM Overall Accuracy = 92.55% (2986767/3226965) Kappa Coefficient = 0.89	SID Overall Accuracy =86.12% (2778695/3226965) Kappa Coefficient = 0.80
		Min Max Mean Std	Min Max Mean Std
Water	Band 1	54 107 74.01 6.44	57 255 76.84 19.87
	Band 2	21 63 34.10 5.04	21 255 36.65 20.02
	Band 3	16 68 24.83 5.83	16 255 28.15 22.56
	Band 4	10 59 18.87 7.39	10 255 21.98 22.85
	Band 5	5 59 16.77 7.53	5 255 20.47 24.79
	Band 7	3 38 9.73 4.13	3 255 12.85 22.39
Urban	Band 1	53 255 101.89 15.89	54 255 99.58 14.76
	Band 2	22 255 54.91 11.11	21 248 53.97 9.85
	Band 3	17 255 66.87 15.70	17 255 67.43 13.33
	Band 4	24 255 75.62 13.02	20 255 76.2211.60
	Band 5	30 255 121.0125.95	26 255 130.48 22.42
	Band 7	13 255 75.17 19.47	10 255 80.17 16.32
Vegeta-tion	Band 1	52 98 64.74 4.03	52 115 66.10 5.02
	Band 2	21 52 31.15 3.17	21 65 32.08 3.75
	Band 3	17 60 27.67 4.51	17 80 29.43 5.71
	Band 4	39 172 89.94 14.41	38 172 87.77 14.23
	Band 5	28 136 71.65 11.77	29 148 74.75 13.15
	Band 7	10 74 28.00 6.18	11 121 30.56 7.75
Soil	Band 1	53 195 77.87 8.94	53 190 80.17 8.55
	Band 2	22 92 39.90 6.23	21 148 41.27 5.88
	Band 3	18 135 44.10 10.62	17 148 46.31 9.30
	Band 4	35 147 78.22 10.31	25 135 77.2910.28
	Band 5	34 255 102.13 21.68	27 255 105.39 19.11
	Band 7	14 206 52.62 15.43	10 195 55.5012.78

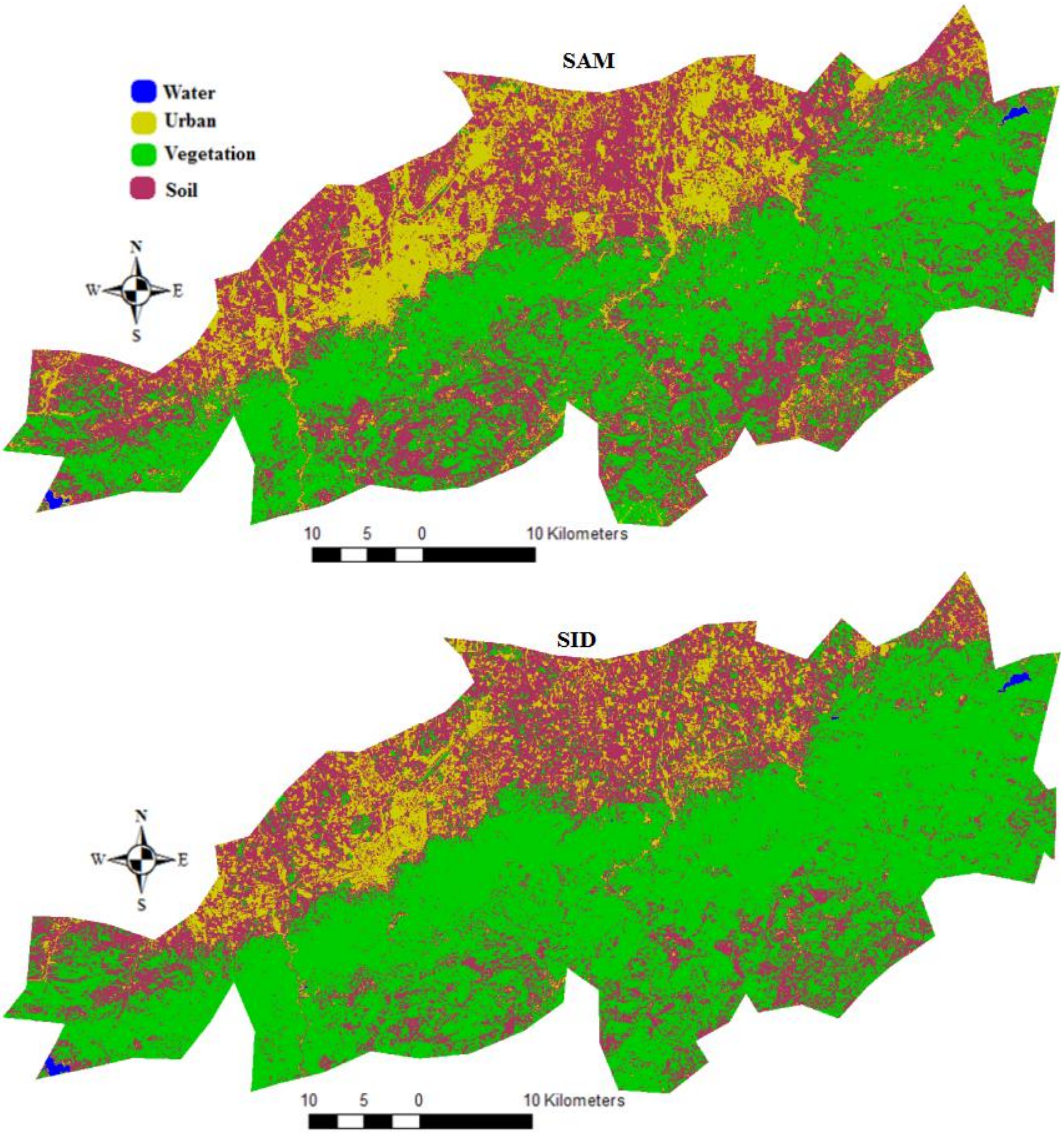

Fig.4 The output classes results from the SAM and SID classification

SAM and SID classification and from the new datasets UI-SAVI, BRIGHTNESS, NDBI-GREENESS and EBBI-BRIGHTNESS using the recoded manipulation method as in Fig.6 and the results are shown in Fig 7 and theirs Overall Accuracy are shown in Fig 8.

III. Results and Discussion

Fig.2 shows the spectral response of the considering LC/LU in the six bands of original image for what the process of land features indexes was chosen, indeed the urban have the high response for band 5, band7 and the low response for band 4, band 3 but the response spectral illustrates also the difficulty to separate the urban from the soil because both have the high reflectance in the same short wavelength, Fig.3 shows the displayed new image for false color SAVI NDBAI UI band combinations, the vegetation appears in red, urban areas are cyan blue, soils in light browns and water is blue and it's obvious that the land features are more distinguishable in the new image rather in the original because the bands in the new image are uncorrelated as in Fig.5. Table III shows the good overall accuracy and Kappa coefficient for both classification but the SAM classification was more accurate than SID and the statistic explains the more difficult to separate the urban from the soil because the values of brightness were very near. The Fig 7 and Fig 8 show that the methods of EBBI-BRIGHTNESS and BRIGHTNESS can extract the urban features with a high Overall Accuracy of 94.77% and 94.65% respectively; also the SAM, SID and UI-SAVI binary images represent the urban land cover with a good Overall Accuracy contrarily with the technique of NDBI-GREENESS which present the worse mapping of the urban with an Overall Accuracy of 92.03%.

IV. Conclusion

In this paper a methods for urban features extraction from TM Landsat based on the urban land features indexes and Tasseled Cap transformation as well as theirs overall accuracy were discussed, the methods show that the process of urban land features can be extracted using several process of spectral classification and logic calculation, for spectral classification the spectral angle mapper and spectral information divergence are very useful and can be mapped the urban land features with an overall accuracy of 94.48% and 94%, for the logic calculation the methods of UI-SAVI, EBBI-BRIGHTNESS and BRIGHTNESS can be represent the urban land use with a high overall accuracy of 93.77%, 94.77% and 94.65%.

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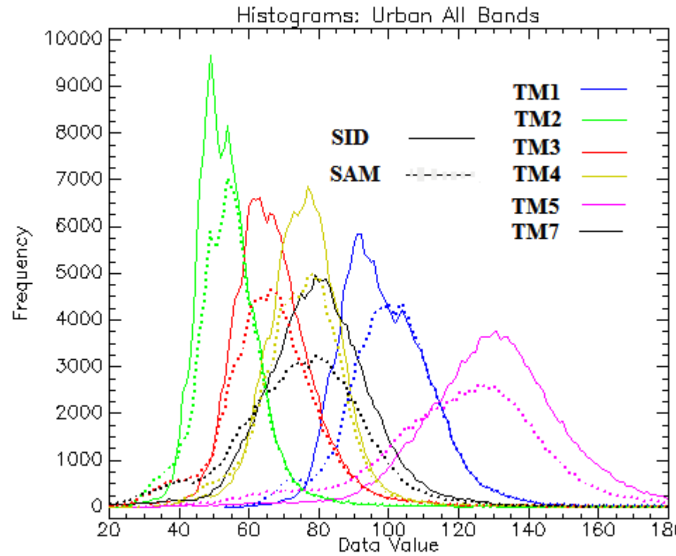

Fig.5 Histograms of urban land cover in the six bands for SAM and SID classification showing that's the bands are mush correlated.

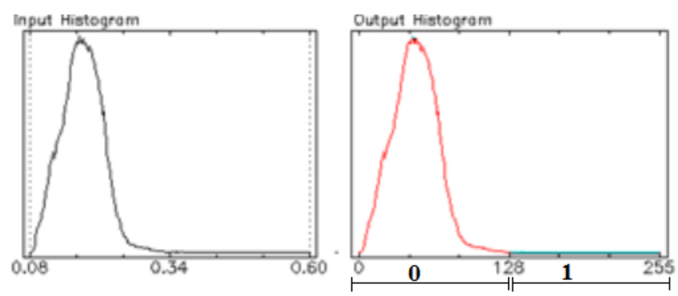

Fig.6 The linear transformation used for recoded images.

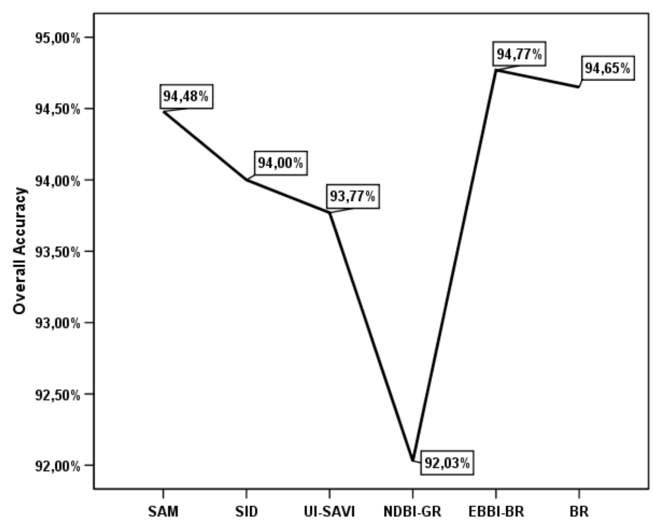

Fig.8 Overall Accuracy of the binary coding images showing that NDBI-GREENESS is the worse extraction

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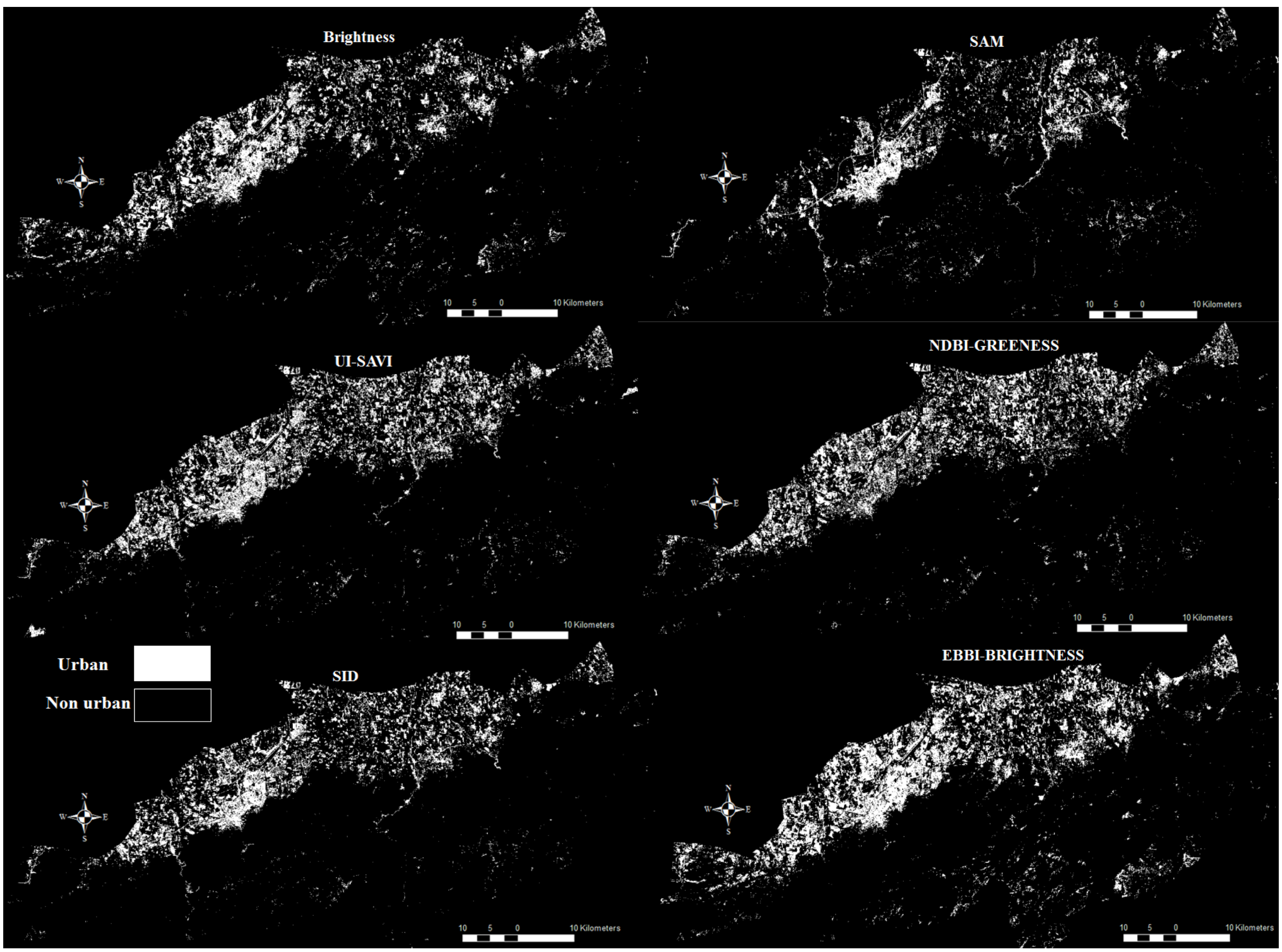

Fig.7 The output urban land features extraction from binary coding images.