Urban Mapping in Landsat Images Based on Normalized Difference Spectral Vector

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***Abstract*—In the last decades the number of natural and anthropic changes affecting population worldwide has raised dramatically. This fact, coupled with the increasing world population living in urban areas, requires the development of a detailed and reliable map of global urban extent. This letter reports on a new approach for urban mapping from Landsat images, based on the Normalized Difference Spectral Vector (NDSV). This spectral transformation allows the creation of a normalized signature that becomes peculiar of each land cover class within the scene. The urban extent classification is obtained by analyzing the NDSV data in conjunction with a Spectral Angle Mapper (SAM) based classifier. The experiments presented in this letter show the effectiveness of the proposed technique in detecting urban areas in extremely different environments. The results of the proposed methodology have been compared with the ones obtained by classifying the NDSV using other classifiers [namely, maximum likehood (ML) and support vector machines (SVM)], and also to the results obtained by classifying the calibrated data using the ML, SVM and SAM classifiers. The NDSV+SAM approach has provided the best results, with an overall accuracy of 97%.**

***Index Terms*—Landsat, Normalized Spectral Difference Vector (NDSV), remote sensing, spectral analysis, urban mapping.**

I. Introduction

ENVIRONMENTAL, social, and economic mutations imply the need to monitor and map continuously the world and its changes. Rapid relocation of population toward big cities, excessive natural resources consumption, disordered land use changes, etc. are all elements that put people at risk. In such a scenario, a detailed and up-to-date global map of urban environment and its rapid changes has become more and more necessary. The accuracy of such information is essential to estimate, and possibly reduce, the impact of natural hazards on human life. It is also crucial to measure the human demand on the ecosystem ("*ecological footprint*") and to relate land-use patterns to socio-economic activities [1], [2].

However, urban environment is a complex tissue that changes temporally and geographically. On one side is obvious that every settlement, town or city changes over time; on the other side apparently similar urban areas, located in different parts of the world, are in reality different in terms of structure, materials and characteristics. It is therefore crucial to have a global and as detailed as possible knowledge of the different kinds of urban tissue.

To this aim, Landsat data are interesting in terms of both spatial and temporal resolution. In fact, Landsat mission provides a 40-year record of the globe evolution and its multispectral resolution of 30 m is enough to identify also "small settlements."[1] Moreover, in 2008 the U.S. Geological Survey (USGS) opened access policy guaranteeing online free access to all data in the US Landsat archive [3].

In this letter, we present the first results of a new methodology for global urban mapping, based on the introduction of the Normalized Difference Spectral Vector (NDSV) and its combined use with a Spectral Angle Mapper (SAM) based classifier. This study is the first stage in the development of a comprehensive spectral database of urban features characteristics. The main objective of this work is to provide an overview of the approach, while describing the NDSV concept and the interaction with a supervised classification methodology; as part of this discussion, we provide information regarding the assessment of the algorithm and its validation.

II. Methodology

A. Data Pre-Processing

In order to mitigate the differences, in time and space, between different acquisitions, the data[2] need to be pre-processed. This phase is made of three main steps: data calibration, anomalies detection and cloud masking.

1) Data Calibration: The Level 1 Terrain (Corrected) (L1T)[3] data have been calibrated in order to derive the corresponding reflectance values. No further corrections were needed thanks to the robustness of the normalized functions that will be described in detail in Section II-B.

2) Anomalies Detection: Acquisition inconsistencies or calibration errors produce anomalous values (0 or NaN) which lead to classification errors. During the acquisition, the sensor captures each band with a slight delay which causes—for a given location—the lack of information, for a certain location, in some bands with respect to the others.

The phenomenon affects all the bands and therefore it increases the portion of the edges that have to be excluded from the processing. To prevent this problem, an automatic masking step has been introduced.

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[1]With the term "small settlement" we refer to urban areas of around 0.1 km^2.

[2]All the data considered have been downloaded from the USGS data webcatalog (http://glovis.usgs.gov/).

[3]For a detailed description of the Landsat L1T products please refer to http://landsat.usgs.gov/documents/LS-DFCB-20.pdf

3) Cloud Masking: Even if each scene has been visually inspected to avoid cloudy images (cloud cover $> 10\%$), it is necessary to check the presence of small clouds that can affect the classification. An automatic procedure has been implemented to mask clouds missed in the visual inspection phase.

B. Normalized Difference Vector

The basic idea behind the NDSV concept is to extract the information contained in the multispectral bands, removing errors and ambiguities due to differences in time, space, acquisition, etc. To this aim, we concentrated our efforts in the analysis of normalized difference spectral indices.

Literature lists a wide range of indices, each of them developed for different land cover discrimination purposes. All indices put two bands (b_i and b_j) of the acquired spectrum in relation, as reported in

$$f(b_i, b_j) = \frac{b_i - b_j}{b_i + b_j}. \tag{1}$$

The most known index is the Normalized Difference Vegetation Index (NDVI) and it is derived from the combination of the red and the near-infrared channels [band 3 and 4 in the case of Landsat 5 Thematic Mapper (TM)]. It takes advantage of the unique spectral signature of the reflectance curve of vegetation and its consistency is useful for global vegetation mapping.

The Normalized Difference Snow Index (NDSI) has been derived from Landsat 5 TM bands 2 and 5 (TM-2 and TM-5) to map glaciers [4]. This index is based on the difference between the strong reflection of the visible radiation and the almost total absorption of the middle infrared wavelengths by snow [5]. It is effective in distinguishing snow from bright soil, vegetation and rock, as well as from clouds [6].

The Normalized Difference Water Index (NDWI) has been used to delineate open water features and enhance their presence in remotely sensed imagery based on reflected near infrared radiation (TM-4) and visible green light (TM-2). It has been also used to estimate the turbidity of water bodies from remotely sensed data [7] and it is sensitive to changes in liquid water contained into vegetation canopies (i.e., it can be considered complementary to NDVI [8]).

Finally, the Normalized Difference Built-up Index (NDBI) has been derived from TM-4 and TM-5 to differentiate urban areas. It has been proven to be suitable for mixed environment but not for the discrimination between urban areas and bare soil. In [9], the combined use of NDBI and NDVI over Landsat TM images has been analyzed and discussed.

Having all these indices available in literature, it was natural to ask ourselves whether these indices could be merged together or considered simultaneously. If so, the new approach would bring several advantages. First, it would produce data that are intrinsically normalized and consistent globally. Second, the information of each index would be correlated, which would provide a good opportunity for analyzing the contribution of different features in mixed urban areas (e.g., residential buildings surrounded by trees, rural areas, etc.). Finally, the method would minimize the risk of ambiguities by compensating the lack of each index, if considered alone.

The solution we propose here envisages the computation of all possible indices by performing the combination of all available bands. Then, by grouping the resulting normalized difference spectral indices, we obtain—for each pixel—an array of elements called Normalized Difference Spectral Vector (NDSV). In this way, each index is used to create a "normalized signature." Then, the NDSV can be given as input to any spectral classifier.

In the case of Landsat TM data, the six 30-m multispectral bands lead to 15 new normalized "bands"[4]

$$NDSV = \begin{bmatrix} f(b_1, b_2) \\ f(b_1, b_3) \\ \cdots \\ f(b_1, b_6) \\ f(b_2, b_3) \\ \cdots \\ f(b_5, b_6) \end{bmatrix}. \tag{2}$$

C. Class Definition and Signature Collection

The classification has been carried out by defining four main classes: Water (**Wa**), Vegetation (**Ve**), Bare Soil (**Bs**), Urban (**Ur**). The robustness of the NDSV causes only few pixels per class (i.e., less than 50) to be required. In order to compensate the heterogeneity of the urban environment, the urban class has been divided into three main sub-classes (low, medium and high density) and then aggregated back in one urban class in the classification step. All the training samples have been visually inspected and validated using fine-resolution satellite data (e.g., Google Earth).

D. Classification

In this letter, we have considered a supervised classification methodology, based on the Spectral Angle Mapper (SAM) value. We have selected this measure because it evaluates the signature similarity and it is invariant to any unknown multiplicative scaling of the spectra that may arise from differences in the illumination and orientation angle [10], [11]. However, in order to justify our choice, the NDSV has been tested in combination with two other well-known classifiers: support vector machines (SVM) and maximum likehood (ML).

E. Validation and Assessment

A preliminary analysis of the achieved accuracy has been performed by extracting a set of test areas and visually inspecting the classification results in those areas. The validation phase has been conducted by comparing the classification results with the Landsat data and other high resolution satellite data (e.g., Google Earth). For each scene a total of 5000 samples per class have been extracted by using a stratified random sampling

[4]From the combination of six elements it can be possible to derive 30 values but in half of the cases, values are just opposite (i.e., $f(b_i, bj) = -f(b_j, bi)$). This means that these redundant values can be omitted from the NDSV.

method and manually inspected. The results are reported and discussed in Section IV.

III. Study Area

The methodology has been tested on two areas very different from each other in terms of landscape: one represents a desert area while the other represents a vegetated one. The areas cover 1247 km^2 and 9700 km^2, respectively and both are portions of wider Landsat scenes.

The first image has been acquired on August 19th, 2003 over the area of Tripoli, Libya. The city is located in the northwest part of the country on the edge of the desert, on a point of rocky land projecting into the Mediterranean and forming a bay. Coastal oases alternate with sandy areas and lagoons along the shores of Tripolitania for more than 300 km. In such a scenario, the city center can be easily identified by just looking at the original data. Nevertheless, several difficulties arise in the detection of the small scattered settlements in the surrounding areas, as the presence of small settlements in the desert landscape becomes challenging due to the spectral similarity between the building materials and the bare soil.

The second image has been acquired on December 28th, 2002 over the city of Lagos, Nigeria. The city is located in the Southwest part of the country and it is surrounded by forests. Lagos is a huge metropolis, which originated on islands separated by creeks fringing the Southwest mouth of the Lagos Lagoon while protected from the Atlantic Ocean by long sand spits such as Bar Beach, which stretches up to 100 km east and west of the mouth. The city center is well detectable in the original data while the detection of mixed areas with bare soil and small settlements is difficult.

The images were selected from relatively cloud-free scenes ($< 10\%$), and no further georeferencing refinement was necessary as the data are available from USGS in L1T level of systematic geometric accuracy.

For the training phase a total set of 20 pixels for each class has been selected for both scenes.

IV. Results

A. Classification Accuracies

In both experiments the introduction of NDSV produces an increase of the classification accuracy for the SVM and SAM, while a strong decrease of the ML accuracy. This decrease can be due to the fact that the introduction of NDSV adds a level of complexity to the statistics of the samples that ML is not able to solve with such a small number of training pixels. On the other hand, this complexity is better managed by the SAM classified since SAM does not go through a "training phase" but it merely compares the "spectrum" of the normalized vector for each pixel with the average spectrum of the training samples used. The SVM classifier instead, improves the classification results when using the NDSV but only to a certain extent due to the limited number of samples available.

One of the key advantages of the combined use of the NDSV and SAM is that few samples are needed as reference spectra.

TABLE I
Confusion Matrices for the Tripoli Image Classification (Calibrated)

%	Ground Truth			
SVM	**Urban**	**Vegetation**	**Soil**	**Water**
Unclassified	0.00	0.00	0.00	0.00
Urban	**63.86**	0.00	0.00	0.00
Vegetation	0.33	99.49	0.00	0.00
Soil	35.81	0.51	100.00	0.00
Water	0.00	0.00	0.00	100.00
Prod. Acc.	**63.86**	99.49	100.00	100.00
User Acc.	**100.00**	99.74	78.63	100.00
Ov. Acc.	**91.58 (k=0.88)**			
ML	**Urban**	**Vegetation**	**Soil**	**Water**
Unclassified	0.00	0.00	0.00	0.00
Urban	**91.59**	3.42	0.00	0.00
Vegetation	0.00	88.39	0.00	0.00
Soil	8.41	8.20	100.00	0.00
Water	0.00	0.00	0.00	100.00
Prod. Acc.	**91.59**	88.39	100.00	100.00
User Acc.	**95.45**	100.00	87.66	100.00
Ov. Acc.	**94.68 (k=0.92)**			
SAM	**Urban**	**Vegetation**	**Soil**	**Water**
Unclassified	0.22	42.44	0.00	0.00
Urban	**85.70**	0.26	0.00	0.00
Vegetation	0.66	52.18	0.00	0.00
Soil	13.43	5.12	100.00	0.00
Water	0.00	0.00	0.00	100.00
Prod. Acc.	**85.70**	52.18	100.00	100.00
User Acc.	**99.62**	99.03	87.04	100.00
Ov. Acc.	**82.74 (k=0.77)**			

B. Desert Environment

The observations made for the desert environment are based on the results obtained for the "Tripoli and surrounding" scene.

In Tables I and II the confusion matrices for the calibrated and NDSV data have been reported. The matrices have been calculated over thousands of samples extracted by using a stratified random sampling method.

The comparison between the results obtained by classifying the calibrated and NDSV data, and also using different classifiers shows interesting results. The analysis of the results obtained by classifying the NDSV using the three classifiers (ML, SVM, and SAM)[5] shows that the ML classifier suffers from the introduction of the NDSV transformation while better accuracies are obtained when using the SVM and SAM classifiers. Despite the good overall accuracies that all classifiers can reach (considering the best results of each classifier), it is interesting to notice that NDSV+SAM shows the best results for the urban class extraction both in terms of accuracy and of over- and under-estimation (i.e., user's and producer's accuracy).[6]

The robustness of the NDSV in conjunction with the SAM capabilities allows an accurate detection of the urban extent even in an ambiguous scenario like the one of Tripoli and its surroundings. Urban class obtained with NDSV+SAM has been reported in Fig. 1.

[5]All the classifiers considered are based on the functions integrated in the ENVI platform. In particular, for SVM a LIBSVM has been considered with a nonlinear kernel (RBF) a gamma coefficient of 0.167 and a penalty parameter of 100. Input data normalization has been automatically performed by the tool. More details can be found in [12].

[6]User's accuracy corresponds to the commission error (inclusion), while producer's accuracy to the omission one (exclusion). They can be considered as a measure of over- and under-estimation, respectively.

TABLE II
CONFUSION MATRICES FOR THE TRIPOLI IMAGE CLASSIFICATION (NDSV)

%	Ground Truth			
SVM	**Urban**	**Vegetation**	**Soil**	**Water**
Unclassified	0.00	0.00	0.00	0.00
Urban	**80.90**	0.85	0.00	0.00
Vegetation	0.55	97.69	0.00	0.00
Soil	18.56	1.45	100.00	0.00
Water	0.00	0.00	0.00	100.00
Prod. Acc.	**54.48**	76.52	100.00	77.47
User Acc.	**67.43**	99.89	71.83	100.00
Ov. Acc.	**94.95 (k=0.93)**			
ML	**Urban**	**Vegetation**	**Soil**	**Water**
Unclassified	0.00	0.00	0.00	17.88
Urban	**54.48**	20.58	0.00	0.00
Vegetation	0.11	76.52	0.00	0.00
Soil	45.41	2.90	100.00	4.65
Water	0.00	0.00	0.00	77.47
Prod. Acc.	**54.48**	76.52	100.00	77.47
User Acc.	**67.43**	99.89	71.83	100.00
Ov. Acc.	**78.84 (k=0.71)**			
SAM	**Urban**	**Vegetation**	**Soil**	**Water**
Unclassified	0.00	0.26	0.00	2.76
Urban	**93.56**	0.00	0.00	0.00
Vegetation	0.66	97.87	0.00	0.00
Soil	5.79	1.88	100.00	0.00
Water	0.00	0.00	0.00	100.00
Prod. Acc.	**93.56**	97.87	100.00	100.00
User Acc.	**100.00**	99.48	94.25	99.57
Ov. Acc.	**97.90 (k=0.97)**			

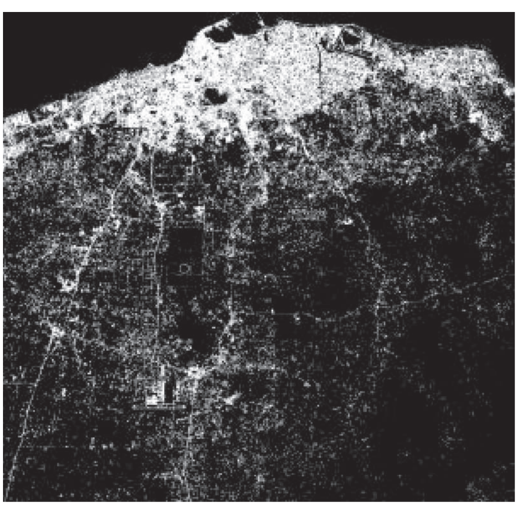

Fig. 1. Urban extent extracted from the NDSV+SAM classification of the Tripoli's scene.

C. Vegetated Environment

Analogously, the observations made for the vegetated environment are based on the scene depicting Lagos and its surroundings. The confusion matrices of the classifications obtained by using the different classifiers are reported in Tables III (calibrated data) and IV (NDSV).

Also, in this second test case, the use of NDSV with ML classification is losing in performances respect to the calibrated data. On the contrary, with SAM and SVM produce an increase in the accuracy measured. The combined use of NDSV+SAM allows an improved extraction of the urban extent, reducing both the over- and under-estimation effects seen when classifying the calibrated data. In Fig. 2 the urban extent extracted by the NDSV+SAM approach is reported.

TABLE III
CONFUSION MATRICES FOR THE LAGOS IMAGE CLASSIFICATION (CALIBRATED)

%	Ground Truth				
SVM	**Urban**	**Vegetation**	**Soil**	**Water**	**Swamp**
Unclassified	0.00	0.00	0.00	0.00	0.00
Urban	**96.93**	0.00	10.44	0.00	0.00
Vegetation	0.00	100.00	16.75	0.00	6.17
Soil	3.07	0.00	72.81	0.00	0.00
Water	0.00	0.00	0.00	100.00	0.00
Swamp	0.00	0.00	0.00	0.00	93.83
Prod. Acc.	**96.93**	100.00	72.81	100.00	93.83
User Acc.	**92.59**	82.78	94.62	100.00	100.00
Ov. Acc.	**93.34 (k=0.91)**				
ML	**Urban**	**Vegetation**	**Soil**	**Water**	**Swamp**
Unclassified	0.00	0.00	0.00	0.00	0.00
Urban	**100.00**	0.00	13.40	0.00	0.00
Vegetation	0.00	99.06	22.07	0.00	3.55
Soil	0.00	0.94	64.53	0.00	0.00
Water	0.00	0.00	0.00	100.00	0.00
Swamp	0.00	0.00	0.00	0.00	96.45
Prod. Acc.	**100.00**	99.06	64.53	100.00	96.45
User Acc.	**90.95**	81.31	98.35	100.00	100.00
Ov. Acc.	**92.97 (k=0.91)**				
SAM	**Urban**	**Vegetation**	**Soil**	**Water**	**Swamp**
Unclassified	11.27	7.11	10.44	0.00	6.84
Urban	**87.71**	0.00	7.59	0.00	0.00
Vegetation	0.00	92.81	2.07	0.00	1.01
Soil	1.02	0.09	79.90	0.00	0.00
Water	0.00	0.00	0.00	100.00	0.00
Swamp	0.00	0.00	0.00	0.00	92.15
Prod. Acc.	**87.71**	92.81	79.90	100.00	92.15
User Acc.	**93.97**	97.05	98.18	100.00	100.00
Ov. Acc.	**90.65 (k=0.88)**				

TABLE IV
CONFUSION MATRICES FOR THE LAGOS IMAGE CLASSIFICATION (NDSV)

%	Ground Truth				
SVM	**Urban**	**Vegetation**	**Soil**	**Water**	**Swamp**
Unclassified	0.00	0.00	0.00	0.00	0.00
Urban	**98.68**	0.00	10.54	0.00	0.00
Vegetation	0.00	99.83	5.42	0.00	2.79
Soil	1.32	0.17	84.04	0.00	0.00
Water	0.00	0.00	0.00	100.00	0.00
Swamp	0.00	0.00	0.00	0.00	97.21
Prod. Acc.	**98.68**	99.83	84.04	100.00	97.21
User Acc.	**92.65**	92.98	97.71	100.00	100.00
Ov. Acc.	**96.34 (k=0.95)**				
ML	**Urban**	**Vegetation**	**Soil**	**Water**	**Swamp**
Unclassified	85.88	28.60	22.27	0.00	0.00
Urban	**12.36**	0.00	20.20	0.00	0.00
Vegetation	0.00	68.92	0.00	0.00	1.35
Soil	1.76	1.11	57.34	0.00	0.00
Water	0.00	0.00	0.00	100.00	0.00
Swamp	0.00	1.37	0.20	0.00	98.65
Prod. Acc.	**12.36**	68.92	57.34	100.00	98.65
User Acc.	**45.19**	98.05	94.02	100.00	98.48
Ov. Acc.	**65.78 (k=0.60)**				
SAM	**Urban**	**Vegetation**	**Soil**	**Water**	**Swamp**
Unclassified	0.00	0.00	0.00	1.84	0.00
Urban	**98.68**	0.00	7.98	0.00	0.00
Vegetation	0.00	99.91	1.77	0.00	0.68
Soil	1.32	0.09	90.25	0.00	0.00
Water	0.00	0.00	0.00	98.16	0.00
Swamp	0.00	0.00	0.00	0.00	99.32
Prod. Acc.	**98.68**	99.91	90.25	98.16	99.32
User Acc.	**94.34**	97.82	97.97	100.00	100.00
Ov. Acc.	**97.49 (k=0.97)**				

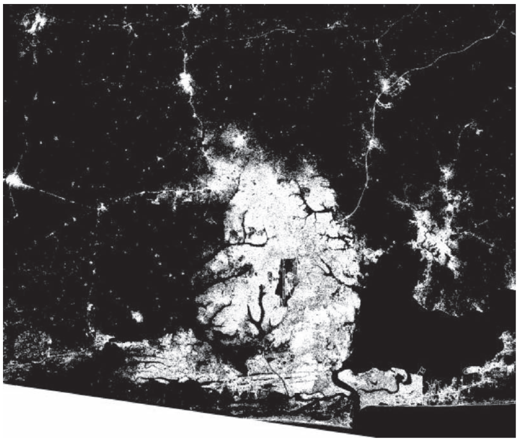

Fig. 2. Urban extent extracted from the NDSV+SAM classification of the Lagos's scene.

V. Conclusion

This work presents a new methodology for urban mapping from Landsat data based on the use of the Normalized Difference Spectral Vector. NDSV has proved to be an extremely robust and globally consistent measure. A comparison between calibrated and NDSV data has been conducted, and the performances of three different classification paradigms (SVM, ML, and SAM) have been evaluated. The proposed methodology has been tested on two extremely different test cases in terms of landscape.

Despite the good accuracies that each classifier can reach with both the calibrated and the NDSV data, the best results are obtained by the combination of NDSV and SAM. In particular, the proposed approach shows a good consistency in the extraction of urban class, strongly reducing the effect of its over- and under-estimation. Further studies will be conducted to better define the limitations in SMV and ML classification accuracies with the use of NDSV.

The quality of the early results presented in this letter also provides strong evidence of the potential of Landsat data in large-scale urban mapping applications. Landsat data clearly provide a significant improvement in terms of quality and resolution, compared to the currently available global urban layers derived from satellite imagery.

Future works will aim to analyze the NDSV behavior at global scale. Moreover, further test will be conducted in order to investigate the effectiveness of unsupervised classification methodologies, that by reducing human interaction-are more suitable for a global application.

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