Received March 28, 2017, accepted April 28, 2017, date of publication May 2, 2017, date of current version June 28, 2017.

Digital Object Identifier 10.1109/ACCESS.2017.2700405

Desertification Monitoring in Biskra, Algeria, With Landsat Imagery by Means of Supervised Classification and Change Detection Methods

SOUFIANE ABDELAZIZ AZZOUZI[1,2], ANA VIDAL-PANTALEONI[1], (Member, IEEE), AND HADJ ADDA BENTOUNES[2]

[1]Instituto de Telecomunicaciones y Aplicaciones Multimedia, Universitat Politècnica de València, Camino de Vera, 46022 València, Spain

[2]Laboratoire des signaux et systèmes, Faculté des sciences et de la technologie, Université Abdelhamid Ibn Badis de Mostaganem, Mostaganem 27000, Algeria

Corresponding author: Soufiane Abdelaziz Azzouzi (souaz@iteam.upv.es)

This work was supported by the frame of EMMAG Erasmus Mundus.

ABSTRACT Desertification is one of the most important problems driven by global climatic change. There are many factors that contribute to the environmental degradation of the Sahara desert surroundings. The first one is related to human activities, such as change of land use. Other factors include natural degradation due to change in temperature, humidity, and wind. All of these complex causes may lead to the movement of sand from the desert to other places, such as cities and roads, affecting everyday life. For that reason, desertification is being analyzed by governmental agencies in the affected countries. This paper studies this phenomenon in the city of Biskra, Algeria, using optical satellite images taken from the freely available Landsat program. It presents a methodology that could help in the temporal evaluation of the desertification process. Land use and land cover change detection in a period of 25 years has been carried out using a support vector machine per object classification. Change indices have been also employed for assessing the degradation. Excellent results using low human operator cost have been fully validated by visual inspection.

INDEX TERMS Change detection, desertification, Landsat, land cover land change, supervised classification.

I. INTRODUCTION

The of desertification is a progressive process that reduces the productive capacity of land cover over a period of years. Desertification is the main cause of land degradation in arid, semiarid, and dry subhumid regions. Natural and human-made aspects play an important role in the process [1]. This fact is known since last century, but the understanding of its causes and consequences is still a topic of great interest [2], [3]. For that reason, the United Nations Environment Program (UNEP) explored this topic in [4] and created the United Nations Convention to Combat Desertification (UNCCD) in 1994. Natural desertification is not new, since it is a cyclic phenomenon that has been taking place for centuries [5]. However, desertification has been increasing in the Sahel area [6] due to human and natural factors. The Sahara desert is sometimes viewed as an imminent threat in the countries of North Africa. It is very important to make an effort in order to establish a scientific base in this topic as explained in [7] for sustainable resource conservation.

The idea of desertification threatening the North of Algeria was seriously taken into account by the Algerian authorities (Ministry of Agriculture and Rural Development) through national research projects, that were also supported by the international community. The Algerian government fights this serious problem since 1962, with the implementation of several programs. The first project was based on the plantation of vegetation barriers in the steppe surroundings to prevent the advance the Sahara desert [8]. This project was continued during the 1970s with a massive reforestation program called the Green Dam [7]. The objective of this large vegetation barrier, located in the extreme North of Sahara with 20 km in width, was to stop the progression of erg (area of mobile sand dunes in Sahara) [7], but this goal was not completely achieved, and today there are only traces of that barrier formed by a few aleppo pines trees. In 1970s, another project called the Agrarian Revolution was launched. The main objective in that case was to regulate the use of the steppe through livestock farming [8]. This program was not successful due to numerous conflicts of interest that arose.

Even after the previous programs were developed, desertification was growing. Therefore, in 1983, a special institution was created under the name 'Haut Commissariat

2169-3536 © 2017 IEEE. Translations and content mining are permitted for academic research only.
Personal use is also permitted, but republication/redistribution requires IEEE permission.
See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.

au Développement de la Steppe (HCDS)', whose objectives were the conservation of the environment, and the development of strategies to fight against desertification, taking into account natural and socioeconomic aspects. This institution was mainly devoted to the rehabilitation of degraded courses and to the creation of water well areas. Now, 3.3 million hectares have been preserved by this program of an potential area of 30 million hectares. However, this institution has failed to develop a comprehensive and coherent strategy for the sustainable development of the steppe zones [8].

The last attempt to fight desertification was developed in 2000s under the program 'Programme National de Développement Agricole (PNDA)' for the agricultural exploitation on steppe marginal lands.

Scientific research about global desertification has been carried in the past and specially in Algeria [8], [9]. However, the complexity of the problem and its causes turns the desertification evaluation to a real challenge. More detailed studies taking into account location dependent characteristics, like the methodology presented in this paper could lead to very valuable results.

Systematic analysis of satellite observations in the optical spectrum, with the same incidence angle and similar sensors for a long time, enable the correct evaluation of the land cover change. Besides, a large number of sensors and platforms offer now open access to their satellite databases. The problem of desertification in Algeria using Remote Sensing was previously analyzed at In-Salah (Adrar, Algeria) in [9]. In that work, the chosen classification method was a supervised per pixel Maximum Likelihood algorithm and the main goal was to characterize mobile sand dunes.

The objective of this work is to present an easy and semiautomatic methodology for monitoring land degradation in an arid region using a per object approach based on a supervised Support Vector Machine (SVM) classifier. A small number of classes was used for that purpose, which simplified the procedure. The city of Biskra (Northern Algeria) was selected for the validation of the proposed methodology. Optical Landsat images obtained from year 1986 to year 2011 were chosen. Then, some change detection indices were used in order to determine the change that took place in the period of study. Visually inspected pixels were taken as true data for validation in order to establish the methodology quality. Finally, the change information was linked to the major contributing factors that influenced land degradation. This methodology with low cost in terms of human processing could help local authorities to minimize and prevent degradation processes using freely available Landsat data.

II. STUDY AREA

The area of study is an arid region in the northeastern region of Algeria, determined by the limits of 34°52' N and 34°42' N in latitude and of 5°32' E and 5°51' E in longitude, as shown in Fig. 1. It covers an area of 551.39 km^2 with an altitude range from 87 m to 115 m above Mediterranean Sea level. This arid region around Biskra is known as the Door of the Desert. It is surrounded by sands dunes (Occidental Grand Erg) in the south direction and the Mountains of Aurés in the north direction. The population of Biskra has grown significantly from 95000 in 1977 to over 307987 in 2015 making a threefold increase in a period of 38 years.

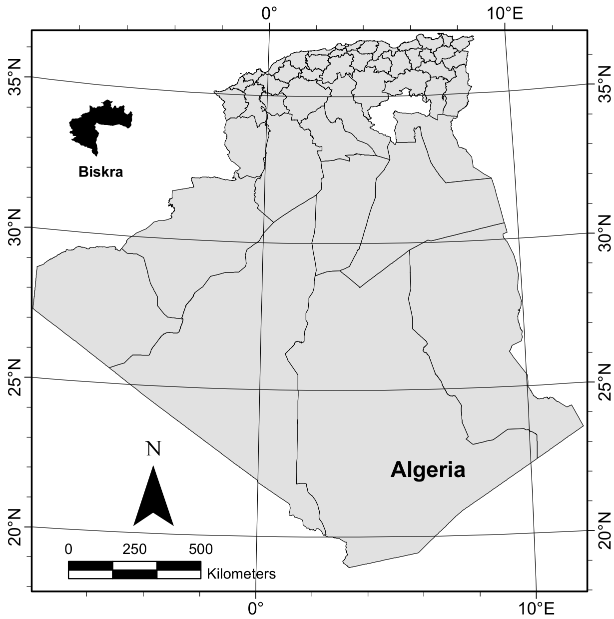

FIGURE 1. Geographic location of the study area.

The meteorological data was provided by the Russian Federal Service for Hydrometeorology and Environmental Monitoring. The mean minimum temperature is in the range from 17.39°C to 18.35°C, whereas the mean maximum temperature goes from 26.13°C to 28.35°C. The daily temperature is very high from June to August with a maximum value of 47.2°C. The mean minimum relative humidity is in the range from 27.75% to 32.33%, where the mean maximum relative humidity goes from 55.03% to 62.72%. The total value of rainfall is around 135 mm per year.

The prevalent wind direction goes from southeast to northwest along the Sahara Atlas. The maximum wind speed achieved in this case is around 15 m/s. Fig. 2 represents the wind rose of the study area. This wind is effective at summer (June, July and August), when large temperature and high dryness cause the movement of soil particles. Sand transportation can be provided by three types of movement: suspension, saltation and rolling. However, some factors can affect the accumulation of sand and the wind effectiveness. The first one is the biological factor through the existence of vegetation. The second one is the slope terrain provided by the local topography and the third one is the mechanical factor given by soil conditions.

III. DATA

The Land Use and Land Cover study was based on the analysis of multitemporal satellite images with low cloud

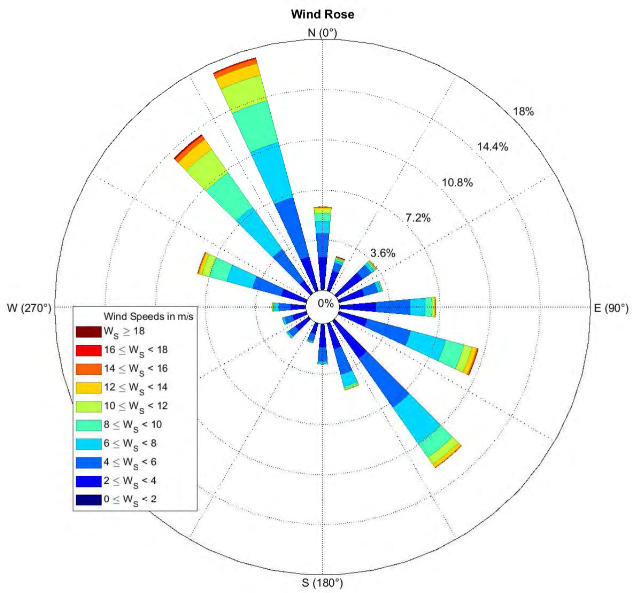

FIGURE 2. Direction and amplitude of wind at the study area from 01/02/2005 to 28/10/2015.

content. The images used in this study were chosen from the freely available archive of the United States Geological Survey (USGS). Different scenes from the Landsat-5 program taken at June with low cloud presence were chosen and their characteristics are shown in Table 1. The month of June was used for this study because it belongs to the hot and dry season, which is the most useful season for desertification monitoring.

A subarea of 944 × 649 pixels was chosen for further analysis, with pixel spatial resolution of 30 × 30 m. Fig. 3 shows a composition of three bands (red, green and blue) of the Landsat image taken at 2011 and its corresponding Digital Elevation Model (DEM), that was useful to estimate the terrain slope and its influence in the final sand transportation.

IV. METHODS

A. IMAGE PRE-PROCESSING

In optical Remote Sensing, energy reflected from the Earth surface depends on the surface slope and its orientation and the atmospheric components among other factors [10]. It obviously also depends on the cover of the surface, which is usually the goal of the analysis. In this study, the objective is to detect sand movement in a period of time. For that purpose, it is very important to assure the co-location of the images under comparison. Therefore, necessary pre-processing includes radiometric calibration, atmospheric normalization, geometric correction and image registration [11]. In the present work, radiometric correction was carried out using the dark substraction algorithm included in ENVI software. Geometric correction was also applied using ground control points as described in [12]. Finally, the co-registration of the study area was carried out [13] following the procedures provided by ENVI tools using 255 control points. The measured Root Mean Square Error (RMSE) was computed and it was in a range between 0.001 pixels and 0.16 pixels.

TABLE 1. Characteristics of the landsat images.

Acquisition Date	Landsat ID N°	Instrument	Path/ Row	LPGS version	Data type	Solar azimuth	Solar elevation
04/06/1986	TM 5	SAM	194/036	12.5.0	L1T	107.09	61.18
13/06/1995	TM 5	SAM	194/036	12.6.1	L1T	101.37	57.74
14/06/2007	TM 5	Bumper	194/036	12.5.0	L1T	113.70	67.11
03/06/2009	TM 5	Bumper	194/036	12.5.0	L1T	114.27	65.89
09/06/2011	TM 5	Bumper	194/036	12.5.0	L1T	113.19	66.25

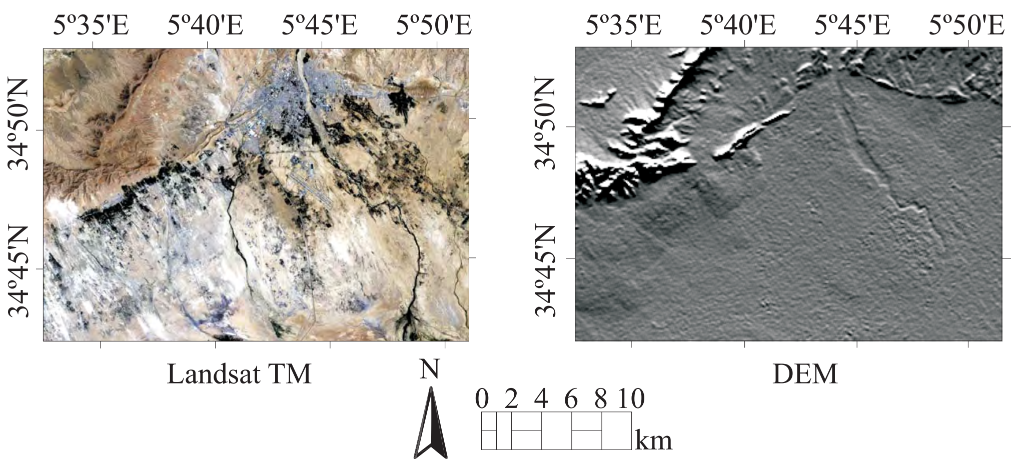

FIGURE 3. Landsat image taken at 2011 and its corresponding Digital Elevation Model (DEM).

B. IMAGE CLASSIFICATION

The Feature Extraction tool from ENVI was used to classify the images using an object based approach, where an object is a group of pixels with similar spectral, spatial, and texture attributes. The selected segmentation process was based on an edge detection algorithm with a scale level of 35%, and the merging process used a Full Lambda Schedule approach with a merge value of 80% and a texture kernel size of 3 pixels. This choice was adjusted in order to get an optimum object size. Support Vector Machine (SVM) algorithm was then selected for classification after considering different techniques because it provided the best results in terms of overall accuracy. SVM is a supervised classification method derived from statistical learning theory as described in [14]. It makes a separation between classes with the decision that maximizes the margin between them because that minimizes the risk of misclassification. The Gaussian Radial Basis Function (RBF) was selected for the classification stage. The RBF kernel requires to chose two parameters, the optimum Gaussian radial basis function γ, which controls the kernel width, and the regularization parameter C, which controls the penalty of misclassification errors. An auxiliary cross validation test was carried out to obtain the optimum values for γ (0.03) and C (100) in order to handle nonseparable classification problems as described in [15]. The Library for Support Vector Machines (LIBSVM) program developed by [16] and supported by ENVI was used in this study. This supervised method was based on some training samples for each land use type selected by the human operator. An example-based methodology was selected and the number of training samples was chosen from 497 to 1131 pixels for each one of the five images of Landsat 5 TM. Six land cover classes were selected for the study, which are shown in Table 2. This is the minimum set of classes needed to assess the sand movement in the area of study.

TABLE 2. Classes of land cover selected in the study.

Land Cover class	Description
Urban	Buildings, cities, villages, roads
Vegetation	Oases, parklands
Sand	Sands, dunes, erg
Rock	Rock, desert rose, desert mountain
Water	Rivers, lakes, reservoirs
Low dense vegetation (LDV)	Crop fields, grassland

C. CHANGE DETECTION MATRIX

Change detection analysis is the procedure that identifies change, in location and type, during a period of time [17]. Post Classification Comparison (PCC) is used in the present study to obtain the type of change [18]. This process identifies the change classes "from-to" [19] and its degree of success depends on the reliability of image classification [20]. In this study, change detection evaluation was applied by pairs of images with different date acquisition: 1986-1995, 1995-2007, 2007-2009, 2009-2011 and 1986-2011. For the assessment of land cover change, different useful indices were calculated for all the pairs of images taken at different dates as described in [21]. The following indices were used: Gain, Loss, Persistence, Total change, Swap and absolute value of Net Change. Gain and Loss are the increment and the decrement respectively of a class land use in a period of time. Persistence is the proportion of class land use that does not change in a period and it is computed by the difference between the class use at the end of the period and its Gain. Swap represents the simultaneous Loss and Gain of a class land use as described in [21]. The Swap analysis needs the pairs of each gained and lost pixels of the study area [21], [22]. The Total Change is the sum of the corresponding Gain and Loss for one class and the absolute value of Net Change is the absolute value of the difference between Total Change and Swap as explained in [22].

There are also ratios between indexes that are useful in order to evaluate a transition matrix. The Loss to Persistence ratio L_p assesses the exposure of a land cover for a change. The Gain to Persistence ratio G_p evaluates the probability of gain of class and the Net Change to Persistence ratio N_p evaluates the probability of overall change of a class during the period under study as described in [22].

V. RESULTS AND DISCUSSION

A classification accuracy assessment was first performed comparing the classified results to some visually selected regions from the images, which were obviously different from the training set used in the classification stage. Table 3 shows the confusion matrix for the 2011 Landsat image classification using the selected procedure. For this validation process, 6668 random pixels were visually classified, covering 6.00 km^2 of ground truth data (1.1% of the total area). Once the classification procedure was validated, the same process was applied to the Landsat images taken in the years 1986, 1995, 2007, 2009. Confusion matrices were produced for 1986, 1995, 2007, 2009, and 2011 resulting in an overall accuracy of 93.95%, 84.89%, 86.92%, 93.12%, and 92.91%, and Kappa values of 0.88, 0.78, 0.81, 0.89 and 0.91, respectively. The overall accuracy and Kappa coefficient were calculated obtaining excellent results according to [23]. The classification results are presented in Table 4 and they show the dynamics of spatial changes of land cover and land use in the study area during a period of 25 years. Pairs of images were then compared through the transition change matrices described in [21] for the multitemporal change analysis. Table 5 presents the land cover change transition matrix for the image pairs 1986-1995, 1995-2007, 2007-2009, 2009-2011, and 1986-2011. The diagonal of each matrix gives an idea of the persistence of each class and entries out of the diagonal represent class transition during that period.

In the study from 1986 to 1995, sand was found in 44.77% of the study area in 1995. Low dense vegetation was the major contributor with 5.29% to the new sandy areas. The transformation from low dense vegetation to sand was caused by wind and environmental variations. Therefore, wind was the main factor in the transportation of sand particles to the

TABLE 3. Confusion matrix for validation of 2011 image classification.

	Classes	Ground truth (Pixels)						
		Urban	Vegetation	Water	Sand	Rock	LDV	Commission error
Classified image	Urban	1353	15	0	1	0	0	1.17%
	Vegetation	0	1056	39	0	0	26	5.80 %
	Water	0	0	18	0	0	0	0.0%
	Sand	0	3	4	1346	23	8	2.75%
	Rock	0	23	0	81	1010	0	9.34%
	LDV	7	173	6	0	64	1412	15.04%
	Omission error	0.51%	16.85%	73.13%	5.74%	7.93%	2.35%	
Overall accuracy 92.91%, Kappa coefficient 0.91								

TABLE 4. Surface (km^2) of the classes in the study area between 1986 and 2011.

Class\Year	1986	1995	2007	2009	2011
Urban	13.53	25.54	38.09	38.62	40.41
Vegetation	61.36	20.70	30.34	30.16	35.52
Water	4.12	0.45	0.068	0.15	0.05
Sand	262.71	246.88	236.65	275.52	272.42
Rock	119.58	58.95	101.006	90.63	93.19
LDV	90.08	198.85	145.23	116.32	109.79

arid northwestern part of the region. During the period from 1995 to 2007, from 2007 to 2009, and from 2009 to 2011, the main change was found again from low dense vegetation to sand, causing degradation to critical areas, that include crop fields. In the total period from 1986 to 2011, the sand class had the highest gain with 22.57% in 2011 and it also presented the highest loss with 20.82% of the total land cover change in 1986. That means that this class was the most dynamic one in the change map. The corresponding cross-tabulation matrix shows that the most prominent transition from 1986 to 2011 was a conversion from low dense vegetation to sand, which accounts for 12.08% of the transition. The transition from vegetation to sand had a proportion of 6.10%, and the change from rock to sand was contributed with 4.28% of the total transition. There was also a minimum percentage of urban area converted into sand with a proportion equal to 0.08% of the transition. The dryness during the summer, joined to the presence of strong wind allowed the migration of sand grains from the erg toward the northwestern area under study. The accumulation of those sand particles caused the creation of sand dunes, which could lead to further land degradation.

Table 6 presents the values of Gain, Loss, Persistence, Total change, Swap and Net Change for each LULC class for the period between 1986 and 2011. The land use categories that experienced the highest gains were sand with 22.57%, low dense vegetation with 16.87%, rock 6.08%, and urban 5.56%. The largest losses in the same period were observed for sand with 20.82% and low dense vegetation with 13.29%.

The sand and the low dense vegetation classes showed high levels of Swap with 41.63% and 26.57%, when compared to other classes. That means that these classes are influenced by the movement of the sand grains at a great extent. The erg area at the Southwest of Biskra, Algeria, contains dunes, which are the main source of desertification that threatens crop areas in the North of Biskra.

Water did not show significant change with a Swap of 0.02% and a Net Change of 0.74%, and this was probably caused by its low presence in the South of Algeria.

During the studied period, a great proportion of land showed a significant change in the arid area of Biskra. The land cover transition was higher for sand class, low dense vegetation and the urban class, which was related to the increase of the population. The amount of unaltered land cover between 1986 and 2011 was found equal to 44.16%. Therefore, the studied region showed some kind of change in the 55.74% of the area.

The Loss to Persistence ratio L_p assesses the risk of a land cover to suffer transition as explained in [22]. When the value of L_p is higher than 1, land cover is highly exposed to changes to other land cover class than will persist in time. Urban, water and sand classes presented a value of L_p lower than 1 (shown in Table 7), that confirm the low tendency of transition to other land classes. Vegetation and low dense vegetation classes presented large values of L_p equal to 5.20 and 4.39 respectively, and this fact suggests that these classes were prone to decrease their representation in the future. Therefore, L_p ratio is a very valuable tool to monitor vegetation degradation, which is one of the most critical elements in desertification. Gain to Persistence ratios G_p higher than one indicate a larger chance of class to gain presence [22]. Urban, vegetation and low dense vegetation classes with G_p values equal to 3.14, 2.59 and 5.57, respectively, presented the highest G_p ratios, showing more Gain than Persistence. The G_p value for water, sand and rock was lower than 1, which implied that their Gain values were lower than their corresponding Persistence values during the studied period. The Net Change to Persistence ratio N_p of the urban class was equal to 2.76 and this could be explained by the population growth in Biskra.

In order to validate the change results, overall accuracy and Kappa coefficient was obtained for the changed/unchanged final product. The validation set was different from the training data set used for supervised classification in order to get a rigorous accuracy assessment. For that purpose, 24.55 km^2 (4.45% of the area) of ground truth data with 14471 unchanged pixels and 12807 changed pixels were selected using visual inspection. The changed/unchanged confusion matrix using the pair of images taken at 1986 and

TABLE 5. LULC transition matrices (%): in a) from 1986 to 1995, in b) from 1995 to 2007, in c) from 2007 to 2009, in d) from 2009 to 2011, in e) from 1986 to 2011.

A) 1986-1995	Urban	Vegetation	Water	Sand	Rock	LDV	Total 1995	Gain
Urban	1.54	0.25	0.03	0.98	1.44	0.39	4.63	3.09
Vegetation	0.13	2.17	0.44	0.34	0.61	0.07	3.75	1.58
Water	0.01	0.00	0.00	0.04	0.01	0.01	0.08	0.08
Sand	0.22	0.22	0.05	34.39	4.60	5.29	44.77	10.38
Rock	0.03	0.00	0.00	1.48	9.16	0.01	10.69	1.53
LDV	0.53	8.47	0.22	10.41	5.86	10.58	36.07	25.49
Total 1986	2.45	11.12	0.75	47.65	21.69	16.34	100	42.15
Loss	0.92	8.96	0.74	13.25	12.52	5.76	42.15	
B) 1995-2007	Urban	Vegetation	Water	Sand	Rock	LDV	Total 2007	Gain
Urban	3.69	0.28	0.02	1.58	0.18	1.15	6.90	3.21
Vegetation	0.20	2.91	0.02	0.28	0.08	2.02	5.50	2.59
Water	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.01
Sand	0.21	0.03	0.01	28.04	0.28	14.23	42.80	14.76
Rock	0.32	0.09	0.02	6.28	9.83	1.62	18.15	8.32
LDV	0.21	0.44	0.02	8.40	0.32	16.88	26.27	9.39
Total 1995	4.64	3.75	0.08	44.57	10.69	35.90	100	38.28
Loss	0.94	0.84	0.08	16.53	0.86	19.02	38.28	
C) 2007-2009	Urban	Vegetation	Water	Sand	Rock	LDV	Total 2009	Gain
Urban	5.04	0.21	0.01	0.67	0.28	0.80	7.00	1.96
Vegetation	0.22	4.07	0.00	0.12	0.37	0.68	5.47	1.39
Water	0.00	0.01	0.00	0.00	0.00	0.02	0.03	0.03
Sand	0.62	0.02	0.00	34.87	6.09	8.28	49.88	15.01
Rock	0.17	0.12	0.00	2.47	10.35	3.27	16.39	6.04
LDV	0.85	1.07	0.00	4.71	1.13	13.26	21.02	7.76
Total 2007	6.90	5.50	0.01	42.84	18.21	26.31	100	32.19
Loss	1.86	1.43	0.01	7.97	7.87	13.05	32.19	
D) 2009-2011	Urban	Vegetation	Water	Sand	Rock	LDV	Total 2011	Gain
Urban	5.23	0.31	0.00	0.54	0.09	1.15	7.33	2.10
Vegetation	0.10	4.29	0.02	0.06	0.21	1.73	6.42	2.13
Water	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.01
Sand	0.39	0.19	0.00	41.34	1.70	5.62	49.24	7.90
Rock	0.28	0.06	0.00	3.67	11.86	0.99	16.87	5.01
LDV	0.99	0.61	0.00	4.25	2.48	11.54	19.87	8.33
Total 2009	7.00	5.47	0.03	49.87	16.34	21.03	100	25.47
Loss	1.77	1.17	0.03	8.52	4.48	9.49	25.47	
E) 1986-2011	Urban	Vegetation	Water	Sand	Rock	LDV	Total 2011	Gain
Urban	1.77	0.78	0.03	2.36	1.74	0.65	7.33	5.56
Vegetation	0.18	1.79	0.54	2.05	1.46	0.42	6.44	4.65
Water	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.01
Sand	0.08	6.10	0.02	26.78	4.28	12.08	49.35	22.57
Rock	0.09	0.01	0.01	5.84	10.79	0.13	16.87	6.08
LDV	0.33	2.44	0.15	10.56	3.38	3.03	19.90	16.87
Total 1986	2.45	11.13	0.75	47.60	21.66	16.31	100	55.74
Loss	0.68	9.33	0.75	20.82	10.87	13.29	55.74	

TABLE 6. LULC change parameters within the landscape in 1986 and 2011 (%).

Classes	Total 1986	Total 2011	Gain	Loss	Persistence	Total Change	Swap	Absolute value of Net Change
Urban	2.45	7.33	5.56	0.68	1.77	6.24	1.37	4.88
Vegetation	11.13	6.44	4.65	9.33	1.79	13.98	9.30	4.68
Water	0.75	0.01	0.01	0.75	0.00	0.76	0.02	0.74
Sand	47.60	49.35	22.57	20.82	26.78	43.38	41.63	1.75
Rock	21.66	16.87	6.08	10.87	10.79	16.95	12.16	4.79
LDV	16.31	19.90	16.87	13.29	3.03	30.16	26.57	3.59
Total	100	100	55.74	55.74	44.16	55.74	91.05	20.43

2011 is shown in Table 8. Excellent results with a Kappa coefficient of 0.90 and an overall accuracy equal to 95.15% were obtained. These results show the effectiveness of the change detection methodology in the selected region using Landsat data.

The spatial distribution of land use transitions for the different image pairs is shown in Fig. 4. Many pixels were changed due to urban growth, years of drought, and sand movement with the prevalent air flow from southeastern Sahara. In this zone, topography and wind play an important role in the accumulation of sand at the bottom of the first Atlas slopes. Fig. 4 shows class transition during the overall period 1986-2011, where a large brown area describes the transition from other classes to sand. This fact confirms a very fast progression of the sand dunes that can precede a desertification process in the North of the zone under study.

In this study, we have shown that the previous programs were unsuccessful in its goal of limiting the desert growth and soil erosion has increased lately. Therefore, more effective planning and monitoring tools should be made by

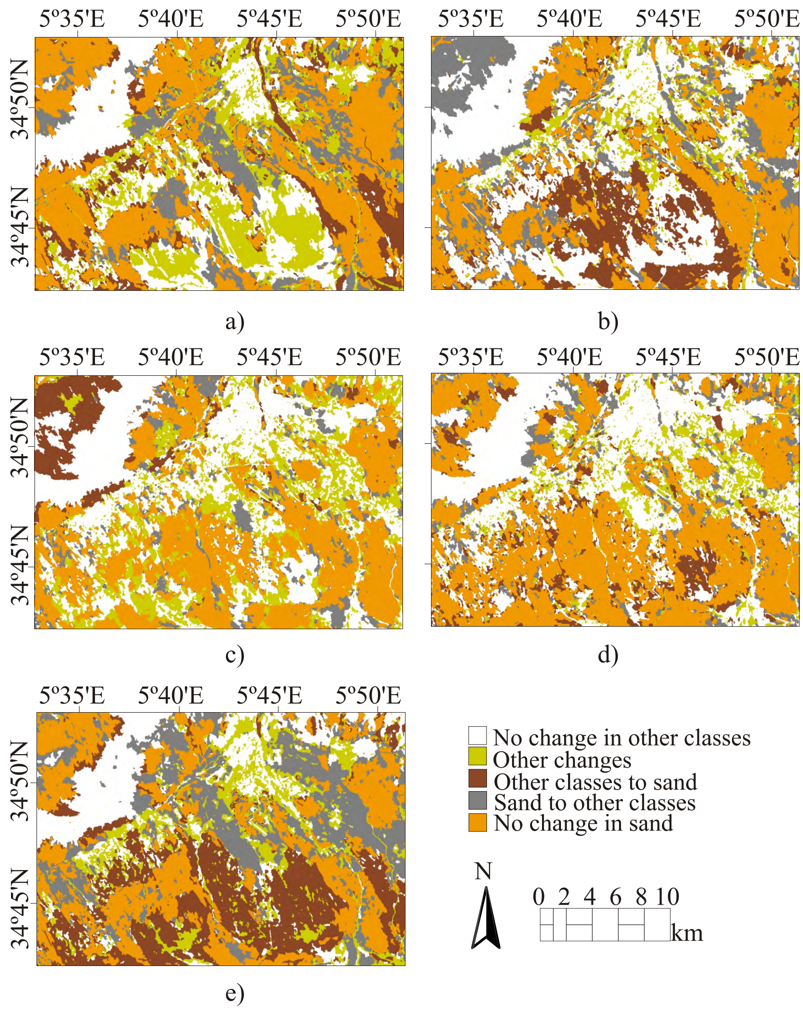

FIGURE 4. Distribution of LULC change in the following pairs of images: in a) using the pair 1986-1995, in b) 1995-2007, in c)2007-2009, in d) 2009-2011 and in e) using the complete period 1986-2011.

TABLE 7. Gain to Persistence ratio G_p, Loss to Persistence ratio L_p, and Net Change to Persistence ratio N_p in the period 1986 to 2011.

Land cover	G_p	L_p	N_p
Urban	3.14	0.39	2.76
Vegetation	2.59	5.20	2.61
Water	0.00	0.00	0.00
Sand	0.84	0.78	0.07
Rock	0.56	1.01	0.44
LDV	5.57	4.39	1.18

TABLE 8. Change confusion matrix in the period of study 1986-2011.

Number of pixels		Reference			
		Unchanged pixels	Changed pixels	Sum	Commission error
Classified result	Unchanged pixels	13932	783	14715	5.32%
	Changed pixels	539	12024	12563	4.29%
	Sum	14471	12807	27278	
	Omission error	3.72%	6.11%		
Overall accuracy 95.15%, Kappa coefficient 0.90					

the Algerian authorities for an efficient protection against desertification in the area. A simple and accessible methodology using open access data like the one presented in this work could help the local authorities in planning future initiatives against desertification.

VI. CONCLUSION

This work has presented a simple methodology for the study of the desertification process in Biskra (Algeria) during 25 years (from 1986 to 2011) using freely available data and local information. This town is chosen because it is critically threatened by desertification, taking into account the local combination of wind and topography. A methodology based on post-classification change detection has been introduced. The use of a tool like the Feature Extraction of ENVI software with a low number of classes simplifies the classification procedure. The most relevant change indices have been identified for our application. Finally, change transition maps have been obtained for the analyzed periods. The method accuracy has been measured by classification and change detection confusion matrices. It is remarkable that very accurate results are obtained with a low amount of training pixels, that represents low operator cost. The most important output for the user is a combination of change maps in graphical support and a compact form of indices and ratios that can be easily processed. This kind of methodology using freely available data enables to obtain key information for local and regional authorities with very low economic cost. The obtained results show that the problem is clearly detected its causes can be carefully evaluated in a complex scenario. Once a study of this kind is performed, a better plan for the establishment of a natural barrier could be designed with important benefits for the population in the area. Studies of this type are very interesting for local authorities in regions where economic activities and population are threatened by climatic and environmental factors.

ACKNOWLEDGMENT

The authors would like to thank the United States Geological Survey (USGS) for offering Landsat data through the Glovis tool and the Met Office for the meteorological data provided under the license of Russian Federal Service for Hydrometeorology and Environmental Monitoring.

REFERENCES

[1] A. Grainger, "The role of science in implementing international environmental agreements: The case of desertification," *Land Degradation Development.*, vol. 20, no. 4, pp. 410–430, 2009.

[2] J. Li *et al.*, "Spatiotemporal variations in grassland desertification based on landsat images and spectral mixture analysis in Yanchi county of Ningxia, China," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 7, no. 11, pp. 4393–4402, Nov. 2014.

[3] S. Li and Y. Xie, "Investigating coupled impacts of climate change and socioeconomic transformation on desertification by using multitemporal landsat images: A case study in central Xilingol, China," *IEEE Geosci. Remote Sens. Lett.*, vol. 10, no. 5, pp. 1244–1248, Sep. 2013.

[4] S. Hirano, "UNCED managing fragile ecosystems: Combating desertification and drought," in *Proc. Rep. United Nat. Conf. Environ. Develop.*, Rio de Janeiro, Brazil, 1992, pp. 104–118.

[5] M. K. Tolba, "Desertification in Africa," *Land Use Policy.*, vol. 3, no. 4, pp. 260–268, 1986.

[6] A. Aubréville, *Forêts et Désertification de l'Afrique Tropicale*. Paris, France: Société d'éditions géographiques, maritimes et coloniales, 1949.

[7] M. T. Alberto Marini, *Desertification and Risk Analysis Using High and Medium Resolution Satellite Data*. Dordrecht, The Netherlands: Springer, 2009.

[8] D. Nedjraoui and B. Slimane, "La désertification dans les steppes Algériennes: Causes, impacts et actions de lutte," *VertigO—la revue électronique en sciences de l'environnement*, vol. 8, no. 1, pp. 1–15, 2008.

[9] N. Boulghobra, T. Hadri, and M. Bouhana, "Using Landsat imagery for monitoring the spatiotemporal evolution of sanding in dryland, the case of in-Salah in the Tidikelt (Southern Algerian Sahara)," *Geograph. Techn.*, vol. 9, no. 1, pp. 1–9, 2014.

[10] J. Srinivasulu and A. Kulkarni, "Estimation of spectral reflectance of snow from IRS-1D LISS-III sensor over the Himalayan terrain," *Proc. Indian Acad. Sci. Earth Planetary Sci.*, vol. 113, no. 1, pp. 117–128, 2004.

[11] W. Y. Yan and A. Shaker, "Radiometric correction and normalization of airborne LiDAR intensity data for improving land-cover classification," *IEEE Trans. Geosci. Remote Sens.*, vol. 52, no. 12, pp. 7658–7673, Dec. 2014.

[12] X. She, C. Li, and Y. Sun, "Comparison and analysis research on geometric correction of remote sensing images," in *Proc. Int. Conf. Image Anal. Signal Process.*, 2010, pp. 169–175.

[13] R. Reji and R. Vidya, "Comparative analysis in satellite image registration," in *Proc. IEEE Int. Conf. Comput. Intell. Comput. Res.*, Dec. 2012, pp. 1–6.

[14] G. M. Foody and A. Mathur, "A relative evaluation of multiclass image classification by support vector machines," *IEEE Trans. Geosci. Remote Sens.*, vol. 42, no. 6, pp. 1335–1343, Jun. 2004.

[15] C. Huang *et al.*, "Use of a dark object concept and support vector machines to automate forest cover change analysis," *Remote Sens. Environ.*, vol. 112, no. 3, pp. 970–985, 2008.

[16] C.-C. Chang and C.-J. Lin, "Training V-support vector classifiers: Theory and algorithms," *Neural Comput.*, vol. 13, no. 9, pp. 2119–2147, 2001.

[17] A.-O. Yeh and X. Li, "An integrated remote sensing and GIS approach in the monitoring and evaluation of rapid urban growth for sustainable development in the Pearl River Delta, China," *Int. Planning Stud.*, vol. 2, no. 2, pp. 193–210, 1997.

[18] F. Yuan, K. Sawaya, B. Loeffelholz, and M. Bauer, "Land cover classification and change analysis of the Twin cities (Minnesota) metropolitan area by multitemporal Landsat remote sensing," *Remote Sens. Environment.*, vol. 98, nos. 2–3, pp. 317–328, 2005.

[19] J. Jensen, *Introductory Digital Image Processing: A Remote Sensing Perspective*, 2nd ed. Englewood Cliffs, NJ, USA: Prentice-Hall, 1996.

[20] D. Yuan and C. Elvidge, "NALC land cover change detection pilot study: Washington D.C. area experiments," *Remote Sens. Environment.*, vol. 66, no. 2, pp. 166–178, 1998.

[21] R. Pontius, Jr., E. Shusas, and M. McEachern, "Detecting important categorical land changes while accounting for persistence," *Agricult. Ecosyst. Environ.*, vol. 101, nos. 2–3, pp. 251–268, 2004.

[22] A. K. Braimoh, "Random and systematic land-cover transitions in northern Ghana," *Agricult. Ecosyst. Environ.*, vol. 113, nos. 1–4, pp. 254–263, 2006.

[23] R. Congalton, "A review of assessing the accuracy of classifications of remotely sensed data," *Remote Sens. Environ.*, vol. 37, no. 1, pp. 35–46, 1991.

SOUFIANE ABDELAZIZ AZZOUZI received the master's degree in industrial computing from University Abdelhamid Ibn Badis of Mostaganem in 2012. He is currently working toward the Ph.D. degree in telecommunication with Universitat Politècnica de València. From 2013 to 2016, he was an ERASMUS Grant student with Universitat Politècnica de València.

ANA VIDAL-PANTALEONI received the Telecommunication Engineering and Ph.D. degrees from Universitat Politècnica de València. She joined the European Space Agency for two years as a Research Trainee, where her main activity was the study and implementation of software for synthetic aperture radar (SAR) image processing. She is currently an Assistant Professor with Universitat Politècnica de València. Her interests are SAR data processing and remote sensing classification for Earth observation.

HADJ ADDA BENTOUNES received the Ph.D. degree in physics of plasmas from University of Orsay, Paris XI, in 1984. He is also a Graduate with the Higher School of Electricity, Gif/Yvette, Paris. He has been a Professor with Université Abdelhamid Ibn Badis de Mostaganem, Algeria, since 1985. His main subjects of interest are materials physics and environmental systems. He is also the President of the Scientific Council of the Mediterranean Foundation of Sustainable Development.