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Detecting land use/land cover changes and forest degradation: A case study of the lower Soummam valley, northern Algeria

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Abstract: The environment is characterised by subtle and major mutations that cause changes in land use/land cover. Analysis of its dynamics and identification of vulnerable areas are critical to maintaining ecosystem services. The aim of this research is to quantify and qualify land cover dynamics over a 30-year period. It will also highlight forest degradation from a supervised classification of Landsat satellite imagery (L5 TM1987, L7 ETM+ 2000, and L8 OLI/TIRS 2019). The dynamics of land use/land cover were investigated by a maximum likelihood approach using geographic information system (GIS) and remote sensing (RS). Six major land use and land cover (LULC) types were mapped (build-up, agriculture, forest, clearing, matorral and olive cultivation). The classification reports made it possible to assess a reduction in forest cover (from 14 470.11 ha to 5 203.26 ha) and an increase in buildings (from 6 033.69 ha to 9 515.61 ha), and agricultural land (from 9 517.59 ha to 12 338.19 ha). The results were validated by a kappa coefficient of 0.93, 0.91, and 0.96, which showed that the model had successfully predicted LULC changes. We anticipate that the results will provide a basis for decision-making as well as a starting point for further in-depth studies in sustainable management and development of natural resources in the study region.

Keywords: change detection; deforestation; dynamics; geographic information system (GIS) remote sensing

Land cover changes directly impact forest ecosystems, goods and services (Navarro Cerrillo et al. 2019). Despite the biological potential of large valleys, there are many reasons for their transformation. Population growth and inappropriate management practices are considered the main causes (Sangare et al. 2020). It has led to increased demand for natural resources, which has affected land use and land cover (LULC) in different ways (Long, Leveiller 2016). At the same time, the surrounding agricultural land intended for food resources is increasing, and deforestation is active (Byun, Chang 2020), affecting sustainable development, disrupting ecological

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functions and initiating processes that generate environmental problems (Izakovičová et al. 2018). There are many issues related to LULC (Huang et al. 2020). Literature shows that related studies are complex and difficult to analyse and review, but at the same time they are necessary for decision support in land use planning and management (Barau, Qureshi 2015). Land use and land cover changes (LULCC) are seen as a fundamental variable that influences the physical and human environment (Kilama et al. 2020), dramatically affecting Earth-atmosphere interactions, ecosystem services, climate change, biogeochemical cycles and biodiversity (Chu 2020; Ji et al. 2021). Decades of research have revealed the global environmental impacts of LULCC (Chu 2020). For example, natural vegetation in the Mediterranean region has been strongly affected by human activities for millennia (Xystrakis et al. 2017). Recent research has revealed the impact of LULCC around the world. For example, in many African cities; ecological sustainability is continuously threatened by intensive land cover changes caused by unplanned urbanisation (Akubia et al. 2020). LULCC coupled with climate change has directly affected the distribution of an important tree family in the Philippines (Pang et al. 2021). Land cover change can affect the risk of flooding in a peri-urban environment as in the case of the metropolitan area of Rome in Italy (Recanatesi, Petroselli 2020), as well as stream flow and sediment yield in the Koga watershed (Ayele et al. 2023), and also can impact soil degradation (Ma et al. 2023). Several research studies have been carried out on LULCC, among which we cite the study of Juliev et al. (2019) in the Bostanlik district of Uzbekistan, which describes significant changes occurring in a major class of land use and land cover of this area and observes an increase in forest. A study carried out in the grasslands of Rio de la Plata from 2000 to 2014 (Baeza, Paruelo 2020) showed a strong process of land use change, mainly due to the advance of the agricultural frontier at the expense of grassland. Satellite imagery and geographic information system (GIS) have led to several works dealing with LULCC (Shen et al. 2015). Satellite imagery is an essential tool for monitoring the evolution of LULC over time and space (Boulaassal et al. 2020). Examples of research using integrated GIS and remote sensing include the case studies of Sangare et al. (2020) in the Korola watershed (Mali), where land use maps were developed using Landsat satellite imagery classification and the geographic information system. These maps show that the watershed has undergone a depth change of land use, largely due to human activity. The study by Fang et al. (2022) highlights the impact of changes on ecosystem services in ecologically fragile regions. A very significant change was observedin the Bedadung watershed as a result of human-induced activities (Hakim et al. 2023).

In northern Algeria, unsustainable logging practices, urban expansion, and the demand for agricultural land, driven by population growth and economic factors, are causing the transformation of forests and natural habitats into developed areas and farmland (Amrouni et al. 2022; Hind et al. 2022). Our study area, with its agricultural activities, urbanisation, industrialisation, oil mills, sandpits, and public dumps, has become a frontline of alarming degradation, the impact and extent of which remains unknown. The unchecked human exploitation of these ecosystems, persisting without restraint, has now reached a critical threshold. Faced with the urgent need for conservation measures, decision-makers are grappling with an increasing demand for information.

In general, LULCC identification is crucial for evaluating global, regional, and local environmental change. Monitoring land use and land cover changes in the lower Soummam valley is integral to sustainable development, environmental protection, and the well-being of the region's communities. This effort not only contributes to a deeper understanding of the region's dynamics but also aids policymakers in developing regulations and guidelines for sustainable land-use practices. It directs reforestation efforts to potential areas, aligning with the United Nations Sustainable Development Goals by enhancing our understanding of interactions between ecosystems, biodiversity, and sustainable development. In the context of global changes, humanity deals with several challenges in this century such as climate change. The main indicator of climate change is CO_2 emissions, which increase with deforestation. This study could provide insights into the local impacts of climate change, strengthening research on global climate variations.

Despite growing awareness of the climate change, global deforestation trends have continued to accelerate in recent years. This is leading to a rapid degradation of soils and terrestrial ecosystems, with associated declines in biodiversity and productivity.

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This study represents a contribution to the restoration of degraded ecosystems in the lower Soummam valley. Specifically, its aims to analyse the spatio-temporal dynamics and changes in land use using Landsat images from the years 1987, 2000, and 2019. The results will serve as a reference point for in-depth studies on impacts and future modelling of land use and land cover changes (LULCC). Additionally, they will serve as support tools for decision-makers, assisting in informed decision-making processes.

MATERIAL AND METHODS

Study area. The lower Soummam valley shown in Figure 1 is located in the northern central part of Algeria between 36°43'N and 05°04'E. It covers an area of about 808.5 km^2, of which only 0.75 km^2 is plain, all the rest being a forested mountain area (cork forests occupying the high mountains, shrub formations of kermis oak, holm oak, and Aleppo pine formations). The Mediterranean climate has two levels, namely the humid one on the northern slope with rainfall higher than 900 mm per year, and the sub-humid one in adret with an average rainfall of 600 mm to 900 mm per year. The topography of the study area is characterised by elevations ranging from 200 m a.s.l. to 1 400 m a.s.l. (Figure 1D). The region contains a dense hydrographical network of temporary and permanent wadis that drain into the main wadi, Soummam wadi. Human settlements take the form of small villages of rarely more than 3 000 people, built on hills and ridges.

Data collection. The data used in this study consisted of Landsat satellite imagery collection 1 level 1, freely downloaded from the Earth Explorer (USGS) website Landsat archives (USGS 2017). The selection process focused on the use of images acquired during the dry season (Karnieli et al. 2014), which allowed differentiation between the different types of land cover, especially vegetation (Suleiman et al. 2017). Each image in Figure 2 contains spectral bands and an MTL file in a single folder. The MTL file describes the characteristics of the images. In addition, during visits to the study area, 387 ground

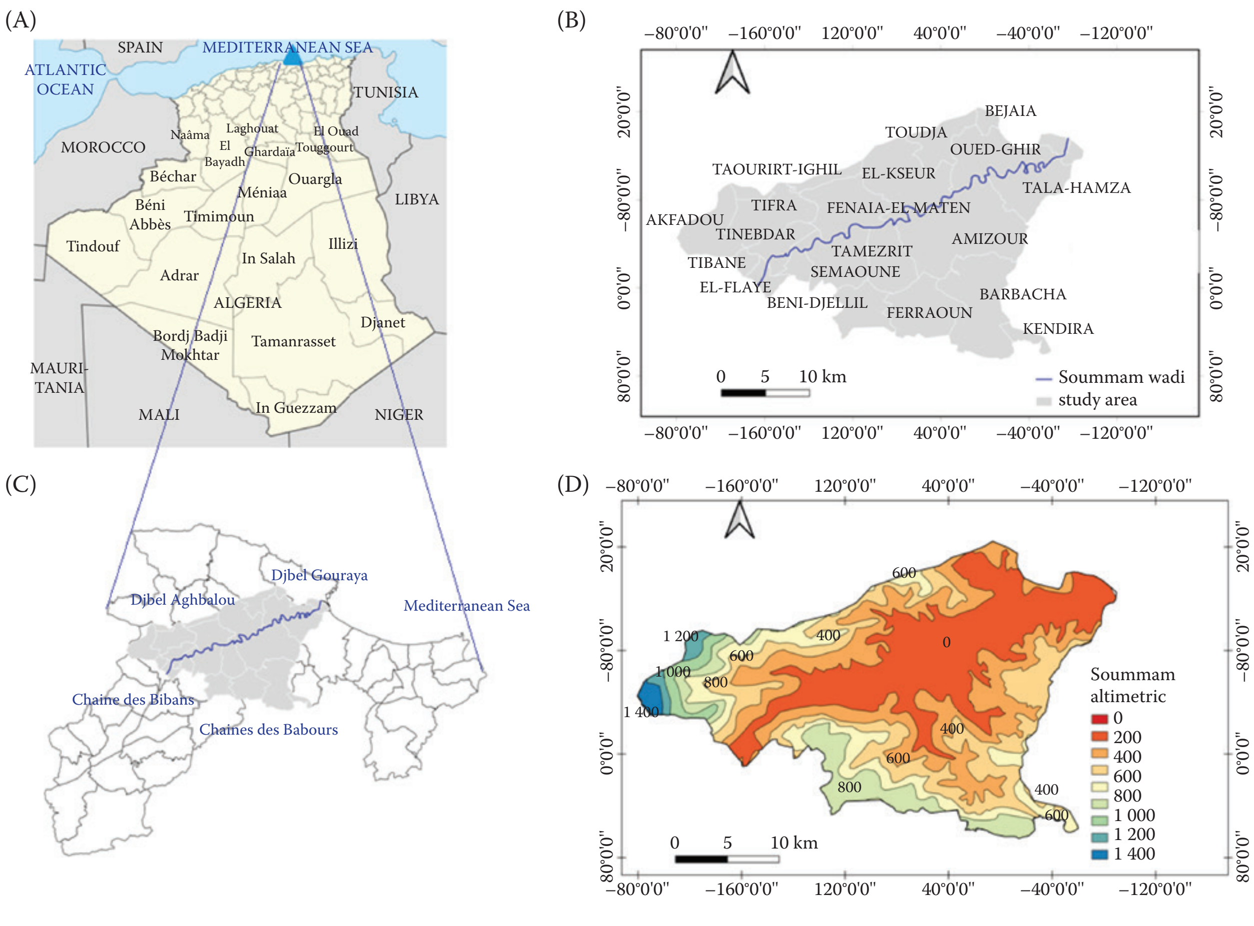

Figure 1. Study area showing the location of the lower Soummam valley

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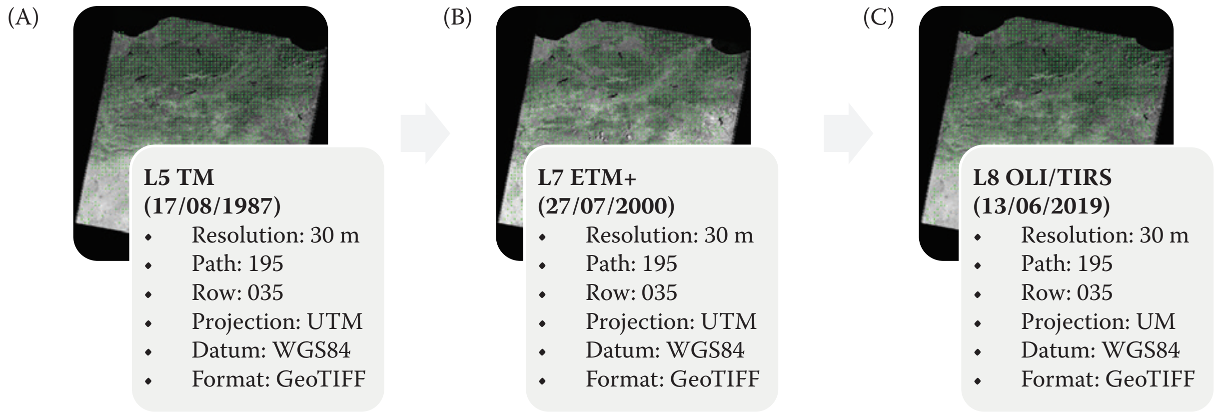

Figure 2. Landsat archive image from (A) 1987, (B) 2000, and (C) 2019

control points were recorded throughout the valley using a Global Positioning System (GPS) receiver (Garmin, USA) with an accuracy of 5 m.

Data pre-processing. QGIS information system (Version 3.4.3, 2018) was used for image processing. Each image underwent simultaneous atmospheric correction and conversion of DN values to radiance values [TOA (top of atmosphere) reflectance]. For the atmospheric correction, we used the DOS (dark object subtraction) method, which is widely used (Chavez Jr. 1989).This method allows to suppress the atmospheric effects on the spectral data, thus allowing the comparison between multi-temporal images (Vittek et al. 2014). At the end of the process, we used the SCP (Semi-Automatic Classification Plugin) multiple clip raster of QGIS and the boundary map shape file to clip the different spectral bands.

Image classification and change detection. The first step in classification was to create a band set by assigning three spectral bands to each of the three primary colours (RGB). This allowed preliminary distinction between vegetation and other types of land use. When we selected 4-3-2, we saw that the image colours on the map changed and the vegetation was highlighted in red. For L5 TM 1987 and L7 ETM+ 2000 images, we have selected the 1, 2, 3, 4, 5, 7 bands and (1E-6m) wavelength, in μm (microns). For the L8 OLI/TIRS 2019 image, we have selected 2, 3, 4, 5, 6, 7 bands. The selected wavelength allowed us to display the value of *NDVI* (normalised difference vegetation index) value on the image. This is the *NDVI* value of the pixel under the cursor on the map. The image L8 OLI/TIRS 2019 was used as a reference for the classification of L5 TM 1987 and L7 ETM+ 2000. The *NDVI* was useful to identify spectrally clean pixels because dense vegetation such a forest has higher *NDVI* values compared to less dense vegetation such as olive and matorral. The actual *NDVI* values would, by definition, lie between –1 and +1, with increasing positive values indicating increasing green vegetation and negative values indicating non-vegetated surface features such as water and barren land. The normalised difference vegetation index (*NDVI*) is automatically calculated by the SCP of QGIS according to a formula mathematically written

$$NDVI = \frac{NIR - R}{NIR + R},$$

it is calculated as the ratio between the red (*R*) and near infrared (*NIR*) values.

In Landsat (Versions 4–7, 2018):

$$NDVI = \frac{Band\,4 - Band\,3}{Band\,4 + Band\,3}$$

In Landsat (Versions 8–9, 2018):

$$NDVI = \frac{Band\,5 - Band\,4}{Band\,5 + Band\,4}$$

where:
NDVI – normalised difference vegetation index.

A zero indicates no vegetation and a value close to +1 (0.8–0.9) indicates the highest possible density of green leaves (Landsat Missions 2018).

Secondly, the .csv file of the collected GPS points was overlaid on each satellite image to see which pixels on these images corresponded to one type of land cover or another. In the ROI generation of SCP Dock, we selected several regions of interest (ROIs) for

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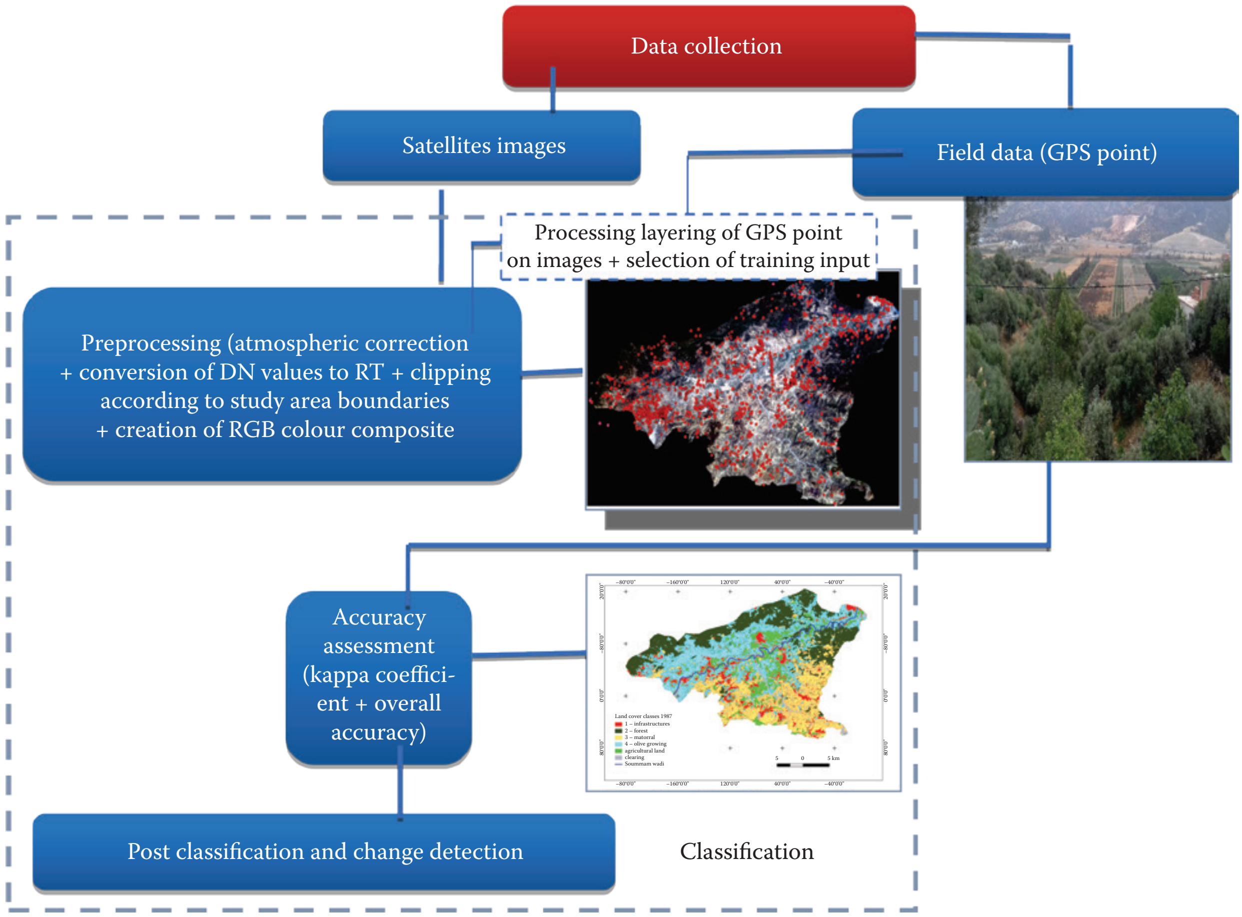

Figure 3. Methodological approach for mapping change detection

each land cover class. The stored ROI is shown on the map as a dark polygon. As for the classification itself, the images were being classified according to the so-called supervised method. It is the most commonly used method (Zhao et al. 2012). We used the maximum likelihood method, which is also used by several authors, namely Hussain and Karuppannan (2023); Seyam et al. (2023); Shekar and Mathew (2023). Images classified in raster format were filtered and vectorised. Change detection was automatically calculated using the post-classification method of the SCP extension in QGIS by superimposing two raster classifications of Date 1 and Date 2, of which Date 1 is taken as the reference (Figure 3).

Accuracy assessment. To assess the accuracy of the cartographic products, the data from the ground control points were compared with the classified data. The classified images were validated using ground control points collected in the field. A confusion matrix was also created to determine the probability of correctly identifying pixels and the accuracy of pixels' classification (Congalton 1991). Congalton (1991) explained the principle of this matrix, which gives two main values, namely the overall accuracy and the kappa coefficient (Xu et al. 2012). The overall accuracy characterises the proportion of well-classified pixels and the kappa coefficient characterises the ratio between the well-classified pixels and the total number of the probed pixels. The kappa coefficient (Figure 4) is always confined bounded between –1 and 1. Figure 4 shows the scale used to interpret its values (Santos 2010).

Figure 4. Kappa coefficient values

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RESULTS

Land use and land cover dynamics

Mapping of land use and land cover change in the study area. The overall accuracy reached 92%, 90%, and 95% with kappa coefficients of 0.93, 0.91, and 0.96, respectively, which is greater than 90% for the three dates, respectively. The land cover maps show the spatial distribution of six land use types. The classification reports estimate that the area occupied by each of these classes varies from one date to another. According to the data collected, the following trends can be observed: Infrastructure increased from 6 033.7 ha in 1987 to 9 227.25 ha in 2000. In 2019, this expansion exceeded 9 515.7 ha. The forest class experienced a sharp decline from 14 470.1 ha in 1987 to only 5 203.2 ha in 2000, before recovering to 7 675.1 ha in 2016. Agricultural land increased from 9 517.6 ha in 1987 to 11 484.9 ha in 2000 and 12 338.2 ha in 2019. Scrub land increased significantly from 15 397 ha to 16 924 ha. The area under olive trees decreased from 21 707 ha in 1987 to 15 615 ha in 2019. Finally, for clearing, an increase in area was observed in 2000 and 2019 compared to 1987, with the area increasing from 2 113 ha to 7 171 ha. In 1987 (Figure 5), olive cultivation dominated the landscape from upstream to downstream and from the Soummam wadi to the medium-slope. In the mountainous ar-

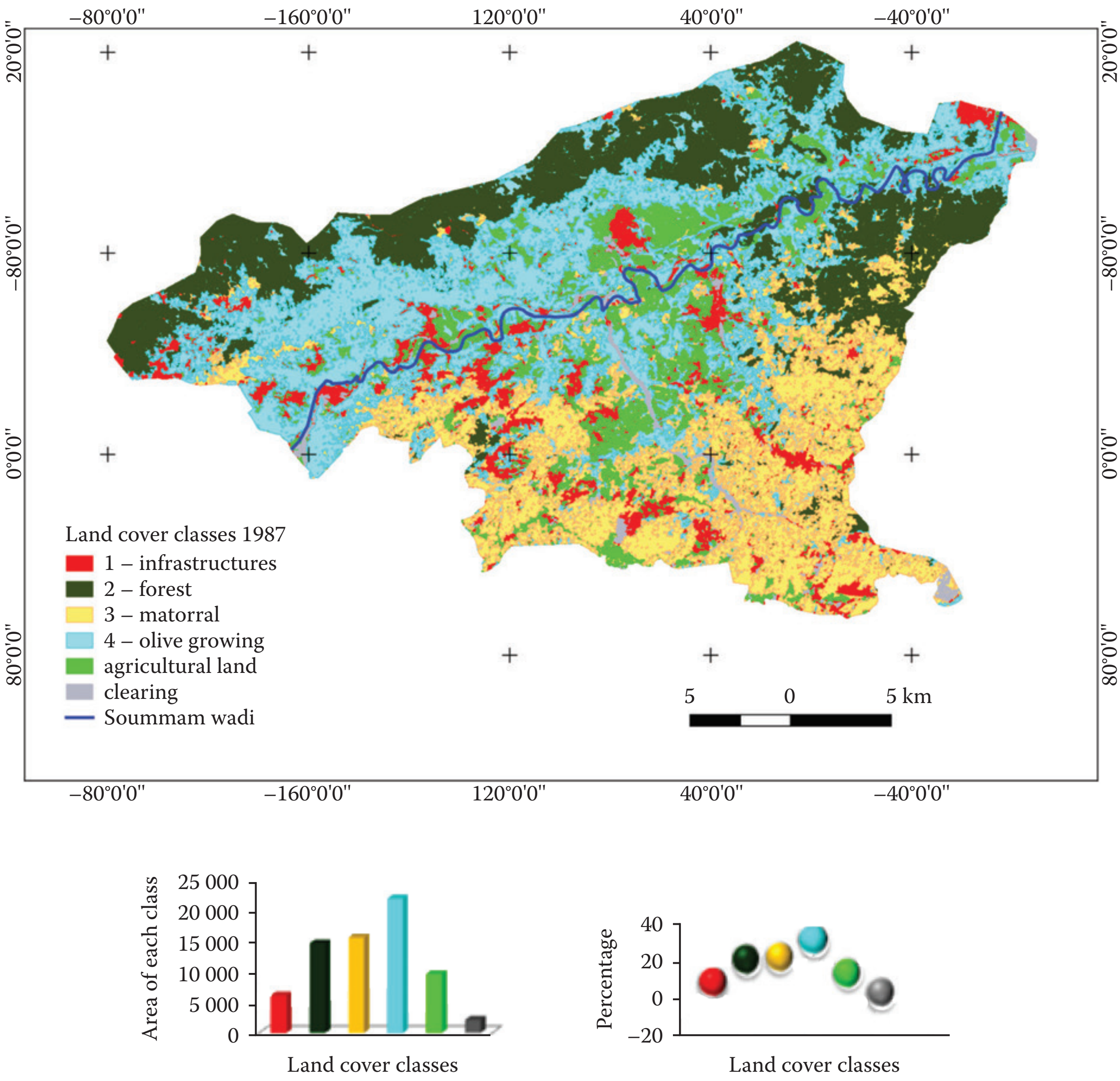

Figure 5. Land use and land cover maps of lower Soummam valley in 1987

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eas to the North, the forest covered 14 470.11 ha. Infrastructure and clearings represented only 9% and 3%, respectively.

In 2000 (Figure 6), olive cultivation remained the dominant class with 31% of the total area. Woodland was converted with only 7% of the total area (5 203.26 ha). Matorral replaced it with 31% of the total area. There was also a slight increase in agricultural land and clearings which reached 17% and 11% of the total area, respectively. The area of infrastructures has increased to about 3 000 ha.

The year 2019 (Figure 7) map shows a significant reduction in olive cultivation, which occupies only 24% compared to 31% in 2000. Forests are recovering again to reach 11% of the total area. As far as infrastructure is concerned, we find that it is increasingly concentrated in large cities. There is an increase in agricultural land (18%) compared to 2000.

Spatiotemporal quantification of deforestation and change of LULC. Post-classification was carried out, and transition matrix was obtained (Table 1). The analysis of the transition matrix from 1987 to 2000 (Table 1) shows that out of 14 470.11 ha, only 4 857.93 ha of forest did not change, the rest of the area is transformed into matorral (6 847.65 ha) and clearing (1 686.05 ha). Of the matorral (15 397.29 ha), only 4 270.77 ha remained unchanged. An area of 10 667.25 ha, 3 737.43 ha and 24.21 ha remains unchanged for

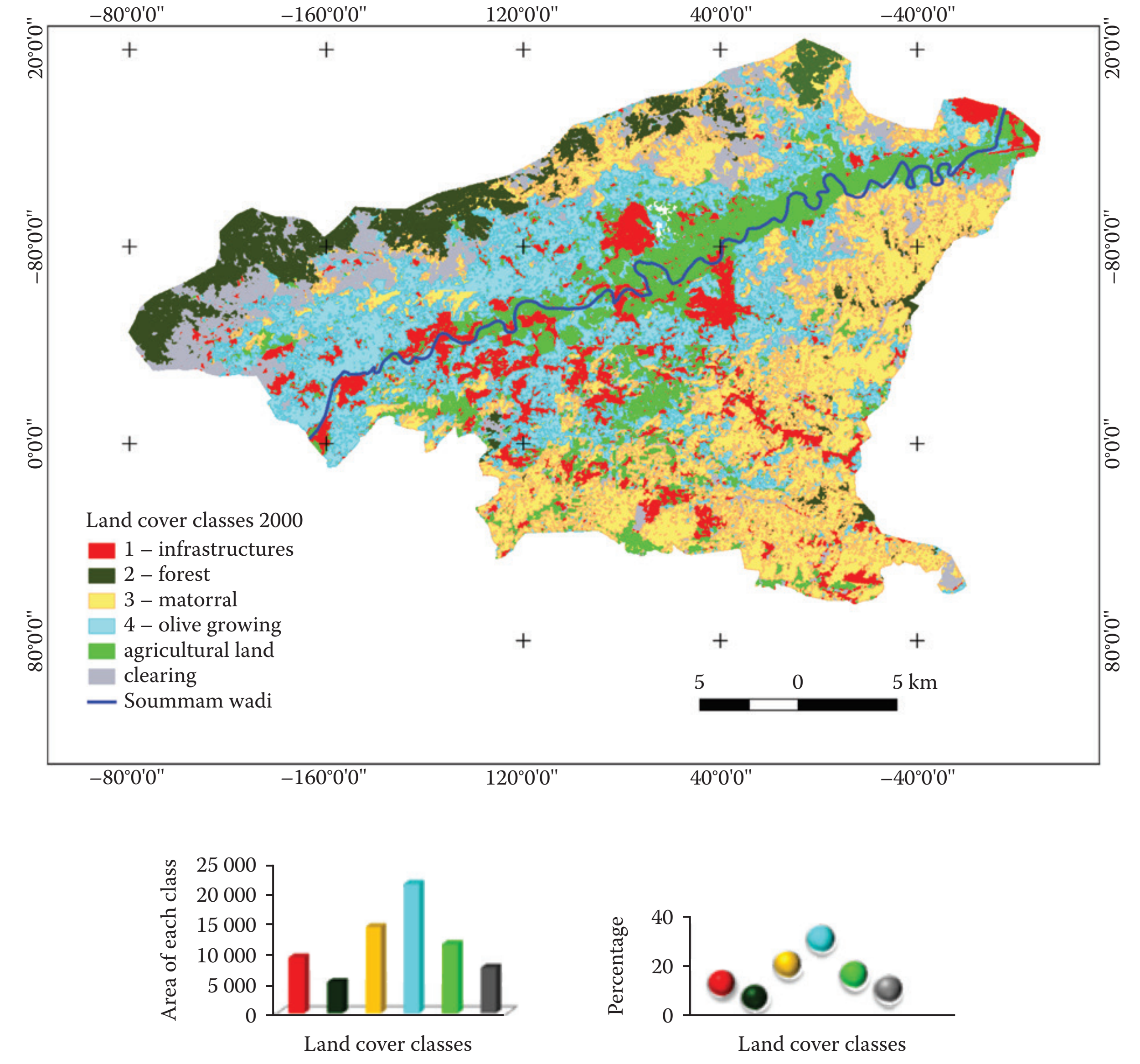

Figure 6. Land use and land cover maps of lower Soummam valley in 2000

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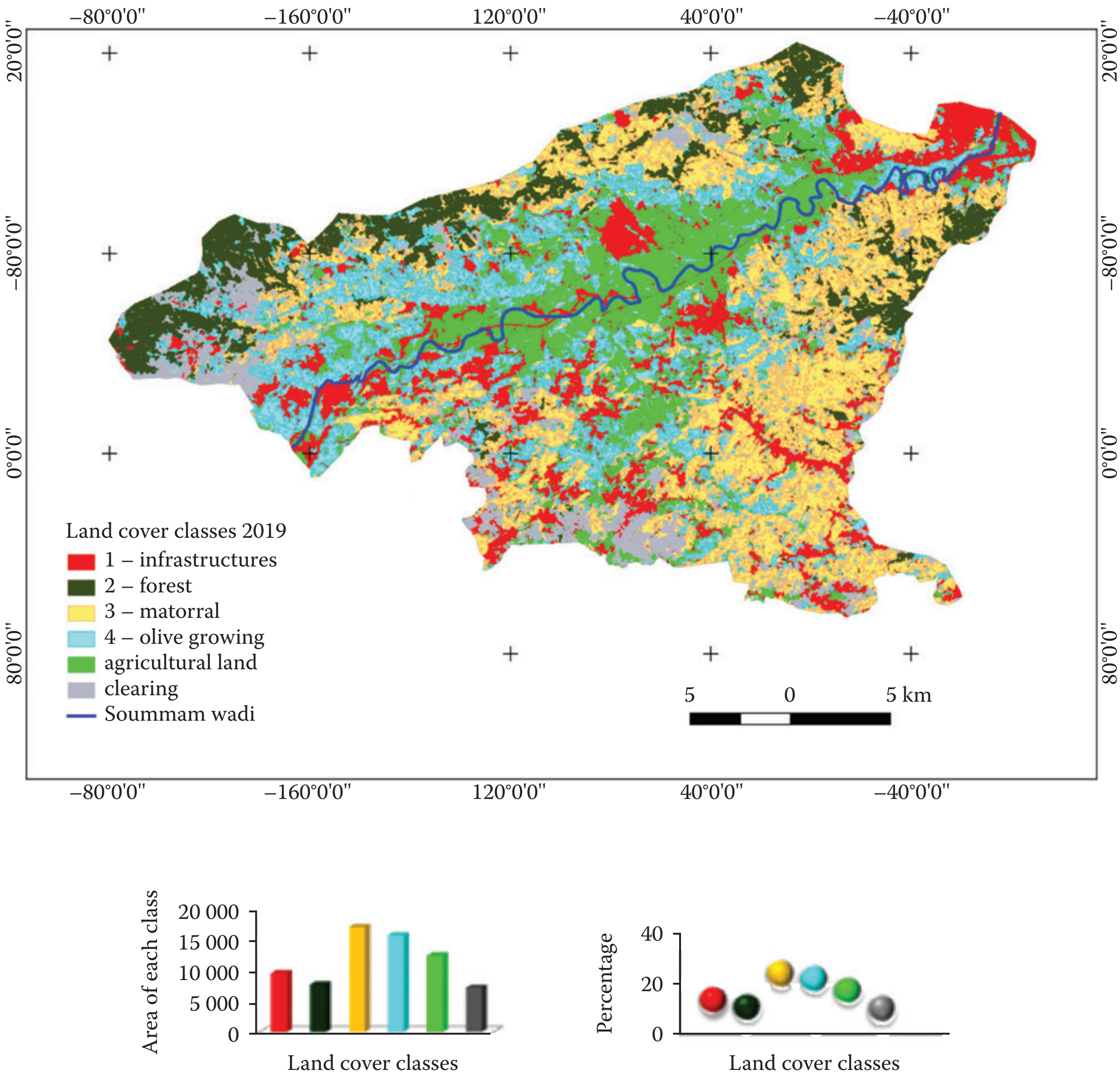

Figure 7. Land use and land cover maps of lower Soummam valley in 2019

olive cultivation, agriculture and clearing, respectively. From 2000 to 2019, the results show that out of 5 203.26 ha, only 907.92 ha of forest did not change, the rest of the area was transformed into matorral (3 478.02 ha) and clearing (454.86 ha). Of the matorral (14 323.23 ha), only 5 345.55 ha remained unchanged. An area of 13 998.15 ha, 4 137.66 ha, and 2 117.7 ha remain unchanged for olive growing, agriculture and clearing, respectively.

Table 1 indicates a strong dynamic between classes. Three major changes are (*i*) the increase in agricultural land and infrastructure, (*ii*) the decrease in the olive cultivation area, and (*iii*) the degradation of the forest. It shows a transition of LULC towards a more anthropogenic and agricultural environment at the expense of forested areas.

From 1987 to 2000, around 9 612.09 ha of forest have been transformed to matorral (6 847.65 ha), clearing (1 686.15 ha) and olive (441.99 ha). Agricultural land increased (from 9 517.59 ha in 1987 to 11 484.9 ha in 2000 to reach 12 338.19 ha in 2019). Two essential classes contributed to this change, namely olive (2 893.05 ha) and matorral (2 637.81 ha).

Olive cultivation dominated the landscape in 1987 and 2000. By 2019, however, olive cultivation had moved into second place, with the matorral taking the lead with 23% and 24% of the total area, respectively.

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Table 1. Change detection from 1987 to 2019 (ha)

Classes	Infrastructure	Forest	Matorral	Olive	Agriculture	Clearing	1987
Infrastructure	**6 033.69**	0	0	0	0	0	6 033.69
Forest	44.37	**4 857.93**	6 847.65	441.99	592.02	1 686.15	14 470.11
Matorral	748.26	107.37	**4 270.77**	6 341.94	2 637.81	1 291.14	15 397.29
Olive	903.06	220.41	3 014.46	**10 667.25**	2 893.05	4 009.23	21 707.46
Agriculture	2 787.75	2.52	94.23	2 702.16	**3 737.43**	193.50	9 517.59
Clearing	1 146.60	0.27	74.34	359.01	509.04	**24.21**	2 113.47
2000	9 227.25	5 203.26	14 323.23	21 451.50	11 484.90	7 549.56	69 239.61
Classes	infrastructure	forest	matorral	olive	agriculture	clearing	2000
Infrastructure	**9 227.25**	0	0	0	0	0	9 227.25
Forest	5.13	**907.92**	3 478.02	249.57	107.55	454.86	5 203.26
Matorral	122.67	1 010.97	**5 345.55**	4 503.06	944.73	2 396.25	14 323.23
Olive	891.81	473.94	1 670.85	**13 998.15**	2 205.54	2 211.21	21 451.50
Agriculture	2 962.26	12.24	343.08	3 620.97	**4 137.66**	408.69	11 484.90
Clearing	741.51	226.08	524.16	2 862.81	1 077.30	**2 117.70**	7 549.56
2019	9 515.61	7 675.11	16 924.05	15 615.45	12 338.19	7 171.29	69 239.61

Bold – no change in the class

From 1987 to 2019, infrastructure areas continued to expand in the two periods and all classes have contributed to this change:

– From 1987 to 2000: forest (44.37 ha), matorral (748.26 ha), olive (903.06 ha, agriculture (2 787.75 ha), clearing (1 146.6 ha).

– From 2000 to 2019: agriculture (2 962.26 ha), olive (891.81 ha), clearing (741.51 ha).

DISCUSSION

In this study, we have analysed the landscape dynamics in the lower Soummam valley, northern Algeria, highlighting forest degradation. The data used were selected according to the purpose of the study. The downloaded images are freely available on the United State Geological Survey [USGS (Suleiman et al. 2017)]. These satellite images are characterised by their homogeneity in terms of spatial resolution, projection, datum and format. On the other hand, if our data are of different scales and resolutions, it becomes necessary to remove this difference in order to make comparisons between data (Bamba et al. 2008). The supervised classification method is very advantageous (Dewan, Yamaguchi 2009). Thanks to the maximum likelihood classifier, it has allowed us to obtain reliable results (Fichera et al. 2012). In addition, the confusion matrix was considered as the best classification accuracy assessment according to Thapa and Murayama (2009) and Usman et al. (2015). The resulting matrix gave a kappa coefficient that is greater than 0.70 for all classifications. Several authors consider its values to be statistically satisfactory (Zhao et al. 2012).

Land use and land cover change is the result of the interaction of socioeconomic, institutional, and environmental factors (Chu 2020). Driving forces vary in time and space, according to specific human-environment conditions (Verburg et al. 2003). In general, changes in land use and land cover are driven by a combination of factors that act gradually and factors that act intermittently (Lambin et al. 2001).

In lower Soummam valley, human pressure is causing three major changes: the increase in agricultural land, the decrease in the olive cultivation area in the hills and the degradation of forest. The decline of olive cultivation in the hills is due to the neglect by the rural population which is leaving the countryside for other areas closer to economic opportunities and urban services. There are huge differences between urban and rural areas in terms of infrastructure, employment opportunities, education levels, and health care. So, cities attract a significant proportion of the rural population by way of permanent and circulatory migration, and the wages earned in the city are often remitted by migrants to rural homelands, in some

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cases transforming the use of croplands and creating 'remittance landscapes' (Lambin et al. 2001).

According to Xystrakis et al. (2017) such socio-economic changes play an important role in changes in LULC. In the case of climatic hazards, these factors are at the origin of land use change in the lower valley, specifically:

– Extension of agricultural land, especially traditional agriculture, which is generally not far from the forest (Mekasha et al. 2020). The significant increase in cultivated land in the sub catchment can be explained by the increase in the local population. The Department of Planning and Budget Monitoring (DPSB) reports that the number of inhabitants per km^2 went from 412 258 in 1987 to 476 135 in 2019. As a result, more land will be dedicated to housing, transportation, and industry. According to the study made by Abadie (2018) on Mediterranean forests, reforestation can take place in case of abundance of traditional agriculture and grazing.
– Another issue is the sensitivity of the vegetation to forest fires, considering that the forests of this zone are mainly composed of flammable species such as the cork oak, also in the last thirty years [1985–2012 (Meddour-Sahar, Bouisset 2013)]. This devastation has caused cuts in the connectivity of ecosystems and the proliferation of invasive plant species compared to primary vegetation types; the same observation was made by Mezgebu and Workineh (2017).
– In addition, the change in rainfall affects negatively the forest ecosystem as it may probably affect the density of tree plants, as well as their biological ability to regenerate naturally, as is the case in Savanah woodland in Nigeria (Suleiman et al. 2017).

This area, which provides goods and services essential to human survival, including biodiversity, natural resource reserves, fresh water, cultivated land and other services, has been severely affected by these changes.

The study carried out by Mahdi and Kheta (2020) reveals that the degradation of vegetation exposed the soil to water erosion. A similar study in Malaysia shows the impact of LULC on the water quality of rivers and how conversion of land to agricultural areas greatly increases the introduction of eroded soils into water bodies (Razali et al. 2018).

To better explain these variations, we agree on the need to integrate other sources of information about causes, which may be at the origin of the modifications within landscape. As suggested by Herzog and Lausch (2001), administrative entities could be subdivided into ecological sub-regions for which environmental indicators could be measured. This would allow a comparison between regions of similar ecology but located in different administrative units. In addition, the authorities should develop an environmentally sensitive form of agriculture and industry that combines traditional and modern practices in order to develop both the environment and the economy.

Scientists associated with the LUCC research community share a common, geographic, interest: the future of the land, while LUCC simulation models are effective and reproducible tools for analysing both the causes and consequences of future land-use dynamics under various scenarios.

Much of the integration of knowledge on land-use change takes place through spatial models that aim to explain the causes, locations, consequences, and trajectories of land-use change (Verburg, Veldkamp 2005). The diversity of disciplinary origins of the researchers contributing to the LULCC study has resulted in wide range of different modelling approaches and techniques to support the analysis of the causes and consequences of land-use change in order to better understand the functioning of the land-use system and to support land-use planning and policy. We can conclude from this study that the lower Soummam valley has suffered serious degradation which could be exacerbated in the future. Indeed, it is desirable to continue this work to predict changes by simulation for sustainable development, as well as for more in-depth studies, such as studies on the impact of LULCC on the environment. The results of this study deepen the debate on the search for solutions for sustainability of the landscape.

CONCLUSION

The objective of our study was to qualitatively and quantitatively analyse the dynamics of land use and land cover changes over a 30-year period, with a specific focus on highlighting forest degradation. The findings from our research clearly demonstrate tangible changes in the Soummam valley. The examination of land cover maps reveals a transformation of the landscape into an anthropogenic environment, where human activities have significantly altered the natural trends.

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Between 1987 and 2000, olive cultivation dominated the landscape from upstream to downstream and from the edges of the Soummam wadi to areas with medium slopes. However, by 2019, olive cultivation had taken the second position, with matorral now occupying the leading position at 23% and 24% of the total area, respectively. Over the three decades from 1987 to 2019, infrastructure and agricultural areas continued to expand, while forested areas experienced a notable decrease. This marked shift in land use indicates a transition toward a more anthropogenic and agricultural environment, at the expense of forested areas. These transformations are primarily attributed to population growth, resulting in significant environmental modifications. In order to prevent the loss of ecological resources, environmental protection is essential to ensure the sustainability of this area. A more in-depth exploration across different scales would enhance the efficiency of our approach, providing more precise and detailed insights to explain the various processes leading to the regression of the land.

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REFERENCES

Abadie J. (2018): Ecologie historique des forêts méditerranéennes: Déterminants du changement du couvert forestier et effets des usages passés sur les sols et la flore actuels. [Ph.D. Thesis.] Marseille, Aix-Marseille University. (in French)

Akubia J.E.K., Ahmed A., Bruns A. (2020): Assessing how land-cover change associated with urbanisation affects ecological sustainability in the Greater Accra Metropolitan Area, Ghana. Land, 6: 182.

Amrouni Y., Berrayah M., Gelabert P., Vega-Garcia C., Hellal B., Rodrigues M. (2022): Recent land cover trends in the transition region of Tiaret, Algeria. Catena, 210: 105861.

Ayele A.H., Aga A.O., Belayneh L., Wanjala T.W. (2023): Hydrological responses to land use/land cover changes in Koga watershed, upper Blue Nile, Ethiopia. Geographies, 3: 60–81.

Baeza S., Paruelo J.M. (2020): Land use/land cover change (2000–2014) in the Rio de la Plata grasslands: An analysis based on MODIS NDVI time series. Remote Sensing, 12: 381.

Bamba I., Munyemba K.F., Defourny P., Vancutsem C., Ngongo L.M., Bogaert J. (2008): Analyse de la structure spatiale des forêts au Katanga. Annales de la Faculté des Sciences Agronomiques de l'Université de Lubumbashi, 2: 12. (in French)

Barau S.A., Qureshi S. (2015): Using agent-based modelling and landscape metrics to assess landscape fragmentation in Iskandar Malaysia. Ecological Processes, 4: 8.

Boulaassal H., Anaki S., Yazidi O.A., Maatouk M., Wahbi M. (2020): Cartographie des changements de l'occupation du sol entre 2002 et 2016 à partir des images Landsat. Cas de la région Tanger Tetouan Al-Hoceima (Maroc). African Journal on Land Policy and Geospatial Sciences, 3: 14–31. (in French)

Byun Y.U., Chang E.C. (2020): Impact of land use land cover change on East Asia. In: 22nd EGU General Assembly Copernicus Meetings, held online, May 4–8, 2020.

Chavez Jr. P.S. (1989): Radiometric calibration of Landsat Thematic Mapper multispectral images. Photogrammetric Engineering and Remote Sensing, 9: 1285–1294.

Chu D. (2020): Introduction. In: Chu D.: Remote Sensing of Land Use and Land Cover in Mountain Region. Singapore, Springer Singapore: 1–13.

Congalton R.G. (1991): A review of assessing the accuracy of classifications of remotely sensed data. Remote Sensing of Environment, 1: 35–46.

Dewan A.M., Yamaguchi Y. (2009): Using remote sensing and GIS to detect and monitor land use and land cover change in Dhaka Metropolitan of Bangladesh during 1960–2005. Environmental Monitoring and Assessment, 150: 237–249.

Fang Z., Ding T., Chen J., Xue S., Zhou Q., Wang Y., Wang Y., Huang Z., Yang S. (2022): Impacts of land use/land cover changes on ecosystem services in ecologically fragile regions. Science of The Total Environment, 831: 154967.

Fichera R.C., Modica G., Pollino M. (2012): Land cover classification and change-detection analysis using multitemporal remote sensed imagery and landscape metrics. European Journal of Remote Sensing, 45: 1–18.

Hakim F.L., Indarto I., Hidayah E., Cahyono B.E. (2023): Five decades of land use and land cover change in Bedadung watershed: Learning from Landsat data. AIP Publishing: AIP Conference Proceedings, 2583: 060007.

Herzog F., Lausch A. (2001): Supplementing land-use statistics with landscape metrics: Some methodological considerations. Environmental Monitoring and Assessment, 72: 37–50.

Hind M., M'hammed S., Djamal A., Zoubida N. (2022): Assessment of land use-land cover changes using GIS, remote sensing, and CA-Markov model: A case study of Algiers, Algeria. Applied Geomatics, 14: 811–825.

Huang H., Xue Y., Chilukoti N., Liu Y., Chen G., Diallo I. (2020): Assessing global and regional effects of recon-

https://doi.org/10.17221/86/2023-JFS

structed land-use and land-cover change on climate since 1950 using a coupled land-atmosphere-ocean model. Journal of Climate, 33: 8997–9013.

Hussain S., Karuppannan S. (2023): Land use/land cover changes and their impact on land surface temperature using remote sensing technique in district Khanewal, Punjab Pakistan. Geology, Ecology, and Landscapes, 7: 46–58.

Izakovičová Z., Špulerová J., Petrovič F. (2018): Integrated approach to sustainable land use management. Environments, 5: 37.

Ji Q., Liang W., Fu B., Zhang W., Yan J., Lü Y., Yue C., Jin Z., Lan Z., Li S., Yang P. (2021): Mapping land use/cover dynamics of the Yellow River basin from 1986 to 2018 supported by Google Earth Engine. Remote Sensing, 13: 1299.

Juliev M., Pulatov A., Fuchs S., Hübl J. (2019): Analysis of land use land cover change detection of Bostanlik District, Uzbekistan. Polish Journal of Environmental Studies, 28: 3235–3242.

Karnieli A., Qin Z., Wu B., Panov N., Yan F. (2014): Spatio-temporal dynamics of land-use and land-cover in the Mu Us sandy land, China, using the change vector analysis technique. Remote Sensing, 6: 9316–9339.

Kilama L.J., Bamutaze Y., Mwanjalolo J.G.M., Waiswa D., Pilesjö P., Mukengere E.B. (2020): Impacts of land use and land cover change in response to different driving forces in Uganda: Evidence from a review. African Geographical Review, 40: 378–394.

Lambin E.F., Turner B.L., Geist H.J., Agbola S.B., Angelsen A., Bruce J.W., Coomes O.T., Dirzo R., Fischer G., Folke C., George P.S., Homewood K., Imbernon J., Leemans R., Xiubin L., Moran E.F., Mortimore M., Ramakrishnan P.S., Richards J.F., Skånes H., Xu J. (2001): The causes of land-use and land-cover change: Moving beyond the myths. Global Environmental Change, 11: 261–269.

Landsat Missions (2018): Landsat Normalized Difference Vegetation Index. Reston, USGS. Available at: https://www.usgs.gov/landsat-missions/landsat-normalized-difference-vegetation-index

Long N., Leveiller T. (2016): Comment les politiques d'urbanisation se traduisent-elles dans le paysage urbain: Une approche par les métriques spatiales. VertigO, 16: 1–2. Available at: https://www.erudit.org/en/journals/vertigo/2016-v16-n2-vertigo02855/1038189ar/ (in French)

Ma S., Wang L.J., Wang H.Y., Zhao Y.J., Jiang J. (2023): Impacts of land use/land cover and soil property changes on soil erosion in the black soil region, China. Journal of Environmental Management, 328: 117024.

Mahdi M., Kheta K. (2020): Estimation de l'érosion hydrique des sols sur le sous bassin versant de Boussellam – Soummam. [MSc. Thesis.] M'sila, University of M'sila. (in French)

Meddour-Sahar O., Bouisset C. (2013): Les grands incendies de forêt en Algérie: Problèmes humains et politiques publiques dans la gestion des risques. Méditerranée. Revue géographique des pays méditerranéens, 121: 33–40. (in French)

Mekasha S.T., Suryabhagavan K.V., Gebrehiwot M. (2020): Geo-spatial approach for land-use and land-cover changes and deforestation mapping: A case study of Ankasha Guagusa, Northwestern, Ethiopia. Tropical Ecology, 61: 550–569.

Mezgebu A., Workineh G. (2017): Changes and drivers of afro-alpine forest ecosystem: Future trajectories and management strategies in Bale eco-region, Ethiopia. Ecological Processes, 6: 1–13.

Navarro Cerrillo R.M., Vieira D.J.E., Ochoa-Gaona S., Jong B.H.J., Serrano M.M.D. (2019): Land cover changes and fragmentation in mountain neotropical ecosystems of Oaxaca, Mexico under community forest management. Journal of Forestry Research, 30: 143–155.

Pang S.E.H., Alban J.D.T.D., Webb E.L. (2021): Effects of climate change and land cover on the distributions of a critical tree family in the Philippines. Scientific Reports, 11: 1–13.

Razali A., Ismail S.N.S., Awang S., Praveena S.M., Abidin E.Z. (2018): Land use change in highland area and its impact on river water quality: A review of case studies in Malaysia. Ecological Processes, 7: 19.

Recanatesi F., Petroselli A. (2020): Land cover change and flood risk in a peri-urban environment of the metropolitan area of Rome (Italy). Water Resources Management, 34: 4399–4413.

Sangare H., Daou I., Keita I. (2020): Évolution de l'occupation du sol dans le bassin versant de Korola (région de Sikasso, Mali) à partir des images satellitaires Landsat. La Revue Ivoirienne des Sciences et Technologie, 36: 193–207. (in French)

Santos F. (2010): Le kappa de Cohen: Un outil de mesure de l'accord inter-juges sur des caractères qualitatifs. Bordeaux, UMR 5199 PACEA: 5. Available at: https://docplayer.fr/71703588-Le-kappa-de-cohen-un-outil-de-mesure-de-l-accord-inter-juges-sur-des-caracteres-qualitatifs.html (in French)

Seyam H.M.M., Haque M.R., Rahman M.M. (2023): Identifying the land use land cover (LULC) changes using remote sensing and GIS approach: A case study at Bhaluka in Mymensingh, Bangladesh. Case Studies in Chemical and Environmental Engineering, 7: 100293.

Shekar P.R., Mathew A. (2023): Detection of land use/land cover changes in a watershed: A case study of the Murredu watershed in Telangana state, India. Watershed Ecology and the Environment, 5: 46–55.

Shen G., Nasser A., Wang Z., Ma C., Gong J. (2015): Spatial-temporal land-use/land-cover dynamics and their impacts on surface temperature in Chongming Island of Shanghai, China. International Journal of Remote Sensing, 15: 4037–53.

https://doi.org/10.17221/86/2023-JFS

Suleiman M.S., Wasonga O.V., Mbau J.S., Elhadi Y.A. (2017): Spatial and temporal analysis of forest cover change in Falgore Game Reserve in Kano, Nigeria. Ecological Processes, 6: 11–13.

Thapa R.B., Murayama Y. (2009): Examining spatiotemporal urbanization patterns in Kathmandu Valley, Nepal: Remote sensing and spatial metrics approaches. Remote Sensing, 1: 534–556.

USGS (2017): Global Visualization Viewer (GloVis). Reston, USGS. Available at: http://glovis.usgs.gov/

Usman M., Liedl R., Shahid M.A., Abbas A. (2015): Land use/land cover classification and its change detection using multi-temporal MODIS NDVI data. Journal of Geographical Sciences, 25: 1479–1506.

Verburg P.H, Veldkamp A. (2005): Introduction to the special issue on spatial modeling to explore land use dynamics. International Journal of Geographical Information Science, 19: 99–102.

Verburg P.H, Groot W.T., Veldkamp A.J. (2003): Methodology for multi-scale land-use change modelling: Concepts and challenges. In: Dolman A.J., Verhagen A., Rovers C.A. (eds): Global Environmental Change and Land Use. Dordrecht, Springer: 17–51.

Vittek M., Brink A., Donnay F., Simonetti D., Desclée B. (2014): Land cover change monitoring using Landsat MSS/TM satellite image data over West Africa between 1975 and 1990. Remote Sensing, 6: 658–676.

Xu Y.M., LiY., Ouyang W., Hao F.H., Ding Z.L., Wang D.L. (2012): The impact of long-term agricultural development on the wetlands landscape pattern in Sanjiang Plain. Procedia Environmental Sciences, 13: 1922–1932.

Xystrakis F., Psarras T., Koutsias N. (2017): A process-based land use/land cover change assessment on a mountainous area of Greece during 1945–2009: Signs of socio-economic drivers. Science of the Total Environment, 587: 360–370.

Zhao Y., Zhang K., Fu Y., Zhang H. (2012): Examining land-use/land-cover change in the Lake Dianchi Watershed of the Yunnan-Guizhou Plateau of southwest China with remote sensing and GIS techniques: 1974–2008. International Journal of Environmental Research and Public Health, 9: 3843–3865.

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