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Land Use/Land Cover change detection in the wetlands. A case study: Al-Aba Oasis, west of Ras Tanura, Kingdom of Saudi Arabia

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Abstract: In addition to unthinking anthropogenic meddling with the subtle ecological balance, the territories of Al-Aba Oasis are witnessing various Land Use and Land Cover (LULC) changes. Comprehending LULC is a central facet of upholding a sustainable, friendly, and fit environment. This paper presents a spatiotemporal study of land use and land cover trends in the wetlands of Al-Aba Oasis, an ecologically sensitive area in the west of Ras Tanura in the east of the Kingdom of Saudi Arabia. The study area faces several environmental problems, including the rise in groundwater levels, expansion of agricultural land, urban expansion, and anthropogenic interference with the ecological balance. In this paper, a verified representation of the changes in each LULC class has been made using satellite images. Remote sensing imagery is helpful for studying temporal changes in LULC and providing environmental monitoring data. We analysed Landsat-5 and Sentinel-2 imagery for 1985, 2000, and 2021. The overall precision besides the kappa coefficient for precision assessment indicates the relevance of the LULC classification. LULC map products were overlaid and interpreted based on post-classification change detection methods. The LULC aspects were classified into six classes: water body, waterlogged area, sabkha soil, sandy area, cultivated area, and built-up area. The results prove that from 2001 to 2021, the extension of the built-up area (2.6%) and agricultural land (6.85%) is directly proportional to the population growth (36.5% between 1992 and 2004) and the sabkhas are subject to constant metamorphosis under the joint influence of urban and agricultural land expansion. 100 samples were collected for the years 1986, 2001, and 2021 to assess the accuracy. We reviewed the outcomes of this study by evaluating the accuracy (77, 81, and 84% for 1986, 2001, and 2021 respectively) and comparing the field truth using a GPS (Global Positioning System) sensor. The results of this study are useful in the development of environmental policies during the development of sustainable territorial development programmes of the oasis.

Keywords: geographic information systems (GIS), oasis, post-classification, remote sensing, sabkha

INTRODUCTION

Wetlands are complex habitats composed of a wide variety of natural and artificial habitats. Whether they are coastal or not, wetlands are critically important for biodiversity [Coletti *et al.* 2017; van den Broeck *et al.* 2015; Xu *et al.* 2019]. They also perform numerous ecosystem functions. For example, they play a vital role in the hydrological cycle (water storage, groundwater recharge, evaporation, and binding of pollutants thanks to their self-purification potential) and the carbon cycle, with each type of wetland having a different role to play [Adhikari *et al.* 2009; Bullock, Acreman 2003]. They are widely perceived as unhealthy spaces, especially because of the presence of mosquitoes [Chouari 2013; Johnson *et al.* 2012] although this view is contested by the recent research [Dale, Connelly 2012; De Bell *et al.* 2017; Mitsch *et al.* 2015].

Wetlands by nature are often located in coastal areas or in valleys, which are regions favoured by socioeconomic development. Wetlands have been harshly impacted by anthropic activities, including agricultural expansion and intensification, as well as urbanisation [CHOUARI 2013; 2015; MONDAL *et al.* 2017]. The eastern coast of Saudi Arabia, owing to its greater aridity, features numerous temporary wetlands, such as sabkhas, and temporary lakes created by cultivation and urbanisation. The study of sabkhas in the Al-Aba Oasis is particularly interesting. The complexity of these wetlands is related to their location in a tension between siltation, urbanisation, and agriculture, as well as their involvement in improving the living environment of citizens. They are ideal for studying the dynamics of land use due to natural influences (water, vegetation) and human influences (urbanisation and agriculture). The use of cartography through geomatics is an appropriate approach to show the dynamics of land use. In these environments, land use is an indicator of people's relationship with their natural environment. This is why it is imperative to detect changes in land use in order to integrate environmental issues into the imperatives of economic development besides meeting the immediate needs of populations without jeopardising the aspirations of future generations [O'BRIEN *et al.* 2017]. Identifying changes in land use in the wetlands of Al-Aba Oasis and their surroundings can be highly beneficial to the management of these complex environments.

Geoinformatics is an important tool for monitoring spatiotemporal changes in land use. Remote sensing tools and geographic information systems (GIS) provide a complete view of Land Use and Land Cover (LULC) data. Remote sensing and GIS techniques have been used since the 1990s in order to map dynamics and provide a decision-making tool, especially in terms of land use planning and agricultural land management [ANSARI, GOLABI 2019; PRASAD, RAMESH 2019; REBELO *et al.* 2007]. Remote sensing offers a safe and efficient method of collecting information to map the type area dedicated to farming crops and quantify it. This method makes it possible to follow changes in the different classes of land use in time and space [MAHMUD *et al.* 2011; OZESMI, BAUER 2002]. A comprehensive assessment of LULC variations is indispensable to interpreting landscape dynamics besides ensuring sustainable management. Modelling and planning via remote sensing make it possible to monitor changes in land use at a lower cost and with greater precision.

To obtain a decision-making tool that would enable local authorities to protect or even develop the ecosystems that make up wetlands, this research aims at understanding recent changes in land cover and land use. Remote sensing, which is a preferred analysis and monitoring tool for the study of land cover and land use changes, offers new perspectives and methodological challenges for this research problem. Therefore, it seems essential that the scientific community should be able to have "spatially explicit quantitative data" on the way in which humans have modified land use in the recent decades. The methodological approach applied for this purpose consists of the spatiotemporal analysis of land cover changes in Al-Aba Oasis wetlands in 1986, 2001, and 2021. The main hypothesis is that the joint use of remote sensing and GIS improves land cover classification. Moreover, the identification of land cover classes improves the evaluation and prediction related to people's relationship with their environment.

The novelty is that this research aims at understanding the dynamics of land cover and land use as a complex system based on the "human–environment" relationship at both local and regional levels, as well as identifying the main factors responsible for the changes. Thus, the following questions will help us in this research: To what extent can we identify past and current changes in land cover and land use that have significant impacts on the environment, local population, and local territory? What are the tools and methods that best allow them to be identified, characterised, and monitored over time? What are the factors that motivate and promote these changes in land cover and land use? What are and will be the impacts of these changes?

This research concerns an experimental site located in eastern Saudi Arabia. The 451.29 km^2 study area includes part of the Oasis of Al-Aba, west of Ras Tanura and northwest of Al-Qatif. Al-Aba Oasis is dotted with several large sabkhas, including extensive reed beds. With water bodies, waterlogged areas, and sabkha soil, the current wetland area reaches 298.26 km^2, or about 66% of the total study area. The oasis of Al-Aba is characterised by an arid climate with a very hot summer. The average monthly temperature varies between 20.5 and 35.5°C and the average annual rainfall is 65.4 mm [NCM 2022]. The altitude of the oasis varies between 2 and 10 m a.m.s.l. and the slope ranges between 0 and 0.5%. The Al-Aba Oasis is composed of urban and rural settlements. Its main classes of land use include water bodies, waterlogged areas, sabkha soils, sandy areas, cultivated areas, and built-up areas (Fig. 1).

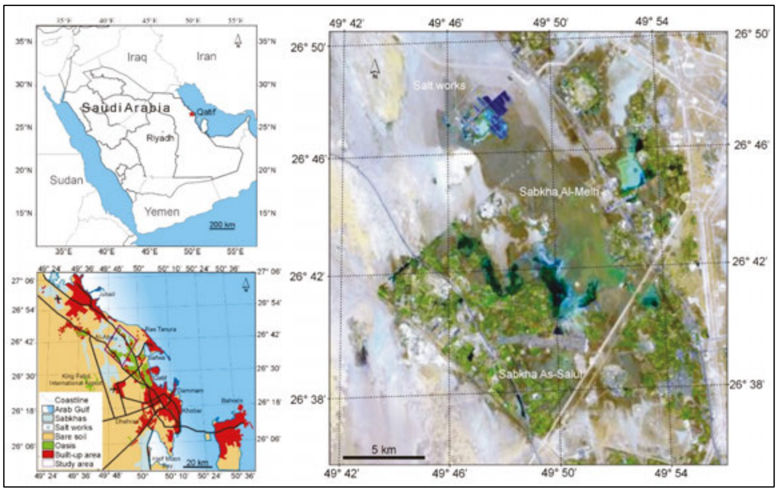

Fig. 1. Location map of the study area; source: own elaboration

MATERIALS AND METHODS

PREPROCESSING OF THE IMAGES

The present study was conducted to assess the development of LULC classes around sabkhas Al-Meleh and As-Salul in Al-Aba Oasis by means of the geographic information system and remote sensing. The selected images were enriched, captured, and geo-referenced. Using auxiliary field data, topographic maps, and Google Earth imagery, geometric enrichment, and data validation were performed (Tab. 1).

Data acquisition was followed by data processing. Therefore, we geo-referenced and calibrated the images, which was essential for diachronic analysis. The images were geometrically rectified and projected into the UTM/WGS 84/ ZONE 39 North cartographic projection system. Landmark coordinates on the 1986 imagery were gathered using a GPS (Garmin model 62St).

The rectified 2021 images were used as a reference for image-to-image calibration of the previous images. To validate the geometric corrections, the images were overlaid with several data on the screen to verify the overlay of notable elements and infrastructures on the site or nearby (road, vegetation, buildings). A satisfactory overlay of the images allows for extracting different layers in order to define the landscape units and study their evolution in different periods (1986, 2001, and 2021).

Radiometric calibration enabled the conversion from digital count values to reflectance values (physical values) using the formula proposed by Chander *et al.* [2009]. Image histogram enhancement was performed to extend the intensity levels or shades of grey from 0 to 255. To maintain the brightness value of the unaffected pixels, the algorithm of a nearby pixel was used to resample the data. A pre-set value was assigned to the output pixel from the neighbouring pixel to preserve the subtleties and extremes in the pixel values. A multilayer image was created by superimposing the visible and infrared bands of the images. A buffer zone of 300 m was added to the image at the edge of the study area.

Information about LULC transformations is an essential starting point for resource management and vulnerability assessment of oases. A well-designed methodology was used for this study. The land cover maps were produced according to a supervised classification using the ERDAS IMAGINE 9.2 software.

EVALUATION METHOD FOR LAND USE/LAND COVER CHANGE

Classifications were followed by a change detection study to distinguish unlikely trajectories with precision. Once the images were classified and improved, the quality of post-processing was evaluated to validate the corrections (Fig. 2).

Table 1. The inputs for classifying images in 1986, 2001, and 2021

Image	Band and feature	Wave length (μm) and description	Resolution (m)
Landsat 5 (TM) (1986) and Landsat 5 (TM) (2001)	band 1 – visible blue	0.45–0.52	30
	band 2 – visible green	0.52–0.60	30
	band 3 – visible red	0.63–0.69	30
	band 4 – Near-Infrared (NIR)	0.76–0.90	30
	band 5 – Short-Wave Infrared (SWIR 1)	1.55–1.75	30
	band 6 – thermal	10.40–12.50	120
	band 7 – Short-Wave Infrared (SWIR 2)	2.08–2.35	30
Sentinel 2 (2021)	band 1 – ultra blue (coastal and aerosol)	0.421–0.457	60
	band 2 – blue	0.439–0.535	10
	band 3 – green	0.537–0.582	10
	band 4 – red	0.646–0.714	10
	band 5 – Visible and Near Infrared (VNIR)	0.694–0.714	20
	band 6 – Visible and Near Infrared (VNIR)	0.731–0.749	20
	band 7 – Visible and Near Infrared (VNIR)	0.768–0.796	20
	band 8 – Visible and Near Infrared (VNIR)	0.767–0.808	10
	band 8A – Visible and Near Infrared (VNIR)	0.848–0.881	20
	band 9 – Short Wave Infrared (SWIR)	0.931–0.958	60
	band 10 – Short Wave Infrared (SWIR)	1.338–1.414	60
	band 11 – Short Wave Infrared (SWIR)	1.539–1.681	20
	band 12 – Short Wave Infrared (SWIR)	2.072–2.312	20

Source: own elaboration based on USGS [2022].

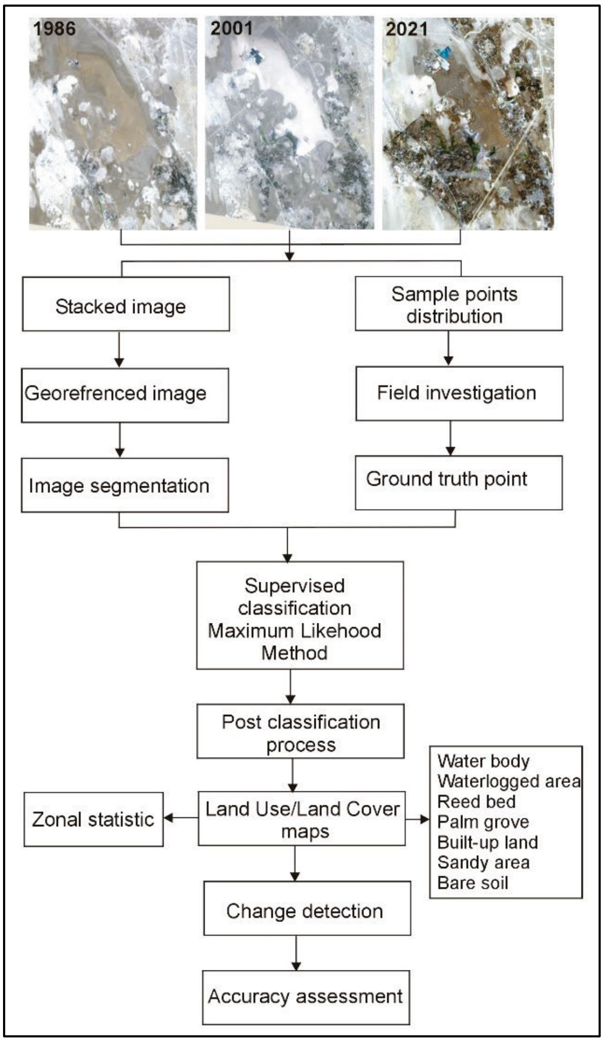

Fig. 2. Flowchart of the methodology applied in the study; source: own elaboration

THE CLASSIFICATION METHOD

The classification procedure can be divided into three phases: selection of training points and signature analysis, a classification implemented with an object-oriented approach, and the using of the supervised Maximum Likelihood Classification (MLC).

THE SIGNATURE ANALYSIS

Within each image, we identified a sample of the relevant types of information (i.e. LULC classes). Training locations for signature generation were determined from the ground truth data used in this research. To ensure that each spectral class representing each LULC category was represented in each image, 20 locations were used as training locations. The reflectance of each information class was characterised by image processing software. This step, frequently called "signature analysis" entails developing a statistic for each image band (such as mean, variance, and covariance) or exhaustive analyses of the mean, variance, and covariance for all bands. An image is classified by inspecting the reflectance of each pixel and comparing it with the signatures with the greatest similarity to it after statistical characterisations have been determined for each class of information [EASTMAN 2003].

THE OBJECT-BASED CLASSIFICATION

With the development of remote sensing of wetlands, object-based image analysis offers a broader range of applications, from detecting wetland boundaries to analysing changes in the types and sizes of wetlands. Satellite imagery has been classified using an object-based image classification method. Analysing objects from input images typically begins with segmenting the pixels into local groups of objects, which are then classified and analysed. The size, shape, and spectral characteristics of the object will depend on the research objectives and segmentation procedure applied [BLASCHKE *et al.* 2014; DRONOVA 2015; MA *et al.* 2017]. In the case of objects viewed as spatial entities, there are more ways to facilitate discrimination than pixel-based analysis.

Objects can be categorised using supervised, unsupervised, and rule-based methods, very similar to pixel-based analysis. Their classification can be based on their spectral variables as well as their physical characteristics such as geometry (area, perimeter, and various shape indices), texture (metrics for the variation in pixel values of a given band within an object), or "contextual" metrics which describe proximity or distance to other classes, differences in spectral properties to neighbours, or relationships to objects from higher levels in a segmentation hierarchy. Each reference year was subjected to an accuracy assessment. Accurate data on LULC feature detection and change were obtained by newly developed software algorithms [AMIN, FAZAL 2012; DRONOVA 2015].

THE CLASSIFICATION BY MAXIMUM LIKELIHOOD CLASSIFICATION

In fact, the patterns used as a knowledge engine to group the number of pixels of the image according to the maximum likelihood were analysed by Maximum Likelihood Classification (MLC) in the formation of signature files of patterns per pixel [HOGLAND *et al.* 2013; LIU *et al.* 2011; SUN *et al.* 2013]. MLC aids the coding of overlapping signatures by using statistical decision-making criteria. MLC is the most commonly used classification method. It is founded on the supposition that the probability of land cover occurrence is equal. However, a priori probability of occurrence has a significant impact on the classification results. Landsat imagery provides a good evaluation of changes in LULC while utilising the MLC algorithm as a supervised classification tool [ALQURASHI *et al.* 2016; ALQURASHI, KUMAR 2014; LU *et al.* 2004].

ACCURACY ASSESSMENT

Accuracy assessment is the essential procedure for abstracting the features of classified images. It identifies the most likely source of errors in a classified image, and improves the accuracy of the analysed data as a result [FOODY 2002; LYONS *et al.* 2018; RWANGA, NDAMBUKI 2017]. Overall accuracy depicts how a single pixel ranks in relation to individual land use conditions based on ground truth data. According to BRADLEY [2009], an image sort cannot be considered wholly until its correctness has been assessed. Ground truth and statistical testing are vital for confirming the precision of the material utilised in the decision-making process [FOODY 2010; PRASAD, RAMESH 2019].

The "error or confusion matrix" is the most frequent and widely used technique for representing the accuracy of remote sensing image classifications. This method can be used to compare the pixels of a classified image to corresponding pixels in a referred image. Three alternative scales are employed in the estimation of accuracy in an error matrix based on the omission and commission errors: overall accuracy, user accuracy, and producer accuracy [FOODY 2002; TSUTSUMIDA, COMBER 2015]. However, the matrix produces aggregate values for the user, producer, and ensemble accuracy, but ignores geographical components of accuracy. Land cover errors are well-known for being spatially auto-correlated and having a specific geographical distribution. Change detection, environmental monitoring, and modelling that utilises land cover data can all be hampered by spatio-temporal inaccuracies [TSUTSUMIDA, COMBER 2015]. The kappa coefficient, which indicates the required classification accuracy for all elements, i.e. counting diagonal elements, is another measure of image classification accuracy [FOODY 2010].

In this study, 100 samples were drawn for the years 1986, 2001, and 2021 in order to assess accuracy. Using a GPS (Global Positioning System) sensor, we gathered at least fifteen true data points in the field for each LULC class using a stratified random sampling strategy. We noticed that all resampling methods generated correct estimates of the error as well as significant confidence ranges for the classifier's performance and uncertainty.

For 1986, 2001, and 2021, the estimated overall accuracy for the classified images was 77, 81, and 84% respectively, with complete kappa values of 0.765, 0.785, and 0.835 respectively (Tab. 2).

Table 2. Land Use/Land Cover (LULC) category-wise assessment of kappa coefficient for the years 1986, 2001, and 2021

LULC category	1986	2001	2021
Water-body	0.81	0.82	0.89
Waterlogged area	0.75	0.79	0.83
Sabkha soil	0.74	0.77	0.82
Cultivated area	0.84	0.85	0.88
Sandy area	0.73	0.74	0.80
Built-up area	0.72	0.74	0.79

Source: own study.

The use of image segmentation as an object-oriented method using zonal statistics is the study's key advantage over similar studies. For example, in research conducted by FROHN and CHAUDHARY [2008], the overall classification accuracy was 93.6 and 98.0% for water. In a study conducted by ZEBARDAST and JAFARI [2011], visual interpretation achieved an overall accuracy of 80%, while classified surveys and consideration of a huge number of control points improved accuracy in this study by 89%. The detection accuracy of different land use classes at the research area's boundaries was studied with the use of a large number of training points.

RESULTS AND DISCUSSION

LAND USE CHANGE BETWEEN 1986 AND 2021

Post-classification analysis by GIS was used to detect the changes. The ability to detect changes in land use is imperative for understanding the current state of a wetland and determining how it should be managed in the future. Using remote sensing and GIS, this study endeavoured to detect changes in the wetlands of Al-Aba Oasis and their consequent repercussions during a period of 35 years. To identify changes in land use during the period 1986–2021 in the study area, we compared land use maps for the years 1986, 2001, and 2021 (Tab. 3, Fig. 3).

Table 3. Area of each Land Use/Land Cover (LULC) class in Al-Aba Oasis for the years 1986, 2001, and 2021

LULC category	1986		2001		2021	
	area					
	km^2	%	km^2	%	km^2	%
Water-body	0.42	0.11	9.37	2.07	36.89	8.17
Waterlogged area	24.79	5.49	69.91	15.49	10.99	2.44
Sabkha soil	330.78	73.29	255.77	56.67	250.38	55.48
Cultivated area	8.18	1.82	33.46	7.41	64.38	14.27
Sandy area	86.15	19.08	80.17	17.76	74.32	16.47
Built-up area	0.97	0.21	2.61	0.57	14.33	3.18
Total	**451.29**	100	451.29	**100**	**451.29**	**100**

Source: own study.

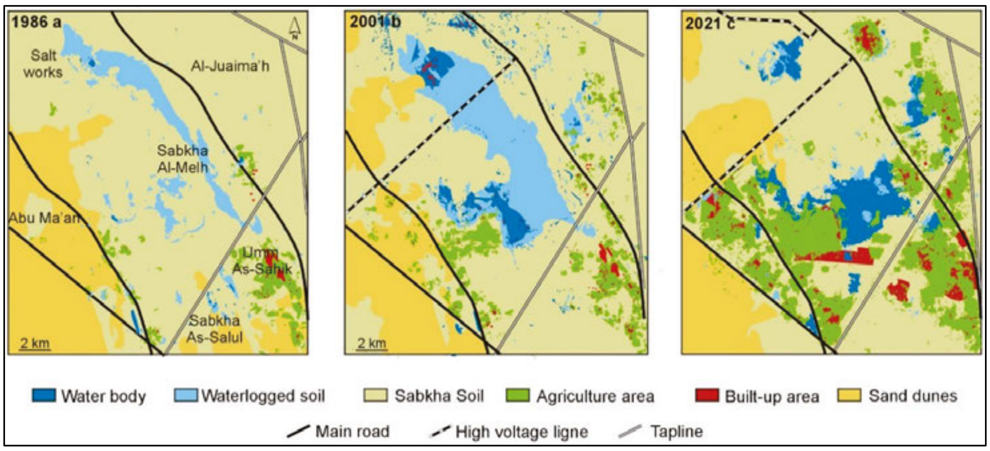

Fig. 3. Land use maps of Al-Aba Oasis for the years: a) 1986, b) 2001, c) 2021; source: own elaboration

In this study, an overlay of Landsat image bands was required to capture various landscape features such as water bodies and waterlogged areas. For example, the overlay of Landsat bands 1, 4, and 5 was designated for the built-up area, salty marshes, and coastal zone waters. Similarly, crops and other vegetation cover were classified using the common image of bands 3 and 4 [CHEN *et al.* 2003].

Multitemporal land use statistics show significant modifications in land use in Al-Aba Oasis during the study period. According to a change analysis performed on them (1986–2021), the six LULC classes displayed various change patterns across the 35-year period. The same methodology was used to detect LULC changes.

Al-Aba Oasis (451.29 km^2) includes different land use classes: water bodies, waterlogged areas, sabkha soil, sandy area, cultivated areas, and built-up areas. In this analysis, land use classes in 1986, 2001, and 2021 were evaluated by calculating the areas and percentages for each land use class (Tab. 3). The pie chart below illustrates the distribution of land use for each land use class in Al-Aba Oasis from 1986 to 2001 and from 2001 to 2021 (Tab. 4).

Table 4. Changes in Land Cover/Land Use (LULC) between 1986 to 2001 and 2001 to 2021

LULC category	LULC change			
	1986–2001		2001–2021	
	area			
	km^2	%	km^2	%
Water-body	8.95	1.98	27.52	6.10
Waterlogged area	45.12	10.00	–58.92	–13.06
Sabkha soil	–75.01	–16.62	–5.39	–1.19
Cultivated area	25.28	5.60	30.92	6.85
Sandy area	–5.98	–1.33	–5.85	–1.30
Built-up area	1.64	0.36	11.72	2.60

Source: own study.

The percentage changes in land use classes in the periods 1986–2001 and 2001–2021 were calculated. It is evident that the built-up area, cultivated land, and permanent waters have increased in their distribution from 1986 to 2021. The results calculated on the basis of data for these years are as follows (Fig. 4).

BUILT-UP AREA

According to Table 3, out of the total study area, built-up areas increased from 0.21% in 1986 to 0.57% in 2001. Urban areas have experienced the highest growth rate (3.18%) from 2001 to 2021. According to the census data, the population of Umm Sahik was 9523 in 1992, 11602 in 2004, and 12998 in 2010, showing a population growth of almost 36.5% between 1992 and 2010 [GaStat 2022]. The dynamics of land use from 1986 to 2021 in Al-Aba Oasis show that urban sprawl is now taking place towards the lower part of Al-Meleh and As-Salul sabkhas. During this time, the growth of built-up regions increased the extent of impervious surfaces, resulting in an increase in yearly runoff towards the sabkhas' bottom. In addition to that, high population growth due to urban development has resulted in widespread soil deterioration. Similarly, according to Greater Jabodetabek, Jakarta, [PRIBADI, PAULEIT 2015], growing urbanisation is the primary cause of large-scale agricultural land loss and increasing land fragmentation.

Moreover, CHOUARI [2013] showed that the banks of the Essijoumi sabkha are currently under pressure from urban expansion, due to the proximity of the city of Tunis, resulting from the rapid development of spontaneous habitats. Indeed, the ecological framework of this sector has been profoundly changed by the growing pollution and degradation of the natural environment, which could become irreversible. CHOUARI [2015] has shown that knowledge of the spatial and temporal evolution of the Ariana sabkha and its watershed in the northern suburbs of Tunis (morphometrics, land use) is an essential prerequisite for sound and adapted management. This area is losing its function as a natural area and flood regulator and is the subject of development activity. The situation of the wetland has become critical and may become a problem that hinders further development.

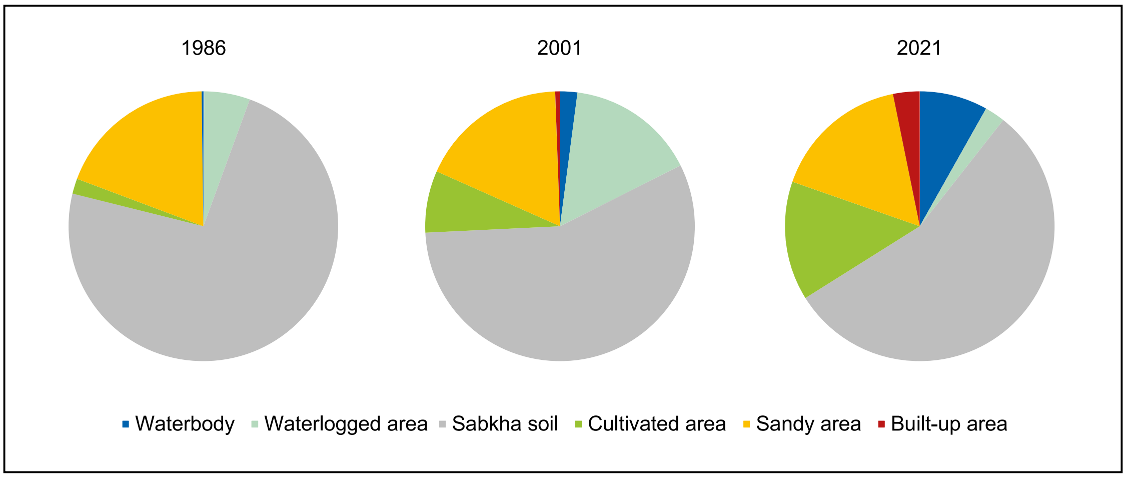

Fig. 4. Statistics of Land Cover/Land Use in % of Al-Aba Oasis for the years 1986, 2001, and 2021; source: own study.

CULTIVATED AREA

The identification of changes in various land use classes reveals that cultivated land has increased owing to population pressure (Tab. 4). The vegetation includes primarily settlement vegetation such as palms, seasonal crops, and reed beds. In 1986, the cultivated area was 8.18 km^2 It increased to 64.38 km^2 by 2021, showing an 8-fold increase (Fig. 3c). This is also supported by Sun and Zhou's [2016] results, which identified fast agricultural land growth and subsequent farm abandonment as the primary land use changes in western dryland China. In addition to that, Verhoeven and Setter [2010] have addressed a variety of contemporary events that are likely to contribute to pressures to destroy wetlands, including the ongoing need for expanded output to feed a growing global population and increased farming. Due to the oxidation of the peat soil, intensive agricultural use of drained/regenerated peatlands has been found to be causing serious issues. This not only results in considerable carbon dioxide emissions, but also creates flood-prone lowlands that must be preserved.

SANDY AREA

There were no major changes in the water bodies or the waterlogged areas (Figs. 3a, b, c). Figure 3c shows that the extent of sand dunes has decreased very slightly. The area of sand dunes has decreased from 19.08% in 1986 to 16.47% in 2021 as a result of the expansion of cultivated land, conversion of uncultivated fallow land to cultivated land, and emergence of sabkhas soils associated with increasing input of agricultural drainage water (Fig. 3a, b, c). This is also confirmed by the observations made by Chouari [2021], who reported a persistent conflict between sand and water in the endorheic system of Al-Asfar wetland in Al-Ahsa, south of the study area.

SABKHA SOIL

As indicated in Table 3, the sabkha soil class showed a tendency to decrease between 1986 and 2021. Satellite imagery shows a significant decrease in the area of sabkha soil from 73.29% in 1986 to 55.48% in 2021, which may be ascribed to the change of sabkha soil to agricultural and built-up land due to population growth and agricultural development.

WATER BODY AND WATERLOGGED AREA

According to the findings of this study, the area of water bodies in sabkhas has increased in the last 35 years. The findings reveal that the size of permanent water bodies has grown from 0.42 km^2 in 1986 to 36.89 km^2 in 2021 due to an increase in drainage water input from agricultural lands. The increase in flooded areas occurred in the periphery of cropland and the lowest-lying areas. The water area and waterlogged areas expanded from 25.21 km^2 to 47.88 km^2.

As shown in Table 4, only water bodies, cultivated land, and built-up areas expanded continually during the research period. To put it another way, these classes grew the most. The most significant drop of 14.25% was observed for waterlogged areas and sabkha soil and has been explained by the conversion of waterlogged areas and sabkha soil into permanent water bodies, urban and cultivated land. Such a rapid change in land use in a short period of time must be a matter of concern for the authorities.

Many researchers, including Wagner *et al.* [2013] in India, Gustard and Wesselink [1993] in the Balquhidder Basin in Scotland, Chouari [2013, 2015] in Tunisia, and Tellen and Yerima [2018] in the Northwest of Cameroon, have confirmed the negative impacts of land use change at the expense of wetlands. They admitted that deforestation and subsequent agriculture had adverse effects on the physical properties of soil. Anthropogenic and environmental threats to wetlands, including significant loss of land use owing to urban growth and agricultural land development, exist. Agriculture is recognised as the greatest threat to the freshwater wetland ecosystems in eastern Saudi Arabia as during the agriculture activities, wetlands are exposed to significant volumes of fertilisers, sewage, and pesticides. Thus, other issues, such as poor water quality and environmental degradation, emerge [Chouari 2021]. It is worth mentioning that the expansion of neighbouring agricultural fields, more extensive use of chemical fertilisers, and higher water use levels all put wetlands at the risk of increased pollution loading. As a result, proper fertiliser usage in agriculture as well as modifications in cropping and drainage patterns are highly recommended solutions. Implementing sustainable agricultural plans in the study area might be another method for addressing the problem of wetland pollution and sedimentation.

During the study period, riparian vegetation developed on the south-western banks of the Al-Meleh sabkha. Another environmental issue stems from the fact that wetlands have traditionally been seen as unproductive and harmful. The majority of the local population believe the sabkhas to be a nuisance, primarily due to an abundance of mosquitoes, and utilise them as a dump for agricultural drainage water.

All these man-made influences jeopardise the survival of the ecosystem, which has already been degraded by ongoing urbanisation. However, although the sabkhas have become a highly humanised space, some of their functions and ecosystem services can be preserved. Their role in temporarily regulating water levels in the urban environment through storage and release is undoubtedly the most important one. Better awareness of the hydrologic function of wetlands at the watershed level, along with the definition of an appropriate regulatory status that stops urbanisation, would help optimise and maintain that function. Moreover, any effort to uncover natural water flow pathways in the sabkhas system would be a major success in creating a sustainable environment dominated by wetlands and green spaces. Providing the population with a sewage disposal system and the farms with more adequate drainage would also reduce water pollution while helping in saving the wetlands. However, anthropogenic pressures on these "fragile" environments are contributing to the alteration of their surface and thus to the loss of their biodiversity. The socioeconomic and environmental challenges facing wetland ecosystems and the conflicts they generate necessitate more global management that incorporates the environment, resources, and activities that develop there.

CONCLUSIONS

The foremost goal of this study was to map land use from 1986 to 2021 to determine various pressures on wetland ecosystems. For supervised classification, we employed the maximum likelihood method. The mapping of the land use in Al-Aba Oasis was then performed in ArcGIS. This study shows the interest in using remote sensing and GIS tools to analyse land use changes in the Al-Aba Oasis on a spatiotemporal scale. To accomplish sustainable development goals, accurate monitoring of land use changes is required. Environmental impact evaluations should be used to guide land use rehabilitation.

The accelerated growth of built-up areas and agricultural land around 2021 was due to increasing urbanisation and anthropogenic influences. There has been a remarkable decrease in sabkhas and wastelands during this period, which was clearly due to the drainage of built-up and agricultural land. Population growth is directly proportionate to the development in built-up and agricultural areas, which disrupts the fragile ecological balance by overexploiting natural resources and exacerbating drainage problems. Human systems have a negative influence on wetland ecosystems because they are not closed-loop. The likely result is ecosystem change through the formation of a permanent water body such as Al-Asfar and Al-Hubail Lakes in Al-Ahsa Oasis.

As a result of this, developing a thorough management plan is crucial for avoiding significant changes in the natural potential of the study area. All stakeholders must work together to achieve this. The natural qualities of wetlands will be lost if this does not happen. A well-designed land use plan is indispensable for ecological balance and sustainable growth. A sound land use strategy that focuses on controlling built-up areas that encroach into the oasis, waterlogged areas, and water bodies should be developed and ecological conservation principles should be incorporated into LULC management to preserve biodiversity while protecting the environment.

We intend to utilise the results of this research to draw planners' attention to the smart use of resources for both short-term and long-term advantages and self-sustaining growth. In addition to that, the present findings can be improved by including high-resolution satellite images, which enable the investigation of additional land use classes. To provide a realistic portrayal of LULC changes, these satellite images may be compared with aerial photographs of the region taken in earlier years.

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