Scientific Journal of Agricultural Sciences 4 (1): 142-151, 2022
Print (ISSN 2535-1796) / Online (ISSN 2535-180X) DOI:10.21608/sjas.2022.123525.1198

Land Use/Cover Changes in Al-Jouf, KSA in Response to Water Management Strategies Using Multi-Sensor/-Temporal Data in Google Earth Engine

Ali G. Mahmoud

Soils and Water Department, Faculty of Agriculture, Fayoum University, Postal Code: 63514, Fayoum, Egypt

*Corresponding Email: agm02@fayoum.edu.eg

Received on: 23-2-2022 **Accepted on: 26-3-2022**

ABSTRACT

The water resources are limited and need to be managed in different demand areas. As agriculture consumes the major quantity of water, thus water management is an essential process. In KSA, new regulations have been issued to manage the water consumption in agriculture. This led to a shift within agriculture use from the more consumption crops to the lower ones in some areas, apart from the areas that stopped cultivation activity. This study aims at evaluating the land use/cover changes within an agricultural area in Al-Jouf region, KSA. Therefore, multi-temporal Sentinel-1 (S-1) and Sentinel-2 (S-2) data were analyzed with the aid of the valuable capabilities of the cloud-based platform Google Earth Engine (GEE). The cultivated areas during the period 2017 to 2021 were calculated based on monthly normalized difference vegetation index (NDVI). The results revealed a significant decrease in the annual average of cultivated area from 121,161 to 74,468 ha in 2021, with a high variation between winter and summer cultivated area. On the other hand, the multi-sensor/-temporal classification of S-1 and S-2 data showed a decrease in the agriculture area, and the shift to orchards. The orchards area increased by 84.0% (from 9,202 to 16,929 ha), the crops area decreased by 24.3% (from 125,512 to 95,016 ha), while the bare land increased by 9.7% (from 235,009 to 257,779 ha) as comparing areas in 2017 and 2021, respectively. The proposed approach provides near-real-time tracking of the changes in land use/cover for updating the water management strategies.

KEYWORDS: Change detection, Sentinel-1, Sentinel-2, Google Earth Engine, Al-Jouf, KSA.

1. INTRODUCTION

Water resources across the world are becoming under stress because of population growth, agricultural area expansion to meet the population demand, modern lifestyles, in addition to climate change and deterioration of water quality (Mostafa et al. 2021; Musa 2021; Valjarevic et al. 2021). Increasing water consumption in many countries has led to deficiency of water availability to satisfy water demand and consequently significantly affects agricultural productivity and food security (Gino Sophia et al. 2020; Jiang 2009). As water resources in most countries of the Middle East Region are more limited and vulnerable, therefore, the situation seems to be critical (Abdelhaleem et al. 2021; Kazemi Moghaddam et al. 2017).

With a rapid development in Saudi Arabia, the promotion of standard living, in addition to the increase in population from 6.9 to 34 million in 1972 and 2019, respectively, the water demand has significantly increased to 263 L per capita per day (LPCD) in 2019 (Almulhim et al. 2021). In 2020, the total water demand reached 15979 MCM, from which 10%, 23%, and 67% for industrial, domestic, and agriculture use, respectively (MEWA 2020). In the agriculture sector, about 90% of its consumption comes from groundwater aquifers (Alotaibi and Kassem 2021). Moreover, due to the climate change impacts on water resources, there is a possibility of rainfall decrease, and temperature increase which may cause a significant increase in water consumption in many areas in KSA (Djoundourian 2021; Mallick et al. 2021) and consequently increase the stress on water scarcity (Bahrawi et al. 2021). In KSA, generally, the net annual recharge compared to the withdrawal rate of groundwater is very low, causing a decline in its level and consequently the quantity and quality of groundwater (Mallick et al. 2021). Therefore, there is a challenge to meet the increasing water demand, and thus a proper water management of available water resources is required (Musa 2021). Notwithstanding such water scarcity, cultivated area, production of green fodder, and water-depleting crops have been significantly expanded in KSA, in addition to the production of fresh milk (Alrwis et al. 2021).

Therefore, various strategies are applied to manage the water and wastewater aiming to reduce the use of the resources, and resources reuse, recycle, and to recharge groundwater (Alrwis et al. 2021; Djoundourian 2021). The Ministry of

Environment, Water and Agriculture (MEWA 2014) formulated the National Pasture Strategy and Plan (NPSP), which suggested that KSA can compensate for the water shortage by applying the NPSP and green fodder cultivation suspension. Where one hectare of alfalfa requires water quantity to grow that is sufficient to grow 48 ha of improved pastoral plants producing more than 56% of the digestive feed per hectare. Besides the positive effects on ecotourism, animal production, combating desertification, conservation of water resources, water quality, biodiversity, and the standard of living of breeders (Alrwis et al. 2021). Moreover, “Strategic plan 2030” was developed by MEWA to maintain sustainable water management through supporting water infrastructure projects, rising water awareness, reducing the water-intensive crops area, encouraging the adoption of sustainable water management among farmers, and ensuring compliance with water legislation and laws (Alotaibi and Kassem 2021).

In this regard, land use/cover (LU/LC) diversity under such conditions is critical to water consumption (Turk et al. 2021). Since different types of field crops, vegetables, fodder crops and orchards vary in water requirements, accordingly, the combination of such types in a particular area can be planned for optimum water management. Therefore, LU/LC monitoring is important for a proper water management strategy (Rajmohan et al. 2021). Accordingly, remote sensing can be utilized to extract the corresponding information at the required spatial and temporal scales (Johansen et al. 2021). Several studies have applied remote sensing in LU/LC studies in KSA (Alharthi et al. 2020; Aly et al. 2016; Turk and Aljughaiman 2020; Youssef et al. 2019). In general, there are various sources of remotely sensed data including commercial and free data. The free sources support the optical remote sensed data, i.e., Landsat and Sentinel-2 data, as well as microwave remote sensing, i.e., Seninel-1 SAR data (Rapinel and Hubert-Moy 2021).

Since 2017, the European Space Agency (ESA) has provided high-resolution images (having 10, 20, and 60 m), with Sentinel-2A and 2B satellites, worldwide coverage, and revisit interval of 5-day. Such data enables to study and monitor the crop composition at no cost, especially in vegetation mapping, with the aid of enhanced definition in the red-edge spectral reflectance (Jiang et al. 2020). On the other hand, the synthetic aperture radar (SAR) data has the advantage that the SAR signal interaction with the surface depends mainly on the studied object characteristics (i.e., surface roughness, shape, and dielectric properties), also on the sensor characteristics, i.e., polarization, wavelength, and incidence angle (Paluba et al. 2021). Several studies showed that LU/LC classification could be improved through the combination of Sentinel-1 and Sentinel-2 data (Amani et al. 2020b; Chong et al. 2021; Hu et al. 2021). Recently, the cloud-based RS data processing has been supported by several platforms, from which Google Earth Engine (GEE) is the most popular one (https://earthengine.google.org), launched by Google in 2010 (Amani et al. 2020a), for pixel-based land cover classification and crop mapping (Shelestov et al. 2017). In GEE, “multi-petabyte” analysis-ready data, combined with several image processing capabilities are located, where the user can access these data and perform the required analysis via a web browser. It is freely available for education, research, and nonprofit use (Paluba et al. 2021).

The current study aims at mapping the changes in LU/LC in the study area during the period 2017-2021 using multitemporal Sentinel-1 and Sentinel-2 data with the capability of GEE. This will help to prepare, monitor, and update the water management programs.

2. MATERIALS AND METHODS

2.1. Study area

The selected test site is located in Al-Jouf Region in the northern part of Saudi Arabia and covers an area of 369,724.7 ha (Figure 1). It lies between latitudes 29° 37′ 40″ and 30° 19′ 13″ N and between longitudes 37° 58′ 30″ and 38° 44′ 2″ E. From the agricultural area and water use point of view, Al-Jouf is considered one of the top five agricultural regions, with the majority area of central pivots and most of the agriculture is managed by large commercial farms. Over the last three decades, the irrigated area in Al-Jouf has increased from being practically non-existent in the 1980s to an area of about 1500 km^2 by 2005 (Valencia et al. 2020) and, recently, recognized by the largest modern olive farm in the world. The area has hot desert climatic conditions with an annual average temperature of 22.2 °C and a rainfall average of 59 mm (Youssef et al. 2019). The main water resource in the study area is groundwater (Lopez et al. 2020) which is utilized in irrigation, domestics, and industrial process. In the study area, besides the bare land, the agriculture activities include field crops, vegetables, fodder crops, and orchards.

2.2. Data used and processing

The data used in this study were 10-m multi-temporal (2017 to 2021) Sentinel-1 (S-1) C-band SAR data, and Sentinel-2 (S-2) optical data (the European Space Agency) in order to utilize different potentiality of imageries that support land cover classification. The S-1 mission includes a constellation of two satellites, Sentinel-1A/-1B,

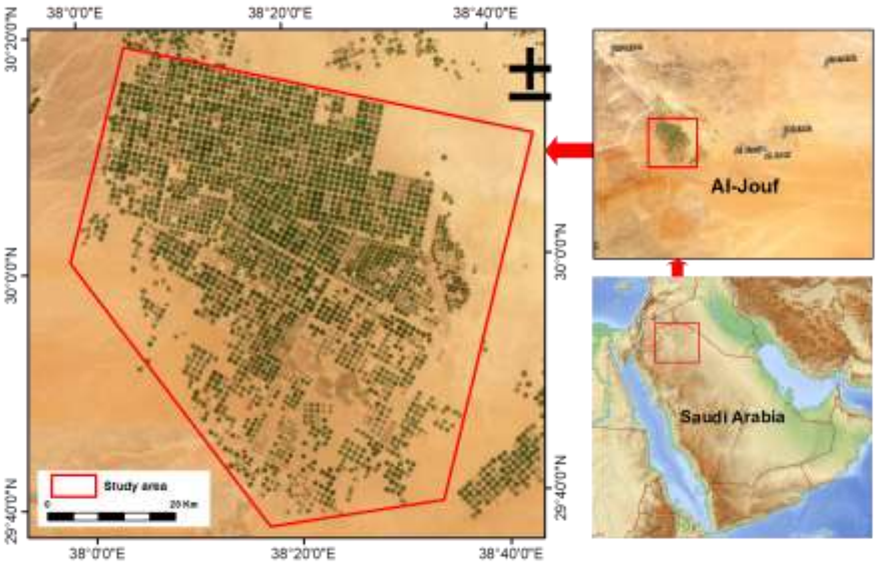

Figure 1. Location of the study area

sharing the same orbital plane with a 12-day repeat cycle per satellite (Paluba et al. 2021). The S-2 satellites consist of two satellites as S-2A (launched in 2015) and S-2B (launched in 2017) with a 10-day revisit cycle. Thus, the data from both satellites can be obtained at 5-day interval which offers dense time-series observations. S-2 data acquired by a multispectral imager (MSI) onboard with a spatial resolution varying from 10 m to 60 m and covering 13 spectral bands (Luo et al. 2021).

In the current study, S-2 data was used to produce the monthly normalized difference vegetation index (NDVI) for monitoring the cultivation activities along the period 2017-2021. On the other hand, the land use/cover (LU/LC) classification was only applied for two years; 2017 and 2021. Where S-1 level-1 Ground Range Detected (GRD) scenes available in GEE in combination with S-2 data were used and processed for LU/LC classification. With the coding capabilities in GEE, Sentinel-2 imageries were filtered to a cloud cover < 10%; from which five individual months (January to May) during the winter season of 2017 and 2021 were investigated. These months were chosen according to the monthly changes in cultivated area, and to represent the growth period of winter crops. The classification was applied using the same period to compare, almost, the same conditions. Also, the winter season with higher cultivated area was selected to represent the most agriculture area and overcome or reduce the effect of the fallow land on the comparison process. So, for each month (January- May), one image was generated based on the mean pixel value of available imageries per month. In addition, the S-1 SAR images covering the same periods were combined with S-2 for LU/LC classification. Ground Range Detected (GRD) images were obtained in Interferometric Wide swath mode (IW) for VV- and VH-polarization. Scenes taken in descending orbit were chosen to be processed for LU/LC classification. And speckle effects were filtered using the median filter, according to (Schulz et al. 2021).

2.3. Temporal changes in cultivated area

To examine the changes in cultivated area during the period from 2017 to 2021, the analytical capabilities of GEE with the available S-2 data were employed to extract the normalized difference vegetation index (NDVI). Then, NDVI was classified as vegetation and non-vegetation according to a threshold value which is set based on the interpretation of the S-2 data and the high-resolution data of Google Earth. Various studies deployed such NDVI-based approach for cultivated area mapping (Abdelhaleem et al. 2021; Sakuma and Yamano 2020; Wang et al. 2021). Thus, a proper script was written in JavaScript code editor in GEE to calculate the NDVI for the available S-2 data within each month, then the mean filter was applied to generate one NDVI image per month along the defined period. From which the monthly cultivated area (as a vegetation class), and annual average of cultivated area were calculated.

Furthermore, the Google Earth Engine App (https://jstnbraaten.users.earthengine.app/view/landsat-timeseries-explorer), which supports the monitoring concept and provides annual changes based on Landsat data, was utilized. For the selected area, the GEE App creates a Landsat time series chart with chips of image that represents the median annual composites for the selected area. In the current study, two examples were selected to represent the reduction in cultivated (pivot) area, and another one to show the expansion in orchards area.

2.4. Land use/cover classification

Multi-temporal S-1 and S-2 data were utilized for image classification as a multi-sensor approach for agriculture area mapping in 2017 and 2021. Afterwards, the changes in LU/LC were evaluated. The training and validation samples for each acquisition date were collected through the visual interpretation of multi-temporal S-2 imagery and the available high-resolution data in Google Earth (Luo et al. 2021). A randomly stratified sampling technique was applied to collect regions of interest (ROI) that represent each class. The total number of ROIs were 157, 251 and 198 in 2017, and 145, 171, and 199 in 2021 for orchards, crops, and bare land, respectively. According to the proposed GEE script, the ROIs were divided as 75% for training and 25% for validation process. The pixel-based image classification was applied using the random forest classifier (Schulz et al. 2021; Vogels et al. 2019) within GEE. In addition, the validation overall accuracy was calculated, and confusion matrix was obtained within GEE. In the current study, the main LU/LC classes were defined as orchards, crops (including field crops, vegetables, and fodder crops), and bare land.

3. RESULTS AND DISCUSSION

3.1. Changes in cultivated area

Sentinel-2 data covering the period from 2017 to 2021 were utilized to monitor the monthly changes in the cultivated area based on the calculated NDVI values where the threshold for vegetation was set to NDVI greater than 0.20 (Gandhi et al. 2015; Karakani et al. 2021). The cultivated area per month gives an indicator about the agriculture activities, and consequently, the irrigation water demand for each month. The results indicate a general decline in the cultivated area (Figure 2). In 2017, the annual average of the cultivated area was 121,161 ha, while it is decreased in 2021 to 74,468 ha (reduction of 38.5%). It is also clear that there is a monthly variation within each year, with a higher cultivated area of winter crops than that in the summer season, and such variation is higher in 2021. This could be attributed to the water management strategies, as the evapotranspiration is increased in summer, leading to higher consumption of irrigation water. However, some areas might be left as fallow for specific period, the monthly sequence of NDVI-derived cultivated area shows general decreasing trend in the cultivated area for the last three years. Which could refer to a decline in the agriculture area.

Exploring the study area using GEE app for tracking changes using Landsat time-series imageries showed a significant decrease in the agriculture area. Recently, applying the water use regulations that ban fodder cultivation according to some criteria, such as the farm size, it appears that some groups of pivots at different locations have been altered to not-cultivated land (Figure 3). This agrees with the reports which declared that some agriculture companies had stopped fodder cultivation. While some farms have been shifted to other crops (i.e., field crops or vegetables) or orchards (i.e., olive trees). The sequence of the images demonstrates that some pivots are left without cultivation during the last three years. With the same GEE app, Figure (4) illustrates an example of orchards area expansion. It is clear that some pivots in 2017 were converted to orchards in 2021, which indicates the changes from the pre-defined use of such areas (field or fodder crops) to orchards.

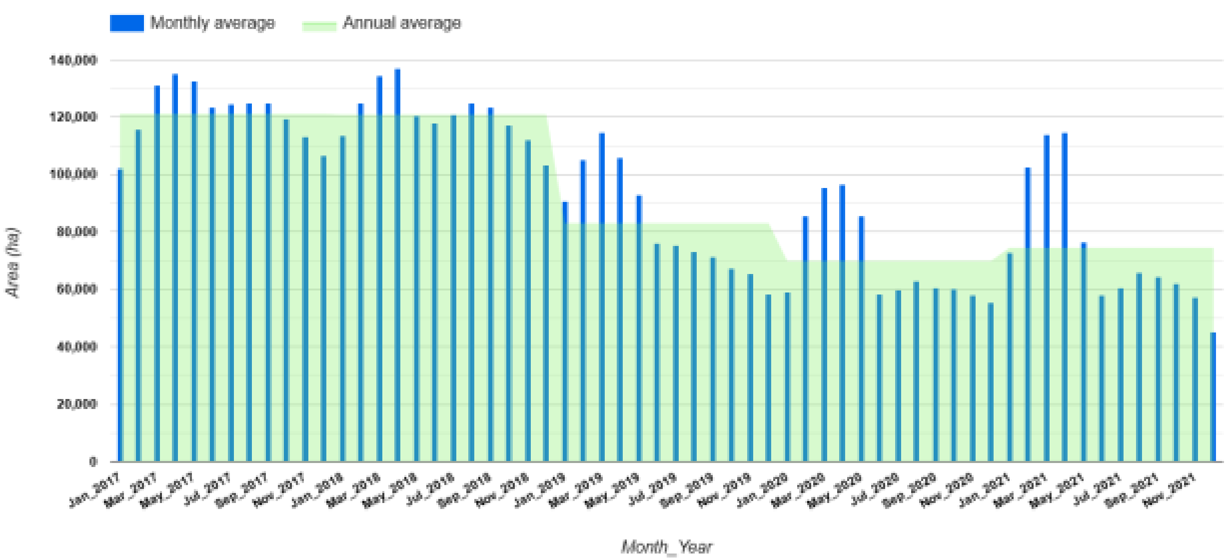

Figure 2. Monthly and annual average of vegetation area from 2017 to 2021

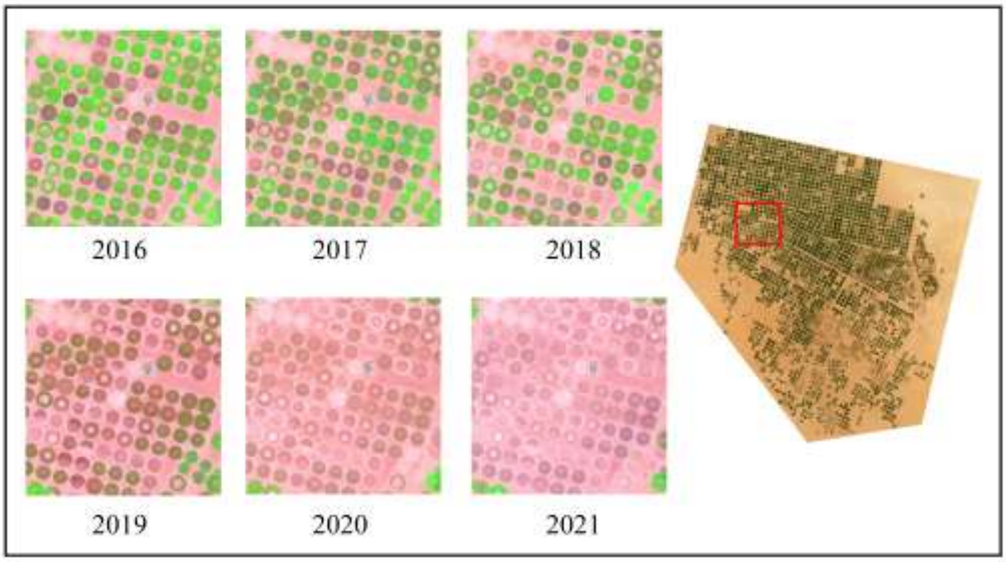

Figure 3. Landsat time-series images (RGB: SWIR1/NIR/Green) show decreasing in agriculture area

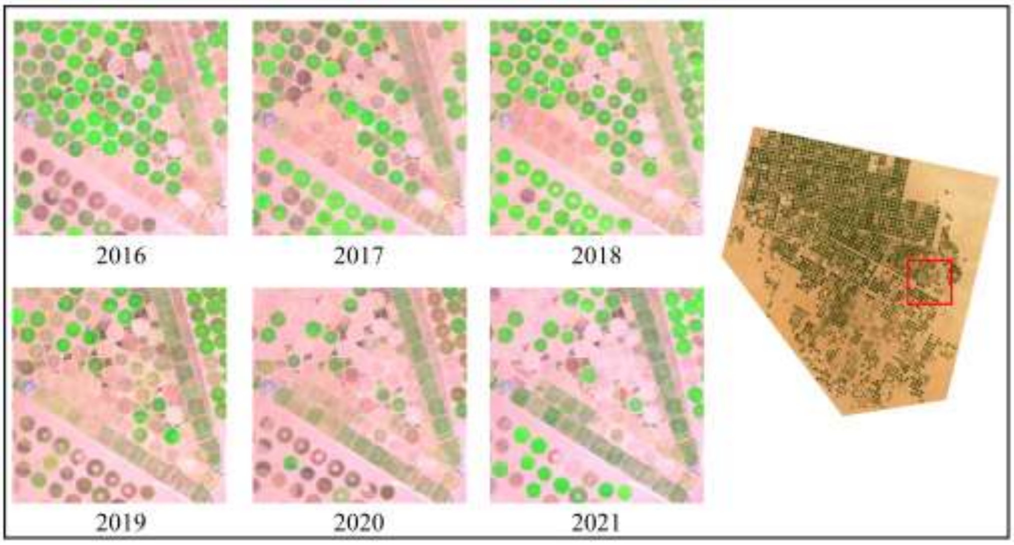

Figure 4. Landsat time-series images (RGB: SWIR1/NIR/Green) show increasing in orchard area

3.2. Land use/cover classification

The classification of S-1 and S-2 imageries of 2017 and 2021 (Figure 5) showed that, in general, there is a decline in the agriculture area. However, the orchard area (Table 1) is increased from 9,214 to 16,929 ha (increased by 83.7%), the crops area decreased from 125,557 to 96,016 ha (decreased by 23.5%). Thus, the total agriculture area (crops and orchards) decreased by 16.2%, from 134,771 to 112,945 ha in 2017 and 2021, respectively. While the bare land increased from 235,240 to 256,816 ha (Figure 6). The random forest classifier revealed high classification accuracy (Table 2) with an overall accuracy of 0.97 and 0.96 in the case of 2017 and 2021, respectively. The current classification is applied for the winter season to represent most of the entire agriculture area with a wide range of variation in crops, while for the summer season, the cultivated area is lower than the winter one, as shown in Figure (2).

The analysis of LU/LC changes revealed that there is an area of 39,857 ha changed from crops to bare land, which appears mainly as patches of pivots. Such areas require further investigations of land evaluation and water requirements; thus, optimum reuse can be defined to get benefits of the previously applied soil management practices in these areas. The mentioned changes confirm that some companies have stopped their fodder cultivation and shifted to import the required fodders from other countries (i.e., Sudan).

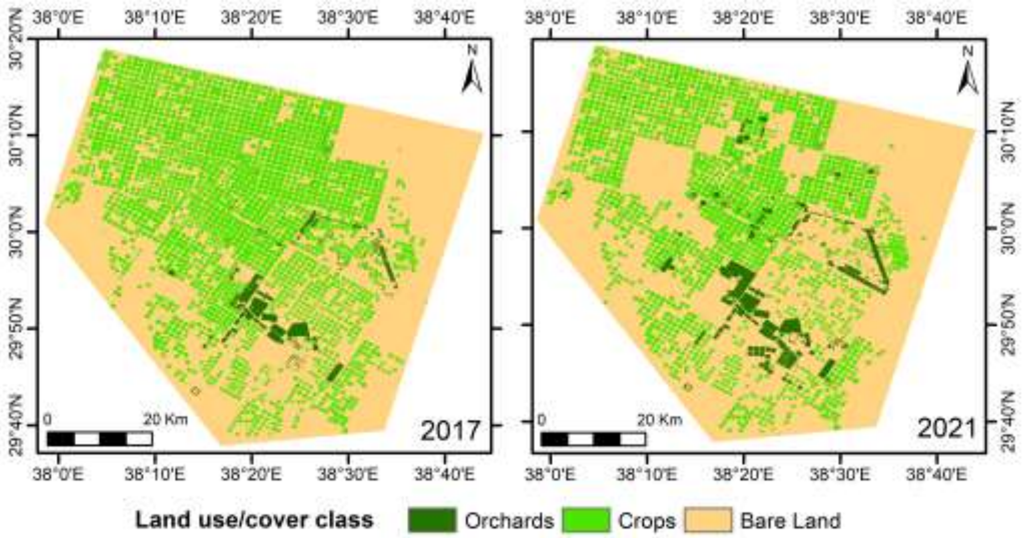

Figure 5. Land use/cover map of the study area in 2017 and 2021

Table 1. Land use/cover classes area and changes between 2017-2021

	2017		2021		Class changes	
Class	**Area (ha)**	**%**	**Area (ha)**	**%**	**Area (ha)**	**%**
Orchards	9,202.58	2.5	16,929.21	4.6	7,726.6	84.0
Crops	125,512.52	33.9	95,016.23	25.7	-30,496.3	-24.3
Bare land	235,009.60	63.6	257,779.26	69.7	22,769.7	9.7
Total	369,724.70		369,724.70			

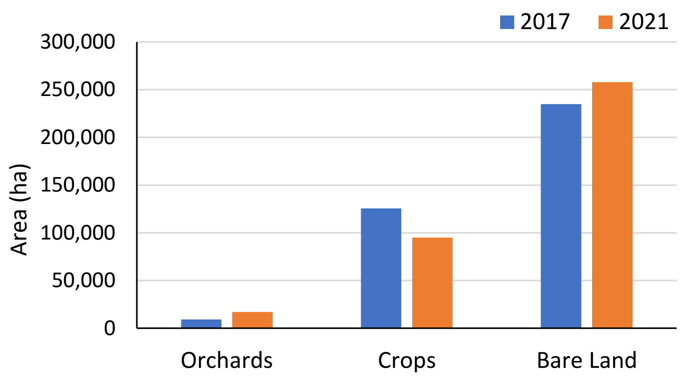

Figure 6. Land cover area in 2017 and 2021

Table 2. Error matrix for the land use/cover map in study area

	2017					2021				
Class	**Orchards**	**Crops**	**Bare Land**	**Total pixels**	**User accuracy**	**Orchards**	**Crops**	**Bare Land**	**Total**	**User accuracy**
Orchards	2236	1	74	2311	96.8	7007	4	17	7028	99.7
Crops	26	2919	152	3097	94.3	312	5282	163	5757	91.7
Bare Land	0	14	4899	4913	99.7	32	76	5420	5528	98.0
Total pixels	2262	2934	5125	10321		7351	5362	5600	18313	
Producer accuracy	98.9	99.5	95.6			95.3	98.5	96.8		
	Overall accuracy				**97.4**	**Overall accuracy**				**96.7**

On the other hand, 1,875 ha of crops area was converted to orchards area in 2021. The analysis further showed that 6,855 ha of bare soil in 2017 had been changed to orchards in 2021. However, it is clear from the imageries that most of these extension areas had a shape of pivots then converted to orchards, which means that the planned use for such area was either for crops or fodders. Also, the orchard area has increased mainly as an extension of the existing orchards area of 2017 in addition to other small fields distributed over the study area (Figure 7).

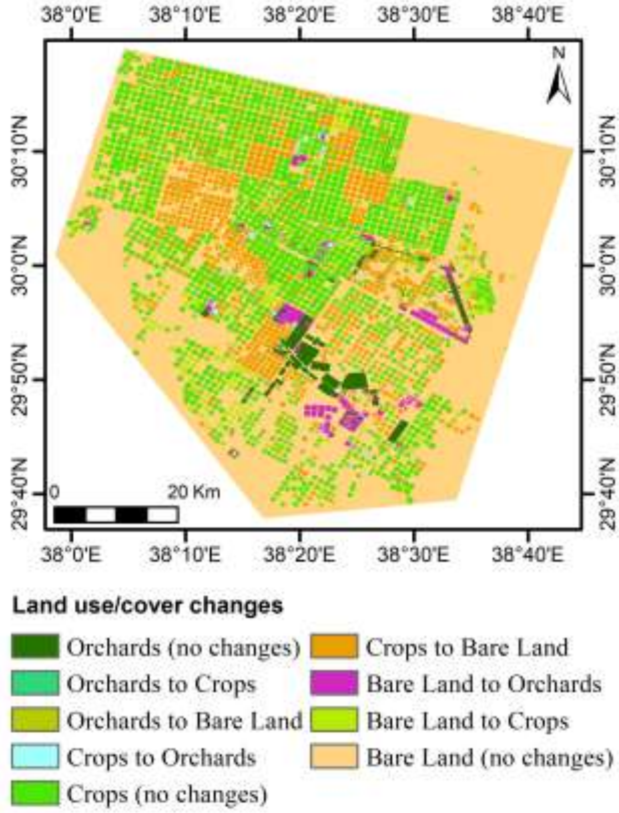

Figure 7. Land use/cover change map of the study area between 2017 and 2021

The results confirm the capability of GEE platform in different steps, such as selecting the required imageries according to the defined criteria, applying the proper processing and LU/LC classification, and producing various outputs, i.e., charts. Moreover, with adapted codes, GEE reduces significantly acquiring and processing time and the operational cost, and big data could be managed apart from the capacity of the local hardware (Capolupo et al. 2020).

4. CONCLUSION

Land use/cover (LU/LC) data is crucial for several applications, i.e., water management. In KSA, increasing water demand by various usages, especially agriculture which has the highest share, besides the limited water resources, led to the need for applying numerous water management strategies. One of these strategies is to ban or reduce the area of the fodder crops according to some criteria, i.e., farm size. The current work aims at monitoring the changes in LU/LC during the period 2017 - 2021 through the combination of multi-temporal Sentinel-1 and Sentinel-2 data with the help of Google Earth Engine. The study area was selected in Al-Jouf Region which represents one of the major agricultural regions in KSA.

Monitoring the monthly changes in the cultivated area based on NDVI, showed a general decline in the cultivated area from 121,161 to 74,468 ha as annual average in 2017 and 2021, respectively. In addition to the monthly variation, the winter cultivated area is higher than that in summer. On the other hand, LU/LC classification using random forest classifier revealed a high overall accuracy of 0.97 and 0.96 in 2017 and 2021, respectively. The results indicated an increase in the orchard area from 9,202 to 16,929 ha (about 84%) and a decrease in crops area from 125,512 to 95,016 ha (about -24%). Thus, the agriculture area decreased (about -17%) from 134,715 to 111,945 ha in 2017 and 2021, respectively. While the bare land increased from 235,240 to 256,816 ha.

The changes analysis showed that an area of 39,857 ha has changed from crops to bare soil, which appears mainly as patches of pivots. Thus, it is recommended to apply further investigation for water requirement and land evaluation to define the potentiality of reusing such area, especially after receiving soil management practices for several years. In addition, 1,875 ha of crop area was converted to orchard area in 2021. The analysis further showed that 6,855 ha of bare soil in 2017 had been changed to orchards in 2021.

In general, integrating of multi-temporal S-1 and S-2 imageries produced high classification accuracy. In addition, cloud computing such as GEE offers a powerful approach to utilize the increasing remote sensing data availability. The proposed approach can be applied to other regions in KSA to evaluate the changes in LU/LC. Further study is recommended to map the crop type distribution in addition to the water requirements based on the remotely sensed data.

5. REFERENCES

Abdelhaleem F.S., Basiouny M., Ashour E., Mahmoud A. (2021). Application of remote sensing and geographic information systems in irrigation water management under water scarcity conditions in Fayoum, Egypt. Journal of Environmental Management, 299

Alharthi A., El-Sheikh M.A., Elhag M., Alatar A.A., Abbadi G.A., Abdel-Salam E.M., Arif I.A., Baeshen A.A., Eid E.M. (2020). Remote sensing of 10 years changes in the vegetation cover of the northwestern coastal land of Red Sea, Saudi Arabia. Saudi J Biol Sci, 27, 3169-3179

Almulhim A.I., Aqil M., Ahmad S., Abdel-Magid I.M. (2021). Sustainable water planning and management research in Saudi Arabia: a data-driven bibliometric analysis. Arabian Journal of Geosciences, 14

Alotaibi B.A., Kassem H.S. (2021). Adoption of Sustainable Water Management Practices among Farmers in Saudi Arabia. Sustainability, 13

Alrwis K.N., Ghanem A.M., Alnashwan O.S., Al Duwais A.A.M., Alaagib S.A.B., Aldawdahi N.M. (2021). Measuring the impact of water scarcity on agricultural economic development in Saudi Arabia. Saudi J Biol Sci, 28, 191-195

Aly A.A., Al-Omran A.M., Sallam A.S., Al-Wabel M.I., Al-Shayaa M.S. (2016). Vegetation cover change detection and assessment in arid environment using multi-temporal remote sensing images and ecosystem management approach. Solid Earth, 7, 713-725

Amani M., Ghorbanian A., Ahmadi S.A., Kakooei M., Moghimi A., Mirmazloumi S.M., Moghaddam S.H.A., Mahdavi S., Ghahremanloo M., Parsian S., Wu Q.S., Brisco B. (2020a). Google Earth Engine Cloud Computing Platform for Remote Sensing Big Data Applications: A Comprehensive Review. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 13, 5326-5350

Amani M., Kakooei M., Moghimi A., Ghorbanian A., Ranjgar B., Mahdavi S., Davidson, A., Fisette T., Rollin P., Brisco B., Mohammadzadeh A. (2020b). Application of Google Earth Engine Cloud Computing Platform, Sentinel Imagery, and Neural Networks for Crop Mapping in Canada. Remote Sensing, 12

Bahrawi J., Alqarawy A., Chabaani A., Elfeki A., Elhag M. (2021). Spatiotemporal analysis of the annual rainfall in the Kingdom of Saudi Arabia: predictions to 2030 with different confidence levels. Theoretical and Applied Climatology, 146, 1479-1499

Capolupo A., Monterisi C., Caporusso G., Tarantino E. (2020). Extracting Land Cover Data Using GEE: A Review of the Classification Indices. Computational Science and Its Applications, Iccsa 2020, Part Iv, 12252, 782-796

Chong L., Liu H.J., Lu L.P., Liu Z.R., Kong F.C., Zhang X.L. (2021). Monthly composites from Sentinel-1 and Sentinel-2 images for regional major crop mapping with Google Earth Engine. Journal of Integrative Agriculture, 20, 1944-1957

Djoundourian S.S. (2021). Response of the Arab world to climate change challenges and the Paris agreement. International Environmental Agreements: Politics, Law and Economics, 21, 469-491

Gandhi G.M., Parthiban S., Thummalu N., Christy A. (2015). Ndvi: Vegetation Change Detection Using Remote Sensing and Gis – A Case Study of Vellore District. Procedia Computer Science, 57, 1199-1210

Gino Sophia S.G., Ceronmani Sharmila V., Suchitra, S., Sudalai Muthu T., Pavithra B. (2020). Water management using genetic algorithm-based machine learning. Soft Computing, 24, 17153-17165

Hu B., Xu Y.Y., Huang X., Cheng Q.M., Ding Q., Bai L.Z., Li Y. (2021). Improving Urban Land Cover Classification with Combined Use of Sentinel-2 and Sentinel-1 Imagery. ISPRS International Journal of Geo-Information, 10

Jiang Y. (2009). China's water scarcity. J Environ Manage, 90, 3185-3196

Jiang Y.L., Lu Z., Li S., Lei Y.D., Chu Q.Q., Yin X.G., Chen F. (2020). Large-Scale and High-Resolution Crop Mapping in China Using Sentinel-2 Satellite Imagery. Agriculture-Basel, 10

Johansen K., Lopez O., Tu Y.-H., Li T., McCabe M.F. (2021). Center pivot field delineation and mapping: A satellite-driven object-based image analysis approach for national scale accounting. ISPRS Journal of Photogrammetry and Remote Sensing, 175, 1-19

Karakani E.G., Malekian A., Gholami S., Liu J.G. (2021). Spatiotemporal monitoring and change detection of vegetation cover for drought management in the Middle East. Theoretical and Applied Climatology, 144, 299-315

Kazemi Moghaddam V., Changani khorasgani F., Mohammadi A., Hadei M., Ashabi R., Majd L., Mahvi A. (2017). Sustainable development of water resources based on wastewater reuse and upgrading of treatment plants: a review in the Middle East. Desalination and Water Treatment, 65

Lopez O., Johansen K., Aragon B., Li T., Houborg R., Malbeteau Y., AlMashharawi S., Altaf M.U., Fallatah E.M., Dasari H.P., Hoteit I., McCabe M.F. (2020). Mapping groundwater abstractions from irrigated agriculture: big data, inverse modeling and a satellite-model fusion approach

Luo J.S., Ma X.W., Chu Q.F., Xie M., Cao Y.J. (2021). Characterizing the Up-To-Date Land-Use and Land-Cover Change in Xiong'an New Area from 2017 to 2020 Using the Multi-Temporal Sentinel-2 Images on Google Earth Engine. ISPRS International Journal of Geo-Information, 10

Mallick J., Singh C.K., AlMesfer M.K., Singh V.P., Alsubih M. (2021). Groundwater Quality Studies in the Kingdom of Saudi Arabia: Prevalent Research and Management Dimensions. Water, 13

MEWA (2020). Statistical Report. In: Ministry of Environment ,Water and Agriculture

Mostafa S.M., Wahed O., El-Nashar W.Y., El-Marsafawy S.M., Zelenakova M., Abd-Elhamid H.F. (2021). Potential Climate Change Impacts on Water Resources in Egypt. Water, 13

Musa A.A. (2021). Goal programming model for optimal water allocation of limited resources under increasing demands. Environment Development and Sustainability, 23, 5956-5984

Paluba D., Lastovicka J., Mouratidis A., Stych P. (2021). Land Cover-Specific Local Incidence Angle Correction: A Method for Time-Series Analysis of Forest Ecosystems. Remote Sensing, 13

Rajmohan N., Masoud M.H.Z., Niyazi B.A.M. (2021). Assessment of groundwater quality and associated health risk in the arid environment, Western Saudi Arabia. Environmental Science and Pollution Research, 28, 9628-9646

Rapinel S., Hubert-Moy L. (2021). One-Class Classification of Natural Vegetation Using Remote Sensing: A Review. Remote Sensing, 13

Sakuma A., Yamano H. (2020). Satellite Constellation Reveals Crop Growth Patterns and Improves Mapping Accuracy of Cropping Practices for Subtropical Small-Scale Fields in Japan. Remote Sensing, 12

Schulz D., Yin H., Tischbein B., Verleysdonk S., Adamou R., Kumar N. (2021). Land use mapping using Sentinel-1 and Sentinel-2 time series in a heterogeneous landscape in Niger, Sahel. ISPRS Journal of Photogrammetry and Remote Sensing, 178, 97-111

Shelestov A., Lavreniuk M., Kussul N., Novikov A., Skakun S. (2017). Exploring Google Earth Engine Platform for Big Data Processing: Classification of Multi-Temporal Satellite Imagery for Crop Mapping. Frontiers in Earth Science, 5, 1-10

Turk K., Zeineldin F., Aljughaiman A.S. (2021). Mapping and assessment of evapotranspiration over an oasis in arid ecosystem using remote sensing and biophysical modelling. Arabian Journal of Geosciences, 14

Turk K.G.B., Aljughaiman A.S. (2020). Land use/land cover assessment as related to soil and irrigation water salinity over an oasis in arid environment. Open Geosciences, 12, 220-231

Valencia O.M.L., Johansen K., Solorio B.J.L.A., Li T., Houborg R., Malbeteau Y., AlMashharawi S., Altaf M.U., Fallatah E.M., Dasari H.P., Hoteit I., McCabe M.F. (2020). Mapping groundwater abstractions from irrigated agriculture: big data, inverse modeling, and a satellite-model fusion approach. Hydrology and Earth System Sciences, 24, 5251-5277

Valjarevic A., Milanovic M., Valjarevic D., Basarin B., Gribb W., Lukic T. (2021). Geographical information systems and remote sensing methods in the estimation of potential dew volume and its utilization in the United Arab Emirates. Arabian Journal of Geosciences, 14

Vogels M.F.A., de Jong S.M., Sterk G., Douma H., Addink E.A. (2019). Spatio-Temporal Patterns of Smallholder Irrigated Agriculture in the Horn of Africa Using GEOBIA and Sentinel-2 Imagery. Remote Sensing, 11

Wang L.J., Wang J.Y., Qin F. (2021). Feature Fusion Approach for Temporal Land Use Mapping in Complex Agricultural Areas. Remote Sensing, 13

Youssef A.M., Abu Abdullah M.M., Pradhan B., Gaber A.F.D. (2019). Agriculture Sprawl Assessment Using Multi-Temporal Remote Sensing Images and Its Environmental Impact; Al-Jouf, KSA. Sustainability, 11

الملخص العربي

تغيرات استخدام/غطاء الأراضي في الجوف بالمملكة العربية السعودية استجابةً لاستراتيجيات إدارة المياه باستخدام بيانات متعددة المستشعرات/الفترات الزمنية في Google Earth Engine

علي جابر محمد محمود

قسم الأراضي والمياه ــ كلية الزراعة ــ جامعة الفيوم ــ الفيوم ــ مصر

تعتبر المياه من الموارد المحدودة وتحتاج إلى إدارتها في مناطق الطلب المختلفة. ونظراً لاستهلاك الزراعة للكمية الاكبر منها، لذا فإن إدارة المياه تعد عملية ضرورية. في المملكة العربية السعودية، تم إصدار بعض القرارات تهدف لإدارة استخدام المياه في الزراعة. وقد أدى ذلك إلى تحول في الاستخدام الزراعي من المحاصيل الأكثر استهلاكًا للمياه إلى المحاصيل الأقل استهلاكا، في بعض المناطق، بالإضافة الى مناطق اخري قد توقفت عن النشاط الزراعي. تهدف هذه الدراسة إلى تقييم التغيرات في استخدام/غطاء الأراضي في منطقة زراعية بمنطقة الجوف بالمملكة العربية السعودية. لذلك تم تحليل بيانات Sentinel-1 (S-1) و(S-2) Sentinel-2 في تتابع زمني وبمساعدة الامكانيات المتاحة في Google Earth Engine (GEE) والمعتمد على نظام الحوسبة السحابية. فقد تم حساب المساحة المنزرعة خلال الفترة من ٢٠١٧ إلى ٢٠٢١ بناءً على مؤشر الغطاء النباتي (NDVI) الشهري. وأظهرت النتائج انخفاضًا معنويًا في المتوسط السنوي للمساحة المنزرعة من ١٢١١٦١ إلى ٧٤٤٦٨ هكتارًا في عام ٢٠٢١، مع وجود تباين كبير بين المساحة المنزرعة في الشتاء والصيف. من ناحية أخرى، أظهر التصنيف المعتمد على بيانات في تتابع زمني لكل من S-1 وS-2 انخفاضًا في المساحة الزراعية بشكل عام، مع وجود توجه في زراعة المحاصيل البستانية. حيث ازدادت مساحة البساتين بنسبة ٨٤.٠٪ (من ٩٢٠٢ إلى ١٦٩٢٩ هكتارًا)، وانخفضت مساحة المحاصيل بنسبة ٢٤.٣٪ (من ١٢٥٥١٢ إلى ٩٥٠١٦ هكتارًا)، بينما زادت الأراضي غير المنزرعة بنسبة ٩.٧٪ (من ٢٣٥٠٠٩ إلى ٢٥٧٧٧٩ هكتارًا) وذلك بمقارنة المساحات في عام ٢٠١٧ و٢٠٢١ على التوالي. وتمكن الطريقة المقترحة من تتبعً التغيرات في استخدام/غطاء الأراضي - في الوقت الفعلي تقريبًا - مما يدعم تحديث استراتيجيات إدارة المياه.