

Title of Paper: The land use impact evaluation on soil properties through remote sensing in an arid area in southern Iran

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ABSTRACT

Objective: Soil is a fundamental component of terrestrial ecosystems, crucial for cycling energy and materials. The mapping of key soil parameters like Soil Organic Carbon (SOC) and Soil Moisture (SM) has been revolutionized by the growth of Earth observation data and cloud-computing platforms like Google Earth Engine (GEE). This study aimed to evaluate soil parameters derived from GEE and examine their relationship with topsoil properties across various land-use types in the Roudan Basin, Hormozgan Province, southern Iran.

Methods:

The methodology integrated extensive field sampling with advanced geospatial analysis. A total of 205 topsoil samples (0-10 cm) were collected from five primary land-use/land-cover (LULC) classes: Poor Rangeland (PR), Medium Rangeland (MR), Farmland (FL), Gardens (G), and Water Areas (WA). Laboratory analyses measured soil texture (sand and clay content), pH, SOC using the Walkley-Black method, and SM using Time Domain Reflectometry (TDR). For spatial analysis, soil parameter maps (clay, sand, SM, SOC) were generated using pre-processed datasets from the Open Land Map and FLDAS/NOAH01 collections within GEE at a 250m resolution. Simultaneously, an LULC map was created using Copernicus Global Land Service data at 100m resolution. The accuracy of the LULC classification and the correlation between laboratory-measured soil properties and GEE-derived estimates were evaluated using error matrices, correlation coefficient (r), Mean Absolute Error (MAE), and Root-Mean-Square Error (RMSE).

Results:

Results showed estimation accuracy varied by property and land use. Soil moisture and clay content showed the highest estimation accuracy in farmlands ($r = 0.92$ and $r = 0.89$, respectively), while pH and sand estimates were less reliable ($r = 0.33$ and $r = 0.55$). Spatial analysis revealed that farmland and garden areas retained the highest soil moisture due to high clay content (26%) and low sand presence (49%). A strong positive correlation was found between SOC and clay content ($r = 0.82$), while a negative correlation was observed between SOC and sand content ($r = -0.89$). Land use classification achieved high accuracy (95% overall, Kappa = 0.93), with poor rangeland showing the best classification results (98.4% accuracy). Farmland contained 8.5 times more SOC than poor rangeland (1.7 vs. 0.2 g/kg).

Conclusions:

In conclusion, this study confirms the efficacy of GEE as a powerful platform for the spatial analysis of soil parameters and land-use changes in the Roudan Basin. The findings highlight that the reliability of remote sensing estimates is dependent on land use. Furthermore, anthropogenic activities profoundly influence soil characteristics, as evidenced by the significantly higher SOC and moisture in managed agricultural lands compared to degraded rangelands. The depletion of SOC in agricultural land over time could be linked to structural erosion from repeated cultivation. Integrating GEE into digital soil mapping and land-use planning processes provides a robust, efficient tool for supporting sustainable land management and agricultural decision-making in the region.

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Introduction

Soils are fundamental to terrestrial ecosystems, providing essential services such as nutrient cycling, water regulation, and carbon sequestration (Lal, 2020; Dominati, 2013). Among the many factors influencing soil health and productivity, land use is a primary driver of changes in soil properties (Wei et al., 2020). Anthropogenic land use practices - such as agriculture, forestry, urbanization, and grazing - can lead to significant alterations in soil physical, chemical, and biological characteristics, thereby affecting the sustainability of ecosystems and the provisioning of ecosystem services (Amundson et al., 2015). One key soil property influenced by land use is soil organic carbon (SOC), which plays a critical role in maintaining soil structure, fertility, and biological activity. Changes in vegetation cover, tillage, and organic matter inputs across different land uses can result in either the depletion or enhancement of SOC stocks (Guo & Gifford, 2002; Lal, 2020). Similarly, topsoil moisture, essential for plant growth and microbial activity, is sensitive to land use changes that modify infiltration, evapotranspiration, and soil cover (Poeplau & Don, 2017). Soil pH, which influences nutrient availability and microbial processes, also varies under different land use regimes due to inputs like fertilizers, lime, and organic amendments (Blanco-Canqui & Lal, 2008).

Furthermore, the texture of soil, particularly the proportions of clay and sand, though largely inherent, can be indirectly influenced by land use through erosion, sediment deposition, and soil management practices (Li et al., 2017). While short-term land use changes may not drastically affect soil texture, long-term practices can lead to measurable shifts, especially in areas subject to significant physical disturbance or degradation.

The growing recognition of the social, economic, and environmental benefits associated with understanding soil properties underscores the importance of leveraging this knowledge to achieve effective management objectives in agriculture, grazing, forestry, and other land uses (Padarian et al., 2015). Land Use and Land Cover (LULC) maps are used for modeling and monitoring the land surface, for example, studying the carbon cycle, the energy balance, and parameters related to soil health and water conditions (Malinowski et al, 2020; Khatami et al, 2016). Earth observation (EO) is well suited for regular LULC mapping (Topaloglu et al, 2016; Inglada et al, 2015; Defourny et al, 2019) due to the spatial coverage, temporal continuity, and low cost of deployment (Khatami et al, 2016). The free availability of vast amounts of remote sensing data offers exceptional opportunities to render LULC maps over large areas (Hansen et al, 2012; Brown et al, 2022). In this context, Copernicus Sentinel-2 (S2) high-resolution data have become an essential tool for LULC surveying especially concentrated on agricultural activities (Immitzer et al, 2016; Phiri et al, 2020). Worldwide agricultural maps could be generated and provide helpful information to policymakers and farmers (OneSoil, 2022). Some examples of application of S2 in agriculture are crop type mapping, crop production and irrigation monitoring, as well as nitrogen content and crop health assessments (Phiri et al, 2020). In 2018, the LUCAS collection strategy was further improved with the so-called “Copernicus module” that includes field observations more easily comparable to the spatial sampling of EO image data (d’Andrimont et al, 2020). Using these data, in combination with S1 image data, d’Andrimont et al. (2021) produced a 10 m crop type map of the 28 Member States of Europe (EU-28). The study classified 19 specific crop type classes alongside 2 broad Woodland and Shrubland and Grassland classes using the random forest (RF) algorithm, achieving an overall accuracy (OA) of 74.0%. Ghassemi et al. (2022a) extended this work to S2 data achieving an OA of 77.6%. The Copernicus Global Land Service (CGLS) provides operational land cover monitoring at a global scale with the release of annual GLC maps for 2015–2019 containing discrete and fractional land cover layers (CGLS-LC100m) (Buchhorn et al., 2020). provides operational land cover monitoring at a global scale with the release of annual GLC maps for 2015–2019 containing discrete and fractional land cover layers (CGLS-LC100m) (Buchhorn et al., 2020). The data used for the disaggregation are freely available data produced by the Copernicus Land Monitoring Service.

Numerous studies have demonstrated that land use change—especially the conversion of natural ecosystems to agricultural or urban land—has led to reductions in SOC, alterations in moisture retention, changes in pH, and variability in soil texture (Wei et al., 2020). However, the magnitude and direction of these impacts are context-dependent, varying with regional climate, soil type, land

management intensity, and duration of use. Consequently, localized studies are essential to elucidate these patterns and inform sustainable land use strategies.

Hormozgan province is one of the provinces in the south of Iran that includes about 0.0425% of the total range. Ranges in Hormozgan are used as winter ranges (Mostafaei et al, 2013). The Roudan basin sustains approximately 244,132 hectares of rangeland. This basin includes several ephemeral rivers and streams that flow during seasonal rain events. The average volume flow is about 112.89 MCM. It drains toward the Persian Gulf through seasonal rivers and channels, making it a crucial component of regional hydrology. These watercourses are vital for groundwater recharge and local irrigation. The basin has a diverse land use pattern, including irrigated agriculture, date palm groves, rangelands, and scattered forests. Farming is the primary livelihood for many local communities. Crops grown in the area include cereals, vegetables, citrus, and dates, often relying on groundwater or seasonal surface water for irrigation. However, unsustainable land use, deforestation, and overgrazing have led to soil degradation, erosion, and declining productivity in some parts of the basin (Planning of Range Management, 2008). The Roudan basin was selected as the study area due to the availability of a comprehensive database encompassing a range of environmental and agricultural parameters. This region plays a significant role in agricultural production and sustains approximately 244,132 hectares of rangeland (Mostafaei et al, 2013), which supports around 120,000 livestock units. Accordingly, investigating the soil characteristics of the Roudan watershed is of considerable importance for understanding and enhancing the productivity of its horticultural, agricultural, and pastoral systems. The objective of this study is to assess the impact of land use on selected physical and chemical soil properties—including sand and clay content, pH, soil organic carbon, and surface soil moisture (0–10 cm) by comparing laboratory-measured data with remotely sensed estimates derived from Google Earth Engine imagery. The analysis is conducted within the Rodan watershed across areas characterized by differing land use types.

Materials and Methods

Site description

The Roudan Basin is situated in the southwest of Hormozgan Province, near the border with Kerman Province. The basin encompasses a mix of mountainous, hilly, and lowland areas. The elevation of the watershed ranges from 134 to 1285 meters above sea level. The alluvial plain slope area has a range of 0 to 14.9 percent, while the mountain area's slope ranges from 24.7% to 100%. The average annual rainfall is 242 mm, mostly 77% concentrated in the winter months, with high evapotranspiration rates of about 2858.8 mm, making water availability a critical issue. According to FAO climatic classification Roudan ranges are located in Ommanian Gulf -Balouchian zone. Its climate is nearly the same as semi-Equatorial and Sahara-Sandi climate (Mostafaei et al, 2013). The area has an average annual temperature of 25.7 °C, with the minimum and maximum temperatures being 18.1 °C and 33.02 °C, respectively. The hot and dry climate influences land cover, vegetation, and soil moisture patterns. According to the USDA soil taxonomy great groups (1999), the main soil taxonomy area is Torriorthents. Soil profiles in the area have a small depth. The main soil in the plain is Qal and Qt2, with the property of loose alluvium and low terraces, and young fans (pluvial sandy) respectively. The soils in the basin range from sandy to clayey, depending on elevation and proximity to riverbeds. They are often low in organic carbon, and prone to salinity, particularly in irrigated areas. A visual representation of the study area is shown in Figure 1.

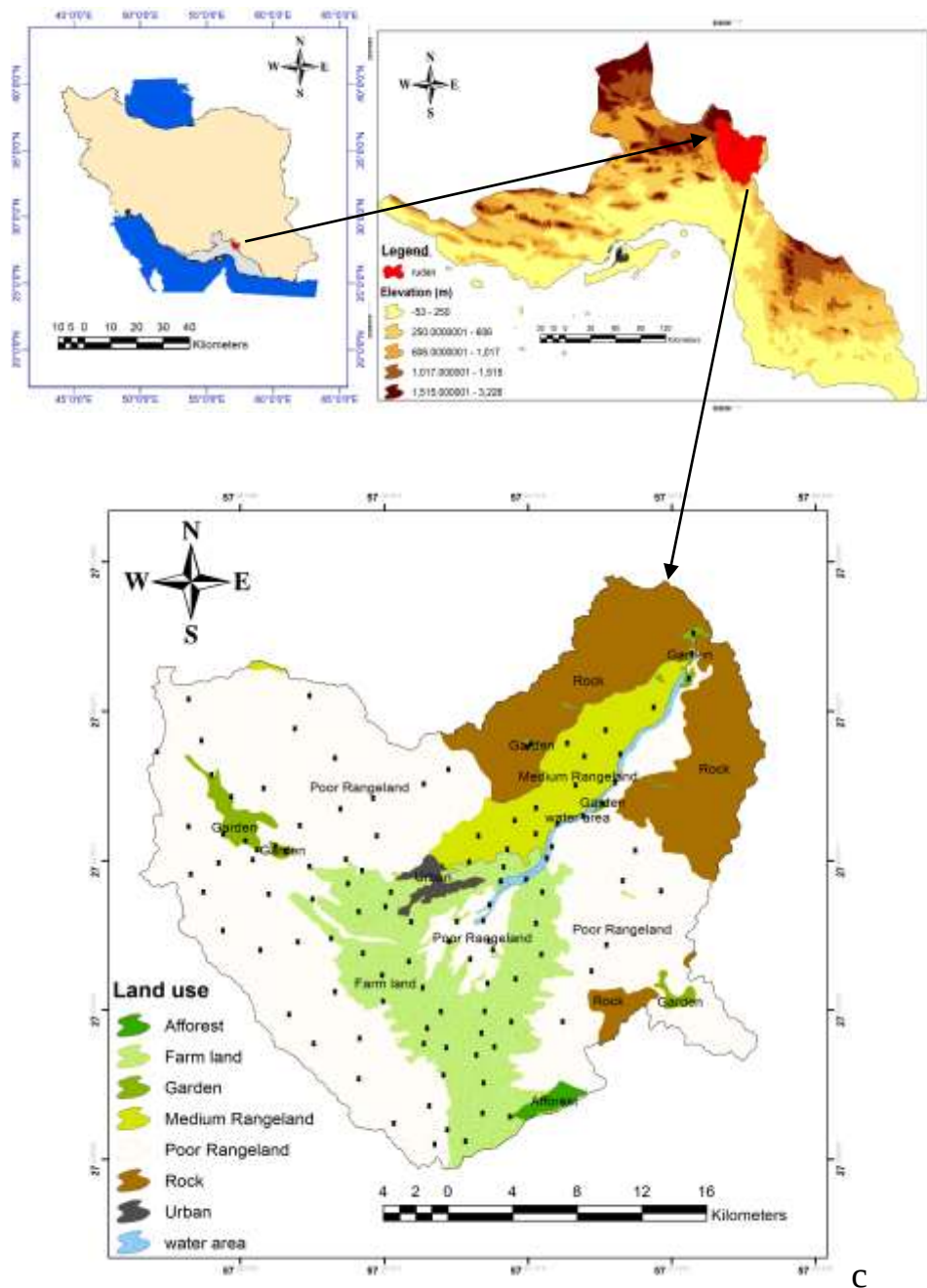


Fig. 1- Location of the Roudan Basin in the Iran and Hormozgan province and the soil sample points in each Land use

The Roudan Basin encompasses three distinct agricultural and ecological zones, as well as areas of barren land. According to the land use classification conducted by the Hormozgan Provincial Management and Planning Organization (2019), the study area is categorized into six land use classes: agricultural lands, orchards, irrigated areas, medium-quality pastures, poor-quality pastures, and mountainous regions (Heydarzadeh and Nohegar, 2022).

Methodology

This phase involved the initial identification of land use/land cover (LULC) types and the selection of appropriate soil sampling locations. Within the Roudan Basin, five primary LULC categories were identified: Poor Rangeland (PR), Medium Rangeland (MR), Farmland (FL), Water Area (WA), and Gardens (G). Rangeland conditions were classified based on vegetation cover percentages, where 0–25%, 26–50%, 51–75%,

and 76–100% corresponded to poor, fair, good, and excellent conditions, respectively, as described by Eghdami et al. (2021). To facilitate spatial analysis and classification, ArcGIS 10.3 software was employed to map and categorize land use across the basin. Soil samples were collected from representative locations within each LULC class using a simple random sampling method at a depth of 0–10 cm from the soil surface. A total of 205 soil samples were obtained for analysis. The sampling locations were geo-referenced using a Global Positioning System (GPS). According to Ghazali et al (2020), field surveys are necessary to estimate soil properties from satellite images. To this end, Soil samples were extracted using a hand-driven soil auger, air-dried, and subsequently passed through a 2 mm mesh sieve in preparation for laboratory analysis. The analyzed soil parameters included clay and sand content, pH, soil organic carbon (SOC), and surface soil moisture. Soil moisture is a critical parameter for understanding soil-water dynamics and land productivity. In this study, soil moisture content was measured using a Time Domain Reflectometer (TDR), which provides accurate in-situ readings of volumetric water content (Sinha et al, 2017). The Walkley-Black method was also used as a standard method for estimating soil organic carbon (Nelson et al, 1996; Sarkar et al, 2014; Sepahvand et al, 2020). To determine soil pH, the Extract of soil samples was prepared, then its value was measured using a pH meter. Also, the Bouyoucos hydrometer method (Bouyoucos, 1962) with sodium hexametaphosphate as a dispersing agent (Sahlemedhin and Taye,2000) was utilized to determine particle size distribution (Asadzadeh et al, 2019).

Image processing in Google Earth Engine (GEE)

Google Earth Engine system images were used to check the values of each soil parameter, including clay, sand, soil moisture, and soil organic matter. To achieve quantitative and qualitative changes of each parameter in the region, soil maps (Open Land Map) have been used based on digital satellite data provided in GEE, which do not require pre-processing and initial corrections (geometric, radiometric, etc); they are supplied ready for processing. Data processing is very time-consuming in conventional systems, which is one of the major advantages of GEE. Defining the location of the studied area within the Google Earth Engine system was the first task undertaken for this project. The data used includes the Landsat series images used in the Open Land Map image collection with a resolution of 250 meters, based on the USDA system, the values of bands b0 and b10. Soil maps (Open Land Map) have been used based on digital satellite data provided in GEE to obtain quantitative changes in soil moisture in the region, and they do not require pre-processing and initial corrections (geometric, radiometric, etc.). They are ready for processing. Surface soil moisture and Soil organic carbon factor up to a depth of 10 cm (00 _ 10 cm _ tavg) were also calculated with the help of FLDAS images (NASA/FLDAS/NOAH01/C/GL/M/V001) (McNally et al, 2017) and (OpenLandMap/SOL/SOL_ORGANIC-CARBON_USDA- 6A1C_M/v02) respectively, with 250 m resolution for the studied area. The purpose of this section is to prepare land cover and land use data at a resolution of 100 m, as detailed in Version 3 of the Copernicus Global Land Service for the study area by (CGLOPS1_PUM_LC100m-V3.0) (Horvat and Krvavica, 2023).

Analysis Soil Physical and Chemical Properties

To examine the relationship between the soil samples and GEE image outputs, statistical methods such as Pearson's correlation coefficient (r), mean absolute error (MAE), and root-mean-square error (RMSE) were employed to investigate, correlate, and evaluate the results (Asadzadeh et al, 2019; Nikdad et al, 2023).

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (Y_i - X_i)^2} \quad \text{Eq (1)}$$

$$MAE = \frac{1}{N} \sum_{i=1}^N |y_i - x_i| \quad \text{Eq (2)}$$

Where Y_i and X_i are the the mean of the measurements observed and simulated in space-time at point N is calculated from all available data (observation and execution of multiple simulations). The Pearson correlation coefficient (r), shown in (Equation 3), describes the linear correlation between two random variables (x, y) and does not depend on the unit of measurement.

$$r = \frac{\sum_{i=1}^n (x_i - \bar{x}) * (y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}} \quad \text{Eq (3)}$$

As this coefficient approaches 1 correlation in the observed data grows stronger.

Results

Table 1 shows some statistical characteristics of the parameters. The results indicated that the coefficient of variation (CV%) shows moderate variability in clay and sand content, high variability in moisture and pH levels, and very high variability in soil organic carbon (SOC). This variability in SOC is particularly important for soil health. The CV% values reflect significant fluctuations in moisture content, pH, and organic carbon levels, all of which can influence soil management practices. Understanding these variations is essential for making informed decisions regarding soil amendments and crop selection.

Table 1. Selected physical properties of soils

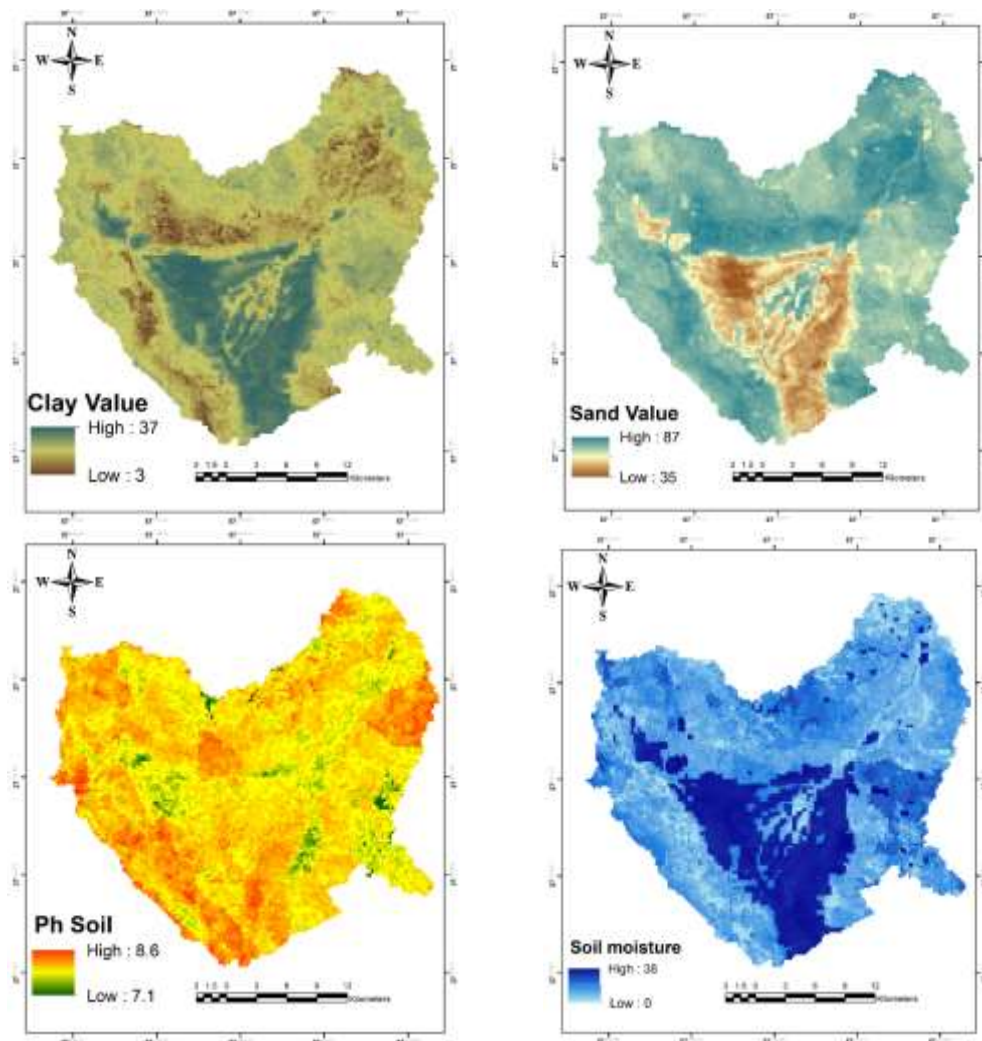
	Std. Deviation	mean	mod	min	max	CV (%)
Mois	8	23	28	3	30	35
Clay %	5.6	25.9	24	13	34	22
Sand %	8.1	49	38	38	67	17
Ph.	2.8	7.9	7.8	7.4	8.8	36
SOC %	3.8	1.5	1	0	3	41

Table 2 compares the measured and estimated soil properties, highlighting their differences. The evaluation of estimative models for soil properties is critical for agricultural management, ecological studies, and land-use planning (Smith et al., 2021). In farmland land use, Mois exhibited high accuracy ($r = 0.92$, MAE = 1.91), indicating reliable predictions. SOC had a moderate correlation ($r = 0.63$) but elevated RMSE (0.81), suggesting large error. Also, Clay predictions were strong ($r = 0.89$, RMSE = 0.79), while sand and pH performed poorly ($r = 0.55$ and 0.33 , respectively). In poor rangeland land use, Mois and clay showed robust correlations ($r = 0.90$ and 0.77 , respectively), but pH predictions were unreliable ($r = 0.30$, RMSE = 5.9). In Medium Rangeland, SOC and sand demonstrated moderate accuracy ($r = 0.74$ and 0.66), whereas clay predictions were weak ($r = 0.20$), possibly due to soil heterogeneity (Parras-Alcántara et al., 2016). In Garden land use, Exceptional performance for Mois ($r = 0.93$) and pH ($r = 0.83$) suggests stable predictive models. Sand had a high correlation ($r = 0.86$) but notable RMSE (8.9), indicating outliers. In the Water Area, pH predictions were highly correlated ($r = 0.91$) but had high RMSE (4.7), implying errors.

Table 2: the value of soil properties between measured and predicted soil

Land use	soil properties	MAE	RMSE	r
farm land	Mois	1.91	2.23	0.92
	SOC	0.26	0.81	0.63
	clay	1.93	0.79	0.89
	Sand	8.9	10.9	0.55
	PH	3.25	9.7	0.33
Poor Rangeland	Mois	1.25	1.4	0.9
	SOC	0.6	0.59	0.54
	clay	1.7	2	0.77
	Sand	2.9	4	0.58
	PH	1.79	5.9	0.3
Medium Rangeland	Mois	0.8	0.9	0.7
	SOC	0.71	0.64	0.74
	clay	1	1.34	0.2
	Sand	3.8	4.7	0.66
	PH	0.65	0.76	0.6
Garden	Mois	1.9	2.4	0.93
	SOC	0.83	1.1	0.69
	clay	1.9	2.1	0.78
	Sand	7.1	8.9	0.86
	PH	1.06	1.23	0.83
water area	Mois	0.7	0.8	0.6
	SOC	0.59	0.57	0.64
	clay	1.6	1.7	0.76
	Sand	2.7	3.9	0.79
	PH	2	4.7	0.91

The spatial distribution of soil properties, as depicted in Figure 2, was generated using Google Earth Engine. The soil moisture estimation maps reveal elevated water content in the central watershed region, with farmland and garden land-use areas exhibiting the highest moisture retention (Figure 2). These zones also demonstrate contrasting particle size distributions, with clay content reaching maximum levels and sand content remaining minimal. The high soil moisture concentration in the watershed's central region suggests favorable conditions for agricultural and horticultural activities. This is attributed to the elevated clay content, which enhances water retention and nutrient availability for crops (Osterman et al., 2019). Conversely, the low sand content in these areas facilitates adequate drainage, reducing the risk of waterlogging (López-Felices et al, 2020). The interplay of these soil characteristics—moisture retention, high clay content, and optimal drainage—creates an environment conducive to productive farming and gardening practices. Clay content exhibited significant spatial variability across the study area. Farmlands recorded the highest clay concentrations, whereas the lowest levels were observed in hillside regions (Wokhe et al., 2013). This variability underscores the influence of topography and land use on soil composition.



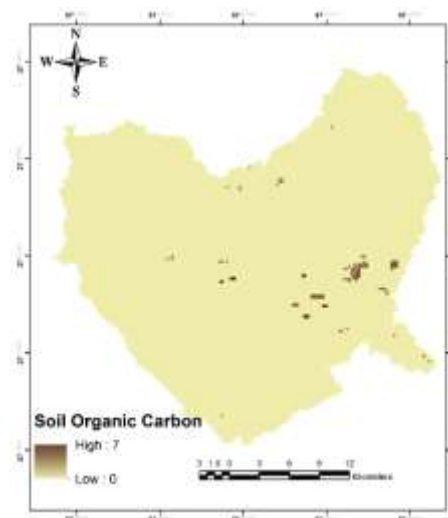


Fig. 2- Output maps from GEE images

Soil pH is a critical determinant of soil physical and mechanical properties, exerting significant control over nutrient availability, microbial activity, and structural stability (Woldeyohannis et al., 2022). The pH of a soil system is primarily governed by the composition of its parent material and climatic factors such as precipitation (Mahjoory, 2013). Furthermore, anthropogenic activities—including agricultural practices, irrigation methods, and fertilizer application—can substantially modify soil pH levels (Brady & Weil, 2016). The pH value indicates that lower pH levels are associated with higher soil organic carbon (SOC) in water areas, with a correlation coefficient of $r = 0.64$. In contrast, farmland shows a weaker correlation ($r = 0.33$). Acidic conditions, which are common in soils adjacent to water, tend to slow down the decomposition of organic matter (Schmidt et al., 2011). However, gardens present an exception. They exhibit a moderate correlation between SOC and pH ($r = 0.69$), despite having a near-neutral pH (1.06 MAE). This suggests that management practices in gardens can override natural trends.

Accuracy Assessment and Observed LULC Changes in the basin

The error matrix presented in Table 3 provides a comprehensive evaluation of the LULC classification performance across five land cover classes. The overall classification accuracy of 95% with a Kappa coefficient of 0.93 indicates excellent agreement between the classified data and reference data (Congalton & Green, 2019). The Producer's Accuracy result showed Poor Rangeland demonstrated the highest accuracy (98.4%), with min commission errors (1.4% misclassified as farmland and gardens). Medium Rangeland showed strong performance (96.4%), with only 3.6% confusion with water areas. Farmland achieved 95% accuracy, with 5% confusion from Poor Rangeland. Water areas had the lowest user accuracy (87.5%), showing confusion with all other classes (3.1-6.3% each). The Gardens performed well (92%), with minor confusion from Poor Rangeland (3.7%). On the other hand, the matrix reveals asymmetric error distribution (Foody, 2020), so that Water areas were the most frequently misclassified (12.5% error rate). Poor Rangeland showed the least error (1.6%), suggesting distinct spectral characteristics. The 6.3% confusion between water areas and Medium Rangeland may indicate seasonal water variation.

Table 3: The accuracy assessment matrix for LULC

Classification Class	Reference class					Row Total	User' accuracy (100)
	Poor Rangeland	Medium Rangeland	farm land	water area	Gardens		
Poor Rangeland	62	0	1	0	1	63	98.4
Medium Rangeland	0	54	0	1	0	56	96.4
farmland	2	0	38	0	0	40	95
water area	1	2	1	28	1	32	87.5
Gardens		1	0	0	25	27	92
Overall accuracy	95%						
Kappa coefficient	93%						

Figure 3 presents the land use map of the region, created using Sentinel images from the Copernicus dataset on GEE. A visual comparison indicates that the resulting map closely resembles the actual land use of the region. Furthermore, the overall accuracy of 95% and a Kappa coefficient of 93% demonstrate the effective performance of the Copernicus land use data.

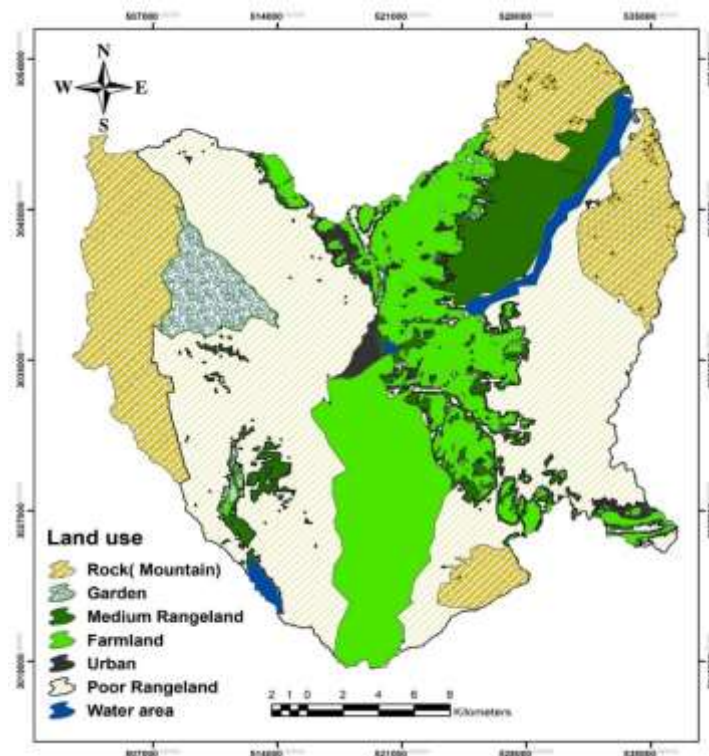


Fig. 3- The LULC map generated using GEE

Physical and Chemical Soil properties under different land use

The analysis revealed notable variations in sand grain size across different land use types, with values ranging from a minimum of 49% in arable land to a maximum of 78% in medium pasture land. Despite these numerical differences, statistical analysis indicated that the variations in sand content were not significant ($p > .05$). Among the evaluated land uses, arable fields exhibited the lowest sand content (Table 4). Similarly, the distribution of clay particle size differed across land use types, ranging from 6.5% in medium-range land to 26% in arable land (Table 3). An inverse relationship was observed between clay and sand contents. Furthermore, soil moisture content was significantly influenced by land use type ($p \leq .05$), with values ranging from 1.5% to 23%. The highest moisture contents were recorded in farmland and garden soils, at 23% and 19.6%, respectively ($p \leq .01$), suggesting a substantial impact of land use on soil moisture retention. Soil pH also varied across land uses, although the observed differences were not statistically significant at the 0.01 level ($p > .01$). The lowest pH value (7.5) was found in soils from water-affected areas, while the highest (7.95) was measured in garden soils. In terms of soil organic carbon (SOC), land use had a highly significant effect ($p \leq .01$). Farmland exhibited the highest SOC content at 1.7 g/kg, followed by garden land (1.0 g/kg), while the lowest SOC content (0.2 g/kg) was found in poor rangeland areas.

Table 4: The main effects of land use on the physical and chemical properties of selected soils.

	Soil moisture (%)	Sand (%)	Clay (%)	Ph	SOC (g/kg)
Poor Rangeland	1.5*	69	12*	7.8	0.2
Medium Rangeland	2.5*	77	6.5*	7.8	0.5*
farmland	23**	49	26*	7.9	1.7*
water area	4*	71	10*	7.5	0.3
Gardens	19.6**	58	21*	7.95	1*

*. significant 95% **. significant 99%

The data presented in Table 4 reveal significant variations in soil properties across different land use types, demonstrating the profound impact of anthropogenic activities on edaphic characteristics. These findings align with established pedological principles while highlighting land-use-specific patterns of soil modification. Farmland exhibited the highest moisture content (23%), followed closely by gardens (19.6%), while rangelands showed minimal moisture retention (1.5-2.5%). This may indicate Intensive irrigation practices in agricultural systems (Siebert et al., 2015), vegetative cover effects on evapotranspiration (Li et al., 2017), or Soil structural modifications from tillage (Robinson et al., 2014). The result of the soil texture showed that medium rangeland contained the highest sand fraction (77%), consistent with its low moisture retention. Farmland showed the highest clay percentage (26%), explaining its superior water-holding capacity (Saxton & Rawls, 2006). Chemical Properties of soil showed all sites were neutral to slightly alkaline (7.5-7.95), with minimal variation. Farmland contained 8.5× more SOC than poor rangeland (1.7 vs. 0.2 g/kg). This can be caused by organic matter inputs from crop residues (Mastrolonardo et al, 2015) and reduced erosion in managed systems. On the other hand, the data revealed two significant correlations, first, a Negative relationship between sand content and soil moisture ($r=-0.89$, $p < 0.05$), second positive association between clay content and SOC ($r=0.82$, $p < 0.05$).

Conclusion

In this study, to examine the images of Google Earth Engine, soil samples were randomly taken in different parts of the Roudan basin. PH, water soil, SOC, clay, and Sand experiments on samples were done. The use of GIS and GEE applications is suitable based on the results obtained for the review and evaluation of different parameters of land cover/land use. This study confirmed the use of GEE techniques in the analysis of land use changes in the Roudan basin by using different components of GIS. Quantitative data production about the parameters of soil and land use was possible. Changes in soil organic carbon content cause apparent specific gravity, and also show statistically significant differences between land uses. Increasing the amount of soil organic carbon from 0.5 to 3% in all soil texture classes increases the usable water capacity by more than 2 times; Of course, for pastures and road uses, the value of this index is limited. The results thus show that the amount of soil moisture is highest in farmland and garden land. However, the depletion of soil organic carbon in agricultural land can be attributed to the erosion of soil structure caused by repeated cultivation and the removal of crop leftovers. Soil organic carbon is the result of the deposition of vegetation residues. The organic carbon levels decrease with continuous farming on agricultural lands (Dor et al, 2023). The decline in organic carbon levels could result in soil deterioration and reduced fertility in the long run. Overall, the LULC situation showed that the Garden and water areas' soil samples have the highest correlation with images. The use of ground truth datasets ensures the reliability of the classification results, with overall accuracies of 95% and a Kappa coefficient of 0.93. This agrees with findings by Ghassemi et al (2022b), Rosina et al(2018) and, Congalton and Green (2019). The Poor Rangeland achieved the highest producer's accuracy (98.4%), while Water areas had the lowest user accuracy (87.5%) due to cross-class confusion (Foody, 2020). So Woldeamlak and Solomon (2013) reported that removing vegetation reduces the recycling of organic carbon in the soil. Soil organic carbon is the result of the deposition of vegetation residues. Findings Doa et al (2011) suggested that land use changes can influence soil properties. Changes from a garden or forest to rangeland or bare soil type remove the addition of litter that decreases the nutrient content of soils and increases rates of erosion and loss of soil organic matter, these results agree with Rawat and Kumar (2015). Google Earth Engine presents a new platform that can be integrated into a Traditional Digital Soil Mapping process. It is precisely designed to deal with vast datasets, vital in DSM, for mapping soil characteristics. One main advantage of using GEE is that there are lots of rasters that can be easily assessed and used to make both data gathering and application of an algorithm much easier, hence increasing computational efficiency to a huge degree. Whereas GEE is under constant development and has its shortcomings, it is not a strictly digital soil mapping software. Rather, it is a tool for mapping the wider environment, and its potential for the soil science and environmental community is vast.

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