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RESEARCH PAPER

EVALUATING ESRI 10-M LAND USE/LAND COVER (LULC) PRODUCTS FOR MOROCCAN MOUNTAINOUS LANDSCAPES

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ABSTRACT. The task of precise Land Use/Land Cover (LULC) mapping in mountainous areas is a significant challenge due to the complexity of the terrain and spectral confusion. High-resolution global products like Esri's 10-m LULC maps present valuable opportunities, yet their performance in these contexts remains underexplored. This study aims to fill this gap by evaluating and improving the precision of Esri 10-m LULC datasets (2017 and 2021) in the mountainous areas of Morocco. The results of this study are of practical significance for more accurate land use monitoring. To maximize map coherence, we used stratified random sampling and high-resolution Google Earth imagery to assess classification accuracy, then refined the classification. The results revealed a wide range of classification accuracy for mountainous units (OA ranges between 69.3% and 93.4%), and the misclassification of the "Built Area" class was also found. Particularly in more diverse landscapes, the calibration steps significantly improved accuracy and visual coherence. Analysis of Esri's 10-m LULC maps further showed substantial LULC changes, including losses of forests, water bodies and expansion of rangelands and built-up areas. In light of the observed limitations, especially in detecting fine-scale anthropogenic features, we propose the integration of artificial intelligence tools—alongside remote sensing data and field verification—as a promising approach to improve the detection and delineation of critical land features, thereby reinforcing the reliability of LULC products in complex mountainous terrains.

KEYWORDS: remote sensing (RS), Sentinel-2, Esri land cover, accuracy assessment, LULC, mountainous areas

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INTRODUCTION

Land Use/Land Cover (LULC) has been a major concern in environmental research over recent decades because it reflects dynamic changes on Earth's surface resulting from both natural processes and human activities (Verhoog 2014; Yin 2014). Land cover refers to the existence of physical features (natural or anthropogenic) such as forests, water bodies, and land settlements[1]. The use of landscapes by humans (e.g., farming, building cities and towns) is referred to as "land use" (Meyer and Turner 1992). A rigorous monitoring of the relationship between land cover and land use is fundamental to achieving sustainability, enhanced climate adaptation, better biodiversity conservation, and more effective management of natural resources (Feddema et al. 2005).

During recent decades, LULC patterns worldwide have become more complex due to climate variability, urban sprawl, and intensifying agricultural management practices (MohanRajan et al. 2020; Pongratz et al. 2018). These global trends have local manifestations in Morocco, where demographic pressure and socio-economic transitions have contributed to land degradation, vegetation change, and hydrological imbalances (Driouech et al. 2021; Ouhamdouch and Bahir 2017). The natural ecosystems in the High and Middle Atlas were

[1]Di Gregorio, A. and Jansen, L.J.M. (2000). Land Cover Classification System (LCCS): Classification Concepts and User Manual. For Software Version 1.0. Rome: Food and Agriculture Organization of the United Nations. Available at: https://www.fao.org/4/x0596e/x0596e00.htm (accessed 12 July 2026).

significantly altered by agricultural expansion, livestock grazing, and deforestation, which has resulted in soil erosion (Ben-Said et al. 2025; El Aich 2018; Nguyen et al. 2023).

Although recent progress has been made in developing and evaluating high-resolution global LULC products (Naboureh et al. 2025; Venter et al. 2022; Wang et al. 2023; Xu et al. 2024), the accuracy assessment of these datasets in Moroccan mountainous areas has received little attention, despite evidence that their performance varies substantially across regions and landscape types. Therefore, this study quantitatively assesses the accuracy of Esri 10-m LULC datasets for 2017 and 2021 across Moroccan mountainous regions using overall accuracy, the Kappa coefficient, and class-level accuracy metrics, while identifying the main sources of classification error.

Rapid advances in remote sensing (RS) and geographic information systems (GIS) technology have promoted the monitoring of LULC with greater accuracy and at broader scales (Kaya and Görgün 2020). The use of high-resolution satellite data (e.g., Sentinel-2 imagery) and the application of machine-learning and deep-learning techniques lead to better land-cover classification and change detection, especially in complex mountain environments (Delalay et al. 2019; Gao et al. 2019). The cloud-based platforms and global land cover products that have been developed, such as the annual Esri dataset and ESA WorldCover, are some practical tools for environmental monitoring, urban planning, and ecosystem management[2].

Even with these developments, accurately mapping LULC in such mountainous and complex landscapes is still difficult considering topographic variability, heterogeneous land cover, and data constraints (Arrechea-Castillo et al. 2023). Classification errors can have a profound adverse impact on monitoring and land management decisions (Congalton 1991). Advanced classification assessment methods involving probabilistic and object-based approaches increase map accuracy, thereby contributing to better disaster-management preparedness in ecologically sensitive regions (Morales-Barquero et al. 2019). Additionally, studies in hydrology, rangeland management, and biodiversity monitoring show the practical utility of high-precision LULC data (Alawi and Ozkul 2023; Bao et al. 2023; Erdenechimeg et al. 2023; Muminov et al. 2025; Nandintsetseg et al. 2024).

Morocco is currently undergoing rapid environmental and socio-economic changes, particularly in mountain regions where accurate LULC maps are essential for sustainable land-use planning and ecosystem conservation. The present study explores the precision of LULC maps in mountainous Moroccan landscapes, identifies areas that were incorrectly classified, and provides recommendations for improving methodology to facilitate more robust environmental monitoring. This work on the integration of remote sensing with GIS and advanced classification processes will provide decision-making support for land managers, scientists, and policymakers to better contextualize and address LULC issues within Morocco's complex terrains, with the approach also applicable to similar mountainous environments, particularly in the Mediterranean region.

MATERIALS AND METHODS

Study Area

Morocco's mountainous region is ecologically fragile and demographically significant—one out of every four Moroccans resides there. Given their key ecological and socio-economic role, the Moroccan authorities have pursued a policy of sustainable development aimed at reconciling demographic growth, resource management, and nature conservation. Accurate (LULC) data are necessary to assess natural resources and climate change impacts and support decision-making in planning adaptation and mitigation efforts. Mountains in Morocco are generally defined as areas above 500 meters in altitude and were classified in 2015, with 738 mountainous communes being identified as the first step for integrated mountain development programs[3]. It should be noted that this threshold (500 meters) does not capture some lower-elevation mountainous areas, such as the coastal mountains in the Extended Rif, the Western High Wet Atlas, and the Anti-Atlas, which still exhibit significant mountainous characteristics.

In this study, the term "mountain units" refers to structural and geomorphological units rather than administrative divisions. However, the mapped spatial framework is based on administrative communes whose territories fall entirely or partly within these geomorphological units. Accordingly, Morocco's mountainous communes were grouped into eight main mountain units, along with two associated mountain areas, for sampling and accuracy assessment purposes (Fig. 1 and Table 1). Half of these communes are located in the Western Wet High Atlas and the Extended Rif, while three regions – Drâa-Tafilalet, Tangier-Tetouan-Al Hoceima, and Fès-Meknès – contain nearly half of them. Mountain communes account for 48% of Morocco's 1,538 communes and, when the associated areas are included, cover about 38% of the national territory. Strictly defined mountain areas, excluding the High Plateaus and high-altitude oases, represent about one-quarter of the country's total area. Given their ecological fragility and socio-economic vulnerabilities, these regions require integrated and adaptive governance to achieve sustainable development, conserve natural resources, and strengthen their capacities to cope with environmental challenges.

Data Preparation and Processing

LULC in the Moroccan mountains was analyzed using the Esri Land Cover dataset linked with the Impact Observatory. This global dataset provides 10-meter-resolution classifications of Sentinel-2 imagery processed by the Microsoft Planetary Computer. Raster land-cover maps from 2017 and 2021 were used to detect temporal changes. The dataset includes nine classes: water, trees, flooded vegetation, crops, built-up areas, bare soil, snow/ice, cloud, and rangeland. A detailed, stepwise analysis framework is illustrated in Fig. 2. Exploiting classified categories derived from satellite imagery requires careful evaluation to assess the reliability of cartographic analyses. Given the large number of pixels, performing an exhaustive evaluation of the entire dataset is impractical. Thus, a representative sample was selected for evaluation, and the

[2]Esri and Impact Observatory (2023). Esri Land Cover 10m Annual (2017–2023). Available at: https://livingAtlas.arcgis.com/landcover/ (accessed 4 July 2026); European Space Agency (ESA) (2021). WorldCover 2020 Product. ESA WorldCover Portal. Available at: https://esa-worldcover.org/en (accessed 27 March 2026).

[3]Conseil Économique, Social et Environnementall (2019). Le développement rural : Espace des zones montagneuses (Saisine n° 21/2017). Available at: https://www.cese.ma/media/2020/10/Rapport-Le-développement-rural_Espace-des-zones-montagneuses.pdf (accessed 4 July 2026).

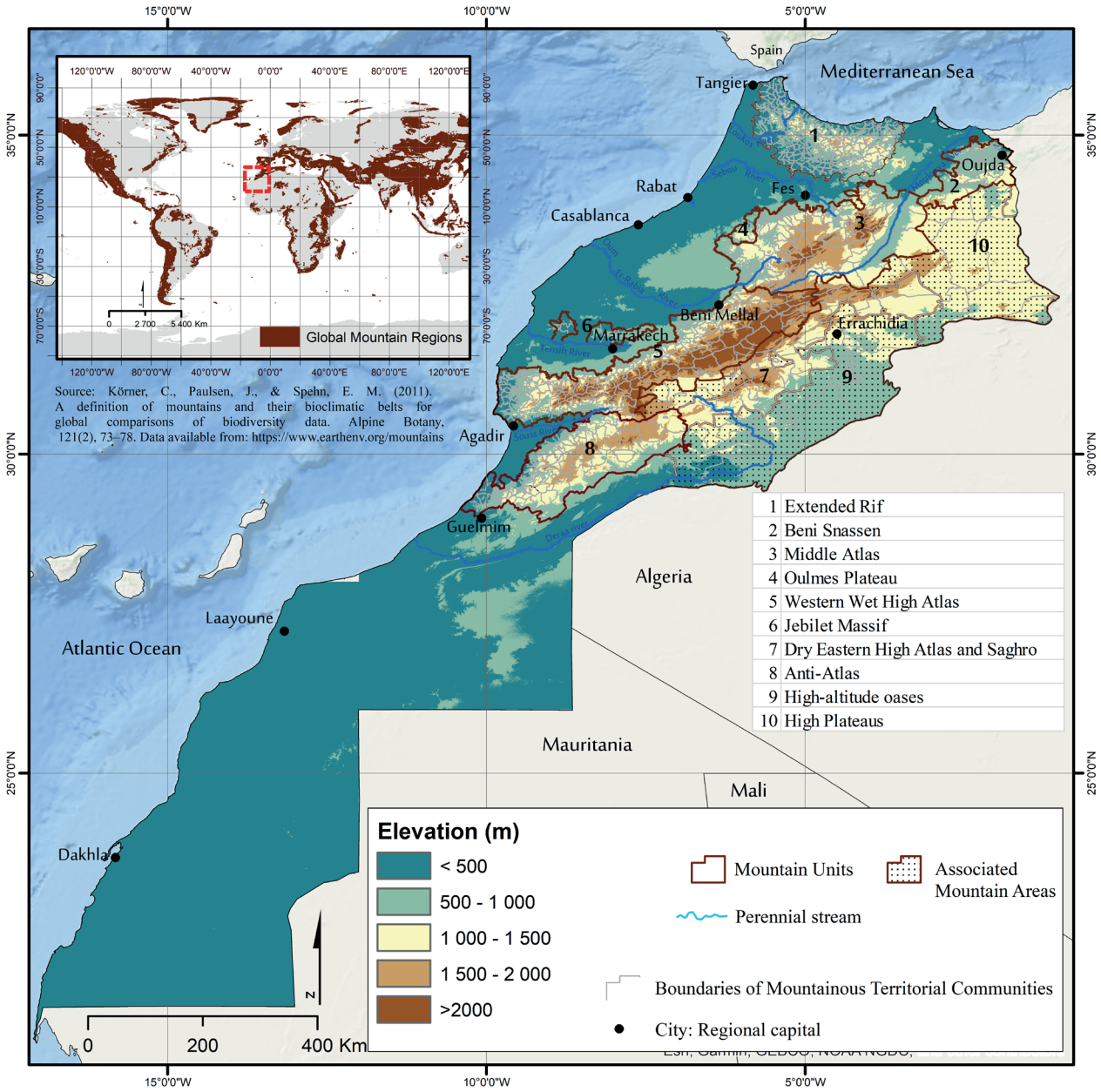


Fig. 1. Study area location

sample size was determined using Cochran's (1977) sample size formula with finite population correction. The sample size was calculated assuming a 95% confidence level (Z = 1.96), a 5% margin of error (d= 0.05), and maximum variability (p= 0.5). The Eqs. 1–2 used are as follows:

$$n_0 = \frac{Z^2 \times p \times (1-p)}{d^2} \quad (1)$$

$$n = \frac{n_0}{1 + \frac{n_0 - 1}{N}} \quad (2)$$

where N is the total number of pixels in the study area.

This period, 2017–2021, may seem short for LULC studies; however, it was selected because the study aimed to evaluate an existing high-resolution dataset (the Esri Land Cover dataset), and reference points were converted to KMZ for visualization in Google Earth, using high-resolution historical imagery provided by Maxar Technologies and CNES/Airbus, as indicated in Google Earth, from the corresponding year, where available, to ensure temporal consistency with Esri maps. When same-year imagery was unavailable or affected by cloud cover or poor visual quality, imagery from the closest available year, either before or after the target year, was used. Priority was given to cloud-free images acquired during summer and autumn to improve visual interpretation and ensure greater consistency in land-cover identification. This timeframe is sufficient to assess the quality and applicability of the data, particularly in the Moroccan mountain regions.

The total number of pixels over mountainous areas across the different LULC categories in Morocco exceeds 2.6 billion pixels (Table 1). Evaluation points were chosen by stratified random sampling with an area proportional to each category, except that a threshold of 20 was required for the least-represented classes. The resulting minimum and final sample sizes for each mountain unit are reported in Table 1. The points were created in ArcGIS using the Create Random Points tool and then exported to KMZ for comparison against the classified and reference data. The reference data consisted of high-resolution historical imagery available in Google Earth, acquired from multiple commercial satellite providers (e.g., Maxar and CNES/Airbus) depending on image availability. Imagery from

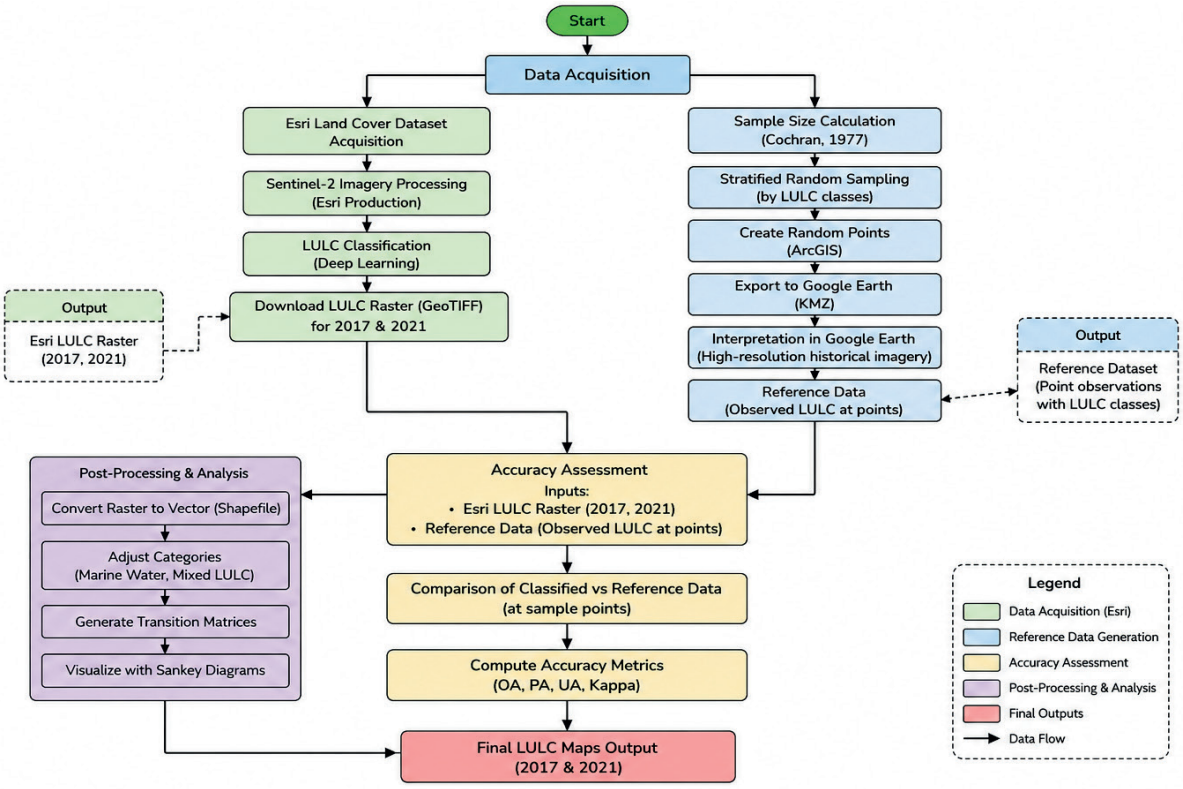


Fig. 2. Methodological steps for evaluating LULC maps derived from Esri land cover imagery

Table 1. Sample sizes for evaluating the classification accuracy of categories inferred from Esri land cover images

		Number of Pixels	Minimum Sample Size	Final Sample
Mountain Units	Extended Rif	204 692 801	385	438
	Beni Snassen	84 996 593	385	456
	Middle Atlas	370 653 883	385	442
	Oulmes Plateau	14 140 775	385	442
	Western Wet High Atlas	426 381 165	385	462
	Jebilet Massif	34 355 330	385	441
	Dry Eastern High Atlas and Saghro	266 427 261	385	462
	Anti-Atlas	291 031 049	385	460
Associated Mountain Areas	High-altitude oases	543 101 095	385	481
	High Plateaus	367 623 425	385	483
Total		2 603 403 377	3850	4567

the corresponding year was used whenever possible; otherwise, the closest available cloud-free image was selected to maintain temporal consistency with the Esri dataset. Reference LULC classes were assigned through manual visual interpretation by examining image color, texture, shape, pattern, size, shadow, and spatial context, following standard visual image interpretation principles. The interpreted class at each reference point was then compared with the corresponding Esri LULC class to compute the accuracy metrics.

The accuracy of LULC classification was assessed using producer's accuracy (PA), user's accuracy (UA), and overall accuracy (OA), as well as the Kappa coefficient. Producer's accuracy (PA) was calculated as the proportion of reference samples of a given LULC class that were correctly classified, while user's accuracy (UA) was calculated as the proportion of samples assigned to a given LULC class that were confirmed by the reference data. Overall accuracy (OA) was calculated as the proportion of correctly classified samples among all reference samples, and the Kappa coefficient was used to measure the agreement between the classified and reference data beyond chance.

The validity of the raster-based LULC classification was checked before the data were converted to shapefiles for post-classification processing. Changes were made to increase specificity in marine areas, reduce confusion, and exclude the categories snow/ice and cloud, as they are not included in the study area. Furthermore, the built-up areas or impervious category was renamed mixed LULC. Transition matrices were then created and visualized using a Sankey diagram to clarify land cover changes, followed by the generation of final LULC maps. All data processing,

post-classification refinements, and visualization were conducted using ArcMap 10.7.1, Microsoft Excel, and the Flourish platform[4].

RESULTS

Accuracy Assessment and Refinement of LULC Classification

Tables 2 and 3 present the classification results for each mountainous unit. These tables provide values for overall accuracy and the variations in Kappa coefficients for 2017 and 2021. In 2017, overall accuracy ranged from a minimum of 75.5% in the high-altitude oases to a maximum of 93.44% on the Oulmes Plateau. In 2021, the Extended Rif unit was the least accurate, with 69.32%, while the highest value again was 93.44% in the Oulmes Plateau. The Kappa coefficient shows a similar trend and ranged from 0.62 for high-altitude oases to 0.90 for both the Oulmes Plateau and the Dry Eastern High Atlas in 2017. In 2021, the Kappa values were lowest for the Jebilet Massif and the Beni Snassen (0.56) and remained the highest for the Oulmes Plateau (0.90).

The evaluation of the Esri 10-m Land Cover dataset against high-resolution Google Earth reference imagery revealed several limitations. The most notable misclassification occurred in agricultural fields located near residential developments. For example, in the Extended Rif, 16 out of 35 pixels were incorrectly classified as built-up areas rather than agricultural land, resulting in a user's accuracy of just 42.86% in 2021. Additionally, the Esri dataset does not distinguish between inland and saltwater bodies.

To improve the thematic consistency of the LULC maps, several post-classification refinements were applied. These refinements were applied to the Esri LULC maps, while high-resolution Google Earth imagery was used solely as reference data to guide and verify the reclassification process. Certain types of arboreal cover – date palms in the Dry Eastern High Atlas and olive trees in the Jebilet Massif – were reclassified as cultivated land because they correspond to managed agricultural tree crops rather than natural tree cover. Flooded vegetation in the Dry Eastern High Atlas was also reclassified as pastureland where it corresponded to herbaceous or grazing areas. Additionally, the Built-up Area class was updated and expanded to encompass a broader range of anthropogenic land-use categories. Marine and inland water bodies were separated in the coastal mountainous areas of the Extended Rif, Western Wet High Atlas, and Anti-Atlas. Marine waters were mainly confined to harbors and coastal areas, with some areas partially inundated at the time of satellite image acquisition. In contrast, inland waters included dams, reservoirs, lakes, and parts of rivers.

Monitoring and Tracking LULC

Morocco is undergoing vast spatial transformations, both in rural and urban areas, as well as in coastal and inland regions, across mountainous, lowland, and oasis areas in the south and southeast. Figs. 3 and 6 illustrate the dynamic changes observed in mountainous areas from 2017 to 2021. The distribution of rangeland and bare ground, two of the more common LULC types across these regions, varies widely among units. Their distribution is progressively reduced from south to north and from east to west, with the most substantial concentrations in the High Plateaus, Beni Snassen, High-Altitude Oases, the Dry Eastern High Atlas, Saghro, and the Jebilet Massif. Conversely, mountainous areas, such as the Rif, Middle Atlas, Western High Atlas, and Oulmes Plateau, have more diverse LULC classes, including forest, crops, and other land-cover types.

Mountainous areas have undergone changes in LULC patterns over the years. Natural environments (water bodies, trees, and flooded vegetation) have decreased in most mountainous units, except for the Extended Rif, the Oulmes Plateau, and Beni Snassen. Concurrently, rangeland cover has expanded in all mountainous areas except for the Dry Eastern High Atlas, where much of the land had become barren by 2021. In parallel with the decline of vital natural elements, particularly water bodies and trees, croplands have also generally decreased in spatial extent. Conversely, built-up areas and various human-made structures emerged as the LULC category with the greatest increase over the study period.

Quantification also highlights the extent of the changes: 12.83% of the land in mountainous areas changed between 2017 and 2021. However, the rate of change varies between mountainous units. The most significant transformation rate was registered in the Jebilet Massif (30.42%), followed

Table 2. Accuracy assessment of the Esri 10-m land cover product for the mountainous areas of Morocco (2017)

	Extended Rif		Beni Snassen		Middle Atlas		Oulmes Plateau		Western Wet High Atlas		Jebilet Massif		Dry Eastern High Atlas and Saghro		Anti-Atlas		High-altitude oases		High Plateaus	
	UA	PA	UA	PA	UA	PA	UA	PA	UA	PA	UA	PA	UA	PA	UA	PA	UA	PA	UA	PA
Water	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Trees	100.0	100.0	100.0	100.0	97.1	100.0	100.0	100.0	100.0	100.0	100.0	100.0	0.0	0.0	85.0	100.0			100.0	100.0
Flooded vegetation	100.0	100.0			100.0	100.0			100.0	100.0							50.0	100.0	100.0	100.0
Crops	93.0	42.6	97.1	30.1	68.6	46.2	96.3	79.6	90.0	31.0	100.0	22.4	100.0	47.6	85.0	34.7	90.0	42.9	85.0	73.9
Built Area	43.8	87.5	65.0	86.7	80.0	100.0	75.0	83.3	60.0	100.0	80.0	88.9	80.0	100.0	80.0	94.1	95.0	95.0	80.0	100.0
Bare ground	65.0	92.9	70.0	100.0	91.4	96.4	80.0	100.0	84.3	86.8	73.5	97.0	100.0	87.8	94.9	82.4	64.8	76.9	88.2	75.0
Rangeland	65.4	91.6	79.9	99.3	90.4	93.8	92.6	97.3	85.7	95.0	68.9	95.0	89.4	99.0	82.1	97.3	86.0	74.9	94.3	96.6
OA	76.03		81.92		89.73		93.44		86.43		75.17		89.83		86.30		75.05		93.37	
Kappa	0.68		0.65		0.84		0.90		0.78		0.64		0.90		0.79		0.62		0.87	

[4]https://app.flourish.studio/projects

Table 3. Accuracy assessment of the Esri 10-m land cover product for the mountainous areas of Morocco (2021)

	Extended Rif		Beni Snassen		Middle Atlas		Oulmes Plateau		Western Wet High Atlas		Jebilet Massif		Dry Eastern High Atlas and Saghro		Anti-Atlas		High-altitude oases		High Plateaus	
	UA	PA	UA	PA	UA	PA	UA	PA	UA	PA	UA	PA	UA	PA	UA	PA	UA	PA	UA	PA
Water	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
Trees	98.3	90.8	100	100	97	100	100	100	100	100	55	100	0	0	65	100	35	100	100	100
Flooded vegetation	100	100			100	100			100	100	100	100					50	100	100	100
Crops	91.7	32.5	100	20	92.9	57.4	96.3	76.7	95	36.5	100	17.6	100	37.7	85	41.5	85	44.7	90	81.8
Built Area	42.9	62.5	65	72.2	80	100	65	100	85	94.4	75	93.8	60	100	85	94.4	70	100	90	100
Bare ground	55	68.8	75	75	96.2	96.2	100	100	86.5	69.6	80.6	96.2	93	86	95.8	85.6	97.1	87.8	96.2	35.2
Rangeland	55.6	99.2	71.2	99.6	91.4	98.8	91.9	97.7	86.3	98.2	64.6	100	93.9	91.4	88.9	98.7	94.2	94.2	86.3	98.7
Overall	69.32		75.28		92.52		93.44		88.4		70.96		85.03		89.78		89.38		88.34	
Kappa	0.6		0.56		0.87		0.9		0.79		0.56		0.74		0.84		0.83		0.75	

by the Dry Eastern High Atlas (21.33%) (Figs. 4 and 5), and much lower rates were observed in the High Plateaus and Beni Snassen (7.06% and 7.10%, respectively). These changes also varied by LULC type, with flooded vegetation changing the most (84%) and rangeland changing the least (approximately 1.9%).

Over the period 2017–2021, mountainous areas experienced significant environmental changes, notably a substantial decrease in freshwater bodies, tree cover, and flooded vegetation areas. The most affected areas were the High-Altitude Oases, the Western Wet High Atlas, the Middle Atlas, and the Extended Rif. Aggregated data analysis showed that 25% of inland water surfaces and large portions of forested land (which were mainly converted to rangelands and barren land) were affected. In contrast, the vegetation of the floodplains (particularly in the Middle Atlas) nearly disappeared. Crop areas also decreased significantly, particularly in the Extended Rif, Middle Atlas, and Western Wet High Atlas, primarily in favor of rangelands and, to a lesser extent, built-up areas. Bare areas and other uses were dynamic, often transitioning to rangeland or being re-cultivated. At the same time, some mountainous regions, including the Extended Rif and Oulmes Plateau, recorded an increase in surface water, and some areas showed local advances in tree cover.

To assess the consistency of the resulting LULC patterns, a visual comparison was performed between the enhanced Esri Land Cover dataset and the ESA WorldCover product (2021). The overall spatial patterns are largely comparable between the two datasets, particularly for major land cover classes such as water and vegetation. However, some differences in class allocation were observed. In particular, areas classified as "Trees" in the Esri dataset correspond, in some cases, to a combination of the "Shrubland" and "Grassland" classes in the ESA dataset. These differences are also reflected in the classification schemes, as Esri uses a 9-class system, whereas ESA WorldCover distinguishes 11 land cover classes.

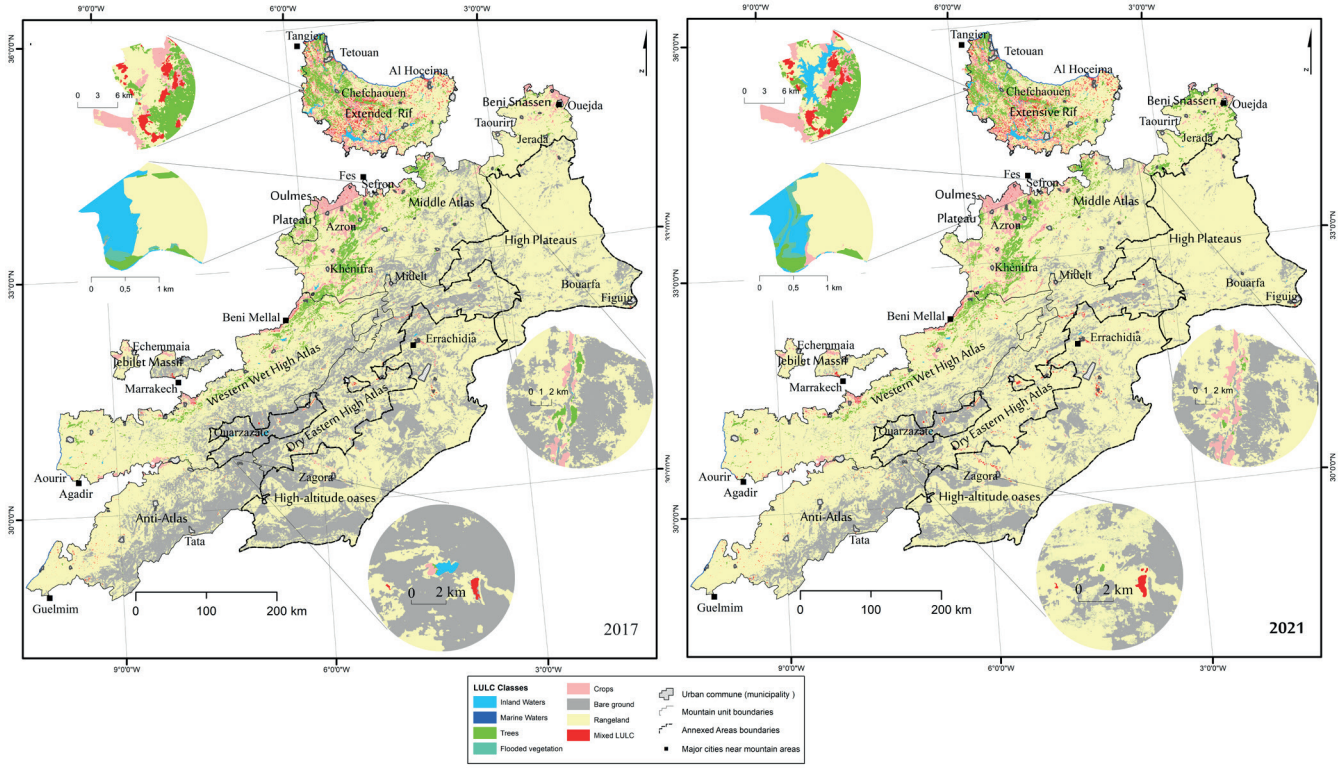


Fig. 3. LULC maps of Morocco's mountainous areas for 2017 and 2021

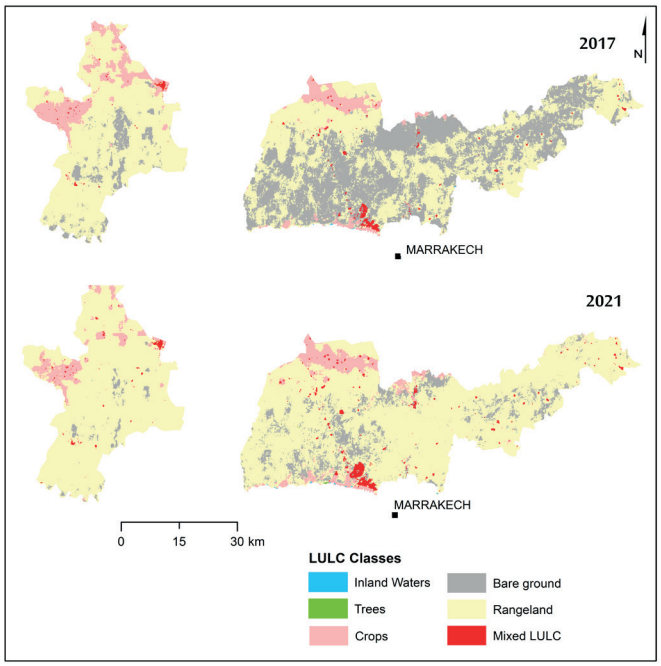


Fig. 4. Detailed view of major LULC changes in the Jebilet Massif (2017–2021)

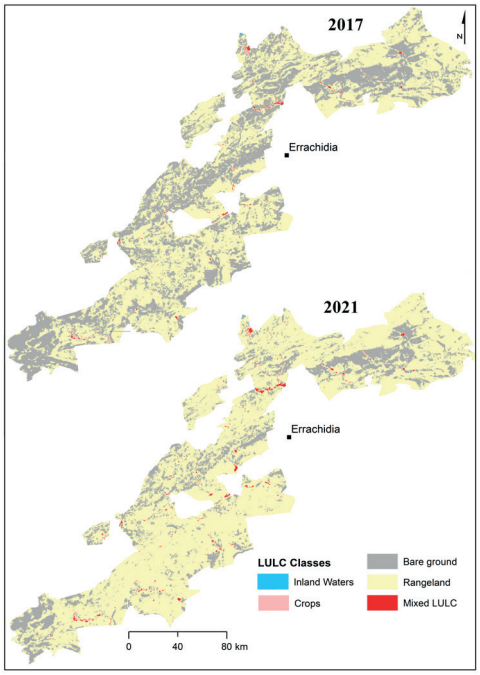


Fig. 5. Detailed view of major LULC changes in the Dry Eastern High Atlas and Saghro (2017–2021)

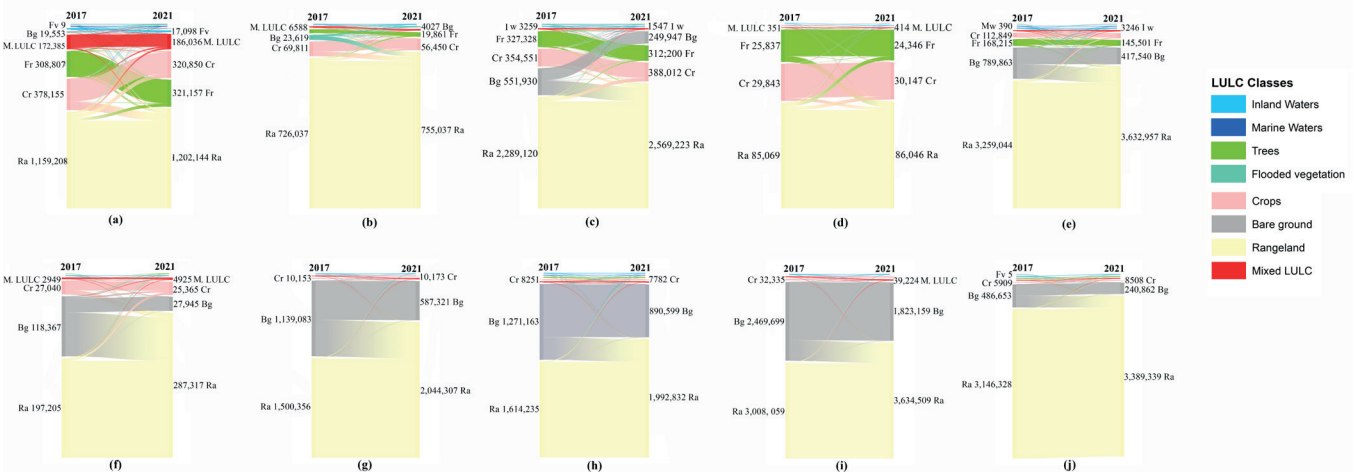


Fig. 6. Sankey diagram explaining the dynamic evolution of LULC in mountainous areas of Morocco for 2017 and 2021. (a) Extended Rif; (b) Beni Snassen; (c) Middle Atlas; (d) Oulmes Plateau; (e) Western Wet High Atlas; (f) Jebilet Massif; (g) Dry Eastern High Atlas and Saghro; (h) Anti-Atlas; (i) High-altitude oases; (j) High Plateaus

DISCUSSION

Classification Difficulties and Options for LULC Mapping in Hilly Areas

This study has shown a persistent LULC mapping problem across the topographically complex terrains of Morocco. Esri's annual LULC product had an average overall accuracy of 75% (Esri and Impact Observatory 2023). However, classification accuracies varied considerably across the mountainous units, some of which recorded significantly lower reliability. This result is consistent with earlier findings reporting lower accuracies across different land-cover types (Chidodo et al. 2025). The challenge here is to separate the built-up regions from vegetated cover (Ursu et al. 2025). In mountainous areas, two main factors related to the spectral characteristics of these environments impact classification accuracy. These include variations in slope and aspect that create uneven illumination of the ground (resulting in shadow effects and radiometric differences between pixels of the same land cover type), as well as the heterogeneity of mountainous landscapes, which increases the occurrence of mixed pixels. These factors lead to spectral confusion among vegetation types (forest, shrubland, grassland) and difficulty in discriminating between land cover classes in mountainous environments. This issue is illustrated, for example, by the misclassification of palm groves as forests in high-altitude oases, a phenomenon also reported by Sari et al. (2022) in Indonesia, who experienced similar difficulties distinguishing native tropical forests from other land uses. Although our analysis did not use multi-source indices as proposed by Truong et al. (2024), their suggestion for improving LULC mapping through additional data integration supports our reclassification approach in this case study. In addition, our findings align with those reported by Aguirre-Gutiérrez et al. (2012), who found that combining pixel- and object-based classification offers a slight advantage. Furthermore, they suggest that per-pixel methods alone may not be effective in accurately mapping heterogeneous landscapes with diverse vegetation types.

Our results emphasize the need to refine the methods developed in this study, as well as to conduct rigorous on-site validation supported by additional datasets, to improve the accuracy of LULC mapping in complex terrain. Previous research has demonstrated that combining multiple classification approaches can reduce variability

and enhance predictive accuracy (Elmahdy and Mohamed 2023; Amin et al. 2024). This finding is consistent with the work of Huan (2022), who showed that incorporating topographic variables such as slope and elevation into classification models improves performance. Integrating the present results with earlier studies underscores the importance of using high-resolution imagery across representative land covers, combined with fine-scale ground data, to intelligently address classification errors. Nevertheless, misclassification alone does not explain the observed changes in LULC patterns. Interpreting the underlying drivers of land-use change is equally essential for providing a comprehensive understanding of landscape dynamics in topographically complex regions.

Interpretation of LULC Dynamics

Precipitation and temperature primarily influence landscape and land use patterns in Morocco's mountain regions. Arid zones, including the Dry Eastern High Atlas, Saghro, the Anti-Atlas, the High Plateaus, and mountain oases, receive very low annual rainfall throughout the year and experience prolonged periods of high temperatures, reflecting a weak effect from Atlantic humid air masses (Benabdelouahab et al. 2020). In contrast, areas influenced by Atlantic moisture, such as the Extended Rif, the Middle Atlas, the Oulmes Plateau, and the Western Wet High Atlas, exhibit large forest cover and substantial water bodies. This climatic gradient establishes the ecological context that shapes the distribution, productivity, and resilience of LULC types across mountainous regions, highlighting how environmental conditions govern landscape dynamics in complex terrains.

In recent decades, climate change has amplified these naturally occurring gradients. From 1984 to 2016, temperatures in Morocco increased markedly, with new record-high levels being seen throughout the year, especially during the summer, with extreme events observed in 2020 (Driouech et al. 2021; World Meteorological Organization 2021). These trends, along with decreased rainfall and a shortened rainy season, have exacerbated water scarcity, reduced flooded vegetation, and increased stress on ecosystems. The combination of climatic variability and extreme weather events highlights the vulnerability of natural resources in mountain regions and their susceptibility to degradation and spatial contraction.

Human activities have also influenced LULC dynamics. Forest degradation, primarily caused by fires, overgrazing, logging, and land clearing, has been significant in densely populated regions, notably the Rif and Middle Atlas (El Hairchi et al. 2023). Although specific measures, such as small private irrigation dams, have alleviated water scarcity in certain areas (Hmamou and Bounakaya 2020), anthropogenic pressures—including agricultural expansion and illegal cannabis cultivation—have exacerbated deforestation, transformed natural landscapes into agricultural zones, and intensified strain on water resources (Linares et al. 2011; Esteban et al. 2010; Jennan 1996; Afsahi 2011; Chouvy 2023; Hmamou et al. 2023).

Soil erosion and desertification are major structural drivers of further LULC change. Elevated erosion rates in the High Atlas, Ourika Basin, and Toubkal, coupled with declining groundwater levels and overexploited rangelands, result in the degradation of arable land and increase the vulnerability of mountain communities (Brahim et al. 2020; Klik et al. 2002; Modeste et al. 2016; Tairi et al. 2021; Mahyou et al. 2016; Linstädter and Baumann 2013; Moumane et al. 2022; Ait Lamqadem et al. 2018). These pressures have driven socio-economic transformations, prompting populations to shift from traditional herding to more intensive or profitable land uses, thereby further altering landscapes and resource management practices.

In recent decades, tourism has been one of the most important drivers of new land-use patterns and LULC change in some mountainous regions. The expansion of tourism has converted agricultural lands and natural areas into tourist infrastructure, such as hotel complexes, resorts, roadways, and recreational amenities (Ait Zamzami 2024). The observed LULC changes demonstrate a complex interaction of climatic, ecological, and socio-economic factors. Effective management techniques that incorporate climate adaptation, forest and water conservation, and sustainable land-use planning are crucial for preserving ecosystem services and ensuring the long-term resilience of mountain communities.

Despite the improvements achieved, some limitations remain, including classification uncertainties and constraints related to 10-m spatial resolution in complex mountainous environments. Poor classification accuracy may hinder the effective implementation of land management policies and decision-making. In Morocco's mountainous regions, the environmental conditions are highly variable; these ecosystems are sensitive, and LULC information is essential for water resource management, forest degradation monitoring, and land-use planning. Ambiguities in the classification of forest, shrubland, and cropland can lead to misinterpretation of environmental conditions and changes, as well as of natural resource dynamics. LULC assessment requires accurate information for change detection, sustainable land management, and territorial planning. Improving classification accuracy in these regions can improve environmental decision-making by providing more reliable data on land-use changes, which is essential for effective policy formulation and resource management. Future improvements in LULC mapping should also consider artificial intelligence (AI)-based approaches. In heterogeneous mountainous landscapes, the 10-m spatial resolution of global LULC products may be insufficient for detecting fine-scale anthropogenic features such as scattered buildings, roads, and small infrastructure. AI methods, particularly convolutional neural networks (CNNs) and object-based image analysis, offer promising opportunities to improve feature extraction and reduce misclassification in these complex environments.

CONCLUSION

This study presents a comprehensive accuracy assessment of the Esri 10-m LULC product for 2017 and 2021. To our knowledge, this is the first such assessment conducted for the mountainous regions of Morocco. Land cover in these regions is complex and heterogeneous, making classification challenging. The results indicate that classification accuracy varies significantly across mountain units, ranging from 69.32% to 93.44%. The Kappa coefficient ranged from 0.56 to 0.90, indicating the level of agreement between classified data and reference data. These findings indicate spatial variability in classification accuracy, closely linked to the intrinsic characteristics of the mountain units. Approximately 12.83% of mountainous areas experienced land cover changes between 2017 and 2021, with transformation rates reaching up to 30.42% in the Jebilet Massif, highlighting the intensity of recent landscape dynamics.

Esri's 10-m LULC maps are a valuable tool for local-scale researchers, providing standardized data to document LULC changes over time. However, their use at larger scales (particularly in heterogeneous and complex

landscapes, such as mountainous areas in Morocco) shows clear limitations. In particular, considerable pixel misclassification, especially in detecting built-up areas in rural zones, can reduce the overall accuracy of LULC assessments. Addressing these limitations will require improvements in computational classification capabilities and the development of approaches that leverage targeted annotation efforts to reduce misclassification and improve thematic accuracy. Such improvements are critical for researchers working at the regional or national scale, as they provide more robust results without relying solely on remote sensing or field validation. Future improvements should consider advanced AI-based approaches to better detect fine-scale anthropogenic features in complex mountainous environments.

Finally, there is an urgent need to enhance both the quality and accessibility of LULC data. These improvements are crucial for effectively addressing the challenges of climate change. With further resources allocated to advanced classification systems and shared monitoring programs, such data can play a pivotal role in promoting sustainable land management and resilience in mountainous environments. Improving the quality of LULC data will provide more reliable information to support climate adaptation and environmental decision-making in mountainous environments.

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