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Data Descriptor

Data on the Land Cover Transition, Subsequent Landscape Degradation, and Improvement in Semi-Arid Rainfed Agricultural Land in North–West Tunisia

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Abstract: Understanding past landscape changes is crucial to promote agroecological landscape transitions. This study analyzes past land cover changes (LCCs) alongside subsequent degradation and improvements in the study area. The input land cover (LC) data were taken from ESRI's ArcGIS Living Atlas of the World and then assessed for accuracy using ground truth data points randomly selected from high-resolution images on the Google Earth Engine. The LCC analyses were performed on QGIS 3.28.15 using the Semi-Automatic Classification Plugin (SCP) to generate LCC data. The degradation or improvement derived from the analyzed data was subsequently assessed using the UNCCD Good Practice Guidance to generate land cover degradation data. Using the Landscape Ecology Statistics (LecoS) plugin in QGIS, the input LC data were processed to provide landscape metrics. The data presented in this article show that the studied landscape is not static, even over a short-term time horizon (2017–2022). The transition from one LC class to another had an impact on the ecosystem and induced different states of degradation. For the three main LC classes (forest, crops, and rangeland) representing 98.9% of the total area in 2022, the landscape metrics, especially the number of patches, reflected a 105% increase in landscape fragmentation between 2017 and 2022.

Dataset: https://hdl.handle.net/20.500.11766.1/FK2/YUXPQY; https://hdl.handle.net/20.500.11766.1/FK2/U4JHNU; https://hdl.handle.net/20.500.11766.1/FK2/UN7DKQ.

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Keywords: agroecology; landscape; land cover; landscape metrics; landscape transition; landscape degradation

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1. Summary

There is a growing focus on promoting agroecological landscape transitions, i.e., the transition from current agricultural landscapes to new stages of development, with improvements in the principles of agroecology. In Tunisia, an ongoing initiative led by OneCGIAR focuses on agroecological transitions (more information about this initiative can be found at https://www.cgiar.org/initiative/agroecology/, accessed on 8 July 2024). The focal zone of the intervention for the implementation and demonstration of landscape transitions is the region composed of the Kef and Siliana governorates (Figure 1). This zone covers six different sites (i.e., the focal community areas), which together form the Agroecology Living Lab Landscape (ALL) (Kesra, Chouarnia, Elles, Sers, Rhahla, and Hammam Biadha), a concept adopted by the project's research team [1]. Under this long-term research strategy, which remains in development, the effective transition of the current agricultural landscape system towards improved agroecology should be based on a correct understanding of the key landscape change processes that occurred in the past.

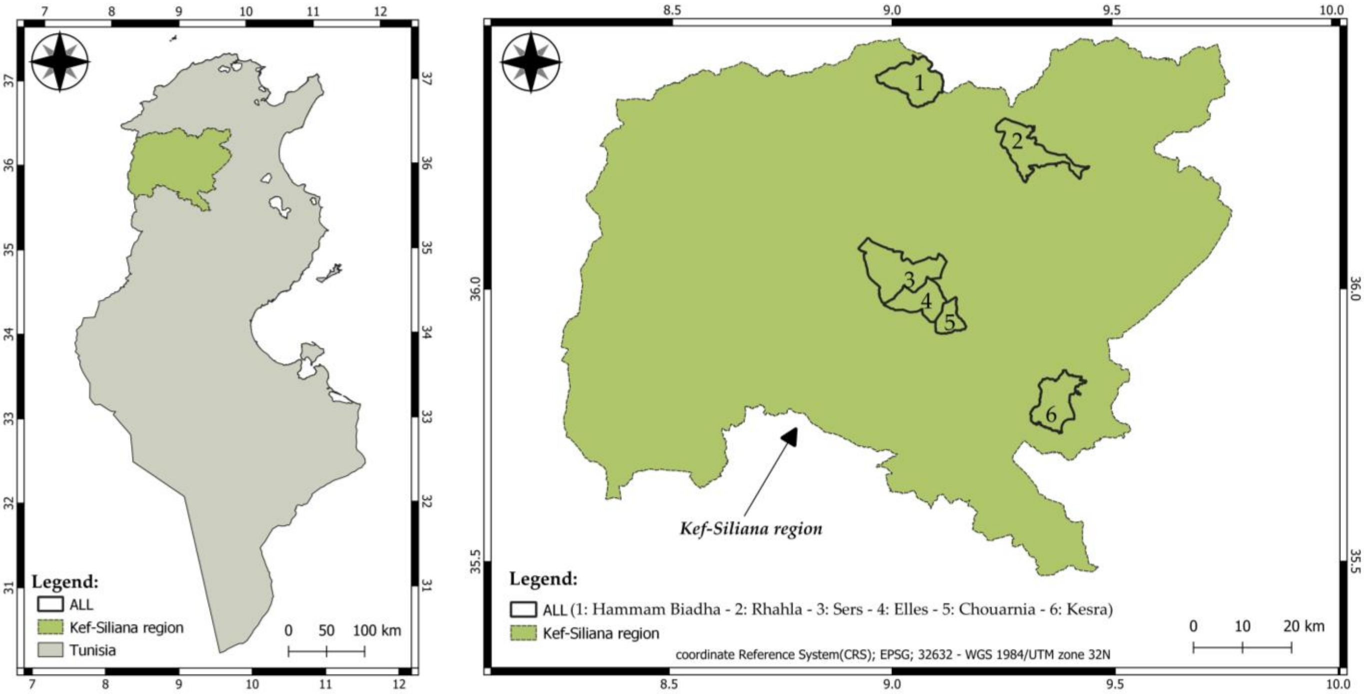

Figure 1. Maps of the study area. Left map: Kef–Siliana region in Tunisia; right map: boundaries of the Kef and Siliana governorates and the six focal community areas forming the Agroecological Living Lab Landscape (ALL) of the One CGIAR Initiative on Agroecology.

An LCC is usually a primary change in an agricultural landscape that leads to other changes, thereby forming a landscape transition [2–5]. Firstly, a land conversion type can be ecologically negative (e.g., from forest to scrubland or cropland) or positive (e.g., mono-cropland to mixed cropland with improved biological management practices or agroforestry). Secondly, the particular spatial distribution of an LCC represents the degree of changes in terms of ecological connectivity in the landscape (e.g., the formation or breaking of green corridors). This factor is important in determining environmental integrity and health. Measuring landscape metrics is one of the key tools used to evaluate agroecosystems, habitat functionality, and regulatory functions [6]. These measurements provide scientific evidence on landscape changes and the impact of different agricultural activities on biodiversity, soil quality, and ecosystem resilience [7]. LCCs and Land Use Change-induced landscape alterations and the identification of degradation hotspots can be assessed to aid decision making processes, support effective natural resource management, preserve biodiversity, help ensure food security, and benefit climate change mitigation research [8]. Both of these assessment types facilitate the identification of areas of concern, offer guidance towards achieving Sustainable Land Management (SLM), and help to strengthen agricultural system resilience [9]. Monitoring the data from these landscape processes is essential for policymakers, researchers, and practitioners involved in sustainable intensification efforts, specifically the promotion of agroecological practices [10].

The data in this study include three interrelated sets: (1) the LCCs in the study region over the period of 2017–2022, (2) the ecological degradation and/or improvements induced by past LCCs, and (3) changes in landscape fragmentation indicating current trends related to particular ecosystem services. The latter two datasets concern subsequent landscape degradation and improvements derived from LCCs. While the first two datasets are pixel based (with a 10 m pixel size), the last dataset includes landscape metrics calculated for whole landscape boundaries at two different levels: the whole study region and the focal community area. We also provide the aspects of agroecological services that the landscape metrics are intended to indicate.

The input LC data were taken from ESRI's ArcGIS Living Atlas of the World and then assessed for accuracy using ground truth data points randomly selected from high-resolution images on the Google Earth Engine. The LCC analyses were performed on QGIS 3.28.15 using the SCP to generate LCC data for seven LC classes relevant to the national LC classification. The degradation and improvements derived from the analyzed data were assessed using the UNCCD Good Practice Guidance (GPG) [11] to generate land cover degradation data. The GPG is a reference document providing a theoretical framework to evaluate land degradation for reporting on the United Nations' Sustainable Development Goals. This GPG describes the development of analytical methods for measuring Indicator 15.3.1, as well as Land Degradation Neutrality (LDN) and its three sub-indicators: (1) the level of negative changes in land cover, (2) the level of land productivity decline, and (3) the level of soil organic carbon decline. The pursuit of "good practices" is due to the incorporation of recent advances in related research, along with national stakeholder engagement in the review of the GPG. This review focused on the scientific relationship between the indicator/sub-indicator metrics and actual land degradation and improvements, presenting a clear and reproducible analytical procedure for calculating and interpreting the indicator/sub-indicators and discussing how to improve data quality and availability [11].

Using the LecoS plugin in QGIS, the input LC data for 2017 and 2022 were processed to provide landscape metrics across various geographic boundaries. For several reasons, quantifying landscape metrics plays an important role in ecological landscape research. The procedure aims to analyze the ways in which different ecological functions are impacted by changes in the land cover and to understand the relationships between ecosystem processes and land cover and changes. Quantifying landscape metrics is also essential to guide the efficient management of landscapes and successful conservation initiatives. Various landscape metrics already exist. However, the implications of these metrics for landscape management always depend upon the features of the specific study landscape, e.g., the scale of the study, the development and management goals, and the specific objectives of users.

2. Data Description

Three types of data are included in the present study: (1) An LCC map for the Kef–Siliana region covering 2017–2022, (2) land cover degradation data at different scales, including the Kef–Siliana region and sub-spatial units of the ALL in Tunisia, and (3) landscape metrics data at different scales: the Kef–Siliana region and sub-spatial units of the ALL in Tunisia (2017–2022). These three datasets, produced by processing and analyzing input data with the QGIS 3.28.15 software, are referenced in the ICARDA Dataverse and freely available for download. The quality and accuracy of the input data were verified with Google Earth satellite imagery and a comparison with a set of GPS points in different fields within the study area.

The global ESRI LC data (with a pixel size of 100 m^2) from 2017 and 2022 were clipped to cover the Kef–Siliana region. The accuracy of these data was assessed using the following steps:

1. For each LC class, one hundred points (i.e., sampling points) were randomly selected, for a total of seven hundred sampling points across all seven LC classes.
2. These sampling points were located on Google Earth Pro. The historical time function was then used to locate the target year (i.e., 2017 then 2022). Then, we zoomed in to visualize land regions with true color, high resolution satellite images.
3. For each sampling point, we observed and identified the LC type.
4. For each target year, we constructed an accuracy assessment table, which counted sample points with ESRI LC classes matching the visual identification using Google Earth Pro (Figure 2).

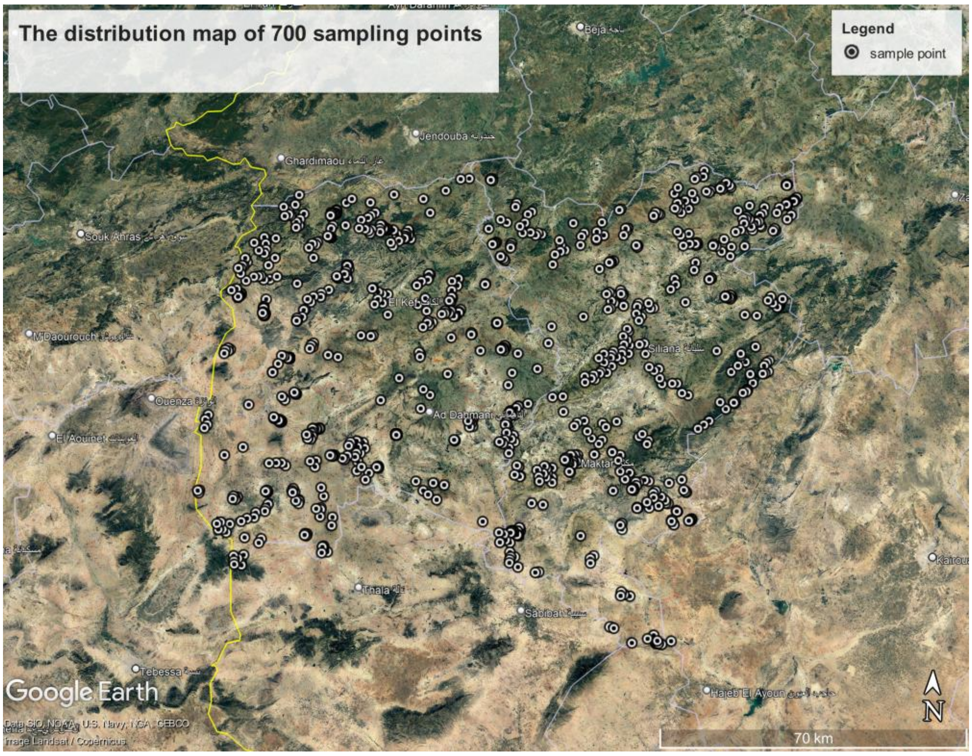

Figure 2. Map of sampling points in the Kef–Siliana region.

The results of the accuracy assessment are reflected in Tables 1 and 2.

Table 1. Accuracy assessment of ESRI LC data in 2017 in the Kef–Siliana region.

LC Class	No. of Sample Points	No. Point Matched with Visual Identification by Google Earth Pro	Accuracy (% Correct)
Water	100	95	95%
Forest	100	98	98%
Flooded vegetation	100	97	97%
Crops	100	98	98%
Built area	100	99	99%
Bare land	100	93	93%
Rangeland	100	87	87%
TOTAL	700	667	95.3%

Table 2. Accuracy assessment of ESRI LC data in 2022 in the Kef–Siliana region.

LC Class	No. of Sample Points	No. Point Matched with Visual Identification by Google Earth Pro	Accuracy (% Correct)
Water	100	96	96%
Forest	100	99	99%
Flooded vegetation	100	96	96%
Crops	100	97	97%
Built area	100	99	99%
Bare land	100	97	97%
Rangeland	100	89	89%
Total	700	673	96.1%

Tables 1 and 2 show that the LC data in 2017 and 2022 had accuracy values of 95.3% and 96.1%, respectively, which are sufficient for LCC analyses in research and development.

2.1. Land Cover Change Map for the Kef-Siliana Region over 2017–2022

The map in Figure 3 illustrates the LCC between 2017 and 2022 (https://hdl.handle.net/20.500.11766.1/FK2/YUXPQY, accessed on 8 July 2024) (Figure 3) with a legend including 49 types of LCCs, as presented in Table 3. Additionally, a Sankey diagram (Figure 4) is used to visualize the LC transitions, illustrating the different changes in LC classes within the Kef–Siliana region from 2017 to 2022.

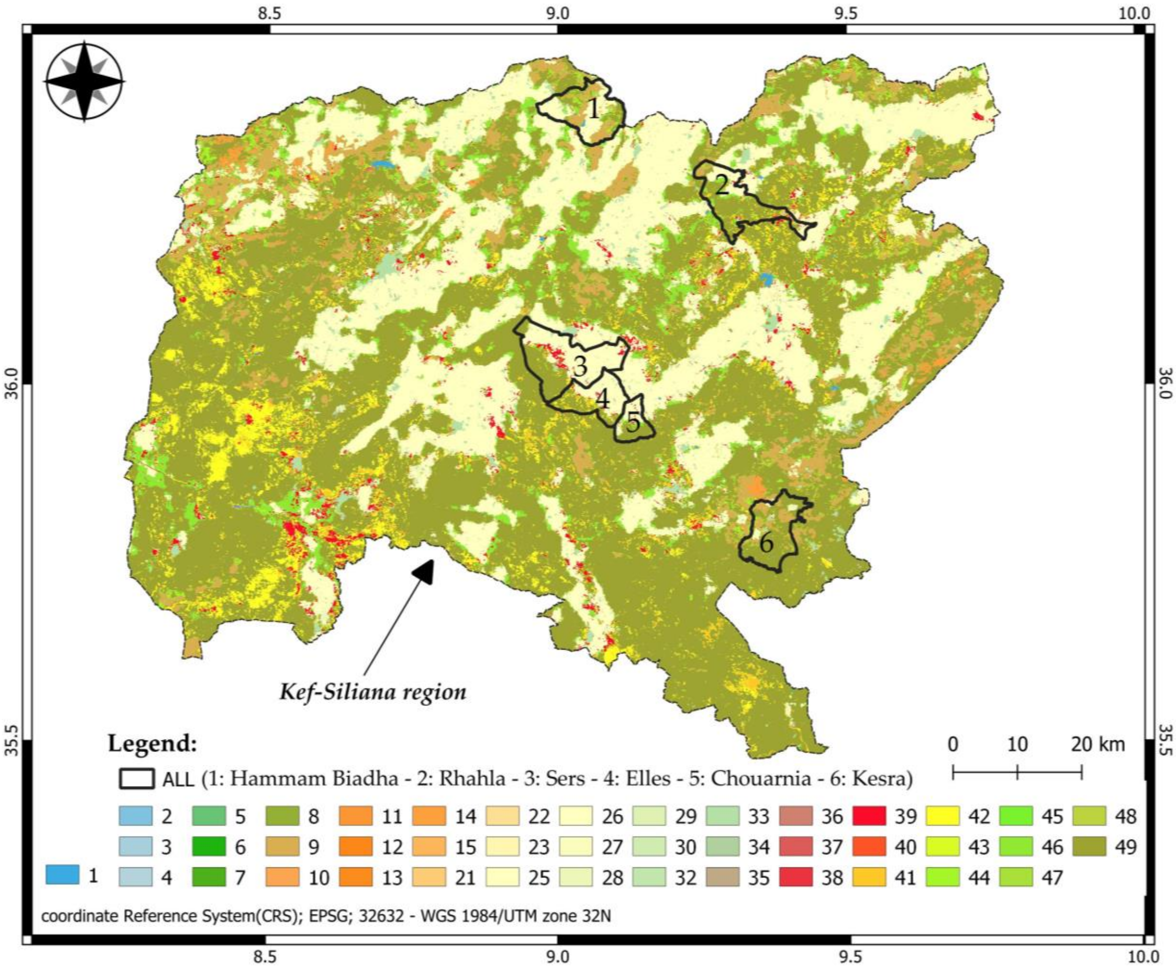

Figure 3. Map of land cover changes between 2017 and 2022. The legend codes are provided in Table 3.

Table 3. Legend codes for the LCC map (Figure 2).

		To LC Classes (2022)						
		Water	**Forest**	**Flooded Vegetation**	**Crops**	**Built Area**	**Bare Land**	**Rangeland**
From LC classes (2017)	Water	1	2	3	4	5	6	7
	Forest	8	9	10	11	12	13	14
	Flooded vegetation	15	16	17	18	19	20	21
	Crops	22	23	24	25	26	27	28
	Built area	29	30	31	32	33	34	35
	Bare land	36	37	38	39	40	41	42
	Rangeland	43	44	45	46	47	48	49

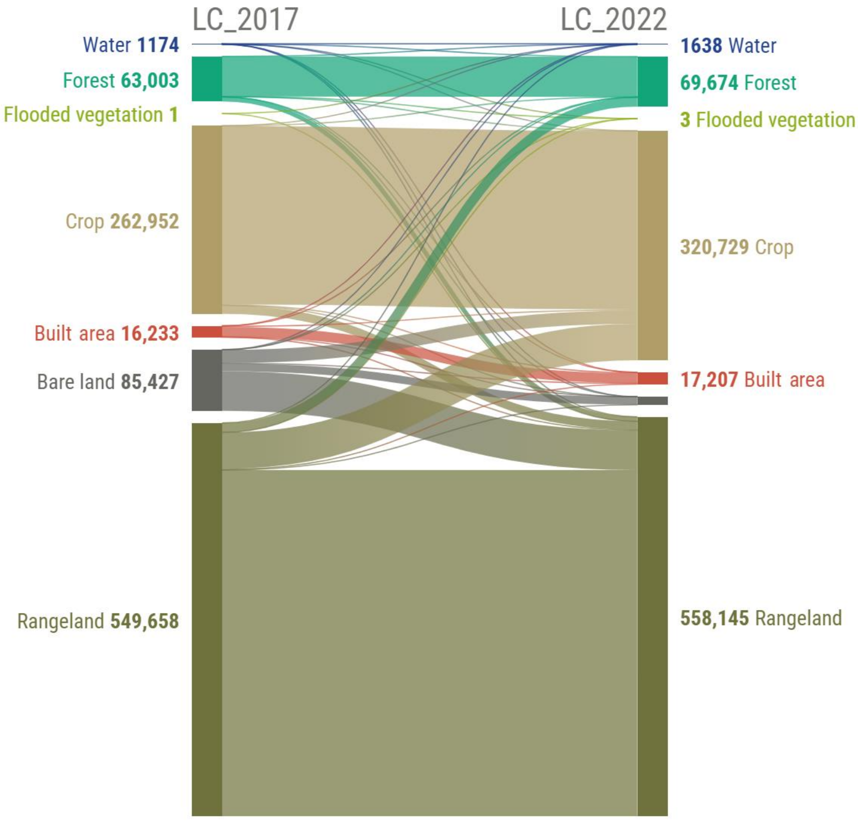

Figure 4. Sankey plot describing the LCC transitions from 2017 to 2022. Bands represent the actual proportion of land that changed class over time.

Tables 4 and 5 present the area (in ha) of gain or loss for each type of LC, as well as the percentage of change in the Kef–Siliana region and across the six focal community areas of the ALL.

Table 4. Area differences in land cover between 2017 and 2022 in ha.

	Region	**Focal Community Areas in Agroecology Living Lab Landscape (ALL)**					
	Kef–Siliana	**Kesra**	**Chouarnia**	**Elles**	**Sers**	**Hammam Biadha**	**Rhahla**
LC Classes	**LCC between 2017 and 2022 (ha)**						
Water	(+)465	(+)1	0	−1	0	(+)4	0
Forest	(+)6671	(+)233	(+)7	−22	(+)16	(+)394	(+)86
Flooded vegetation	(+)3	0	0	0	0	0	0
Crops	(+)57,777	−65	(+)170	(+)125	(+)568	(+)384	(+)909
Built area	(+)974	(+)31	(+)12	(+)31	(+)53	(+)32	−13
Bare land	−74,377	−110	−77	−625	−830	−50	−565
Rangeland	(+)8487	−91	−112	(+)492	(+)193	−764	−418

Note: To calculate the area of LCC between periods, we employed the following equation: $A = AT2 - AT1$, $(T2 > T1)$, where A refers to the area of LCC in ha between periods, AT2 is the area of the LC at year T2, and AT1 is the area of the LC at year T1. The (+) and (−) symbols indicate the area's gain and loss, respectively.

Table 5. Area differences in land cover between 2017 and 2022 in percentage.

	Region	Focal Community Areas in Agroecology Living Lab Landscape (ALL)					
	Kef–Siliana	**Kesra**	**Chouarnia**	**Elles**	**Sers**	**Hammam Biadha**	**Rhahla**
LC Classes	**LCC between 2017 and 2022 (%)**						
Water	(+)39.6	(+)7.9	0	−100	0	(+)12.7	0
Forest	(+)10.6	(+)18.3	(+)228.9	−72.7	N/A *	(+)19.3	(+)30
Flooded vegetation	(+)455.4	0	0	0	0	0	0
Crops	(+)22.0	−16.6	(+)14.4	(+)4.2	(+)8.7	(+)11.2	(+)44.7
Built area	(+)6.0	(+)30.1	(+)71.8	(+)40.1	(+)21.8	(+)24.7	−15.4
Bare land	−87.1	−78.9	−91.7	−85.3	−95.3	−93.6	−75.3
Rangeland	(+)1.5	−1.6	−7.8	(+)26.9	5.4	−34.0	−8.4

Note: N/A * not applicable: undivided by zero. For the percentage of LCC between periods, we employed the following equation: $A(\%) = ((AT2 - AT1)/AT1) \times 100$, $(T2 > T1)$, where A(%) refers to the change in the percentage of LC between periods, AT2 is the area of the LC at year T2, and AT1 is the area of the LC at year T1. The (+) and (−) symbols indicate the area's gain and loss, respectively.

Rangeland, crops, and forest are the main LC classes in the Kef–Siliana region showing constant improvement, with increases of 1.5%, 22%, and 10.6%, respectively, between 2017 and 2022. The highest gain was recorded for crops (5777 ha), and the highest loss was recorded for bare land (−74,377 ha). At the ALL level, the forest improved in Hammam Biadha and Kesra by 19.3% and 18.3%, respectively, with an area of 394 ha and 233 ha. Crop improvements of 44.7%, 14.4%, 11.2%, 8.7%, and 4.2% took place in Rhahla, Chouarnia, Hammam Biadha, Sers, and Elles, respectively, with decreases of −16.6% representing −64 ha. Rangeland experienced 26.9% and 5.4% improvement covering 491 ha and 193 ha, respectively, in Elles and Sers. For the other ALL units, rangeland decreased in Rhahla, Hammam Biadha, Chouarnia, and Kesra by 34%, 8.4%, 7.8%, and 1.6%, respectively.

2.2. Land Cover Degradation Data at Different Scales: The Kef-Siliana Region and Sub-Spatial Units of the Agroecological Living Lab Landscape in Tunisia

The land cover degradation matrix, based on the Good Practice Guidance by the UNCCD [11], can help visualize and categorize the changes from one LC class to another with reference to the work in [4]. This reference enabled us to provide data (https://hdl.handle.net/20.500.11766.1/FK2/U4JHNU, accessed on 8 July 2024) on where (Figure 5) and how (Table 6) the changes took place, as well as the geographical boundaries of degradation and improvement hotspots.

Table 6 provides information on the degradation state in different locations of the Kef–Siliana region and the ALL, showing the areas classified as stable, degraded, and improved. Additionally, the results are presented as hectares (ha) and percentages (%) for each category.

The results in Table 7 for the Kef–Siliana region indicate that 83.4%, equivalent to 816,371 ha in area, is considered stable, whereas 2.2%, corresponding to 21,595 ha, is in a state of degradation. On the other hand, 14.4% of the area, which covers 140,482 ha, has shown improvement.

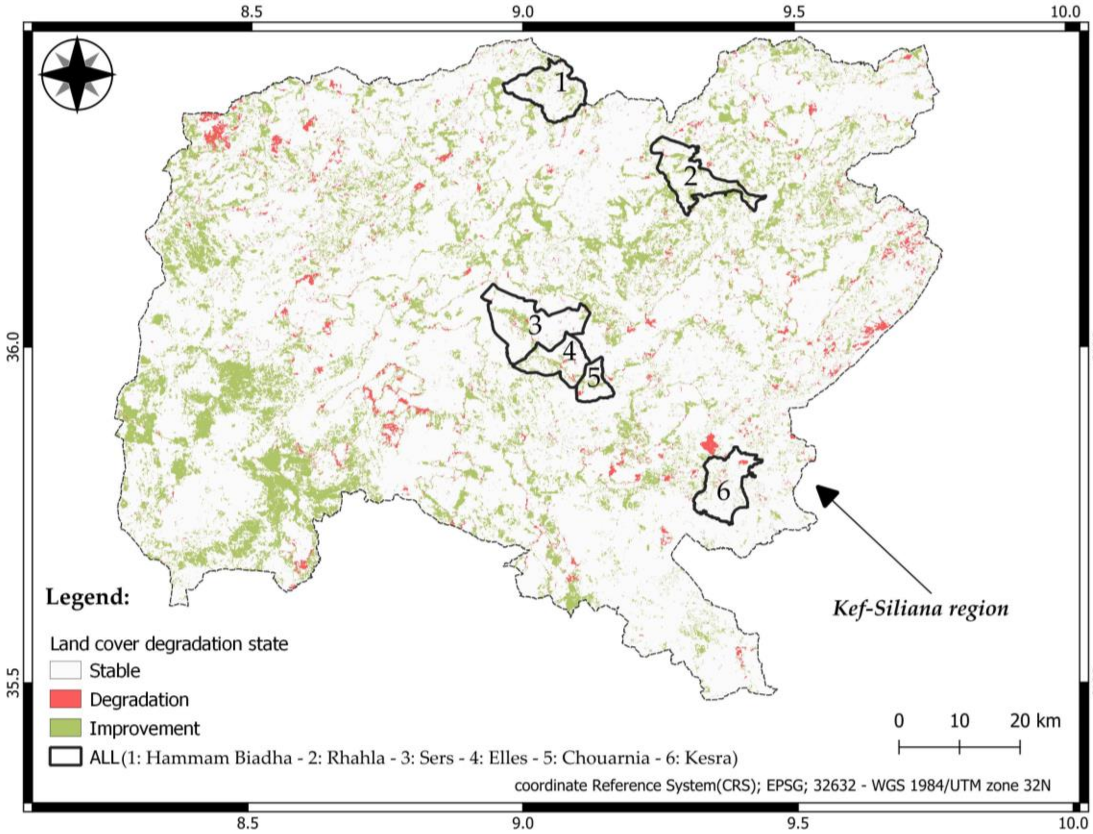

Figure 5. Land cover degradation map between 2017 and 2022.

Table 6. Land cover degradation matrix (numbers in ha) and related LC transition type (in text).

	Forest	Rangeland	Crops	Flooded Vegetation	Built Area	Bare Land	Water
Forest	56,130 Stable	6262 Vegetation loss	581 Vegetation loss	0.4 Inundation	19 Deforestation	0.3 Vegetation loss	10
Rangeland	13,082 Afforestation	483,810 Stable	50,861 Agricultural expansion	1 Inundation	1471 Urban expansion	64 Vegetation loss	370
Crops	383 Afforestation	11,877 Withdrawal of agriculture	249,339 Stable	0	1297 Urban expansion	22 Vegetation loss	33
Flooded Vegetation	0	0.2 Waterbody drainage	0	0	0	0	0.4
Built Area	17 Afforestation	890 Vegetation establishment	1299 Agricultural expansion	0	13,952 Stable	75 Withdrawal of settlements	0.5
Bare Land	51 Afforestation	55,200 Vegetation establishment	18,622 Agricultural expansion	2 Wetland establishment	468 Urban expansion	10,873 Stable	212
Water	11	105	27	0	0.6	17	1012.44

Note: To visualize the LCC criteria developed for relating LC transitions to degradation and non-degradation processes, red is used for LC transitions with the potential to degrade ecosystems during 2017–2022, green is used for improvements, and grey is used to depict stable areas that remained unchanged [4]. All values are rounded in ha.

Table 7. Land cover degradation state.

	Kef–Siliana Region	Focal Community Areas in Agroecology Living Lab Landscape (ALL)					
		Kesra	Chouarnia	Elles	Sers	Rhahla	Hammam Biadha
	In ha						
Stable	816,371	7021	2379	4814	10,006	6681	6913
Degradation	21,595	207	264	205	310	811	530
Improvement	140,482	365	84	633	877	683	490
	In %						
Stable	83.4	92.5	87.2	85.2	89.4	81.7	87.1
Degradation	2.2	2.7	9.7	3.6	2.8	9.9	6.7
Improvement	14.4	4.8	3	11.2	7.8	8.4	6

Most land in the ALL is classified as stable, with percentages of change ranging from 81.7% to 92.5% in different areas. Areas of degradation represent a smaller proportion of the total land, with percentages ranging from 2.7% to 9.9%. The areas showing improvement range from 3% to 11.2%. The highest degradation percentages were observed in Rhahla and Chouarnia, with values of 9.7% and 9.9%, respectively. The highest improvement was observed in Elles, with a percentage of 11.2%. Finally, Kesra presented the highest level of stability with a percentage of 92.5%.

2.3. Data on Landscape Metrics at Different Scales: the Kef-Siliana Region and Sub-Spatial Units of the Agroecological Living Lab Landscape in Tunisia

A portion of the results for landscape metrics (with definitions and significance to ecological integrity/health as described in Table 8 and presented in Table 9) and all corresponding calculations are available in an Excel file (https://hdl.handle.net/20.500.11766.1/FK2/UN7DKQ, accessed on 8 July 2024). These results indicate that the three major classes of LC in the Kef–Siliana region, forest, crops, and rangeland, occupied a total landscape proportion of 98.9% in 2022, with changes of +105.6% and +108.6%, respectively, in the number of patches (NP) and Largest Patch Index (LPI) for the three LC classes together. For the Median Patch Area, forest presented a change of +105.2%, while rangeland yielded a decrease of −25%, and crops maintained the same value of 300 m^2 between 2017 and 2022. Similar trends were observed for these metrics across different units of the ALL.

Table 8. List of computed landscape metrics and their significance for ecological integrity and health.

Landscape Metrics	Abbreviation	Description (Unit)	Significance for Ecological Integrity and Health
Landscape Proportion	LP	Proportion of the landscape occupied by an LC class (index between 0 and 1)	The high forest and woodland LP supports greater species diversity among plants and animals [12].
Number of Patches	NP	Number of patches with the same LC class in the landscape (index ≥ 1)	The high NP for health vegetative covers indicates unwanted fragmentation, which reduces species diversity and forest recovery [13]. However, more patches of woody (e.g., forest and woodland) and non-woody (e.g., crops and grassland) cover may yield specific types of expected fragmentation that provide greater friction to reduce the risk of crop pests and diseases in agriculture [14].

Table 8. *Cont.*

Landscape Metrics	Abbreviation	Description (Unit)	Significance for Ecological Integrity and Health
Median Patch Area	MePA	Median area of patches with the same LC class (m^2)	High MePA and/or LPI indicate less defragmentation of the LC class. Agroecological interpretations of this parameter should be specific to the nature of the LCC class and the specifics of the studied landscape (e.g., a protected forest watershed or agricultural production region).
Largest Patch Index	LPI	Area of the largest patch of the corresponding patch type divided by the total landscape area × 100 (m^2)	

Table 9. Landscape metrics at different scales: the Kef–Siliana region and different units of the Agroecology Living Lab Landscape (2017–2022).

Geographic Boundary	Land Cover	LP		NP		MePA		LPI	
		2017	2022	2017	2022	2017	2022	2017	2022
Kef–Siliana Region	Forest	0.064	0.071	4559	4648	1900	2000	0.565	0.377
	Crops	0.269	0.328	12,410	17,379	300	300	8.181	9.928
	Rangeland	0.562	0.57	20,223	17,321	400	300	47.401	50.717
Kesra	Forest	0.168	0.199	104	107	2800	3200	4.685	4.786
	Crops	0.051	0.043	68	84	400	700	2.008	2.154
	Rangeland	0.748	0.736	92	90	300	500	73.659	71.855
Chouarnia	Forest	0.001	0.004	3	2	9700	49,500	0.073	0.329
	Crops	0.433	0.495	58	22	250	350	36.073	49.355
	Rangeland	0.529	0.488	37	77	300	300	52.626	46.464
Elles	Forest	0.005	0.001	15	10	1000	2900	0.25	0.066
	Crops	0.528	0.55	83	109	200	200	52.382	54.427
	Rangeland	0.324	0.411	103	66	300	300	31.81	40.215
Sers	Forest	0	0.001	0	9	0	2400	0	0.1
	Crops	0.58	0.631	161	103	300	300	55.942	62.857
	Rangeland	0.32	0.338	94	141	300	400	27.956	29.406
Hammam Biadha	Forest	0.258	0.307	77	85	2400	2600	15.176	18.607
	Crops	0.431	0.48	136	87	300	300	27.599	29.354
	Rangeland	0.284	0.187	186	195	400	600	12.325	8.921
Rhahla	Forest	0.039	0.05	57	50	3100	2400	3.164	4.04
	Crops	0.249	0.36	115	207	400	400	19.219	23.62
	Rangeland	0.61	0.559	152	171	350	300	55.767	52.92

3. Methods

To generate the data described in Sections 2.1–2.3, we followed the mixed methodology illustrated in Figure 6.

Firstly, we obtained LC maps covering 2017 and 2022 for the Kef–Siliana region with a resolution of 10 m from the Esri Sentinel-2 Land Cover Explorer ArcGIS Living Atlas of the World. Esri Sentinel-2 data are characterized by their consistency and reliability and are considered a dependable resource for LC studies. Moreover, the free open-source policy governing these data encourages widespread use and facilitates access without financial barriers. This resource is commonly used to monitor and assess land degradation in arid regions [5,15] with independent accuracy assessments using high resolution true-color images in Google Earth Pro [16].

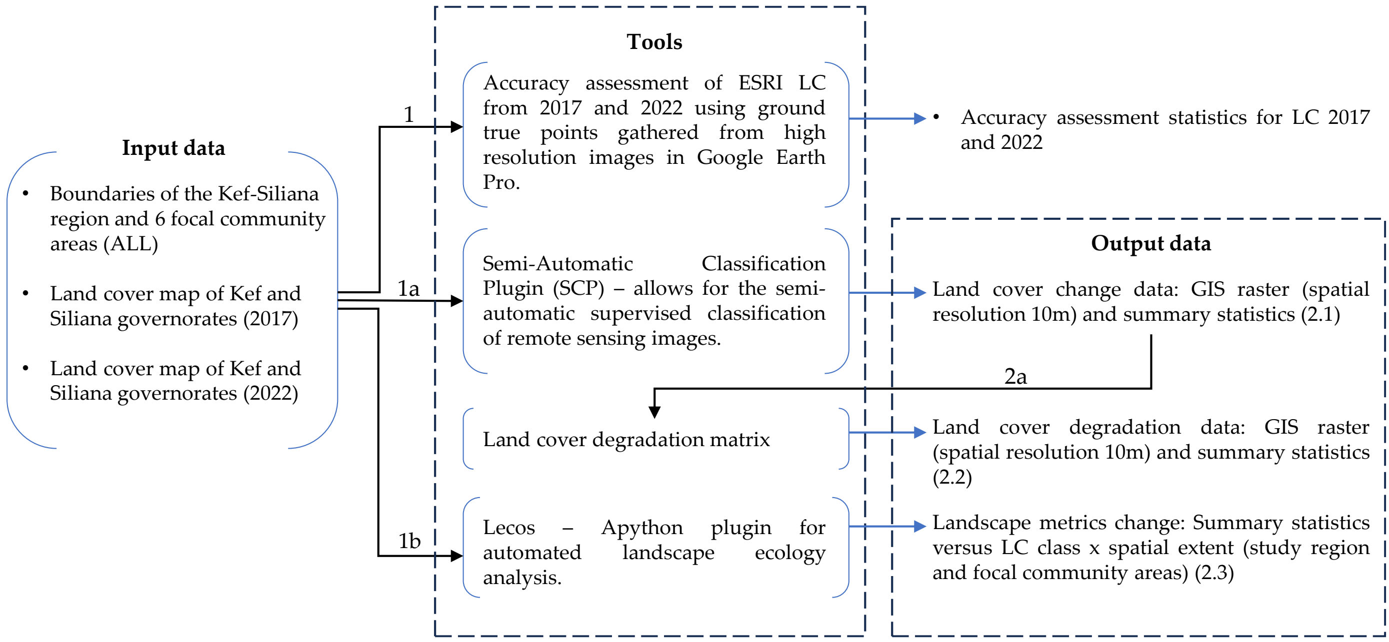

Figure 6. Flowchart of connected methods–tasks.

Next, the data were treated with QGIS 3.28.15 using the SCP Python plugin 8.2.2 (1a). This algorithm automates the LC classification phases, including downloading raw data; preprocessing, processing, and postprocessing the acquired data; and generating LCC data. The output of this process was then used as an input associated with a predefined land cover degradation matrix (2a) to generate land cover degradation data. This matrix labels and quantifies each land cover change as either degraded, improved, or stable. When a transition has the potential to deteriorate ecosystems, it is considered to represent degradation; otherwise, a transition to other LC classes is considered an improvement, such as when a degraded site is restored.

The same LC maps (2017–2022) were subsequently treated using the Landscape Ecology Statistics (Lecos) Python plugin in QGIS (1b) to generate landscape metrics and provide several functions to conduct landscape analyses from raw raster data.

The presented method for generating data on land cover transition, subsequent landscape degradation, and improvements works well for several reasons. First, the data analysis results are reproducible, which is important for scientific research. The tool use procedure is also designed to be simple, easy, and accessible for users without advanced technical skills, requiring minimal training. Additionally, free access is crucial for projects with limited financial resources. Overall, the use of open-source plugins with publicly available data significantly reduces costs. This method also reduces the time required, making it advantageous for quick evaluations and fast data processing.

The validity of the presented output data is mainly relevant for studying the spatial and temporal patterns of landscape changes captured by remote sensing corresponding to land surface attributes (e.g., land cover). Although these pattern changes are evidenced by physical reflectance, the classification of land cover types and the translation of land cover changes into levels of land cover degradation always retain certain levels of human subjectivity. Therefore, further evaluations of the results with independent reference data and information are recommended (e.g., land cover change mapping based on other source data and agreement with local expert opinions). Field observations at the change hotspots presented in this study are also encouraged. However, the relationship between field-based observations and mapped degradation should be interpreted through two types of observations: (1) observations that validate the land cover degradation (e.g., observed discrete conversions among land cover types) and (2) observations that reflect other aspects of land degradation (e.g., degrading signals within a given land cover type, such as soil erosion or a reduction in vegetation biomass and/or species richness).

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