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Review

Land Use and Land Cover Transitions in Mountainous Landscapes: A Systematic Review of Soil Carbon Dynamics, Challenges, and Research Perspectives

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Abstract

Globally, land use and land cover (LULC) change is a major driver of soil organic carbon (SOC) dynamics in mountainous ecosystems, where steep slopes, shallow soils, and strong climatic gradients amplify land use impacts. This review systematically synthesises empirical evidence regarding how LULC transitions influence SOC dynamics in mountainous landscapes, with particular emphasis on dominant trends, underlying mechanisms, methodological bottlenecks, and future research perspectives. Following PRISMA guidelines, we evaluated 30 carefully screened peer-reviewed studies that explicitly link temporal LULC change to carbon dynamics in mountainous environments. The results show SOC losses across most LULC transitions, especially following forest and rangeland conversion to cropland and built-up land. In contrast, SOC recovery is time-lagged, partial, and often decoupled from rapid aboveground biomass recovery. Methodologically, while static carbon models (e.g., InVEST) are demonstrated to systematically underrepresent lateral erosion-driven SOC losses, they have been highly adopted in the synthesised studies, highlighting their practical scalability in data-scarce and complex mountain terrains. Finally, the synthesis reveals a strong geographic bias in the literature, with most studies emerging from Asia, highlighting substantial knowledge gaps in other regions. Prioritising empirical multidecadal SOC monitoring in highly vulnerable and underrepresented regions, such as African mountainous systems, where socioeconomic pressures are expected to intensify, is critical for developing integrative, evidence-based strategies for sustainable land management under accelerating LULC change.

Keywords: land use land cover; mountainous ecosystem; LULC change drivers; soil organic carbon; carbon assessment

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Academic Editor: Meirong Su

Received: 19 March 2026
Revised: 22 April 2026
Accepted: 8 May 2026
Published: 11 May 2026

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1. Introduction

Mountain ecosystems occupy over 20% of the Earth's terrestrial surface across the globe. They are essential in ecological services provision as well as supporting human livelihoods [1]. Particularly, they store substantial amounts of soil organic carbon (SOC) and act as a stable sink for methane (CH_4) due to cooler temperatures, high organic matter inputs,

and limited decomposition rates, while significantly supporting large rural livelihoods and diverse land use systems [1–4]. Mountain ecosystems also contribute significantly to the provision of survival essentials such as water, forests and agricultural products [5,6]. While the foundational literature has clearly established higher-altitude permafrost ecosystems as stable ecosystem service providers and reservoirs, recent global syntheses on permafrost-affected systems highlight that these pools are highly vulnerable. The evidence further demonstrates that shifting climate dynamics and land use conversions are dramatically accelerating soil carbon turnover in these regions, shifting them from historical carbon sinks to active emission sources [7,8]. These changes are occurring mostly as a result of key factors such as growth in human populations, urbanisation, agricultural land expansion and intensification, rangeland expansion and degradation, forest conversion or extraction for fuel and building and construction materials, extensive and climate variabilities such as recurrent and prolonged droughts, and variability in precipitation [9–16]. In North Africa, for example, the High Atlas Mountains of Morocco are a significant economic ecosystem, providing livelihoods for many indigenous communities through agriculture, forest products, tourism, and general contributions to the climate conditioning of the region. In agreement with this, Montanari [17] postulated that the High Atlas Mountains perform key ecosystem functions such as the provision of agricultural and forest products, water yield and regulation, carbon sequestration, and tourism. The ecological impact of the rapid LULC changes and transitions, and land use intensifications manifests as a decline in the carbon storage capacities of various ecosystems, environmental degradation (i.e., by erosion), loss of biodiversity, decline in soil fertility, and livelihood and food insecurity in many countries and regions [9,12,13,18]. Also, due to the nature of such systems (i.e., steep slopes, heterogeneous and shallow soils, and high erosion susceptibility), land use transitions often result in rapid and long-standing SOC losses [19,20].

While a growing body of literature has examined the carbon consequences of these transitions, much of the literature has focused separately on various carbon pools: total ecosystem carbon or aboveground biomass (AGB), frequently inferred through remote sensing and model-based approaches. On the other hand, SOC dynamics, especially depth-dependent changes and erosion-induced losses, remain under-represented by comparison, despite SOC representing the most persistent and arguably largest terrestrial carbon pool [3,21]. This asymmetry is challenging, especially in mountainous landscapes. Due to the complementary impacts of soil disturbance, reduced organic inputs, and unbridled erosion, SOC losses are fast-paced following land use intensification, whereas its recovery is typically slow and often incomplete, even under reforestation and other restoration practices [19,20,22,23]. To wit, an increase or regrowth of vegetation (AGB), mostly following afforestation or natural regrowth, or land abandonment, does not necessarily translate into SOC recovery, leading to the potential overestimation of carbon sequestration when soil processes are overlooked, as postulated by Solomon et al. [24], where just a little over 50% of the variance in SOC is explained by the AGB parameters.

In terms of methodological approaches in carbon accounting, modelling is a key pathway. Several models, for example, the InVEST [25], is one of the most frequently used models in carbon accounting, especially in mountain ecosystems. This strategy, coupled with remote sensing approaches such as the use of Landsat imagery, allows for the operation and assessment of sequestered or stored carbon in complex landscapes, as evident in mountain landscapes. Notwithstanding the expanding corpus of the literature, global evaluations of mountain carbon dynamics remain fragmented. A significant knowledge gap exists as numerous extensive spatial studies conflate aboveground biomass with sub-surface soil organic carbon (SOC) or depend excessively on static carbon accounting methods that inadequately account for the complex, erosion-induced carbon losses characteristic of steep

terrains. Therefore, there is an immediate necessity for a systematic synthesis to distinctly isolate soil carbon pools, examine the temporal sensitivity of soil organic carbon recovery, and evaluate the methodological constraints of existing carbon modelling techniques in these particularly susceptible ecosystems.

To this end, the objective of this study is to synthesise empirical evidence on LULC transitions and their implications for soil carbon dynamics in mountainous landscapes. Specifically, to identify dominant LULC transitions affecting SOC, as well as their underlying drivers. The study also evaluated SOC responses across transition types, depths, and timescales, assessed methodological patterns and limitations in SOC assessment, and finally, highlighted key bottlenecks and future research perspectives.

It is important to note that Africa accounts for more than 25% of global net forest loss since 2010 [26], with losses predominantly concentrated in mountainous regions, although dryland areas also make a substantial contribution. Hence, this synthesis builds some use cases for African mountain ecosystems to describe the state and extent of SOC as influenced by LULC changes, providing a critical understanding to enhance the formation and practical land use planning for climate change adaptation and mitigation.

2. Overview of LULC Change in Mountain Ecosystems

2.1. Global Patterns of LULC Change in Mountain Ecosystems

LULC change is a crucial topic in climate change discussions due to its immense influence on the Earth's surface properties and ecosystem services' regulation [9,27–30]. Predominantly, these changes are human-induced [31–33], and they affect global, regional, and local climate patterns and trends through carbon emissions [34,35]. The impacts of this transcend biodiversity, ecosystem services' provision, such as regulating carbon cycles, water supply, agricultural productivity, and the general well-being of mankind [36]. It is important to mention that (i) LULC in mountain areas is a major natural carbon reservoir, especially in forests and cold soils, and (ii) remote sensing and its applications are essential to monitor LULC in these environments because of their inaccessibility, steep slopes, and rapid response to climate change.

Globally, it is estimated that human activities have directly altered over 70% of Earth's ice-free terrestrial surface properties and functions [31,33,37]. Among these, the most affected land cover classes are forests, croplands, and pasturelands; i.e., massive areas of natural vegetation have been converted for other purposes over the years [38,39]. According to IPCC [32], agriculture, forestry, and other land uses (AFOUL) were responsible for about 23% of global greenhouse gas emissions between 2007 and 2016. Furthermore, deforestation in Asia, Latin America, Sub-Saharan Africa (SSA), and other tropical regions has significantly facilitated carbon and biodiversity loss. Agricultural lands, due to food security demands, have been on the rise over the years, spreading swiftly into previously forested and reserved areas [26], further exacerbating the emission of greenhouse gases (GHGs), especially CO_2 [40]. In contrast, regions such as America and Europe have recorded marginal net gains in their forest cover due to afforestation practices and land abandonment [41]. Nevertheless, these gains are compensated for by shifts in species composition and ecosystem quality. According to Seto et al. [42], the extent of growth in built-up areas in the developing world, especially in Africa and some parts of Asia, is expected to triple by 2030 compared to 2000 due to the rapid nature of development and industrialisation, further exacerbating the worries of the ever-increasing temperatures and other climate change indicators.

2.2. Overview of LULC Change in the African Mountain Ecosystem Context

While the majority of the global literature on mountain SOC emerges from Asian mountain ranges, we place an introductory emphasis on African mountain ecosystems to highlight the critical geographical data gap. On the continent, LULC changes are inspired mainly by the continent's distinct characteristics of fast-paced changes in socioeconomic dynamics, due to the ever-growing population and food security demands over the past 50 years [43]. Not only that, but it is also faced with environmental issues such as mining activities, forest wood logging for domestic and industrial fuel, land tenure, and shifting cultivation practices that raid vast areas of reserved and forested lands over short periods [44,45]. According to the FAO [26], Africa is responsible for over 25% of the global net forest loss after 2010. These losses are mostly mapped to the continent's mountainous regions, even though dryland areas also contribute significantly. These areas are characterised by high levels of land degradation due to erratic rainfall and fragile soils, indicating that the continent has no safe levels of climate change under any scenario [16]. Particularly in East Africa, the Sahel, and parts of Central and Southern Africa have undergone significant conversion of natural forests and reserved lands into human settlements and arable croplands [46,47]. The Ethiopian highlands, for example, are experiencing a rapid land use change due to a massive expansion of cropland and urban sprawl, leading to the significant depletion of SOC and loss of grazing lands [48]. West Africa, similarly, has experienced severe land and forest degradation due to rainfall variability, the expansion of croplands, and the indiscriminate exploitation of mineral deposits in reserved areas [11,43,49]. Like the other subregions of the African continent, in Northern Africa—for example, in Morocco and its Atlas Mountains—even though there is limited available information about this subject, the limited existing literature indicates that land use transformation is predominantly driven by agriculture and tourism development, urban sprawl, and the intensive expansion of irrigation systems, forming a complex pattern of change [50–52]. The degradation of rangeland, deforestation, and the invasion of agricultural lands into steeper slopes of the Middle and High Atlas Mountains have led to significant levels of soil erosion and SOC loss [50,53]. While facing these challenges, locals face socioeconomic marginalisation, lose grip on their indigenous farming systems, and experience increasing climate stress. In contrast, Mohajane et al. [54] revealed that portions of the Middle Atlas of Morocco have seen an increase in high-vegetation classes, stabilising the overall forest cover. This contrast underscores a high level of inconsistency even in the limited existing data.

2.3. Overview of Drivers of LULC Change in Mountain Ecosystems

The fundamental drivers of LULC change present a canon of interdisciplinary assessment of technological, economic, demographic, institutional, and environmental factors. At the global level, the most prevalent LULC change drivers include agriculture expansion and intensification, urbanisation, population growth, and infrastructure and industrialisation expansions [9,12,27,42]. In the present era, climate change acts as a reinforcing driver, moving the natural suitability of many lands for forestry and agriculture, creating disturbance regimes, and escalating the uncertainty of ecosystem services and functions [27,30]. Also, the surge in technological innovation adoption in various land use domains, such as extraction industries and mechanisation in agriculture, has intensified land use scenarios across many regions. Nevertheless, countervailing factors such as conversion incentives and policy intervention have spatially slowed, and, in some instances, have displaced the intensive use of lands, creating a mosaic look of degradation–restoration change over the Earth's surface [55–57].

In mountainous regions, limited arable lands, steep topography, and extensive dependence on natural resources have created a unique and complex socioeconomic system. This

is linked to the extreme intensification of most of the drivers of land use change [1,56]. In most cases, these regions are also faced with scenarios such as marginalisation, institutional neglect, and rural poverty, which further hinder national integration. The overlapping of these factors leaves indigenous communities with limited choices other than to intensify land use, making the system further vulnerable to degradation.

Across Sub-Saharan Africa (SSA), deforestation, smallholder agriculture, charcoal production, and pasteurisation, coupled with unstructured land tenure systems and exponential population growth, are the main drivers of LULC change [26,46,47]. For example, the Ethiopian highlands and Eastern Arc Mountains in Kenya and Tanzania have been associated with extensive and indiscriminate cropland expansion due to food and nutrient security demands. These accelerate the loss of SOC and soil erosion through the removal of significant natural vegetation cover [48,58,59].

Northern Africa, particularly the Moroccan Middle and High Atlas Mountains, exhibits different types of land use drivers. In contrast to factors such as agriculture intensification and urbanisation dominating land use change almost across the globe, the subregion's key land use change drivers include rural depopulation and agriculture abandonment in marginal areas [51,52,60]. The subregion, however, has also experienced some significant levels of forest reduction [61]. In the past, traditional terracing farming systems dominated agriculture in this region, which regulated critical issues such as soil erosion and gully formation along the steep slopes [62]. Over time, there has been a significant loss of indigenous land management knowledge and an increase in aid-driven land intensification programmes. There have also been substantial changes in the grazing patterns and routes of livestock due to climate change and variability [60,63,64]. According to Ben-Said et al. [50] and Nguyen et al. [65], many lands in Morocco, previously covered with vegetation, have been transformed into urban or peri-urban centres due to road, infrastructure, and tourism developments. These systems have created a complex and fast-paced trend in land use transition. Such transitions play a significant role in climate change indicators such as rainfall, temperature, and relative humidity in the subregion.

2.4. Influence of Land Cover Classes and Practices on SOC Stock

Undoubtedly, LULC changes significantly influence SOC stocks, among the top 10% of the most significant sources of anthropogenic greenhouse gas emissions [66–69]. Among other factors, it is well-established that activities such as agriculture expansion, indiscriminate deforestation, settlement, and urbanisation are key contributors to SOC stock depletion due to their high decomposition rate compared to deposition [38,69,70]. For example, according to Don et al. [67], agriculture and forested land conversion can lead to over 30–50% SOC loss over a short period. Carbon sequestration-friendly approaches, such as reforestation and forest reservation, agroforestry, and conservation agriculture, depict how land use changes and their dynamics could influence carbon sequestration and its long-term storage, even though the recovery in many scenarios seems slow [71,72]. Comparing these changes in the LULC classes reveals clearly that the levels or extent of change in SOC storage are highly dependent on land use type and its inherent properties. For example, forests, natural reserves and native grasslands that are not disturbed for a very long time (decades to centuries) will typically have high baseline SOC levels as compared to croplands, settlement areas or urban centres and other forms of intensified land use. This is because in the natural reserve ecosystem, there is a continuous deposition and accumulation of organic matter and a comparatively stable microclimate, whereas in the intensified land use systems, there is accelerated microbial decomposition that is, in many scenarios, accompanied by physical erosion [73]. However, it is also worth mentioning that the extensive variation among different studies across the globe regarding SOC

accumulation and storage could be ascribed to localised conditions. This is to say, SOC is highly influenced by site-specific conditions such as climate, land use history before conversion, and time, which govern the decomposition and stabilisation rates of organic matter [74]. Evaluating these changes over several years reveals that the turnover rates of SOC are primarily nonlinear. For example, according to Hernandez-Ramirez et al. [75], native grass cultivation rapidly leads to an initial carbon depletion, and then slowly, over centuries, it bounces back to reach a new equilibrium. However, in an agroforestry scenario, there is a high initial buildup phase, which has an average accumulation rate higher than that of sole grassland, depicting a strong nonlinear path between the two scenarios. In the quest to assess the long-term impacts of these changes, it is important to acknowledge these nonlinear characteristics to avoid the overestimation of carbon accumulation in ageing forests or the underestimation of severe and immediate losses after converting reserved lands to cultivated lands.

2.5. SOC Measuring, Estimation and Carbon Modelling Under LULC Changes

To understand carbon distribution and dynamics in an ecosystem, it is crucial to have accurate assessment methods and strategies. Traditionally, most strategies revolve around direct sampling of soil and laboratory analysis. Key among them is the Walkley–Black method, or the dry combustion method, to measure the SOC content of a given sample [76,77]. Contemporary approaches, such as the use of geospatial technologies and remote sensing, have led to the development of predictive models for estimating SOC. Machine learning algorithms, for example, Random Forest and Support Vector Machines, have been used at various scales to map SOC [78]. Such algorithms incorporate environmental variables such as vegetation indices, topography, and climate variables to estimate SOC accumulation over time. Studies have also explored employing hyperspectral and multispectral remote sensing data to predict and map SOC [78,79]. Even though these contemporary methods have been handy in assessing SOC in many ways, such as speed and reaching unreachable areas, they are also limited in many ways, including in terms of accuracy. For example, Žížala et al. [80] observed a reduced level of accuracy with multispectral data compared to hyperspectral data when they attempted to predict SOC with the two. To minimise these errors, it is worth mentioning the necessity of calibration data. Contemporary satellite-derived statistical methodologies for determining carbon are highly dependent on good-quality calibration data. Also, these methodologies do not typically account for hysteresis effects in carbon dynamics, compared to vegetation cover.

Modelling is one of the key strategies to quantify the impacts of LULC on carbon sequestration and other ecosystem services. Several such tools have been developed for this quantification (commonly used ones are highlighted in Table 1), both process-based and static-based. Prominent among these are the Integrated Valuation of Ecosystem Services Trade-offs (InVEST), CA-Markov, RothC, and CENTURY/Daycent. These tools can map ecosystem dynamics over different land use scenarios through simulations [81,82]. The InVEST model, for example, facilitates the modelling of key ecosystem services such as carbon stocks by using biophysical parameters and user-determined land cover and land use input data [81,82]. It uses LULC raster maps (as GeoTIFF) and carbon pool tables (as a CSV file) as its main inputs. It has been successful across many landscapes, including mountain ecosystems. It is also prudent to distinguish between static-based accounting tools, for example, the InVEST carbon storage, and the process-based biogeochemical models, e.g., CENTRY and RothC. The static models mostly apply fixed carbon pool coefficients to LULC classes, whereas the process-based models simulate the temporal carbon fluxes and mineralisation dynamics. Table 1 presents a synthesis of several of these

models with their core functions and mechanisms, limitations for SOC studies, and their best use-case scenarios.

Table 1. Summary synthesis of common and widely used tools and models to stimulate SOC changes over time through different ecosystems.

Model Category	Specific Model	Core Function and Mechanism	Application in SOC-LULC Studies	Limitations for SOC Studies	References
Stock-Based Accounting Models	InVEST (Carbon Storage)	Applies fixed carbon density coefficients (biomass, soil, dead organic matter) to discrete LULC classes.	Estimating the spatial distribution of carbon storage based on current or future landscape composition.	Static nature: Does not simulate dynamic biogeochemical processes, erosion-driven losses, or nonlinear SOC turnover.	[25,81,82]
	IPCC Tier 1 Methodologies	Utilises default global or regional carbon stock change factors based on broad climate and soil types.	Providing standardised, baseline estimates for national greenhouse gas inventories.	Coarse resolution; fails to capture the high micro-topographic variability in mountain ecosystems.	[83]
Process-Based SOC Models	CENTURY	Simulates dynamic biogeochemical processes, including decomposition, mineralisation, and organic matter turnover over time.	Assessing long-term temporal SOC dynamics under specific climate, soil, and land management scenarios.	High parameterisation data requirements (e.g., precise historical climate and soil data) which are often lacking in steep, remote terrains.	[84,85]
	RothC	Models the turnover of organic carbon in non-waterlogged topsoils based on temperature, moisture, and plant cover.	Evaluating changes in topsoil carbon under different agricultural or forestry practices.	Primarily focuses on topsoil and requires extensive localised calibration to be accurate.	[86]
Land Use Change Simulators	PLUS (Patch-generating Land Use Simulation)	Utilises rule mining based on land expansion analysis and cellular automata to project future landscape patterns.	Simulating future LULC scenarios (e.g., urban expansion, deforestation) at the patch level.	Does not model carbon. Output must be coupled with stock-based models (e.g., PLUS-InVEST) to infer carbon impacts.	[87,88]
	CA-Markov/CA-ANN	Combines Markov chain analysis or artificial neural networks with cellular automata to predict spatial transitions.	Forecasting spatial and temporal land cover changes based on historical transition probabilities.	Focuses only on spatial transition probabilities; lacks any biogeochemical or ecological mechanism.	[89,90]
Habitat/Machine Learning Classifiers	MaxEnt (Maximum Entropy)	Uses statistical algorithms to map probability distributions based on presence-only data and environmental covariates.	Identifying areas highly susceptible to specific land use transitions or ecological shifts.	Not a carbon model. Predicts spatial likelihoods but provides no mechanistic carbon quantification.	[91,92]
	Random Forest/SVM	Employs ensemble learning or spatial hyperplanes to classify remote sensing imagery into highly accurate land cover maps.	Generating the foundational, high-resolution LULC maps needed as inputs for carbon models.	Dependent on the quality of training data; purely statistical with no physical modelling of soil properties.	[93,94]
Dynamic Global Vegetation Models	LPJ-GUESS/ORCHIDEE	Simulates ecosystem processes, vegetation dynamics, and carbon/water cycling at massive spatial scales.	Evaluating macroscopic terrestrial carbon sinks and sources under global climate change scenarios.	Spatial resolution is generally too coarse to accurately represent the complex, fragmented land uses of mountainous regions.	[95,96]

3. Materials and Methods

3.1. Literature Search Strategy

In this study, a structured review was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-analysis (PRISMA) 2020 guidelines [97] (see the Supplementary Materials). A formal review protocol was not prospectively registered in PROSPERO or any other systematic review registry prior to conducting this synthesis.

Scopus and WOS databases were selected for this study because they form part of the well-established, most reliable and widely used sources for peer-reviewed research and citation globally [98,99]. To do this, a search was conducted in each of the two databases using the same keywords: land use and land cover, soil carbon dynamics, mountainous ecosystem, and modelling and remote sensing. To capture a comprehensive dataset, the search strategy was structured around the four core conceptual layers, incorporating primary keywords and their synonyms combined via Boolean operators:

- Layer 1: The Phenomenon (LULC Change): This layer targeted the land use transition, utilising terms such as ("land use" OR "land cover" OR "LULC" OR "land use land cover") AND (change* OR transition* OR dynamic* OR conversion*).
- Layer 2: The Target Variable (SOC Dynamics): This layer focused on the primary outcome, using terms including ("soil organic carbon" OR "SOC" OR "carbon stock*" OR "carbon sequestration" OR "carbon flux*" OR "soil carbon dynamic*").
- Layer 3: The Geographic Context (Mountainous Ecosystems): To restrict the synthesis to the specific terrain of interest, this layer applied terms such as (mountain* OR highland* OR upland* OR "hilly region*" OR montane).
- Layer 4: The Methodological Approach (Modelling and Remote Sensing): To capture the specific analytical tools used to measure these patterns, this final layer included ("remote sensing" OR "satellite imagery" OR "GIS" OR "geospatial" OR "spatial modelling" OR "process-based model" OR "carbon model" OR "simulation model" OR "machine learning" OR "earth observation").

These four distinct layers were interconnected using the Boolean "AND" operator. This combination aimed to systematically isolate studies that have been published on land use and land cover dynamics globally, streamlining the results strictly to studies reporting the impacts of LULC changes on SOC within mountainous ecosystems using spatial or modelling techniques. Furthermore, to execute this query within the selected databases, the search was applied to the title, abstract, and keywords fields using the TITLE–ABS–KEY prefix in Scopus and the Topic Search (TS=) tag in Web of Science. The same keyword combinations were used for the two databases (please see the PRISMA checklist in the Supplementary Materials for the complete search string). Finally, in both databases, the search was limited to peer-reviewed journal articles (excluding books, literature reviews, and conference proceedings, etc.) published in the English language. We relied solely on the two primary database searches and did not perform snowballing (manual backwards/forward citation tracking). All searches were conducted on 11 November 2025.

To maintain consistency in study selection while recognising the diversity in topographic classification, mountainous ecosystems were defined using accepted global criteria. Rather than relying just on elevation in isolation, this review adopts the global mountain definition framework established by Kapos et al. [100], which identifies mountainous landscapes based on a combination of elevation thresholds, slope, and terrain ruggedness. This generally encompasses areas above 300 m in elevation that satisfy specific requirements for slope and local relief, a standard extensively utilised description in international mountain evaluations [101] and modern high-resolution global mountain mapping [102]. This review includes papers that specifically identified the subject location as mountainous, highland, montane, alpine, or hilly, based on features such as elevation gradients, slope features, or terrain descriptors. Due to the global variability in the shape and height range of mountain systems, a fixed numerical threshold (e.g., minimum elevation alone) was not established. Inclusion was determined by the interplay of topographic complexity, elevation gradient, and ecological characteristics aligned with recognised mountain definitions. Before the initial screening, the results from the two databases were merged, and duplicates were re-

moved. Manual screening and evaluation were conducted based on the titles and abstracts of retrieved articles to determine their relevance to the topic under investigation.

After the initial screening of the titles and abstracts, a full-text assessment was done to select the eligible articles. Studies were included only if they met the following criteria: (a) original research; (b) published in English; and (b) reporting LULC changes and their implications on SOC over time. These criteria were deemed strictly essential because calculating the direction of SOC flux resulting from a land use transition fundamentally requires a baseline. Including single-timepoint inventories would mix up inherent, static soil properties with dynamic, transition-driven changes, thereby compromising the objective of the synthesis. The screening process, at both the title/abstract and full-text stages, as well as the subsequent data extraction, was performed by a single reviewer. The detailed exclusion and inclusion criteria are presented in Table 2, while the complete overview of the search and screening following the PRISMA 2020 guidelines is presented in Figure 1.

Table 2. Inclusion and exclusion criteria for documents.

Step	Description	Decision
I	Articles that assessed land use or land cover without documenting temporal transitions.	Excluded
II	Articles that were conducted in landscapes other than mountainous, highland, or hilly environments.	Excluded
III	Articles that do not quantify or infer SOC change, or report ecosystem carbon changes directly attributable to LULC transitions.	Excluded
IV	Articles that are not based on primary empirical data, remote sensing analyses, or scenario-based modelling.	Excluded
V	Only articles that met all the inclusion criteria and did not fall under exclusions I–IV were selected for the systematic synthesis.	Included

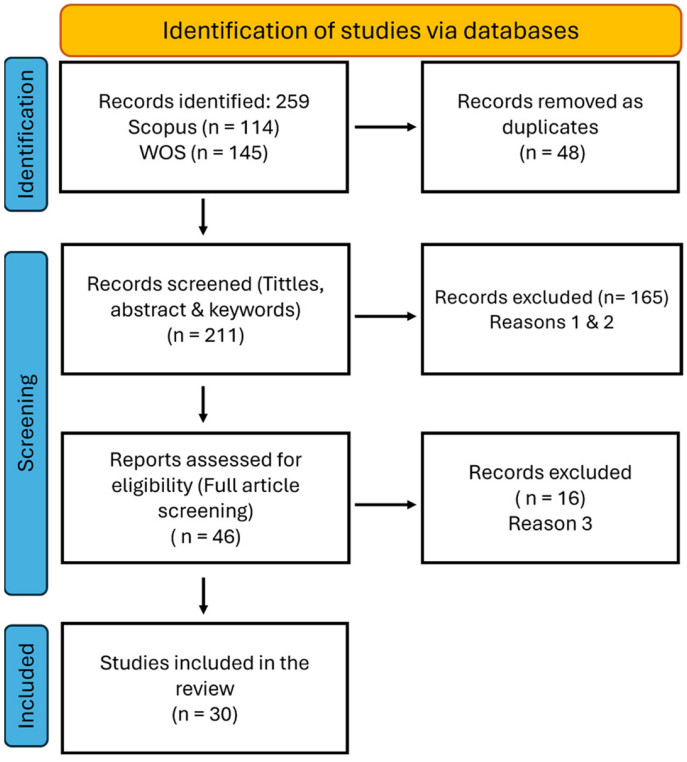


Figure 1. PRISMA flow diagram. Reason 1: Articles do not apply to mountainous ecosystems. Reason 2: Articles do not assess the impact of LULC on carbon sequestration or storage. Reason 3: Articles do not cover two distinct periods to allow assessment of LULC change.

3.2. Data Extraction, Analysis, and Synthesis

Following a standardised extraction framework, the included studies after the full-text screening were examined independently, and data were extracted under domains capturing LULC classes and transitions, SOC sampling depth (where applicable), direction and magnitude of carbon change, drivers of LULC change, analytical tools, satellite application, and modelling approaches. In addition to directional synthesis, studies reporting explicit quantitative values of SOC changes were extracted for descriptive comparison. Quantitative data reported encompassed percentage change, changes in SOC content/concentration (g kg^{-1}), and stock-based metrics (e.g., Mg C ha^{-1}, Tg, Mt, and Gg), in addition to specified soil depth ranges. Due to the extreme variations in reporting units, baseline definitions, spatial scales, and sampling depths across the reviewed literature, quantitative values could not be standardised to a single metric nor aggregated using a formal statistical meta-analysis. However, to move beyond a purely descriptive narrative and provide quantitative context, we systematically extracted the minimum and maximum effect sizes reported across dominant land use transitions. These quantitative ranges, capturing both absolute changes (e.g., Mg C ha^{-1} and g kg^{-1}) and relative percentage shifts, were synthesised. Original units were maintained as reported to prevent conversion-related bias and preserve the integrity of the underlying empirical data. Data from the included studies were manually extracted into a customised spreadsheet matrix designed to capture specific variables, including LULC transition type, geographic location, assessment methodology, sampling depth, and SOC baseline. To minimise extraction errors, the extracted quantitative values and qualitative findings were manually cross-referenced against the original full texts.

4. Results

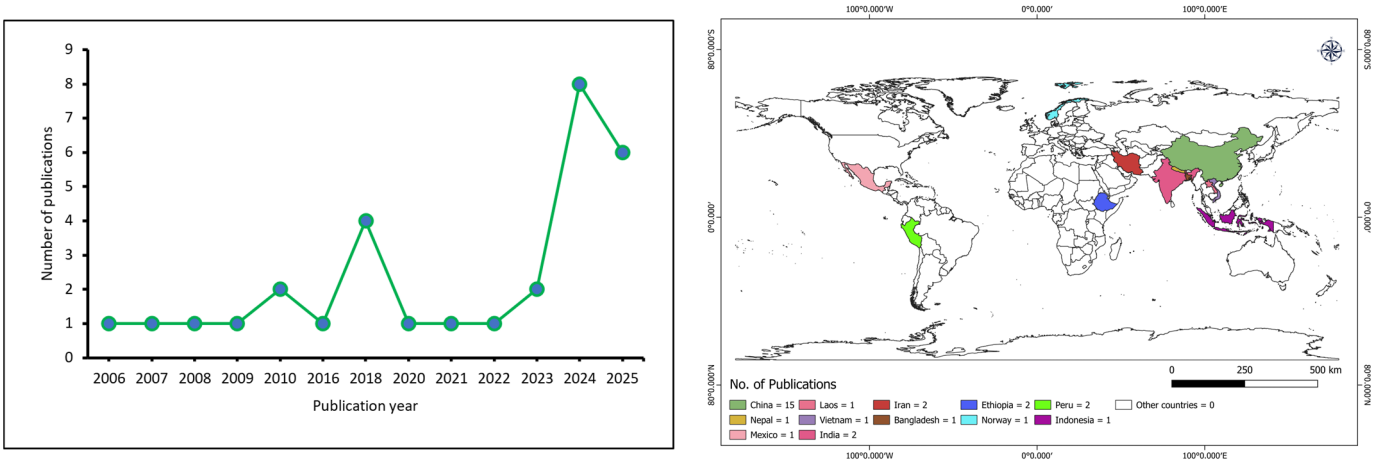
4.1. Geographical Distribution of Studies

The literature search resulted in the identification of a total of 259 publications (114 from Scopus and 145 from WOS). This number was reduced to 211 after the removal of publications that were duplicates from the two databases. A critical screening was conducted on the remaining 211 publications, during which titles, abstracts, and, when necessary, full texts were assessed for their direct relevance to the specific objectives of this study. Based on this rigorous evaluation, 30 publications [24,103–131] met the inclusion criteria (Supplementary Table S1). Even though there were no limitations to publication dates during the search, the 30 studies were published in the last two decades (between 2006 and 2025), with over 70% (n = 23) being published after 2018, showcasing an evident post-2018 escalation and indicating a growing attention to LULC change and carbon interactions in mountainous regions (Figure 2a). Geographically, the literature is highly heterogeneous, with Asia, particularly China (n = 15), dominating, with 80% (n = 24) of the total publications, while Africa is represented by only two studies, both from Ethiopia. Europe (n = 1) and the Americas (n = 1 each for South and North) are sparsely represented, highlighting substantial geographic research gaps (Figure 2b).

4.2. Dominant LULC Transitions, Soil Carbon Responses, and Timescale Sensitivity

In this synthesis, the magnitude and direction of SOC responses are intrinsically driven by complex variations across sampling depths, temporal assessment scales, the choice of model (i.e., static or dynamic), and the severe, localised impacts of slope-driven lateral erosion. Across the reviewed studies, the most common LULC transitions were forest to cropland (n > 8), rangeland or grassland to cropland (n = 4), cropland to forest (n = 4), and forest to built-up land (n = 5). Primarily, these transitions were driven by both biophysical and economic factors, including agricultural expansion (cropland and grazing land), population pressure, and urban or infrastructure development. Restoration-oriented

transitions, for example, cropland to forest, and from grazing land to forest, were less frequent and largely policy-driven (Tables 3 and 4).



(**a**) (**b**)

Figure 2. Spatiotemporal distribution of publications. (**a**) Number of publications by year; (**b**) global distribution of publications.

Table 3. Dominant LULC transitions and SOC responses in mountainous ecosystems.

Dominant LULC Transition	Frequency	Dominant Pools	Quantitative Effect Size (Absolute/Relative Range)	Typical Depth	Typical Timescale
Forest → Cropland/Agriculture	High (n > 8)	AGB Only/Both (AGB and SOC)	Stock Loss: −7.78 to −41.6 Mg C ha^{-1} (Relative: −26.9% to −55.0%)	0–30 cm	Short–Medium
Grassland/Rangeland → Cropland	Moderate (n = 4)	TOC (Lumped)/Both SOC and AGB	Conc. Loss: up to −2.7 g kg^{-1} (Relative: up to −17%)	0–100 cm	Medium
Forest → Built-up/Infrastructure	Moderate (n > 5)	TOC (Lumped)	Total Landcape Loss: -20.5×10^3 to -16.3×10^6 Mg (Total spatial area depletion)	Not depth resolved	Short
Cropland → Forest (Afforestation)	Moderate (n = 4)	AGB Only/SOC Only	Conc. Gain: +4.07 g kg^{-1} (Total regional accumulation: +0.21 Tg)	0–20 cm	Long
Rangeland degradation/Overgrazing	Moderate (n = 3)	TOC (Lumped)/Both SOC and AGB	Total Landscape loss: Over 1 million tons	0–30	Medium
Alpine wetland Meadow/Steppe	Low (n = 2)	SOC only	Total Landscape Loss: −336.6 Gg SOC (Total spatial area mass loss)	0–50	Medium
Scenario-based land use optimisation	Moderate (n > 5)	Scenario-dependent	Mixed Outcomes: highly dependent on scenario-specific parameters	Model-defined	Long

Stocks refer to mass per unit area (Mg C ha^{-1}); Conc. (concentration) refers to mass per unit soil mass (g kg^{-1}); and Landscape/Total Loss refers to aggregated regional carbon mass (Tg or Gg). Long-term (≥30 years), medium-term (15–30 years), and short-term (≤15 years).

Table 4. Dominant drivers of LULC change in mountainous ecosystems.

Driver Category	Key Drivers Identified	Frequency (n = 30)
Socioeconomic	Agricultural expansion; urbanisation; population growth; market demand	High
Biophysical	Climate warming; slope; erosion susceptibility; permafrost thaw	Moderate
Institutional/Policy	Restoration programmes; land use planning; weak governance	Moderate
Land management	Overgrazing; tillage; biomass extraction	Moderate

High (>20%), moderate (10–20%), and low (<10%).

Primarily, SOC responses were negative following land use intensification. For example, forest and rangeland conversion to a more intensified land use like cropland consistently led to a severe SOC loss, particularly in surface layers (0–20 or 0–30 cm) (Table 3). Particularly, forest conversion to cropland led to a loss in SOC stocks of between −7.78 and −41.6 Mg C ha^{-1}, a relatively 26–55% loss. The conversion of grassland/rangeland to cropland also led to a relative SOC loss of between 1.7% and 17.8% at the 30 cm layer of the soil. In addition, fragile high-altitude transitions, such as the degradation of alpine swamp and meadow to steppe, triggered massive regional deficits (e.g., losses exceeding 336 Gg SOC). SOC gains under afforestation or other restoration practices were generally slow; however, they could be variable depending on the scale (for example, there was a regional SOC concentration of up to 4.07 g kg^{-1}; regardless, this is also highly dependent of key factors such as initial levels or time), and often lagged behind AGB recovery, indicating a decoupling between vegetation regrowth and soil carbon recovery (Figure 3 and Table 3). This decoupling was evidenced by what can be called a "Greening Paradox", where surface vegetation proxies (like NPP and NDVI) indicated widespread recovery (e.g., greening in a short period), yet total ecosystem carbon simultaneously declined due to persistent sub-surface SOC deficits. Importantly, because the majority of the assessed studies in this synthesis restricted soil carbon quantification to the top 30 cm, the true magnitude of these long-term SOC deficits across deeper mountain soil profiles remains systematically underestimated.

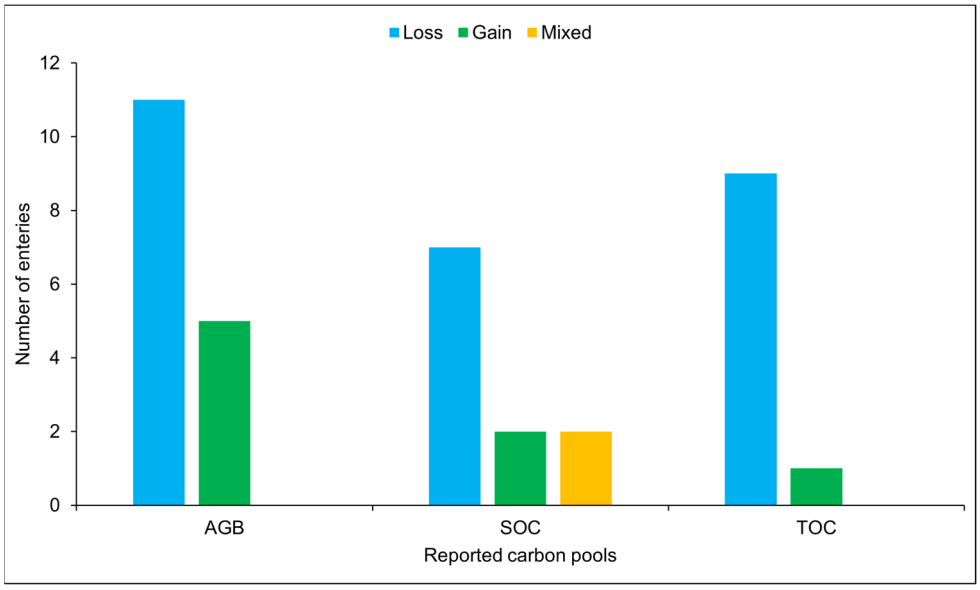
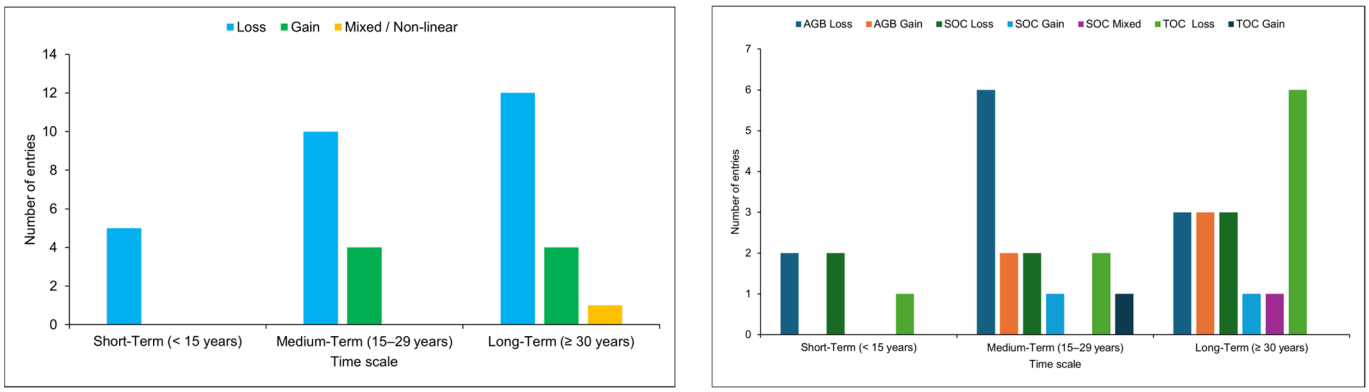


Figure 3. Direction of carbon response by carbon pool across mountainous ecosystems (n = 30 entries, studies that measured both AGB and SOC are tallied in both the AGB and SOC for their respective directional changes).

SOC responses in this synthesis exhibited a strong timescale dependence (Figure 4a). Short-term studies primarily functioned as degradation detectors, universally recording carbon losses after land use intensification. While medium-term studies (≤30 years) overwhelmingly reported carbon losses across different pools, this timeframe simultaneously recorded a spike in AGB increase (Figure 4b). This divergence reveals a severe methodological risk such that the rapid surface vegetation recovery during this window could often create an illusion of ecosystem carbon gain, masking the persistent, underlying sub-surface SOC deficits. Long-term studies (≥30 years) and scenario-based assessments exhibited notable mixed or positive outcomes. Even in the long-term studies, SOC recovery was

often incomplete, underscoring a persistent deficit driven by land use legacies in mountain soils, regardless of several policy implementations across the globe.



(**a**) (**b**)

Figure 4. Timescale sensitivity of carbon responses to land use and land cover change. (**a**) Overall direction of ecosystem carbon response across short- (<15 years), medium- (15–29 years), and long-term (≥30 years) baselines. (**b**) Breakdown of the temporal carbon response by specific carbon pool (AGB, SOC, and TOC).

4.3. Satellite Data and Model Usage and SOC Implications

The methodological partners in the synthesised studies reflect a strong reliance on integrated remote sensing, modelling, and, to a lesser extent, field-based methods (Table 5).

Table 5. Satellite, software, and model usage and SOC implications.

Analytical Category	Tools Reported	No. of Studies	SOC Representation	Erosion Representation	Key Limitation
Stock-Based Carbon Accounting Models	InVEST; IPCC Tier-1	12	Static carbon coefficients assigned to LULC classes	Not modelled	Cannot simulate temporal SOC turnover, time lags, or erosion-driven lateral export
Land Use Change Simulators	PLUS; FLUS; CA–Markov	7	Indirect (SOC derived from stock models)	Not modelled	Focus on land transition, not soil processes
Machine Learning SOC Mapping	Random Forest; ANN; XGBoost	6	Empirical SOC prediction (surface biassed)	Inferred	Requires calibration; limited process explanation
Field-Based SOC Measurement	Soil core sampling	11	Direct SOC measurement	Inferred via site description	Often limited to surface layers (0–30 cm)
Remote Sensing Classification Only	Landsat; MODIS	26	No direct SOC measurement. Strong for land use and land cover change mapping and area transitions	Not modelled	SOC inferred indirectly from land cover

The methodological tools identified in this review were classified into five categories: (i) stock-based carbon accounting models, (ii) land use change simulators, (iii) machine learning-based SOC mapping approaches, (iv) field-based SOC measurements, and (v) remote sensing-based LULC classification tools. Across the 30 studies, Landsat imagery was the dominant satellite platform for LULC detection, often processed within GIS environments such as ArcGIS or Google Earth Engine (GEE). However, remote sensing platforms were used primarily for land cover classification rather than direct SOC measurement. SOC

estimation in many studies relied on stock-based accounting frameworks, most notably the InVEST carbon storage model and IPCC Tier-1 approaches (>40%). A smaller subset of studies (20%) employed machine learning techniques, such as Random Forest, artificial neural networks (ANN), or XGBoost, to predict SOC spatial distribution. Field-based SOC measurements were incorporated in fewer than half of the studies (37%). Even where field sampling was conducted, sampling was often restricted to surface horizons (commonly 0–20 cm or 0–30 cm), and repeated measurements across time were limited. Erosion processes were rarely modelled explicitly and were more often inferred qualitatively based on terrain and land use descriptions (Table 5).

Notably, the application of fully process-based soil carbon turnover models (e.g., CENTURY or RothC) within mountainous systems was not reported in the synthesised studies. The absence of these mechanistic SOC models highlights a methodological gap, particularly given the recognised importance of erosion, depth stratification, and land use legacies in mountain carbon dynamics. The dominance of stock-based and model-driven approaches likely contributes to the underrepresentation of depth-resolved and erosion-mediated SOC losses in mountainous landscapes.

5. Discussion

This review provides robust and consistent evidence that SOC is highly vulnerable to changes in LULC, especially in mountainous landscapes. Across all the geographical regions represented in this synthesis, there were significant SOC losses. Predominantly, this is attributed to land use intensification, mainly following transitions from forest/dense vegetation or rangeland to cropland and human settlement or industrialised areas. This exposition accentuates the vulnerability of SOC as a carbon pool in the face of LULC transitions, especially in situations where the transitions are vegetation-centric. Rapid losses of SOC due to the expansion of agricultural land and forest–rangeland degradation illustrate the combined implications of soil disturbance, reduced organic inputs, and unbridled erosion, processes which are further worsened by steep terrain and shallow soils in mountain ecosystems [19,20]. Within general conceptual frameworks of carbon storage in relation to LULC change, conversion of dense vegetation, such as forest and rangeland, to cropland facilitates rapid depletion of surface SOC via both physical erosion and subtle soil disturbance. In contrast, SOC recovery under restoration is slow and usually not complete, even where long-term restoration systems result in significant recoveries in AGB. This lack of proportionality between carbon pools evidences the fact that biomass-centric carbon assessments are limited [3,24], corroborating long-standing soil carbon studies, which suggest that SOC loss follows a steep slope under vegetation loss, whereas its recovery remains very slow [3]. As revealed in Table 3 and Figure 3, these variations demonstrate that while there may be instances where vegetation recoveries occur rapidly, SOC deficits may persist for a while, depending on underlying factors like baseline levels. It further confirms that the mere regrowth of vegetation is not a proportionate proxy for surface or sub-surface carbon restoration. For example, studies from Asia, Africa, and Southern America [24,105,113,114] harmoniously reported rapid losses of SOC, most times exceeding 20% of surface SOC stocks, within the first two decades after converting land cover from one form to another. These findings are comparable across climatic zones, suggesting that topography and land use intensity have significant implications for SOC loss compared to climate alone in mountainous settings.

This review further presents a fundamental premise that physical mechanisms, such as soil erosion and the lateral transport of vegetation litter, are key contributors to the loss of SOC in mountainous landscapes. These assertions align with multiple studies focused on SOC that report that a decline in SOC stocks or concentration often exceeds

what can be explained by enhanced microbial decomposition alone [105,115]. For example, in steep terrain, runoff and sediment transport are facilitated by vegetation removal and soil disturbance practices, which increase the exportation of SOC-rich topsoil downslope and into lowlands and aquatic systems [19]. This erosion-induced perspective is in line with process-based studies, demonstrating that erosion redistributes rather than simply SOC mineralisation, resulting in non-reversible local losses even where some carbon may be buried elsewhere in the landscape [19,20,22,23]. However, it is important to also note that while erosion is frequently cited as a primary mechanism of SOC stocks or concentration loss in these complex topographies, in many of the reviewed studies in this synthesis, erosional loss is inherently inferred from topographic proxies rather than directly quantified through field-based measurements (e.g., sediment traps or isotopic tracers). Consequently, the actual magnitude of erosion-driven carbon export remains a critical gap requiring more direct pedological observation. Also, studies that rely solely on static carbon models, such as the InVEST carbon sequestration and storage model or surface SOC coefficients, tend to underrepresent these losses, which explains why model-based assessments often report smaller SOC gains or declines or mixed response trajectories [126]. Importantly, because these spatial models in most scenarios aggregate all carbon pools into a single lumped Total Organic Carbon (TOC) value, they mathematically ignore the inverse dynamics between surface vegetation and sub-surface soil activities, and erosion, effectively masking the decoupling phenomenon [132].

Another key premise in this review is the systematic disconnection between the recovery of vegetation and SOC even after afforestation and/or other restoration practices in mountainous ecosystems. On the other hand, several studies, for example, Kohestani et al. [119] and Zarandian et al. [112], reported a significant gain in AGB under land use transition trajectory from cropland-to-forest or natural regrowth. Regardless, even though there were these AGB gains, SOC gain trajectories were predominantly slow or negligible when compared to the loss magnitude over similar timescales. This trend is commonly evident in most montane forests, landscapes where biomass recovery occurs in a fast-paced manner in most cases over a short time, yet SOC remains significantly depleted relative to pre-disturbance levels [117,125]. This manifests as a 'Greening Paradox', i.e., the phenomenon where surface vegetation proxies (such as NDVI) indicate obvious ecological recovery, yet the total carbon ecosystem does not reflect the same measure due to persistent or unmeasured sub-surface SOC deficits. As demonstrated in our synthesis of cropland-to-forest transitions, while these areas show rapid surface greening within a decade, true SOC concentration gains (e.g., up to +4.07 g kg^{-1}) are predominantly realised only over long-term timeframes ($\geq$30 years). In the short term, SOC stocks often remain stagnant or even experience temporary depletion due to initial pedological disturbance during planting and the decadal lag times required for stabilisation. These findings, however, are in contrast with earlier assumptions postulated by some carbon accounting frameworks that proportionate biomass recovery as a proxy for ecosystem carbon recovery. Instead, it substantiates growing evidence that the recovery of SOC is significantly emaciated by limited accumulation of organic matter in steep terrains, shallow root penetration at depth due to profuse surface and subsoil rocks, and persistent unbridled erosion (which can continue sub-surface, masked from satellite view by a healthy-looking forest canopy). These characteristics are typical in most mountain ecosystems across the globe [3]. SOC recovery trajectories, which are highly timescale-dependent, further complicate these interpretations. In this synthesis, studies with study periods less than 15 years overwhelmingly reported fast-paced trajectories of SOC loss, while those with study periods more than 30 years and scenario-based analyses (mostly long-term of up to or more than 50 years or beyond) capture actual biological stabilisation and reveal slow-paced or even nonlinear recovery

trajectories, based on scenario options. Even with that, in the cases where long-term gains are reported, the recovery of SOC is typically confined to just within the top 30 cm and remains highly vulnerable to recurring disturbance. This nonlinear behaviour challenges linear extrapolations of SOC trends and further shows the significance of periodic and long-term monitoring. The findings corroborate the wider soil carbon literature, demonstrating that recovery rates of SOC are slower than loss rates, especially in landscapes that are prone to erosion [19,20].

The application of the African use-case demonstrates how globally identified mechanisms contributing to SOC loss operate under conditions of high vulnerability and limited data availability. Regardless of the limited amount of identified literature from the continent for this synthesis, the findings align with the global patterns of erosion-driven SOC loss following the conversion of forest and rangeland to agricultural land, settlements and industrial areas [24]. Also, contributing factors such as smallholder agriculture, grazing pressure, and fuelwood extraction interact with steep slopes and intense rainfall to exacerbate SOC losses [50]. These dynamics are in synch with the global observations, particularly in Asian mountain systems. However, the African context is often exacerbated by limited soil conservation measures and weak monitoring infrastructure. Importantly, the African context further supports the global observations that biomass recovery does not guarantee soil carbon restoration, evidenced in the limited recovery of SOC despite vegetation regrowth. This alignment reinforces the premise that African mountain systems do not represent an isolation of distinct SOC response regimes but rather an intensified expression of globally observed SOC loss mechanisms, making them a critical priority for land use and management planning in relation to terrestrial carbon sequestration and storage.

Finally, the methodological bias shaping contemporary knowledge of SOC dynamics in mountainous landscapes indicates a dominance of Landsat-based LULC mapping coupled with static carbon models (e.g., InVEST carbon sequestration and storage model). As demonstrated in our synthesis, nearly 60% of the reviewed literature was physically unable to detect AGB–SOC decoupling because studies either measured only a single pool or utilised these static models that lumped together TOC. This, in a wider lens, enables broad spatial analysis, even to unreachable places and more complex landscape terrains like mountains. However, this approach limits the representation of impacts of key factors such as depth, erosion, land use legacies, and SOC measurements. It is worth mentioning that studies that integrate field-based SOC measurements consistently report larger and more persistent SOC losses [24,113,114]. This contrast suggests that SOC losses or gains in mountainous regions are likely systematically underestimated or perhaps gains are overestimated in model-only driven assessments.

Limitations and Perspectives

In this review, the key challenges identified include limited field-based SOC measurements, the inadequate representation of subsoil (>30 cm) and lateral SOC fluxes, a reliance on static carbon coefficients, and a strong geographic bias toward a few regions. These bottlenecks hinder the accurate assessment of long-term SOC dynamics and the potential of mountainous ecosystems to sequester and store carbon. We hypothesise that the strong geographical bias and widespread reliance on static modelling approaches may be due to factors such as severe budget limitations and the difficulty of taking soil samples in areas with limited accessibility and snow cover, especially with the complex and rocky nature of mountainous landscapes. If this hypothesis holds true, it suggests that overcoming these financial and physical barriers is a prerequisite for generating the high-resolution, process-based data currently missing from global syntheses, especially in typically underrepresented regions like Africa. The improved connection of LULC scenarios with soil

process models will further enhance the reliability of SOC-based land management and climate mitigation strategies. A critical limitation identified in the synthesised literature is the predominant focus on shallow soil horizons (typically 0–30 cm). In mountainous ecosystems, vertical SOC heterogeneity is pronounced; deep soil layers often sequester significant carbon through root exudates and pedogenic processes that are not captured in surface-level sampling. Consequently, by restricting the analysis to the topsoil, the reported SOC losses and recovery rates likely represent a conservative estimate. The exclusion of sub-surface dynamics may lead to an underestimation of the total landscape carbon debt, particularly in areas prone to deep-seated erosion or where deep-rooted perennial vegetation is replaced by shallow-rooted annual crops. While this synthesis provides crucial insights into the dynamics of LULC and carbon storage, we also acknowledge its own methodological limitations. To begin with, the final inclusion of 30 studies from an initial pool of 259 records reflects both our strict inclusion criteria—i.e., papers are required to explicitly assess LULC change and its impacts on SOC in two distinct periods to allow for change assessments—and the actual scarcity of the literature that intersects mountain ecosystems, LULC change, and SOC change. Also, a potentially biassed selection may have been introduced by our search strategy, i.e., the inclusion of keywords that emphasise remote sensing and spatial modelling may have excluded purely empirical studies. Finally, while we acknowledge that a formal, standardised, quality appraisal scoring tool was not independently applied to the final included studies, we ensured that predefined inclusion and exclusion criteria were strict and uniformly applied to mitigate subjectivity. We further acknowledge that the initial database screening and data extraction were conducted by a single reviewer approach, which could inherently carry a higher risk of selection bias or inadvertent omission compared to dual-independent screening. Nevertheless, to safeguard data integrity and systematically minimise subjective bias, all screening and extraction phases strictly adhered to the predefined, standardised inclusion protocols and data extraction matrices.

6. Conclusions

This review illustrates that LULC transitions in mountainous landscapes have significant and largely detrimental implications for SOC dynamics. The findings of this synthesis support robust evidence that SOC loss following LULC transitions in mountainous landscapes is rapid and persistent, erosion-dominated, and difficult to reverse. Also, recovery is slow, depth-limited, and temporally asynchronous, and lacking proportionality with aboveground biomass recovery. These findings reinforce the need to place SOC, rather than biomass regrowth alone, at the centre of carbon assessments and land use and management planning in mountainous ecosystems. However, it is also worth mentioning that this synthesis highlights a significant limitation in the existing literature, specifically a pronounced geographic bias towards Asian mountain systems and a prevalent methodological dependence on static carbon models that frequently overlook complex, erosion-driven sub-surface dynamics. Future research must prioritise empirical, process-oriented SOC monitoring in under-represented and extremely vulnerable places, such as African mountain systems, to address these deficiencies. Addressing these methodological limitations is crucial for creating localised, climate-smart strategies and precise carbon accounting in steep slope landscapes.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/environments13050269/s1. Table S1. Dominant LULC Transitions and SOC Responses in Mountainous Ecosystems. PRISMA 2020 Checklist [97].

Author Contributions: All the authors (I.B.A., A.L., A.C. and W.A.) have contributed substantially to this Manuscript. Conceptualization, I.B.A. and A.L.; methodology, I.B.A. and A.L.; software, I.B.A.; validation, I.B.A. and A.L.; formal analysis, I.B.A.; investigation, I.B.A. and A.L.; resources, A.L. and I.B.A.; data curation, I.B.A.; writing—original draft preparation, I.B.A.; writing—review and editing, I.B.A., A.L., W.A. and A.C.; visualisation, I.B.A.; supervision, A.L. and W.A.; project administration, A.L.; and funding acquisition, A.L. and A.C. All authors have read and agreed to the published version of the manuscript.

Funding: The lead author (I.B.A.) received funding from the Africa Carbon Flagship Programme (ACFP 2024, a flagship program between the OCP Foundation and the UM6P) for this work.

Data Availability Statement: No new data were created. Data extracted and analysed for this systematic review are available in the Supplementary Material. Data sharing does not apply to this article.

Acknowledgments: This study was conducted within the framework of the African Carbon Flagship Project (ACFP), financially supported by the OCP Foundation through the Mohammed VI Polytechnic University (UM6P). The lead author (I.B.A.) received additional financial support from UM6P and its College of Agriculture and Environmental Sciences. The authors acknowledge all the support from the leadership and colleagues at the ACFP programme. The authors acknowledge the use of a writing assistant (QuillBot version 1.6.4.0) to improve the grammar and readability of the manuscript. The tool was used solely for language refinement. All screening, data extraction, analysis, and interpretation were conducted independently by the authors.

Conflicts of Interest: The authors declare no conflicts of interest.

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