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Review

Land Change Science and the STEPLand Framework: An Assessment of Its Progress

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Abstract: This contribution assesses a new term that is proposed to be established within Land Change Science: Spatio-TEmporal Patterns of Land ('STEPLand'). It refers to a specific workflow for analyzing land-use/land cover (LUC) patterns, identifying and modeling driving forces of LUC changes, assessing socio-environmental consequences, and contributing to defining future scenarios of land transformations. In this article, we define this framework based on a comprehensive meta-analysis of 250 selected articles published in international scientific journals from 2000 to 2019. The empirical results demonstrate that STEPLand is a consolidated protocol applied globally, and the large diversity of journals, disciplines, and countries involved shows that it is becoming ubiquitous. In this paper, the main characteristics of STEPLand are provided and discussed, demonstrating that the operational procedure can facilitate the interaction among researchers from different fields, and communication between researchers and policy makers.

Keywords: In-deep reading analysis; LUCC patterns; spatial modeling of driving forces; socio-environmental consequences; future scenarios

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1. Introduction

Landscape and ecosystem transformations, and their implications for global environmental change and sustainability, are a major research challenge for both ecological and social sciences [1]. As a result, the analysis of changes in land use and land cover is considered essential for researching major environmental issues such as desertification, eutrophication, acidification, greenhouse effects, biodiversity loss, and climate warming [2]. The progress in these studies was extensively coordinated from 1994 to 2005 by the Land-Use and Land-Cover Change (LUCC) core project of the International Geosphere-Biosphere Programme (IGBP) and the International Human Dimensions Programme (IHDP) [3,4], which represent the starting point of other global and regional initiatives, such as the ESA GlobCover [5] and the NASA LCLUC Programme [6]. In 2006, an even broader initiative, the Global Land Project, was established with the aim of synthesizing and integrating insights, knowledge, and research methodologies, thereby identifying scientific priorities and a research agenda [7]. Two major challenges faced by this initiative were (i) a refined understanding of complex feedbacks between societal and environmental components of the integrated land system, and (ii) up-scaling local and regional processes of change to reach a "truly global" understanding [8]. Consequently, a new research field, called Land Change Science (LCS), has attracted increasing interest and efforts to better understand LUCC patterns and dynamics that affect the structure and functioning of Earth systems [9]. This perspective requires using specific analysis tools, e.g., Geographical Information Systems (GIS), to integrate specific knowledge in socio-economic and ecological subsystems.

LCS has carried out research at many spatial and temporal scales with the objectives of explaining human–environmental system dynamics that generate landscape changes;

improving spatially explicit LUCC models that are compatible with Earth systems models; and, finally, assessing system intrinsic properties and the related outcomes, such as vulnerability, resilience, and sustainability [1]. The refined analysis of interactions between biophysical and socio-economic subsystems has implied the active involvement of researchers from natural, social, and spatial disciplines. The complexity of integrating diverse data, space–time patterns, and socio-biophysical processes has led to some methodological issues related to merging analytical traditions, mainly when people, places and environment are linked [10]. Spatial accuracy and uncertainty, trans-scalar mismatches, and the choice of aggregation levels (from county/district to households/individuals) are examples of these issues [11].

A seminal contribution by [7] defined LCS as an interdisciplinary research field that engages scientists across the social, economic, geographical, and natural sciences, and is conceptually and operationally separate from the broader discipline of Land System Science. This distinction was motivated by the increasing interest in (i) the role of drivers and impacts, (ii) the interactions between socio-ecological systems, and (iii) the connection between world regions, cities, and their rural hinterlands. Changes over time in human interactions with the natural surroundings, including land management and the provisioning of ecosystem services, are the focus of emerging socio-ecological interpretative paradigms [8]. The usual aims of LUCC studies are to identify drivers of change and, based on this knowledge, envisage future scenarios, proposed in both individual (local) cases and more globalized research. Nevertheless, generalization and validation processes can sometimes be difficult due to the diversity of driving forces, study areas, indicators, and modeling approaches [12].

Giving value to long-lasting research, LCS is a (rapidly evolving) disciplinary field that has produced a wealth of methodological innovations and empirical observations when it has been used to assess and interpret LUCC patterns, drivers, and inter-linkages [13]. From this perspective, its development has been characterized by a focus on local case studies and a specific emphasis on methodological developments that have improved remote sensing tools and geo-spatial analysis. It has also promoted the adoption of theoretical and empirical frameworks derived from disciplines such as geography, landscape ecology, and regional science.

After more than 25 years of LUCC research, our hypothesis is that the progress of LCS seems unquestionable in many social and natural disciplines, and it has become relatively ubiquitous because it is applied by experts worldwide. Based on an original meta-analysis of selected literature, our main objective is to assess a specific workflow resulting from LCS that we propose to call STEPLand (Spatio-TEmporal Patterns of Land). By delineating specific analysis criteria of the reference sample, we summarize the main attributes, data typology, and methodological steps, in addition to technical details and issues of practical applications, typical of LCS approaches. Our review reports on the reliability, robustness, and global applicability of operational definitions and frameworks oriented toward the STEPLand perspective, demonstrating the specific contribution of this approach to selecting appropriate methods and models for LUCC research.

2. STEPLand Framework

STEPLand is defined as an operation framework typical of LCS, and composed of four steps, moving from broader to narrower epistemological perspectives (Figure 1):

1. LUCC patterns and dynamics. The main objective of the first step is LUCC assessment using, e.g., remote techniques and geo-spatial approaches, and answering, at least, the following questions: "What LUC are changing?", "Where?", "When?".

2. LUCC modeling. The main objective is to describe the core drivers of LUCC using qualitative or quantitative methods and answering the following questions: "Which causal factors are involved in LUC changes?", "Why?", "How?".

3. Assessment of socio-environmental consequences. The aim is to delineate and understand the socio-environmental consequences of LUCC using qualitative or quantitative

methodologies, and explicitly considering landscape transformations and ecosystem service dynamics to answer the question: "And then?".

4. Compiling future scenarios. The goal of this last step is to establish future LUCC projections, answering questions such as "What happens if (. . .)?".

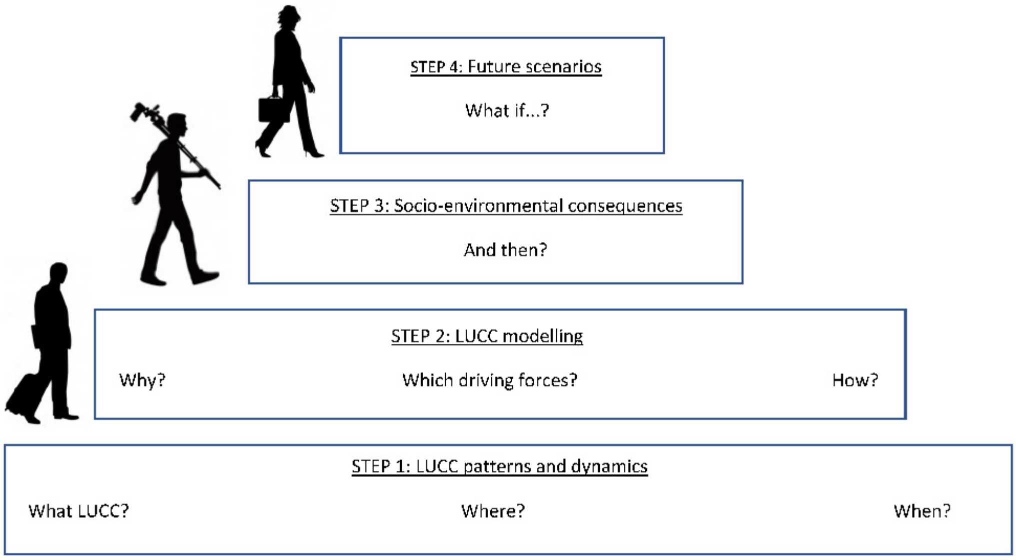

Figure 1. A workflow from broader to narrower knowledge issues illustrating the STEPLand perspective. Source: own elaboration.

2.1. LUCC Patterns and Dynamics

The first step of STEPLand includes a formal assessment and characterization of LUCC, mainly based on Earth Observation (EO) techniques, e.g., remote sensing (RS). EO and GIS data facilitate trans-sectoral research and provide a platform for integrating multiple information layers that may include ancillary (or validation) data [14,15]. RS tools provide valuable multitemporal data for monitoring LUCC patterns and processes at different spatial scales (local, regional, national, continental, and global), and GIS techniques make it possible to analyze them explicitly [16–18]. Spatial, spectral, and radiometric RS resolutions affect the size, condition, and precision of the explicit features to be discriminated in a landscape scene, whereas the temporal resolution of satellite imagery determines the intrinsic territorial, environmental, and socio-economic dynamics of local systems [10,19–21]. Both dimensions represent large technical challenges. During the past 40 years, significant advances in sensor technologies have improved the spatial, spectral, radiometric, and temporal resolutions, and the coverage, of satellite imagery [22]. The classification phase is the process of identifying spectral similarities in the multidimensional spectral space and linking them to LUC categories. This involves assigning pixels to different LUC classes identified in a given study. Diverse classification taxonomy options are now available but, traditionally, these have been divided according to the pixel technique used (per-pixel or sub-pixel), or according to the application of training samples (supervised methods or unsupervised methods), among others [23–25].

Similarity in spectral reflectance properties of natural surfaces at a given moment often impedes consistent identification and mapping of a large range of LUC, such as agricultural crops or individual communities constituted by natural vegetation. Furthermore, the spectral response of many cover types varies throughout the year: LUC categories that appear similar in spring may become distinguishable at earlier or later stages of the annual cycle. Therefore, a multi-temporal approach based on large RS databases is more suitable for revealing the complex LUC patterns characteristic, for instance, of the Mediterranean Basin [26–28]. In order to minimize the classification errors due to seasonal changes, an appropriate strategy is to select images from the same month or, at least, from the same season [29,30]. After a classification is obtained, the next step is to assess the accuracy or how well a classification has worked. This assessment measures the correlation between satellite imagery classification and ground reference samples to quantify the overall agreement between RS classification (global accuracy and user and producer accuracy by categories) and ground truthing data [31].

Once LUC maps are generated and tested, among the available change detection techniques, the most usual method is the post-classification or map-to-map comparison (i.e., a comparative analysis of independently produced LUC classifications from different dates) associated with a transition or change matrix [32,33]. According to [34], post-classification is an accurate procedure that bypasses the difficulties associated with analyzing images acquired at different times of the year or by different sensors, and thus delineating the nature of change [35]. Nevertheless, this method has two well-known critical issues [36,37]: first, misregistration of the polygon boundaries (locational inaccuracy) in the different classifications, and, therefore, the presence of border pixels with false positive or negative changes. With rasters, this is basically the consequence of non-matching pixels [38]; with vector shapes, this problem is known as "sliver", i.e., narrow polygons of uncertain interpretation [39–41]. The second issue relates to problems derived from classification errors: a false positive change may be recorded when no change has taken place because a pixel in one map (or in both maps) is misclassified, or false negative changes, when no change is identified but a change has taken place in the field. Therefore, this approach requires a good accuracy level in both classification maps because the change map accuracy is the product of the accuracies of the individual classifications, and therefore, it is subject to error propagation [42–44].

2.2. LUCC Modeling

Modeling is a process that provides a platform for encoding inferred (or deduced) relationships, thus allowing simulations and projections based on mathematical (algorithmic) specifications or procedures [45]. LUCC modeling is a tool for supporting planners and policymakers in developing robust policies and decisions. At the same time, models can be used to provide an ex ante assessment of policies or serve as an early warning system for environmental impacts. Six conceptual dimensions are considered to be particularly important for carrying out LUCC modeling [46]: (i) analysis level, (ii) cross-scale dynamics, (iii) driving forces, (iv) spatial interactions and neighborhood effects, (v) temporal dynamics, and (vi) level of data integration. In general terms, LUCC is often modeled as a function of a selection of socio-economic and biophysical variables acting as driving forces that shape land change [2,47–49].

Modeling LUCC driving forces comprises a wide variety of methodological approaches, which can be classified in different ways. For instance, [3] divided driving forces into three groups: socio-economic drivers, biophysical drivers, and land management variables; [50] differentiated proximate causes, those actions that directly affect land use, such as wood extraction, from underlying causes, i.e., those "fundamental forces" that underpin the proximate causes, including demographic, economic, technological, institutional, and cultural factors [51]. In general, Ref. [52] identified five driving forces: (i) biophysical constraints and potentials, (ii) economic factors, (iii) social factors, (iv) spatial policies, and (v) spatial interactions and neighborhood characteristics. Others [48,53,54] differentiated actors of change from driving forces. Actors are the decision-making and mediating agents, including individuals (e.g., farmers), households, neighborhoods, agencies (e.g., planning organizations), and institutions, whereas driving forces are the (sometimes materialized) expression of their decisions or acts, e.g., through laws, subsidies, or incentives [55]. Moreover, Ref. [53] provided a specific definition of the "spatial domain" as the institutional (and geographical) context where a given agent interacts with the landscape (e.g., countries, regions, prefectures/provinces, municipalities). Representation of the domain can be facilitated in a geographically explicit model using boundary maps or vector layers. The extent of the study area also influences the selection: larger areas imply a diversification of LUC contexts and may require analyzing a larger variety of driving forces. Therefore, the analysis scale (local, regional, national, or global) can produce a specific representation based on different driving forces. For instance, the presence of small ecologically valuable areas can be the main determinant of LUCC patterns at a local scale, whereas the distance from the market can be a more important factor at a regional scale [46].

Specification and quantification of the intrinsic relationship between driving forces and LUCC are particularly important in model implementation. According to [56], modelers should select the drivers or explanatory variables that are supposed to play an active role in land change. Even in automated approaches, input variables are selected based on expert knowledge, although data availability (e.g., the lack of data for some economic variables, such as land ownership, or, for earlier times, e.g., gross domestic product in 1850) is often a major limitation, as documented in [57].

According to [45], models used for LUCC analysis range from those oriented towards pattern description/recognition to those quantifying and interpreting dynamics. One study [58] provided a more generalized classification, arguing that models can be static or dynamic, spatial or non-spatial, inductive or deductive, and/or agent-based or pattern-based (e.g., emulation of individual decision makers vs. inference of the underlying behavior derived from LUCC patterns). Models can use a large range of information (satellite imagery, official statistics, maps or field surveys, among others) often implemented in GIS and eventually combined in composite indicators. Actor-based, bottom-up models based on household surveys represent the land change agent explicitly by emulating individual decision makers through agent-based approaches. Land evaluation pattern-based top-down models use RS and census data to simulate LUCC through parameterized transition equations that convert land from one cover type to another [59]. Finally, Ref. [60] separated inductive pattern-based models from cellular automata approaches, sector-based economic models, spatially disaggregated economic approaches, and agent-based models.

Therefore, driving forces form a tangled system of interactions that affect multiple temporal and spatial levels, making it difficult to carry out adequate analyses and obtain representation systems. Combining data from the social and natural sciences is a particularly complicated task due to the different operational scales, the complexity in relating social science data to a specific geographic place, and the difficulty involved in integrating qualitative data, which is more common in social science, and less common in ecological disciplines [47]. Moreover, driving forces—and not only LUCC—are also subject to changes, which influence the identification of representative study periods, and thus affects the model's results [61]. Precision of statistical methodologies and data availability are also important. As a summary, identification of LUCC drivers (sensu [26]) implies (i) the clarification of latent relationships between landscape patterns and driving forces (explorative models), and (ii) the projection of future landscapes under different scenarios (predictive models).

Two of the main issues arising when socio-economic and biophysical variables are combined spatially, as a process of data integration or data equalization [62–64] characteristic of STEPLand, are the different data formats and spatial scales. Socio-economic data are usually available from official statistics in tabular format at some administrative boundaries: neighborhoods, districts, census tracks, municipalities, regions, and countries, among others [65,66]. By comparison, biophysical variables are mainly extracted from EO sources, from spatial interpolation techniques (e.g., exploiting point data derived from climate stations) or from other sources (e.g., rasterization of archive maps) having a specific pixel size [67]. When the two types of data are combined, these issues may lead to a loss in spatial precision [68], given the need to integrate data at one specific scale, namely, according to administrative boundaries (i.e., native vector file) or to lattices (i.e., raster file with a given pixel size). As socio-economic data are mostly available for administrative areas, an option is to convert biophysical data into class intervals and calculate the area (or percentage) occupied by each interval within the appropriate spatial (polygon) domain.

For instance, Ref. [69] adopted the area option, whereas [70] calculated the proportion of three different intervals of slopes within each district, and adopted a similar solution for soil moisture. Another study [71] clipped LUC data to the boundaries of each of the 25 watersheds considered in the study, and then calculated zonal statistics for each watershed to extract the relative proportions of each LUC type for subsequent use in statistical analyses. Another option is to calculate the mean value of cardinal variables per spatial (polygon) domain, thus producing a high generalization. It is also possible to assign central (median) or dominant (mode) values for each administrative area. This latter option is appropriate for discrete variables, such as soil type.

When the option is to work at a pixel size, the problem is the inverse, as it affects the socio-economic data: a rasterization is required in order to match the pixel size of biophysical variables and LUCC. The main issue in this case is whether a statistical analysis is applied because all the pixels included in the administrative boundary have the same socio-economic value, showing a maximum spatial autocorrelation, which leads to a violation of the assumption of independent residuals. To minimize this situation, a convenient "solution" is to apply a "reduced factor" through, for instance, a stratified random sampling at a lower number of pixels. This option was applied in [72] using a "contraction factor" amounting to 10. Another option is "data generalization", e.g., using a grid lattice having larger pixel sizes, which is representative of a lower spatial resolution; for example, in [73], all the variables describing deforestation and the respective drivers of change were aggregated to 25 km grid cells.

2.3. Socio-Environmental Consequences

The third step of STEPLand takes the socio-environmental consequences of LUCC into account. For instance, LUCC may affect weather and climate variability by altering biophysical, biogeochemical, and energy exchange processes at local, regional, and global scales. Therefore, the consequences of these processes are scale-dependent because some of them affect the local environment (e.g., local water quality), whereas other impacts extend far beyond the location where they arise (e.g., carbon cycle, climate change). Because not all LUCCs have global effects, and LUCCs are not irreversible, there are several multi-directional impacts that can reinforce, mitigate, or offset multiple consequences, enriching the debate regarding on-site and off-site factors of change [74,75].

One specific repercussion considered in this review is related to landscape, given its particular nature because it contributes significantly to well-being and quality of life. Quantification of spatio-temporal landscape dynamics and the underlying drivers is key for planning appropriate decisions in this field [76]. Landscape metrics are common tools for measuring spatial changes in landscape composition and configuration, including fragmentation and diversity [77]. From a STEPLand perspective, they can be applied to RS and GIS data and simultaneously used with LUCC models and statistical methods. There are several quantitative measures, for example, those in [78], that can be used to assess landscape composition, such as the number of patches (patch richness) and uniformity and variety (evenness and diversity), and to assess the configuration or the spatial distribution of patches in the landscape (landscape pattern); these include patch shape, isolation, spread between classes (contagion), mean patch size, and density.

Another additional consequence considered in STEPLand is the impact on ecosystem services because, in recent years, these services have attracted the increasing attention of researchers, policymakers, and other stakeholders worldwide [79]. The main reason for this is that, when land is used, society changes and modifies the quantity and quality of the provision of these services. According to [80], supply and demand of ecosystem services can be assessed at, and transferred to, different spatial and temporal scales by linking LUCC (e.g., extracted from remote sensing) with other data (e.g., obtained from interviews). Their results reveal patterns of human activities over time and space, and the capacities of different ecosystems to provide ecosystem services under changing LUC. However, Ref. [81] reviewed the "ecosystem services" concept and the various methods applied for mapping and assessing quantitative methods, and the significant problem of there not being a clear distinction between services, functions, and benefits.

2.4. Futures Scenarios

The last stage included in the STEPLand perspective corresponds to the simulation and prediction of future LUCC scenarios. This is a significant process for policy makers because it enables them to better anticipate actions, especially in the context of urban planning and the protection of natural land [82]. A previous study [83] provided a literature review of models applied to predict LUCC, including Markov chains (MCs), landscape models, CLUE-S models, cellular automata (CA), integration of Markov chains and cellular automata (MC-CA), and artificial neural networks. Markov chains, for instance, quantify LUCC probabilities between different states that are recorded in a transition matrix [84]. This matrix is the result of cross-tabulation between satellite images derived from two sequential dates, adjusted by proportional error and translated into a set of probability images, one for each LUC category [85,86]. In addition, CA models are one of the most relevant tools for understanding complex systems, particularly LUC patterns, given their intrinsic sensitivity to both spatial configuration and neighborhood relationships. The future state of the cells is determined by the current state of the cell itself and that of the neighborhood cells, following transition functions based on a set of rules. A variety of methods has been used for calculating transition rules in CA, such as logistic regression, multinomial logit, linear and geometric formulations, support vector machines, and, more recently, artificial neural networks [87].

3. Methodology

Results of the meta-analysis presented in this chapter aim to provide a snapshot of the STEPLand framework, rather than a complete and systematic overview of the whole body of literature, which is particularly vast. The chosen option was to review in great detail, from 2000 to 2019 (20 years of analysis), a relatively large sample of scientific articles, published in journals having an impact factor, with the aim of extracting key variables and attributes useful for assessing the evolution of the STEPLand framework. To identify articles representative of the STEPLand workflow (excluding books), we first selected published papers from the Web of Science database according to pre-determined criteria, such as target keywords including "land-use", "land-cover", and "changes". The search engine reported a total of 9574 entries. Figure 2 shows the total number of publications by year, outlining an exponential increase since 2000. From the total sample, we selected 250 articles. This sample size was considered significant and representative given the deep reading required to extract the information that was the object of this review. These entries were extracted in four stages with the objective of assessing the STEPLand framework progress. These steps were to determine: (i) the presence of target keywords in the title or in the keywords; and (ii) the presence of the main objectives and applied methodology that are considered characteristic of STEPLand (based on a deep, manual reading). A third criterion was to choose papers published in different scientific journals and years, with the objective of determining the evolution of the STEPLand framework. In the last step, we chose papers with a high number of Web of Science citations (having at least 50 citations until 2007) (Figure 3). The full list of articles can be found in Appendix A.

From the 250 publications selected, and after a deep review, the following data for the first step (LUCC patterns and dynamics) were extracted: time period; the country or countries of the study area; number of LUC categories; RS classification method, if applied, and its accuracy; and, finally, whether an overlay of individual classifications was applied (Table 1).

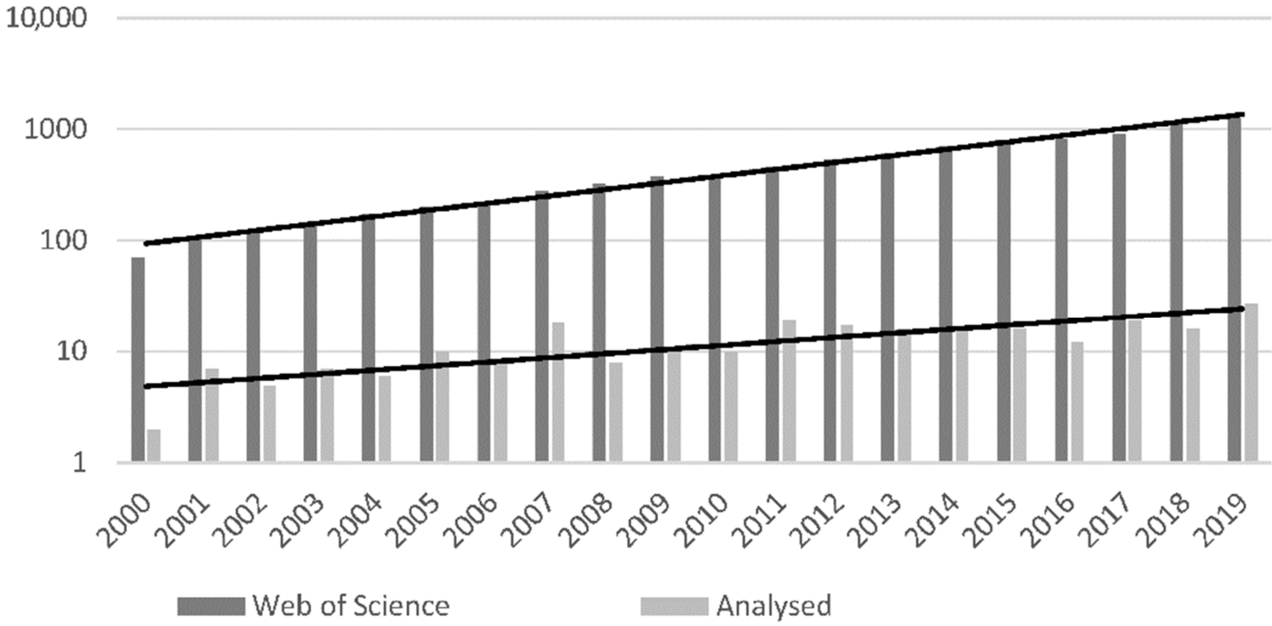

Figure 2. Total number of articles identified by year from Web of Science as potential examples of the STEPLand framework and the 250 manuscripts analyzed.

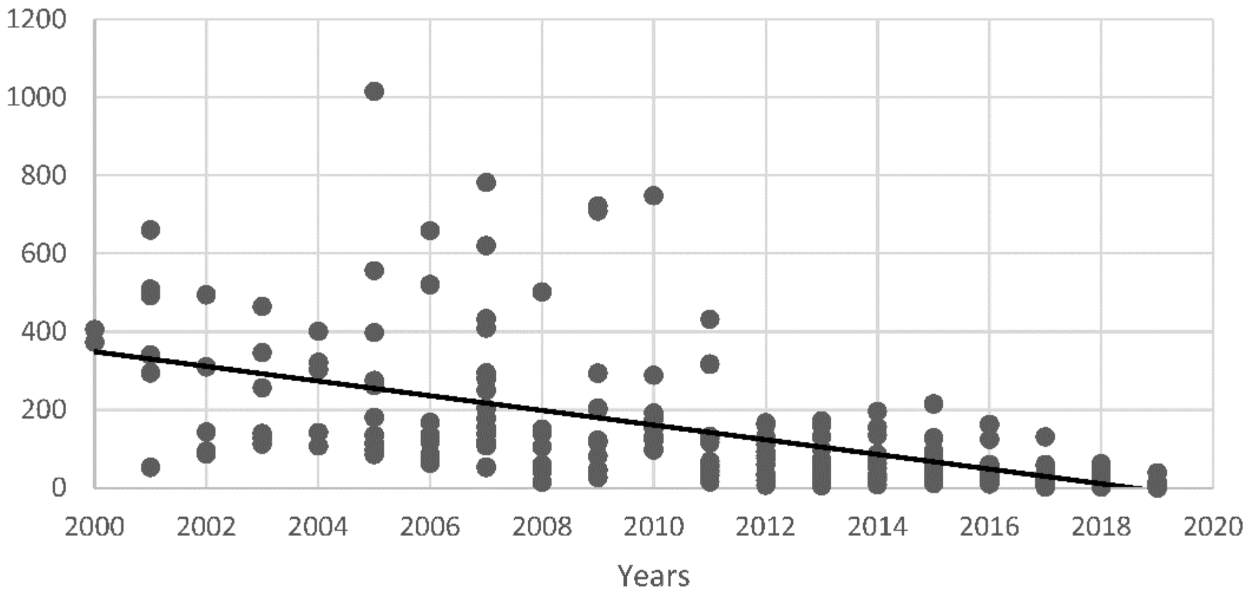

Figure 3. Total number of citations per year.

In the second step ("LUCC modeling"), considering the previous work by [88], our classification of statistical and empirical techniques for identifying the main driving forces of LUCC included: type of analysis (exploratory, training, regression) and objective (data reduction or structure detection, classification, association, graphical model, summarization and data transformation); type of dependent and independent variables (driving forces considered); scale of analysis; and model type (Table 2).

Table 1. Parameters collected in the first STEPLand step, corresponding to "LUCC patterns and dynamics".

Step	STEPLand Aim	Parameters Reviewed
1st	LUCC patterns and dynamics	**Affiliation of first author or co-author**
		Journal of publication
		EO source: Land-cover maps produced by scientific or governmental agencies The same but combined with aerial photographs or remote sensing imagery Only aerial photographs Aerial photographs and remote sensing imagery Only remote sensing imagery
		Temporal extent: Up 10 years From 11 to 15 years From 16 to 20 years From 21 to 25 years From 26 to 30 years More than 30 years
		Country/ies of the study area
		Number of LULC categories: From 1 to 5 From 6 to 10 From 11 to 15 From 16 to 20 More than 20
		Classification method: Photointerpretation Pixel classification, differentiating unsupervised from supervised (maximum likelihood, support vector machine; kNN; decision tree or random forest; artificial neural network) Subpixel classification Object classification
		LULC map accuracy of automatic classifications: Between 60 and 70% Between 71 and 80% Between 81 and 90% More than 90%
		Overlay method

In the third step, the main objective was to report the nature of the socio-environmental consequences of LUCC (e.g., water quality or climate), differentiating a quantitative spatial model from more qualitative patterns (Table 3). If the focus was on landscape, then two variables were analyzed: the software used, and the metrics quantified at class (or landscape) level. Finally, a third option was whether the focus was on ecosystem services (Table 3). In this case, various approaches have been applied, including market prices, productivity, and benefit transfer methods. This latter option is the procedure used to estimate the economic benefits gathered from one site (e.g., considering each biome or LUC type) and applying them to another site with related demographic, economic, and ecological characteristics [79]. The early valuation study by [89] used this approach to extrapolate the overall economic value of 17 ecosystem services provided by 16 main biomes. These estimates were updated based on a larger database of more than 300 case studies from all over the world [90]. Some value modifications are often made according to expert opinion surveys or based on statistical models [91].

Table 2. Parameters collected in the second STEPLand step, corresponding to "LUCC modeling".

Step	STEPLand Aim	Definition
2nd	LUCC modelling	**Type and objective of modelling techniques:** CLUE Exploratory data reduction Data transformation Data classification Data graphical model Data summarization Data training Regression
		Type of explanatory driving forces: Only biophysical or geophysical Only socioeconomic Socioeconomic and biophysical Socioeconomic, biophysical and distances Biophysical and distances
		Type of dependent or response variables: LUC LUCC
		Spatial scale of analysis or domain: Plots, parcels o fields Grids, cells or pixels Administrative boundaries
		Causal nomenclature: Factors Causes Drivers Determinants

Table 3. Parameters considered in the third step, corresponding to "Socio-environmental consequences of LUCC".

Step	STEPLand Aim	Definition
3rd	LUCC consequences	**Socio-environmental:** Water quality Agriculture and forestry (agricultural land degradation) Biodiversity (habitats, native species, . . .) Natural disasters (forest fires, droughts, land or soil degradation, . . .) Climate Weather Energy
		Landscape: Software used Main metrics at class level or/and landscape level
		Ecosystem services: Evaluation model

Finally, in the fourth step, the future scenarios, the main objective was to report which forecasting model was applied and for which horizon (short, medium, or long-term).

4. Results

The results from the entire sample of manuscripts (250) showed that the partial approaches most common in STEPLand include step 1 and 2 together (LUCC patterns and modeling), followed by step 1 and 3 together (LUCC patterns and socio-environmental consequences), and step 1 alone (LUCC patterns) (Figure 4). Only a few studies adopted a more complete framework, integrating step 1 with 2 and 3 (13%); and only 4% of the sample adopted steps 1, 2, and 4 synergistically. Interestingly, none of the 250 reviewed papers included all the steps.

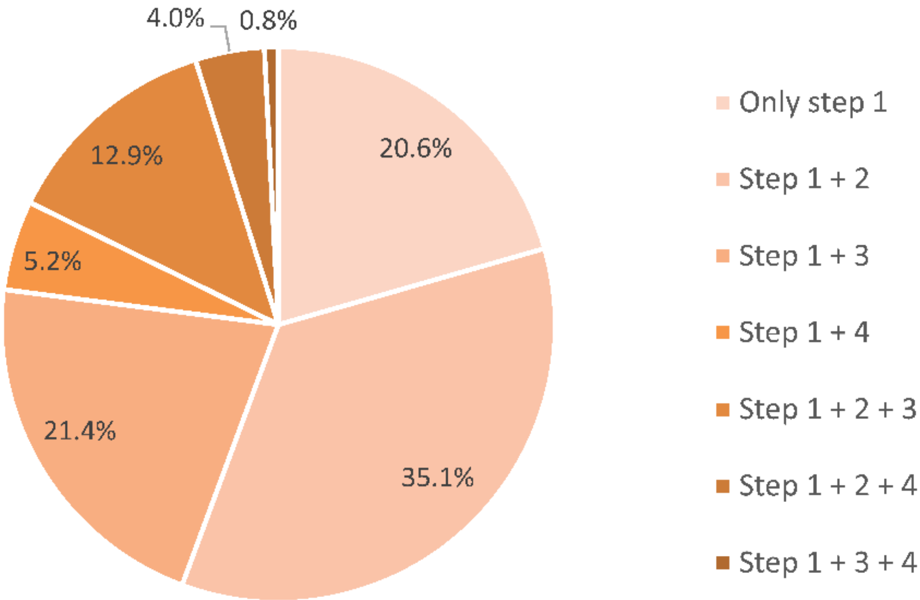

Figure 4. Percentage of articles categorized according to STEPLand steps. Source: own elaboration.

4.1. Step 1: LUC Changes

Figure 5 shows that 68.0% of the first authors were affiliated with geography, environmental sciences, forestry, ecology, rural development, natural resources, or land management. Therefore, STEPLand can honestly be considered a framework that has been followed mainly by geographers, environmentalists, and ecologists, since the purest social scientists (including economists, for instance) were represented in only 4.4% of manuscripts, included in 32% of "Others" category in the figure. Nonetheless, the sample papers were published in 65 scientific journals. Figure 6 shows the top ten journals having the most publications, totaling 164 papers (65.6%); four journals accounted for 71.9%, whereas the impact factor quartiles of all ten were Q1 and Q2.

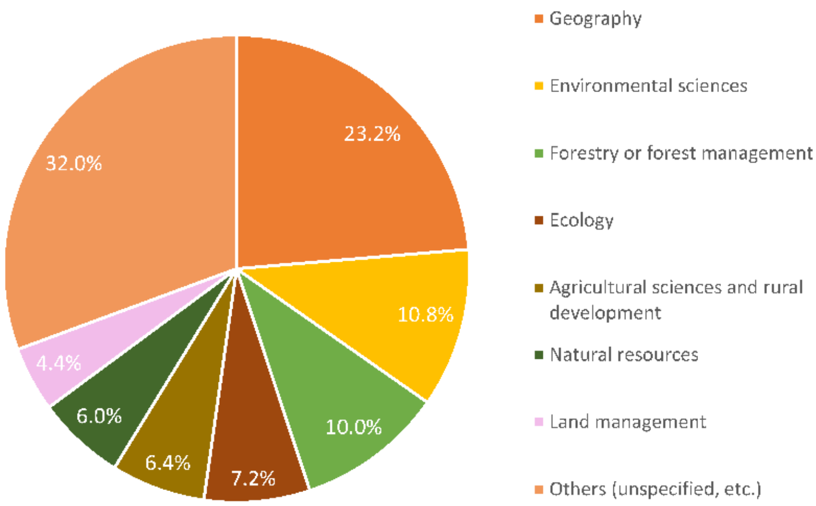

Figure 5. Affiliation discipline of the first author from all papers. Source: own elaboration.

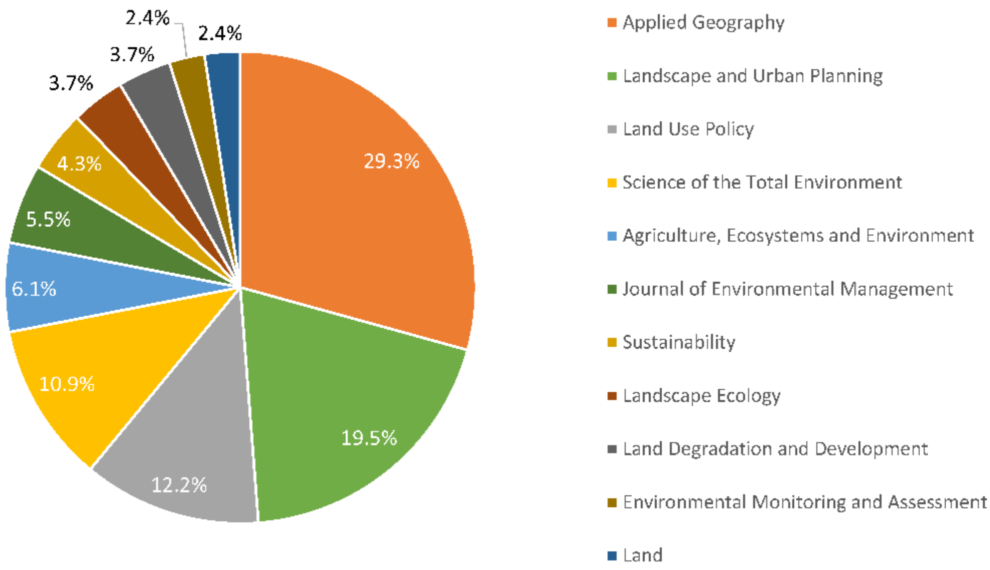

Figure 6. The top ten journals, totaling 164 papers, with most publications analyzed in this review. Source: own elaboration.

From a geographical point of view, the results showed that 74 countries were included in the reviewed articles. Most American, European, and Asian countries were represented, and Africa was the continent that was least represented (Figure 7).

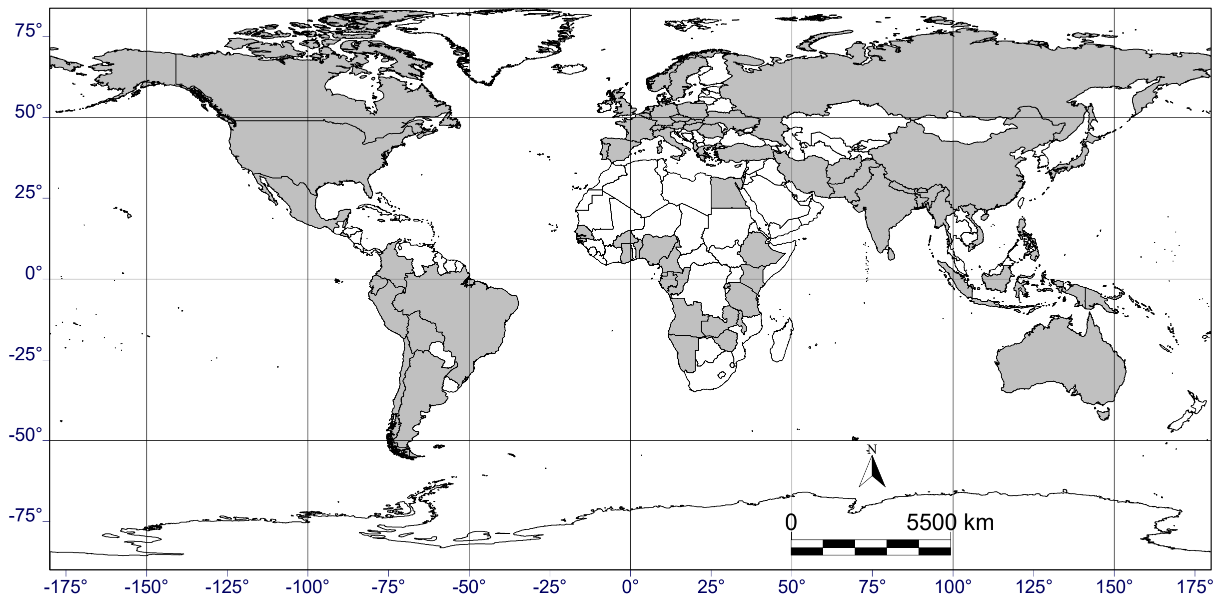

Figure 7. Study areas per country from the 250 papers analyzed. Source: own elaboration.

Figure 8 documents that most of the 250 manuscripts were developed using only RS data as an EO source (51.2% of the total), followed by cartographic databases produced by scientific/governmental agencies (22.4%). The remaining works used aerial photographs only, associated with other sources, and cartographic databases based on other sources. A combination of aerial photographs with satellite imagery was quite common during the first analysis period before the 1970s. From the 128 papers that adopted only satellite images, most of them used Landsat exclusively (78.3%) or combined with other sensors (15.5%).

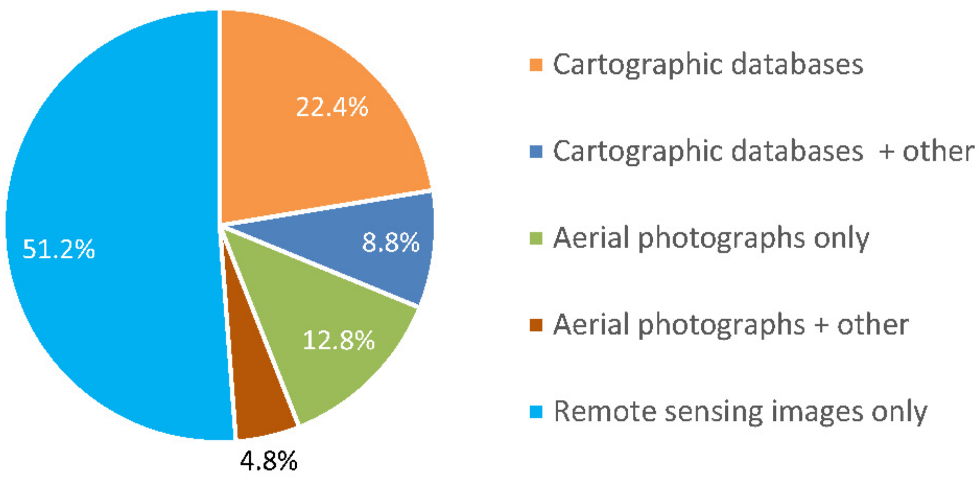

Figure 8. EO data sources from all papers. Source: own elaboration.

The temporal extent analysis showed that long-term analysis (more than 30 years) was the most usual situation, accounting for more than 80 papers (34.8%), followed by the group between 16 and 20 years (16.4), equivalent to the medium term. However, from the total number of works that used methods for identifying and classifying LUC with RS, 8.0% did not explain the methods used, whereas, in 14.4%, the method used was photointerpretation of satellite images. The rest (77.6%) carried out automatic classifications, with diverse options. The supervised methods were the most common, as they were used in 45.6% of the total. The most common supervised classification was maximum likelihood (equivalent to 71.9% of all the supervised classifiers) (Figure 9), whereas the second most common method for automatic classification was the object-based classifier (OBIA) (11.2% of the total).

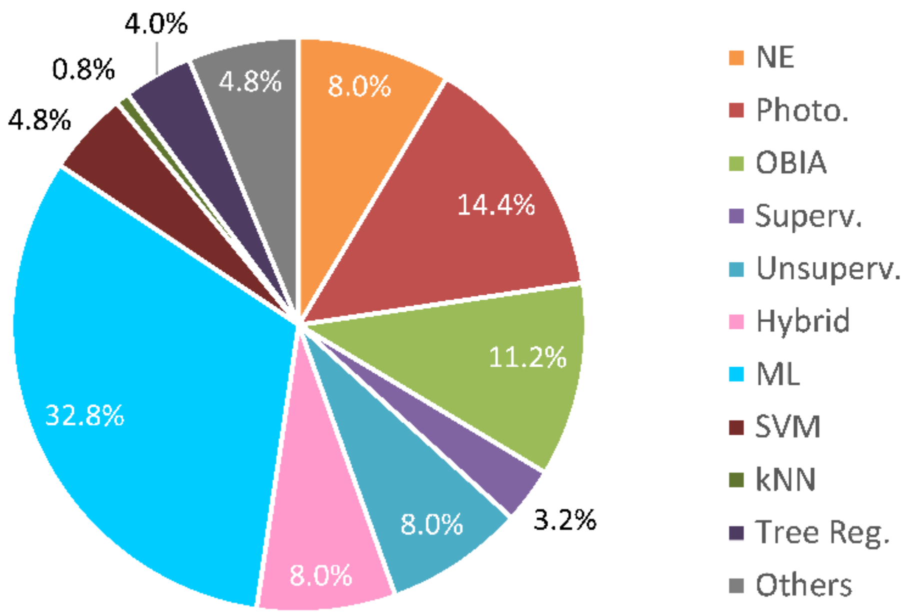

Figure 9. Methods used for obtaining LUC maps only including those developed with RS (128 papers). NE: not explained; Photo: photointerpretation of satellite images; OBIA: object-based image analysis; Superv: supervised classification, without more specifications; Unsuperv: unsupervised classification; Hybrid: hybrid classifier; ML: maximum likelihood; SVM: support vector machine; kNN: k-nearest neighbors; Tree reg: tree regression analysis. Source: own elaboration.

The most common numbers of LUC categories used in RS classifications were between six and ten (60.0%) and below six (28.8%). Working with a rather low number of categories was, in many cases, the result of reclassification processes. Considering the accuracy assessment, 53% of works did not mention any value (133 entries); this percentage includes the studies working with cartographical databases produced by scientific/governmental agencies (e.g., CORINE). In terms of the percentage of overall accuracy extracted from the automatic classifications mentioned before, the groups between 81% and 90% and above 90% were the most frequent (36.8% and 24.0%, respectively).

4.2. Step 2: LUCC Modeling

A total of 129 manuscripts included LUCC modeling (51.6%), and, of these, 74 used a statistical modeling technique, whereas 55 presented a qualitative analysis, in some cases supported by interviews and field surveys. The most-used quantitative model was regression (38.0%) followed by exploratory data reduction (7.7%), such as factor analysis, canonical analysis, or correspondence analysis (Figure 10). It is necessary to highlight the conversion of land use and its effects (CLUE) framework [92]. This framework is based on an empirical spatial analysis for identifying the most important biophysical and socio-economic drivers and their relationships with the extension and intensity of LUCC. A previous study [93] provided core publications and examples of applications for the different CLUE versions (CLUE, CLUE-S, Dyna-CLUE, and CLUE-Scanner). Figure 11 shows that the most-used regression technique was LOR, including multiple logistic regression (53.1%) and LIR (28.6%). GWR and BRT were the other important methods, mainly since 2016 for the latter.

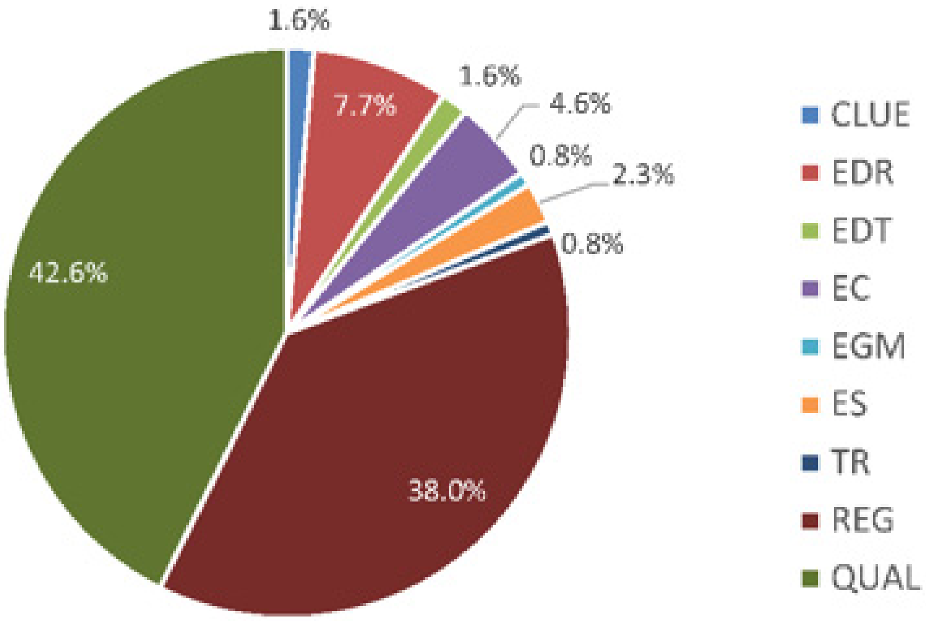

Figure 10. Statistical techniques used for analyzing driving forces of LUCC (129 papers). CLUE: conversion of land use and its effects; EDR: exploratory data reduction; EDT: exploratory data transformation; EC: exploratory classification; EGM: exploratory graphical model; ES: exploratory summarization; TR: training; REG: regression; QUAL: qualitative analysis. Source: own elaboration.

The analysis of the dependent (or response) variable showed that the most-used variable corresponded to LUC (25.3%), followed by LUCC (21.1%) and, to a lesser degree, to forestry (19.7%), specifically related to deforestation, afforestation, and/or reforestation. The group of driving forces most used in modeling techniques was the combination of biophysical, socio-economic, and distance variables (40.8%), followed by biophysical and socio-economic variables (21.1%), and socio-economic variables only (18.3%). The pixel was the most usual spatial domain (61.9%), followed by administrative boundaries (25.3%).

Finally, the word "drivers", together with "driving forces", was used from the first work, in 2000, until the last year of analysis (2019), showing that it has spread successfully.

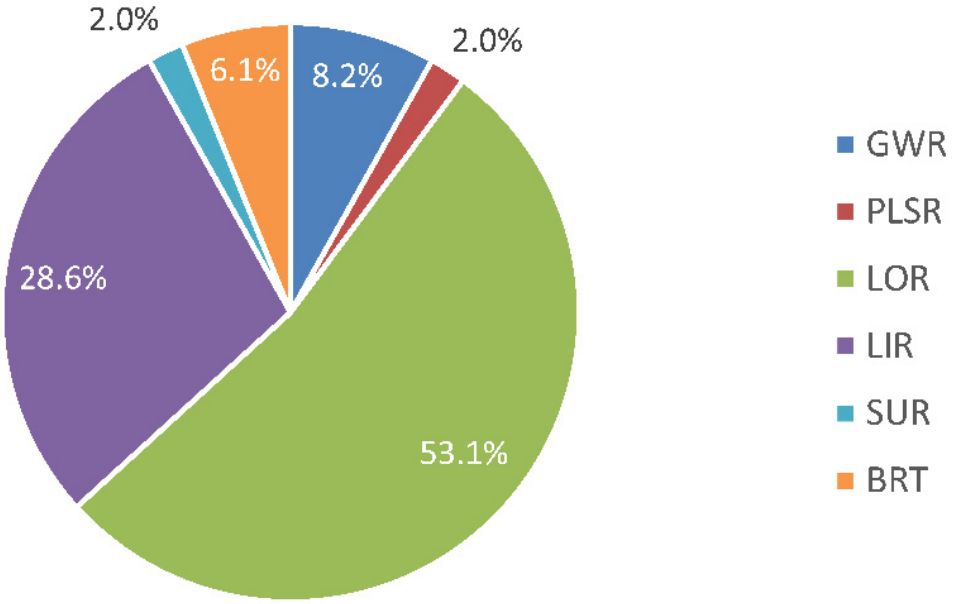

Figure 11. Regression techniques (49 papers). GWR: geographically weighted regression; PLSR: partial least squares regression; LOR: logistic regression; LIR: linear regression; SUR: seemingly unrelated regression; BRT: boosted regression trees. Source: own elaboration.

4.3. Step 3: Socio-Environmental Consequences

A total of 105 manuscripts (42.0% of the total) presented an analysis related to socio-environmental consequences of LUCC. Of these, 41.9% analyzed the socio-environmental consequences using both quantitative (43.2%) and qualitative (56.8%) tools, whereas 43.8% were linked to landscape dynamics, and the rest were mainly connected to ecosystem services (14.3%). Of the total number of manuscripts that analyzed socio-environmental consequences (44), 55.8% corresponded to biodiversity and disasters, followed by agriculture (23.2%). Qualitative analysis was used in 100% of studies of the socio-environmental consequences of LUCC in agriculture, 76.9% of studies of biodiversity, and 45.4% of studies of disasters, whereas analyses of water, climate, weather, and energy were 100% quantitative. The models used in the quantitative analysis were very diverse; some used export coefficients, whereas others used operational indications provided by the Panel on Climate Change, the Unit Stream Power Erosion and Deposition model (USPED), the Soil and Water Assessment Tool (SWAT), the Revised Wind Erosion Equation (RWEQ), or investment in carbon storage.

In the case of landscape consequences, 93.5% of manuscripts calculated some metrics, and the qualitative option was used in the minority. In 63.6% of these papers, FRAGSTATS software was used, followed by Patch Analysis in 13.6% of cases. For both landscape and class levels, the most-used metrics are shown in Figure 12. Those corresponding to configuration were, by order of importance: number of patches, mean patch size, patch density, largest patch index, edge density, landscape shape index and the interspersion and juxtaposition index. For composition, the most-used metric was Shannon's diversity index.

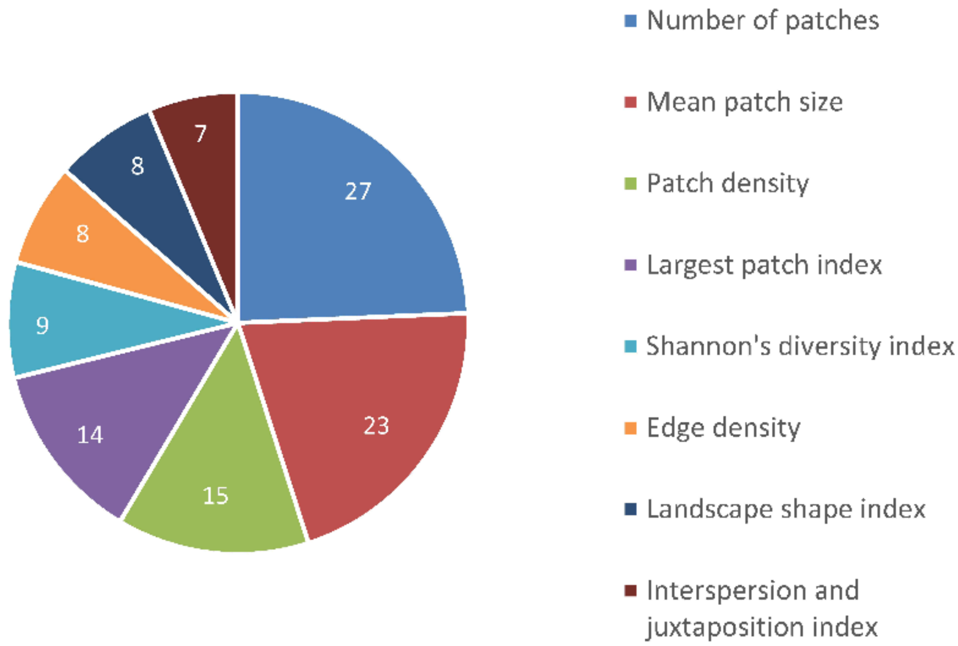

Figure 12. Most-used calculated landscape metrics by number of manuscripts. Own elaboration.

The results of ecosystem services models showed that the benefit transfer method was clearly the most-used option (66.7%). According to some researchers, this is a commonly applied method for assessing ecosystem services due to its feasibility for making a quick assessment, at regional and national scales, and the low cost of collecting the required primary data; however, the local ecosystem conditions are an evident limitation [91]. InVEST was the second most-used option (20%). This is a set of spatial models that analyze and predict the provision of ES from LUCC maps and related biophysical, economic, and institutional data for a given region [94–96].

4.4. Step 4: Future Scenarios

The results of future scenario modeling showed an increasing interest for this topic. A clear predominance of Markov chains as the computation method was evident during the initial years, from 2000 to 2008, and MC-CA dominated the literature in the latter years, with a very fragmented use of the remaining methodologies (Figure 13). The dominance of CA is even greater if we consider (i) the Monitoring Land Cover/Use Dynamics (MOLAND) model, an improved CA version developed by [97]; and (ii) the artificial neural network-based cellular automata (ANN-CA) model, because CA is used to model the LUCC by applying the transition probabilities from the ANN learning process [98].

Another choice is the Land Change Modeler (LCM), which provides a tool for evaluating and modeling LUCC by performing three steps: change analysis, transition sub-models, and LUCC predictions [99]. From the three separate empirical models, the multi-layer perceptron (MLP) neural network is the only procedure that can model multiple transitions at the same time, and it was the selected option in most of the papers analyzed.

Other options that should be highlighted are those models developed specifically for future scenario analysis, such as, for instance, CLUE-S, which is an updated version of the early CLUE model. CLUE-S is based on an empirical analysis of location suitability combined with the dynamic simulation of competition and interactions between the spatiotemporal dynamics of LUC systems, and was specifically developed for the spatially explicit simulation of LUCC [100]. The model includes spatial and non-spatial modules that combine statistical analyses and decision rules that determine the sequence of LUC types [101]. Another alternative is the CLUMondo model, which is the latest addition to the CLUE series, and is a spatially explicit and dynamic land system change model based on the highest transition potential. This variable is the result of a sum of local suitability, conversion resistance, and competitive advantages of a land system [102]. The final parameter analyzed was the temporal extent of future scenarios. The majority was between 11 and 20 years (50%), followed by less than 10 years (26.9%).

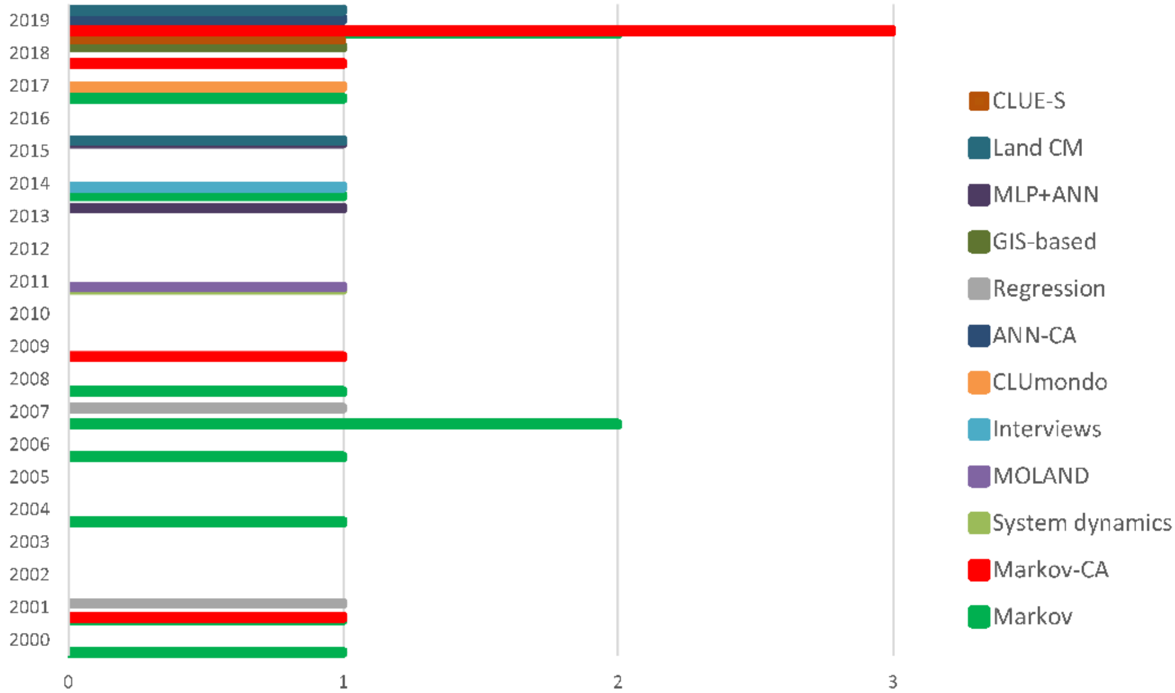

Figure 13. Number of manuscripts (29 in total) including models of future scenarios, by year. CLUE-S: conversion of land use and its effects at small regional extent; Land CM: Land Change Modeler; MLP + ANN: multi-layer perceptron neural network; ANN-CA: artificial neural network-based cellular automata; CA: cellular automata.

5. Discussion

The main objective of this research was to assess the progress of a specific workflow that we proposed to call STEPLand (Spatio-TEmporal Patterns of Land), which involves four identified steps. The study provides a comprehensive picture of the STEPLand framework by analyzing a sample of 250 scientific articles published during the past 20 years. The requirements for inclusion in the analysis were that the papers were published in impact factor journals and had at least 50 citations (until 2007), with the presence of target keywords (land use, land cover, changes) and objectives characteristic of STEPLand (LUCC patterns, spatial modeling of driving forces, socio-environmental consequences, and future scenarios). The analysis also attempted to cover a broad sample of journals. These criteria provided a provisional framework delineating the STEPLand framework that can be improved in future works by changing the conditions if required, and increasing or decreasing the minimum number of citations, for instance. This assumption is made even clearer in the map of analyzed countries (Figure 7), where parts of Africa and the Middle East are underrepresented, and other countries such as New Zealand or Malaysia are missing. Therefore, future work is needed to try to include all countries, while substantially increasing the number of entries.

Once the best indicators, according to the authors' point of view, to characterize the STEPLand framework were established, data extraction was undertaken based on an in-depth reading analysis by both researchers, which was an empirical task for quantifying the results.

Step 1, LUCC patterns and dynamics, is the basis of the STEPLand framework. From the 250 publications analyzed, and according to the affiliation of the first author and the journal titles, a robust outcome was that geography and ecology were the most common fields. Therefore, the "pure" social vision was much less represented. The citation impact of the first ten journals was high, and was mostly Q1 and Q2.

According to EO sources, the use of satellite images was the predominant option, but it should be noted that a non-negligible percentage of cases (22.4%) were carried out using cartographic databases already produced by scientific or governmental agencies. This option is clearly less time consuming because an RS classification can be a complicated task, especially for non-experts, and it also allows other research steps to be carried out more comfortably. Nevertheless, this situation can only be useful if the temporal extent, the spatial resolution, and the number of LUC categories from cartographic databases are suitable for the specific research target.

Landsat images were the most used for analyzing LUCC having a temporal extent longer than 30 years. Therefore, the medium spatial resolution (30 m $\times$ 30 m) was the preferred resolution compared to other options such as MODIS, SPOT, or IKONOS. In fact, this outcome was expected given the difficulties involved in obtaining uninterrupted and continuous time series of data from 1972 onwards, which is the longest-running archive [20,103]. Without doubt, the change to an open (free) data policy in 2012 benefitted its use. However, the use of optical imagery is affected by cloud cover, and, consequently, all of the publications mentioned that images that are free of clouds should be selected as much as possible.

In addition to photointerpretation, supervised classifications were frequently chosen and maximum likelihood was the most-used parametric classifier. This finding strongly agrees with a remote sensing literature meta-analysis carried out by [104], in which 32% of the reviewed articles employed maximum likelihood algorithms, although the highest accuracies were obtained with machine learning methods. This dominance is attributed to the wide availability of these algorithms in conventional remote sensing image-processing software packages. This argument was verified by [105]: these authors stated that the uncertainties regarding the effective use and implementation of machine learning techniques were the main barrier to their use.

Another clear outcome is that researchers adopting the first step of the STEPLand workflow seemed to be aware of the classification issues in differentiating a high number of LUC categories. Conversely, according to the classification accuracy, some LUCC maps using the post-classification technique showed low accuracies (below 80%). This is a technical issue that merits a more in-depth discussion.

A characteristic of the second step, LUCC modeling, is the inclusion, in the materials or data sections, of a table showing the explanatory or independent variables or driving forces used in the model. From our analyzed papers, the table in [106] includes the variable name and a small description indicating the corresponding unit of measurement (proportion, percentage, or index, among others). The tables of other later works also provided the source, the scale, and the model used (raster or vector).

Our review indicates that LUCC modeling is a very important stage in STEPLand because 51.6% of works applied quantitative techniques for identifying the relationship between LUCC and the driving forces [107,108]. The most-used quantitative procedure was regression (38.0%), of which logistic regression was the most frequent, followed by linear regression. Our results agree with earlier studies; as stated by [109], multiple regression is frequently used by ecologists and biologists to identify factors influencing response variables, such as species richness or occurrence. Another study [110] noted that regression models are one of the most-common techniques for identifying relationships between variables, including drivers, and modeling transition potentials. They also stated that logistic regressions were the dominant statistical tool for describing relationships between a dichotomous variable (the categorical nature of LUCC) and a set of explanatory drivers. Some solving methods were applied to avoid criticisms about multicollinearity and spatial autocorrelation [60], such as random selection of pixels, generalization/aggregation of pixel size (coarser resolution), correlation coefficients, or analysis of variance [111].

Furthermore, this review found that the combined uses of biophysical, socio-economic, and distance variables are the most-common drivers applied at the pixel scale. Nevertheless, some studies do not explain, in detail or at all, the combined use of different sources, units of measurement, and scales, i.e., the interrelationships between the driving forces. This is even worse when administrative boundaries are involved [35], although the method chosen to combine them is determinant in the acquisition of useful results.

In step 3, socio-environmental consequences were mainly analyzed, followed by landscape and ecosystem services. Biodiversity and disasters were the topics most studied using generally qualitative models, whereas quantitative models were predominant in the remaining contributions. In ecosystem services, the benefit transfer method was the most applied, followed by the InVEST model. According to [112], this latter model, together with others (e.g., ARIES or CLASSIC), has two problems: it fails to fully consider or simplify the ecological process, and its evaluation accuracy is still controversial.

Finally, in future scenarios, in 2005, Ref. [113] asserted that the Markov-type models were some of the most common methods for predicting change among various categorical states. This clear preponderance can be explained by their spatial and temporal robustness because GIS and RS data can be efficiently incorporated to define the initial conditions to parameterize Markov models, calculate transition probabilities, and determine the neighborhood rules with transitional potential maps [114].

6. Conclusions

STEPLand is a consolidated framework within LCS that has been applied by experts worldwide, mainly from the geographical and natural sciences. The high diversity of journals and countries involved in the research shows that it has become relatively ubiquitous. Issues related to LUCC have attracted interest among a wide variety of researchers, ranging from those who wish to model spatial and temporal patterns of land conversion, to those who aim to understand causes and consequences of land transformation. Therefore, STEPLand facilitates communications and interactions among researchers from different fields, and between researchers and policy makers.

Based on this review, we conclude that step 1 of STEPLand research is characterized by:

- Researchers mainly involved in geographic or environmental sciences.
- Articles published in journals mainly specialized in ecology, geography, or environmental sciences, often having a high impact factor.
- RS data as the main EO source used to obtain patterns, of which, Landsat images were the most used, after reducing the number of images included in the study due to the presence of clouds. Use of the Landsat open (free) archive has been essential to the spread of the STEPLand framework.
- A relatively long horizon (over 30 years), which was the most-used temporal extent.
- Supervised methods, in general, and the maximum likelihood classifier, in particular, which were predominant in the automatic classifications, with LUC legends primarily composed of 6 to 10 classes.
- Post-classification methods (with transition matrix), which were the predominant tool in LUCC analysis.

Step 2 was characterized by:

- The combination of analysis of patterns and dynamics, and modeling.
- Quantitative spatial modeling based on statistics, mainly using regressions, headed by LOR and LIR.
- A dependent variable extracted from LUC or LUCC, with a considerable weight assigned to forest variables.
- The combination of biophysical, socio-economic, and distance variables as the main driving forces, in which data integration was very important.
- Pixels from regular lattices as the main spatial domain.

Step 3 was characterized by:

- Analysis of general socio-environmental consequences using qualitative methods, mainly related to biodiversity and natural disasters, and quantitative models, although very diverse, applied in the rest of topics. Surveys have been used to determine driving forces and the perception of socio-environmental consequences for local people. Spatially combining RS with other data can be difficult.
- A high weight attached to the analysis of LUCC landscape consequences, mainly using the FRAGSTATS software for calculating, at least in many cases, the number of patches and the mean patch size.
- In the analysis of ecosystem services, the application of the benefit transfer method, which was the most common model given its feasibility at regional or national scales to develop a quick assessment and the low cost of collecting the required primary data.

Finally, step 4 was characterized by:

- A clear predominance of Markov chain (between 2000 and 2008) and Markov chain–cellular automata models.
- A substantial weight of CA in other options, such as in the MOLAND model.
- The more recent application of other models, such as CLUMondo or Land Change Modeler.

To conclude, a future scenario for STEPLand includes using improved spatial and temporal resolutions of satellite imagery, which may be implemented by adopting the free Sentinel imagery or with the contributions of drones. This may provide a more refined modeling of LUCC and the resulting socio-environmental consequences. Another challenge is the synergistic application of the four STEPLand stages, which was not documented in the sample of papers reviewed in this work.

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Appendix A

Appendix A contains the references of the 250 selected articles analyzed in this review.

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