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Review

A Comprehensive Review on Land Use/Land Cover (LULC) Change Modeling for Urban Development: Current Status and Future Prospects

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Abstract: Land use land cover (LULC) modeling is considered as the best tool to comprehend and unravel the dynamics of future urban expansion. The present paper provides a comprehensive review of existing LULC modeling techniques and novel approaches used by the research community. Moreover, the review also compares each technique's applications, utility, drawbacks, and broader differences. The rationale behind such a comparison is to highlight the strengths/weakness of individual techniques. The review further highlights the utility of the hybridization of different techniques (e.g., machine learning model combined with statistical models) to LULC modeling to complement their strengths. Although significant progress has been made in LULC modeling, the review highlights the need to incorporate the policy framework into LULC modeling for better urban planning and management. The present review will help researchers and policymakers to achieve better land management practices and ultimately assist in achieving Sustainable Development Goal-15 (SDG-15) (i.e., life on land).

Keywords: hybridization; LULC modeling; policy framework; Sustainable Development Goal-15; urban expansion

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1. Introduction

The whole world is facing a growing wave of urbanization [1,2]. With more than 50% of the worldwide population living in urban regions, the urban population will grow by 2.5 billion from 2018 to 2050, with most of the increase concentrated in Africa and Asia [2]. Subsequently, a tremendous increase in urban dwellers will make governments and policymakers face challenges associated with resource allocation to overcome the problems that will arise in the future. A better understanding of land use land cover (LULC) change may pave the way to unravel urban growth dynamics.

Modeling LULC is the best alternative for predicting future urban trends and growth [3]. These models are crucial tools for sustainable LULC planning and management. If performed spatially explicitly, modeling provides a platform to understand its underlying processes [1]. Over the past several decades, many LULC models have been developed that effectively serve in land management and urban planning. These models are based-on two paradigms commonly used in LULC modeling: the top–down and bottom–up approaches. The top–down approaches rely on the data obtained from satellite imagery, census-based data, and the maps of explanatory variables. These approaches rely on predicting future LULC changes based on historical LULC changes [3]. The drivers, also called explanatory variables, range from bio-physical, institutional, socio-economic, and proximity variables [1]. However, bottom-up approaches to LULC changes are based on actual processes (e.g., household surveys), and are gaining in popularity nowadays [4,5].

A wide range of LULC models exists in the LULC sciences (e.g., spatial or non-spatial, pattern-based or agent-based, and inductive or deductive) [6]. Spatial or non-spatial models differ in estimating the pattern of LULC change versus the rate of change [7].

Inductive models are based on determining model parameters to assess the change, whereas deductive models are based on an explicit description of the processes [6]. Pattern-based models estimate the LULC changes using the available observed patterns (e.g., LULC maps or surveys), whereas agent-based models utilize human perception to calculate the amount of change [8]. In the field of LULC modeling, integrated modeling techniques are widely used, specifically the hybridization of statistical modeling techniques to machine learning (ML) techniques [9,10]. The present review provides a systematic overview of the utility, pros and cons, and each model's broader applications. Moreover, the possible novel approaches for LULC modeling are also discussed.

Generally, these LULC models are embedded in GIS and have eventually become available as an independent application [5]. The present paper also briefly overviews the commonly used LULC modeling software. In this aspect, we reviewed three popular LULC modeling software packages to estimate the LULC changes. Moreover, we considered the features and limitations of individual software packages. Based on the above discussion, the present review has framed the following research questions to answer:

(1). What potential approaches have been used to model LULC?
(2). What are the pros and cons of different LULC models?
(3). What are the prominent novel LULC models?
(4). What are the different software available to carry out LULC modeling?

2. Methods

2.1. LULC Modeling

With the advancement in data acquisition techniques (e.g., satellite imagery, citizen science-based approaches, and big-data platforms) and computational power, LULC modeling practices have made substantial progress. Like other modeling techniques, the major phases associated with LULC modeling are calibration, simulation, validation, and prediction [1,11]. The data collection is the crucial pre-modeling step. Data can be obtained from satellite imagery, land surveys, and different online portals (e.g., census). The collected data are further used to develop the LULC maps using image classification techniques. Moreover, the data are also required for different explanatory variables responsible for the LULC changes. The explanatory variables are the drivers of LULC change ranging from bio-physical, proximity, demographic, socio-economic, economic, and institutional factors. The prominence of explanatory variables varies from region to region; however, the demographic factors (e.g., population growth) are the prominent factors in LULC changes [12].

The first stage of LULC models (i.e., model calibration) utilize the historical LULC information at different time intervals (say t_1 and t_2) and explanatory variables to estimate the amount of change to parameterize the model [6]. The simulation phase generates transition probability maps (TPMs) based on the potential explanatory variables [11]. TPMs, also called suitability or propensity maps, determine the potential location subject to LULC changes in the future [t_3]. The third phase, model validation, estimates model accuracy in predicting the LULC changes. For this purpose, LULC prediction was performed for a time step (say t_3) for which the measured LULC information was also available, and the accuracy of the model was estimated by comparing the predicted LULC with the measured LULC datasets [1]. The last phase of the LULC modeling predicts the future LULC by utilizing a well-calibrated/validated model. Figure 1 presents the schematic of the LULC modeling process. A significant limitation associated with the LULC modeling is that these models can accurately predict the LULC changes for a short time, varying from 2–3 decades. The reason behind this limitation is their dependency on historical patterns of change to predict the future LULC, which can perform reliable predictions for a short duration [13]. The following section discusses the details of different LULC models.

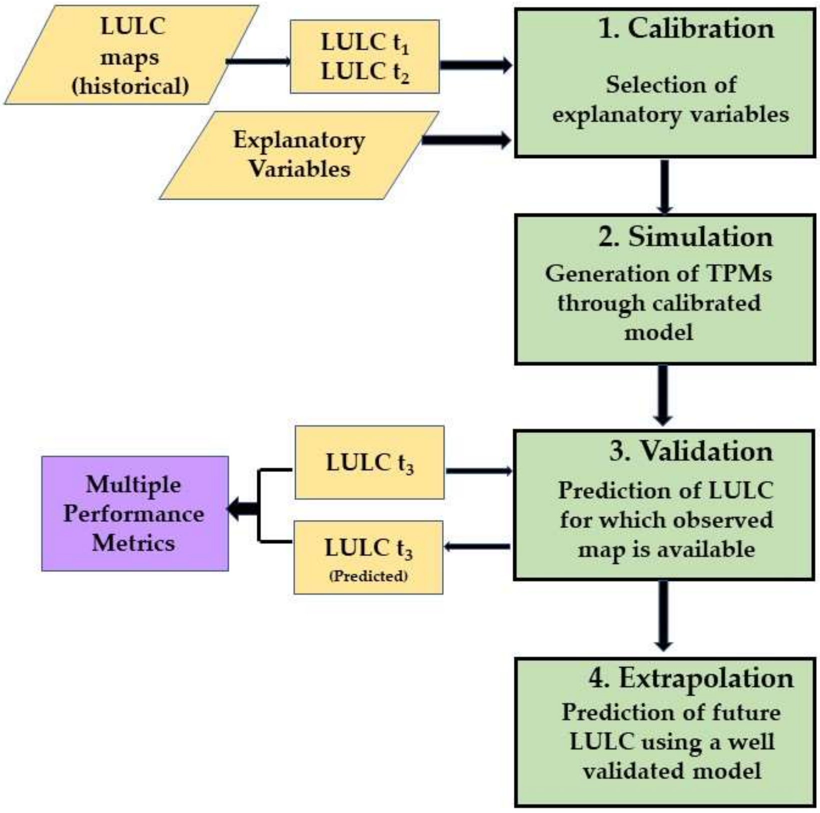

Figure 1. Schematic of the LULC modeling processes.

A wide range of explanatory variables affects the LULC changes including bio-physical, proximity, socioeconomic, and economic variables. The bio-physical variables include the prevailing environmental conditions for LULC change, with a number of biotic and abiotic factors (i.e., soil, terrain, climate, lithology, vegetation, and topography) [1,14]. The proximity factors are based on the proximity concept, so the areas closer to the prevailing LULC class are more inclined to change in the other LULC class. The proximity factors include proximity to roads, rivers, cities, reservoirs (or waterbody), rail networks, and stream networks [13]. The other proximity factor associated with urban planning and management is distance to the city center, distance to shopping stores, and distance to schools. Socioeconomic factors include demographics, literacy rate, urbanization, industrialization, and regional gross domestic product (GDP). Demographic factors such as population growth are the prominent factors in LULC change [13,14]. Moreover, economic factors encompass a direct impact on decision-making (e.g., taxes, subsidies, demands, production and transportation costs, trade, capital flows and investments, technology, and credit access). Among the economic factors, taxes and subsidies are considered the major driving factor for LULC changes.

Accuracy estimation is a very important step for the validation of LULC models. Furthermore, the use of multiple performance metrics is recommended to ensure the credibility of the model. The Kappa-matrix is the most commonly used evaluation measure for LULC prediction, however, several researchers have criticized its use for accuracy assessment in remote sensing applications [15]. Relative operating characteristics are another important quantitative metric used to validate a LULC model. Moreover, Gaur et al. [1] used the chi-square goodness of fit test to evaluate the performance of the LULC model.

2.1.1. Statistical Models

Statistical models predict the LULC changes by establishing a mathematical relationship between the explanatory variables and LULC patterns [16]. The established relationship is utilized further to generate the TPMs. The popular statistical models used to estimate the quantity and patterns of LULC changes are regression-based models (e.g., linear regression and logistic regression, generalized additive models) and stochastic models (e.g., Markov chains). These models are often combined with other models such as cellular automata or genetic algorithms.

The significant advantage of these models lies in their ease of implementation and generalizability. However, these models do not perform well in cases where the explicit representation of human-based decision-making is required (e.g., farmers' perception of agricultural intensification). In such cases, process-based models outperform statistical models. These models primarily deal with the simulation of the temporal analysis of change and lag behind the spatial analysis of changes [9]. Table 1 presents the details of the statistical models.

Table 1. Details of the statistical models.

Model	Underlying Assumptions	Example	Software
Statistical	Stationarity	Logistic regression Markov Models Generalized linear modeling Generalized additive modeling	DYNAMICA/LCM model

2.1.2. Cellular Automata (CA) Models

CA models utilize certain transition rules, neighborhood effects, and expert knowledge to analyze the spatial dynamics of change [16,17]. The spatial discretization units are pixels, cells, and parcels. CA models generate suitability maps instead of TPMs to estimate the spatial analysis of change [18]. These models simulate the LULC changes based on historical patterns and allocation based on the suitability of change and neighborhood interaction.

CA models apply both top–down and bottom–up approaches to simulate the LULC changes. Top–down determines the amount of LULC changes when the observations are available for the entire region of interest; however, the bottom–up approaches allocate the LULC change at the individual spatial unit. The major advantage of these models is that the decision-making process can be easily employed. These models can efficiently simulate the spatial analysis of change, however, lags in the temporal dynamic of change. Table 2 presents the details of the CA models.

Table 2. Details of the cellular automata models.

Model	Underlying Assumptions	Software
Cellular Models	Extrapolation of historical LULC patterns Allocation based on land suitability Allocation by consideration of the state of neighborhood pixels Dynamic CA-based model Model that simulates one-way transformation from one LULC class to another	CLUE-S CA SLEUTH Environment Explorer GEOMOD

2.1.3. Economic Model

Economic models simulate the LULC change as a market process [19]. Two types of economic models (i.e., sector-based and spatially disaggregated economic models) are widely used and differ by scale [20]. The sector-based models focus on the economic sector in the structural form to simulate the decisions on a more aggregated scale. Econometric models consider land as a fixed factor of production and illustrate demand and supply explicitly as contributors to market equilibria. The spatially disaggregated models simulate the decision at a smaller scale (e.g., field and neighborhood levels).

These models are advantageous in improving the trustworthiness of the economic processes leading to LULC changes [5]. However, the models also require assumptions of the market structures, functional forms, and economic processes. Table 3 presents the details of the economic models.

Table 3. Details of the economic models.

Model	Underlying Assumptions	Software
Economic models	Computable general equilibrium (CGE)	FARM; GTAP; EPPA; IMAGE
	Partial equilibrium (PE)	ASMGHG; IMPACT; GTM; AgLU; FASOM; GLOBIOM

2.1.4. Agent-Based Models (ABMs)

ABMs consist of multi-agent systems and their interactions to simulate the complex LULC change processes [21]. Here, agents include farmers, laborers, landowners, policymakers, practitioners, professionals, and decision-makers who make decisions in LULC changes and processes (Figure 2) [22]. ABMs integrate the human decisions on LULC change and ponder the social interactions, adaptation, and development at multiple levels [23].

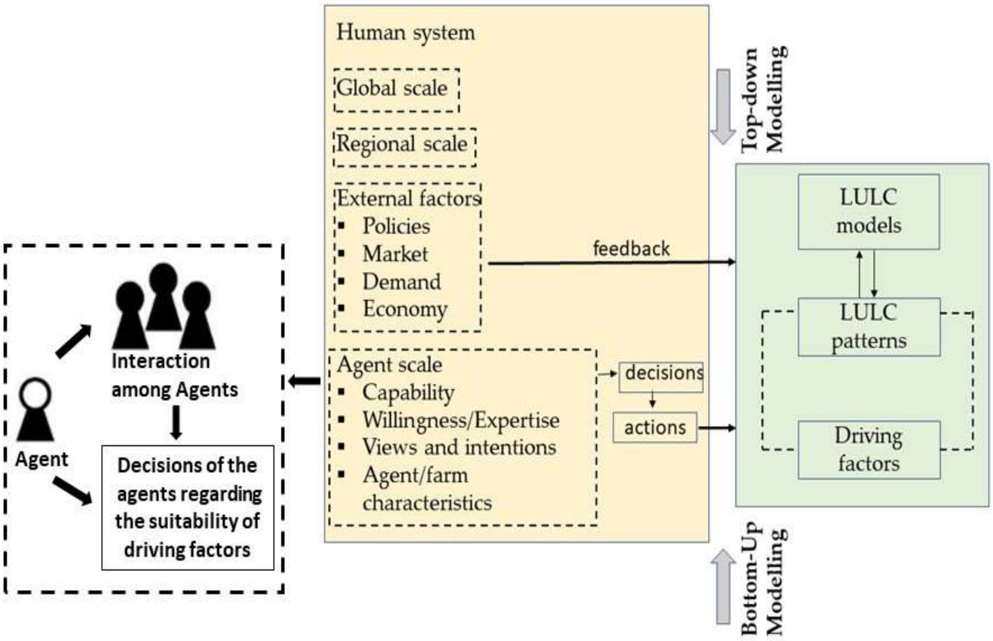

Figure 2. A schematic of agent-based models.

ABMs facilitate the incorporation of expert elicitation and can communicate the model structure and functions to the stakeholders. However, these models lag in terms of generalization.

ABMs consist of independent decision-making entities (i.e., agents), an environment through which agents interact, and the rules that define the relationship between agents and their environment. With reference to a LUCC model, an agent may epitomize a land manager who combines individual knowledge and values, information on different driving factors (e.g., soil quality, climatic conditions, and topography), and an assessment of the land-management choices of neighbors (the spatial social environment) to calculate a land-use decision [24].

2.1.5. Hybrid Models

The idea behind the hybrid models is to combine the strength of individual models [10]. As each model has its advantages and disadvantages, hybrid models were invented to overcome the limitation of each model (e.g., the CA–Markov model is a hybrid of the CA and Markov models (statistical models)) [9,10]. CA models deal well with the spatial dynamics of change; however, it lags in simulating the temporal changes, so their integration with the Markov model could help overcome this issue.

The advantage of hybrid models is developing new methodologies that better represent reality. However, due to their complexity, these models are difficult to calibrate/validate.

2.1.6. Time Series Modeling for LULC Change

The time series modeling of LULC changes is another technique that is still in the evolution phase with the development of Earth observations. It utilizes multiple labeled time-series images for training to predict the LULC class labels of unlabeled time-series remote sensing images [25]. Remote sensing-based LULC monitoring approaches are classified into three categories (i.e., post-classification, pre-classification, and hybrid strategies) [26]. The post-classification approach deals with comparing the classified LULC maps with different time stamps and the overall accuracy determined by the product of individual map accuracies [27]. The pre-classification method has become feasible as satellite imagery has evolved with time, and has the potential to avoid the error accumulation issue that occurred in the post-classification method. The pre-classification method became viable as the satellite imagery archive grew over time [28,29], and has the capability to avoid the error accumulation issue that takes place in the post-classification technique. The LULC changes in the pre-classification technique are determined through the time-series analysis of vegetation indices. Moreover, the hybrid techniques utilize a combination of approaches to improve LULC monitoring (e.g., hybrid strategies such as the continuous change detection and classification algorithm [30]. LULC time-series monitoring has been widely used for the detection of global forest change [31].

2.2. Possible Novel Aspects in LULC Modeling Techniques

Utility of Machine Learning (ML) in LULC Modeling

Conventionally, models like CA have been extensively used for LULC predictions. However, ML techniques such as neural networks (NNs) are recognized as the most powerful tools to tackle unprecedented challenges at different scales in remote sensing [32]. These models learn the relationship between the historical LULC patterns and the explanatory variables [9]. A well-trained mode can be used further to extrapolate the model for testing periods. ML models like multilayer perceptron (MLP) and genetic algorithm (GA) are widely used to predict the LULC.

Aside from this, deep learning (DL) models have recently become popular in LULC modeling. DL models are the extension of NNs with more layers [33]. Moreover, DL models (e.g., convolutional neural networks (CNN) and self-organizing maps (SOMs)) have also emerged as novel techniques for LULC classifications.

CNNs are DL neural networks that have been explicitly designed for image processing. These networks can extract low-level features with a high-frequency spectrum such as the objects' angles, edges, and outlines, which are pertinent to LULC classification. The input layer compiles the model inputs. The convolutional layers filter the inputs through weightings when extracting features from the input image until the NN's residual margin error is the minimum. Therefore, the convolutional layers extrapolate the most important features in the input data regarding the output classifiers. CNN utilizes the backpropagation method for model training. Finally, input images are categorized to the label of the pixels that contain characteristics such as dense forests, agricultural lands, built-up areas, and grasslands.

SOM neural networks are trained to reduce the high-dimensional data (e.g., input map with features) to low dimensions. SOMs utilize competitive learning for unsupervised clustering and visualization through error-correction learning [34]. Therefore, SOMs are considered as an effective means of LULC classification concerning dimensionality reduction.

As discussed earlier in Section 2.1.4, hybrid modeling techniques are gaining in popularity. A hybrid modeling technique (i.e., multilayer perceptron cellular automata Markov model (MLP-CA-MC)), has been developed by [1], which is a combination of multilayer perceptron, cellular automata, and Markov models. Recently, a power ML technique, extreme gradient boosting (XGBoost), has been utilized for LULC predictions [35] where XGBoost outperformed the other integrated modeling approaches, ANN-CA and LR-CA.

ML models are data-driven models, so they efficiently focus on encoding and extrapolating the patterns of LULC change; however, they lag where the simulation of human decision-making or the evaluation of the effect of policies has to be performed [24]. Over the last several decades, ABMs are gaining in popularity in integrating human decision-making into LULC processes [36]. ABMs often face difficulty in decision-making due to data unavailability; hence, their integration with data-driven modeling techniques can help further overcome their limitations.

2.3. Available Modeling Software Packages for LULC Predictions

2.3.1. CLUE-S

CLUE stands for Conversion of Land Use and its Effects. The model is available further in different versions (i.e., CLUE, CLUE-s, Dyna-CLUE, and CLUE-Scanner). The idea of CLUE was first proposed by Tom Veldkamp and Louise Fresco in 1996 [37]. The other modified versions are CLUE-S [38] and Dyna-CLUE [4]. This is an open access model and can be downloaded along with the detailed tutorials (http://www.ivm.vu.nl/en/Organization/departments/spatial-analysis-decision-support/Clue/index.aspx, accessed on 20 October 2022). CLUE is compatible with Windows. The most recent version of CLUE is DYNA CLUE and CLUE SCANNER. CLUE is a flexible and generic LULC modeling platform that allows for scale-specific specifications at regional scales. It utilizes logistic regression to identify prominent explanatory variables and generate suitability maps. CLUE is primarily data-driven and supports the incorporation of expert knowledge. Model applications include the simulation of deforestation, urbanization, land degradation, land abandonment, and integrated assessment of LULC changes. Table 4 summarizes the features of different versions of CLUE.

Table 4. Features of the different versions of CLUE.

Version	Model Features
CLUE (1996)	• Dynamic model • Coarse scale resolution (national or continent-scale) • Data representation at the sub-pixel level • Derivation of LULC data from census or survey
CLUE-CR (1996)	• Application of CLUE in Costa Rica • Applicable at national, regional, and local (grid) scale
CLUE-CH (1999)	• Application of CLUE for China • Incorporate the four sub-modules ○ Demand module ○ Population module ○ Allocation module ○ Spatial analysis module
CLUE-S (2002)	• Dynamic model (spatially explicit in nature) • Fine-scale resolution (local to regional scale) • Data representation for dominant LULC classes • Derivation of LULC data from maps, LULC maps, and satellite images • Based on top–down allocation algorithm
Dyna-CLUE (2009)	• Similar to CLUE-S • Incorporate both top–down and bottom–up approaches • Incorporate a sub-module on neighborhood suitability
CLUE-scanner	• Implementation of Dyna-CLUE model in DMS software of Object Vision

2.3.2. DYNAMICA EGO

DYNAMICA EGO is not only a LULC model but an environmental modeling platform that offers a wide range of possibilities for the design of simple to complex space–time models. Here, EGO stands for Environment for Geoprocessing Objects. It is freely available software and can be downloaded from https://csr.ufmg.br/dinamica/ (accessed on 20 October 2022). DYNAMICA EGO was developed by a dedicated team of software developers and researchers at the Centro de Sensoriamento Remoto da Universidade Federal de Minas Gerais. The software environment is written in C++ and Java programming languages and is compatible with both Windows and Linux. DYNAMICA EGO 7 is the latest version.

DYNAMICA EGO is superior to the other platforms used for LULC modeling due to its flexible nature and ability to interact with other modeling platforms. It allows the combination of map algebra, cellular automata techniques, and tabular statistics to present complex socioeconomic and environmental systems [39]. The TPMs are based on the weight of evidence and genetic algorithm methods and reproduce landscape dynamics using Markov chain matrices to determine the temporal aspects of change and a CA method to reproduce spatial patterns [40,41]. DYNAMICA EGO has been widely used to predict urban growth, carbon emissions, fire regimes, and deforestation.

2.3.3. Land Change Modeler (LCM)

Land Change Modeler (LCM) is a built-in TerrSet (IDRISI) tool and is also available as an ARC-GIS extension. The model was developed in 1976 by Clark Lab. It is a fully automated and user-friendly modeling platform freely available at https://clarklabs.org/terrset/land-change-modeler/ (accessed on 20 October 2022). TerrSet is supported by Windows and programmed in Python, C++, and high-level languages such as Delphi and C++. The latest version of LCM is available in TerrSet 2020.

LCM is applicable for reducing emissions from deforestation and forest degradation (REDD) and climate change mitigation strategies, in addition to assessing LULC changes. LCM simplifies the complexity associated with LULC changes by rapidly analyzing the relationship between explanatory variables and LULC changes [11]. It uses three algorithms—multilayer perceptron (ML-based), logistic regression (statistical), and simweight (ML-based)—to analyze the spatial patterns of change and the Markov model to simulate the quantity and temporal amounts of changes. LCM has also been applied to urban growth, deforestation, erosion, and habitat modeling studies.

2.3.4. SLEUTH

The SLEUTH model was developed by Keith C. Clarke at UC-Santa Barbara as a combination of the urban growth model (UGM) and the Deltatron LULC model (DLM). Several researchers have modified the model further. SLEUTH is also freeware and can be assessed from http://www.ncgia.ucsb.edu/projects/gig/Dnload/download.htm (accessed on 20 October 2022). The source mode of the model is written in C programming language and compatible with both Windows and Linux.

SLEUTH is a CA-based model widely used to simulate LULC changes over the last 15 years [38]. Moreover, the model has been widely used to simulate urban growth. SLUETH contemplates urban areas (built-up areas) as the living organism trained by transition rules that affect the state of changes inside the CA as a set of nested loops [42]. The outer loop performs Monte Carlo iterations, and the inner loop executes the growth rules. Additionally, SLEUTH has also been used to simulate fire regimes, biodiversity, and habitat modeling. The initially developed SLEUTH model had several limitations; hence, the model has been updated to different versions (i.e., Optimal SLEUTH Metric (OSM), pSLEUTH, SLEUTH-3r, and SLEUTH-GA). SLEUTH-GA is the most recent version.

2.3.5. Other Popular Software, Libraries, and Plugins for LULC

Apart from the software above-mentioned, other popular software, libraries, and plugins are also available to perform LULC predictions. Netlogo is a programmable multi-environment for simulating the environmental system developed by Uri Wilensky in 1999. It is freeware supported by Mac, Windows, and Linux. StarLogo is another similar software developed by Mitchel Resnick, Eric Klopfer, and others at the Massachusetts Institute of Technology (MIT). LanduseSim is a GIS-based tool for modeling and simulation. The tool is mainly used to study urban sprawl and regional planning. LanduseSim is only compatible with Windows 7 and 8. Moreover, there are two plugins (i.e., Methods Of Land Use Change Evaluation (MOLUSCE) and semi-automatic classification plugin (SCP)) available in QGIS for LULC modeling and classification. Another helpful library (i.e., FUture Urban-Regional Environment Simulation (FUTURES)) is available in GRASS GIS.

There are also three libraries, LULCC, SIMCOL, and SIMLANDER in R and Janus in Python are available to carry out LULC changes.

3. Discussion

3.1. Credibility of LULC Change Modeling

The selection of the LULC model is mainly driven by the study's objectives (i.e., the modeler's expectancy) as there is no perfect model that can fulfil all of the requirements [1,2]. Moreover, the selection of a model is sometimes constrained by the data availability, governing modeling process, and scale (either temporal or spatial) on which the study is to be performed. If a particular model can address all of the objectives of the study, then it is considered as the best model for the study/region; however, this does not claim the universal superiority of that particular model. Therefore, the selection of the best model is often performed based on its relative performance.

Unlike other modeling practices, LULC modeling also suffers from its uncertainty. Uncertainty in the LULC modeling outcomes may arise from the input datasets, model parameters, model structure and processes, and their interaction with different mathematical representations [43]. Uncertainty in the historical LULC changes arises from rebuilding methods (e.g., image classification method) or sometimes the improper selection of satellite imagery (e.g., presence of cloud in the image), resulting in uncertain outcomes. However, the uncertainty in the future LULC modeling outcomes arises from improper validation of the model (i.e., prediction of future LULC without using a well-validated (tested) LULC model) [44]. Most of the studies performed thus far have not considered the uncertainty associated with LULC modeling; hence, there is scope for further improvement in these methodologies. Incorporating multiple models (using a diverse set of methods) for LULC prediction can potentially help overcome the uncertainty associated with them. Furthermore, the robust validation of the LULC model also plays an essential role in LULC predictions. Most LULC modeling frameworks do not consider the non-stationarity of the explanatory variables during the model validation, but instead use the stationary explanatory variables for model validation and future prediction, resulting in uncertain modeling outcomes.

3.2. Relating LULC Change Modeling to Policy

Over the last couple of decades, a profound increase in LULC change models has been witnessed. However, these models still have little applicability in LULC planning and interventions [45]. The disparities between the LULC change modeling and decision-making support can be ascribed to the difference in the goals of the modelers and decision-makers. Hence, to fill the gap, the LULC model should offer more information and underlying analyses than just presenting the data to engage the stakeholders with modeling frameworks [46]. However, more emphasis should be given to the model's generalizability to increase the policymakers' trust in the modeling outcomes. The present modeling techniques lack the stakeholder's participation during the formation of LULC scenarios and projections. However, the stakeholders' participation is strongly encouraged from the initial steps (i.e., data collection, model formation, and analysis) [5].

3.3. LULC Scenarios for Urban Growth Predictions

Generally, LULC models predict future LULC information based on historical LULC growth. However, under rapid urbanization, the future LULC cannot be accurately extrapolated from the historical LULC changes. Hence, LULC scenario modeling [2] could be helpful in this aspect. Modeling LULC scenarios deals with the simulation of multiple probable futures [47]. Moreover, scenario analysis also aids in overcoming the uncertainty associated with LULC predictions by providing the opportunity to explore all combinations of different possibilities [48]. Under the era of rapid urbanization and globalization, the generation of LULC scenarios dealing with high and uber economic growth can help accurately predict urban growth.

The engagement of stakeholders in formulating LULC scenarios helps identify adequate LULC alternatives by incorporating local preferences in LULC decisions. Furthermore, it enables an understanding of the multifaceted nature of LULC issues from the stakeholders' perspective.

4. Conclusions

The present study comprehensively reviewed LULC modeling by describing and comparing different modeling approaches. The review identified several important research challenges and highlighted issues that must be addressed to improve the current LULC change modeling. The following six recommendations may fill the critical research gaps and stimulate progress in this field:

- Integration of robust modeling platforms to utilize the strength of the individual model;
- Consideration of the uncertainties associated with different sources and their communication with the stakeholders;
- Development of generic protocols and use of online data to provide opportunities to overcome the difficulties in comparing and coupling ABMs;
- Incorporation of policies and relevant stakeholders in the LULC modeling frameworks;
- Development of an open access simple modeling framework and datasets globally applicable;
- Development of generic protocols and the use of online data infrastructures provide opportunities to overcome the difficulties in comparing and scaling ABMs.
- The present review will assist researchers, land managers, policymakers, and urban planners in better land management and urban planning practices, and ultimately assist in achieving Sustainable Development Goal-15 (SDG-15) (i.e., life on land).

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