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A COMPREHENSIVE REVIEW OF SOFTWARE FOR PREDICTING LAND USE AND LAND COVER

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Abstract

Land Use and Land Cover prediction is a critical component in environmental management, urban planning, and sustainable development. With advancements in computational capabilities, numerous software applications have emerged to model and forecast LULC changes based on spatial data and environmental variables. This paper provides a comprehensive review of existing software platforms designed for LULC prediction, analysing their methodologies, features, input requirements, and performance. We explore tools that employ machine learning, cellular automata, agent-based models, and hybrid approaches, highlighting their suitability for different geographical scales and use cases. Additionally, we address key challenges such as data availability, accuracy, ease of use, and integration with GIS systems. The review also identifies trends in the field, including the growing utilization of open-source software and cloud-based solutions for enhancing predictive accuracy. These findings offer valuable insights for researchers, urban planners, and policymakers, assisting them in selecting appropriate tools for LULC analysis and forecasting.

Introduction

Land is an essential space. In 2015, the United Nations put forward the Sustainable Development Goals (SDGs) which aim to deal with development issues in economy, society, and environment during the period 2016–2030, such as poverty, biodiversity loss, and so forth. The SDGs pose new research questions for the communities of sustainability science and land use science: how can we include the SDGs into land use sustainability assessment to inform our land use planning and policy-making for achieving sustainability(Wei et al., 2022).The rapid growth in global population and socioeconomic development has led to an increasing demand for land resources to support human livelihoods and well-being through food, fiber, energy, and living spaces (Ghosh et al., 2021). This poses a significant challenge to the sustainability of natural ecosystems, as the competition for land from various sectors intensifies (Kätsch, 2008). To mitigate the negative consequences of unsustainable land use practices and promote informed decision-making, accurate prediction of future LULC patterns is crucial. These days, a range of analytical tasks are carried out using popular, computer-dependent, time-oriented methodologies such as remote sensing and GIS (Geographic Information System) technology (Kudeshiya et al., 2023). To overcome this challenge, researchers have focused their efforts on developing a range of land use and land cover prediction models that can forecast future land use patterns and changes (Lacher et al., 2023) (Kätsch, 2008) (Ghosh et al., 2021).

One of the key factors driving the need for accurate land use and land cover prediction models is the fundamental uncertainty surrounding the future development of these regions, particularly in the context of climate change. In parallel, the growing availability of geospatial data from remote sensing platforms and the increased computational power offered by cloud computing have further enabled the development of sophisticated land use and land cover modeling frameworks. The scientific literature on this topic has expanded significantly, reflecting the critical importance of this area of research in informing strategic land use planning and conservation efforts.

Software for LULC Prediction

1. TerrSet

The TerrSet Geospatial Monitoring and Modeling System (TGMMS) software package, formerly known as IDRISI, was developed by Clark Labs at Clark University (Gaur & Singh, 2023).The LCM (Land Change Modeler) embedded in the TerrSet software is used for prediction of future LULC for a specified year based on the classified historical satellite images. The LCM determines how the factors influence future LULC change, how much land cover change took place between earlier and later LULC, and then calculates a relative amount of transitions (Leta et al., 2021)(?). As a comprehensive geospatial software solution, TerrSet provides a wide array of tools for analyzing and modeling land use and land cover transformations, as well as for image processing and environmental management decision support. The Land Change Modeler module is a crucial component that allows researchers and practitioners to simulate future LULC scenarios based on historical data, driving factors, and user-defined parameters.

(Singh et al., 2022) predicted the changes in land use ander in Delhi and its surrounding areas. The authors used remote sensing, GIS, and the Land Change Modeler to analyze these changes from 1989 to 2020. The study found that there was a significant expansion of urban areas during this period, primarily due to government policies, population growth, and infrastructure development. This expansion led to a decrease in water bodies and an increase in green cover. The study reported an overall accuracy of 98.63% and a kappa coefficient of 0.96 for their land change predictions.

1.2 Landuse prediction using LCM

The Land Change Modeler is an innovative and specialized component within the TerrSet software suite, utilized for predicting future urban growth patterns with enhanced spatiotemporal characteristics (Hyandye & Martz, 2016)(Hyandye & Martz, 2016), (Keshtkar & Voigt, 2015), (Sayemuzzaman & Jha, 2014).

The following steps are involved to predict the future LULC using the LCM:

A. Images of both earlier and later LULC maps of respective year, use as an input into the change analysis panel to estimate the change between two different LULC that help in predicting respective changes (Singh et al., 2022). The images were reclassified into LULC classes which are important to predict urban growth. There is a spatial trend analysis tool that gives output of pattern of changes. Trends of 3rd and 4th order were calculated.

B. The transition potential panel in the Land Change Modeler identifies the relevant sub-models representing the transitions between different LULC classes, which are used to predict change (Lu et al., 2019). The transition probability matrix is calculated based on the more recent LULC dataset, using a Markov chain approach that compares the transitions of all pixels for each LULC class (Kumar et al., 2016). This transition probability matrix reflects the likelihood and magnitude of anticipated LULC changes from one class to another (Al-sharif & Pradhan, 2013).

C. The driving factors behind the dynamics of LULC changes are often associated with urbanization (Eastman, 1987). Cramer's V coefficient, a statistical measure, has been employed to assess the correlation between these driving factors and urban growth (Eastman, 1987)(Eastman & Toledano, 2017). Factors with higher Cramer's V values indicate a stronger correlation with urban expansion (Eastman, 1987)(Eastman & Toledano, 2017). The major variables typically considered in LULC prediction models include elevation, slope, proximity to roads, proximity to existing urban areas, and higher-order spatial trends (Singh et al., 2022) (Bhanage et al., 2021).

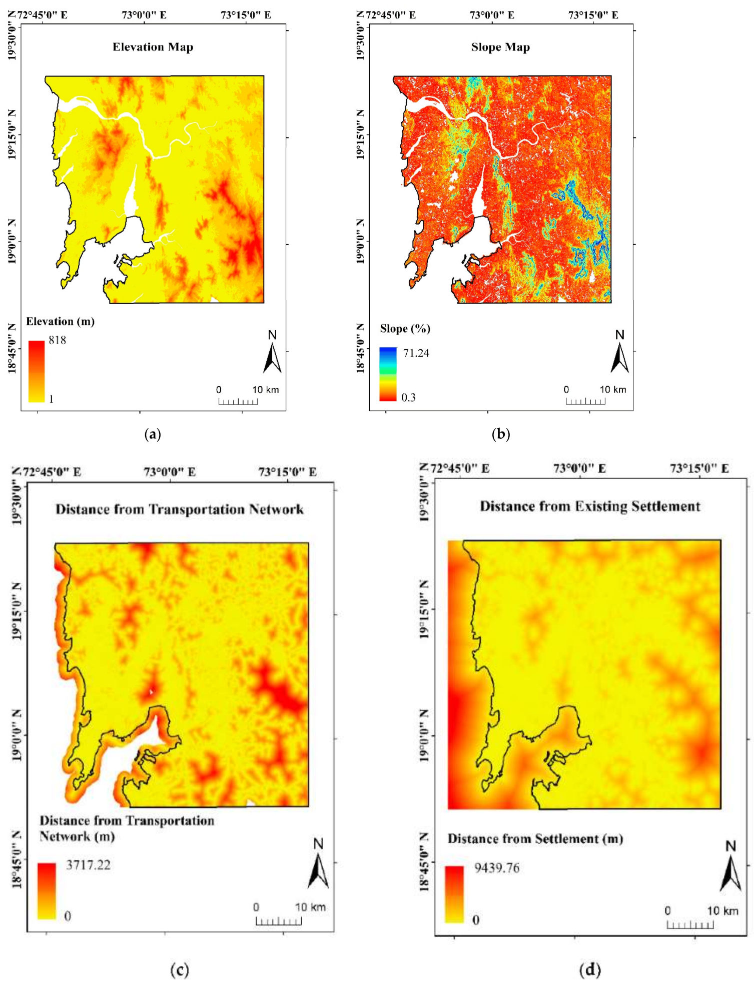

Figure 1. Variable maps used in the study. 1(a)Elevation map, 1(b)Slope map, 1(c) Distance from roads, 1(d)Distance from existing settlement (Bhanage et al., 2021)

D. The Land Change Modeler employs a multi-layer perceptron neural network approach to model land use and land cover transitions. This empirical technique allows for the simultaneous modeling of multiple transitions while maintaining equal sample sizes across classes (Devendran & Gnanappazham, 2019) (Eastman & Toledano, 2017). The method operates in an automated fashion, independently determining how to adjust the model parameters to optimize the output data (Gidey et al., 2017). The dynamic learning procedure starts with a high learning rate and gradually decreases it as the model reaches the target learning rate, with the number of iterations completed (Kumar et al., 2016) (Eastman & Toledano, 2017) (Singh et al., 2022). During each time step, the model reallocates pixels to new land use/cover classes based on their transition probabilities, with pixels having higher transition probabilities being reassigned and the rest remaining unchanged, generating a new land cover map at the end of each iteration (Wang et al., 2019). Once the training process is completed, the model produces transition potential images (Eastman, 1987).

E. The Land Change Modeler utilizes the proximity concept of Cellular Automata to spatially reallocate each land class and generate the output (Kamusoko, 2012). To predict future scenarios for a specific period, the model draws upon historical rates of change and transition potentials (Singh et al., 2022). Additionally, the hard prediction mapping technique, which is based on the multi-objective land allocation module of the Land Change Modeler, is employed (Kumar et al., 2016).

F. Model validation is a crucial step in evaluating the predictive capacity of any model and the reliability of its outputs (Gidey et al., 2017)(Kamusoko, 2012). For this purpose, the study by (Singh et al., 2022) compares the actual and predicted land use/land cover maps for the year 2020 (Singh et al., 2015). The model achieving an overall accuracy greater than 0.8, indicating a strong correlation between the predicted and actual land use patterns (Leta et al., 2021).

Terrset is a licensed software available at https://clarklabs.org/terrset/. It provides a comprehensive suite of tools for environmental monitoring, modelling, and management.

2. Quantum GIS:

QuantumGIS (QGIS) is an open-source geographic information system software that provides tools for working with spatial data. It includes the MOLUSCE plugin, (Modules for Land Use Change Simulations) **that provides a set of algorithms for land use change simulations as well as validation using kappa statistics** which is used to estimate potential land use and land cover changes and is based on a Cellular Automata model. This plugin utilizes four well-established algorithms: Artificial Neural Networks, Logistic Regression, Multi-criteria Evaluation, and Weights of Evidence. The Cellular Automata-Artificial Neural Network model within MOLUSCE is considered a reliable tool for predicting future LULC patterns, making it valuable for land use planning and management (kamaraj & Rangarajan, 2021).

2.1 Landuse prediction using MOLUSCE plugin:

A. It involves defining the inputs for the neural network simulation. The model is cell-based, with each cell possessing a set of n attributes, also called spatial variables, as inputs to the neural network. The spatial variables can be represented using the expression:X=$[x1,x2,x3,\ldots,xn]T$, where xi is the i-th attribute, and T is transposition. The initial and final land use/land cover maps, along with five exploratory maps, are loaded as input data. All datasets are processed to ensure same spatial extent and resolution in raster format.(Saputra & Lee, 2019)

A. The correlation between spatial variables are evaluated through a two-way raster comparison, where the first raster is selected from one variable, and the second raster is selected from another variable. Subsequently, the LULC area and changes for each category are calculated between the initial and final time periods. Additionally, the transition matrix, which depicts the proportions of pixels transitioning from one category to another, is derived from the computations.(Saputra & Lee, 2019)

B. In this step, the transition probability is modeled using an Artificial Neural Network approach. The neural network architecture consists of three distinct layers: the input layer, the hidden layer, and the output layer (as depicted in Fig.1). Each of the spatial variables is associated with a corresponding neuron in the input layer, after undergoing scaling to fall within a specified range [0, 1].(Saputra & Lee, 2019)

1. In the hidden layer, the signal received by the j-th neuron, netj(k,t), from the input layer for the k-th cell at time t was calculated as follows:
2. $netj(k,t)=\sum iwi,kx'i(k,t)$,netj(k,t)=∑iwi,kxi′(k,t),
3. (2)
4. where wi,kwi,k is the weight between the input and the hidden layers, and $x'i(k,t)$xi′(k,t) is the i-th scaled attribute associated with the i-th neuron in the input layer with respect to the k-th cell at time t.
5. The recommended number of neurons in the hidden layer is 2^n + 1, which is suggested to ensure the perfect fit of any continuous functions. However, research by (Kok & Winograd, 2002) indicates that using 2^n/3 hidden neurons can achieve similar accuracy while requiring significantly less training time.(Saputra & Lee, 2019)
6. The l-th neuron in the output layer generates a value that represents the transition probability from the initial type to the l-th (target) type of LULC. The transition probability is obtained by the following equation according to the output function of a neural network.
7. $P(k,t,l)=\sum jwj,l11+e-netj(k,t)$,P(k,t,l)=∑jwj,l11+e−netj(k,t),
8. (3)
9. where $P(k,t,l)$P(k,t,l) is the probability of conversion from the existing to the l-th type of LULC for the k-th cell at time t, and wj,lwj,l is the weight between the hidden and the output layers. A higher value indicates that the transition probability from the initial type to the lth type is larger.

The study by (Saputra & Lee, 2019) employs an iterative neural network based on the back-propagation learning algorithm to simulate land use and land cover changes. At each iteration, the neurons in the output layer generate transition probabilities from the existing land use/cover types to other types. The simulated LULC changes are determined by comparing the transition probabilities, such that a cell's land use/cover is updated to the type with the highest transition probability. If the land use/cover of same type has the highest transition probability, the cell's state remains unchanged.(Saputra & Lee, 2019)

A. After deriving the transition probability, the Cellular Automata simulation is employed to model the LULC changes. The CA framework consists of a regular grid of cells, where each cell can assume one of a finite set of states, determined by the states of its neighboring cells(d'Aquino et al., n.d). CA considers the composition of associations of cells around one cell(Omar et al., 2014) .

10. The CA simulation typically involves multiple iterations to determine whether a cell's state should be updated. To control the rate of change and ensure gradual land use conversions, a predetermined threshold value should be employed. If the highest transition probability for a cell is lower than the threshold, which is set to 0.9 in this study based on Li and Yeh(Li & Yeh, 2002), the cell's state remains unchanged. The threshold value ranges from 0 to 1, and a large value of 0.9 is used to maintain stable LULC changes in each iteration, thereby producing fine simulation patterns(Li & Yeh, 2002).

B. The LULC simulation is validated by evaluating and comparing the real and predicted LULC maps using the Kappa coefficient, a measure of agreement between the two maps(Saputra & Lee, 2019).

Following the validation, the model is used to predict future LULC maps, assuming the continuation of current LULC trends and dynamics. The neural network simulation of these future LULC changes utilizes the same weight values as the previous validation(Saputra & Lee, 2019).

3. Google Earth Engine(GEE)

Google Earth Engine (GEE) Editor is **a cloud-based platform that allows users to analyze and visualize satellite images of the Earth.** As an online platform, Google Earth Engine enables data-driven methodologies to be accessible on researchers' desktops, transforming workflows and eliminating the need for extensive data downloads.(Feizizadeh et al., 2021). The development of cloud-based computing platforms has addressed numerous preexisting challenges, resulting in enhanced efficiency, scalability, cost-effectiveness, and more readily available data access(Ganjirad & Bagheri, 2024). Cloud-based computing platforms have enabled open access to datasets and analysis tools. The abundance of satellite imagery has led to diminished constraints for data sharing among users, improved reproducibility of scientific findings, and the ability to tackle highly specialized research questions. In recent years, Google Earth Engine has sought to offer these capabilities to both academic and non-academic communities(Ganjirad & Bagheri, 2024). While Google Earth Engine has been extensively utilized for land use and land cover change analysis, there is a lack of research exploring its application for LULC future prediction modeling. (Tesfaye et al., 2024) demonstrated the effectiveness of GEE and machine learning in analyzing LULC. It compared the performance of three machine learning algorithms: Support Vector Machine(SVM), Random Forest(RF), and Classification and Regression Trees(CART). Their findings indicated that RF, when combined with auxiliary variables like spectral indices and topographic data, outperforms SVM and CART in accurately classifying LULC(Tesfaye et al., 2024).

(Patel et al., 2024)highlighted the benefits and limitations of using GEE for this application by case studies of Ahmedabad city that demonstrate the effectiveness of the platform. The study conducted a thorough comparative analysis to assess the performance of the GIS and Google Earth Engine approaches. Accuracy was evaluated using ground truth data and well-established validation methods to ensure the reliability of the findings. While Google Earth Engine exhibited impressive accuracy, the GIS software consistently outperformed it in terms of accuracy metrics. The GIS software achieved approximately 89% accuracy, whereas the Google Earth Engine approach reached 80% accuracy(Patel et al., 2024).

Most open-source data analysis tools, such as SciDB and GeoTrellis, provide users with access to the source code, enabling them to thoroughly understand the commands. In contrast, the back-end computing processes in Google Earth Engine do not offer this level of transparency. While users can share scripts openly within their directories, this reproducibility is somewhat limited due to the proprietary nature of the GEE application programming interface. Consequently, users are restricted to utilizing the available JavaScript or Python interfaces provided by GEE(Sidhu et al., 2018). GEE has a code editor that allows users to write JavaScript/Python code to analyze geospatial datasets.

4. CLUE Model

The Conversion of Land Use and its Effects model is a spatial, empirical, dynamic modeling framework used to simulate land use and land cover change. The CLUE-S modeling framework was designed to simulate land use and land cover change by leveraging the empirical relationships between LULC types and influential local factors(Verburg et al., 2002)(Islam et al., 2021). The model comprises two distinct modules: one that calculates the spatial changes in land use types at the aggregate level, and another that translates these demands into LULC modifications at specific locations within the study area using a raster-based approach(Verburg et al., 2002)(Islam et al., 2021).

The CLUE-S model employs statistical analysis to identify the areas suitable for various land use types. The appropriateness of a location is determined by numerous factors specific to the study region(Verburg et al., 2002).

The CLUE-S model employs a stepwise binary logistic regression approach to determine the influential variables for various land use and land cover types across the raster cells in the study area. (Hu et al., 2013); (Zhou, 2011)(Islam et al., 2021). Depending on conditions of the LUCC with surrounding driving force, the prior factors needed to be considered on their availability, data validity, stability, and value. The selective factors stability and value considered to be those that have ability to change the LULC types as a whole as well as any single operational conditions(Islam et al., 2021).

The spatial resolution and cell size in the raster data used for the simulation are the focus of the spatial scale(Islam et al., 2021). While higher spatial resolution provides more detailed information, it can also increase image penetration, thereby compromising the accuracy of predictions(Islam et al., 2021)(Huang et al., 2015)(Lu et al., n.d)(Wu, 2012)(Manandhar et al., 2009). Therefore, an appropriate spatial adjustment is utilized to ensure the accuracy of the forecasts is not compromised(Islam et al., 2021).

CLUE is an open source software with different version of it- CLUE, CLUE-s, Dyna-CLUE, and CLUE-Scanner. Among them, Dyna-CLUE is the most frequently and widely used land-use change models in the past decades (Rakotoarinia et al., 2023). The CLUE-S modeling framework is appropriate for conducting land use and land cover change research at small to medium spatial scales(Zheng & Hu, 2018).

Conclusion

In summary, modeling and analyzing urban land use and land cover change has become a crucial component of urban planning and natural resource management. Though cloud-based computing platforms like Google Earth Engine have mitigated the challenges associated with data access and processing, GIS software consistently outperforms these platforms in terms of accuracy for LULC mapping and forecasting. The graphical user interface of GIS software is more intuitive and accessible compared to the code-based approach required by the Google Earth Engine platform. In terms of cost, open-source software solutions are generally more favorable than licensed alternatives, particularly for researchers who may have limited financial resources to invest in proprietary software. While Google Earth Engine is a powerful platform for geospatial data analysis, the Land Change Modeller in Terrset and MOLUSCE in QGIS are often the preferred choice over GEE and the CLUE model due to their greater ease of use. Currently, researchers are utilizing Google Earth Engine to forecast land use changes, but there is a dearth of published research evaluating the accuracy of these predictions. The demand for robust and accurate land use/land cover forecasting models is persistent and continues to evolve over time.

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