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Earth System and Environment Modeling Dynamics of Land Use and Cover

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Abstract

The extension of agricultural land and the construction of infrastructure are examples of arrogant land use practices that are contributing to deforestation and climate change. The benefits of both cellular and Markov chain analysis are combined in Cellular Automata (CA)-Markov chain, which simulates and forecasts future land use/cover patterns based on historical Land Use Land Cover (LULC) changes. Using IDRISI software and GIS technology, the spatial distribution of LULC and area changed were first computed. The pace of deforestation from 1980 to 2018 was then calculated by evaluating the conversion of forest land cover to other LULC. Second, a CA-Markov chain was run to simulate the spatial distribution of land use and cover in 2018 utilizing transition potential matrices for the years 1999 to 2018. Using the 2018 simulated LULC map with the real LULC.

Keywords: Transition matrix; Transition probability matrix; Transition suitability map

Introduction

Currently, models based on analytical equations, statistics, evolutionary models, cellular models, Markov models, hybrid models, expert system models, and multi-agent models are the most often utilized models in land use change monitoring and prediction. When land cover change modeling goes beyond a predetermined time frame, temporal interpolation or extrapolation is used.

Cellular automata are discrete models where basic principles based on the states of each variable's neighbors determine the states of the variables, or the values associated with grid cell positions. Due to the recent surge in popularity of cellular automata (CA) models—deterministic, stochastic, or hybrid—as spatial simulation tools in a variety of rural and urban modeling domains [1-3].

Methodology

Preparing data and classifying images

Following the completion of all pre-processing tasks, one of the study's key tasks is image classification, which serves as the foundation for prediction and change detection. The land-use/cover category was chosen with the primary goal of the study—predicting land-use-cover change in the future—in mind. Five distinct classes of land uses and land cover were identified, taking into account prior knowledge of the study area as well as additional information from various materials within the study area. Data preprocessing and image classification.

Quality evaluation

The 1980, 1999, and 2018 image accuracy assessments were done in order to evaluate the quality of information derived from the data. The agreement or accuracy between the classification map derived from remote sensing and the reference data, as shown by the major diagonals, and the chance agreement, as shown by the row and column totals, are measured using kappa [4].

Analysis of land use/cover identification of changes

The IDRISI Selva environment v.17 was used to perform LULC change detection using the post-classification detection method, which compares two classified images to generate change information on a pixel basis. Put differently, the way two images are interpreted will yield information about changes in "-from, -to" values. Cross-tabulation is used to compare classified images from two distinct data sets in order to ascertain the qualitative and quantitative aspects of changes for the years 1980 to 2018 [5-7].

Analysis of deforestation

In order to create the deforestation map and the forest area transition matrix for the years 1980–1999, 1999–2018, and 1980–2018, the raster images of the LULC were first transformed into feature types, attributes were chosen using feature names, and single features for each class were combined. The files from 1980 and 1999, from 1999 and 2018, and from 1980 and 2018 were then intersected using the intersection tool, and the area change was added to the attribute table, changing the attribute of area. These are characteristics that were part of a class in a previous era but became part of a different class in a subsequent era. In the end, the four LULC classes matrix—agricultural, built-up, grassland, and water body to other LULC categories—were combined to create the deforestation map and forest area to other LULC change matrix.

Analysis of Markov-chain models: A special and popular tool for Land Use Land Cover modeling that shows LULCCs as stochastic processes is the Markov chain model. Under the Markovian system, a land use system's future state is predicted from its current state. Transition is the change of a system from one state to another, and transition probability is the probability of this state transition. The Markov chain is characterized by its state space and the corresponding transition probabilities.

Where n is the number of land use types, S is the land use status, t is the time point, and p (ij) is the state transition probability matrix.

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Three time periods were used in this study to apply the Markov chain analysis: 1980–1999, 1999–2018, and 2018–2037. Consequently, the transition probability matrix and land use area transfer matrix for the added periods were obtained [8].

Automata Cellular (CA)

Space and time are viewed as discrete units in a CA model, which is a dynamic model with local interactions that depicts the evolution of a system. Space is frequently represented as a regular two-dimensional lattice. Transition rules in CA models should be defined appropriately in order to accurately capture the temporal and spatial complexities of land use and cover systems. The information provided by the CA simulation is crucial for comprehending theories about forest cover, including the evolution of forms and structures.

A bottom-up dynamic model used in a spatiotemporal computation is a cellular automaton. It can perform intricate time-space simulations and is discrete in space-time. Every cell in state St+1 has its own set of data that are determined by itself and by the cells that surround it in state St; in other words, changes to a cell are determined by rules. It is primarily composed of a cell, its neighbor, its space, rules, and time. The neighbors are determined by the CA model's filter. The weight factor will increase with the proximity of the nuclear cell to its neighbor. Land use change is not entirely random; rather, it is predicted for neighboring grid cells by combining the weight factor with the transition probabilities.

Validation of models

Verifying the prediction's accuracy is a desirable step once a model has produced a simulated map. As a result, one of the crucial phases in the land use prediction regime is model validation. Based on the Kappa Index, the simulated and real maps are compared in the VALIDATE module. It differs from conventional Kappa statistics, though, in that it divides the validation into multiple parts, each of which has a unique form of Kappa (K no, K location, K standard, etc.) and the statistics that go along with it.

The model output was compared to a present or actual land use map. Comparing the predicted LULC map representing the 2018 LULC with actual LULC (map of 2018) was based on Kappa Index of Agreement (KIA) approach, which is widely used in validate LULC change predictions Before CA-Markov model can be applied for estimation of the next 38 years. I must be used the validation module is available in IDRISI software for this purpose [9,10].

Results

According to Hoffer RM, change detection is the study of temporal effects as variation in spectral response in scenarios where the spectral properties of the vegetation or another type of cover type in a particular area change over time. Technology has advanced to address this problem, and there are essentially endless possibilities in various application areas that can be addressed with the help of decision support tools like Geographic Information Systems (GIS) and data from earth observation satellites.

According to LULC change analysis, between 1980 and 2018, forest land fell by 52,156.71 hectares, while agricultural land increased by 78,021.35 hectares during that time. As a result, when the Oromo people moved from Central Ethiopia to South Western Ethiopia in the 1970s due to urbanization and political reasons, deforestation began in that area. Additionally, during the study periods, the coverage of water bodies and grasslands decreased by 8143.75 hectares and 18129.07 hectares, respectively, spanning nearly four decades. Additionally, settlement areas grew by 408.16 hectares; in the first year of the study period, this class of land use was not as evident.

Agricultural land accounted for the largest share of the net increase in area, totaling 50,837.56 hectares. The amount of transfer areas for agricultural land that came from forest land, grassland, and water bodies was 44,482.54, 3,629.02 hectares, and 3,556.93 hectares, in that order. Built-up areas accounted for approximately 301.02 hectares of the net increased areas, representing the second-highest proportion of the net increase in area. The transfer-in areas of agricultural and forest land, which were 258.20 and 98.40 hectares, respectively, contributed to the net increase in built-up area. Between 1999 and 2018, there was a decrease in contrast forest land, water bodies, and grassland areas. The corresponding decreasing areas were 44509.78 hectares, 3,548.68 hectares, and 3,081.02 hectares. The majority of the forest's transfer-out area is 1,286.37 hectares and 44,482.54 hectares of agricultural land, respectively. Transfers of grasslands into agricultural land resulted in a changed area of 3,629.02 hectares, while transfers of water bodies into forests and agricultural land affected 3,556.93 and 1,128.77 hectares, respectively.

Discussion

As many people have noted, deforestation is a complicated ecological and socioeconomic process brought on by both natural and human factors. The distance to the village's edge, or the distance between the village and the BGFPA, is a significant factor in changes in the forest area and the growth of new agricultural areas. It also serves as a direct cause of deforestation brought on by the expansion of agricultural land. This suggested that the local village's boundary and the Belete Gera forest priority area were the areas with the highest levels of deforestation. The distance from a road was another proximate factor for the change in forest cover of the BGFPA. The majority of the forest area on slopes less than 65 degrees has been turned into agricultural land. In this study, the study area was predicted and simulated using a forest suitability map.

Visual analysis reveals that while the simulated and real LULC maps are similar, they are not exactly the same, particularly when it comes to the classes of grasslands and water bodies. As a result, the non-diagonal elements will be the best way to take the model accuracy into consideration. The comprehensive statistical analysis based on the Kappa coefficient is used to measure the overall agreement of the matrix, the ratio of diagonal values summation versus the total number of pixel counts within matrix. The agreement between the actual and reference maps is represented by a kappa value of 0, which indicates that there is equal chance agreement. The upper and lower bounds of kappa are +1.00, which occurs when there is total agreement, and -1.00, which occurs when there is less chance agreement.

The K statistics are deemed accurate if the results show that each kappa index agreement is greater than 0.8. The study's accuracy was evaluated using the IDRISI Selva environment v.17 VALIDATE module. According to the results, K values above 0.8 indicate a satisfactory degree of accuracy (K standard=0.8370; K no=0.8780; K location=0.9033; K location Strata=0.9033). As a result, CA-Markov modeling can be used to predict the study area's future LULCs with accuracy. Additionally, this study was helpful for planning and decision-making related to the protection of Ethiopian forests generally and the Belete Gera forest priority area specifically.

According to land use land cover predictions for the year 2037, there will be a reduction in the amount of forest land cover by

64,322.87 hectares from the 94,527.52 hectares that it covered in 2018. This indicates that in nineteen years, 30,204.65 hectares of forest land would be lost. Conversely, it is anticipated that the area covered by agricultural land will rise by 30,693.91 hectares over the next 19 years, from 117,201.65 hectares in 2018 to 147,895.56 hectares in 2037. Furthermore, it is probable that the built-up area will slightly expand over the next 19 years, rising from 408.16 hectares in 2018 to 647.19 hectares. As a result, while forest land covered 44.01% in 2018 and would be expected to decrease by 29.95% in the ensuing nineteen years, agricultural land covered 54.57% of the study area's total land in 2018 and was predicted to increase to 68.86% of the total land in BGFPA in 2037.

Conclusion

Land use/cover maps for the years 1980, 1999, and 2018 were created using Landsat 5 TM image data for the 1980s and 1999s, and Landsat 8 OLI image data for the 2018s. Next, using a CA-Markov model, the overall LULC forms of the study area were predicted for the years 2037 and 2056 as well as simulated for the year 2018. Out of all the LULC taken into consideration, the forest area coverage was the highest according to the classification results of the LULC maps from 1980 and 1999. Additionally, the results indicate that the Belete Gera forest priority Area experienced a minor rate of change in forest land between 1980 and 1999. In 1980, 1999, and 2018, the corresponding forest areas were 146,684.23, 139,037.30, and 94,527.52 hectares. Between 1980 and 2018, the amount of grassland and water bodies decreased yearly as well. On the other hand, there was an increase in agricultural land areas of 39,180.30, 66,364.09, and 117,201.65 hectares in 1980, 1999, and 2018, respectively. In BGFPA, the built-up area was also periodically expanded.

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