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Processing of Satellite Imagery Using Deep Learning Techniques For Developing Land Use Land Cover Images

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Abstract
The remote sensing community is becoming more interested in using deep learning approaches for classifying land use and land cover based on multispectral imaging, as these methods are outperforming traditional machine learning techniques in picture classification. New potential for a wide range of applications are presented by the rapid growth in the volume of timely data available globally due to advancements in remote sensing technologies. Nonetheless, a few issues with resolution, ground truth, and data type have a significant impact on classification success. This work presents the application of deep learning to multispectral image-based land use and land cover classification. This gives the readers a foundation for understanding the current state of deep learning in this particular scenario**.**
Keywords: remote sensing data; multispectral data; LULC classification; deep Learning neural networks;

INTRODCTION
Over the past 50 years, human activity has drastically changed the earth's surface, particularly through urbanization, deforestation, and agriculture. Since World War II, there has been an increase in urbanization that is expected to continue into the twenty-first century and has not showed any signs of stopping.
Growing urbanization causes worries about how the environment is being destroyed and how healthy it is ecologically. In these quickly changing contexts, resource managers and city planners must have a thorough understanding of urban expansion. Modeling and simulation are used in the study of how urban expansion affects the environment. Of all the dynamic models that have been described, cellular automata (CA)-based urban growth simulation models are arguably the most outstanding in terms of their technological evolution with respect to urban applications. The four main parts of a typical cellular automation are the following: cells, states, neighborhoods, and transition rules. The smallest square units of a state are called cells.
When a set of transition rules is followed, the state of a cell will alter in relation to its surrounding cells.
Benefits of cellular automata include their adaptability, ease of use in complicated urban dynamics, and strong connections to remote sensing data and geographic information systems.
A lot of work has gone into creating models of cellular automata, particularly in expanding transition rules to incorporate self-modification, stochasticity, and probabilistic expressions. Current research shows that cellular modeling has developed from an early game-like simulator to a promising tool for predicting urban growth.

LU/LC
LU/LC change has become an essential component in present strategies in environmental management. The term "land cover" describes the surface cover of the earth, including bare soil, water, plant, and urban infrastructure. The process of identifying land cover creates the baseline data needed for tasks like change detection analysis and theme mapping. The term "land use" describes the use of the land, such as agriculture, wildlife habitat, or recreation.

When combined with the term "Land Use/Land Cover," the term "LULC" generally refers to the arrangement of natural features and human activities on the landscape within a given time period, as determined by accepted scientific and statistical techniques of analysing relevant source materials.
A society's social and economic development is the only factor influencing its expansion. This is the main justification for conducting socioeconomic surveys. This kind of survey uses datasets that are both spatial and non-spatial. Planning, managing, and overseeing programmes at the local, regional, and national levels heavily relies on LULC maps. In addition to helping to better understand some aspects of land use, this kind of information is crucial for the creation of the policies and programmes needed for development planning. Monitoring the ongoing process of land use/land cover pattern throughout time is crucial to ensure sustainable development. In order to prevent accidents and promote sustainable urban development.

USE OF ARTIFICIAL NEURAL NETWORKS
Artificial neural networks (ANNs), which are increasingly receiving attention in solving complex practical problems, are known as universal function approximators. They are capable of approximating any continuous nonlinear functions to some arbitrary accuracy.
Its applications are numerous in various fields, including engineering, management, health, biology and even social sciences. Artificial neural networks have been applied in many different environmental

METHODOLOGY
CA-MARKOV MODEL
Markov Chain Analysis is a handy tool for modeling land-use change when changes and processes in the landscape are complicated to describe. A cell's state will change in reference to its neighboring cells when a set of transition rules is adhered to. The versatility, usability in complex urban dynamics, and robust integration with remote sensing data and

geographic information systems are among the advantages of cellular automata.

Cellular automata models have been developed by extensive work, in particular, in extending transition rules to include probabilistic expressions, self-modification, and stochasticity. According to recent studies, cellular modeling has advanced from a simple game-like simulator to a potentially useful instrument for forecasting urban growth. The current study project uses a TERRSET software module called Land Change Modeler to model the future LU/LC image, which incorporates the Markov Chain.

$$P = (p_{ij}) = \begin{vmatrix} P_{11} & P_{12} & \cdots & P_{1n} \\ P_{21} & P_{22} & \cdots & P_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ P_{n1} & P_{n2} & \cdots & P_{nn} \end{vmatrix}, \quad \sum_{j=1}^{n} p_{ij} = 1$$

Where P = the Markov transition matrix.

i, j = the land cover type of the first time period and second time period.

Pij = the probability from land use type i to land use type j.

Ultimately, a collection of transitional potential maps, also known as conditional probability pictures, were created. These maps provide the likelihood that a specific form of land cover would be present at a given pixel after a specified amount of time units. Land-use change causes are not taken into account by Markov analysis. Markov analysis also lacks spatial sensitivity, which is a major issue as it gives no sense of location. Therefore, cellular automata are employed to add the spatial element to the modeling process.

Cellular Automata (CA):

When it comes to animating cells on a lattice, CA may be well-considered as a discrete dynamical system that models the complex behavior based on straightforward, logical rules. In essence, CA uses a uniform "n" dimensional grid of cells—for example, n=1, n=2—to represent the space, with each cell holding a set of data. In CA, a "cell" is the fundamental computing unit; in reality, these cells are typically nonlinear dynamic systems. The group of cells that will immediately interact with the centrally situated cell under consideration is represented by the concept of the neighborhood.

The system's states were represented by finite, integer values, and the space was depicted by a grid. Time was represented by uniform steps. The four components of the CA system were states, neighborhoods, cells, and rules.

Each cell's subsequent state was dictated by the conditions of the cells that surrounded it. The states of the cells in the following time step are determined by rules.

CA_MARKOV: A built-in module named CA_MARKOV, which is compatible with the TERRSET software, was utilized to predict future land cover images using cellular automata and Markov chains.

In order to "grow out" land usage from time two to a later time period, CA_MARKOV applies a contiguity filter to the Transition Area file, which is the result from the Markov Chain Analysis. Essentially, the CA will create a spatially explicit weighting scheme that gives areas closest to current land uses greater weight. This will guarantee that land-use change happens close to current land-use classes rather than at random.

LAND CHANGE MODELER

Land Change Modeler(LCM) is an pioneering land planning and decision support system that are fully incorporated into the TERRSET software. With an automated, user-friendly workflow, Land Change Modeler simplifies the complexities generated in change analysis. Land Change Modeler allows us to rapidly analyze land cover change, empirically model relationships to explanatory variables, and simulate future land change scenarios.

DATA USED

LU/LC images

For the present work, LU/LC images developed in the previous chapters for the years 1995, 2000, 2005,2010,2015 were used.

Road Network

Road network map is used which is developed in ARC GIS from Topo sheets, Master plans and latest Google maps and Google earth map.

Elevation Map

Digital Elevation map was downloaded from SRTM Data from USGS Earth explorer and used in the Land Change Modeler.

The methodology adopted this work is shown in the Figure. Land Change Modeler, a TERRSET software module, is used for the current research project to model the future LU/LC image, which includes the Markov Chain.

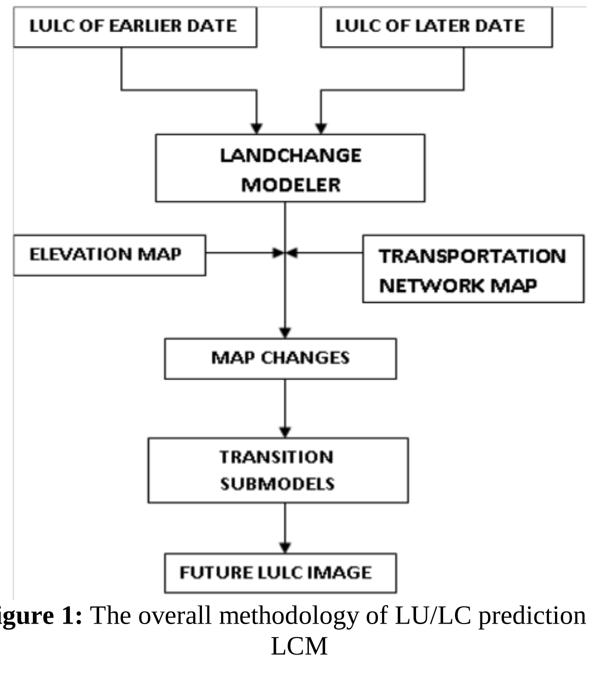

Figure 1: The overall methodology of LU/LC prediction by LCM

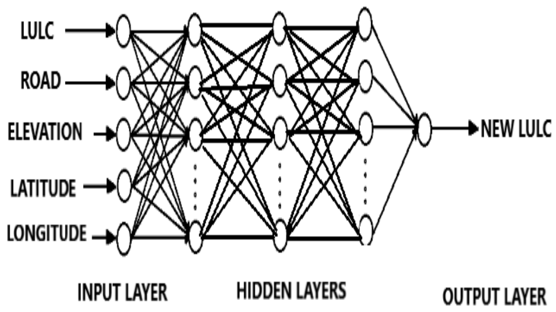

Figure 2. ANN model architecture

RESULTS AND DISCUSSION

The LULC image obtained from the LCM process as well as the input LULC images were presented in the following figure.

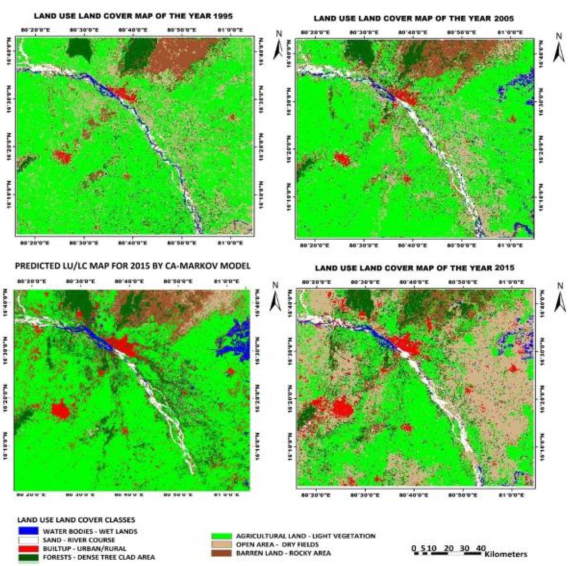

Figure 3. LU/LC images of input and output

VALIDATION OF LCM PREDICTION PROCESS

To validate the LCM prediction process, first the LU/LC of 2015 was predicted and verified. Using LU/LC of 1995 and 2005, with 10-year span, LCM was run to predict LU/LC of 2015. This LU/LC of 2015 is compared with the already developed LU/LC 0f 2015 by ERDAS for accuracy assessment and found to be with good agreement. As we are mainly interested in the urban growth, only contributions to the net change in the built-up area were considered and shown.

The LU/LC maps of 1995 and 2005 were used as inputs to the model. The changes that were taken place in this 10 year span were calculated for each class of LU/LC, and the transition potential will be assessed by the LCM. When the Markov Chain analysis was carried out by the LCM, it will project the changes that were noticed in the past ten years in to 10 years of the future. This will be manifested in the form of an LU/LC image with the help of Cellular Automata, which is in-built in the LCM. The neural network present in the LCM will be trained and tested with the past data and will get ready to predict the future LU/LC.

The LU/LC image of 2015 actually developed from the satellite images was also shown in the Figure 6.4. The predicted and actual LU/LC images may never be equal for several reasons. However, the areas of various classes of the predicted and the corresponding actual LU/LC images were considered for comparison and analysis.

The following Table 6.1 gives the areas of built-up area class of the years 1995 and 2005, the difference in class between the two dates, and expected area as per Markov concept. From the table, it is evident that the difference between predicted and expected is nominal. For built-up area, its percentage is only **-5**. Hence the LCM process is considered to be accurate for prediction of the future LU/LC reasonably.

Table 1: Validation of Predicted LU/LC image of 2015

Year--> Class	Areas in 1995 (Sq.km)	Areas in 2005 (Sq.km)	DIFF in area (Sq.km)	2015 Expected Areas (Sq.km)	2015 Predicted Areas (Sq.km)	% DIFF: Predicted - Expected	Actual Areas 2015 (Sq.km)
BU	99.58	164.75	65.17	229.92	252.26	13.5	265.99

BU: Builtup Urban/Rural

In the validation process only built up class is considered, because in this class the changes from past date to present date will be consistently increase and does not vary according to the season. That means the area of built up class will not change in summer or winter, where as all the other classes like light vegetation, open land etc, would undergo changes. This is considered because, the dates of imagery obtained from satellites of different years does not exactly match. Hence only built up areas were considered for validation process. On the other hand the present research is focussing on the urban microclimate which mainly depends on the built up area.

The other way of validating the predicted LU/LC image proposed by the author is to consider some number of points randomly in the Later and Predicted images. As we know, the Earlier and Later images were used by model to produce Predicted image, note down the transformation of each class at each point from Later and Predicted images. Now, validate each transformation according to the acceptability. For example, no area changes from built up to water body, but water body may turn to open land later light vegetation class. This is how the acceptability of class transformation is determined which is useful for validation of prediction.

CONCLUSION

The applications of deep learning techniques were demonstrated with the use of Land Change Modeler which uses Multiple Hidden Layers in the neural network. LU/LC images of 1995 and 2995 were used to predict LU/LC image of 2015. LU/LC of 2015 was also developed from original satellite image. By selecting one LU/LC class the developed and predicted LU/LC images were compared and validated.

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