Uncertainty modeling for asynchronous time series data with incorporation of spatial variation for Land Use/Land Cover Change

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March, 2013

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ABSTRACT

Land is vital to the survival of all life on Earth and it is important that we understand the various changes that take place on it. Environmental and anthropogenic drivers are constantly changing the face of the Earth and it is essential that we understand what these drivers are and the change they bring about to the Land use/Land cover. Land Use Land Cover (LULC) change analysis is very important for environmental management purposes as it helps the decision maker in planning for future changes that may occur in that area and it also helps the decision maker realize the effects of these changes on humans and their environment. Decision makers also have to identify, what are the factors that affect the LULC change (such as population, agricultural growth etc.). Therefore the quality of the LULC change map is essential for making more accurate decisions. In this project, uncertainty modeling has been performed in Land use/cover change. Uncertainty modeling quantifies the variation in results obtained by a modeling process for decision-making.

Remote Sensing and Geographical Information Systems apply different types of operations (e.g. classification, rescaling) on spatial datasets to produce maps or to extract spatial information from the dataset; there is always some uncertainty in these operations. Uncertainty considers aspects like error and incompleteness of the input data as well as the output data. This project uses a CA-Markov hybridized approach to model LULC change in the Upper Ganaga Basin.

LULC change is detected by using different time period images and various driver datasets (e.g. soil moisture, temperature, and slope). There is some amount of uncertainty in the available observation, spatial distribution and resolution of the datasets. We have to model the redistribution and aggregation uncertainty for the driver data in order to come up with an outcome that has minimum error. Spatial aggregation is used in conversion of LULC datasets to thematic raster datasets. The spatial aggregation methods used for this project are Random role-based and Major role-based

The results show that major rule-based aggregations proved to be more accurate than random rule-based aggregations for the Upper Ganga basin. The highest percentage of change was observed in the classes; snow and ice and barren land.

Keywords: LULC Change, CA-Markov, Major Rule Based, Random Rule Based

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

1. INTRODUCTION

Remote Sensing and Geographical Information Systems apply different types of operations (e.g. classification, rescaling, and interpolation) on spatial datasets to produce maps or to extract spatial information from the dataset; there is always some uncertainty in these operations[1]. Uncertainty considers aspects like error and incompleteness of the input data as well as the output data.

Abbaspour *et al.* [2] mentions that uncertainty is divided into three levels as per the United States Spatial Data Transfer Standards. These three levels of uncertainty are source of uncertainty, form of uncertainty, and resulting uncertainty. The source of uncertainty is the uncertainty that is found in the source data. Inherent, model, measurement, data usage, processing and transformation are examples of source uncertainty. The second level consists of positional, attribute, time, and logical consistency and completeness uncertainties. The third level is the uncertainty of the overall product (e.g. final map).

In this project, uncertainty modeling has performed in Land use/cover change. Uncertainty modeling quantifies variation in results obtained by a modeling process for decision making. In Abbaspour *et al.* has a mention that error propagation takes place in a model from input data to output data and errors also occur due to GIS operations [2].

Land Use Land Cover (LULC) change analysis is very important for environmental management purposes as it helps the decision maker in planning for future changes that may occur in that area and it also helps the decision maker realize the effects of these changes on humans and their environment[3]. Decision makers also have to identify, what are the factors that affect the LULC change (such as population, agricultural growth etc.). Therefore the quality of the LULC change map is essential for making more accurate decisions.

LULC change models are used in finding patterns and predicting LULC change. LULC changes are driven by various bio-physical (temperature, rainfall, slope, drainage etc.) and socio-economic drivers (the growth of population, industrialization, infrastructure and technological growth etc.). LULC changes occur due to driver effects, these changes can be identified by the spatial patterns that can be seen in the area of interest. For example industrial growth results in change in land use classes as there is a reduction in the agriculture and forest areas due to the growth of the industrial areas.

The LULC model applies various geo-information techniques (e.g. Markov, Cellular Automata (CA)) in order to analyze various input drivers and Land use datasets. LULC change is detected by using different time period images and various driver datasets (e.g. soil moisture, temperature, and slope). Driver datasets (such as population data) are not always correct as there is certain information that is always missing. There is some amount of uncertainty in the available observation, spatial distribution, resolution of the datasets etc.[4]. We have to model the redistribution and aggregation uncertainty (e.g. RMSE, ME) for the driver data in order to come up with an outcome that has minimum error. Redistribution methods are basically spatial interpolation methods which are used to predict the value at a known location by observing an existing point. Redistribution and Spatial aggregation is used in conversion of LULC and driver vector datasets to thematic raster datasets.

In LULC change modeling, effective model is required to predict the later LULC classes as per the previous year LULC classes. In LULC modeling most prefer models are Markov Chain and Cellular Automata (CA). Markov chain model create the transition probability matrix from two time period LULC data (t_1, t_2) and give transition probability to predict time period t_3. Stochastic Marko chain model has assumption that LULC change process should be stationary[5]. Markov chain model does not consider the driver data in future change prediction. Markov chain model only gives the temporal dynamics not spatial. As compare to Markov chain model, CA model have spatial component, future change predicted by certain rule from the neighbors cell. In CA the state of each cell depends on the spatial and temporal state of its neighbors. CA -Markov is a combination of two models, the Cellular Automata model and the Markov model. Temporal and spatial pattern of LULC change can be simulated in the CA-Markov model. CA-Markov improves the accuracy of LULC prediction because it considers the driver data [6].

Most LULC Models are grid based. Driver datasets and LULC datasets should have the same spatial grid size. LULC datasets are available for different time periods with varying resolutions of satellite data (LISS dataset 1995, 2005 and 2010, Socio economic dataset of 2001 etc.). These LULC datasets need to be correlated with the driver data but the driver data are of different time period than of LULC datasets (Socio economic dataset of 2001 etc.). It is vital that the spatial and temporal data is synchronized in order to predict the future spatial pattern of LULC changes in an area. LULC and Driver datasets are also of different scales. Re-sampling error occurs when the scale of one dataset is converted from one to another. Also, it is important that the driver and the LULC dataset are of the same time period and in order to see the changes.

1.1. Research Objective

The main objectives of this project find Uncertainty for Land use/cover change in Upper Ganga Basin in the context of India.

1.1.1. Sub-objectives

1) Identifying the drivers which affect the Land use/cover change.
2) Identifying spatial aggregation and distribution technique for LULC datasets.
3) Model uncertainty for aggregation technique of LULC datasets
4) Quantify uncertainty of LULC change with respect to reference LULC dataset.

1.2. Research Question

To reach the above objective the following questions need to be answered.

1) What are the major drivers of Land use/cover change in the study area and relationship between the drivers and the land use classes?
2) Which spatial distribution and aggregation method gives minimum overall uncertainty in Land use/cover change?
3) How much overall uncertainty occurs in the Land use/cover change from 1985 to 2005 in the Upper Ganga Basin?

1.3. Innovation aimed at

Driver datasets are available at different scales and different time periods, and LULC data set also have different scale. For the land use change modeling both should have the same scale. For this study different aggregation approach applied on LULC data to make the data same scale and in order to identify which approach will give minimum error in a predicted LULC map.

1.4. Thesis Strucure

This structure of the thesis describes whole project and the content related to this research in chapters:

Chapter 1: Introduction describes the background of the about project
Chapter 2: Literature Review has done on three parts Land Use Change, Scale and Uncertainty
Chapter 3: Study Area and Data Used, this chapter describe study area and data information
Chapter 4: Methodology, describes methods description used in this project study
Chapter 5: Results and Discussion, in this chapter result analysis has performed
Chapter6: Conclusion and Recommendation, in this chapter research question has been answered

2. LITRATURE REVIEW

2.1. Land Use Land Cover Change with CA Markov

Lo and Yang [7] focuses on the land use/ land cover changes taking place in Atlanta, Georgia. Atlanta is a metropolitan city in America. The approach used to generate these land use/land cover maps was a zone based cellular approach. Drivers of land use/ land cover change were analyzed in this approach. Census data couples with Landsat images for years 1973, 1979, 1987, 1993 and 1999 were used to extract land use/ land cover statistics. Thirteen counties in Atlanta showed a speedy increase in high and low-density urban use. This increase resulted in a decrease in the cropland and forestland of the area. This period also saw a rapid increase in population growth.

In order to understand and analyze these changes it was necessary to comprehend demographic as well as socio-economic data. This data was gathered from censuses and was then integrated with LULC and location data. The results revealed that nearness to roads, highways and shopping malls has led to increase in urban development and this has encouraged suburbanization. This increase in suburbanization has negatively impacted the greenery of the area and has also led to fragmentation and degradation of environment.

Cellular Automation (CA) model was used to generate a land use/ land cover change map from 1999 to 2050. It is predicted that if metropolitan cities keep growing at the present rate then suburbanization will lead to complete loss of forest, around these cities.

Jokar Arsanjani *et al.* [8] are analyze the suburban development and expansion of metropolitan cities. The study area is the metropolitan city of Tehran, Iran. The basic logistic regression model was improved by using Markov Chain (MC), Cellular Automata (CA) in combination with each other. This hybrid model was used in this study to analyze the growing population and expansion of urban cities. Environmental and socio-economic variables that are related to urban development were integrated in order to create a probabilistic scenario of the years 2006, 2016 and 2026.

The model was validated using relative operating characteristic values for different sets of variables. The simulated map for 2006 was compared to the actual map of 2006. It was seen that they matched by 89%, validating the hybrid approach. The future land use/ land cover maps for 2016 and 2026 were based on this hybrid approach. The probabilistic maps generated showed that the western border of Tehran would see an increase in development and expansion over the next few decades.

Pontius and Malanson [9] has compared to models that study landscape ecology. The models compared are the Cellular Automata Markov (CA Markov) model and Geomod. Both of these models permit a specified prediction quantity and also allow for the specification of the position of land classes. CA-Markov can predict change in any number of classes while Geomod is able to predict change only from one class to another one. It was seen that the between predictive models and null models, the predictive one are much more accurate.

Serra *et al.* [3] examines the drivers that are the main force behind the changing land use/ land cover (LULC) in the Mediterranean region. Various tools are used to see the difference between the LULC changes, the drivers behind those changes and the dynamics of the landscape. The LULC changes have been computed using remote sensing and GIS methods. The drivers have been analyzed using logistic regression integrated with anthropogenic and biophysical variables and the landscape dynamics have been comprehended via the use of various metrics.

The results indicate that the in the future we shall see abandonment of vineyards, intensification of herbaceous crops and an increase in forest land in the mountains due to reforestation that is being carried out currently.

Ye and Bai [10] has done study on the Nanjing County in China went through a period of extreme land use and cover change from 1985 to 2000. Remote sensing and GIS methods were employed to detect temporal and spatial changes that took place over this period. It was seen that the forest cover fell from 49.46% to 39.01% and it was the one land use which showed the most amount of change the other major land use change was that there was an increase of more than 10% in croplands. The CA-Markov model was used In order to estimate the changes in land use in 2015 and 2030. The estimated results show that there will be a rise in croplands by 2.53% from 2000 to 2015 and another rise of 2.85% from 2000 to 2030.

Land use and land cover change has affected China the most in the last few years and it is seen that rapid land degradation is resulting from climate change and anthropogenic pressures on the land. [10] Examine and predict the spatial and temporal land use in the Nenjiang County in 2015 and 2030. They estimate this by using the CA-Markov model which is described in their paper.

In this study, LULC change modeling CA-Markov used for predicting the 2005 year map. Biophysical and socio economical driver dataset also integrated with this model and for the driver relation with LULC classes logistic regression used d in this study.

2.2. Scale

GIS techniques coupled with remote sensing data have made it possible to present and manage remotely sensed data in multiple scales. Quattrochi *et al.* [11] express the need of multiscale data in GIS. It is revealed that multi scale data is useful when carrying out 'global change studies'. Multi scale data helps in define spatial properties at various scales and help in understanding spatial processes using information from these various scales. Quattrochi *et al.* [11 also recommended four implications of spatial scale; cartographic scale, geographic scale, operational scale and measurement scale.

Cartographic scale is basically the relationship between the distance that is shown on a map and the distance on ground that it refers to. Geographic scale is the 3D space the study area occupies. Operational scale is the scale at which certain processes work. Measurement scale denotes the smallest discernible objects that are observable in spatial data. In paper Turner *et al.* [12] called measurement scale spatial resolution/ grain. Varying spatial resolutions have importance in various subjects. Forestry, ecology, hydrology and human geography use the same data at different scales.

Data aggregation in remote sensing is used in global studies of landscape patterns. The aggregation of an image leads to a coarser resolution and the spatial characteristics of the data also change.

The majority rule-based (MRB) technique has been defined well by Moody and Woodcock [13]. In their study they superimposed polygonal grids, which are the aggregation grids over classified, per pixel class maps of 30m. The most common class in the polygonal grid was allotted to all the cells of that grid. This sort of an aggregation is known as majority rule-based aggregation. This method was used to get maps with various coarse resolutions. The coarse resolution maps were then used to measure error in regards with the area of the 30m-class map. It was seen that at 90m resolution the error observed was the lowest in all classes. In order to compute the change in class proportion that resulted from change in spatial resolution it was suggested that a regression relationship should be developed.

Aggregating spatial raster data using the Majority Rule-Based (MRB) method has been classically used in the study of landscape ecology by He *et al.*[14] . Earlier studies show that using MRB methods makes the dominant class increase, the minor class decreases and the spatial patterns also undergo a change. This paper studies an alternative method, which is the Random Rule-based (RRB) aggregation method. Here a classified TM image of 30m resolution was used to carry out this aggregation on. Aggregation Index, Fractal Dimension, mean patch size ration and proportion of cover type were used to observe how the RRB approach is different from the MRB approach.

The study showed that aggregation done using the MRB process caused the cover type proportions to be inaccurate. The MRB tended to decrease or even erase out the minority class, which resulted in a clumped looking landscape. These sorts of maps are easy to interpret and prove to be useful for land managers. It helps them in studying the spatial patterns of a certain area. RRB on the other hand preserved the accuracy of the cover type proportions but resulted in some disaggregation. It was seen that the RRB was better for those studies where accuracy of spatial data is important.

For the study in the project aggregation approaches RRB and MRB was used in land use images, and find out the effect of aggregation on final predicted map of year 2005.

2.3. Uncertainty:

Geoprocessing is a method that helps to create new spatial data from original input data. The process uses various algorithms to create new data and most of the algorithms used employ some sort of a prediction method to create new data with new spatial features. Tools used in geoprocessing like overlay, intersect, buffering by Konstantin *et al.* [1] . Basically help the user to combine data from various places and then interpret it in one environment. The outcome is an integrated set of data which is different from the original data and has new spatial features too. For this reason the estimates for the new data are always uncertain. In order to make the results more efficient for decision-making uses it is necessary that the user should be able to calculate and compute the uncertainty that is present so that the impact of the uncertainty on the results may be assessed.

Konstantin *et al.* [1] has discussed various approaches that help in measuring the uncertainty present in the new spatial data that is created in the geoprocessing environment. The paper describes general approaches like sensitivity analysis, geostatistical simulations, fuzzy logic and the Bayesian Belief Network approach. These help in understanding and assessing the uncertainty that results from geoprocessing operations. These approaches can be easily integrated with the GIS framework that is currently available as the geoprocessing environment is flexible and can contain various tools and uncertainty and sensitivity analysis in one environment.

Geographic Information systems allow users to incorporate, examine and analyze data of different scales, different resolutions, different accuracies and different quality. It also allows the user to test the accuracy of and validate a certain set of data by Abbaspour *et al.* [2] . While the advantages of a GIS environment are many, there is also the question of what the effect of combining data from various sources is. Uncertainty comes into the picture as various levels of data are integrated. Uncertainty begins with the data that is a resultant of analysis done on remote sensing data and spatial queries carried out on that data. This uncertainty carries on to the output maps, which are then produced from the derived data.

This paper [2] provides an insight into the propagation of uncertainty and how it is to be assessed using overlay analysis. It also carries out a Monte Carlo simulation to address the problem of uncertainty. The results of both the methods are then analyzed.

Schneider [15] has deals with the study of spatial data uncertainty and its management. It also talks about how one can decrease the data uncertainty and also raise the accuracy of classification. It also looks into raising the efficiency of the data and the output so that the value of decision support can be increased. The fuzzy measurement approach is used to identify uncertainties in classification and prevents them from being transmitted to further processing stages. In those cases where the concept is not clearly defines, features are not measured and the parameters are not estimated appropriately, then fuzzy logic is relevant in such a situation. Using overlay analysis. It also carries out a Monte Carlo simulation to address the problem of uncertainty. The results of both the methods are then analyzed.

Pang [15] studies has showed how visualization can be of use when accessing and understanding large volumes of geo-spatial data. The paper especially looks at some of the challenges faced in the visualization of uncertainty, which is related to spatial data. Uncertainty is represented in various ways and therefore requires various methods for presenting it with the underlying data. The paper looks at various approaches that can be used to present uncertainty values.

Accuracy assessment of remotely sensed data is one of the most important steps of classification. Accuracy assessments help to create a quality assessment of the map produced which is useful to the end user by Congalton [17]. The accuracy of unsupervised and supervised classification is different from each other. Hasmadi *et al.* [18] focuses on carrying out both types of techniques and analyzing the differences in their accuracies. User accuracy, producer accuracy and overall accuracy were obtained for maps classified using supervised classification and unsupervised classification. Kappa statistics were also obtained for both types of methods. The result of the study showed that the supervised classification method is a more accurate technique of classification.

For the study of the project uncertainty used to quantified the final out from the CA- Markov model. Accuracy assessments to find out the error in paper classified image is formed using supervised and unsupervised classification. Error quantified by kappa statistics.

3. STUDY AREA AND DATA USED

3.1. Study Area

India is one country that is made up of a diverse set of physical, geographical, climatic and socio-economical classes. All of our population is highly dependent on the varied river systems that are present in this country. These river systems have been manipulated over the centuries to ensure the on-going success of humans. The Soil and Land Use Survey of India has classified the river systems into fourteen rivers basins. The Upper Ganga Basin is one of the fourteen and this project studies the land use land cover changes that have taken place in this area.

The river Ganges is considered a goddess and is scared to a majority of people in India. It has been a structure on which India and its civilizations have grown and prospered. The river, being highly revered by the Hindus of India, plays a fundamental role in the culture as well as the cultural history of India. The Ganga River Basin covers an area of 981,371 km^2. The river begins at the Gaumukh glacier with an elevation of 3,892m in Gangotri, a town in Uttarakhand, a northern state of India. The current study is based in the Upper Ganga Basin (UGB) which covers an area of 87,787 km^2 and is one of the main branches of the river. The UGB covers and elevation of about 7400 m as it covers elevations of 100m in the plains and goes up to 7500m in the mountainous regions. The UGB also receives a decent amount of rainfall of about 550-2500mm, most of it in the monsoons.

A census that was carried out in 2001 indicates that the average population density in the Ganga basin is 520 persons per square km, which is remarkable when compared to the national average of 312 people per square km. This means that the Ganga River Basin is a densely populated area. India saw an increase of 32% in its urban population from 1991 to 2001. This movement is most likely to keep increasing which puts even more pressure on the already pressured rivers. The increasing usage of fresh water by the industry and the urban population has led to the degradation of both water and land in this area. This is why it is extremely important to study the changing trends in land use and land cover in this delicate area.

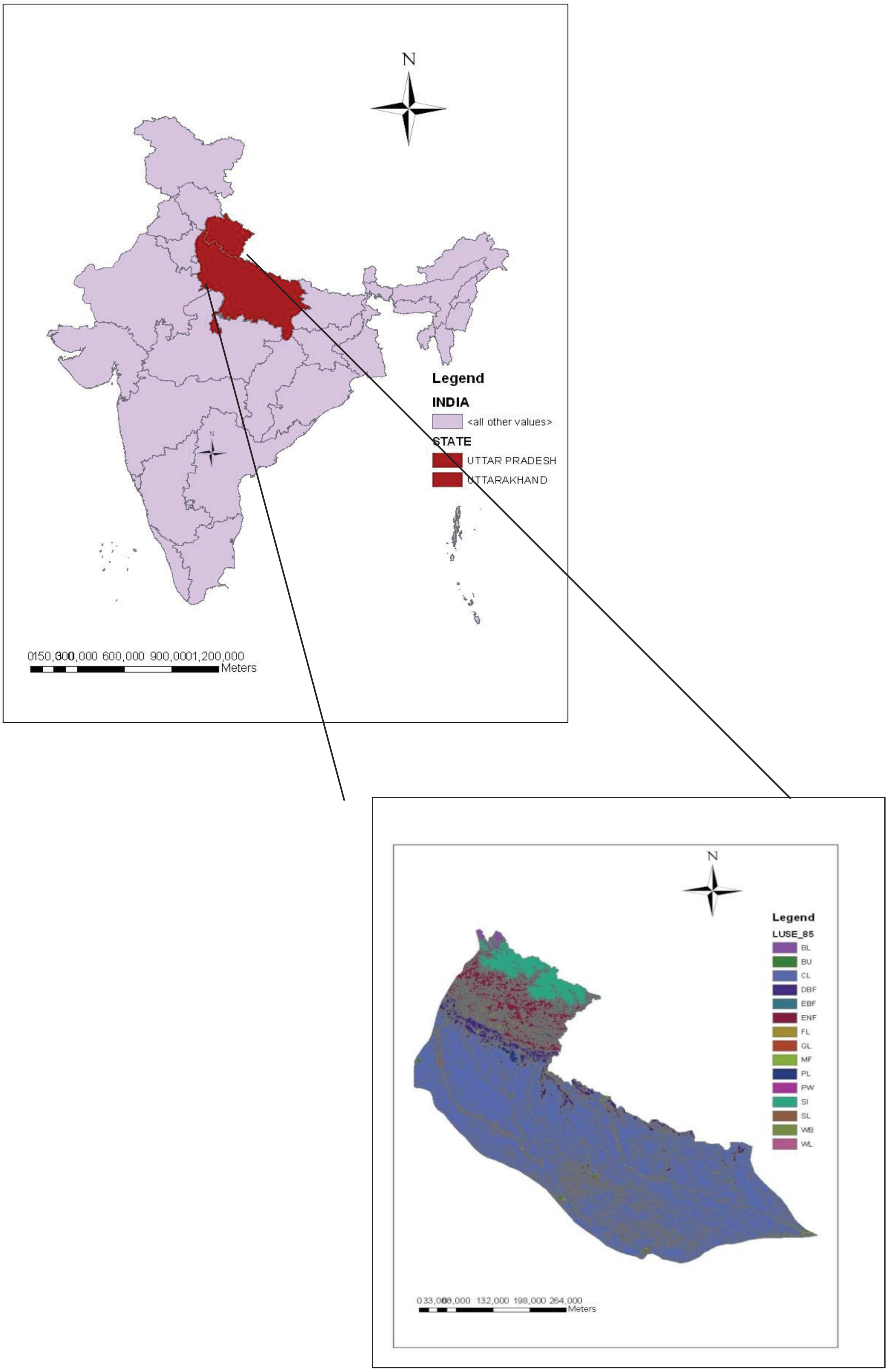


Figure 3-1: Upper Ganga Basin

3.2. LULC and Drivers data information

Land use/ land cover (LULC) change is basically a resultant of several driving factors, also known as drivers, acting in one area. These drivers may be biophysical or socio-economic factors. The following data for drivers was collected for the Upper Ganga Basin. The listed biophysical and socio-economic drivers were chosen for three time frames.

Bio Physical drivers: Rainfall, Temperature, Elevation, Slope, Drainage Network, Soil Depth

Socio- Economical drivers: Road Network**,** Population Density**,** Agricultural Work force

Biophysical drivers:

Elevation: This is a significant parameter that is needed for the accurate generation of a land use/ land cover map. The elevation data was taken from the Shuttle Radar Topographic Mission (SRTM). The data had a resolution of 90m. The downloaded data was in Arc/Grid format and it was possible to use it in Arc GIS directly. The geographic projection used, was WGS 84. Also, because for this area and timespan, the elevation of the area does not change over the years, the same SRTM data was used for the three time periods (1985, 1995 and 2005).

Slope: The percent slope was also extracted from SRTM data. The percent slope was generated in Arc MAP using the slope function.

Rainfall: The Indian Meteorological Department provided rainfall data at 1°×1° grid. For each year the total rainfall was calculated by adding the rainfall from each day of the year. The average for 1985 was calculated by averaging the rainfall for 1984 and 1985. The same was done for 1995 and 2005.

Temperature: The daily highs and lows of temperature were attained from the Indian Meteorological Department which is available at 0.5°×0.5° grid. The annual mean temperature was calculated for the year 1985, 1995 and 2005.

Soil Depth: The soil map at 1:1 million scale made by the National Bureau of Soil Survey and Land Use Planning was used for this study.

Drainage Network: Extracting the drainage layer from the LULC maps that were prepared for this project in addition to DCW (Digital Chart of the World) drainage map, generated the drainage for this project.

Socio-Economical Drivers:

Population Density: The census data for the years 1981, 1991 and 2001 was acquired from the Directorate of Census. In addition to the census the population growth rate by district was also obtained for the years 1981-1991 and 1991-2001. In areas where the growth rate was unobtainable it was estimated by looking at the pattern witnessed in areas around it. The following equation was used to estimate the population for the years 1985, 1995 and 2005.

Population of year Y= Population of year Y-1 ($\log_e{}^X$)

Where:

$\text{Log}_e = 2.17828$

$X = \text{Population growth rate}$

Road Network: Roads are vital to the sociological as well as economic development of any area. The road network information was obtained from a Survey of India toposheet of the area.

Agricultural Work Force: This work force is made of the people that work in the agricultural fields. A census showing the number of people working in the fields in each taluka was used to generate the agricultural work force.

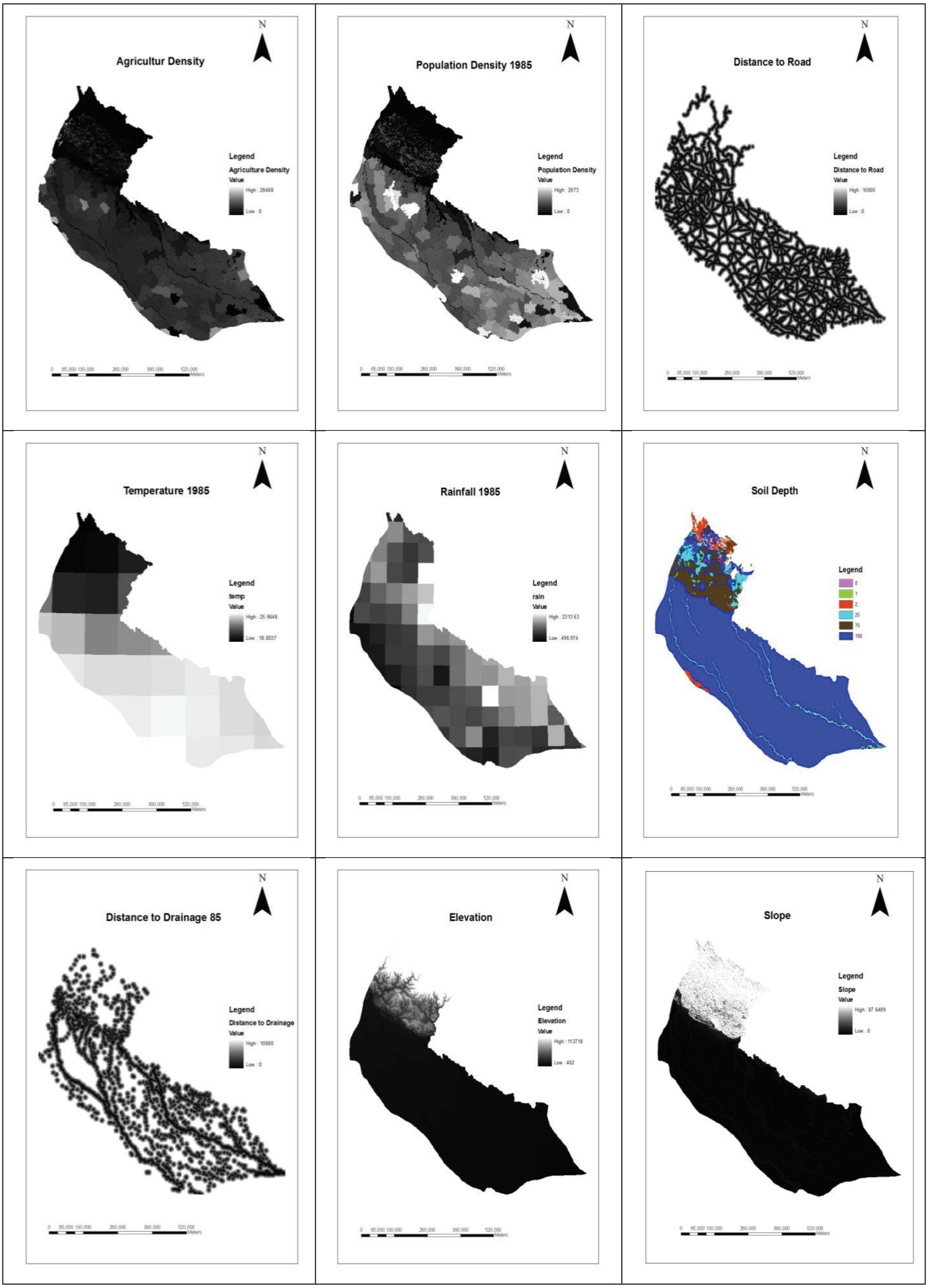


Figure 3-2 Driver Data set

One portion of this study was to also obtain a land use/ land cover map for the UGB for years 1985, 1995 and 2005. The LULC maps were obtained from the IGBP and therefore the classification was in accordance with the classification scheme of the ISRO Geosphere Biosphere Project (IGBP).Cloud free images of satellite data such as LANDSAT MSS (1985), LISS I (1995) and LISS III (2005) were used to generate these land use/land cover maps at a scale of 1:250,000. A total of fifteen land use/ land cover classes were interpreted from the images. The final classes were Built Up (BU) area, Barren Land (BL), Crop Land (CL), Mixed Forest (MF), Ever Green Dense Forest (EDF), Ever Green Needle Forest (ENF), Deciduous Broad Leaf Forest (DBF), Wet Land (WL), Scrub Land (SL), Water Body (WB), Snow and Ice (SI), Grassland (GL) and Permanent Wet Land.(PW).

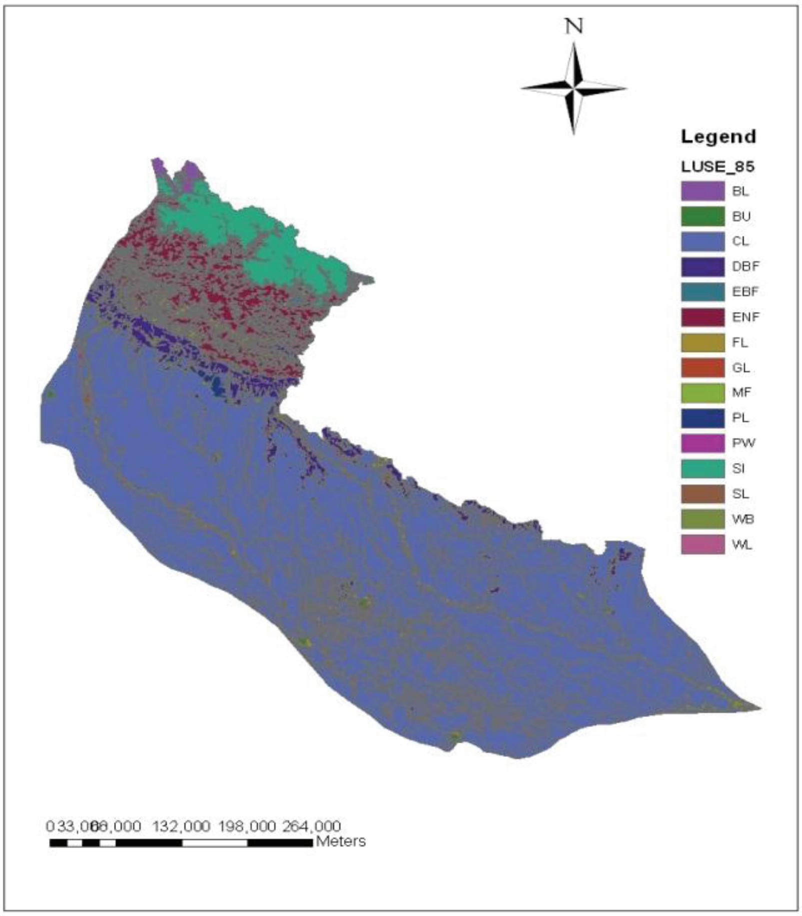


Figure 3-3 LULC Map of Year 1985

4. METHODOLOGY

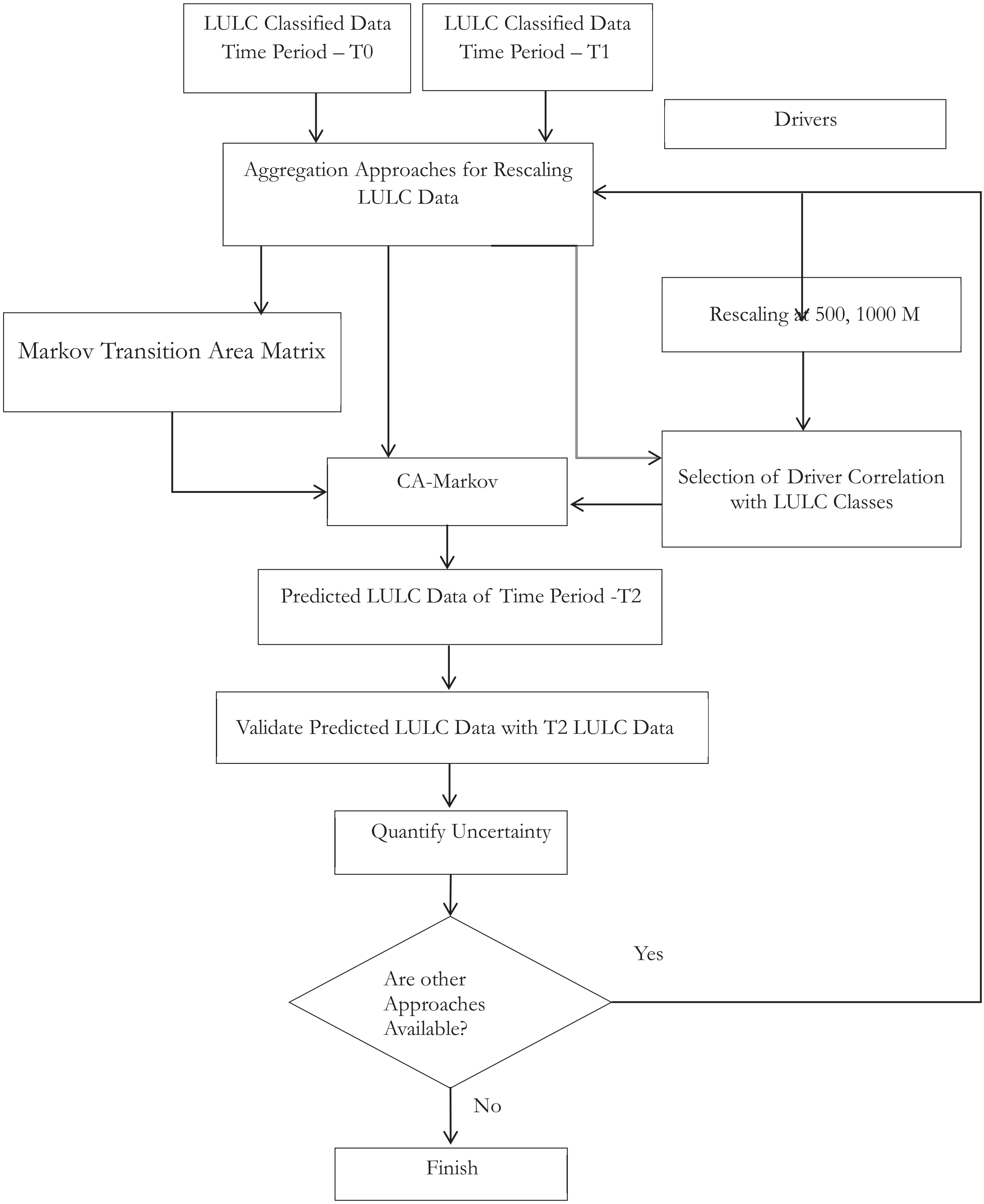


Figure 4-1 Methodology

4.1. Description of Methodology

1) The methodology above shows that the LULC vector datasets of two time periods (1985 and 1995) used for change detection. These datasets are available at 1:250000 scale.

2) The driver dataset is also available for different time periods and different scales (e.g. rainfall, population, temperature, slope, road network, canal network). Data scale at 500, 1000 m.

3) For the LULC change analysis, LULC and driver datasets need to have the same scale. Therefore in the project different aggregation approaches were used (e.g. Feature to raster, Random Rule based, Major Rule Based) in order to convert the LULC dataset to thematic raster datasets with a resolution of 500 and 1000 m. In this case grid resolutions of 500 and 1000 m have been taken to preserve features (e.g. polygon, line) of the driver dataset because the driver datasets are not available at the fine resolution. In aggregation one has to aggregate to the coarsest resolution of the input data so that there is an aggregated set of data that has maximum information content and a minimum amount of introduced noise. This is because noise increases as the resolution gets finer due to larger amounts of detail.

4) The selection of the driver datasets which are important for LULC change was based on logistic regression analysis with LULC dataset (1985, 1995, and 2005). The regression assessed the correlation between independent drivers with LULC classes. For the change analysis those drivers which have high significance with LULC classes were selected.

5) A Markov Transition Area Matrix is created in order to identify how many classes change to other classes from 1985 to 1995.

6) For the prediction of the year 2005, LULC map was used in IDRISI software, which consists of the CA-Markov model. CA-Markov is a powerful model for predicting the LULC change map in time and space. CA-Markov has considered LULC dataset of two years (1985 and 1995), driving factor of the LULC change and the Markov transition area matrix.

7) For the validation of the predicted 2005 LULC change map, the study used the available 2005 LULC vector dataset of the IGBP project. It then quantified the uncertainty in the final LULC change map. Uncertainty due to the different aggregation techniques is also calculated in final LULC change map.

8) The project modeled Overall uncertainty to be calculated for the final LULC change map. These procedures identified how much the uncertainty of driver and LULC datasets affects the overall accuracy of LULC change map.

The purpose of this project is to study the drivers that bring about changes in land use/land cover. The project also focuses on the scale of the change that takes place in the long term in the study area and to display the resultant output of these changes. The result of these changes is an output map depicting those areas where change takes place. It also looks at the various aggregation and modeling methods that are applied in order to predict this change.

4.2. Land Cover Change Detection Analysis

Change detection is a method by which the process of changes that occur in land cover, over a certain number of years, can be observed [19]. Class-level metrics like transition matrix were taken into account in order to carry out the change detection. These metrics are incorporated with patches of different classes. The number of patches of a certain class represent the extent of the class and they also display the fragmentation of that has occurred in that class.

4.3. Stochastic Markov Model

The Markov chain is the simplest Markov model. It simulates the condition of a system using a random variable. This random variable transforms over time. This type of model combines the process of Markov modeling with stochastic modeling[20] . This hybrid model allows for predictive modeling. The user must have knowledge about the trend of past land cover changes in the area. In this process the condition of a particular area at a certain (t+1) depends on the condition of that area at time t [21].

Markov Transition Probabilities:

$$P(\xi_{t+1} = s_j | \xi_t = s_j) \tag{1}$$

Transition matrix (n×n) of the markov chain process

$$P = \begin{bmatrix} p_{11} & \dots\dots & p_{1n} \\ \dots\dots & \dots\dots & \dots\dots \\ p_{n1} & \dots\dots & p_{nn} \end{bmatrix}, p_{ij} \geq 0, \sum_{j=1}^{n} p_{ij} = 1, i = 1, \dots\dots, \tag{2}$$

Where P is the probability matrix of n states
p_{ij} is the transition probability of state i to j

The probability of future states of a cell can be calculated by equation (3)

$$p(t) = p(t-1).p \tag{3}$$

By increasing the time steps of the Markov process, *p(t)* approaches to the constant probability vector which is known as the limiting distribution [22] .

$$p(\infty) = \lim_{t\to\infty} \; p(t) = \lim_{t\to\infty} p(0).P^t \tag{4}$$

4.4. Cellular Automata Markov Model

The CA-Markov is a stochastic model, which is used quite frequently in assessing change in a particular area or system. CA models are spatial models where the basis of the model is the cell. This cell is influenced by its neighboring cells and is able to adopt various states. An advantage of the CA is that it can be integrated with GIS software quite easily[26]. Markov on the other hand is used for assessing the impacts certain policies have on the land. It is useful in the projection of 'the equilibrium land use vector' and can also help predict the land use changes that may take place in the future. The CA-Markov model is adaptable and realistic which is why it is extremely useful when looking are changes in land cover due to urbanization and is commonly used in such studies.

This model is a hybrid of the cellular automata (CA) and the Markov chain. As defined by Wolfram [23] the CA is basically a model that uses mathematical processes to model physical structures. In these physical systems time and space are separate.

The Cellular Automata comprises of the physical space characterized by cells and this is where the mechanism of CA occurs[24]. It also comprises of a cell in which the CA mechanism inhabits, the neighborhood that surrounds this cell, rules of transition that define the performance of the CA and the time-based space in which the entire mechanism exists [25].

Mathematical Notation of CA

$$s^{t+1} = f(s^t, N) \tag{5}$$

Where S = the set of all possible states of CA

N = neighborhood of all cells

f = transition function that defines the change from t to t+1

Simulation with Cellular Automata Markov Model (CA Markov)

The CA Markov uses a contiguity filter, which is defined by the user. It integrates the suitability image of the classes and these are then input into the model. The Markov model uses the contiguity rule pixel and applies it to a certain land cover class, which will in most probability remain the same land cover class as before. This project has used a filter (mean contiguity 5 x 5) for modeling purposes. This filter was then applied on the suitability images for each LULC class. This process outlined the neighborhood. This 5 x 5 filtering window determines the suitability of a pixel. The higher the number of pixels with the same class in the same neighborhood, the higher is the suitability value of that land cover class in that area. If the pixel is of another class it remains the same as it was before. Suitability maps help in defining those pixels, which will change depending on the highest suitability of each LULC class. Suitability of a pixel increases the likelihood of change in neighboring pixels into the same class as the original pixel.

4.5. Categorical aggregation approach

For the aggregation of the LULC map this study used Random Rule based and Major Rule based approach. The RRB is also one type of aggregation method, applied on images with a fine resolution in order to coarsen the resolution of the image. The RRB technique is basically a process that that randomly selects a class from the input grid. It then comes up with different understandings of the image. A class that is randomly selected is then allocated to the aggregated pixel. The MRB aggregation approach selects the majority class in the input grid and assigns this to the output grid. For this current project a code for applying MRB and RRB has been developed in the software R. The first step is to load the classified image in R on which the work needs to be done R accepts this image in ASCII format and produces an output image at the desired level of aggregation in ASCII format t

Random Rule Based Approach:

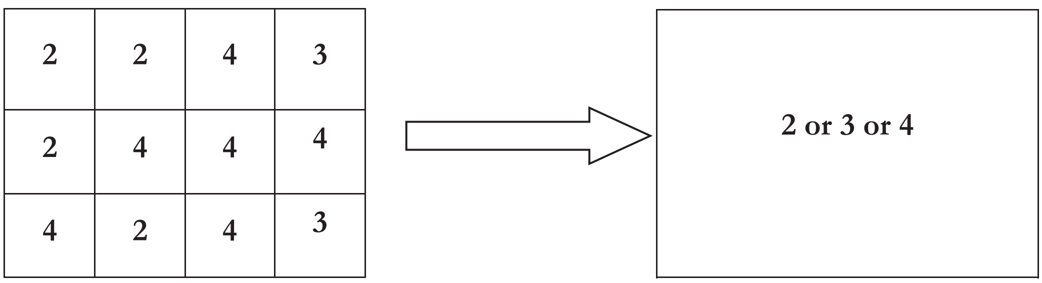


Figure 4-2 Random Rule based Approach

Major Rule Based Approach:

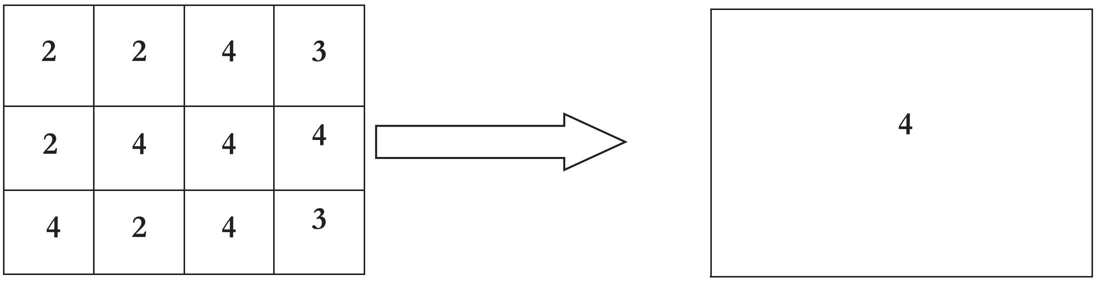


Figure 4-3 Major Rule based Approach:

4.6. Logistic Regression

In order to find the relationship between the driver and the LULC classes, logistic regression is used. In logistic regression, the dependent variable should be binary (0 or 1) and the independent variables can be categorical or continuous, for example soil depth varies with different classes and elevation [26]. Studying spatial analysis found that the result occurs in the categorical form e.g. pass or fail. Such results are in the form of logistic regression. In the logistic regression model fit analysis, has performed on the basis of AIC (Akaike's information Criterion) value[28]. AIC is way to select the best statistical model. According to the AIC value driver selection was performed. Assumption of the model is probability of the dependent variable, which is the flow the curve between 0 and 1. Probability shows at below equation

$$P(y = 1|X) = \frac{\exp(\sum BX)}{1+\exp(\sum BX)} \tag{6}$$

Where P is probability of dependent variable with value 1

X is dependent variable

B is estimated parameter

To linearize eq. (6) of logistic regression model and to remove 1 and 0 from the dependent variable, following transformation model is used

$$P' = \ln\left(\frac{P}{(1-P)}\right) \tag{7}$$

The transformation known as the logit transformation assumes values between $+\infty$ to $-\infty$. Logit transformation changes binary data to continuous data. The predicted probability is continuous within the range of 0-1

$$P' = \ln\left(\frac{P}{(1-P)}\right) = b_0 + b_1 x_1 + b_2 x_2 + \cdots + b_k x_k + \varepsilon \qquad (8)$$

Where P' is logit transformation
x is dependent variable
b is estimated parameter (coefficient)

4.7. Uncertainty Measure

Remotely sensed images can be classified in numerous ways. There are two types of classification techniques, which are mainly used, supervised classification and unsupervised classification. A vital part of classifying remotely sensed data is accuracy assessment. For this study the accuracy assessment is performed for the predicted land use image of 2005. The output map's quality, which is what, makes the map useful for the end user. Land use is images predicted using MRB and RRB aggregation approach.

The output maps are then assessed for accuracy. This assessment of accuracy helps to validate the results and is a warranty of the quality of the classification done[29]. An error matrix is generated in order to carry out accuracy assessment on the output maps. The error matrix displays information on the predicted, classified output map as well as the actual map of the same study area. The classified pixel is then compared to the actual map. The result of the accuracy assessment provides the user with an overall accuracy as well as the accuracy of each class. The formula defined below is the one that is used for assessing overall accuracy:

$$\text{Overall accuracy} = \frac{\text{Total number of correct sample}}{\text{Total number of samples}} \text{ X } 100\ \% \qquad (9)$$

Other than over all accuracy the classification accuracy of the various classes was also computed. Two methods for assessing accuracy were user's and producer's accuracy. The producer's accuracy taking the correct pixels of a class and then dividing them by the total pixels compute. This type of accuracy evaluates the quality of the classification that has been carried out. It also calculates the error of omission. Error of omission is basically those features on the surface of the study area that have not been classified. Taking those pixels that have been classified correctly in a certain class and dividing them by the total number of those pixels that were classified overall in that class define User's accuracy. User's accuracy also computes commission error, which is the probability of a pixel belonging to the class that it has been classified under.

The formula below defines user's and producer's accuracy:

Producer's accuracy (%) = 100% - error of omission (%)

User's accuracy (%) = 100% - error of commission (%)

Another measurement that has been used in this study is the Kappa coefficient (K). The value of kappa varies between 0 and 1. Value 1 means that classes of two different data set are the same and it is classified 100% accurately and 0 means classes are not same, it has 0% classification accuracy. The Kappa statistic is calculated on confusion matrix, which represents the one land use map in *i* row and other land use map in *j* column. Diagonal of the matrix show the both land use map have same classes. Kappa statistic K is calculated by this formula (10):

$$k = \frac{\theta_1 - \theta_2}{1 - \theta_2} \qquad (10)$$

$$\theta_1 = \frac{\sum_{i=1}^{n} X_{ij}}{N}, \theta_2 = \frac{\sum_{i=1}^{n} X_{i+} X_{+i}}{N^2} \qquad (11)$$

Where,
X_{ij}= count of ij_{th} cell
N = total count in confusion matrix
X_{i+}= marginal total of row i
X_{+i}= marginal total of column i

5. RESULT AND DISCUSSION

Land use Land cover change modeling was performed for the years 1995 to 2005. CA-Markov model was used to predict the land use cover change in the Upper Ganga Basin area. LULC modeling has been performed for two scales 500 and 1000 in MRB and RRB Approach. To assess the amount of change in land use, the 9 drivers and the LULC map that was generated were integrated.

Table 5-1 Land Use Change in year 1985 -1995 at 500 Scale MRB

Class Name	1985	1995	Change
BU	85075	141975	56900
CL	13929600	13904650	-24950
FL	562950	519025	-43925
PL	178525	185675	7150
ENF	1458550	1457925	-625
EDF	32650	32550	-100
DBF	883775	885025	1250
MF	92900	91750	-1150
SL	530975	629550	98575
GL	89500	119425	29925
PW	107850	116925	9075
BL	190875	493725	302850
WL	228550	246000	17450
WB	419450	389025	-30425
SI	1038375	616375	-422000

Table 5-1 shows that crop land (CL), fallow land (FL), snow and ice (SI), water body (WB) and. mixed forest (MF), Ever Green Dense Forest (EDF), Ever Green Needle Forest (ENF) have decreased. built up (BU), scrub land (SL), barren land (BL), grass land (GL), wet land (WL) and permanent wet land (PW), deciduous broad leaf forest (DBF) have increased. More change occurred in BL class and SI class. Small change occurred in forest area of the UGB.

Table 5-2 Land Use Change in year 1995 -2005 at 500 Scale MRB

Class Name	1995	2005	Change
BU	141975	167025	25050
CL	13904650	13904675	25
FL	519025	484100	-34925
PL	185675	185250	-425
ENF	1457925	1455775	-2150
EDF	32550	32475	-75
DBF	885025	883700	-1325
MF	91750	89925	-1825
SL	629550	609025	-20525
GL	119425	125450	6025
PW	116925	124075	7150
BL	493725	414100	-79625
WL	246000	249500	3500
WB	389025	363700	-25325
SI	616375	737400	121025

Table 5-2 shows that FL, PL, ENF, EDF, MF, WB and SL have decreased. BU, GL, WL, PW, WL, SI have increased in area from 1995 to 2005. CL has increased and more change occurred in SI and BL area.

Table 5-3 Land Use Change in year 1985 -1995 at 500 Scale RRB

Class Name	1985	1995	Change
BU	86150	143450	57300
CL	13831025	13791225	-39800
FL	569850	530275	-39575
PL	180350	190075	9725
ENF	1439250	1435925	-3325
EDF	32900	32575	-325
DBF	873825	871100	-2725
MF	95700	91850	-3850
SL	539675	642725	103050
GL	90250	119475	29225
PW	113150	125250	12100
BL	192650	495175	302525
WL	238350	257650	19300
WB	504275	478600	-25675
SI	1031750	613800	-417950

Table 5-3 shows that CL, FL, SI, WB have decreased, while BU, SL, BL, GL, WL, PW have increased. All forest area decreases in the duration of 1985-1995

Table 5-4 Land Use Change in year 1995 -2005 at 500 Scale RRB

Class Name	1995	2005	Change
BU	143450	169800	26350
CL	13791225	13788525	-2700
FL	530275	493025	-37250
PL	190075	187450	-2625
ENF	1435925	1441375	5450
EDF	32575	32275	-300
DBF	871100	871475	375
MF	91850	90925	-925
SL	642725	619725	-23000
GL	119475	125125	5650
PW	125250	130200	4950
BL	495175	414850	-80325
WL	257650	259475	1825
WB	478600	455225	-23375
SI	613800	733425	119625

Table 5-4 shows that CL, FL, PL, MF, WB, SL and BL have decreased, while BU, ENF, GL, WL, PW, WL and SI have increased.

Table 5-5 Land Use Change in year 1985 -1995 at 1000 Scale MRB

Class Name	1985	1995	Change
BU	71400	130700	59300
CL	14136000	14120200	-15800
FL	514200	470100	-44100
PL	168100	172100	4000
ENF	1513600	1512700	-900
EDF	33500	33300	-200
DBF	904200	903700	-500
MF	83600	82600	-1000
SL	465500	558900	93400
GL	85100	115400	30300
PW	78800	84000	5200
BL	185100	493200	308100
WL	178400	194300	15900
WB	331200	302400	-28800
SI	1041900	617000	-424900

Table 5-5 shows that CL, FL, SI, WB have decreased between 1985 and 1995, while BU, SL, BL, GL, WL, PW have increased. All forest area has decreased.

Table 5-6 Land Use Change in year 1995 -2005 at 1000 Scale MRB

Class Name	1995	2005	Change
BU	130700	153000	22300
CL	14120200	14117600	-2600
FL	470100	438300	-31800
PL	172100	168800	-3300
ENF	1512700	1506500	-6200
EDF	33300	33300	0
DBF	903700	884500	-19200
MF	82600	80600	-2000
SL	558900	538000	-20900
GL	115400	119600	4200
PW	84000	88000	4000
BL	493200	403000	-90200
WL	194300	198300	4000
WB	302400	275700	-26700
SI	617000	725100	108100

Table 5-6 shows that CL, FL, PL, ENF, MF, WB, SL and BL have decreased, while BU, GL, WL, PW, WL, SI have increase

Table 5-7 Land Use Change in year 1985 1995 at 1000 Scale RRB

Class Name	1985	1995	Change
BU	88900	143400	54500
CL	13788000	13765200	-22800
FL	574200	528900	-45300
PL	182000	186800	4800
ENF	1436600	1438200	1600
EDF	32400	32600	200
DBF	872500	873000	500
MF	91000	92200	1200
SL	542400	637600	95200
GL	88000	118100	30100
PW	111100	127000	15900
BL	193500	495400	301900
WL	232400	255700	23300
WB	508300	463900	-44400
SI	1029100	612400	-416700

Table 5-7 shows that CL, FL, SI and WB have decreased, other class in this approach showing increasing trend. More area of BL has increased

Table 5-8 Land Use Change in year 1995-2005 at 1000 Scale RRB

Class Name	1995	2005	Change
BU	143400	173100	29700
CL	13765200	13745700	-19500
FL	528900	497600	-31300
PL	186800	188600	1800
ENF	1438200	1439400	1200
EDF	32600	31400	-1200
DBF	873000	855900	-17100
MF	92200	90200	-2000
SL	637600	621100	-16500
GL	118100	124000	5900
PW	127000	129300	2300
BL	495400	407400	-88000
WL	255700	264900	9200
WB	463900	455100	-8800
SI	612400	720700	108300

Table 5-8 shows that CL, FL, SL, DBF, BL, MF and WB have decreased, while BU, GL, WL, PW, WL, SI increased.

5.1. User and Producer Accuracy at Different Scale

Table 5-9 User and Producer Accuracy at Different Scale

	500 MRB		500 RRB		1000 MRB		1000 RRB	
Classes	User's Accuracy (%)	Producer' Accuracy (%)	User's Accuracy (%)	Producer' Accuracy (%)	User's Accuracy (%)	Producer' Accuracy (%)	User's Accuracy (%)	Producer' Accuracy (%)
BU	92.84	79.16	84.64	72.22	59.02	52.61	55.47	42.46
CL	98.39	98.12	97.14	95.63	94.94	94.03	92.53	92.01
FL	71.61	81.34	58.34	71.99	37.42	45.86	33.59	38.91
PL	91.8	91.82	79.25	84.49	61.62	61.91	56.57	57.32
ENF	96.55	96.32	91.13	90.89	79.06	78.89	74.61	75.85
EDF	92.82	92.53	79.29	84.82	58.46	59.16	52.24	55.73
DBF	97.47	97.29	93.34	93.34	83.89	85.35	79.94	81.9
MF	89.22	91.33	77.93	76.88	39.88	39.83	36.05	38.25
SL	72.39	74.64	59.86	63.62	29.72	30.82	29.3	28.95
GL	79.2	74.65	69.37	65.87	49.16	46.32	45.72	39.6
PW	82.8	78.78	61.61	68.59	27.72	26.93	25.12	25.14
BL	54.16	38.9	49.81	35.51	47.7	35.26	46.21	31
WL	84.07	82.03	66.9	69.27	28.64	27.28	29.03	27.9
WB	64.34	72.86	49.97	61.04	38.62	47.73	28.1	31.49
SI	74.25	81.17	70.53	77.83	71.77	79.64	68.81	78.24

Table 5-9 Shows the Producer's and User's Accuracy of the predicted map at 500, 1000 MRB, RRB scale. This accuracy calculated from the Transition Matrix, which generated from difference between predicted and reference map

Table 5-10 Change between predicted LULC map and reference map of 2005 at scale 500 MRB

Class Name	Predicted 2005	Reference 2005	Change
BU	142425	167025	24600
CL	13866700	13904675	37975
FL	549925	484100	-65825
PL	185300	185250	-50
ENF	1452300	1455775	3475
EDF	32375	32475	100
DBF	882025	883700	1675
MF	92050	89925	-2125
SL	627925	609025	-18900
GL	118250	125450	7200
PW	118050	124075	6025
BL	297475	414100	116625
WL	243450	249500	6050
WB	411850	363700	-48150
SI	806075	737400	-68675

Table 5-10 shows a comparison between the LULC predicted map and the reference LULC map of 2005. Negative change shows the predicted class cover large as compare to reference map. SI and BL class both are reverse when SI high then BL covers less area. From Table 5-9 producer and accuracy less as compare to other class that more error in prediction of BL class.

Table 5-11 Change between predicted LULC map and reference map of 2005 at scale 500 RRB

Class Name	Predicted 2005	Reference 2005	Change
BU	144875	169800	24925
CL	13574250	13788525	214275
FL	608375	493025	-115350
PL	199850	187450	-12400
ENF	1437600	1441375	3775
EDF	34525	32275	-2250
DBF	871425	871475	50
MF	89700	90925	1225
SL	658725	619725	-39000
GL	118825	125125	6300
PW	144950	130200	-14750
BL	295775	414850	119075
WL	268675	259475	-9200
WB	556025	455225	-100800
SI	809300	733425	-75875

Table 5-11show that FL ,WB,SL,SI have cover large area as compare to other classes it means these class have more error. Table 5- 9 RRB approach found that BL and WB both have less producer and user accuracy.

5.2. Predcited Map of Year 2005

Predicted Map of LULC 2005 at scale of 500 with MRB and RRB approach

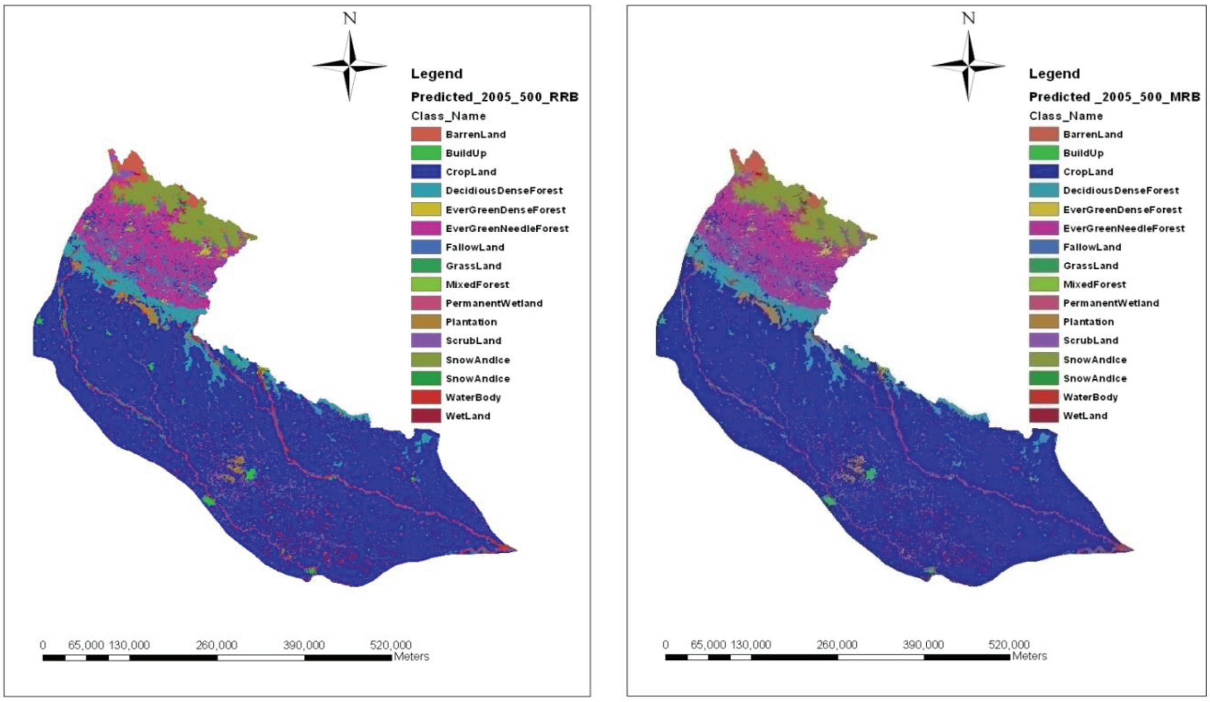


Figure 5-1 Predicted Map of LULC 2005 at scale of 500 with MRB and RRB approach

Table 5-12 Kappa Values

Scale	MRB	RRB
500	0.8744	0.7991
1000	0.6910	0.6259

The maps above show the predicted map of year 2005 at scale of 500m by applying the MRB and RRB approach, Kappa coefficient value of predicted map mentioned in the Table 5-12. As per kappa value is high for the MRB approach.

Table 5-13 Change between predicted LULC map and reference map of 2005 at scale 1000 MRB

Class Name	Predicted 2005	Reference 2005	Change
BU	136400	153000	16600
CL	13981300	14117600	136300
FL	537200	438300	-98900
PL	169600	168800	-800
ENF	1503300	1506500	3200
EDF	33700	33300	-400
DBF	899900	884500	-15400
MF	80500	80600	100
SL	557900	538000	-19900
GL	112700	119600	6900
PW	85500	88000	2500
BL	297900	403000	105100
WL	188900	198300	9400
WB	340800	275700	-65100
SI	804700	725100	-79600

Table 5-13 show that change in area in predicted map. In which some classes cover more or less as compare are form other classes. FL, SI, WB predicted more and PW, BL, MF predicted less. From Table 5-9 PW and SL have the less accuracy.

Table 5-14 Change between predicted LULC map and reference map of 2005 at scale 1000 RRB

Class Name	Predicted 2005	Reference 2005	Change
BU	132500	173100	40600
CL	13667400	13745700	78300
FL	576300	497600	-78700
PL	191100	188600	-2500
ENF	1463300	1439400	-23900
EDF	33500	31400	-2100
DBF	876900	855900	-21000
MF	95700	90200	-5500
SL	613600	621100	7500
GL	107400	124000	16600
PW	129400	129300	-100
BL	273300	407400	134100
WL	254600	264900	10300
WB	509900	455100	-54800
SI	819500	720700	-98800

Table 5-14 shows that all forest has predicted more as per reference map. WB, SI, FL also cover more area in prediction. Form Table 5-9 SL, WL, WB have less producer and user accuracy.

Predicted Map of LULC 2005 at scale of 1000 with MRB and RRB approach

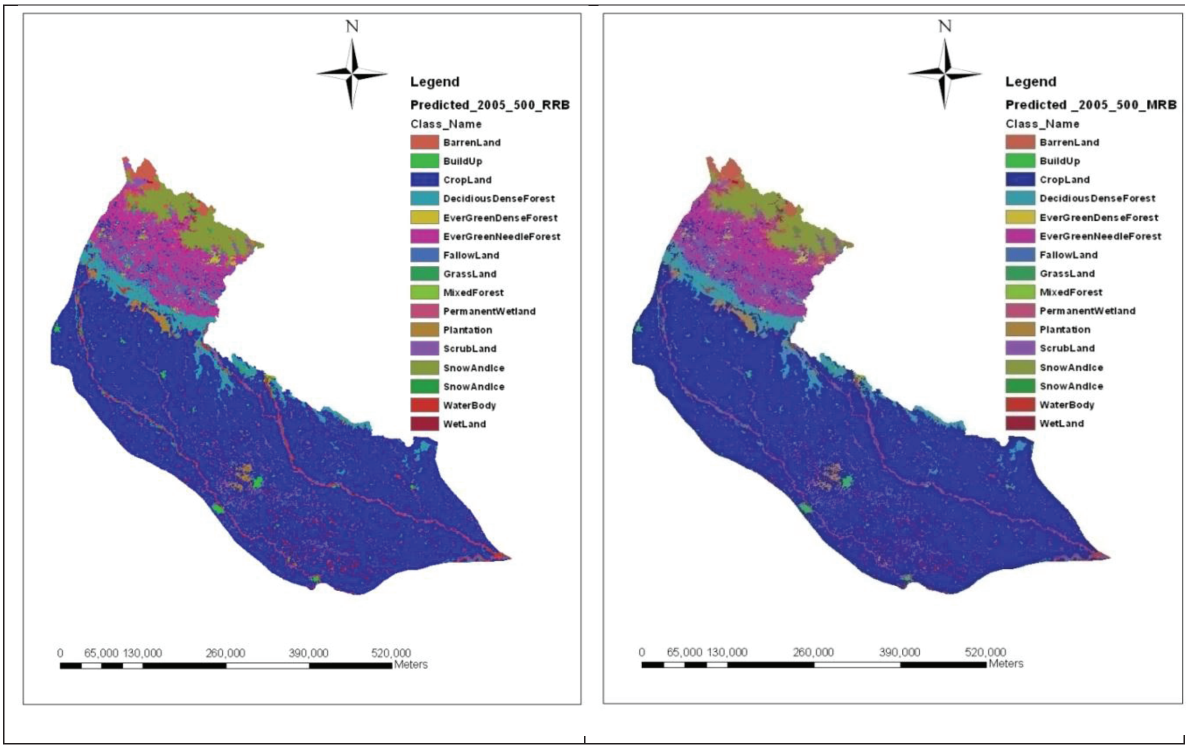


Figure 5-2 Predicted Map of LULC 2005 at scale of 1000 with MRB and RRB approach

Figure 5-2 maps show the predicted map of year 2005 at scale of 1000m by applying the MRB and RRB approach, Kappa coefficient value of predicted map mentioned in the a Table 5-12 kappa value for MRB approach is more than the RRB approach.

5.3. Error in Maps

Overall Error in Predicted Map

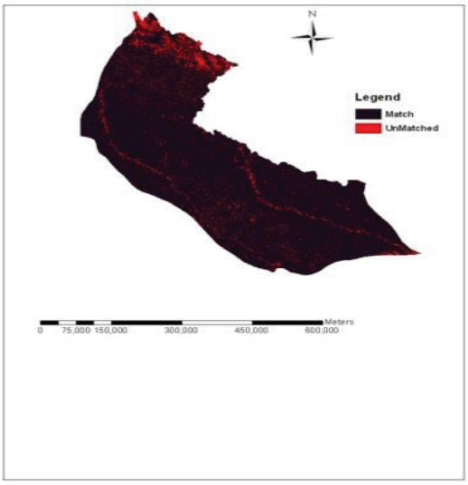


Figure 5-3 Unmatched at 500MRB

Moran's Index:	0.22
z-score:	2016.47

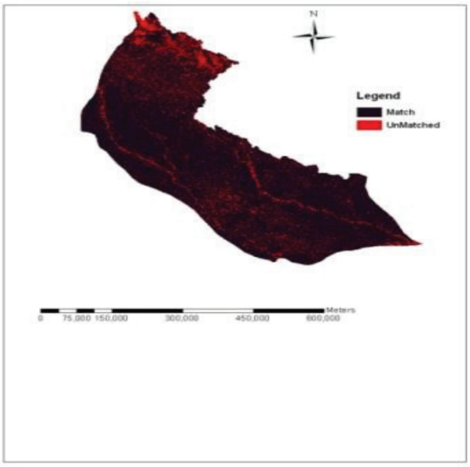


Figure 5-4 Unmatched at 500RRB

Moran's Index:	0.19
z-score:	1690.53

Figure 5-3, 5-4 shows match and unmatched of the class in prediction at scale 500m in MRB and RBB approach. It shows the overall where the classes are predicted wrong. As Form the map sees that more error in RRB approach.

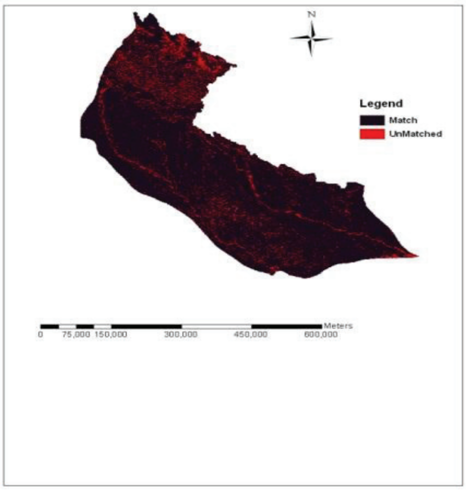


Figure 5-5 Unmatched at 1000 MRB

Moran's Index:	0.14
z-score:	347.4538

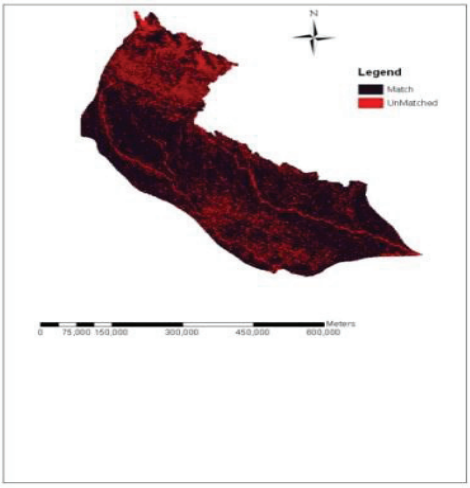


Figure 5-6 Unmatched at 1000 RRB

Moran's Index:	0.19
z-score:	1690.53

Figure 5-5, 5-6 shows match and unmatched of the class in prediction at scale 1000m in MRB and RBB approach. It shows the overall, where the classes are predicted wrong. As from the map see more error in RRB approaches.

Corresponding table show the calculated Moran Index value to check autocorrelation in area. As from the Figure 5-3 to 5-6 there is spatial pattern in matched and unmatched class. Hill part of UGB area have most unmatched area and Where class is SI and WB. In the Figure 5-3 to 5-6 red colour show the predicted class that are error.

Error in Predicted Map with LULC Classes:

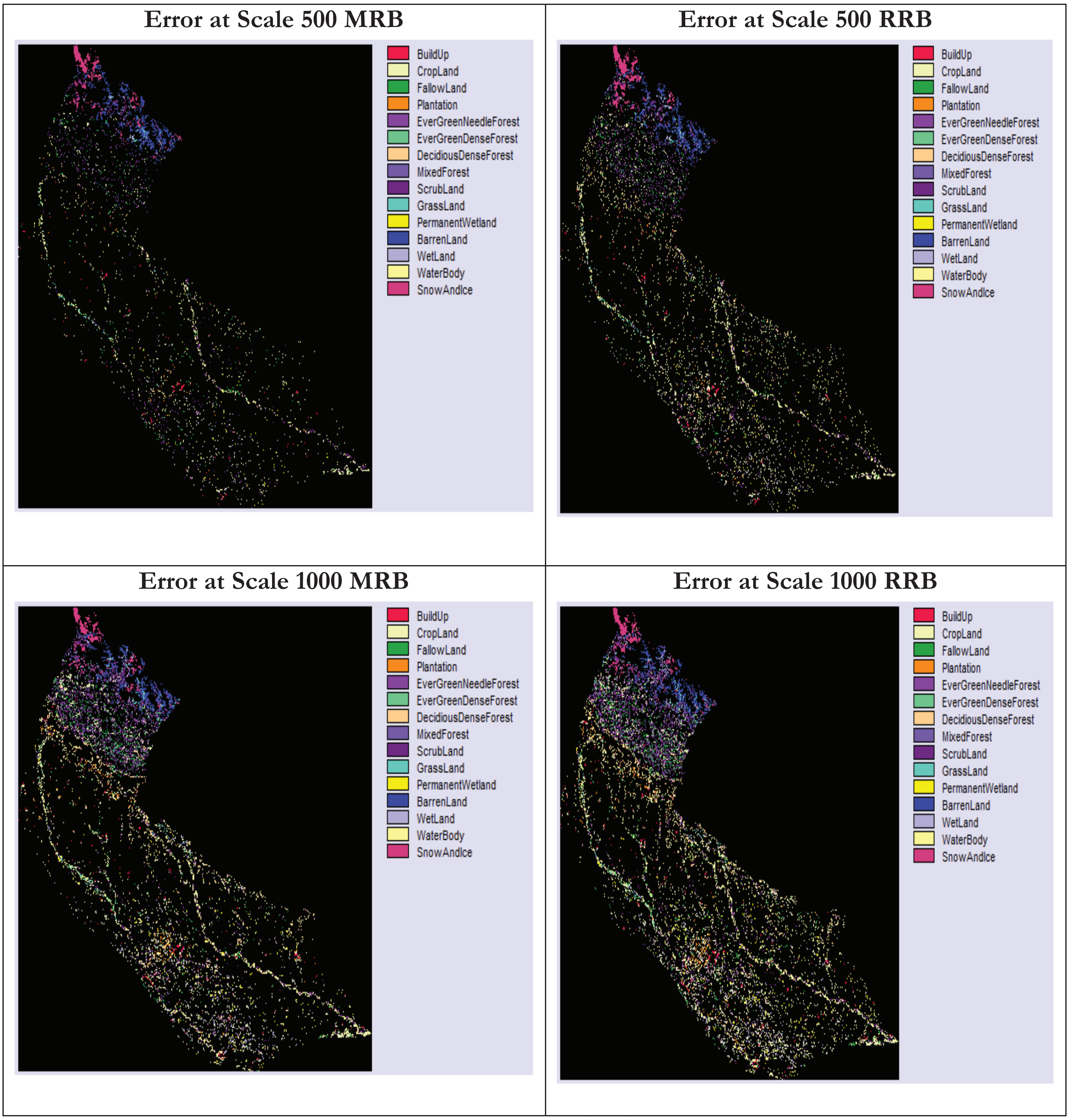


Figure 5-7 Class Error in Predicted image

5.4. Driver Relationship with LULC Classes

Table 5-15 Influenced Driver

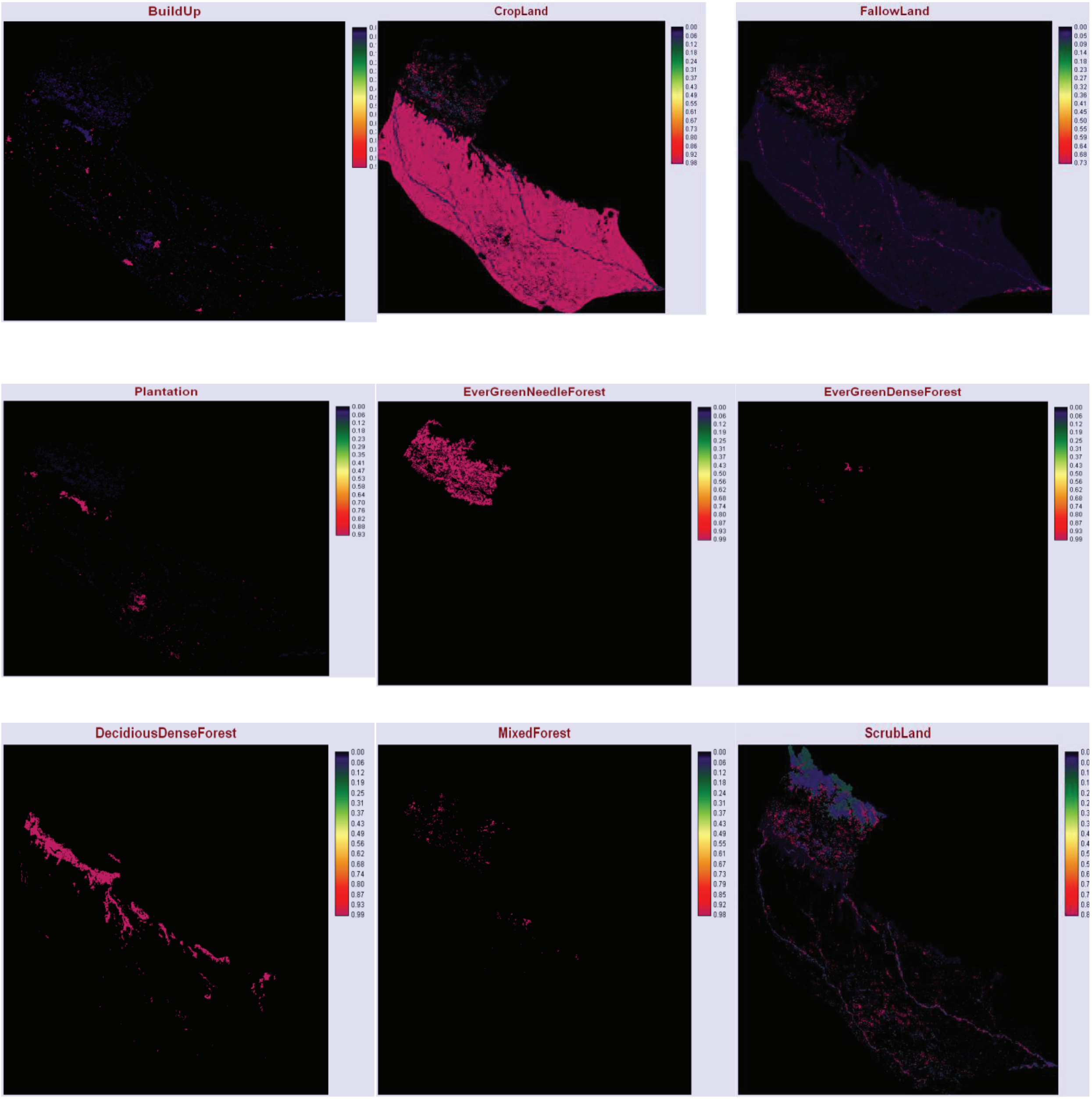
At scale 500 _MRB	
1985	ALD, Pop den ,Slope, Rain
1995	ALD, DTD, Slope, SD, Rain
At scale 500 _RRB	
1985	ALD, Pop den, Slope, SD, Rain
1995	ALD, DTR , Slope, SD, Rain
At scale 1000 MRB	
1985	ALD, Pop den , Slope, SD, Rain
1995	ALD, DTR, Slope, SD, Rain
At scale 1000 RRB	
1985	ALD , Pop den, Slope, SD, Rain
1995	ALD, Pop den, Slope, SD, Rain

The Table 5-15 above displays the influence of the driver in that particular year 1985 and 1995. It is found that in year 1995 and 1985 agriculture density (ALD), population density (Pop den), slope (Slope), rainfall (Rain), soil depth (SD) most influenced the land use classes. As per logistic regression model fitting between driver and LULC class, only those drivers selected which have low AIC value, Driver selection performed for both scale MRB and RRB approach, to see relationship between driver and LULC classes as per using different method.

As per Table 5-15 see not change in relation between driver and LULC as scale changes. Every year driver play different role, Such as bio physical driver temperature, rain fall. If rainfall high in the year that means increase in crop land, grass land. Slop is high then it affects the development of the builtup area, population density also reduces as elevation is increases. Soil depth affect cropland area, high soil depth has capability to storage the rainfall water, Soil depth is more agriculture will more. UGB has well stabilized drainage network so agricultural practices growing in this region. As per classes driver selected show in Appendix, Table A17 for built up area soil depth, rainfall, slope, temperature, and elevation are selected as per the AIC value.

5.5. Suitablity Map

Below image shows the suitability map of the classes, which shows the probability of each class is varies between 0 and 1.



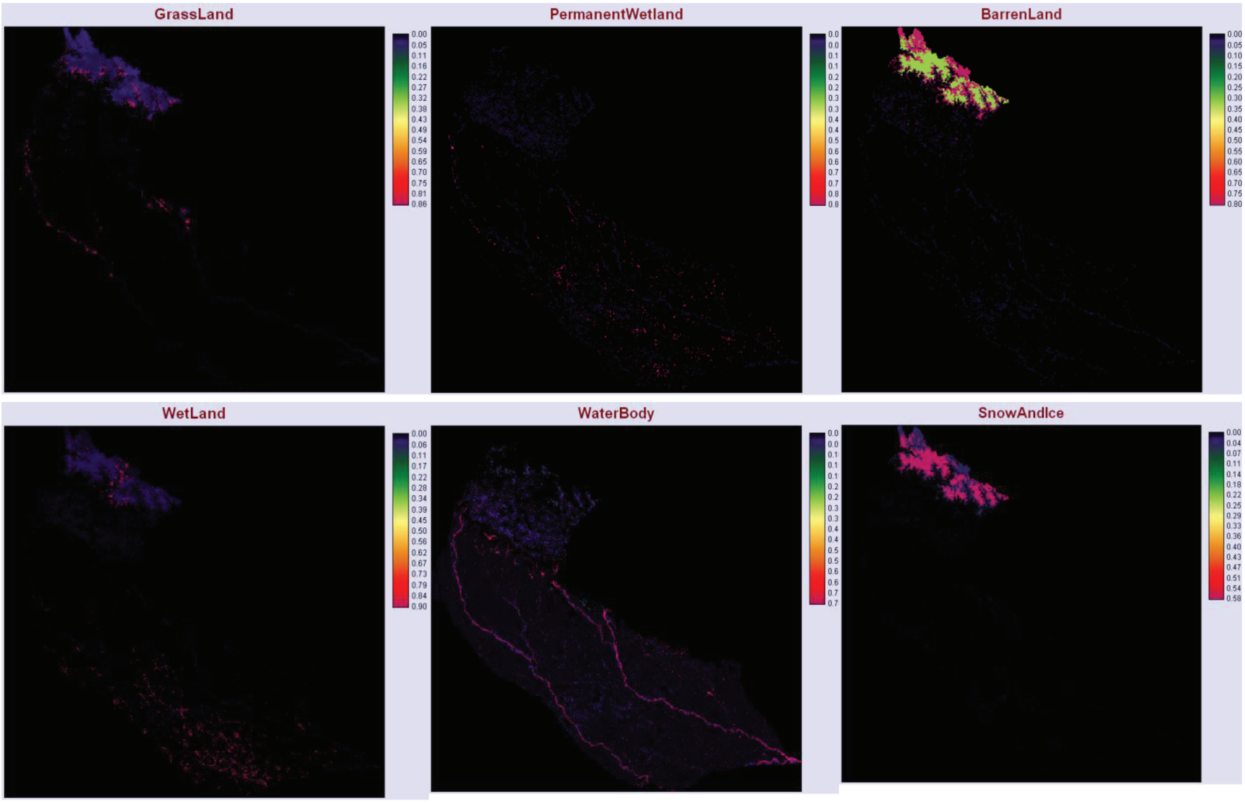


Figure 5-8 Suitability Map

5.6. LULC Change

The Table 5-1, 5-2 shows change in the LULC classes in the 1985-2005 years. Most of the change takes place in SI and BL class as compared to other classes, amount of snow change in between year in UGB area. Snow and ice decreased from the 1985-1995, and increased in year from 1995 to 2005 in the Upper Ganga Basin. From all of the land use classes the most dominant class is crop land which covers 70% of the UGB. Overall classification accuracy is 80% of the land use map which is generated in IGBP project. From 1985 to 2005 it was observed that there is significant change in crop land, it decreased in year 1985-1995, and in year between 1995- 2005 there was an increase in cropland. Crop land increased due to increasing irrigation network in the upper Ganga basin. Built up has an increasing trend from 1995 to 2005. Fallow land, barren land, forest has decreased. CL is dominant class in the UGB so it affects prediction of other classes. Form the different year; see the change pattern in the classes. In year 1985- 1995 as Appendix Table A1 CL class was change to in to BU, FL, WB, and SL class. SI get decreases it change to the BL, SL class. For the Figure 5-3 to 5-6 see that spatial the relationship with BL and SI class. Form the year 1995-2005 clearly see pattern in barren land and snow and ice class.

5.7. Aggregation appraoch impact on prediction

Two aggregation approaches have been used in this study of upper Ganga basin and the driver data set has also been rescaled at 500 and 1000 m. After running the model on a 500 scale, it was seen that the kappa value is high for major rule based approach (MRB) as compared to random rule based approach (RRB). The same method has been applied on the 1000 scale. Table 5-12 shows Kappa coefficient value for the high at 500 scales from 1000m scale. In the 500 m scale the relationship between LULC driver and classes is more defined and that has an effect on the suitability map creation of the LULC class. Suitability map shows the probability of the class in that particular cell. This Suitability map was created by logistic regression method which constructed suitability for land use class.

Figure 5-1 shows the predicted LULC map of the year 2005 using MRB and RRB approach at scale of 500m. As per kappa value is that 87% of classes have been correctly predicted. Error of the prediction is 13%. For the MRB approach 79% of classed are correctly predicted there is a 21% in error in prediction. For further analysis of the classes, Producer's and User's accuracy are calculated which are shown in Table 5-9. Producer's accuracy of the BL is 38.9% and User's accuracy is 54.16 %. This means that there is 62.1% error in the prediction of the BL classes. FL, GL, WB, SI class have more error as compare to other classes. For CL class Producer's accuracy is 98.12% and User's accuracy is 98.39%. CL class prediction is certain where there is less than 2 % error in prediction in MRB approach. As per error matrix Appendix, Table 5 predicted CL classes less changed to BU, FL SL, and WB so it shows high accuracy. BL predicted more area as compare to reference map. It covers the SL, SI area, it means it predicting in wrong area. Prediction for the classes based on the selection of aggregation method and error which come from the modeling approach of the CA-Markov model.

Producer's and User's accuracy are calculated for the RRB approach which is shown in Table 5-9. Producer's accuracy of the BL is 35.51% and User's accuracy is 49.81%. This means that there is 65.5% error in the prediction of the BL class, which 3.4 % more than the MRB approach. FL, GL, WB, SI WL class also have error as compare to other classes. For CL class Producer's accuracy is 95.63% and User's accuracy is 97.14%. CL class prediction is certain where there is less than 4 % error in prediction in RRB approach.

In Figure 5-2 shows predicted LULC map of the year 2005 using MRB and RRB approach at scale of 1000m. It was found that kappa value is larger for the MRB approach than for the RRB approach. Kappa value shows that 69.10% of classes are correctly predicted. Error of the prediction is 30.9 % For the RRB approach and 62.5% of the classes are correctly predicted. There is 38.4 % in error in prediction.

For further analysis of the classes, Producer's and User's accuracy are calculated. This is shown in Table 5-9. The Producer's accuracy and User's accuracy for the classes PW and WL, fall between 25 -28 %. MRB and RRB both show that PW, WL class predictions are more uncertain between 72 to 75 % error. For CL class Producer's accuracy and User's accuracy fall between 92 to 95% so CL class prediction is more certain where there is less than 8% error in prediction. In the MRB approach class wise prediction is correct than RRB approach.

It has been found that the driver selection of the classes affects the prediction for the year 2005. After analysis was performed on the hill areas of the Ganga basins it was seen that this area has much area prediction error as compared to the plain area of the basin. Prediction error may have occurred because of the model and due to the selection of drivers in for SI, BL and SL classes. For these class slope, elevation, rain, soil depth driver not play role in prediction. As well in plain are WB class also show error, it means driver selected for WB rain, distance to road, slope, soil depth not play role in prediction of class. SI and WB have their different dynamics SI changed seasonally in winter snow cover more as compare to summer. WB changed in rainy season also in between 1985-2005 change in found in border of the water body.

Error in of predicted map is shown in Figure 5-3 to 5-6, The Moran test analysis found that class error in predicted map is clustered. For the Moran test analysis 5000m threshold distance was used to check the autocorrelation in the error. This shows that upper part of the Ganga basin has more error. The area that comes under and near the water body also has a larger amount of error. The selection of the driver on this area may affect the uncertainty in those classes. This means that selection of driver is not playing a part in the prediction in of these classes. Error increasing from RBB approach, as compare to the MRB approach.

For analysis of the spatial auto correlation in error Moran test was performed, which shows that error clusters are formed in the images. In the first image of a scale of 500 MRB approach an error cluster was formed in the class SI, BL, WB as compared to CL,BU,FL classes, More error clusters were formed at the scale of 1000 RRB approach.

In Figure 5-7 class wise error is showed in the maps in both MRB and RRB approach, clearly see that in class wise error SL, BL, WB showing more error. As mentioned before error occurred
Is predicted map was depending on which method and which scale used. RRB approach more error see on the plain area of the UGB.

5.8. Driver Impact

The drivers selected for the classes were those that have a significant relation with classes. The relation between drivers and LULC classes changes as per scale changes. The logistic regression analysis based on the AIC value of driver with class. Table A9 to A16 show that coefficient of the each driver and class overall AIC value. The analysis of coefficient has helped in identifying the drivers, which have influenced the LULC classes. In the table, the drivers that are marked in red represent those drivers that have had a significant influence on the classes in that year. According to the class coefficient, the drivers marked in green are those drivers which show a positive relation. Negative coefficients also play an important role, an example is elevation. This shows the negative coefficient which means that the built-up area will decrease with increasing elevation. Selection of driver plays an important role in the prediction of classes.

The suitability map of each class is generated with the help of logistic regression. Suitability maps show the probability of the classes in the predicted map using the driver dataset. Probability of each class depends on the selection of drivers. Figure 5-8 shows those suitability maps that are generated from logistic regression, which show the probability of each class. Driver selection has been performed on the basis of the logistics AIC Value. Less AIC value shows that the models are best fitted to that class so in this project the drivers for each class are selected based on the AIC value.

6. CONCLUSION AND RECOMMENDATION

Conclusion

In study of the LULC change main objective and sub objective are achieved, according to these objective following research question have answered :

1) *What are the major drivers of Land use/cover change in the study area and relationship between the drivers and the land use classes?*

   In the upper Ganga basin area most driving factor for the LULC classes are agriculture density, population density, rainfall, slop. These drivers affect each class of UGB in the future change.

2) *Which spatial distribution and aggregation method gives minimum overall error in Land use/cover change?*

   In the study two methods was used MRB and RRB approach. In scale of 500 and 1000 M. it was found that more error occurs in RRB approach which based on random selection of the class in the aggregation, and MRB which based on the majority of the classes, so as per Figure 5-7 predicted maps spatial see more unmatched classes in the RBB as compare to MRB approach.

3) *How much overall Uncertainty occurs in the Land use/cover change in 2005 in the Upper Ganga Basin?*

   Predicted 2005 map was generated from the map of the 1985 to 1995. With including the driver data set which used to identify suitability of land use classes. Using different aggregation method on LULC dataset, affect prediction of LULC map. So uncertainty is varied using these methods. As form Table 5-12 kappa value high for 500 as compare 1000 scale. Overall kappa value 500 scale varied for 0.799(RRB) to 0.87(MRB) and for 1000 scale varied form 0.6259(RRB) to 0.6910(MRB). Error in prediction occurs due to the scale changes also from the logistic regression model for predicting the suitability map and CA-Markov model.

Recommendations

1) This study focused on different aggregation approach applied (MRB, RRB) on LULC data set. Further other different aggregation method also applied on this LULC data to make the data same scale for LULC change modeling.
2) CA-Marko model used for the prediction of 2005, it can also use different model such as CLUE model, and quantified the uncertainty between two models.

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APPENDIX

Table A1 Transition Matrix between year 85-95 at scale 1000 (MRB)

85/95	BU	CL	FL	PL	ENF	EDF	DBF	MF	SL	GL	PW	BL	WL	WB	SI
BU	696	17	0	0	0	0	0	0	0	0	0	0	0	1	0
CL	295	139543	677	104	48	2	55	5	141	8	70	0	86	326	0
FL	202	555	3673	65	67	3	5	5	288	13	56	0	33	177	0
PL	48	66	5	1541	0	0	2	0	10	0	0	0	3	6	0
ENF	1	44	76	0	14925	0	0	10	48	4	0	24	2	1	1
EDF	0	4	1	0	0	326	0	0	2	0	0	2	0	0	0
DBF	0	53	4	4	1	0	8948	2	11	6	3	0	0	10	0
MF	0	7	6	0	5	0	1	801	1	9	0	1	0	5	0
SL	45	173	45	4	45	0	14	1	3848	15	54	91	53	240	27
GL	1	54	2	0	3	0	4	1	2	717	1	10	1	50	5
PW	1	83	14	1	0	0	1	0	33	0	644	0	2	9	0
BL	0	0	1	0	11	2	0	0	187	61	0	1487	20	1	81
WL	12	97	2	1	2	0	0	0	152	0	7	1	1508	2	0
WB	6	503	191	1	0	0	7	0	341	60	5	1	2	2195	0
SI	0	3	4	0	20	0	0	1	525	261	0	3315	233	1	6056

Table A2 Transition Matrix between year 85-95 at scale 1000 (RRB)

85/95	BU	CL	FL	PL	ENF	EDF	DBF	MF	SL	GL	PW	BL	WL	WB	SI
BU	577	253	9	11	5	2	6	0	11	0	1	0	0	14	0
CL	521	130045	1367	446	531	31	505	54	1137	80	573	6	1041	1543	0
FL	192	1320	2608	69	655	24	58	60	380	18	63	6	54	235	0
PL	51	403	14	1240	0	0	30	0	49	0	1	0	7	25	0
ENF	6	488	684	0	12042	7	24	144	604	41	0	177	35	92	22
EDF	0	19	12	0	17	212	0	10	28	0	0	19	0	7	0
DBF	4	524	54	32	14	2	7662	20	114	54	16	0	4	225	0
MF	0	61	50	0	153	10	17	557	31	14	3	2	0	12	0
SL	50	1061	195	38	598	22	145	49	2659	34	58	109	67	307	32
GL	0	124	22	0	34	1	37	13	36	487	5	25	7	76	13
PW	1	512	7	1	0	0	7	0	38	2	508	0	19	16	0
BL	1	11	2	0	130	9	0	4	185	73	0	1318	27	6	169
WL	10	1017	18	9	17	0	0	0	134	6	27	7	1053	22	4
WB	21	1813	243	22	86	4	239	7	462	91	15	15	21	2042	2
SI	0	1	4	0	100	2	0	4	508	281	0	3270	222	17	5882

Table A3 Transition Matrix between year 85-95 at scale 500 (MRB)

85/95	BU	CL	FL	PL	ENF	EDF	DBF	MF	SL	GL	PW	BL	WL	WB	SI
BU	3141	210	9	4	7	2	8	0	9	0	0	0	2	11	0
CL	1303	545725	3611	647	439	20	417	60	983	62	706	3	995	2213	0
FL	782	2789	15169	337	573	14	47	51	1450	58	267	3	205	773	0
PL	204	431	31	6345	0	0	25	0	54	0	0	0	9	42	0
ENF	2	398	664	0	56274	3	15	149	544	41	0	170	26	49	7
EDF	0	28	21	0	6	1211	0	6	18	0	0	13	0	3	0
DBF	5	401	40	25	10	0	34486	12	135	26	7	0	4	200	0
MF	0	40	47	1	157	9	23	3356	19	41	0	5	0	18	0
SL	168	1168	275	28	521	25	146	18	16671	83	321	415	261	1030	109
GL	4	250	15	0	37	1	33	4	40	2889	7	31	2	238	29
PW	3	703	61	4	0	0	7	0	185	3	3278	0	17	53	0
BL	0	6	3	0	122	7	0	2	841	257	0	5933	83	2	379
WL	48	1004	20	5	18	0	1	0	686	7	62	12	7253	23	3
WB	19	3031	769	31	54	6	193	11	1434	271	29	15	23	10889	3
SI	0	2	26	0	99	4	0	1	2113	1039	0	13149	960	17	24125

Table A4 Transition Matrix between year 85-95 at scale 500 (RRB)

85/95	BU	CL	FL	PL	ENF	EDF	DBF	MF	SL	GL	PW	BL	WL	WB	SI
BU	2823	508	22	15	12	3	11	1	17	0	1	0	2	31	0
CL	1643	5E+05	4448	1224	1084	64	965	128	2606	157	1383	22	2306	4563	0
FL	730	3871	13275	327	1345	37	107	99	1550	82	240	12	202	917	0
PL	225	886	52	5814	0	0	68	0	76	0	2	0	16	75	0
ENF	15	1015	1538	0	52369	8	32	343	1335	92	0	440	69	269	45
EDF	1	59	36	0	23	1077	2	12	70	0	0	19	0	17	0
DBF	23	994	114	59	29	1	32566	39	314	81	42	0	14	677	0
MF	1	149	119	2	393	20	52	2924	61	56	2	13	1	35	0
SL	175	2420	503	55	1352	44	308	64	14233	98	288	406	276	1252	113
GL	2	326	31	0	87	3	81	12	95	2557	15	71	11	282	37
PW	3	1256	67	7	0	0	22	2	161	7	2891	0	48	62	0
BL	0	14	5	0	285	25	0	6	793	274	0	5699	93	20	492
WL	51	2305	48	18	29	0	2	0	657	14	94	23	6219	65	9
WB	46	5196	936	82	246	15	628	38	1662	322	52	35	68	10835	10
SI	0	2	17	0	183	6	0	6	2079	1039	0	13067	981	44	23846

Table A5 Transition Matrix between year predicted 05- reference 05 at scale 500 (MRB**)**

Pre 05/ Ref 05	BU	CL	FL	PL	ENF	EDF	DBF	MF	SL	GL	PW	BL	WL	WB	SI
BU	5289	313	27	30	5	1	5	0	7	1	1	1	2	14	1
CL	970	545755	2115	441	335	19	405	32	1084	82	601	12	958	1859	0
FL	256	2961	15751	52	766	16	42	54	1131	35	96	8	148	680	1
PL	49	398	79	6804	0	0	27	0	29	0	0	0	1	25	0
ENF	5	446	535	0	56087	8	16	169	509	52	0	150	25	48	42
EDF	0	28	11	0	3	1202	0	9	18	1	0	16	0	4	3
DBF	8	409	45	24	18	1	34389	10	148	46	13	0	8	162	0
MF	0	73	48	1	142	9	20	3285	77	11	0	4	0	12	0
SL	75	1164	278	19	578	25	137	21	18183	52	183	2645	209	906	642
GL	0	116	21	0	40	1	40	4	69	3746	26	340	12	216	99
PW	4	588	10	3	0	0	8	1	127	25	3910	0	39	7	0
BL	0	4	1	0	110	10	0	0	616	14	0	6444	7	5	4688
WL	1	1089	16	5	25	0	5	0	176	4	64	87	8187	6	73
WB	24	2817	427	31	60	1	254	9	1661	481	69	26	10	10599	5
SI	0	26	0	0	62	6	0	3	526	468	0	6831	374	5	23942

Table A6 Transition Matrix between year predicted 05- reference 05 at scale 500 (RRB)

Pre 05/ Ref 05	BU	CL	FL	PL	ENF	EDF	DBF	MF	SL	GL	PW	BL	WL	WB	SI
BU	4905	721	35	26	14	3	19	0	31	0	0	0	5	34	2
CL	1258	527441	2673	807	848	39	929	137	1912	128	1072	23	1925	3771	7
FL	294	5139	14197	132	1781	38	87	125	1267	85	100	16	175	897	2
PL	113	1245	71	6335	0	0	62	0	82	0	2	0	11	73	0
ENF	22	1091	1299	0	52402	20	27	395	1331	103	0	392	69	226	127
EDF	0	80	52	0	15	1095	0	19	41	0	0	61	0	17	1
DBF	24	988	124	71	37	1	32536	37	328	107	42	0	15	547	0
MF	0	131	107	1	311	14	48	2796	112	29	1	8	1	27	2
SL	91	3320	514	52	1366	50	281	66	15772	102	200	1810	343	1126	1256
GL	1	324	41	0	79	2	70	13	113	3297	33	331	29	259	161
PW	5	1850	25	5	0	0	46	2	155	31	3572	0	66	41	0
BL	0	9	9	0	299	2	0	4	687	33	0	5893	23	24	4848
WL	20	2715	40	10	50	0	8	0	350	26	96	109	7190	43	90
WB	59	6471	534	59	300	21	746	40	2120	548	90	55	76	11114	8
SI	0	16	0	0	153	6	0	3	488	516	0	7896	451	10	22833

Table A7 Transition Matrix between year predicted 05- reference 05 at scale 1000 (MRB)

Pre 05/ Ref 05	BU	CL	FL	PL	ENF	EDF	DBF	MF	SL	GL	PW	BL	WL	WB	SI
BU	805	438	24	23	15	0	8	0	27	1	0	0	4	18	1
CL	540	132742	778	482	515	28	675	59	1468	109	552	14	1088	763	0
FL	54	1394	2010	11	1171	25	113	84	291	29	15	7	23	145	0
PL	32	501	10	1045	0	0	43	0	38	0	1	0	12	14	0
ENF	15	624	991	0	11885	23	76	227	799	38	0	246	30	12	67
EDF	0	26	31	0	17	197	6	8	33	2	0	16	0	0	1
DBF	24	918	77	49	9	0	7549	30	154	61	15	0	4	109	0
MF	0	77	87	1	199	13	24	321	65	10	0	1	0	7	0
SL	23	1460	242	36	785	26	186	56	1658	59	14	504	54	295	181
GL	5	113	15	0	86	1	42	3	41	554	11	117	21	67	51
PW	4	540	4	3	0	0	15	0	28	1	237	0	20	3	0
BL	0	17	7	0	211	17	0	3	107	20	0	1421	32	0	1144
WL	6	1070	8	11	53	0	5	1	61	14	22	59	541	7	31
WB	22	1253	98	27	8	1	103	7	435	114	13	2	9	1316	0
SI	0	3	1	0	111	2	0	7	175	184	0	1643	145	1	5775

Table A8 Transition Matrix between year predicted 05- reference 05 at scale 1000 (RRB)

Pre 05/ Ref 05	BU	CL	FL	PL	ENF	EDF	DBF	MF	SL	GL	PW	BL	WL	WB	SI
BU	735	476	25	9	15	0	5	0	30	1	1	0	9	19	0
CL	756	126468	1243	590	617	24	715	82	1809	148	817	19	1450	1935	1
FL	73	1586	1936	28	1198	21	118	85	363	36	23	9	41	225	21
PL	42	625	15	1081	0	0	52	0	37	0	0	0	17	42	0
ENF	16	729	1095	0	10918	38	79	248	905	54	1	284	45	110	111
EDF	1	31	36	0	19	175	4	10	37	0	0	18	0	4	0
DBF	26	950	94	64	15	0	7010	38	201	66	28	0	7	269	1
MF	1	111	84	1	240	11	35	345	77	21	1	5	0	21	4
SL	30	1760	262	48	834	22	176	65	1798	72	22	436	69	378	164
GL	1	114	15	0	85	0	50	3	35	491	13	121	22	57	67
PW	3	846	7	4	0	0	23	1	39	3	325	0	27	16	0
BL	1	11	6	0	136	13	0	1	105	10	0	1263	18	9	1160
WL	9	1433	12	19	86	0	6	0	85	10	38	46	739	27	36
WB	37	2316	146	42	101	8	286	14	511	132	24	11	35	1433	3
SI	0	1	0	0	130	2	0	10	179	196	0	1862	170	6	5639

Table A9 LULC driver relation in year 85 at scale 500(MRB)

	ALD	DTD	DTR	Popden	Elev	Slope	SD	Rain	Temp	AIC
BU	-0.0083	-0.0001	-0.0011	0.0024	-0.0004	-0.0837	-0.0019	-0.0006	-0.0468	34100
CL	0.0212	0.0001	0.0000	0.0002	-0.0017	-0.0634	0.0049	-0.0006	0.0129	466200
FL	0.0050	0.0000	0.0001	0.0013	-0.0003	0.0716	-0.0030	0.0006	-0.1913	191200
PL	-0.0132	0.0001	-0.0002	0.0012	0.0000	-0.3282	0.0193	0.0010	-0.2028	73400
ENF	-0.0086	0.0002	0.0001	-0.0091	-0.0008	0.1135	0.0056	0.0004	-0.3589	193000
EDF	-0.0147	-0.0001	0.0000	-0.0033	-0.0005	0.0557	-0.0019	0.0025	-0.2058	13830
DBF	-0.0284	0.0002	0.0000	-0.0174	-0.0036	0.0150	0.0093	0.0023	-0.3839	102600
MF	0.0162	0.0000	0.0001	-0.0025	-0.0005	0.0894	-0.0029	0.0013	-0.2376	40740
SL	0.0045	-0.0001	0.0001	0.0003	-0.0004	0.0856	-0.0026	0.0005	-0.1236	184900
GL	-0.0039	-0.0002	0.0000	0.0004	-0.0001	0.0440	-0.0019	0.0002	-0.0952	43450
PW	0.0027	0.0001	0.0001	-0.0004	-0.0103	0.1858	0.0044	-0.0005	0.0256	50560
BL	0.0008	-0.0001	0.0000	0.0018	0.0006	0.0590	-0.0115	0.0001	-0.2167	52950
WL	0.0060	0.0001	0.0000	0.0002	0.0007	0.1497	0.0060	-0.0016	1.2700	89510
WB	0.0051	-0.0020	0.0001	-0.0080	-0.0018	-0.0954	-0.0116	0.0003	0.0216	70860
SI	0.0488	0.0001	-0.0001	-0.0611	0.0025	0.0241	-0.0007	0.0007	0.1348	39230

Table A10 LULC driver relation in year 95 at scale 500(MRB)

	ALD	DTD	DTR	Popden	Elev	Slope	SD	Rain	Temp	AIC
BU	-0.0050	-0.0001	-0.0010	0.0011	-0.0005	-0.1111	-0.0065	-0.0007	0.0083	56700
CL	0.0210	0.0001	0.0000	0.0001	-0.0018	-0.0470	0.0051	-0.0004	0.0303	462700
FL	0.0110	0.0000	0.0001	-0.0015	-0.0004	0.0681	-0.0021	0.0006	-0.1963	178700
PL	-0.0012	0.0000	-0.0001	-0.0004	0.0000	-0.2925	0.0195	0.0008	-0.2035	77800
ENF	-0.0213	0.0002	0.0000	-0.0091	-0.0008	0.1105	0.0053	0.0004	-0.3635	190600
EDF	-0.0196	-0.0001	0.0000	-0.0045	-0.0005	0.0558	-0.0015	0.0026	-0.2095	13600
DBF	-0.0560	0.0003	0.0000	-0.0138	-0.0037	0.0138	0.0096	0.0023	-0.3918	100100
MF	0.0088	0.0000	0.0001	-0.0012	-0.0005	0.0946	-0.0029	0.0012	-0.2325	40680
SL	0.0112	-0.0001	0.0001	-0.0019	-0.0003	0.0701	-0.0054	0.0004	-0.0820	209300
GL	0.0129	-0.0002	-0.0001	-0.0027	0.0000	0.0622	-0.0056	0.0000	-0.0856	51830
PW	-0.0470	0.0002	0.0001	0.0025	-0.0026	-2.9160	0.0108	0.0004	0.0802	33880
BL	0.0163	-0.0001	0.0000	-0.0049	0.0008	0.0383	-0.0100	-0.0001	-0.1748	87970
WL	0.0050	0.0001	0.0001	0.0002	0.0008	0.0884	0.0009	-0.0014	0.7794	97410
WB	-0.0312	-0.0021	0.0001	0.0001	-0.0017	-0.1068	-0.0099	0.0003	0.0275	68070
SI	-0.4042	0.0001	-0.0001	0.0043	0.0023	0.0091	0.0027	0.0010	0.0545	39640

Table A11 LULC driver relation in year 85 at scale 500(RRB)

	ALD	DTD	DTR	Popden	Elev	Slope	SD	Rain	Temp	AIC
BU	-0.0081	-0.0001	-0.0011	0.0023	-0.0003	-0.0882	-0.0018	-0.0006	-0.0380	34590
CL	0.0201	0.0001	0.0000	0.0001	-0.0017	-0.0633	0.0046	-0.0006	0.0130	487800
FL	0.0041	0.0000	0.0001	0.0012	-0.0003	0.0703	-0.0022	0.0006	-0.1771	194700
PL	-0.0129	0.0001	-0.0002	0.0012	0.0000	-0.3186	0.0203	0.0010	-0.1933	74360
ENF	-0.0073	0.0002	0.0001	-0.0078	-0.0007	0.1166	0.0063	0.0004	-0.3036	202400
EDF	-0.0121	-0.0001	0.0000	-0.0023	-0.0005	0.0601	-0.0013	0.0025	-0.2079	14180
DBF	-0.0272	0.0002	0.0000	-0.0126	-0.0030	0.0167	0.0106	0.0023	-0.2671	113400
MF	0.0159	0.0000	0.0001	-0.0027	-0.0005	0.0862	-0.0018	0.0013	-0.2301	42020
SL	0.0037	-0.0001	0.0001	0.0003	-0.0004	0.0826	-0.0023	0.0005	-0.1152	188200
GL	-0.0037	-0.0002	0.0000	0.0003	-0.0001	0.0446	-0.0020	0.0002	-0.0849	43800
PW	0.0032	0.0001	0.0001	-0.0004	-0.0104	0.1778	0.0038	-0.0005	0.0412	52590
BL	0.0009	-0.0001	0.0000	0.0017	0.0006	0.0576	-0.0112	0.0001	-0.2191	53620
WL	0.0062	0.0001	0.0000	0.0001	0.0006	0.1503	0.0051	-0.0016	1.2410	92640
WB	0.0020	-0.0013	0.0000	-0.0054	-0.0012	-0.0821	-0.0098	0.0004	0.0431	108700
SI	0.0415	0.0001	-0.0001	-0.0611	0.0025	0.0241	-0.0007	0.0007	0.1348	39230

Table A 12 LULC driver relation in year 95 at scale 500(RRB)

	ALD	DTD	DTR	Popden	Elev	Slope	SD	Rain	Temp	AIC
BU	-0.0049	-0.0001	-0.0010	0.0010	-0.0005	-0.1201	-0.0062	-0.0007	0.0161	57300
CL	0.0193	0.0001	0.0000	0.0001	-0.0017	-0.0481	0.0048	-0.0004	0.0259	487700
FL	0.0101	0.0000	0.0001	-0.0015	-0.0004	0.0671	-0.0017	0.0005	-0.1807	182900
PL	-0.0010	0.0000	-0.0001	-0.0004	0.0000	-0.2877	0.0217	0.0007	-0.1967	79570
ENF	-0.0197	0.0002	0.0000	-0.0075	-0.0007	0.1136	0.0060	0.0004	-0.3062	199000
EDF	-0.0197	-0.0001	0.0000	-0.0032	-0.0005	0.0570	-0.0018	0.0026	-0.1999	13740
DBF	-0.0498	0.0002	0.0000	-0.0107	-0.0032	0.0161	0.0109	0.0023	-0.2783	110700
MF	0.0085	0.0000	0.0001	-0.0012	-0.0005	0.0938	-0.0022	0.0012	-0.2281	40820
SL	0.0098	0.0000	0.0000	-0.0018	-0.0003	0.0680	-0.0053	0.0004	-0.0706	213700
GL	0.0118	-0.0001	-0.0001	-0.0026	0.0000	0.0599	-0.0053	-0.0001	-0.0794	52290
PW	-0.0373	0.0001	0.0001	0.0024	-0.0038	-2.3260	0.0110	0.0003	0.0863	41200
BL	0.0151	-0.0001	0.0000	-0.0046	0.0008	0.0377	-0.0098	-0.0001	-0.1743	88700
WL	0.0046	0.0001	0.0001	0.0002	0.0007	0.0858	0.0008	-0.0014	0.7559	101500
WB	-0.0222	-0.0013	0.0000	0.0001	-0.0012	-0.0773	-0.0086	0.0003	0.0448	106400
SI	-0.2722	0.0001	-0.0001	0.0033	0.0022	0.0070	0.0038	0.0009	0.0462	48010

Table A13 LULC driver relation in year 85 at scale 1000(MRB)

	ALD	DTD	DTR	Popden	Elev	Slope	SD	Rain	Temp	AIC
BU	-0.0105	0.0000	-0.0011	0.0026	-0.0008	-0.0872	-0.0042	-0.0010	-0.1774	7155
CL	0.0214	0.0001	0.0000	-0.0001	-0.0019	-0.0910	0.0067	-0.0008	0.0606	107800
FL	0.0028	0.0000	0.0001	0.0013	-0.0005	0.0562	-0.0053	0.0005	-0.4425	43860
PL	-0.0110	0.0001	-0.0002	0.0012	-0.0019	-0.3795	0.0117	0.0007	-0.5892	16480
ENF	0.0025	0.0001	0.0001	-0.0059	-0.0008	0.1048	0.0044	0.0008	-0.8784	53060
EDF	-0.0124	0.0001	0.0000	0.0002	-0.0008	0.0699	-0.0057	0.0032	-0.7195	3499
DBF	-0.0203	0.0001	0.0000	-0.0089	-0.0041	0.0142	0.0062	0.0023	-0.6716	30210
MF	0.0158	0.0000	0.0001	-0.0029	-0.0009	0.0684	-0.0069	0.0014	-0.6437	8990
SL	0.0011	0.0000	0.0001	0.0002	-0.0006	0.0866	-0.0041	0.0005	-0.2275	41960
GL	-0.0029	-0.0002	0.0000	-0.0001	-0.0002	0.0418	-0.0050	0.0001	-0.1795	10390
PW	0.0044	0.0001	0.0001	-0.0005	-0.0111	0.3983	0.0033	-0.0008	-0.0962	9742
BL	-0.0070	-0.0001	0.0000	0.0039	0.0002	0.0481	-0.0126	0.0006	-1.2630	11800
WL	0.0055	0.0000	0.0000	0.0001	0.0007	0.1794	0.0047	-0.0015	1.2220	18540
WB	-0.0060	-0.0010	0.0001	-0.0041	-0.0073	0.0086	-0.0169	0.0002	-0.2148	19070
SI	0.0299	0.0001	0.0000	-0.0163	0.0033	0.0713	0.0030	-0.0001	1.1810	8934

Table A14 LULC driver relation in year 95 at scale 1000(MRB**)**

	ALD	DTD	DTR	Popden	Elev	Slope	SD	Rain	Temp	AIC
BU	-0.0063	0.0000	-0.0010	0.0012	-0.0009	-0.1229	-0.0077	-0.0008	-0.0580	13250
CL	0.0184	0.0001	0.0000	0.0003	-0.0018	-0.0686	0.0073	-0.0006	0.0995	108400
FL	0.0107	0.0000	0.0001	-0.0016	-0.0006	0.0493	-0.0047	0.0004	-0.4913	39970
PL	0.0021	0.0001	-0.0002	-0.0007	-0.0017	-0.3442	0.0128	0.0005	-0.6152	17150
ENF	-0.0046	0.0001	0.0001	-0.0058	-0.0008	0.1049	0.0044	0.0008	-0.8626	52820
EDF	-0.0155	0.0001	0.0000	-0.0001	-0.0008	0.0719	-0.0055	0.0032	-0.6925	3455
DBF	-0.0369	0.0001	0.0000	-0.0071	-0.0042	0.0082	0.0065	0.0023	-0.6972	29930
MF	0.0087	0.0000	0.0001	-0.0011	-0.0009	0.0790	-0.0075	0.0014	-0.6763	8914
SL	0.0072	0.0000	0.0000	-0.0018	-0.0003	0.0765	-0.0071	0.0004	-0.1277	47940
GL	0.0110	-0.0001	-0.0001	-0.0025	-0.0001	0.0613	-0.0076	0.0000	-0.1972	12670
PW	-0.0282	0.0001	0.0001	0.0021	-0.0056	-1.2350	0.0086	-0.0003	-0.0025	8491
BL	0.0136	0.0000	0.0000	-0.0040	0.0006	0.0440	-0.0110	0.0000	-0.5326	21820
WL	0.0028	0.0000	0.0001	0.0002	0.0007	0.1136	0.0006	-0.0013	0.6931	20360
WB	-0.0259	-0.0010	0.0001	-0.0001	-0.0054	-0.0546	-0.0159	0.0001	-0.1585	17290
SI	-0.0237	0.0000	0.0000	0.0021	0.0026	0.0274	0.0086	0.0006	0.4463	12540

Table A 15: LULC driver relation in year 85 at scale 1000(RRB)

	ALD	DTD	DTR	Popden	Elev	Slope	SD	Rain	Temp	AIC
BU	-0.0092	0.0000	-0.0010	0.0023	-0.0007	-0.1024	-0.0040	-0.0007	-0.1657	9007
CL	0.0185	0.0001	0.0000	-0.0001	-0.0016	-0.0884	0.0059	-0.0008	0.0466	126200
FL	0.0017	0.0000	0.0001	0.0012	-0.0005	0.0578	-0.0055	0.0004	-0.3737	48750
PL	-0.0101	0.0001	-0.0001	0.0011	-0.0018	-0.3420	0.0130	0.0005	-0.5419	18020
ENF	0.0023	0.0001	0.0001	-0.0056	-0.0008	0.1010	0.0048	0.0008	-0.8696	52650
EDF	-0.0078	0.0000	0.0000	0.0002	-0.0007	0.0707	-0.0047	0.0033	-0.6902	3453
DBF	-0.0189	0.0001	0.0000	-0.0078	-0.0039	0.0220	0.0061	0.0022	-0.6248	31900
MF	0.0166	0.0000	0.0001	-0.0032	-0.0008	0.0615	-0.0060	0.0014	-0.6479	9702
SL	0.0017	0.0000	0.0001	-0.0003	-0.0006	0.0821	-0.0046	0.0005	-0.1900	47570
GL	-0.0044	-0.0002	0.0000	-0.0002	-0.0002	0.0387	-0.0038	-0.0002	-0.1568	10750
PW	0.0038	0.0001	0.0001	-0.0007	-0.0112	0.3119	0.0020	-0.0007	-0.0049	12950
BL	-0.0073	-0.0001	0.0000	0.0037	0.0002	0.0493	-0.0115	0.0005	-1.2550	12350
WL	0.0050	0.0000	0.0000	0.0003	0.0008	0.1761	0.0054	-0.0016	1.3430	22720
WB	-0.0058	-0.0004	0.0001	-0.0026	-0.0017	-0.0838	-0.0119	0.0003	-0.0380	36150
SI	0.0252	0.0001	0.0000	-0.0139	0.0031	0.0709	0.0022	-0.0001	1.1460	9561

Table A16 LULC driver relation in year 95 at scale 1000(RRB)

	ALD	DTD	DTR	Popden	Elev	Slope	SD	Rain	Temp	AIC
BU	-0.0050	0.0000	-0.0009	0.0010	-0.0007	-0.1605	-0.0077	-0.0007	-0.0599	14500
CL	0.0158	0.0001	0.0000	0.0002	-0.0016	-0.0716	0.0063	-0.0005	0.0723	127400
FL	0.0085	0.0000	0.0001	-0.0015	-0.0006	0.0484	-0.0039	0.0003	-0.4100	45010
PL	0.0015	0.0001	-0.0001	-0.0007	-0.0017	-0.3199	0.0136	0.0003	-0.5583	18770
ENF	-0.0037	0.0001	0.0001	-0.0054	-0.0007	0.1021	0.0042	0.0008	-0.8500	52810
EDF	-0.0106	0.0001	0.0000	-0.0006	-0.0007	0.0697	-0.0026	0.0030	-0.6596	3512
DBF	-0.0343	0.0001	0.0000	-0.0065	-0.0041	0.0142	0.0061	0.0022	-0.6589	31240
MF	0.0097	0.0000	0.0001	-0.0015	-0.0008	0.0580	-0.0066	0.0013	-0.6602	9963
SL	0.0053	0.0000	0.0000	-0.0015	-0.0003	0.0745	-0.0066	0.0004	-0.0992	53570
GL	0.0089	-0.0001	-0.0001	-0.0025	-0.0001	0.0621	-0.0067	-0.0001	-0.1590	13040
PW	-0.0220	0.0001	0.0000	0.0019	-0.0054	-1.7620	0.0100	0.0001	0.1073	13010
BL	0.0116	0.0000	0.0000	-0.0036	0.0006	0.0415	-0.0102	0.0001	-0.5316	22100
WL	0.0028	0.0000	0.0001	0.0003	0.0008	0.1172	0.0010	-0.0013	0.8208	25260
WB	-0.0177	-0.0004	0.0001	0.0001	-0.0017	-0.0596	-0.0120	0.0004	-0.0080	33700
SI	-0.0148	0.0000	0.0000	0.0007	0.0025	0.0339	0.0077	0.0006	0.4261	13180

Table A17 AIC value as per Class with Driver

Class	Driver	AIC Value
BuiltUp	SoilDepth	34108
	Temperature	34138
	Elevation	34153
	Slope	34166
	Rain	34186
	DistanceToDrainage	34273
	AgricultureLabourDensity	34412
	PopulationDensity	37426
	DistanceToRoad	39232
CropLand	PopulationDensity	466271
	DistanceToRoad	466409
	SoilDepth	466908
	Slope	467403
	Rain	468949
	DistanceToDrainage	470211
	Elevation	477233
	AgricultureLabourDensity	495082
FallowLand	SoilDepth	191356
	DistanceToDrainage	191498
	DistanceToRoad	191893
	AgricultureLabourDensity	192053
	Rain	192211
	Elevation	192243
	PopulationDensity	193094
	Slope	194180
	Temprature	195744
Plantation	Elevation	73395
	DistanceToDrainage	73523
	SoilDepth	73866
	PopulationDensity	74074
	DistanceToRoad	74078
	Rain	74129
	Slope	74354
	AgricultureLabourDensity	74965
	Temperature	75742

EverGreenNeedleForest	AgricultureLabourDensity	193461
	DistanceToRoad	193581
	Rain	193655
	SoilDepth	193796
	PopulationDensity	198806
	DistanceToDrainage	201489
	Temperature	206478
	Slope	213477
	Elevation	216104
EverGreenDenseForest	DistanceToRoad	13831
	DistanceToDrainage	13847
	PopulationDensity	13851
	AgricultureLabourDensity	13857
	Slope	14076
	Temperature	14083
	Elevation	14163
	Rain	15137
DecidiousBroadLeafForest	Slope	102637
	SoilDepth	103269
	AgricultureLabourDensity	106023
	DistanceToDrainage	106327
	Rain	110302
	Temperature	110950
	PopulationDensity	111218
	Elevation	131494
MixedForest	DistanceToDrainage	40745
	SoilDepth	40766
	PopulationDensity	41004
	DistanceToRoad	41025
	Elevation	41364
	AgricultureLabourDensity	41407
	Rain	41722
	Slope	42017
	Temperature	42446

ScrubLand	PopulationDensity	184939
	SoilDepth	184950
	AgricultureLabourDensity	185339
	DistanceToRoad	185624
	Rain	185673
	DistanceToDrainage	185695
	Temperature	186176
	Elevation	186742
	Slope	189116
GrassLand	DistanceToRoad	43453
	SoilDepth	43454
	Rain	43464
	PopulationDensity	43467
	Elevation	43495
	AgricultureLabourDensity	43497
	Temperature	43611
	Slope	43724
	DistanceToDrainage	44254
PermanentWetland	Temperature	50560
	Slope	50563
	SoilDepth	50573
	PopulationDensity	50576
	AgricultureLabourDensity	50582
	DistanceToDrainage	50642
	Rain	50655
	DistanceToRoad	50672
	Elevation	51081
BarrenLand	AgricultureLabourDensity	52950
	Rain	52961
	DistanceToRoad	53042
	DistanceToDrainage	53196
	PopulationDensity	53250
	SoilDepth	54082
	Temperature	54839
	Slope	54921
	Elevation	56812

WetLand	SoilDepth	89600
	DistanceToRoad	89628
	Elevation	89769
	AgricultureLabourDensity	89813
	DistanceToDrainage	89827
	Slope	90283
	Rain	91385
	Temperature	94471
WaterBody	Rain	70936
	DistanceToRoad	71014
	Slope	71104
	AgricultureLabourDensity	71139
	SoilDepth	71759
	Elevation	73502
	PopulationDensity	83391
	DistanceToDrainage	98231
SnowAndIce	SoilDepth	35828
	DistanceToDrainage	36034
	DistanceToRoad	36050
	Slope	36152
	Temperature	36178
	Rain	36321
	AgricultureLabourDensity	37791
	PopulationDensity	47982
	Elevation	125909