SPATIALLY EXPLICIT SIMULATION OF LAND USE CHANGE IN MYSURU-NANJANGUD LOCAL PLANNING AREA: A SCENARIO BASED STUDY

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Abstract: Simulation of Land use is a turnkey solution to portray the plausible scenarios of land use change in any study area, the current study was conducted to design the alternative futures of land use change in Mysuru-Nanjangud Local Planning Area, spatially explicit data were used for the study, satellite images act as a base input for study and driving forces of distance and topographic variables were used for training the model. The simulation were taken in a GIS environment, four different scenarios were designed to see the alternative possibilities of the land use change. The Cellular Automata were used to grow or decay the cells, Markov Chain chain used to predict the probability of change and Multi-Layer perceptron were helped to test and train the model. The model accuracy were tested with Kappa statistics and validated with actual land use data. The simulated data can be used for further decision making in study area.

Keyword: Land use, Cellular Automata, Multi-Layer Perceptron, Scenario, and Simulation.

1. Introduction:

Simulation of landscape changes over a period of time requires deep understanding of social, biophysical, geographical and political settings. The property of landscape considered as a system comprising 2-D plane defined by raster data models with information of feature classes will be associated in a pixel (Cell). Each cell has its own and unique coordinate values such as (X_i, Y_j). In practical, these X and Y values will be longitude and latitude values in specific units (Ex:, Degree, Minutes, Seconds: Decimal Degrees: or Meter: which is differentiated by defined coordinate system) respectively. The landscape is categorized by discontinues patches of land use and land cover. Also, these patches are not static but dynamic in nature, which means every land use patches can transform to another land use feature by the impact of external driving force. The concept of Cellular Automata (CA) algorithm were developed by Stanislaw Ulam and John von Neumann during 1940s, Later these CA models are widely used and applied to various complex systems to study the behavior of a subsystem. CA is dynamical system (Basse, R. M., Omrani, H., Charif, O., Gerber, P., & Bódis, K. (2014))., the discrete cells in CA model on lattice grid either will grow, degrade or remains static under the transition rules defined based on state of the cell, neighborhood interaction and driving forces. Several Algorithms are loosely and tightly coupled with cellular automata model, In GIS and Remote sensing, Cellular automata is successfully integrated with Markov Chain Model, which helps to find the probability of the transition cells, with respect to transition rules (key driving forces) from initial period of time(t) to simulation period of time ($t+n$).

Through the technology advancement in Information technology era, the Artificial Intelligence (AI) concepts are getting pace, the different algorithms such as Artificial Neural Network (ANN) Pijanowski, B. C., Brown, D. G., Shellito, B. A., & Manik, G. A. (2002), Support Vectors Machines (SVM), Self-Organizing Maps (SOM) (Wang, Y., & Li, S. (2011))., Genetic Algorithms are notable. These models helps to mimic the behavior of a complex systems through learning the existing state of systems, later calibrates the model and classifies the end product. In landscape simulation models, ANN is well- known for its reliability, ANN(Pijanowski, B. C., Tayyebi, A., Delavar, M. R., & Yazdanpanah, M. J. (2009)) uses Multi-Layer perceptron (MLP) (Erbek, F. S., Özkan, C., & Taberner, M. (2004)), these MLP(Rocha, J., Ferreira, J. C., Simoes, J., & Tenedório, J. A. (2007)) helps to learn, relate and calibrate impact of the driving forces or agents with respect to the condition of the systems under dynamic state(Losiri, C., Nagai, M., Ninsawat, S., & Shrestha, R. P. (2016)). It also helps to generate transition potential models through calibrating the input datasets (endogenous and exogenous drivers). The landscape simulation models are powerful enough when hybrid approach is developed such as CA-Markov-ML(Mishra, V. N., & Rai, P. K. (2016)). Simulation of Scenarios helps to see the plausible futures (Hundecha, Y., & Bárdossy, A. (2004).) and help to check the interventions and impact from altered land use (Rounsevell,M.D(2006)).

2. Study Area: Mysuru is the second largest city in the state of Karnataka, India. This Vibrant royal city of South, with a large area of heritage sites, has hit the fast track of urbanization off late, altering the landscape that will in the coming years go beyond recognition. With the government planning to develop this area under various Projects which has invited the surge of investors to invest heavily in this heritage city, especially the IT Companies. Realizing the importance, Mysore city planning authority was first constituted in the year 1966 for the LPA for Mysore city, which included entire Mysore City Municipal Area, 13 numbers of villages of Srirangapatna and 43 villages of Mysore Taluk. The LPA has been revised by government several times on the recommendations of the State Town Planning Board, in view of the need to bring these additional areas for regulation of development, from time to time. The development plans for these LPA have been prepared and enforced by the City Planning Authority as provided under the provisions of KTCP Act 1961. The present LPA includes Mysore City Corporation area, Nanjangud Town Municipal Council area, 84 villages within Mysore Taluk, 19 villages within Nanjangud Taluk and 14 villages within Srirangapatna Taluk. It covers an area of 509.03 km2 (Figure 1).

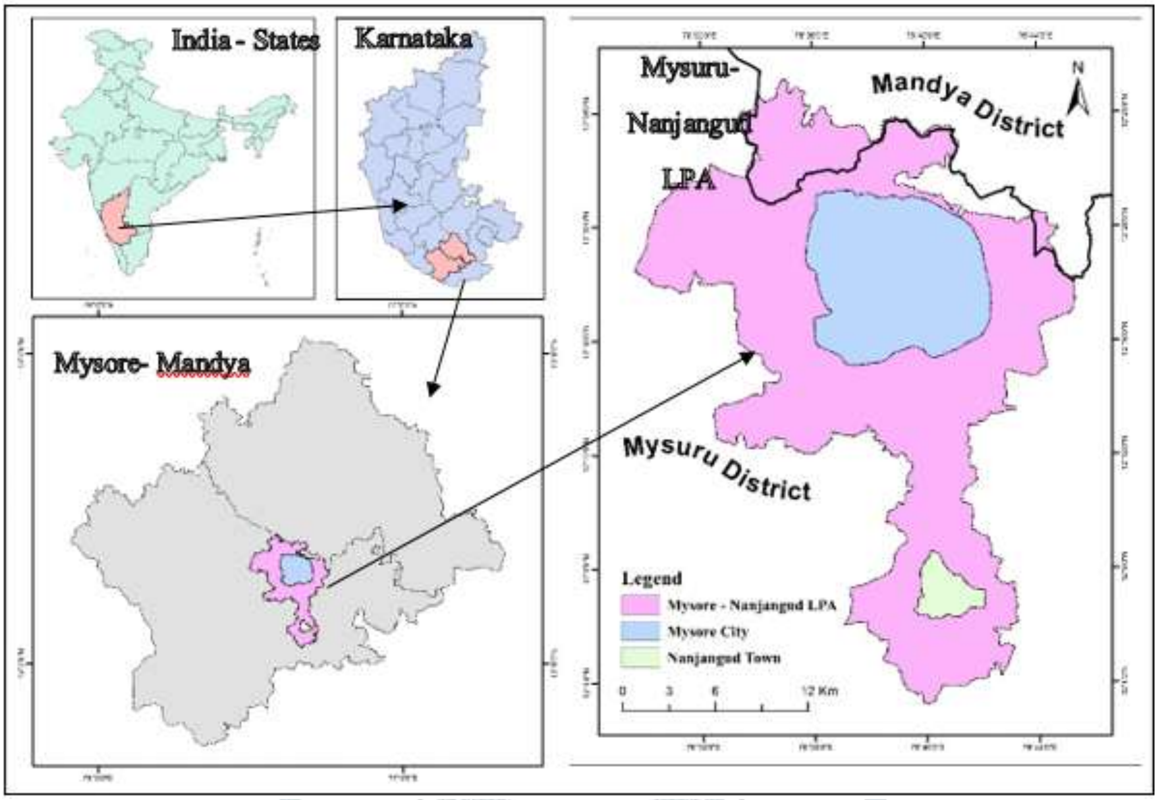

Fig. 1: Mysuru-Nanjangud Local Planning Area. (Source: Modified after Vinay.M, 2017)

3. Methodology:

To model the future land use change in MNLPA, it requires a two different land use set of data, for that year 1997 and 2017 landsat satellite images were considered(Fig:2). These images were atmospherically corrected with ATCOR plugin in ERDAS imagine software to reduce the errors in data. Later these satellite bands were layer stacked and extracted to the area of interest. The transition probability were estimated based on the cross tabulation between the image. To simulate the future land use change, we have considered the driving forces which are spatially derived such as Distance from Edge of Existing Built-up (Var1), Distance from Urban Centers (Var2), Distance from Rural Centers(Var3), Distance from Industry and Markets (Var4), Distance from Tourism Centers (Var5), Distance from Major Roads (Var6), Distance from State Highway (Var7), Distance from National Highway (Var8), Distance from Airport(Var9) Distance from Railway Network (Var10), Elevation (Var11), Slope in Degrees (Var12). All these distance variables are derived from the Euclidean distance algorithm in ArcGIS software. Based on these drivers transition potential for one class to another class were trained and tested with Artificial Neural Network based Multi-Layer Perceptron algorithm in TerrSET Land Change Modeler module(Mishra, V. N., Rai, P. K., & Mohan, K. (2014))., the calibrates the model by testing and training the network based on the hidden neurons in the model. After generating the transition potentials, we have tested the reliability of the simulation environment by simulating the model to known year such as 2018. The actual land use of 2018 and simulated land use of 2018 were compared and the accuracy were quantified. Based on the accuracy level, we have designed four different scenarios of land use change for better decision making in planning of landscape and its aesthetics. The results obtained from the simulation can be used for further ecological studies in study area.

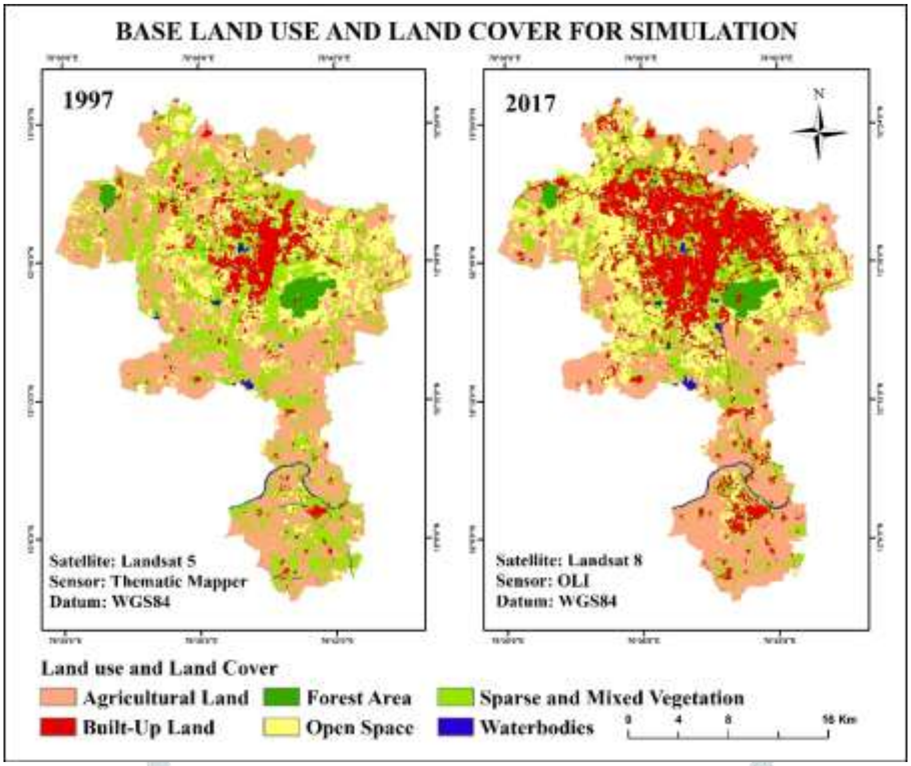

Fig: 2:

4. RESULT: CA-MARKOV-ANN Simulation for Scenarios of Urban Expansion in a GIS Environment.

4.1 Driving Variables and its Explanatory Power

Driving variable (Table:1) are the exogenous and endogenous agents that modifies the land use over a period of time. For the analysis, twelve different variable from topographic and distance decay variables were chosen Distance from Edge of Existing Built-up (Var1), Distance from Urban Centers (Var2), Distance from Rural Centers(Var3), Distance from Industry and Markets (Var4), Distance from Tourism Centers (Var5), Distance from Major Roads (Var6), Distance from State Highway (Var7), Distance from National Highway (Var8), Distance from Airport(Var9) Distance from Railway Network (Var10), Elevation (Var11), Slope in Degrees (Var12).

Cramer' V Explanatory Power of Variables						
	Var1	***Var2***	***Var3***	***Var4***	***Var5***	***Var6***
Overall V	0.2795	0.2113	0.1405	0.2328	0.2179	0.0515
AG	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
BU	0.3464	0.2191	0.1449	0.3517	0.2411	**0.0809**
FA	**0.6502**	**0.3615**	0.2169	**0.4721**	0.3166	0.0681
OS	0.0892	0.2209	**0.2237**	0.1756	**0.3243**	0.0632
VG	0.2029	0.2969	0.1384	0.1769	0.2597	0.0253
WB	0.1392	0.1020	0.0403	0.1026	0.1043	0.0286
	Var7	***Var8***	***Var9***	***Var10***	***Var11***	***Var12***
Overall V	0.1438	0.1923	0.1657	0.1676	0.3323	0.2590
AG	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
BU	**0.2281**	**0.3466**	0.1743	0.1798	0.4433	0.1477
FA	0.2258	0.2494	0.2143	**0.2549**	0.2906	0.0993
OS	0.1526	0.2148	**0.2676**	0.1836	**0.6295**	**0.6139**
VG	0.1479	0.2080	0.1400	0.2304	0.2740	0.0736
WB	0.0945	0.0936	0.1180	0.1268	0.0802	0.0577

Table:1

Var1, Var2, Var4 abd Var10 has strong predicting capability for forest change, Var3, Var5, Var9, Var11 and Var12 has strong predicting capability for open space, Var7 and Var8 has strong predicting capability for built-up change.

4.3 Scenarios Quadrants of Land use change with Change Probability Matrix

Four plausible scenarios (Fig 3) are developed using various inclusions and exclusions of key driving forces predominantly explains the possible change and which first scenario is developed namely Business–as-Usual (BAU) which is having low development of infrastructure with unplanned environment in nature, Second scenarios called Rapid Economic Development (RED) which is having high development in infrastructure with unplanned environment in nature. Similarly third scenario is policy driven development (PDD) which is having high development in infrastructure and planned environment. The fourth scenario is constrained and planned growth (CPG) which is having limited developmental activities and also planned in nature.

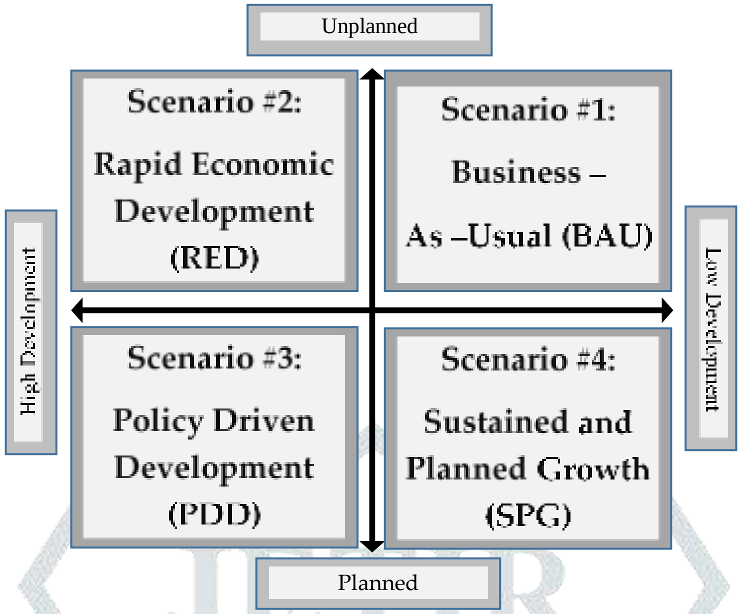

Fig: 3 Scenario Quadrants

These transition probabilities can be modified by altering the actual transition probability though reducing the half of the transition value for deceleration of change, and doubling of values leads acceleration of change in changing classes (Kotaro Iizuka, 2017).

The Change Allocation (Olmedo, M. T. C., Pontius Jr, R. G., Paegelow, M., & Mas, J. F. (2015)). is an interface which helps predicts future scenarios of LULC change by optionally adding dynamic road development, dynamic infrastructure changes, adding incentives (Binary value One) and adding constraints(Binary Value Zero) into the prediction. (Eastman, J.R. 1995).

Scenario #1: Business –As – Usual (BAU): This scenario represents the next twenty years (2017-2037) of possible LULC change, hypothetically assuming that development follows its current rate and no prior policy were made for regional governance. In other words these may follows the previous trends. The tends to grow based on existing rate of expansion, No Incentive and constraints for Urban Development, No Incentive and constraints for Agricultural Protection and No Policy Intervention, based on the defined criteria the transition probability matrix(table 2) have generated, and simulated the fig 4.

	AG	BU	FA	OS	VG	WB	Total
AG	0.5482	0.1514	0.0000	0.3004	0.0000	0.0000	1
BU	0.0000	1.0000	0.0000	0.0000	0.0000	0.0000	1
FA	0.0000	0.0378	0.9006	0.0615	0.0000	0.0001	1
OS	0.1679	0.4129	0.0001	0.2891	0.1264	0.0016	1
VG	0.1111	0.2060	0.0001	0.1910	0.4816	0.0102	1
WB	0.0001	0.0001	0.0001	0.1185	0.0002	0.8810	1

Table: 2 Modified Markovian Probability of Changing to 2047 for Business as Usual Scenario

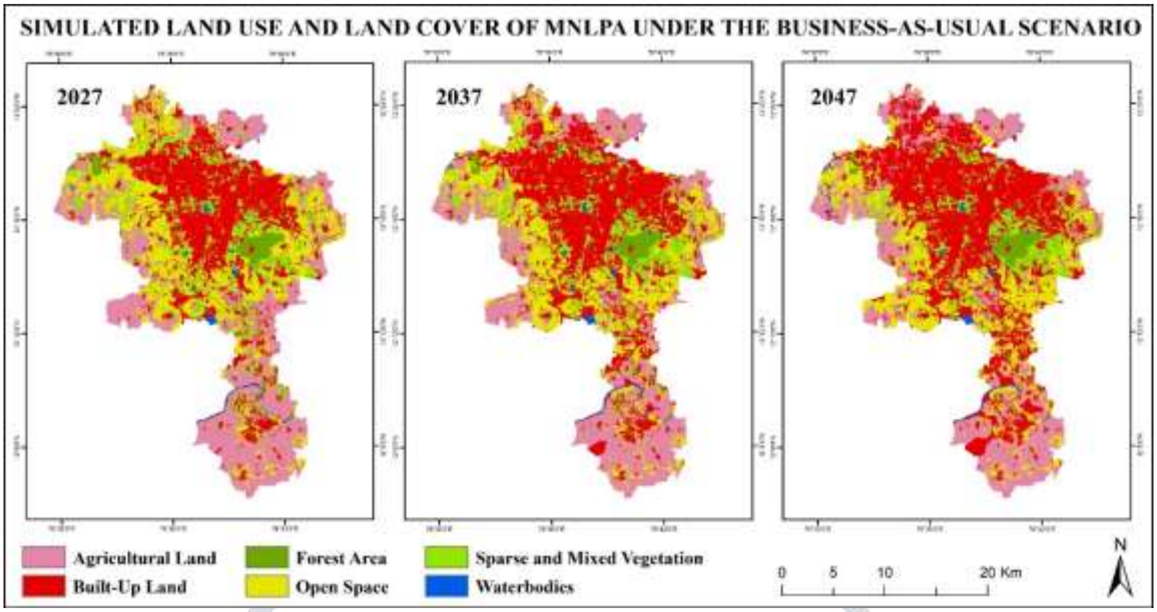

Fig: 4

Scenario #2: Rapid Economic Development (RED): This RED Scenario is Social and Economic oriented growth, in this scenarios the commercial and industrial activities are very high. Establishment of the new market centers, companies laid this growth. High Rural push towards urban. Here developments may also takes place in transit corridors. Here Economic Reform takes place, Increased Industrial Areas, Settlements tends to grow around industrial areas, Increased Demand for open space for residential activities, and all village centers act as Central Business District, Increased Land value in Urban-Rural Fringe, Urban Growth faces linear development along the existing Mysuru-Nanjangud corridors. based on the defined criteria the transition probability matrix(table 3) have generated, and simulated the fig 5.

	AG	BU	FA	OS	VG	WB	Total
AG	0.2000	0.3028	0.0000	0.4393	0.0579	0.0000	1
BU	0.0000	1.0000	0.0000	0.0000	0.0000	0.0000	1
FA	0.0000	0.0756	0.8536	0.0307	0.0400	0.0001	1
OS	0.0001	0.6193	0.0001	0.3157	0.0632	0.0016	1
VG	0.1617	0.2060	0.0003	0.3510	0.2690	0.0102	1
WB	0.0001	0.0001	0.0001	0.1185	0.0002	0.8810	1

Table:3 Modified Markovian Probability of Changing to 2047 for Rapid Economic Growth

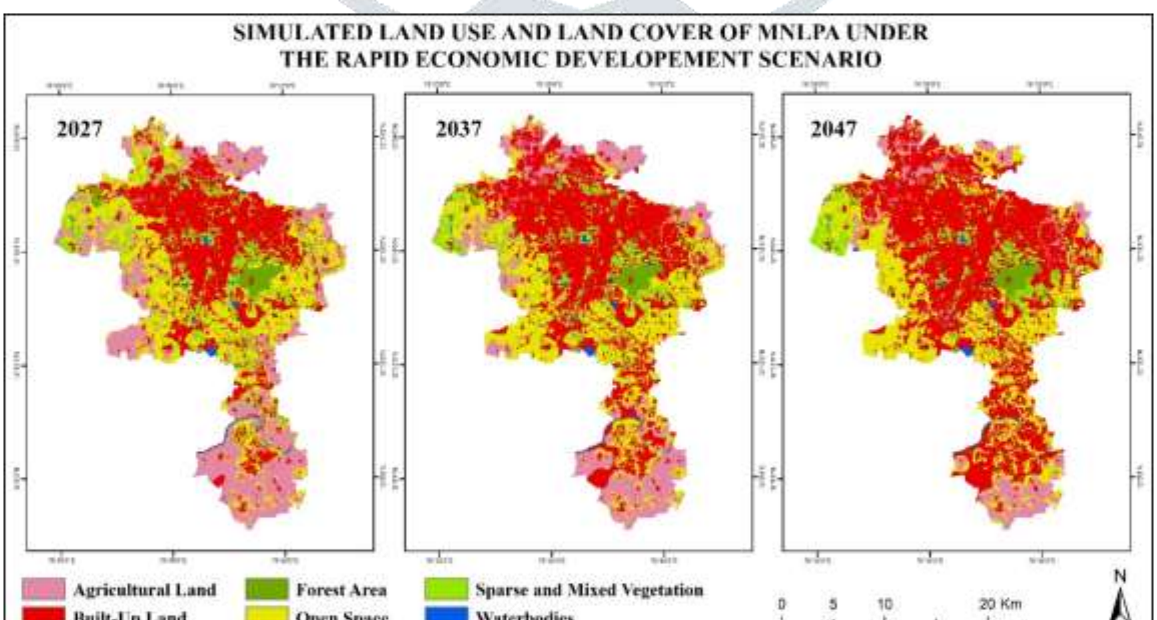

Fig: 5

Scenario #3: Policy Driven Development (PDD): Policy Driven Development is based on urban renewal and reform based growth. Here most of the direct investment will be provided for infrastructural development. Proposed policy may increase the land value in proximity regions of the land. New Investment for Infrastructure development, Incentives on Land Allocation for Specific Activities such as film city, extension of airport runway in MNLPA regions (Source: MUDA, Mysore), More built-up land can be expected in buffer regions of Mysuru City and Nanjangud Town, based on the defined criteria the transition probability matrix(table 2) have generated, and simulated the fig 6.

	AG	BU	FA	OS	VG	WB	Total
AG	0.3000	0.2464	0.0000	0.3933	0.0603	0.0000	1
BU	0.0000	1.0000	0.0000	0.0000	0.0000	0.0000	1
FA	0.0000	0.0002	0.9997	0.0000	0.0000	0.0001	1
OS	0.0010	0.5161	0.0000	0.3913	0.0900	0.0016	1
VG	0.3200	0.2060	0.0003	0.0100	0.4508	0.0102	1
WB	0.0000	0.0000	0.0000	0.0009	0.0000	0.9991	1

Table 4: Modified Markovian Probability of Changing to 2047 for Policy Oriented Development

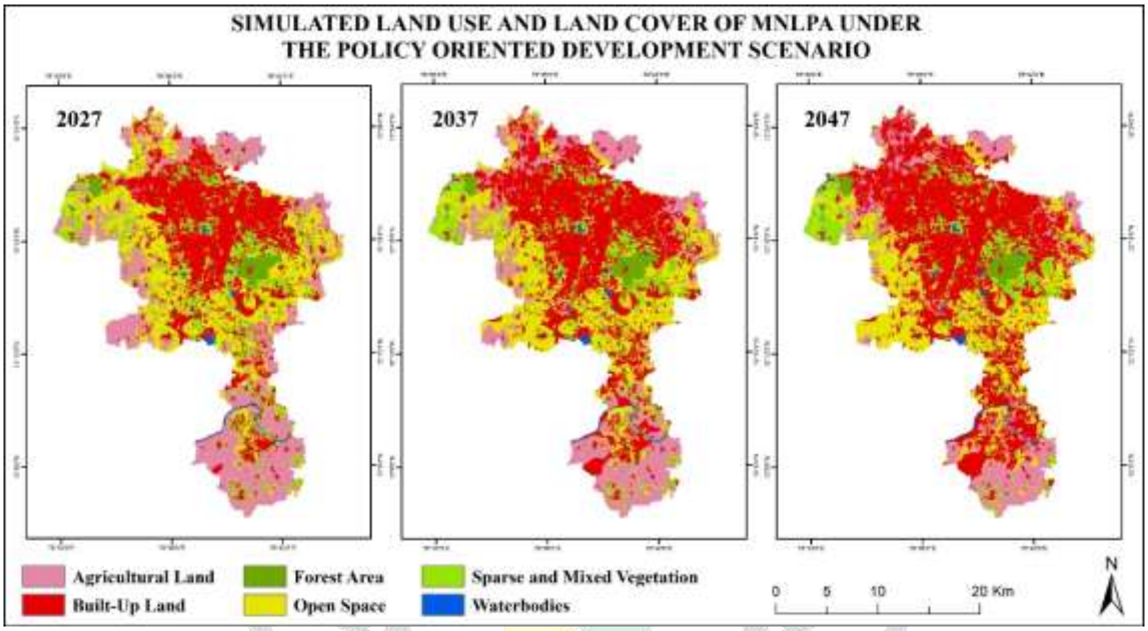

Fig:6

d) Scenario #4: Sustained and Planned Growth (SPG): This is well planned and preserved scenario which helps for conservation of natural resources, regional ecosystem and environment for better livelihood. Some key highlights include Sustainable Design of Infrastructure, More Stress given to conservation of natural resources such as natural vegetation's, aesthetics, Constraints for developmental activities near lakes, streams and water bodies, Preservation of wetlands, Constraints for Mining activities near water bodies, Constraints on Reserved Forest Areas in MNLPA region. Based on the defined criteria the transition probability matrix (table 2) have generated, and simulated the fig 7.

	AG	BU	FA	OS	VG	WB	Total
AG	0.8520	0.1211	0.0000	0.0100	0.0158	0.0011	1
BU	0.0000	1.0000	0.0000	0.0000	0.0000	0.0000	1
FA	0.0000	0.0000	1.0000	0.0000	0.0000	0.0000	1
OS	0.0800	0.7742	0.0000	0.1440	0.0002	0.0016	1
VG	0.1617	0.0000	0.0000	0.0090	0.8191	0.0102	1
WB	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	1

Table 5: Modified Markovian Probability of Changing to 2047 for Sustained and Conserved Growth

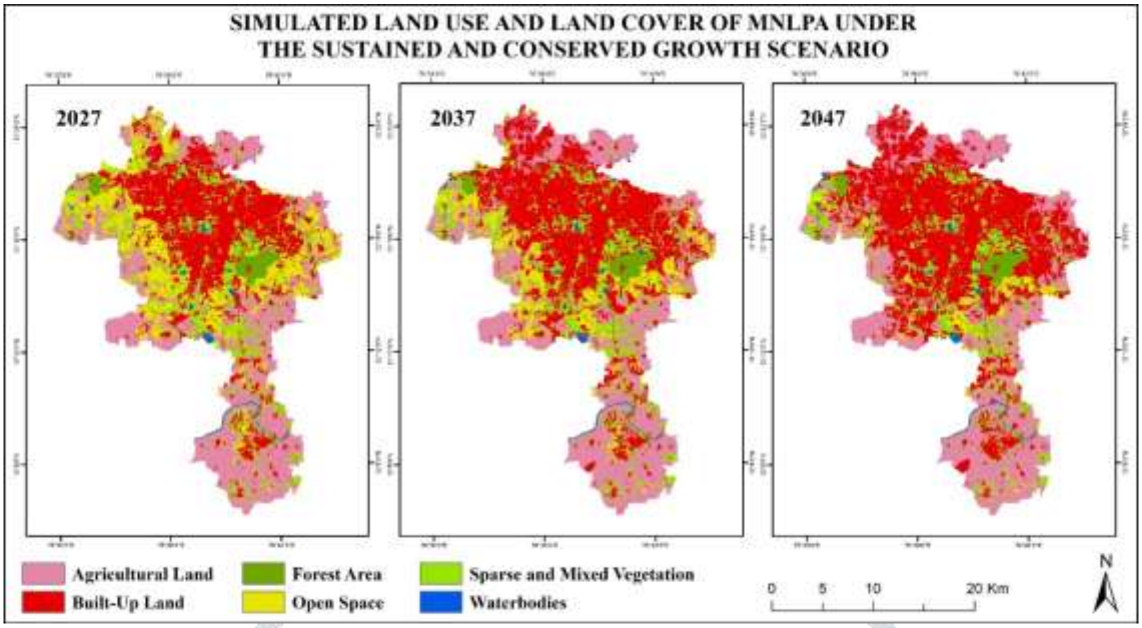

Fig: 7

Conclusion: The scenarios of land use change were spatially modelled with integration of cellular automata, Markovian chain rule and multi-player perceptron. The scenarios were designed by altering the transition probability matrix based on the defined criteria of land use change. The results are used for further studies such as ecosystem service modelling and eco-hydrological studies in the study area.

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