HYDROLOGICAL SIMULATION OF A SMALL URBAN UNGAUGED CATCHMENT: A CASE STUDY OF SMART CITY NAVI MUMBAI

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CANDIDATE'S DECLARATION

I hereby certify that the work contained in this report entitled **"HYDROLOGICAL SIMULATION OF A SMALL URBAN UNGAUGED CATCHMENT: A CASE STUDY OF SMART CITY NAVI MUMBAI"** in partial fulfilment for the award of the award of the degree of Master of Technology with specialization in in Water Resources Development, submitted to the Department of Water Resources Development and Management, Indian Institute of Technology Roorkee, India, is an authentic record of my work carried out under the supervision and guidance of **Dr. Deepak Khare**. The matter embodied in this dissertation report has not been submitted by me for the award of any other degree.

Date: 11th May 2018

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CERTIFICATE

This is to certify that the above statement made by the candidate is correct to the best of my knowledge.

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CONTENTS

CANDIDATES DECLARATION……………………………………………………………i

ACKNOWLEDGEMENTS……………………………………………………………..ii

LIST OF FIGURES………………………………………………………………...v

LIST OF TABLES…………………………………………………………………...vii

ABSTRACT…………...……………………………………………………………viii

1 INTRODUCTION 1

1.1 General 1

1.2 Need of Urban Land Use Modelling 1

1.3 Using Artificial Neural Network (ANN) for Land Use Modelling................ 2

1.4 Hydrological Modelling of Catchments 3

1.5 Hydrological Modelling of Ungauged Catchments 3

1.6 Rationale 4

1.7 Objectives.. 4

2 LITERATURE REVIEW 5

2.1 Land Use Change Modelling 5

2.2 Hydrological Modelling 7

2.3 Concluding Remark 9

3 STYDY AREA AND DATA USED 10

3.1 General 10

3.2 Location... 10

3.3 Population 11

3.4 Climate data 11

3.5 Smart City 12

3.6 Datasets used 12

4 METHODOLOGY 14

4.1 General 14

4.2 Land Use/ Land cover Transition... 14

4.2.1 Image Processing 14

4.2.2 Image Classification... 14

4.3 Future Land use/ Land cover prediction 15

4.3.1 Land Change Modeler (LCM) 15

4.3.2 Change Analysis 15

4.3.3 Transition Potential Modelling 15
4.3.4 Multi-Layer Perceptron 16
4.3.5 Change Demand Modelling 16
4.4 SWAT Model 21
4.4.1 SWAT for Urban Areas 24
4.4.2 SWAT Model Setup 24
4.4.3 SWAT Model Data Inputs 25
4.4.4 Digital Elevation Model (DEM) 25
4.4.5 Delineated Watershed 26
4.4.6 Soil Data 27
4.4.7 HRU Definition 29
4.4.8 Weather Data 29
4.4.9 Land Use/ Land Cover Data 30
4.5 Regionalization Technique 31
4.6 SWAT Sensitivity Analysis 32
4.6.1 Model Calibration 32
4.6.2 Model Validation 32
4.6.3 Model Performance Criteria 32
4.7 Concluding Remark 33
5 RESULT AND DISCUSSIONS 34
5.1 Land Use/ Land Cover Change Analysis 34
5.2 Future land use/ land cover prediction 38
5.3 Application of Regionalization Technique 43
5.4 SWAT Model Output 46
5.5 Sensitivity and Uncertainty Analysis 48
5.6 Concluding Remark 52
6 CONCLUSION 53
6.1 General 53
6.2 Conclusion 53
6.3 Scope for Further Work 54
REFERENCES 60

LIST OF FIGURES

Figure 3-1: Location Map of Navi Mumbai ... 11
Figure 4-1: Navi Mumbai DEM ... 17
Figure 4-2: Distance from Nearest Urban Area ... 18
Figure 4-3: Navi Mumbai Slope Map ... 19
Figure 4-4: Navi Mumbai Distance Map ... 20
Figure 4-5: Land Change Modeler Flowchart ... 21
Figure 4-6: SWAT Hydrologic Cycle ... 22
Figure 4-7: Navi Mumbai Catchment DEM ... 26
Figure 4-8: Delineated watershed ... 27
Figure 4-9: Navi Mumbai Soil Map ... 28
Figure 4-10: Navi Mumbai Catchment LULC Map ... 30
Figure 4-11: SWAT Model Flowchart ... 31
Figure 5-1: Navi Mumbai LULC Map (2000) ... 34
Figure 5-2: Navi Mumbai LULC Map (2008) ... 35
Fig.5.3: Figure 5-3: Navi Mumbai LULC Map (2016) ... 36
Figure 5-4: Land Change Modeler Result ... 38
Figure 5-5: Spatial trend of change ... 38
Figure 5-6: Navi Mumbai LULC Map (2030) ... 39
Figure 5-7: Navi Mumbai LULC Map (2050) ... 40
Figure 5-8: Variation of LULC classes from 2000 to 2050 ... 42
Figure 5-9: Donor catchment ... 45
Figure 5-10: Subbasin ... 45
Figure 5-11: Donor catchment LULC Map ... 45
Figure 5-12: Subbasin LULC Map ... 45
Figure 5-13: Donor Catchment Soil Map ... 46
Figure 5-14: Subbasin Soil Map ... 46
Figure 5-15: SWAT Hydrological Cycle ... 47
Figure 5-16: Hydrograph for the monsoon season of year 2013 ... 47
Figure 5-17: Scatter plot between observed and simulated discharge values during the calibration period (2003-2008) ... 50
Figure 5-18: Scatter plot between observed and simulated discharge values during the validation period (2009-20013) ... 50

Figure 5-19: Plot between observed and the simulated surface runoff values during calibration period 51
Figure 5-20: Plot between observed and the simulated surface runoff values during validation period 51

LIST OF TABLES

Table 3-1: Datasets used for the study and their description 13
Table 4-1: Soil details of the catchment 29
Table 5-1: Area covered by the LULC classes for years 2000, 2008 and 2016 37
Table 5-2: Transition Matrix from the year 2000 to 2016 37
Table 5-3: Area covered by the LULC classes 41
Table 5-4: Regionalization analysis 43
Table 5-5: Similarity index calculations 44
Table 5-6: SWAT parameters with ranges and their best fitted values 48
Table 5-7: Model Performance criteria 49
Table 5-8: SWAT model performance during calibration and validation period 49

ABSTRACT

Land use/ land cover (LULC) is a dynamic and continuous spatio-temporal phenomenon, especially in all the developing countries, showing no sign of stopping, reason being the economic developments and population increase. This study presents a simulation model using Multi-Layer Perceptron integrated with Markov chain, Remote Sensing (RS) and Geographic Information (GIS) for the city of Navi Mumbai, India. Artificial neural networks were used to train on the predictor variables of urban expansion. Navi Mumbai is facing on-going challenges concerning its urban sprawl, due to rapid population increase. In this research we assess the past urban land use transitions in Navi Mumbai between 2000 and 2016, as the major development in Navi Mumbai started after 1992. This is done by a combination of multi-criteria evaluation processes originating transition probabilities that allow a better understanding of the regions urban future by 2030 and 2050, while the transition probabilities are incorporated from the Markov chain model. By the year 2030 about 48% and by 2050, 57% of Navi Mumbai will be urbanized. Major contribution to the urban class is coming from tree cover and barren class. Very less advancement is shown wetland and forest areas, which shows the predicted results are ensuring sustainability. The accuracy rate is 99.98% and calculated with a skill measure of 0.9997. It indicates that model has been trained very efficiently and can be used for understanding the spatio-temporal land use change dynamics of Navi Mumbai. The structure of the model allows for urban growth simulation and it therefore carries scope of being used to anticipate growth for other cities and help government agencies to better understand the consequences of their decisions on urban growth and development.

Soil and Water Assessment Tool (SWAT) is a physically based semi - distributed model is implemented to understand the behaviour of urban ungauged catchment of Navi Mumbai, India. Prediction in an ungauged basin (PUBs) has always been a challenging task due to the inability to perform calibration and validation as there is no observed gauge-discharge data. To address this problem well known catchment characteristics similarity technique is adopted. SUFI-2 algorithm is used for calibration (2003-08) and validation (2009-13) of the surface runoff performed on a monthly basis. For the monthly time step the NSE values were 0.76 and 0.86, R^2 values were 0.79 and 0.85, PBIAS values were +3.25% and -5.45% RSR values were 0.006 for calibration and validation period respectively. Hence this model can be successfully used for hydrological modelling of an ungauged catchment of Navi Mumbai.

Keywords – LULC, Multi-layer perceptron, Markov chain, SWAT, PUBs, SUFI-2.

1 INTRODUCTION

1.1 General

Urban growth is taking place at an unprecedented rate in India (MOUD, 2011). Although urbanization in all the developing countries differs in percentage. According to United Nation Population Fund the urban population of the developing countries will increase from 2.05 billion in 2000 to 4 billion (United Nations Population Fund, 2007). Our narrow understanding of the spatio-temporal urban growth and its dynamics is possibly the reason for poor urban planning methods (Brown et al., 2013). Because of demographic shifts and economics centres, urban areas are increasing in their extent. The methods implemented for preparing urban development plans at the statutory level have been criticized (Adhvaryu, 2011). To address these issues and ensure sustainability we have to understand the existing land use/ land cover (LULC), the possible changes in the future, what repercussions it would have on the urban ecosystem and how urban planners should incorporate this information while planning the future infrastructural developments (Koomen et al., 2007; Bagan et al., 2012). Predicting daily runoff time series in ungauged catchments is equally challenging and important. The rainfall–runoff modelling approach has been showing efficient results for evaluating the catchment runoff response. Predicting catchment runoff time series is still a challenging task in surface water hydrology since many catchments around the world are ungauged or poorly gauged (Sivapalan et al., 2003). The International Association of Hydrological Sciences launched a decade-long initiative, Predictions in Ungauged Basins (PUB) (http://www.iahs-pub.org/) in 2003, which has been the subject of great interest by hydrologists around the world.

1.2 Need of Urban Land Use Modelling

Land use/ land cover (LULC) change focussing on urbanization has gained significant attention recently, there are very limited studies on developing areas (Arsanjani et al., 2011). Dynamics and spatial patterns of urban sprawl can be analysed and predicted because of the developments of tools like remote sensing and the geographic information system (Masser, 2001). Several spatio-temporal modelling techniques that are based on Remote Sensing (RS) and Geographical Information System (GIS) have been used to predict growth of urban areas. Modelling and simulation of urban areas can be done very efficiently and less computational effort by symbiotic action of GIS and models.

The factors that lead to changes in urban land use vary spatially and temporally in a complex way, to analyse them all at once models are required (Brown et al., 2007). To assist in planning and identifying the places where the future growth is feasible, we do modelling and try to predict the change in different land use classes. Models based on cellular automata (CA) (Han et al., 2009; Wang et al., 2013). Markov chain algorithms (Cheng et al., 2011; Kamusoko et al., 2009; Benito et al., 2010). Spatial logistic regression models (Al-sharif et al., 2014). However each model when applied individually has limitations. Logistic regression models cannot explicitly obtain the temporal changes in urban expansion nor can it quantity land use change (Al-sharif et al., 2014). The cellular automata model cannot evaluate urban change driving forces (Al-sharif et al., 2014) and the Markov chain model is unable to determine the spatial pattern of urban expansion and Markov chain only computes transition probabilities (Arsanjani et al., 2011). To cope up with the individual drawbacks of a single model, we must use some of these modelling approaches in conjunction.

1.3 Using Artificial Neural Network (ANN) for Land Use Modelling

An artificial neural network (ANN), a machine learning tool. Spatial cell shares their border with another spatial cell with land use classes. This contact enables the two way understanding of characteristics and the interaction with the spatial cells.

ANNs are massive and parallel distribution computation devices consisting of neurons, which are usually arranged in layers. The neurons have to store the knowledge acquired by the system, which is then interpreted for further use (Haykin, 1999). An artificial neural network generally has one input layer, one output layer, and some layers hidden in between. The successive layers processes the neurons present in the connection travelling from all the neurons in one layer to all the neurons in another layer. These connections are the ones actually given the responsibility of passing the information through the entire network, and their characterization is done by assigning weights, which in the beginning are set in a random manner (Bishop, 1995). All neurons, except the ones belonging in the input layer, perform two processing functions; receiving the signal from the neurons in the layer before and then transmitting a new signal in form of input to the next layer.

ANNs are not dependent on fix functional relationships and also do not require any understanding of the variable relationships beforehand (Cheng, 2003). Non dependency on relationships is a major advantage of ANN because it enables them to be used as future prediction tools while dealing with non-linear problems of severe complexity (Olden & Jackson, 2001). Artificial intelligence algorithms are competent when it comes to detecting urban land use/ land cover change patterns in a non-parametric approach and has the ability to handle data of higher spatial heterogeneity. (McDonald et al., 2006; Wang et al., 2011).

ANNs are having the benefit of facilitating the development of complex models wherein we integrate parameters that are based on different land uses, different types of soils present, their elevation and slopes, distances from nearest roads (Yang et al., 2008; Soares, 2008). Though while calibrating and validating the models, it is quite a challenging problem.

1.4 Hydrological Modelling of Catchments

For sustainable development and management, it is imperative that the hydraulic infrastructure can perform efficiently in cases of event extremities. Thus it is necessary to perform hydrological modelling. Understanding the behaviour of the watershed to extreme events helps the policy makers while preparing development plans. Rainfall-runoff modelling has always been very important while studying the surface water hydrology. As the information related to streamflow/ runoff is a key input for practical applications like designing of hydraulic structures, hydropower potential, flood forecasting and others.

Computer based have better accuracy and can save a lot of time as they can perform longer simulations in shorter period of time. These models when used for hydrologic simulation of watersheds helps in studying the effects of the hydrologic cycle on water balance, land management practices, sediment and pesticide details and water quality. For the modelling and simulation, the most commonly used hydrological models are SWAT (Arnold et al., 1998), HEC-HMS (HEC, 2000), SHE (Abbot et al., 1986) and others.

SWAT is a semi-distributed continuous time model. From these outputs hydrographs and flow-duration curves can be developed which play a vital role while designing hydraulic structures. But modelling in an urban area is complex because of heterogeneity in the urban ecosystem. After modelling, calibration and validation is required, which can be done quite easily in case of a gauged catchment (Bárdossy, 2007).

1.5 Hydrological Modelling of Ungauged Catchments

Measurement of streamflow in ungauged or gauged basins are carried out using data-driven models, semi-distributed models, physically-based models, conceptual models. As prediction from distribution models which are physically based come with high levels of uncertainty it is recommended to use a semi-distributed model or a conceptual model (Coulibaly et al., 2012). Usually small catchments are devoid of observed datasets (Ibrahim et al., 2015). Transferring of optimized model parameters from a gauged catchment to an ungauged catchment is one of the ways to quantify the numerous hydrological processes taking place in the ungauged catchments. The process of transferring parameters is regionalization (Blöschl et al., 1995; Oudin et al., 2010). Hence, regionalization is a way for quantification of parameters like surface runoff, sediment load in ungauged catchments. There are some cases of where different regionalization methods were implemented, as the major developments in regionalisation techniques have occurred in the late 1990s (Blöschl, 2016; Hrachowitz et al., 2013). Regionalization approaches vary from one place to other because of differences in regional climate, area of catchment, land use, soils and slope. One of the common regionalisation techniques is evaluating the physical similarity, based on the hypothesis that catchments with physical similarities will have similar hydrological runoff response. Another technique is on the basis on spatial proximity with the underlying assumption that the area just in the neighbourhood will have similar hydrological runoff response.

1.6 Rationale

As the city (study area – Navi Mumbai) is expanding at an unprecedented rate and the population is growing exponentially, urban planners need to come up with efficient expansion plans. Also apart from change in the hydrologic cycle, land use/ land cover affects the entire urban ecosystem. Knowing the possible future land use helps in getting an idea while planning the upcoming infrastructure. It is necessary to quantify the effect of urbanization on the hydrological process and the water resources. Limited research has been done on the behavior of an urban ungauged catchment, as there is limited or no observed data, which makes calibration and validation difficult.

1.7 Objectives

1) Mapping land use/ land cover maps for the year 2000, 2008, 2016 and performing change detection.
2) Predicting land use/ land cover maps for the year 2030 and 2050.
3) Demonstration of method of Regionalization for ungauged catchments.
4) Hydrological modelling of Navi Mumbai.
5) Calibration and validation of the results.

2 LITERATURE REVIEW

2.1 Land Use Change Modelling

Arsanjani et al. (2013) in his study on urban expansion simulation of an area in Tehran, Iran used a hybrid model which was an integration of three different models namely, cellular automata, Markov chain and linear regression model. Socio-economic and environmental factors affecting urban sprawl were also included to find the spatiotemporal changes in land use for 2006, 2016 and 2026. One of the limitations of this hybrid model is that it does not take into consideration the changes in and conversions of land use due to governmental actions.

Yang et al. (2012) researched a spatio-temporal model of land cover change based on Markov chain, cellular automata and ant colony optimization. These three techniques have been used in combination. For studying the spatio-temporal changes in land cover cellular automata and ant colony optimization have been used whereas for total magnitude of land use coverage Markov chain and cellular automata have been used.

Sang et al. (2011) studied the spatial changes in the land use pattern based on CA-Markov model. The magnitude of the changes is given by the Markov model and the spatial changes in the pattern are given by cellular automata model. The Markov model gives the matrix of transition probabilities of different land use types and also at which rate they will occur.

Guan et al. (2011) carried out his study on modelling urban land use change using cellular automaton and Markov model. Transition among different land use types was found out using transition matrices. Socio-economic factors like population density and gross domestic product per capita was also taken into consideration and were given much weightage and other factors like distance form nearest road and river were given less weightage.

Moghadam et al. (2013) in his research on spatio-temporal urbanization of Mumbai, India used Markov chain and cellular automata. Weightage for different factors like distance from nearest road, distance from water bodies/wetlands, slope, urban distance map and the land use categories were given based on AHP and fuzzy standardization. A correlation between population and urban expansion was also made.

Kantakumar et al. (2016) studied the spatio-temporal urban expansion of Pune city. Urban fringe, scatter development and ribbon development were studied for Pune. Fertile agricultural land was converted into built-up areas. This kind of land use change could affect the food security, but there has also been some increase in the agricultural area in other locations due to development of irrigation system. The method used in this study are of direct relevance to urban planners.

Munshi et al. (2014) used cellular automata and logistic regression for modelling urban development in the city of Ahmedabad, India. Cellular automata was used to simulate the change in urban growth and linear regression was done to find out the transition potentials of each land use types.

Pielke et al. (2002) studied the influence of land-use change and landscape dynamics on the climate system. The changes in land use impacts the global climate through surface-energy budget and carbon cycle, though the effects of surface-energy budget are more important than carbon cycle. The effects of tropical changes in land use is somewhat similar to effects due to El Nino event, which is due to spatial consonance of the ocean warming and its large magnitude. Deliberate land use change brings about a change in the amount of CO_2. Due to change in land use there are difference in the surface-energy flux values. These surface-energy flux perturbations cannot be considered analogous to global warming potential, since the global warming potential is an index requiring an expression in terms of atmospheric parameters, which the land use is not.

Liu et al. (2015) studied the simulation of urban sprawl pattern by combining auto-logistic regression, Markov chain and cellular automata model. Dynamic evaluation of the eco-security of the environment was given much importance. Different urban scenarios were considered like historical development trend, priority to protect the environment were incorporated in the CA model through self-modification.

Basse et al. (2014) did their study on land use changes modelling using artificial neural networks. The primary objective was the use of big data for modelling of land use change and the application of ANN to calibrate the models. ANNs can learn from a large amount of data in spite the quality. They consider the non-linearity in the relationship between different land use types at each modelling step. When this model handles large amount of data it might be challenging to execute land use change modelling. The model overestimated the growth of the urban classes between 1990 and 2000, nonetheless the unforeseen increase in the urban land use, although not actually existing in the observed land use makes has emerged in a developing area.

Omrani et al. (2017) in their study on land-use concept with the artificial neural network. ANN has effectively determined the CA transition rules, so both ANN and CA were integrated. Multi-label concept was used, in which a same cell can be assigned to various land use types simultaneously. The paper limited the forcings to land use changes such as slope, distance from nearest road, distance from nearest urban area. Based on the results the ML-CA-LTM model outperformed the CA-LTM in all of the evaluation measures. The new model gave an accuracy of 69.1%, whereas the ml-CA-LTM model gave a lower accuracy of 39.7%.

Pijanowski et al. (2014) researched on a big data urban growth simulation. In the land transformation model within the neural network multi-layer perceptron was used to approximately develop a relation between the inputs and the output. Inputs include nearest distance to roads, slope. The LTM simulates land use change based on bio-physical & socio-economic factors. The algorithm first learns to determine the weights, value for biases and activation function to fit input and output values. A primary attribute of HPCs is the integration of software and hardware systems that are configured to break up huge processing jobs into smaller parallel tasks. Parallel implementation of the data and modelling was done on a cluster of processors using HPC as a data parallel programming framework.

2.2 Hydrological Modelling

Wagner et al. (2016) did their research on the dynamic integration of land use changes in a hydrologic assessment of a rapidly developing Indian catchment. The main objective of the study is to incorporate the land use predictions obtained from SLEUTH and using it as input for SWAT and studying its impacts on water resources. Climate scenarios namely baseline, A1B, dry and wet were analysed rom 2009-2028. The SLEUTH model while finding the transitions of land use the existing urban growth is taken as the main driving force.

Sisay et al. (2017) studied hydrological modelling of ungauged urban watershed using SWAT model. NSE values were 0.53 and 0.61, R^2 values were 0.69 and 0.51, PBIAS values were 5.3% and 10.4%, and RSR values were 0.71 and 0.63 for the periods of the calibration and validation respectively done for monthly data. There are no gauge-discharge stations inside or near the outlet of city catchment. The closest gauge-discharge station to it is located in North West of the catchment. SUFI-2 is iterated so that 95% prediction uncertainty band (95PPU) brackets most of the measured data (p factor), maintaining a small width band (*r*-factor).

Narsimlu et al. (2015) did their research on SWAT model calibration and uncertainty analysis for streamflow prediction using SUFI-2. SWAT simulations showed that during calibration the r-factor and p-factor were as 0.76 and 0.82, respectively, while during validation the r-factor and p-factor were obtained as 0.72 and 0.71, respectively. The R^2 and the NSE between the observed and the simulated values were 0.77 and 0.74 respectively during calibration. The validation also indicated a satisfactory performance with R^2 of 0.71 and NSE of 0.69. Most sensitive parameters were ALPHA_BNK, ESCO, CH_K2 and CN2.

Mishra et al. (2017) carried out their studies on an ungauged catchment using SWAT. The most sensitive parameters were CN, ESCO, SOL_AWC, SOL_Z, BLAI, GWQMN, GW_REVAP, CANMX, CH_K2 and REVAPMN. Parameters showing least sensitivity were SLSUBBSN, SLOPE and BIOMIX. NSE was of the order 0.77 between the observed and simulated ETP during calibration. PBIAS was found to be 3.19. The RSR value was found to be 3.97.

Ang et al. (2018) in their study on simulating streamflow in an ungauged catchment using SWAT model. NSE of 0.38 and -6.61, PBIAS of 5.1% and -78.33%, RSR of 0.79 and 2.67 in calibration and validation period respectively. These results were for daily simulation results. The streamflow results for monthly simulation were improved with NSE of 0.60, PBIAS of 1.14 and RSR of 0.63. The monthly simulation results were accepted.

Halefom et al. (2017) in their study on hydrological modelling of urban catchment using SWAT model and SUFI-2 algorithm. The two neighbouring catchments having of about 92.33% similarity of slopes when classified in five classes and discharge data can be transferred from each other. When land use was considered about 55.79% homogeneity of the two catchment was observed and taken accordingly. The calibrated and validated R^2 of 0.54 and 0.57 for the period of 1979–2000 and 2001–2013, respectively and NSE for the same period is 0.53 and 0.57 respectively. These results were for monthly simulation flows.

Pandey et al. (2017) did their research on assessing the impacts of climate change on hydrology of a watershed using SWAT. SWAT model is implemented for the assessment of the water balance components on the basis of HRU with the base years being from 1961–1990 and future climate scenarios from 2071–2100. Calibration period was taken from 1987–1994 and the validation period being from 1995–2000 was performed using the observed streamflow data. HadRM3, a regional climatic model has been used as an input for assessing the impacts climate change impact on the hydrology of the area. Two scenarios namely A2 and B2 were considered. Parameters for sensitivity analysis were CN2, ESCO, GWQMN, SOIL_AWC, SOIL_Z, ALPL_BF, GW-REVAP. For monthly flow simulation results R^2 was 0.8 and 0.77 and NSE was 0.69 and 0.54 for calibration and validation periods respectively.

Iskender et al. (2016) evaluated the surface runoff in ungauged catchments using SWAT and GIUH. In the case of ungauged catchments GIUH can be employed for the simulation of flood events. SWAT does continuous modelling. SWAT could also be implemented on hourly rainfall data, but as its accuracy when it comes to daily flow is less as compared to monthly flow, so for hourly flow it is yet to be assessed. GIUH is interpreted as a probability density function of the travel time of rainfall to the outlet, rainfall is uniformly and randomly distributed over the catchment. GIUH parameters are area ratio, bifurcation ratio and length ratio. RMSE error of runoff was observed to be better.

Swain et al. (2017) carried out their studies on streamflow estimation in ungauged catchments using regionalization techniques. IDW, kriging and physical similarity were the regionalization techniques employed, integrating with SWAT model for streamflow estimation in each catchment. IDW and kriging gave superior results than other approaches in terms of NSE, RSR and PBIAS. For the calibration period 1995-2006 and validation period 2007-2011, NSE varied from 0.59-0.81 and 0.48-0.77, RSR was 0.07-0.91 and 0.07-0.95 and PBIAS was 16.8% and 12.5% respectively.

2.3 Concluding Remark

From the literature review, it can be concluded that hydrological modelling of ungauged catchments is quite challenging and requires regionalization. Moreover the regionalization technique being implemented should justify the selection of the donor catchment. Also for land use/ land cover prediction the methods discussed involve individual shortcomings and have to be used in integration to complement each other.

In the present study we will be using multi-layer perceptron neural networks for model training and Markov chain for future prediction. As the neural networks trains on its own according to the internal modules and algorithms set into it, it becomes very user friendly. Spatial Proximity and comparison of catchment characteristic has been done for regionalization to test the reliability of model for ungauged catchment.

3 STYDY AREA AND DATA USED

3.1 General

Among the six divisions, Navi Mumbai lies in the Konkan division. Navi Mumbai is majorly categorized in two parts, namely South Navi Mumbai and North Navi Mumbai. The area was proposed in 1971 to be an urban cluster by the Government of Maharashtra. The main objective of planning the city was to create affordable housing for people who could not afford living in Mumbai. It was decided that any slums should not pop up but it failed. As per the 2001 census, three fifth of the population of municipalised Navi Mumbai lives in slums and *gaothans* (urban villages) with thousands of buildings built violating building construction norms. The City and Industrial Development Corporation of Maharashtra (CIDCO) then carved out 14 nodes to facilitate comprehensive development. These 14 nodes are, Airoli, Ghansoli, Kopar khairane, Juhunagar, Vashi, Sanpada, Nerul, CBD Belapur, Kharghar, Kamothe, New Panvel, Kalamboli, Ulve, Dronagiri. The famous Mumbai-Pune Expressway starts from here. These nodes are further divided into sectors. Later on in 1991 Navi Mumbai Municipal Corporation (NMMC) was constituted by the Government of Maharashtra for maintaining some of the developed nodes of Navi Mumbai. NMMC was handed 9 node out of the 14. The nine nodes maintained by NMMC are CBD Belapur, Nerul, Juhunagar, Vashi, Kopar khairane, Ghansoli, Airoli and Sanpada. Recently it has been declared as a Smart City and a Special Purpose Vehicle (SPV) has been formed. Out of the 14 nodes, the most developed nodes are Kharghar, Kamothe, New Panvel and Kalamboli which are under the jurisdiction of CIDCO. However the Smart City has been planned in the area under the jurisdiction of NMMC. In the Smart City the nodes covered are namely, Airoli, Ghansoli, Kopar khairane, Vashi, Sanpada, Nerul and CBD Belapur.

3.2 Location

Navi Mumbai is planned city off the west coast of Maharashtra in the western suburbs of Navi Mumbai. Navi Mumbai is located in between 19°04' N latitude and 73°02' E longitude. Navi Mumbai is situated across two districts namely Mumbai and Raigad. In the Fig. 3.1, the location of Navi Mumbai is shown.

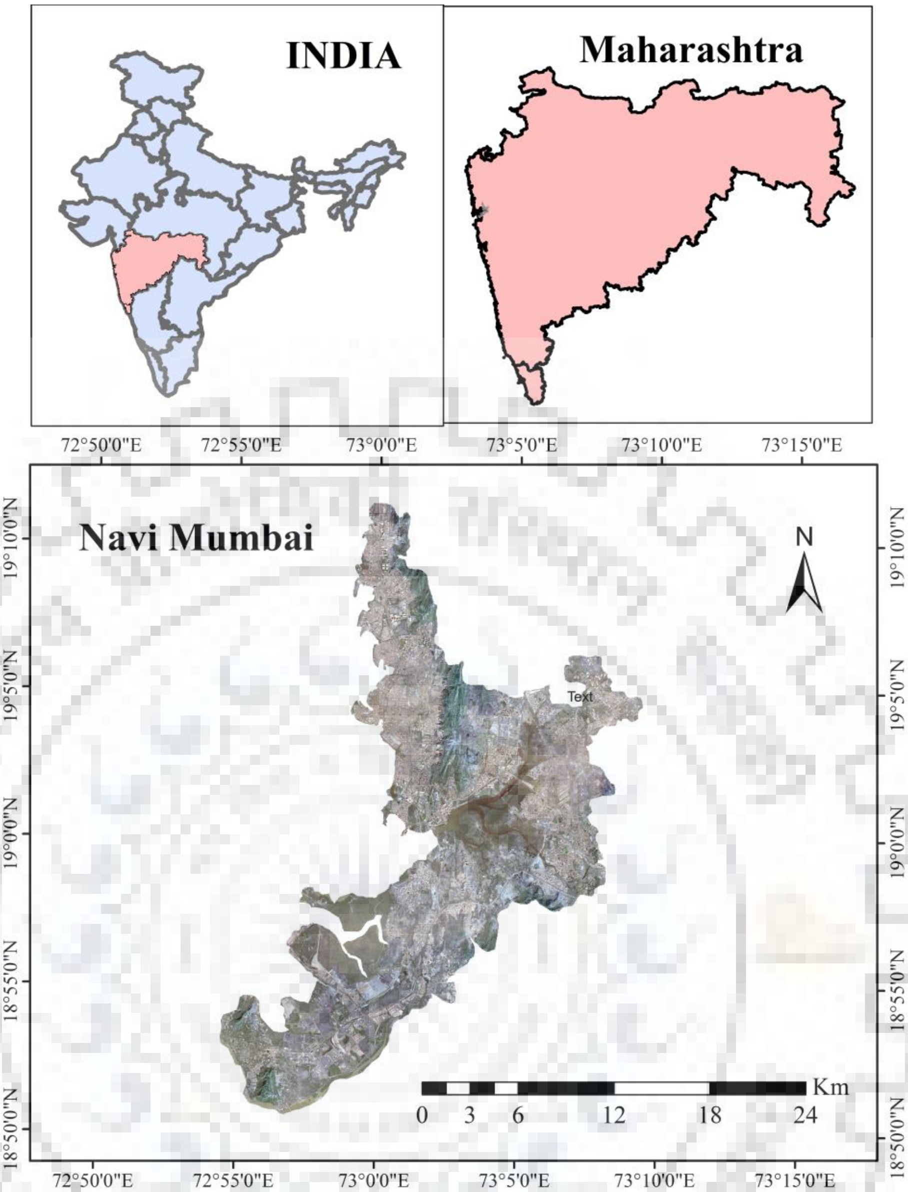

Figure 3-1: Location Map of Navi Mumbai

3.3 Population

According to the Census India, population of Navi Mumbai in 2011 was 1,120,547. By the end of 2018 the estimated population is about 1.6392 million. Appropriate means of infrastructure will be required to cater the need of the increasing population.

3.4 Climate data

The overall climate of Navi Mumbai is tropical. The temperature in summer varies from 36 °C to 41 °C while in winter the temperature ranges from 17 °C to 20 °C. The average annual temperature in Navi Mumbai is 26.8 °C. May is the warmest month of the year. The average temperature in May is about 30 °C. In January, the average temperature is about 23.3 °C which is the lowest average temperature throughout the year. The average temperature varies during the year by 6.7 °C.

The average rainfall in Navi Mumbai is about 3044 mm. The driest month is January, with 0 mm of rain. Majority of the precipitation occurs in the month of July, with an average of about 1160 mm. There is a difference of 1160 mm of precipitation between the driest and wettest months. 80% of the total precipitation occurs from June to October. The humidity is about 61-86 %.

3.5 Smart City

Maharashtra will have its first Smart City spread across in Navi Mumbai by 2019. For the smart city project, CIDCO has teamed up with Zensar, Accenture, SAP, Stockholding Corporation. SAP India´s Smart City solutions will be using the latest technology to keep up with advancements; for instance, sensor technologies are a game changer in waste management practices. CIDCO´s brownfield and greenfield projects will extend the benefits of development to adjoining areas. The brownfield project will cover Panvel, Dronagiri, Kamothe, Kalamboli, Kharghar, Ulwe and Taloja nodes where existing infrastructure such as transportation, water supply and wastewater management will be retrofitted using smart technologies. The greenfield project in Pushpak Nagar, a modern township will be developed from scratch. Further, a MoU is signed between NMMC and European Business and Technology Centre (EBTC), thus making EBTC the Handholding Agency for the project. The idea is to incorporate technology options developed by European nations related to smart cities. Besides, it will pave the way for European funding organisations. EBTC will be a facilitator. The Navi Mumbai Smart City and other projects will be totally funded by CIDCO and not require funding from the state government. The speciality is that we are generating all the funds on our own. This is a peculiar model not covered under the Smart Cities Challenge and is currently being discussed with the State Chief Minister.

3.6 Datasets used

Major datasets required for the work are Satellite imagery, Digital Elevation Model (DEM), Soil Map, Meteorological data, Gauge-Discharge data. Satellite images were downloaded from the USGS Earth Explorer, SRTM DEM was used, Food and Agricultural Organization (FAO) Soil Map was used. Meteorological data related to solar radiation, relative humidity, temperature and wind speed was downloaded from the Climate Forecast System Reanalysis (CFSR). India Meteorological Department (IMD) gridded data was used. Gauge-discharge daily data was downloaded from India-WRIS.

Table 3-1: Datasets used for the study and their description

Data Used	**Sources**	**Scale OR Period OR Grid**	**Data Description**
Satellite imagery	USGS Earth Explorer	30m x 30m	Landsat7 and Landsat 8 imagery was used
DEM	USGS Earth Explorer	30m x 30m	Elevation value of pixels is given
Soil Map	FAO Soil Map	1/150000	ESRI shapefile format
Solar radiation, Wind Speed, Relative Humidity, Temperature	CFSR	2000-2013	0.33°
Precipitation	IMD	2000-2013	0.33°
Land Cover	ESA CCI	300m x 300m	NA

4 METHODOLOGY

4.1 General

Two models were implemented for carrying out the research. For the land use change, land transition matrices were developed. The future land use/ land cover (LULC) prediction was done using artificial neural network (ANN) which makes use of multi-layer perceptron algorithm. For the surface runoff generation SWAT model was implemented, from which hydrographs and flow-duration curve was plotted. This also documents the input data preparation and output processing. As the urban watershed is ungauged certain difficulties were faced which are also documented.

4.2 Land Use/ Land cover Transition

4.2.1 Image Processing

Satellite images were downloaded from USGS Earth Explorer. For detecting the transition in between the land use/ land cover types land use/ land cover of three years namely 2000, 2008 and 2016 was considered. Satellite images from Landsat 8 and Landsat 7 of 30m x 30m resolution. Care was taken that while downloading the satellite images there is no cloud cover. After downloading the satellite images stacking of the bands was done. Four bands Red, Green, Blue and Near Infrared (NIR) were used while stacking the layers. After stacking satellite images were prepared, edge enhancement of the images was done.

4.2.2 Image Classification

A hybrid method was implemented for preparation of the land use/ land cover maps. ERDAS Imagine 2015 software environment was used for this purpose. When we do supervised classification we have to mark some color signatures. This is less time consuming process, but very easy. First unsupervised classification was done and later on they were post corrected by using Google Earth Pro. Post correction of land use/ land cover is very important since the study area is largely urbanized and the terrace area of a building is sometimes clubbed in barren areas. Six types of land use/ land cover classes were formed namely Water, Urban, Tree Cover, Barren, Wetland and Forest.

After the land use/ land cover maps were prepared to find out from which class the area is shifted to another class over the period of time Matrix Union was done in ERDAS Imagine and transition matrices were prepared.

4.3 Future Land use/ Land cover prediction

4.3.1 Land Change Modeler (LCM)

The LCM is a software interface integrated within TerrSet directed to address the spatial problem of land change. There are three steps for predicting land change in the Land Change Modeler.

1) Change Analysis
2) Transition Potential Modelling
3) Change Prediction

4.3.2 Change Analysis

Change is evaluated in between the two land use/land cover maps. The changes that are detected are transitions from one land use type to another. Each sub-model of transition can be modeled separately, but in the final change prediction process all sub-models will be grouped together. Optional inputs can be a digital elevation model or a road layer. We took Digital elevation model as an optional input. Change maps like Persistence, losses and gains by land cover types can also be created.

Land use which is dominated by human interference, the trend of change is complicated and difficult to interpret. To decipher, a spatial tend of change is found out. This is the best fit polynomial for the change. Trends up to the 9th order can be calculated. From literature review for an urban area 4th order polynomial was considered. TREND module is the implemented to do the analytical work for finding out the spatial trend of change.

4.3.3 Transition Potential Modelling

Transition potential is the transition between the two land use maps into a set of sub-models. All the transition that are possible between the two land use maps are listed. These transition can be removed using area threshold and transition can be assigned to specific sub-models.
For our study only five transitions were considered,

1) Water to Urban
2) Natural Vegetation to Urban
3) Barren to Urban
4) Wetland to Urban
5) Forest to Urban

All the possible transition were grouped in a single transition sub-model named ALL_TO_URBAN, since our main objective was to find out the transition from other land use class to Urban.

4.3.4 Multi-Layer Perceptron

The MLP neural network is developed to offer an automatic mode that requires no user involvement. MLP can be used to model multiple transitions in to one sub model.

MLP starts training on the pixels of the land use maps that have or have not undergone the transitions being modeled. From this point the MLP is doing the process by itself, it decides which parameters to use and how the parameters should be updated to better model the data. This dynamic learning procedure starts with an initial learning rate and reduces it progressively overt the iteration, until the end learning rate is reached and maximum number of iteration are performed. After the training is completed, a HTML file is generated of information about the training process.

Evidence likelihood transformation was used for variable transformation. The procedure looks at the relative frequency of pixels belonging to the different categories of that variable within areas of change. To each variable it asks the question, "How likely is it that you would have a value like this if you were in an area that would experience change?"

4.3.5 Change Demand Modelling

For determining the magnitude of change that will occur to a land use class in the future is by Markov Chain. A Markov process is one in which the state of a system can be determined by knowing its previous state and the probability of transition from one state to another state. Using the two land cover maps along with date, Markov Chain evaluates exactly how much land from a land use class is expected to undergo transition from the later date to the prediction date based on transition potentials listed in the sub-models.

The digital elevation model for the city of Navi Mumbai is presented in Fig.4.1. In a generic manner it can be stated that the majority of area lies between an elevation levels of 0-30m.

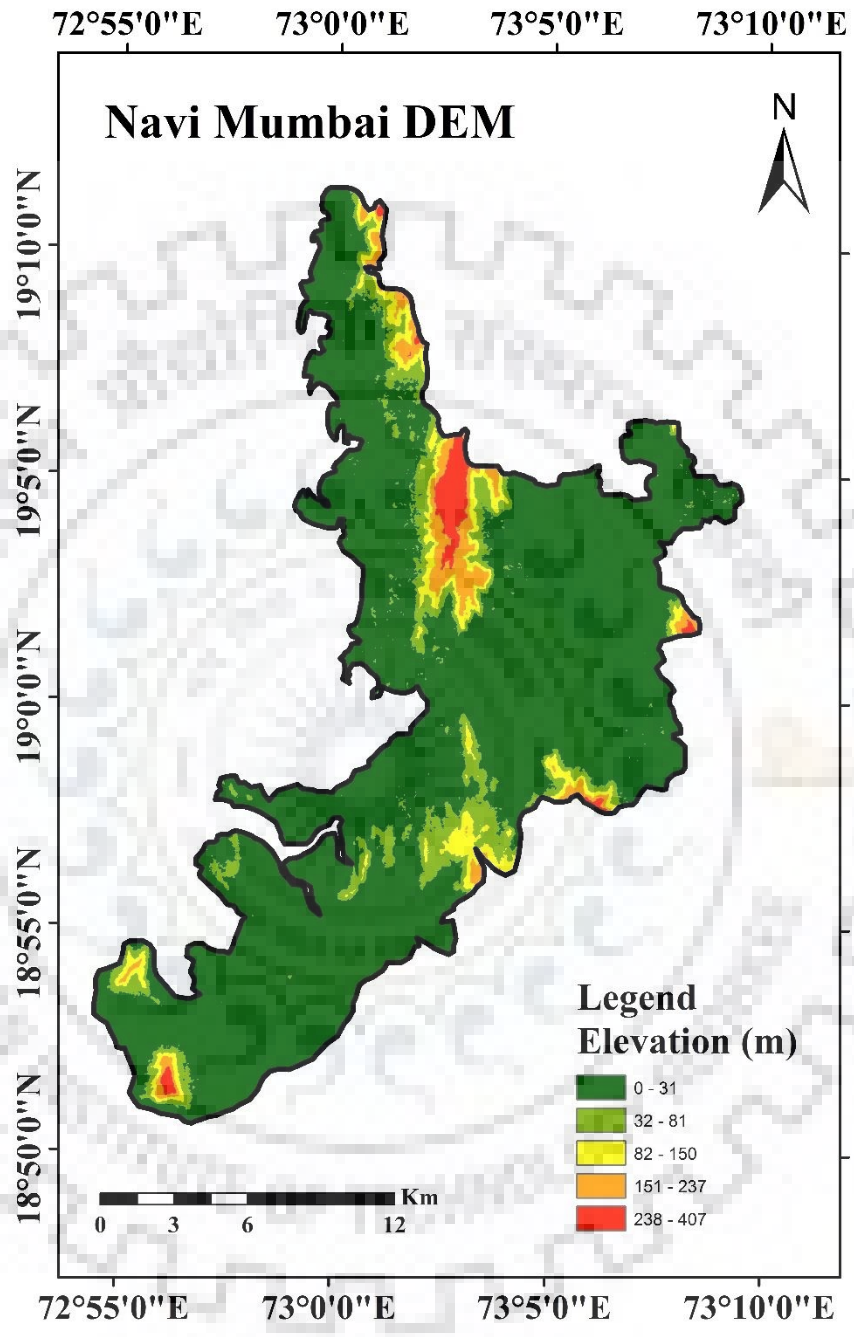

Figure 4-1: Navi Mumbai DEM

Digital elevation model is an important input for land use/ land cover change prediction as the urban planners will not prefer an area of higher altitude, as it will involve cutting and filling which will further increase the cost of the project.

Figure 4.2 is the map showing distance from the nearest urban area, as whenever any township is planned it is, preferred to have it located near another township, as it will have supply to daily stores and services.

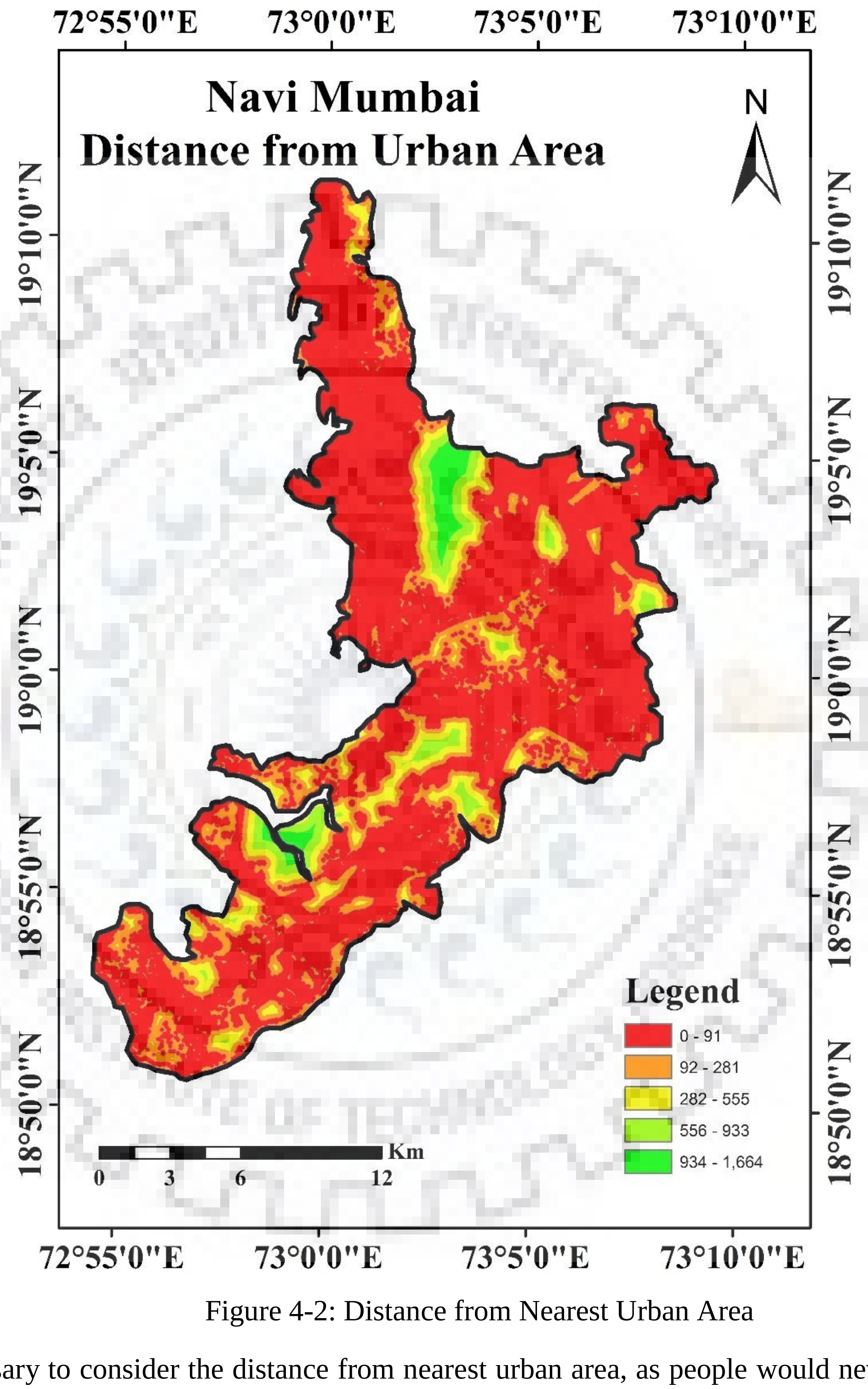

Figure 4-2: Distance from Nearest Urban Area

It is necessary to consider the distance from nearest urban area, as people would never wish to stay at place which is far from the main city or township and live in isolation as it imposes security threats.

The slope map of Navi Mumbai is presented in Fig.4.3. The reason why it is a driver variable is that, it is tried to plan a township on a plain area as it involves less cutting and filling, which inturn improves the economy.

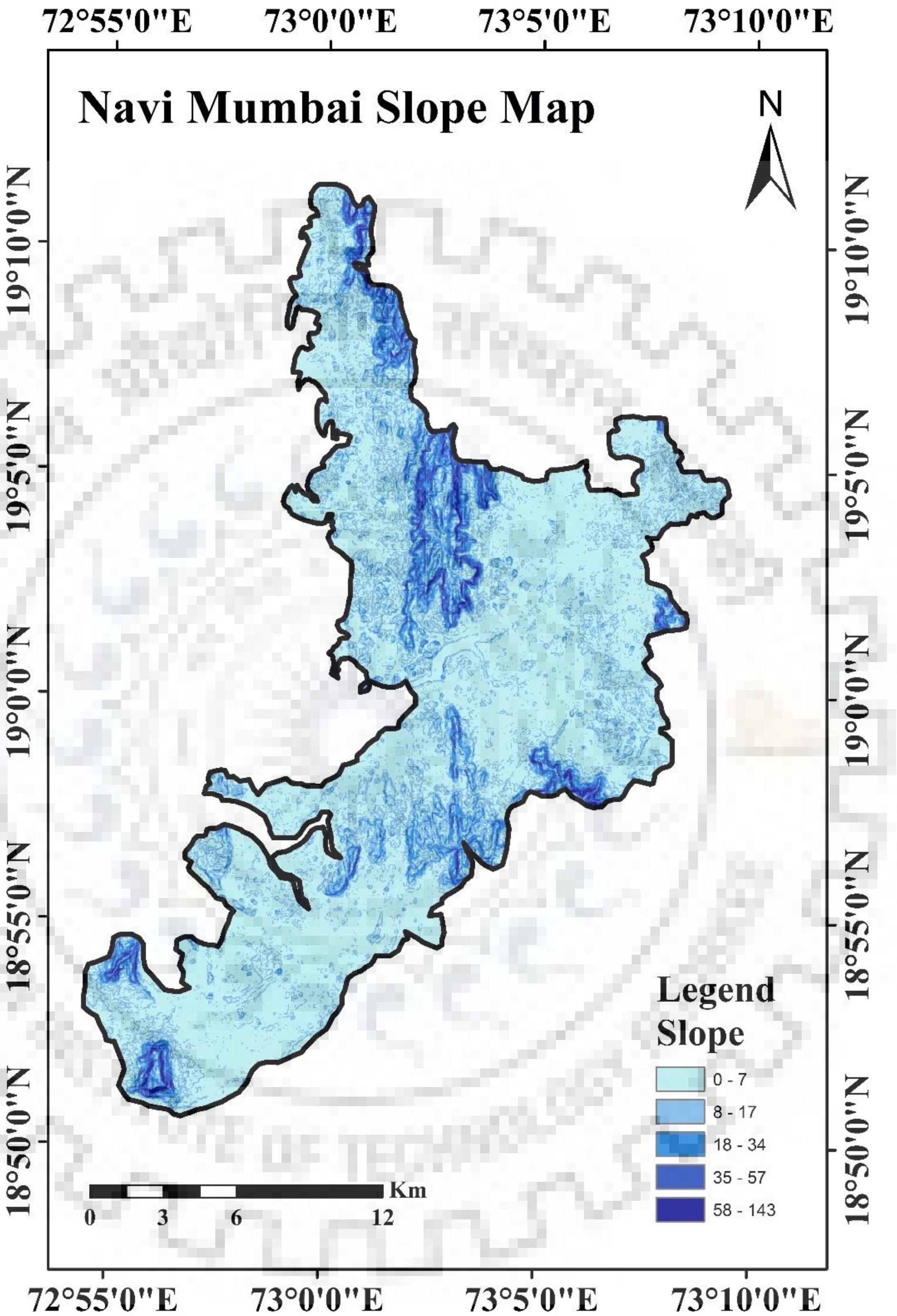

Figure 4-3: Navi Mumbai Slope Map

Slope Map is also a very important input while planning infrastructure, as construction of roads drainages is always at a particular gradient, which helps in avoiding water logging.

Figure 4.4 is the map of distances from the nearest road for the city of Navi Mumbai. As is in the case of distance from nearest urban area so is the case for distance from nearest road. Usually we consider a properly constructed road network as the first sign of development. As once roads are constructed other services can be transported at the location.

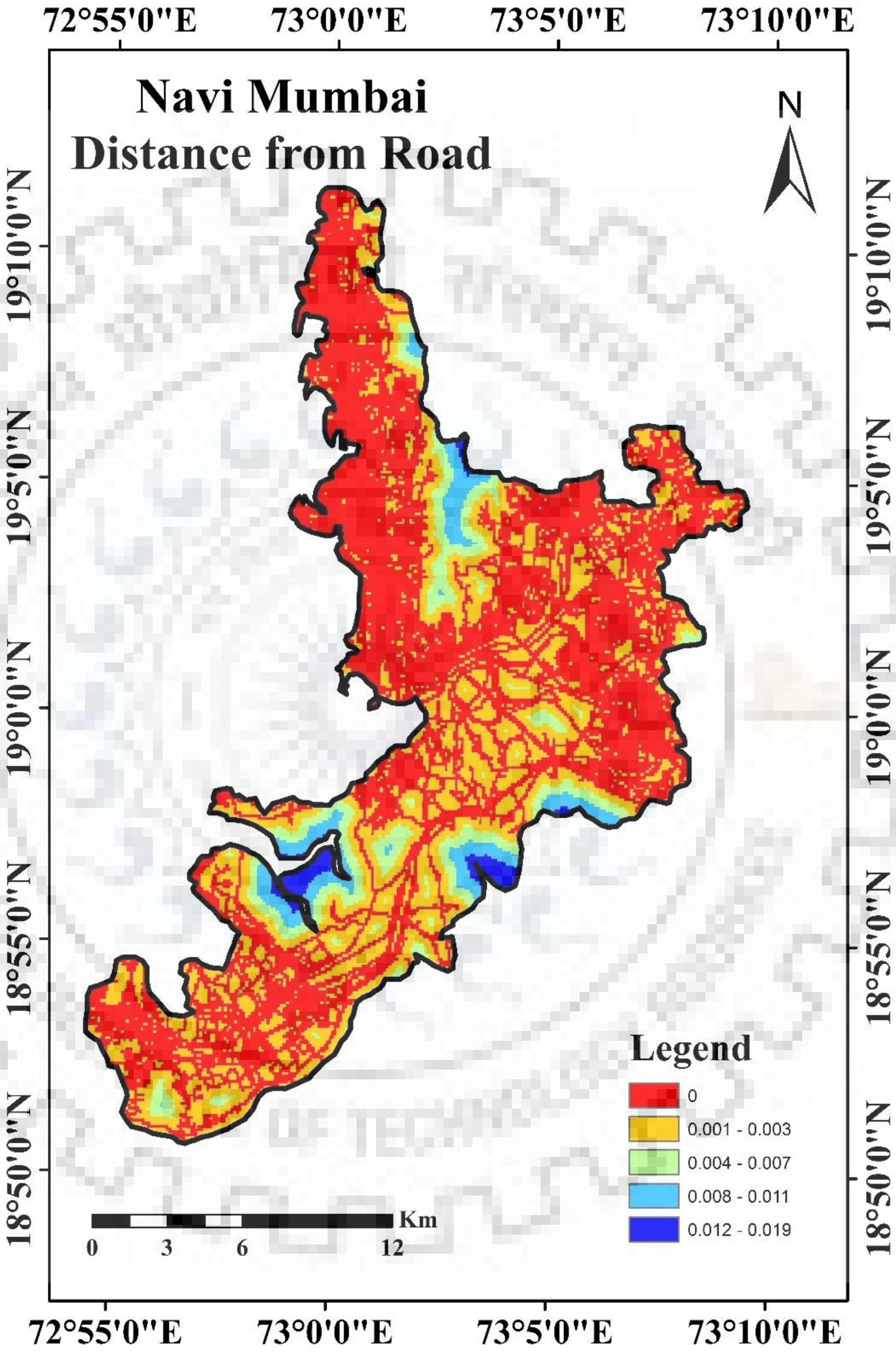

Figure 4-4: Navi Mumbai Distance Map

Also no one would wish to stay at a place where the road network is not proper like in case of an health emergency.

Figure 4.5 presents the flowchart of the methodology applied to map the land use/ land cover for the years 2030 and 2050.

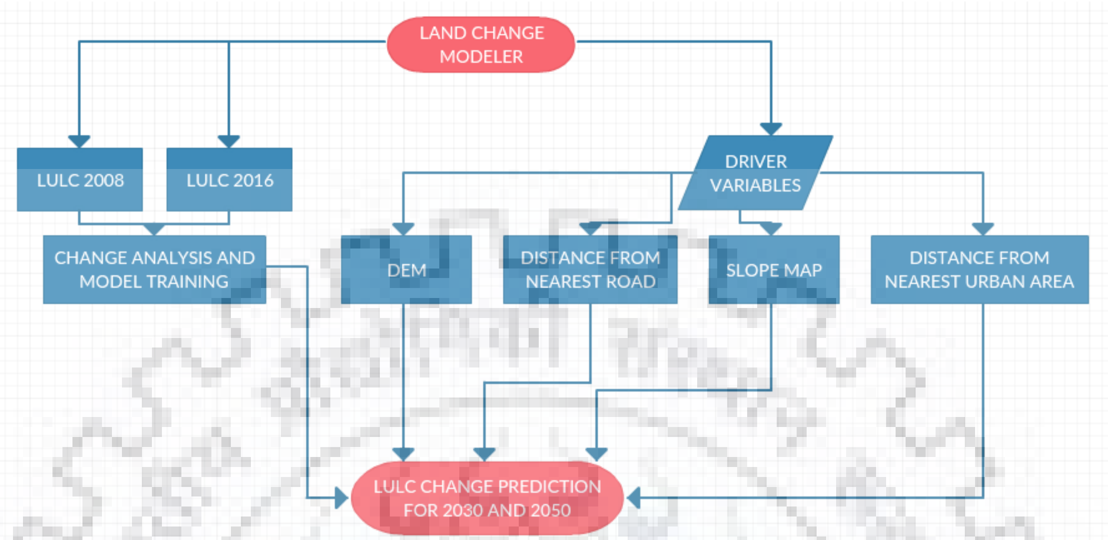

Figure 4-5: Land Change Modeler Flowchart

4.4 SWAT Model

SWAT stands for Soil and Water Assessment Tool. It is physically based and instead of implementing regression equations to develop a relationship between the input variables and output variables, it requires specific information about the land management practices, soil properties, weather data and topography of the watershed. Using these data sets as inputs the physical process of water movement, sediment transport are modeled by SWAT.

This is primarily helpful when the study area is an ungauged watershed. Inputs for running the SWAT model are readily available and can be easily obtained from government organizations. SWAT has high computational efficiency, is a continuous time model and is not designed to simulate single event short term flood routing.

During modeling a watershed is divided into a number of subwatersheds or subbasins. Dividing of a watershed into subwatersheds is particularly beneficial when the different subwatersheds are influenced by land uses or soils dissimilar enough that it would change the hydrology of the area. When we divide watersheds into subbasins, we can differentiate in between the areas spatially.

Watershed which are divided into multiple subbasins, which are then further subdivided into hydrologic response units (HRUs) that consist of homogeneous land use, topography and soil characteristics. The HRUs are represented as a percentage of the subwatershed area and may not be contiguous or spatially identified within a SWAT simulation. Hydrologic Response Units are land areas within the subwatershed that have a unique land use, soil, management combinations.

Runoff is predicted separately for each HRU and routed to obtain total surface runoff from the watershed.

SWAT is implemented for solving numerous problems, but water balance plays the vital role behind everything that occurs in a watershed. To accurately predict the water movement and sediment transport, it is necessary that the hydrologic cycle must confirm with what is happening in the watershed. Water Balance Equation is the basis of SWAT simulation. Land phase and the routing phase are the two phases in which a hydrologic cycle can be divided.

$$\boldsymbol{SWt = SWo + \sum_{i=1}^{t}(Rday - Qsurf - Ea - Wseep - Qgw)} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \boldsymbol{(4.1)}$$

SW_t: Final soil water content (mm H_2O)

SW_0: Initial soil water content at day i (mm H_2O)

R_{day}: Precipitation on day i (mm H_2O)

E_a: Evapotranspiration on day i (mm H_2O)

W_{seep}: Water entering the vadose zone from the soil on day i (mm H_2O)

Q_{gw}: Return flow on day i (mm H_2O)

Figure 4.6 represents the SWAT hydrological cycle and how it considers the movement of water in the catchment.

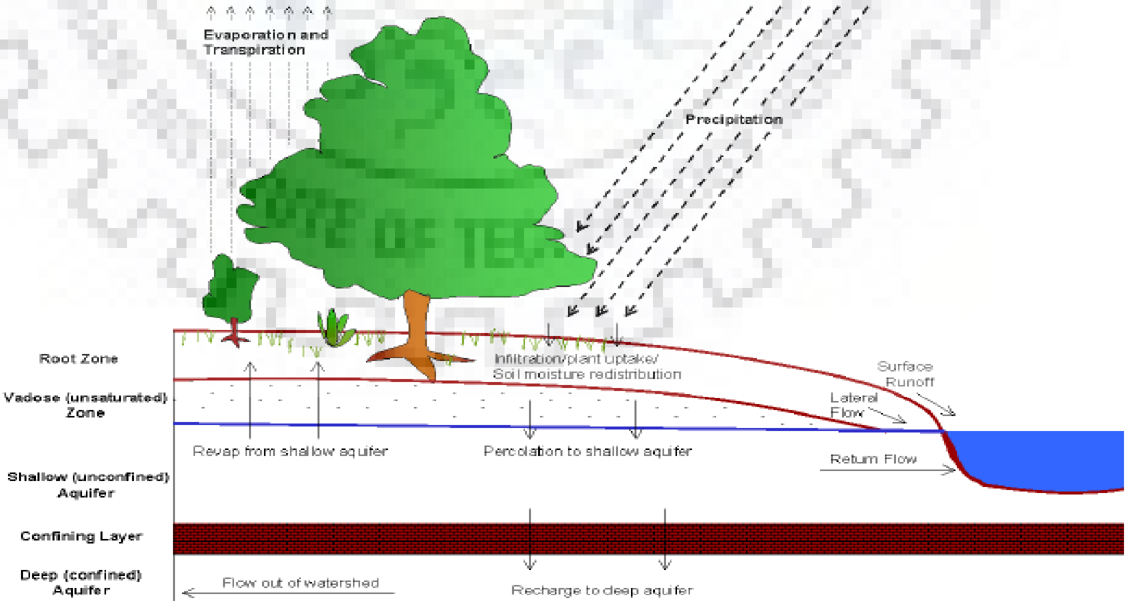

Figure 4-6: SWAT Hydrologic Cycle

The SWAT model primarily consists of,

1) Surface runoff calculated either by SCS-CN method (USDS-SCS 1972) or by Green Ampt Mein-Larson method (1911). SCS-CN method requires daily data whereas the Green Ampt Mein-Larson requires sub-daily precipitation data.
2) Evapotranspiration calculated by means of either the Penman-Monteith method (1965), Hargreaves method (1985) or Priestley and Taylor method (1972).
3) Channel routing estimated by using either Muskingum method (1959) or variable storage coefficient method (1969).

For our analysis, we used SCS-CN method and Penman-Monteith method for estimation of surface runoff and evapotranspiration, respectively.

As the water balance equation during the simulation of hydrologic cycle plays a key part, so is in the case of SCS-CN method. It is based on rainfall depth and relies on only one parameter Curve Number (CN).

$$\boldsymbol{Q} = \frac{(\boldsymbol{P} - \boldsymbol{I}_{\mathrm{a}}\boldsymbol{S})^2}{(\boldsymbol{P} - \boldsymbol{I}_{\mathrm{a}} + \boldsymbol{S})} \quad \ldots (\mathbf{4.2})$$

Q: Direct runoff

P: Total precipitation

Ia: Initial abstraction

S: Maximum retention

As the initial abstraction is some part of the retention,

$$\boldsymbol{I}_{\mathrm{a}} = \boldsymbol{\lambda}\,\boldsymbol{S}$$

Where; $\lambda = 0.2$

Therefore $\boldsymbol{I}_{\mathrm{a}} = \mathbf{0.2}\boldsymbol{S}$

Combining the equations, we get

$$\boldsymbol{Q} = \frac{(\boldsymbol{P} - \mathbf{0.2}\boldsymbol{S})^2}{(\boldsymbol{P} + \mathbf{0.8}\boldsymbol{S})} \quad \ldots (\mathbf{4.3})$$

The maximum potential retention is a function of soil type-land use-vegetation. For ease during application the maximum potential retention *S* is represented by a dimensionless number called Curve Number (CN).

$$\boldsymbol{S} = \frac{\mathbf{25400}}{\boldsymbol{CN}} - \mathbf{254} \quad \ldots (\mathbf{4.4})$$

The Curve Number has a range from 0-100, with 0 expressing infinitely abstracting catchment and 100 denoting a situation of zero maximum potential retention. During determination of Curve

Number, soil classification is used, which classifies the soil into four types on the basis of runoff potential (Low, Moderately Low, Moderately High, High)

The Curve Number also depends upon the Antecedent Moisture Condition, which denotes the amount of moisture present in the soil before the commencement of the rainfall-runoff event. These conditions are Dry, Average, Wet.

4.4.1 SWAT for Urban Areas

The main underlying difference between and river basin and a urban area is the total fraction of area, that is impervious. Construction of paved roads, buildings, etc. lead to reduced infiltration and increased imperviousness. This leads to a spatial change in the flow of water, which results into higher velocity and volume of runoff and changes in the shape of hydrograph. Impervious areas can be divided into two groups, the area that does not have a direct hydraulic connection to the drainage and the area that is directly connected to the drainage. Following are the SWAT input variables that relate to the urban areas during surface runoff estimation.

CN2: SCS AMC II CN for pervious areas

CNOP: SCS AMC II CN specified in plant/ harvest/ tillage operation.

URBCN2: SCS AMC II CN for impervious areas

FIMP: Impervious urban land

FCIMP: Urban land area that is impervious and connected to drainage

4.4.2 SWAT Model Setup

SWAT was incorporated in the ArcSWAT 2012 interface within ArcGIS. For running the ArcSWAT model following setup was to be done.

1) Preparation of the input datasets and maps
2) Delineating the watershed using DEM
3) HRU Analysis which covers HRU Definition using soil, slope, land use data
4) Preparing the input tables and uploading of the weather files
5) Final running of the SWAT Model

After completing one step, if any error is there it is to be rectified and then only the next step is activated.

4.4.3 SWAT Model Data Inputs

Before starting to prepare model inputs we have to make some changes in the computer system, as SWAT was originally made for areas situated in USA and we will be using it for India. The date panel in the computer should be formatted to mm/dd/yyyy.

To achieve maximum accurate results and error free execution of the SWAT Model it is necessary that while preparing the inputs care should be take and not prepared in haste. Temporal and spatial resolution of data being used will greatly influence the modelling and simulation procedure, in turn its performance. Whenever any input is uploaded and it is not as per the specific cell size, dimensions, spatial reference it will show an error which we will have to rectify at later stage. The spatial data inputs necessary for execution of ArcSWAT 2012 interface are Digital Elevation Model (DEM), Soil data, Land use/ Land cover (LULC) data and Weather data. All these datasets were projected in WGS84 UTM Zone 43N, for which ArcGIS 10.2 was used. To have an error free execution it is necessary that all the datasets be projected in the same co-ordinate system.

4.4.4 Digital Elevation Model (DEM)

For delineating the watershed DEM is required. A DEM consists of arrays or grid cells of regularly spaced elevation values referenced horizontally for every point of the area. In this study a 30m x 30m DEM was used, downloaded from the SRTM website. After sub-setting for the study area it was projected to WGS84 UTM Zone 43N. For this the ArcGIS environment was used. There were few small streams in the area, so to cover entire Navi Mumbai 8 outlets had to be marked.

Figure 4.7 presents the digital elevation model of Navi Mumbai, which is used for watershed delineation, outlet formation and calculation of subbasin parameters. It covers area more than Navi Mumbai.

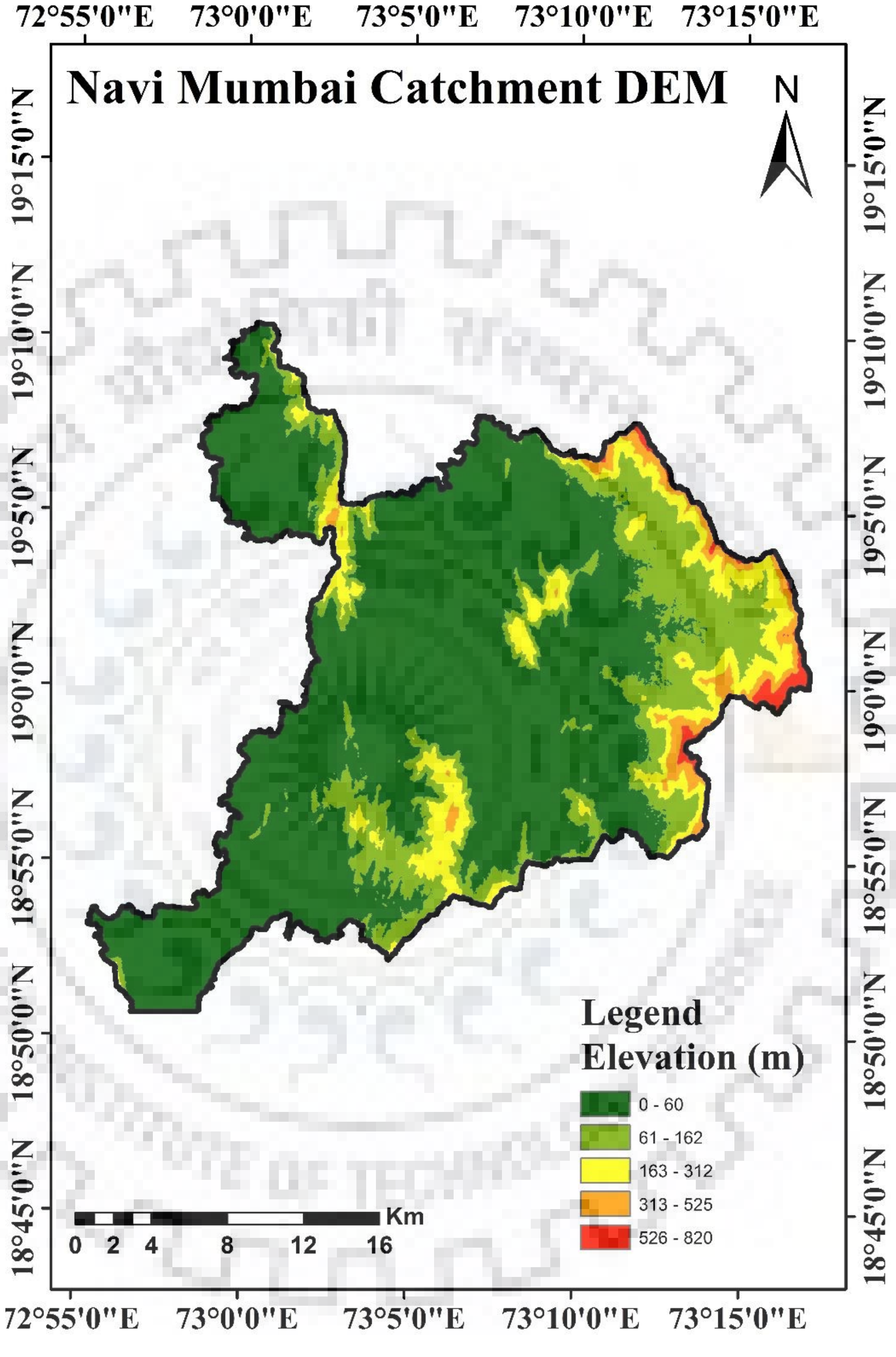

Figure 4-7: Navi Mumbai Catchment DEM

4.4.5 Delineated Watershed

During delineation process a boundary is created which represents the area that is contributing to generate runoff for a particular outlet. For this automatic flow direction and flow accumulation process is done and streams are created on the DEM, and we have to select outlets. From Fig.4.8

it can be inferred that to cover entire Navi Mumbai 8 outlets had to be marked and 8 subbasins were created.

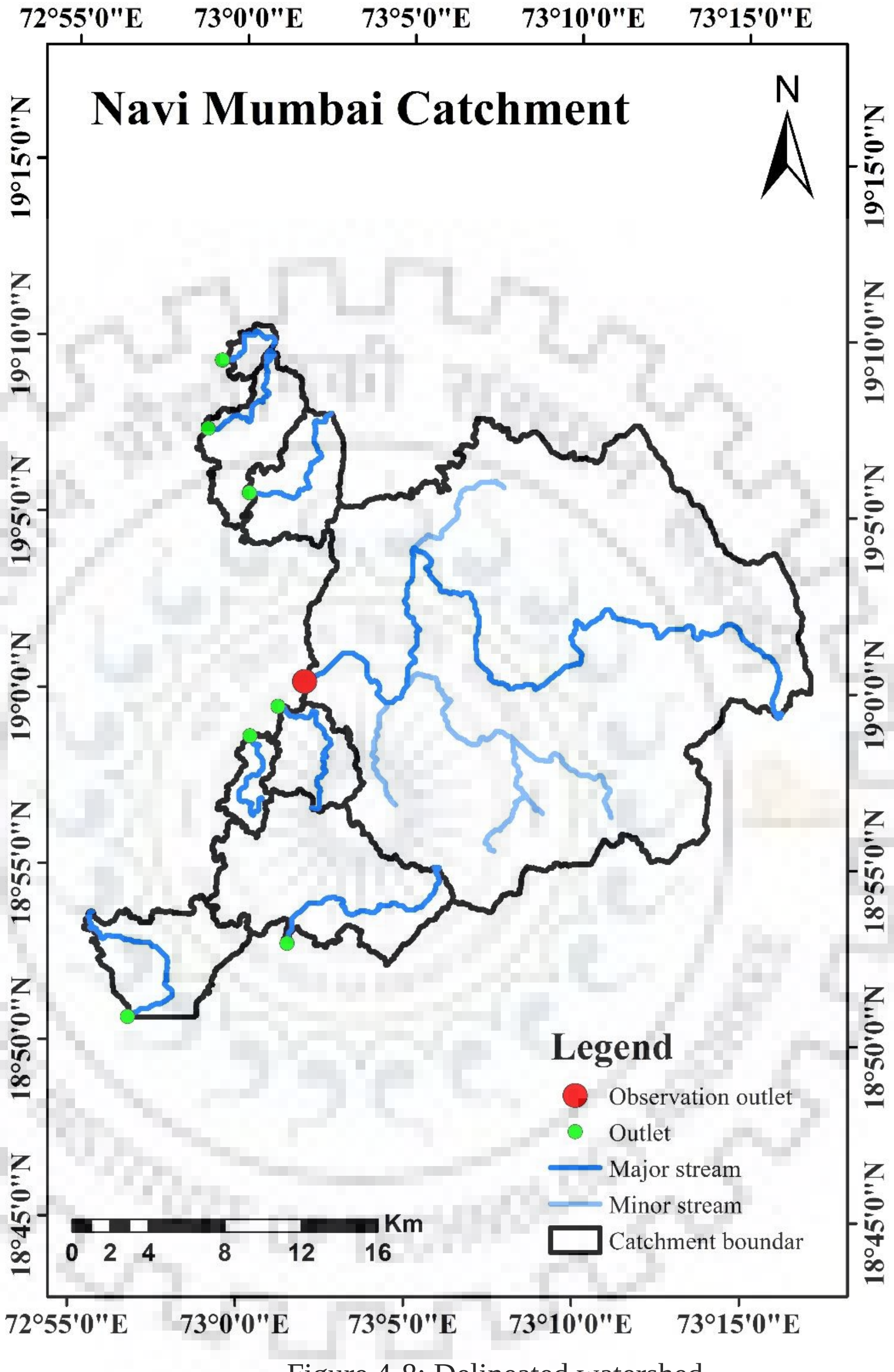

Figure 4-8: Delineated watershed

4.4.6 Soil Data

The various properties of soils such as texture, available water content, hydraulic conductivity, pH value, bulk density, organic carbon content which are required for SWAT Model. The soil data was extracted from World Soil Database; developed by the Food and Agricultural Organization which is a specialized agency of the United Nations; having data of about 6998 different types of soil classes. Figure 4.9 indicates that in the catchment area of Navi Mumbai, three types of soils are found, which are mapped below, their proportion and composition is represented in detail in the tabular form.

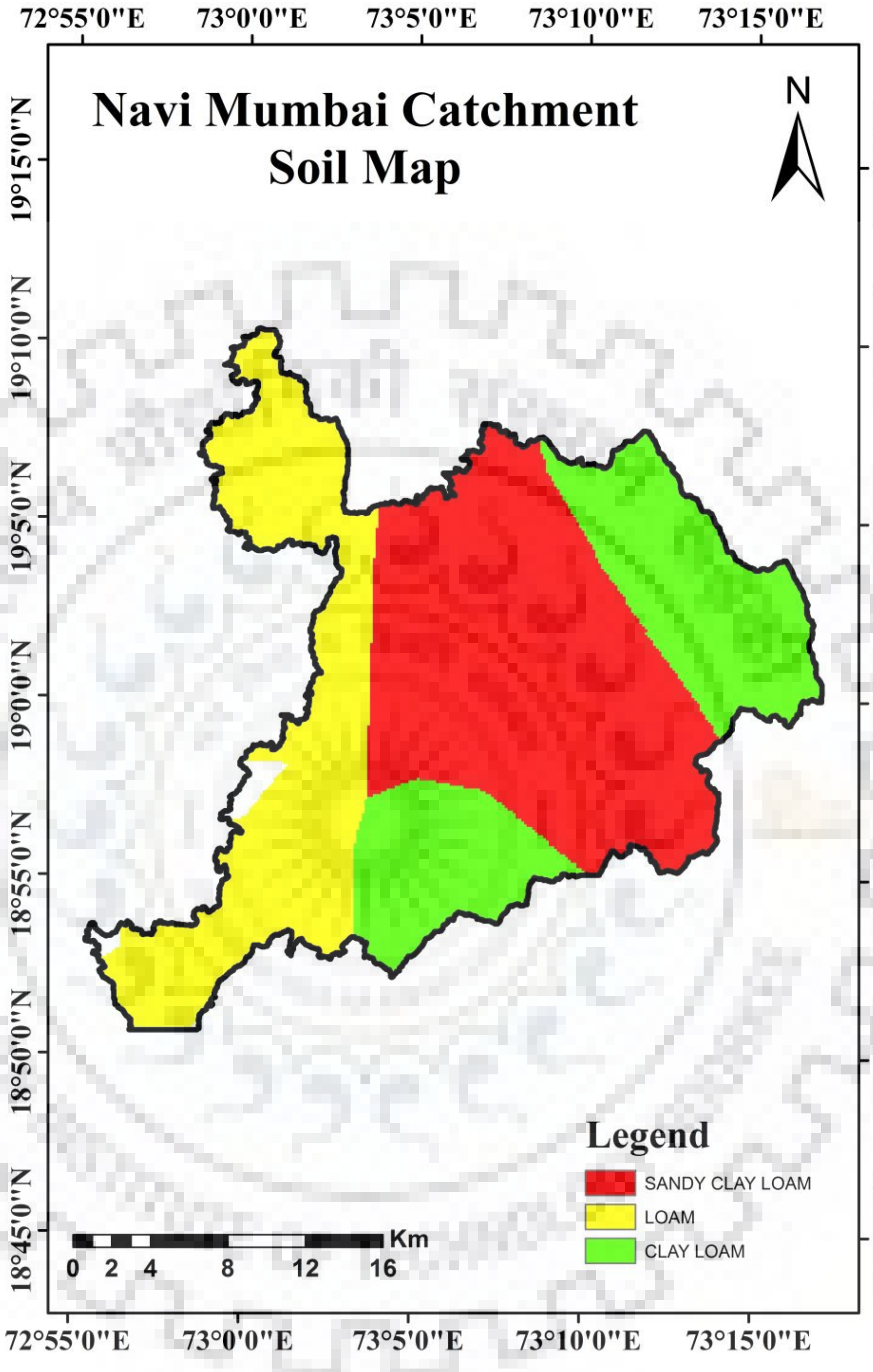

Figure 4-9: Navi Mumbai Soil Map

In the soil Bc24-2b-3658 clay is 22%, silt is 25% and sand is 53%. In the soil Je68-2a-3756 clay is 22%, silt is 38% and sand is 40%. In the soil Ne56-2b-6669 clay is 29%, silt is 27% and sand is 44%.

Table 4.1 enlists the details pertaining to the soils in the catchment area along with their percentage and soil codes assigned by FAO in the area in tabular form.

Table 4-1: Soil details of the catchment

Soil Code	Soil Type	Area (km^2)	Percentage (%)
Bc24-2b-3658	Sandy Clay Loam	271.7	42.72
Je68-2a-3756	Loam	187.109	29.42
Ne56-2b-6669	Clay Loam	177.069	27.84

4.4.7 HRU Definition

HRU is an acronym for Hydrologic Response Unit, which is a unique combination of land use/ land cover, soil and slope. HRU Definition was done using a combination of 10% land use percentage over subbasin area, 15% soil class percentage over land use/ land cover area and 15% slope class percentage over soil area. After this all three were reclassified and then overlaid. A total of **x** HRU's were created with these combinations.

4.4.8 Weather Data

Meteorological data is one of the most important datasets which act as inputs while simulation. The daily weather data can either be taken from an observed dataset or from a weather generator model. Meteorological data required to run SWAT are precipitation, solar radiation, relative humidity, temperature and wind speed. All these datasets except precipitation were obtained from National Centers for Environmental Prediction (NCEP) Climate Forecast System Reanalysis (CFSR) website. This portal gives us these inputs as daily data in the format required for SWAT. Especially for precipitation India Meteorological Department (IMD) gridded datasets were used. IMD after analyzing the rain gauge data distributes it spatially in grids. CFSR doesn't consider the IMD gridded data. Also the method of spatial distribution of the rainfall data implemented by IMD differs from that of CFSR. Since the precipitation dataset was in a different grid than other CFSR datasets (wind speed, relative humidity, solar radiation, temperature) interpolation was done to bring them to same grids. The data was downloaded for a period of 2000-2013, out of which the first three years were warm up period, and the simulation was for a period of 2003-2013.

4.4.9 Land Use/ Land Cover Data

Figure 4.10 maps the land use/ land cover of the catchment area. LULC of an area plays an important part in its water movement. An urban area will have more impervious area which will lead to change in surface runoff and hydrograph characteristics.

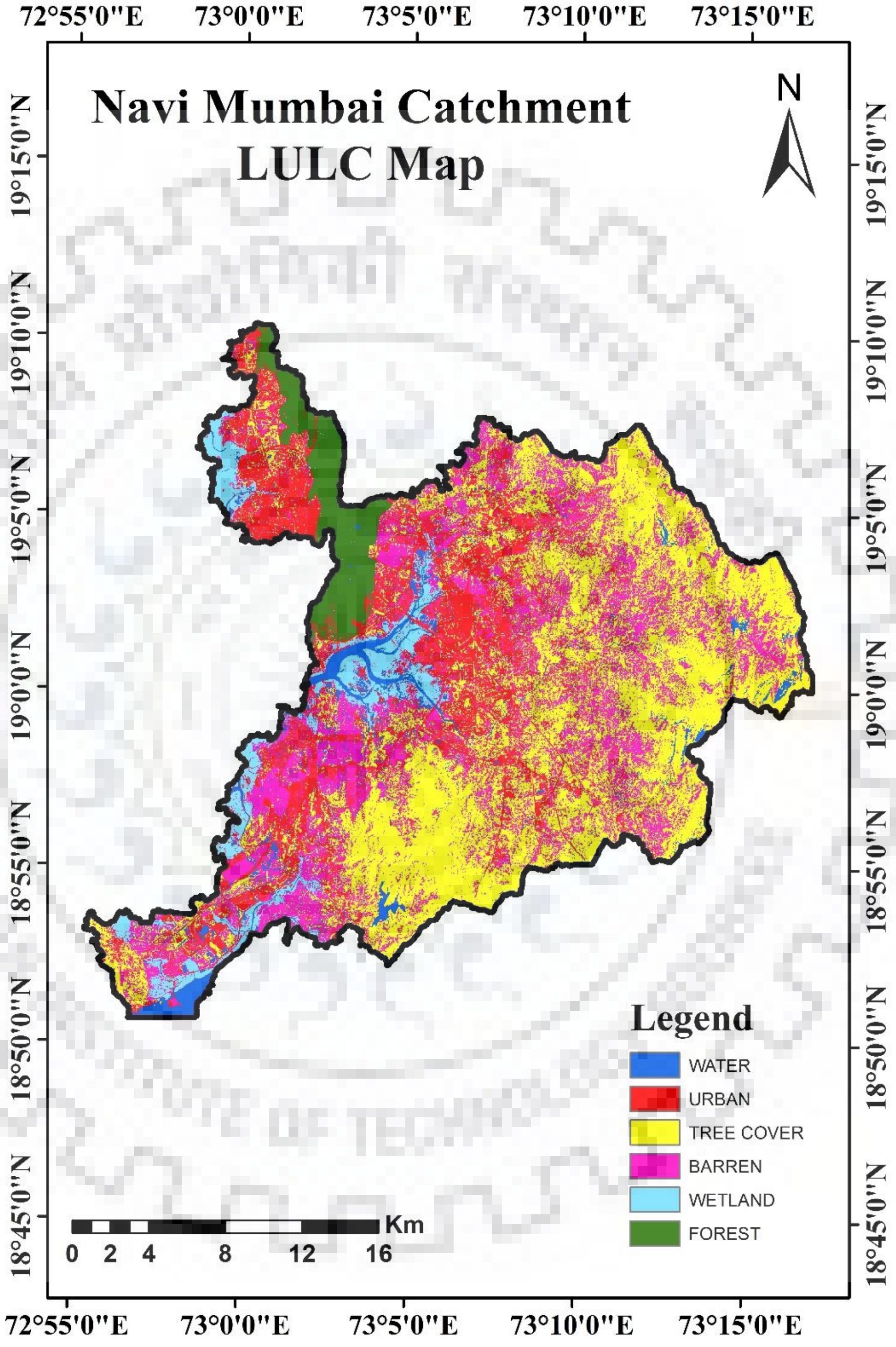

Figure 4-10: Navi Mumbai Catchment LULC Map

For preparing the land use/ land cover, images were downloaded from USGS Earth Explorer and Landsat 8 satellite having a resolution of 30m x 30m. Image processing was done in ERDAS Imagine 2015 environment. Hybrid method of unsupervised classification constituted with post-correction was implemented. Figure 4.11 represents the SWAT model flowchart with every step.

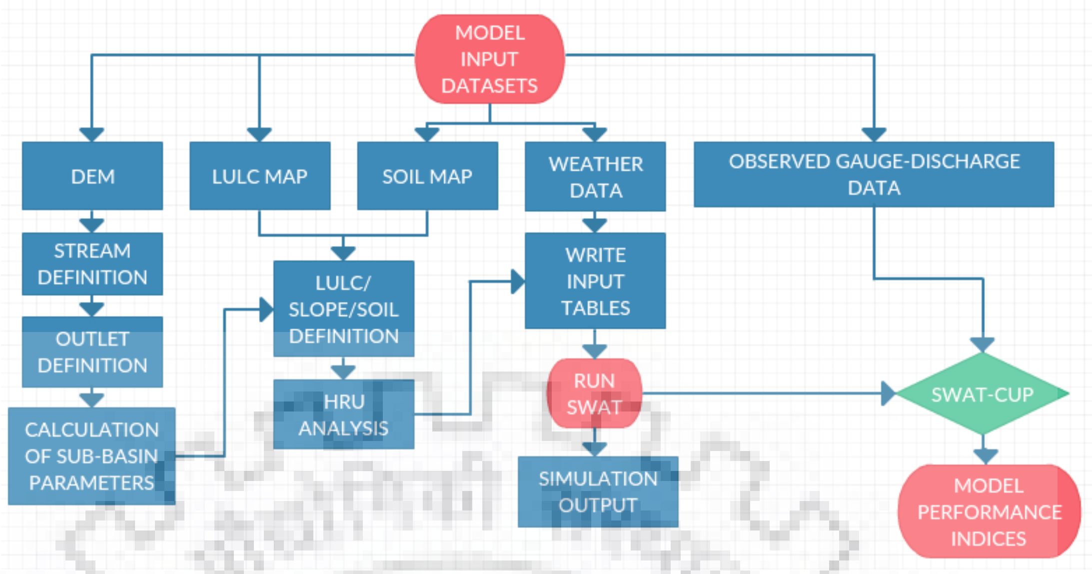

Figure 4-11: SWAT Model Flowchart

4.5 Regionalization Technique

Navi Mumbai is an ungauged area, so there observed dataset for gauge-discharge is not available. This makes the calibration and validation of SWAT model very complex. Regionalization techniques have been developed like IDW, Kriging, catchment similarities, flow-duration curves and others. Another complexity associated with regionalization is that one promising method might show negative results when used at another location, which leads us to testing of the regionalization techniques till required model performance criteria is achieved.

In this study we used catchment similarity technique of regionalization wherein catchment characteristics like land use/ land cover (LULC), Slope, Soils and area in between the study area and donor catchment.

By spatial proximity, the Pen gauge-discharge station is nearest to Navi Mumbai, whose daily data is available. These catchment characteristics dominate the surface runoff. The Pen gauge-discharge data was modified using the Similarity index (S). Similarity index gives us an indea about the similarity in between the study area and the donor catchment.

$$\boldsymbol{S = 1 - \sum_{i}^{N} \alpha \frac{\Delta X}{Max(\Delta X, X')}} \quad \ldots\ldots\ldots \quad \mathbf{(4.5)}$$

S: Similarity index (0-1)

N: Number of catchment characteristics considered

α: Weights assigned to each catchment characteristic ($\sum = 1$)

ΔX: Absolute difference between the study area and donor catchment

X': Average value of study area and donor catchment

4.6 SWAT Sensitivity Analysis

During the performance evaluation of the model, it is necessary to determine the sensitive parameters in the initial stage. After making changes in input parameters what changes will be reflected in the output parameters is sensitivity analysis. After sensitivity analysis, we get to know which input parameter is bringing a major change in the output and with that we can rank the input parameters. Sensitivity analysis is categorized in two types, Local and Global. In local one parameter is changed at a time, whereas in global all parameters are changed.

4.6.1 Model Calibration

It is the second step during the performance evaluation of a model. The purpose of model calibration of a hydrological model is to obtain the optimized parameters which have an impact on the catchment response. These parameters might have any physical meaning or not, but it has a high level of uncertainty associated with it (Heuvelmans et al., 2004). By comparing the model input parameters with the observed datasets of the same condition, calibration is performed.

4.6.2 Model Validation

Model validation is performed to confirm whether the calibrated model is efficiently comparing the simulated data with the observed dataset after making the adjustments in the input parameters.

4.6.3 Model Performance Criteria

The underlying purpose of doing calibration and validation is to improve the performance of SWAT model. Three quantitative statistical parameters can be used in model performance: Nash-Sutcliffe Efficiency (NSE), percent bias (PBIAS) and ratio of root mean square error to standard deviation of measured data (RSR) (Moriasi et al., 2007).

Coefficient of determination R^2 explains the proportion of the total the total variance in the observed data that can be explained by the model and it evaluate model goodness, the value ranges from 0 to 1.

$$\boldsymbol{R^2} = \left[\frac{\sum_{i=0}^{n}\left(y_i^{obs} - y_{mean}^{obs}\right)\left(y_i^{sim} - y_{mean}^{sim}\right)}{\sqrt{\sum_{i=0}^{n}\left(y_i^{obs} - y_{mean}^{obs}\right)^2}\sqrt{\sum_{i=0}^{n}\left(y_i^{obs} - y_{mean}^{obs}\right)^2}}\right]^2 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(\mathbf{4.6})$$

The Nash-Sutcliffe simulation efficiency (NSE) indicates how well the plot of observed versus simulated value fits the 1:1 line. If the measured value is the same as all predictions, NSE is 1. If the NSE is between 0 and 1, it indicates deviations between measured and predicted values. If NSE is negative, predictions are very poor, and the average value of output is a better estimate than the model prediction (Nash and Sutcliffe, 1970).

$$\boldsymbol{NSE = 1 - \left[\frac{\sum_{i=0}^{n}\left(y_i^{obs} - y_i^{sim}\right)^2}{\sum_{i=0}^{n}\left(y_i^{obs} - y_{obs}^{mean}\right)^2}\right]} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (\mathbf{4.7})$$

Percent bias (PBIAS) measures the average tendency of the simulated values to be larger or smaller than their observed counterparts. The optimal value of PBIAS is zero, indicating exact simulation of observed values. In general, a lower value of PBIAS signifies accurate model simulation (Moriasi et al., 2007).

$$\boldsymbol{PBAIS = \left[\frac{\sum_{i=0}^{n}(y_i^{obs} - y_i^{sim})}{\sum_{i=0}^{n}(y_i^{obs})}\right] \times 100} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (\mathbf{4.8})$$

The RSR is an error index that standardizes the root mean square error using the observations' standard deviation. RSR ranges between 0 and 1, with low values indicating good model performance. When RSR=0 it indicates that the model simulation fits perfectly to the measured data, while the large positive RSR values indicate a poor model performance (Moriasi et al., 2007).

$$\boldsymbol{RSR = \frac{RMSE}{STDev_{obs}}} = \frac{\sum_{i=0}^{n}(y_i^{obs} - y_i^{sim})^2}{\sum_{i=0}^{n}(y_i^{obs} - y_{obs}^{mean})^2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (\mathbf{4.9})$$

4.7 Concluding Remark

The most important aspect while using neural network is its training data. Here while preparing LULC maps post correction was done till pixel level, which results in efficient model training. Regionalization using catchment characteristics was performed and all classes/ types of the catchment characteristics were considered while deriving the value of the similarity index. The results of regionalization can be confirmed by the model performance criteria.

5 RESULT AND DISCUSSIONS

5.1 Land Use/ Land Cover Change Analysis

The LULC Map of Navi Mumbai for the year 2000, 2008 and 2016 with six different classes namely, water, urban, tree cover, barren, wetland and forest are prepared in the present study. The LULC Map for 2000 is shown in Fig.5.1.

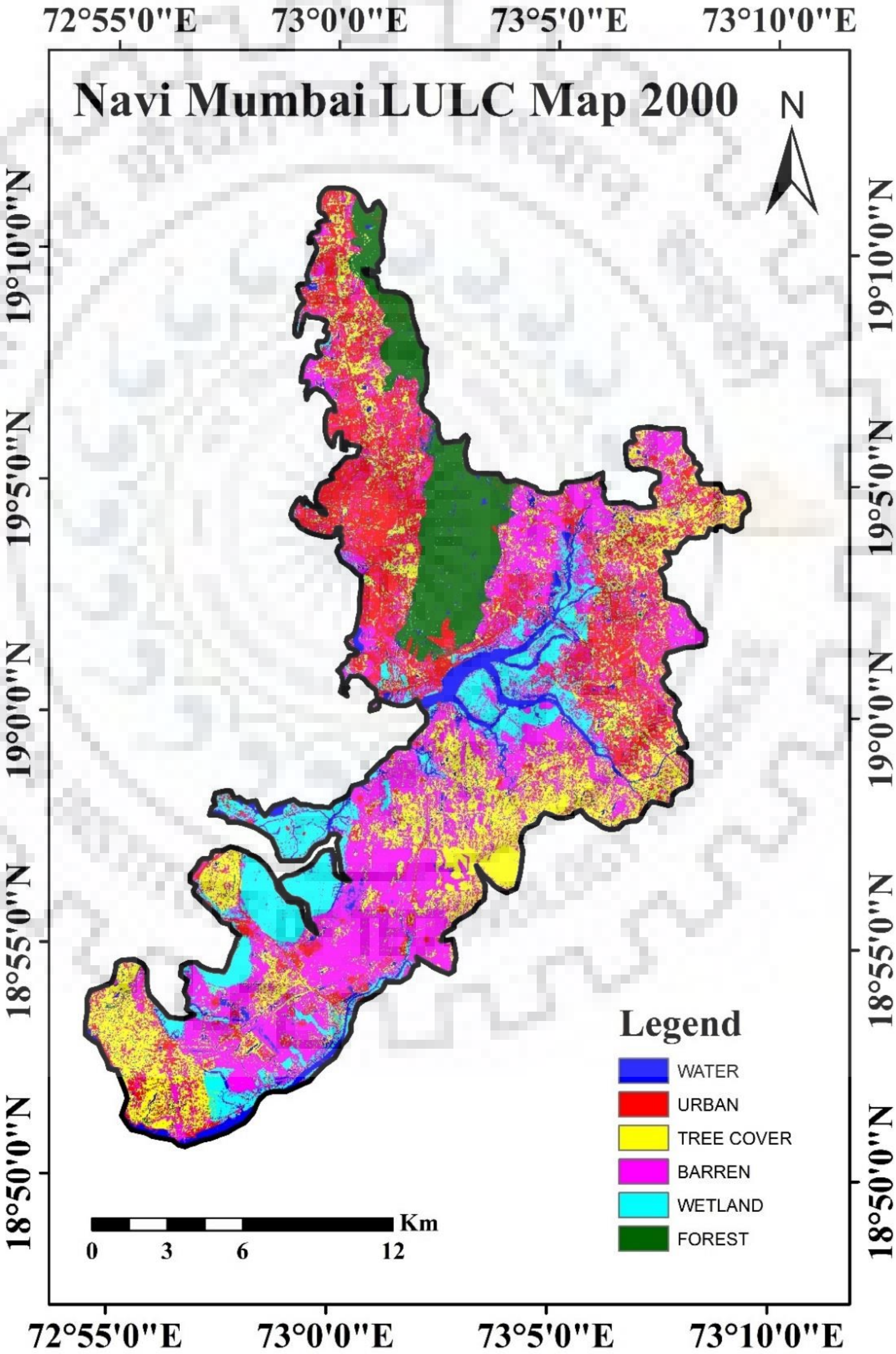

Figure 5-1: Navi Mumbai LULC Map (2000)

Figure 5.2 prsents the Navi Mumbai land use/ land cover map for the year 2008. From the map it can be inferred that in the year 2008, there has been an increase in the urban class as some area from tree cover underwent urbanization.

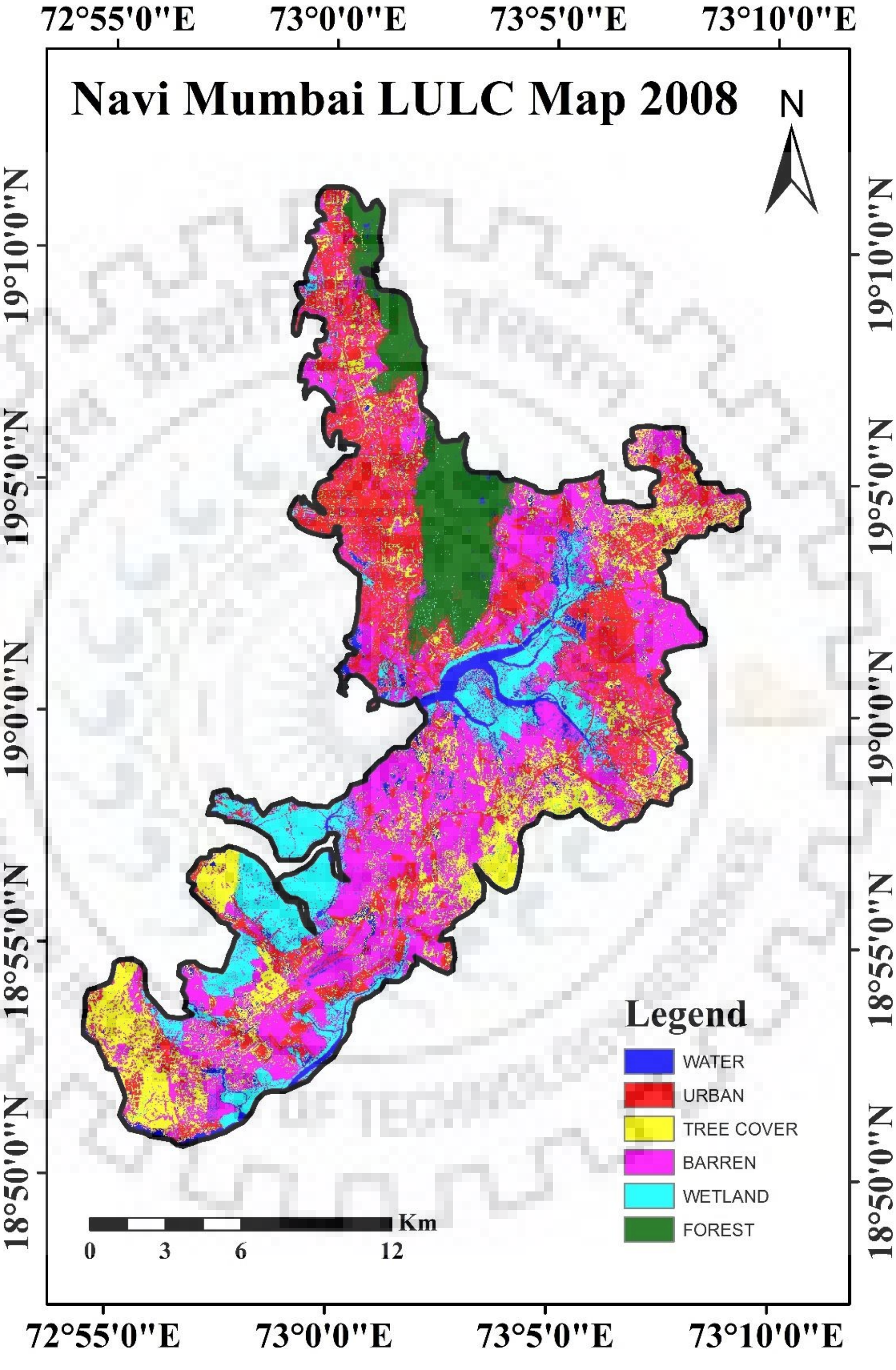

Figure 5-2: Navi Mumbai LULC Map (2008)

Figure 5.3 presents the Navi Mumbai land use/ land cover map for the year 2016. From the map it can be inferred that the increase in the urban land use class is due to the contribution from tree cover and barren class.

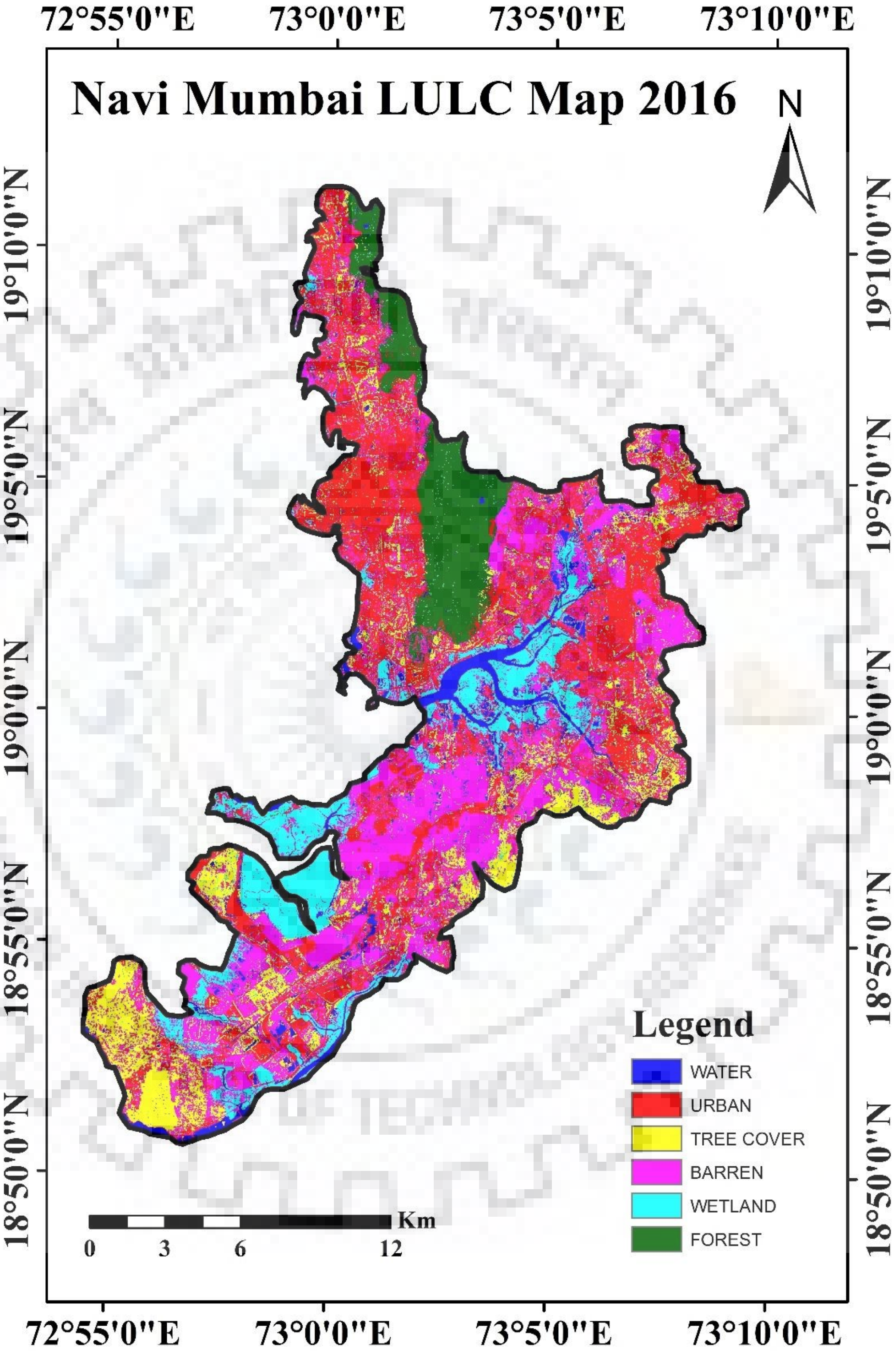

Fig.5.3: Figure 5-3: Navi Mumbai LULC Map (2016)

Table 5.1 shows how the land use/ land cover has changed from the years 2000 to 2016. Very little change has been observed in the water and wetland class in the passage of time. The reduction in the area covered by forest is also not very substantial. Area covered by urban class increased by 13.87 km^2 in between 2000 and 2008 and by 29.12 km^2 in between 2008 and 2016. The tree cover has reduced statistically in between 2000 and 2016 by 27.05 km^2. The barren area has reduced by an amount of 13.05 km^2 in between 2000 and 2016.

Table 5-1: Area covered by the LULC classes for years 2000, 2008 and 2016

LULC classes	2000		2008		2016	
	AREA		AREA		AREA	
	km^2	%	km^2	%	km^2	%
WATER	20.73	6.05	20.75	6.06	20.66	6.03
URBAN	59.21	7.28	73.08	21.33	102.2	29.83
TREE COVER	74.18	21.65	61.09	17.83	47.13	13.75
BARREN	113.84	33.22	114.13	33.31	100.79	29.41
WETLAND	40.54	11.83	42.36	12.36	40.86	11.92
FOREST	34.14	9.96	31.22	9.11	31.01	9.05
TOTAL	342.64	100	342.64	100	342.64	100

Table 5.2 shows the transition matrix from the year 2000 till the year 2016 for all the land use classes. It basically shows which class in 2000 had contributed to which class in 2016.

Table 5-2: Transition Matrix from the year 2000 to 2016

LULC classes	WATER	URBAN	TREE COVER	BARREN	WET LAND	FOREST	2016
WATER	9.57	1.28	1.86	4.85	2.86	0.25	20.66
URBAN	2.53	36.70	19.43	37.31	3.86	2.36	102.20
TREE COVER	1.06	5.87	24.35	12.59	1.39	1.87	47.13
BARREN	2.91	12.01	25.02	51.03	7.49	2.33	100.79
WETLAND	4.13	2.26	2.52	6.81	24.63	0.51	40.86
FOREST	0.52	1.09	1.01	1.26	0.31	26.82	31.01
2000	20.73	59.21	74.18	113.84	40.54	34.14	342.64

5.2 Future land use/ land cover prediction

After this the Land Change Modeler was run. Fig.5.4 and Fig.5.5 shows the interface of the model where the parameters are mentioned. The accuracy rate is 99.98% and the skill measure is 0.9997. The model was set for 10000 iterations but as the maximum accuracy was attained at 7370 iteration the model stopped its procedure there itself. Both the accuracy rate and skill measure are very good. The model trains on its own and the user cannot interfere with it.

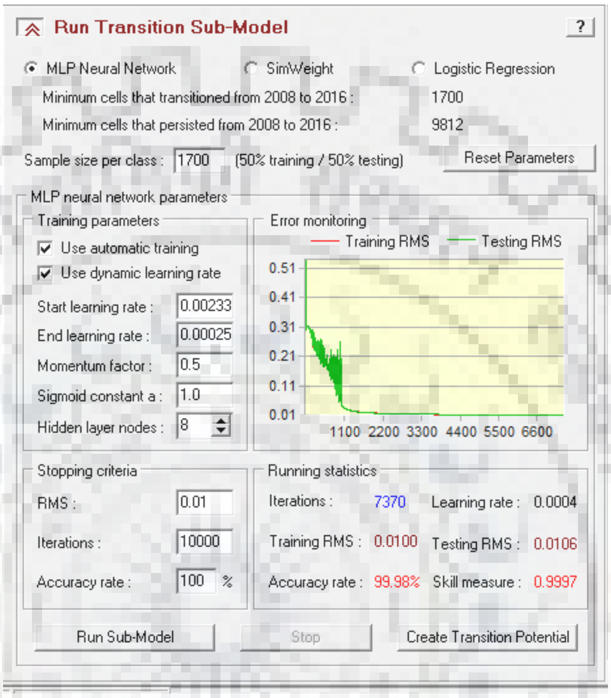

Figure 5-4: Land Change Modeler Result

Fig.5.5 depicts the spatial trend of change. 4th order spatial trend of change was considered for analysis. Spatial trend of change gives us the idea about where the change has taken place and where there is a potential for change.

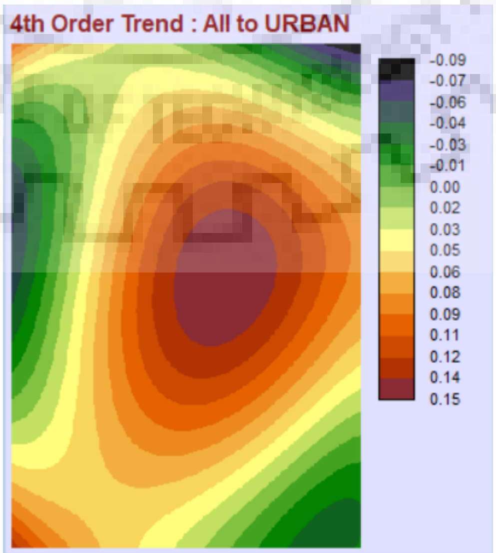

Figure 5-5: Spatial trend of change

After running the Land Change Modeler, Fig.5.6 maps the predicted land use/ land cover for the year 2030.

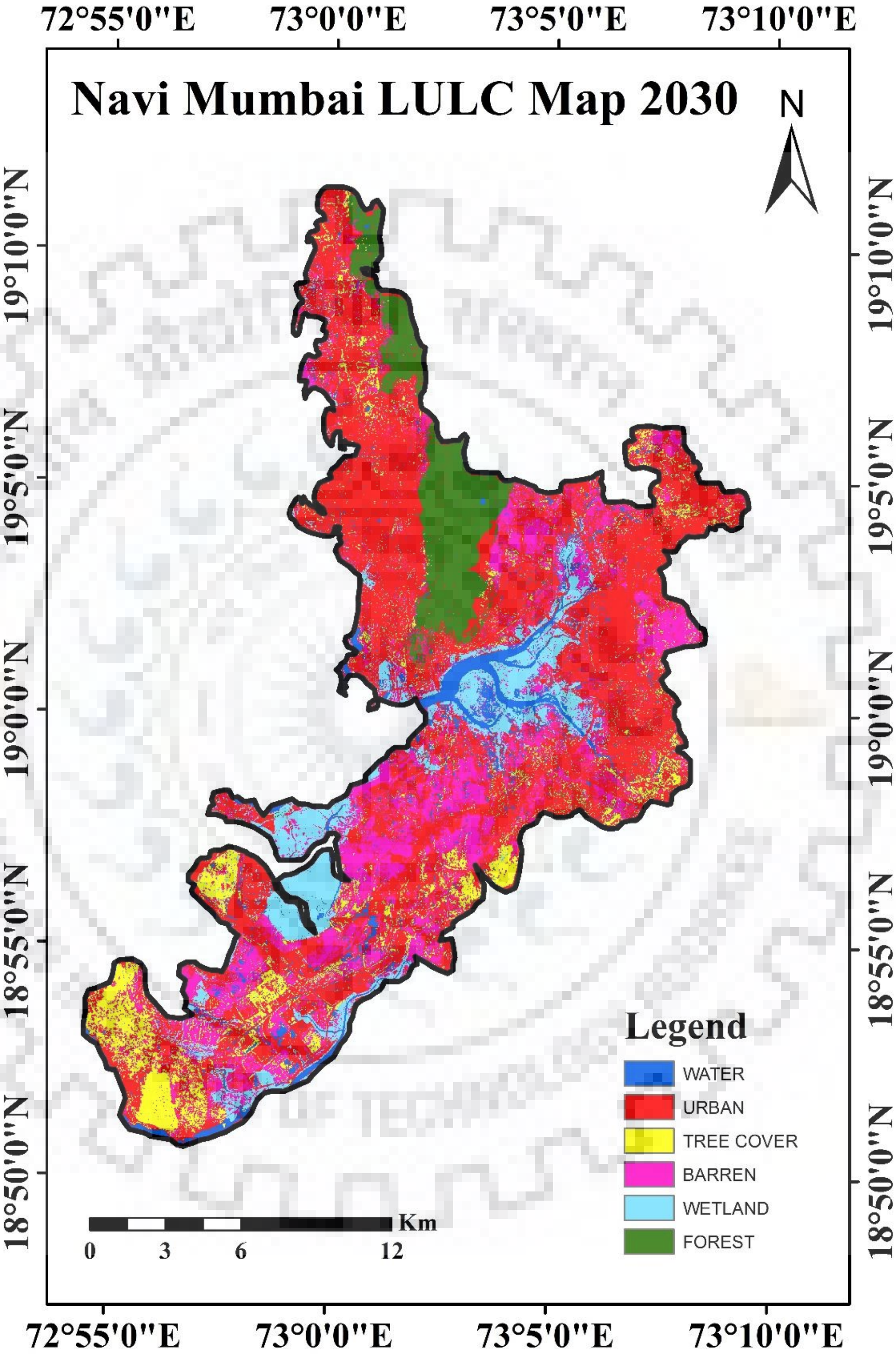

Figure 5-6: Navi Mumbai LULC Map (2030)

From the above figure it can be observed that major change in increased urbanization is because of barren area being turned into built-up area.

After running the Land Change Modeler, Fig.5.7 gave the predicted land use/ land cover for the 2050.

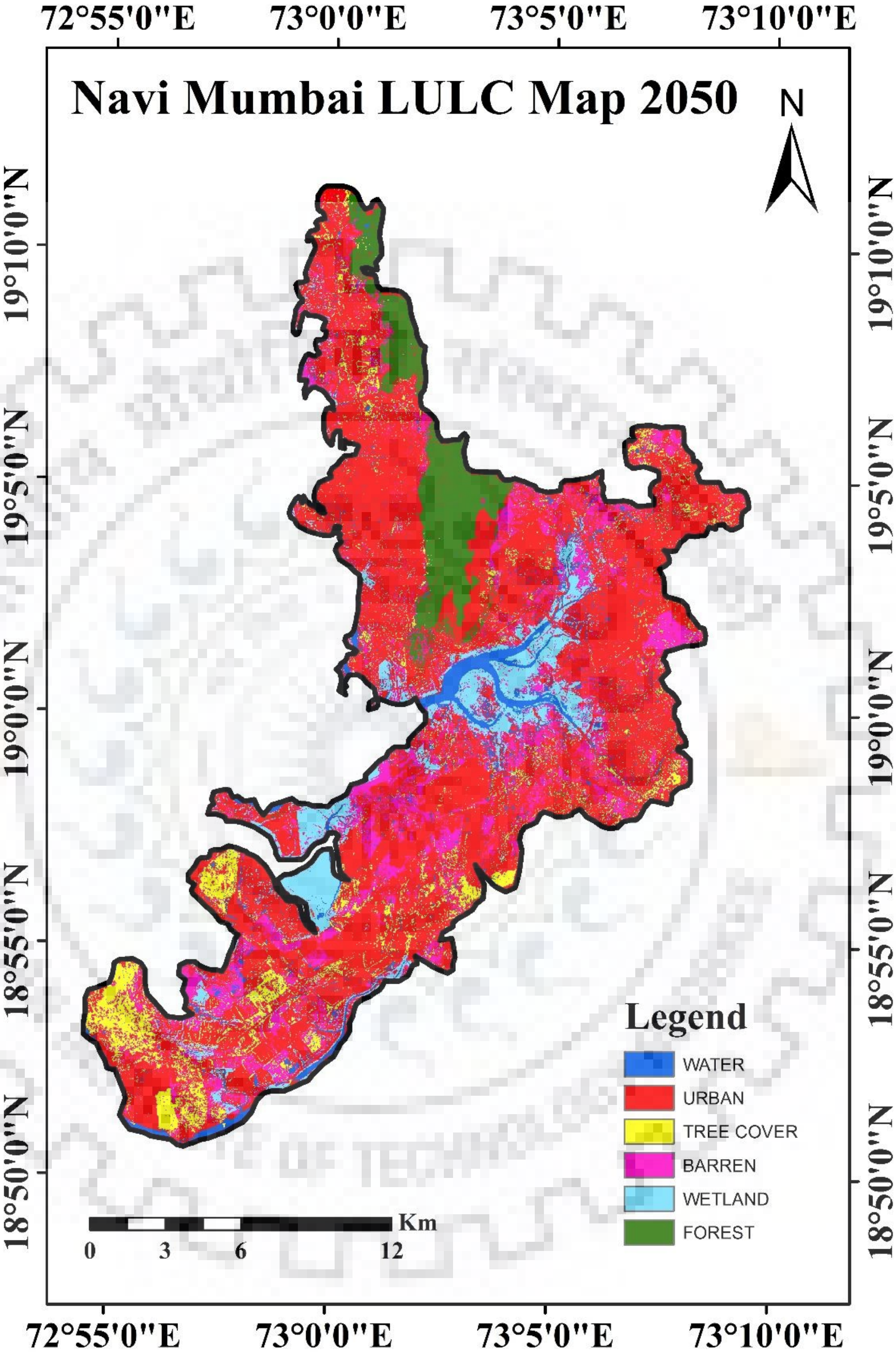

Figure 5-7: Navi Mumbai LULC Map (2050)

Table 5.3 shows the percentage of land use/ land cover class variation from 2000 till 2050. By 2030, 47.6% of Navi Mumbai will be urbanized and by 2050, 57% of Navi Mumbai will be urbanized. In 2016, the barren area is 100.8 km^2 and in 2050 it is 47.1 km^2 which indicates the scope for further infrastructural development. In 2000 the area covered by forests is about 34 km^2 whereas in 2050 it is about 25 km^2 which indicates that in a span of 50 years very less advancement has occurred and predicted, which ensures sustainable development. Also from strictly engineering point of view as can be seen from the slope maps and digital elevation model less development is predicted in areas which are at higher elevation.

Table 5-3: Area covered by the LULC classes

LULC classes	2000		2008		2016		2030		2050	
	AREA		AREA		AREA		AREA		AREA	
	km^2	%	km^2	%	km^2	%	km^2	%	km^2	%
WATER	20.7	6.1	20.8	6.1	20.7	6.0	20.5	6.0	17.7	5.2
URBAN	59.2	17.3	75.9	22.1	104.9	30.6	163.2	47.6	195.4	57.0
TREE COVER	74.2	21.7	61.1	17.8	47.1	13.8	31.7	9.3	27.4	8.0
BARREN	113.9	33.2	114.1	33.3	100.8	29.4	63.8	18.6	47.1	13.7
WET LAND	40.5	11.8	39.5	11.6	38.1	11.2	35.0	10.2	29.3	8.6
FOREST	34.1	9.9	31.2	9.1	31.0	9.0	28.5	8.3	25.8	7.5
TOTAL	342.6	100.0	342.6	100.0	342.6	100.0	342.6	100.0	342.6	100.0

The percentage area covered by wetlands has reduced from 11.8% to 8.6% in a period of 50 years. Wetlands are very high in ecological biodiversity and there is a reduction in its area. This should be brought to attention and appropriate steps should be taken if a wetland area is encroached. Conservation of wetlands is necessary as they help in attaining sustainability, which is a need of the century and something which cannot be compromised.

Figure 5.8 shows how the six land use/ land cover classes namely, water, urban, tree cover, barren, wetland and forest change over a period of time with respect to their area.

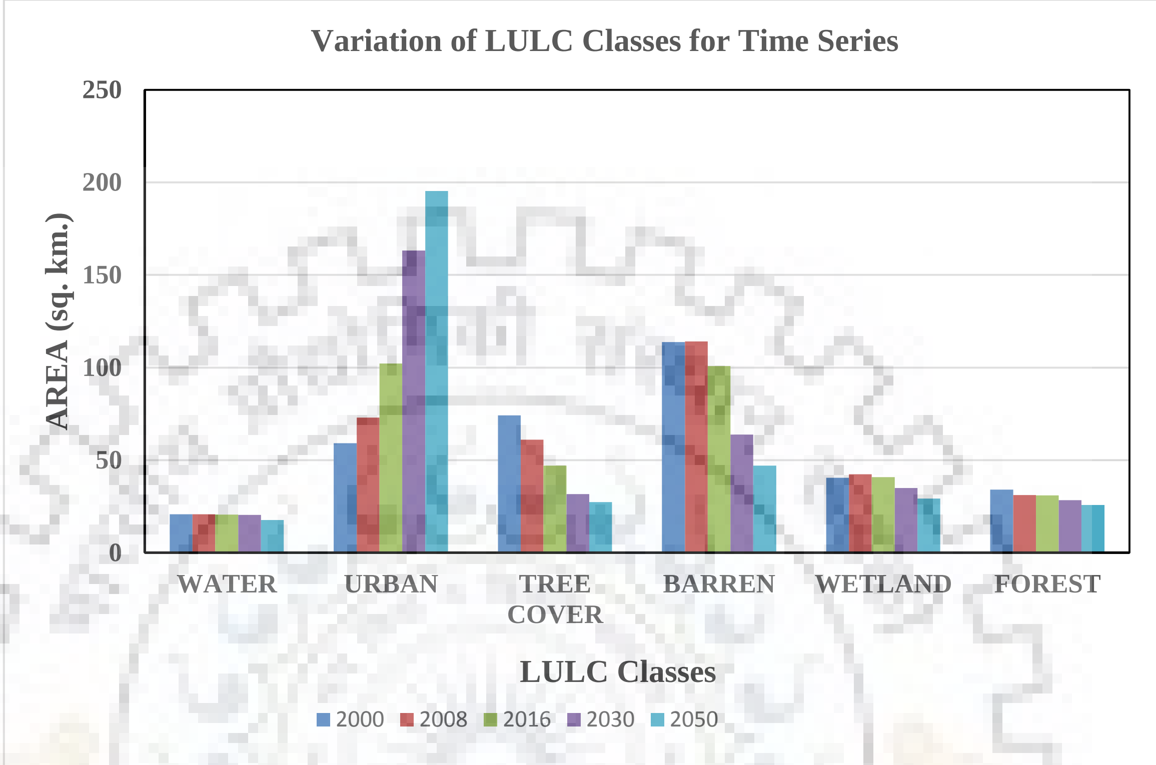

Figure 5-8: Variation of LULC classes from 2000 to 2050

5.3 Application of Regionalization Technique

From the 8 subbasins generated by SWAT, subbasin 4 was considered for analysis and it covers maximum part of the catchment. Comparison of catchment characteristics like lope, soils, land use/ land cover and area were made between subbasin 4 and donor catchment considering the Pen gauge-discharge station as the outlet for the watershed. All the maps were also generated so that they can be compared and the results are tabulated as shown below.

From the Table 5.4 it can be understood that a comparison between the catchment characteristics of the subbasin and donor catchment has been made. Land use class like urban is not present in the donor catchment and only one type of soil is present in the donor catchment, whereas in the subbasin three types of soils are present.

Table 5-4: Regionalization analysis

Catchment characteristic	Class/ Type	Subbasin (%area)	Donor catchment(%area)
Land use/ land cover	WATER	3.76	4.83
	URBAN	14.93	0
	TREE COVER	47.08	47.54
	BARREN	26.72	2.03
	WETLAND	3.37	3.31
	FOREST	4.13	42.29
Soil characteristic	Ne56-2b-6669	33.75	100
	Bc24-2b-3658	59.32	0
	Je68-2a-3756	6.93	0
Slope characteristic	0-50	93.55	99.99
	50-224	6.45	0.01
Area (sq. km.)		438.06	103.94

All the factors have been considered in the regionalisation analysis and the procedure of calculating the similarity index is explained below in detail. Weights have been assigned for all the classes in a specific catchment characteristic and a constant value was obtained for each catchment characteristic which is then multiplied by the final weight assigned to the entire catchment characteristic. The summation of the weights has to one and the similarity index should take a value in between 0 to 1. The comparison of donor catchment properties with the study area are presented from Fig.5.9 to Fig.5.14.

Table 5-5: Similarity index calculations

Catchment characteristic		ΔX	X'	Max. of $(\Delta X, X')$	$\frac{\Delta X}{Max(\Delta X, X')}$	$Class\ \alpha$	$Constant$	$Characteristic\ \alpha$	$S = 1 - \frac{\Delta X}{Max(\Delta X, X')}$
Land use/ land cover	WATER	1.07	4.3	4.3	0.249	0.16	0.04	**0.25**	**0.15**
	URBAN	14.93	7.47	14.93	1	0.18	0.18		
	TREE COVER	0.46	47.31	47.31	0.01	0.16	0.002		
	BARREN	24.69	14.38	24.69	1	0.17	0.17		
	WETLAND	0.06	3.34	3.34	0.018	0.16	0.003		
	FOREST	38.16	23.21	38.16	1	0.17	0.17		
							0.565		
Soil characteristic	Ne56-2b-6669	66.25	66.88	66.88	0.99	0.33	0.33	**0.55**	
	Bc24-2b-3658	59.32	29.66	59.32	1	0.34	0.34		
	Je68-2a-3756	6.93	3.47	6.93	1	0.33	0.33		
							1		
Slope characteristic	0-50	6.44	96.77	96.77	0.07	0.99	0.069	**0.05**	
	50-224	6.44	3.23	6.44	1	0.01	0.01		
							0.079		
Area		334.12	271	334.12	1	1	**1**	**0.15**	

Equation below explains how the value of similarity index has been calculated.

$$\boldsymbol{S = 1 - [(0.565 * 0.25) + (1 * 0.55) + (0.079 * 0.05) + (1 * 0.15)] = 0.15} \dots \dots \dots \dots (10)$$

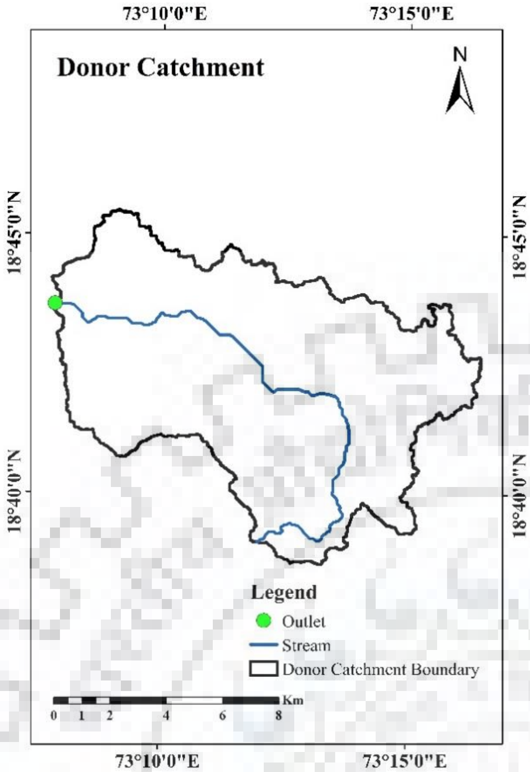

Figure 5-9: Donor catchment

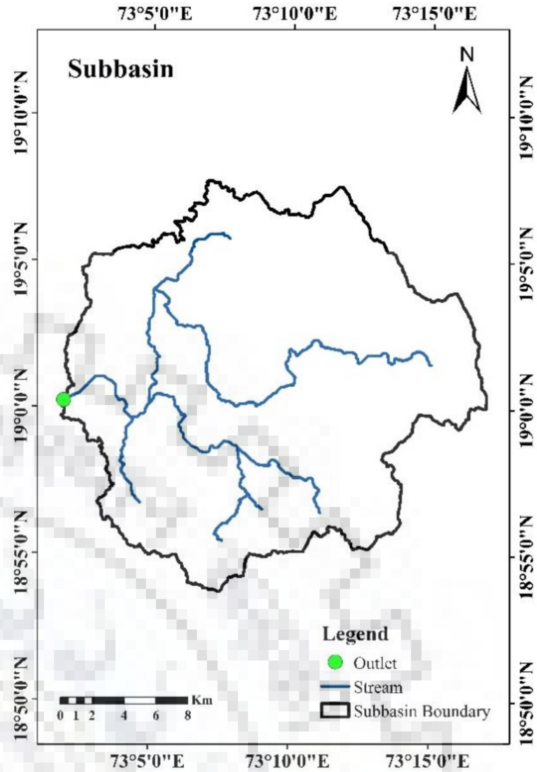

Figure 5-10: Subbasin

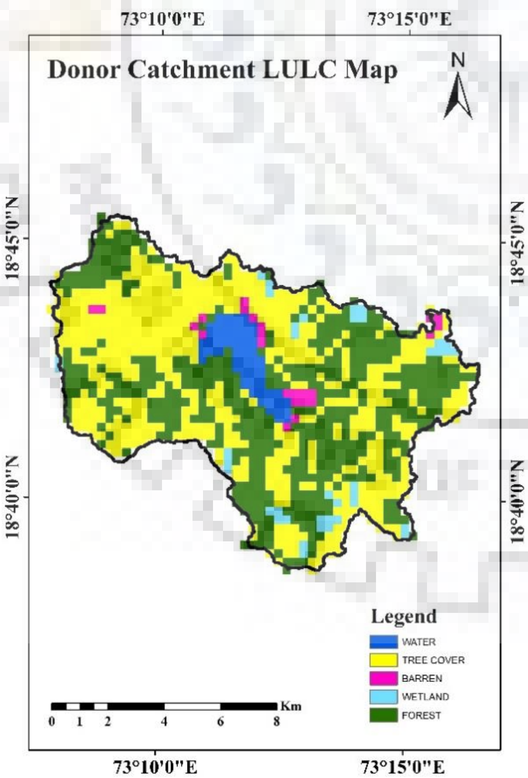

Figure 5-11: Donor catchment LULC Map

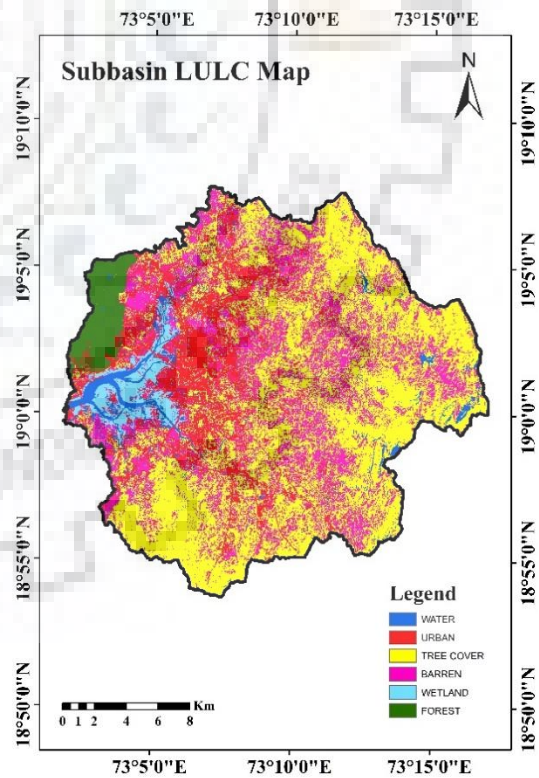

Figure 5-12: Subbasin LULC Map

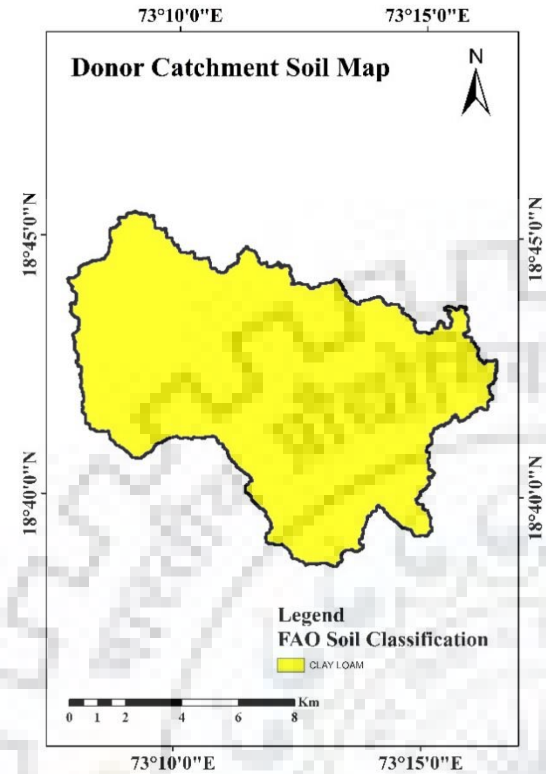

Figure 5-13: Donor Catchment Soil Map

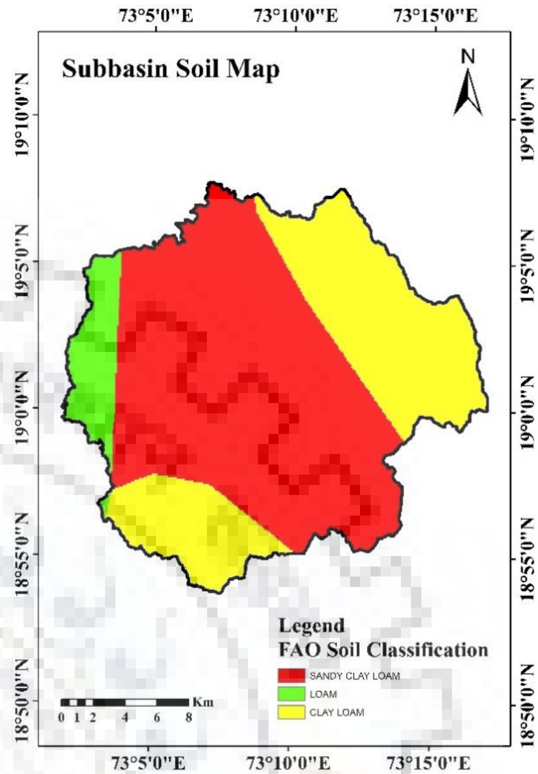

Figure 5-14: Subbasin Soil Map

The catchment characteristics have been considered for deriving the similarity index. Comparison between the donor catchment and the subbasin has been made. In the donor catchment only one kind of soil Clay Loam is present whereas in the subbasin three types of soil are present. Urban class which constitutes about 15% of the study area is not present in the donor catchment at all.

5.4 SWAT Model Output

In the present study 8 catchments constituting 68 HRUs were generated by SWAT. The total precipitation is 3091.9 mm, the evapotranspiration accounts for 562.6 mm, recharge to shallow and deep aquifer is 663.39 and surface runoff is 1782.01 mm. About 58% of the precipitation is converted to surface runoff.

The average Curve Number for the catchment is 81.46.

Figure 5.15 below shows how the hydrological cycle simulated by SWAT, and the behaviour of the catchment with the hydrological cycle.

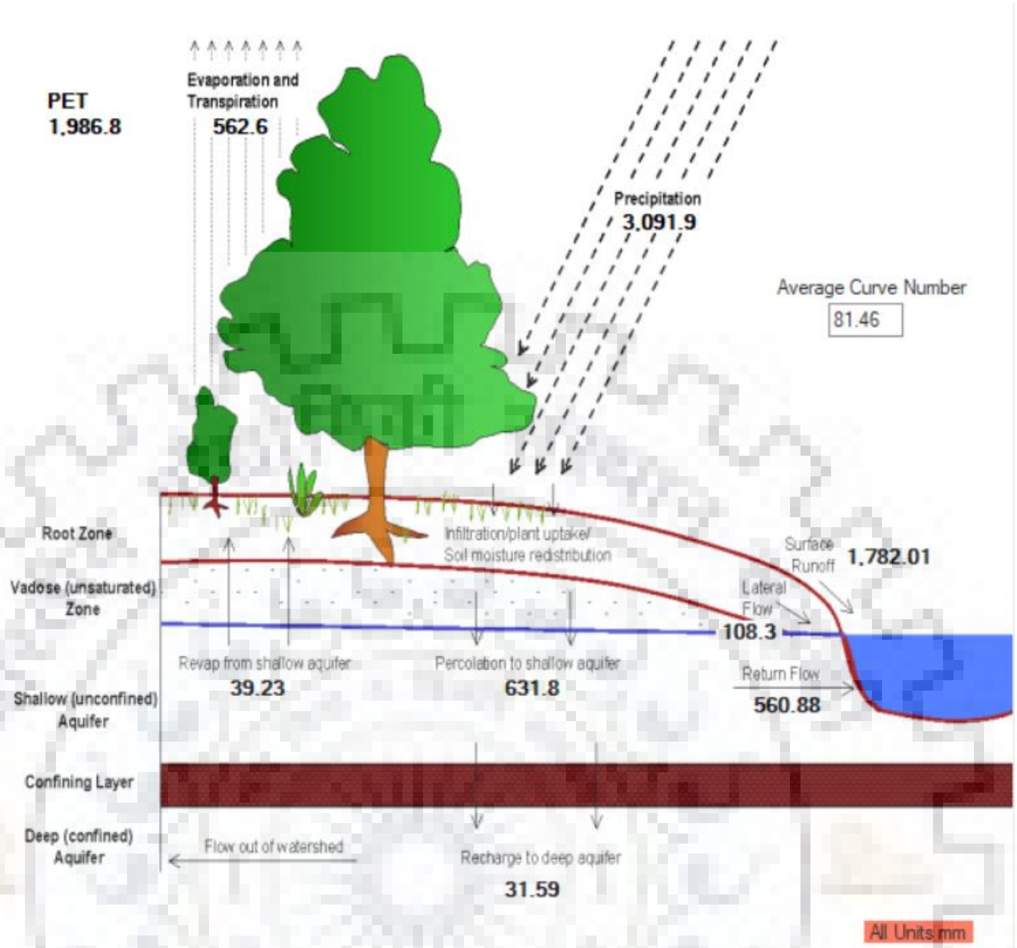

Figure 5-15: SWAT Hydrological Cycle

Figure 5.16 below shows a hydrograph for the year 2013 for the monsoon season starting from June and ending in September using daily data.

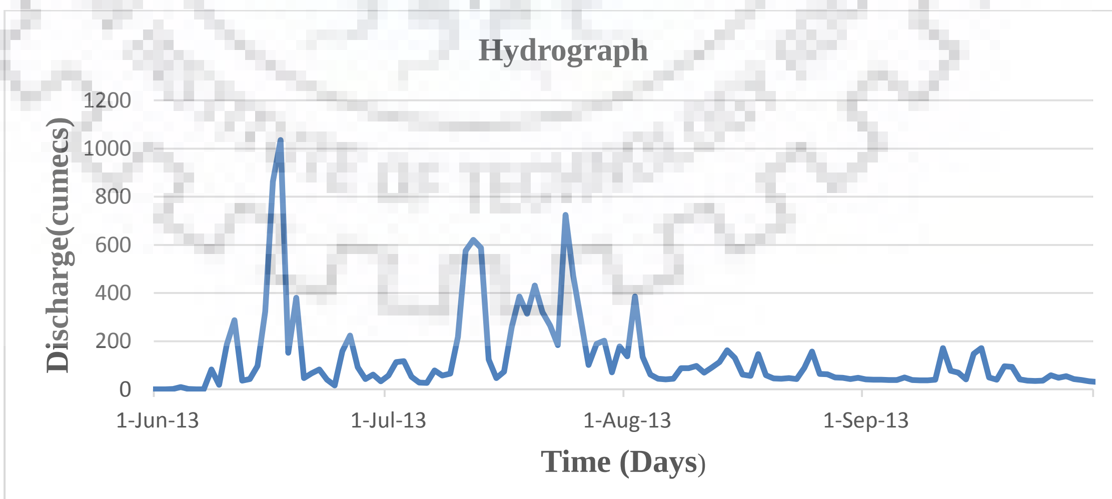

Figure 5-16: Hydrograph for the monsoon season of year 2013

From the hydrograph it can be observed that in the end of the June month huge quantity of surface runoff was generated.

5.5 Sensitivity and Uncertainty Analysis

From the 8 subbasins generated by SWAT, subbasin 4 was considered for analysis and it covers maximum part of the catchment. Simulated SWAT flow data of the outlet considered for the calibration and validation process. While performing model calibration and validation doing sensitivity analysis is very important as it important to know that which SWAT parameter bring a change in the catchment hydrological behaviour. Sequential Uncertainty–Fit (SUFI-2) algorithm is used for performing uncertainty analysis of the study. Simulation area results are expressed by 95 percent prediction uncertainty (95PPU) and cannot be compared with the NSE, R^2, RSR and PBIAS of the observed dataset. Each SWAT parameter is set in a maximum and minimum ranges and a best fitting value is obtained by performing iterations. Table 5.6 below gives the details about the SWAT parameters. They are listed with their ranks to determine which SWAT parameters affect the catchment hydrology the most. Their minimum and maximum ranges are to be set and the most fitted value was obtained at the 190th iteration.

Table 5-6: SWAT parameters with ranges and their best fitted values

Sr. No.	SWAT Parameter	Minimum value	Maximum value	Best fitted value	Rank
1	CN2	-0.200000	0.200000	-0.130000	1
2	ALPHA_BF	0.000000	1.000000	0.745000	2
3	GW_DELAY	30.000000	450.000000	30.420000	3
4	GWQMN	0.000000	2.000000	1.570000	4
5	GW_REVAP	0.000000	0.200000	0.086600	5
6	ESCO	0.800000	1.000000	0.947000	6
7	SOL_AWC	-0.200000	0.400000	0.141400	7
8	SOL_K	-0.800000	0.800000	-0.376000	8

The most to least sensitive parameters from the parameters under consideration are CN2, ALPHA_BF, GW_DELAY, GWQMN, GW_REVAP, ESCO, SOL_AWC and SOL_K.

SWAT simulation were run for 11 years (2003-2013) with 3 years of warm-up period from 2000-2002. While performing SWAT-CUP analysis the observed dataset was divided into two parts, one for calibration (2003-2008) and one for validation (2009-2013) in such a manner that, the number of dry months and wet months in approximately same. Monthly data was assessed for doing the analysis. From the analysis for calibration period (2003-2008) the value of coefficient of determination R^2 was 0.79 and in the validation period (2009-2013) it is 0.85. The Nash-Sutcliffe Efficiency (NSE) for the calibration period (2003-2008) is 0.76 and for the validation period (2009-2013) it is 0.86. The percentage BIAS (PBIAS) value during calibration period (2003-2008) is +3.25% and during the validation period (2009-2013) it is -5.45%. The RMSE-Observation Standard Deviation Ratio (RSR) during the calibration period (2003-2008) and validation period (2009-2013) is 0.006. As the NSE values lie between 0.75-1.00 their performance rating is very good. The PBIAS values are < ±10% which is also very good. The RSR values are tending to 0 which makes it very good.

In Table 5.7 the values for model performance criteria as given by Moriasi et al. (2007), are presented.

Table 5-7: Model Performance criteria

Performance Rating	RSR	NSE	PBIAS (%)
Very good	$0 \leq RSR \leq 0.5$	$0.75 < NSE \leq 1$	PBIAS < ±10
Good	$0.5 \leq RSR \leq 0.6$	$0.65 < NSE \leq 0.75$	± 10 ≤PBIAS <±15
Satisfactory	$0.6 \leq RSR \leq 0.7$	$0.5 < NSE \leq 0.65$	±15 ≤ PBIAS <±25
Unsatisfactory	$RSR > 0.7$	$NSE \leq 0.5$	PBIAS ≥ ±25

The results of model calibration and validation along with the model performance criteria are given in Table 5.8.

Table 5-8: SWAT model performance during calibration and validation period

Year	Period	SWAT model evaluation statistics			
		R2	NSE	PBIAS(%)	RSR
2003-2008	Calibration	0.79	0.76	+3.25	0.006
2009-2013	Validation	0.85	0.86	-5.45	0.006

Figure 5.17 shows the scatter plot between the observed and simulated flow values for the calibration period (2003-2008) with the R^2 value.

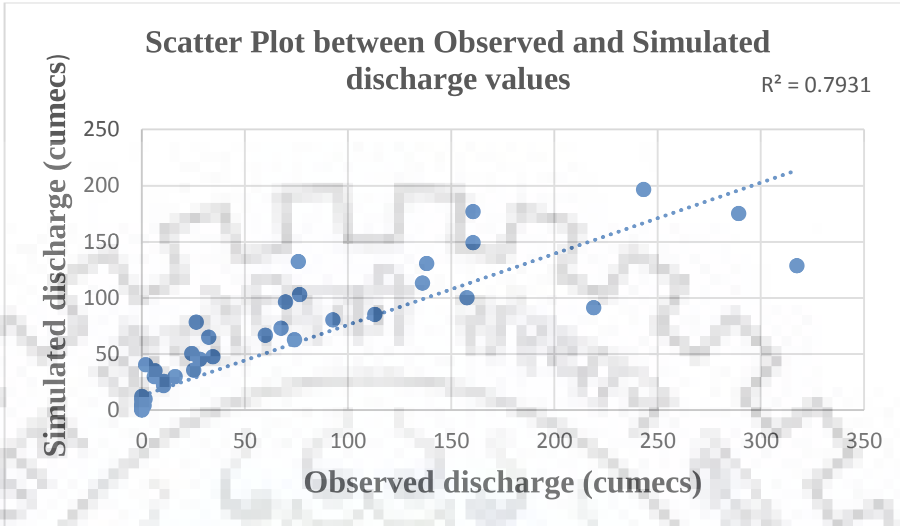

Figure 5-17: Scatter plot between observed and simulated discharge values during the calibration period (2003-2008)

The scatter plot between the observed and simulated flow values for the validation period (2009-20013) with the R^2 value is presented in Fig.5.18.

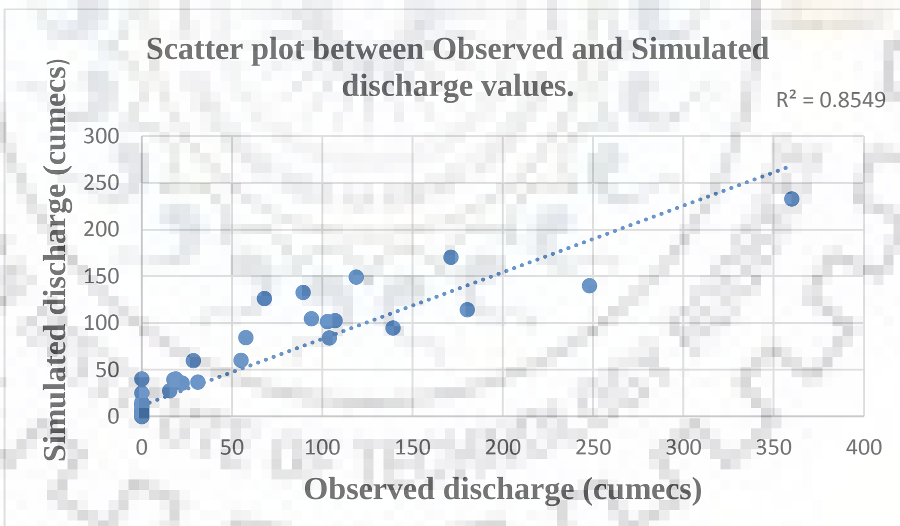

Figure 5-18: Scatter plot between observed and simulated discharge values during the validation period (2009-20013)

Figure 5.19 shows the plot between observed and simulated surface runoff during the calibration phase.

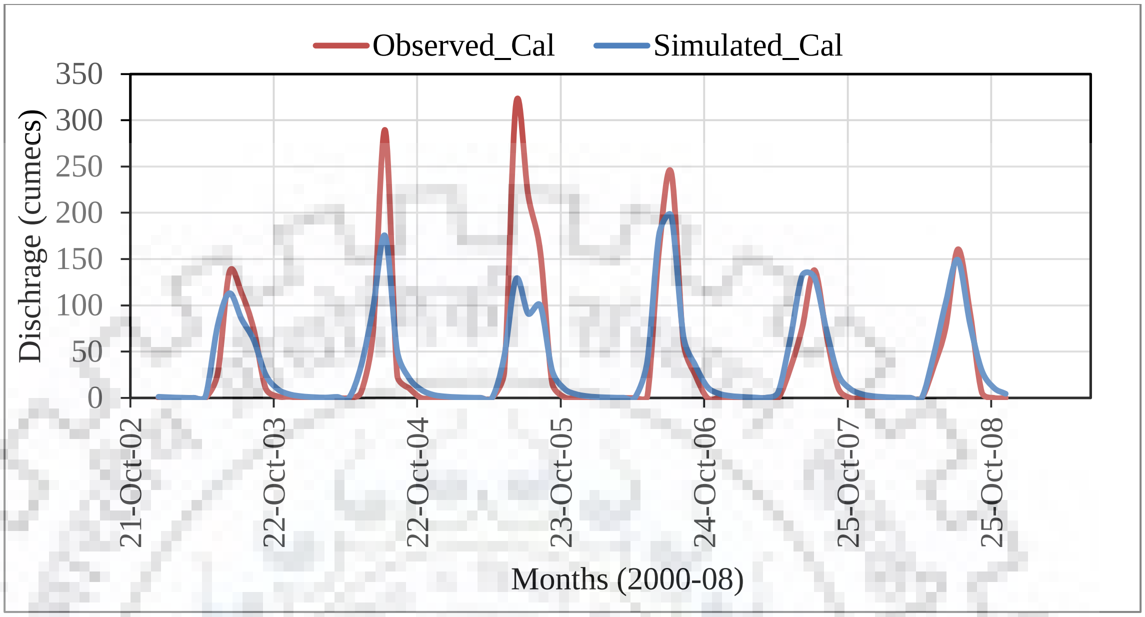

Figure 5-19: Plot between observed and the simulated surface runoff values during calibration period

Figure 5.20 shows the plot between observed and simulated surface runoff during the validation phase.

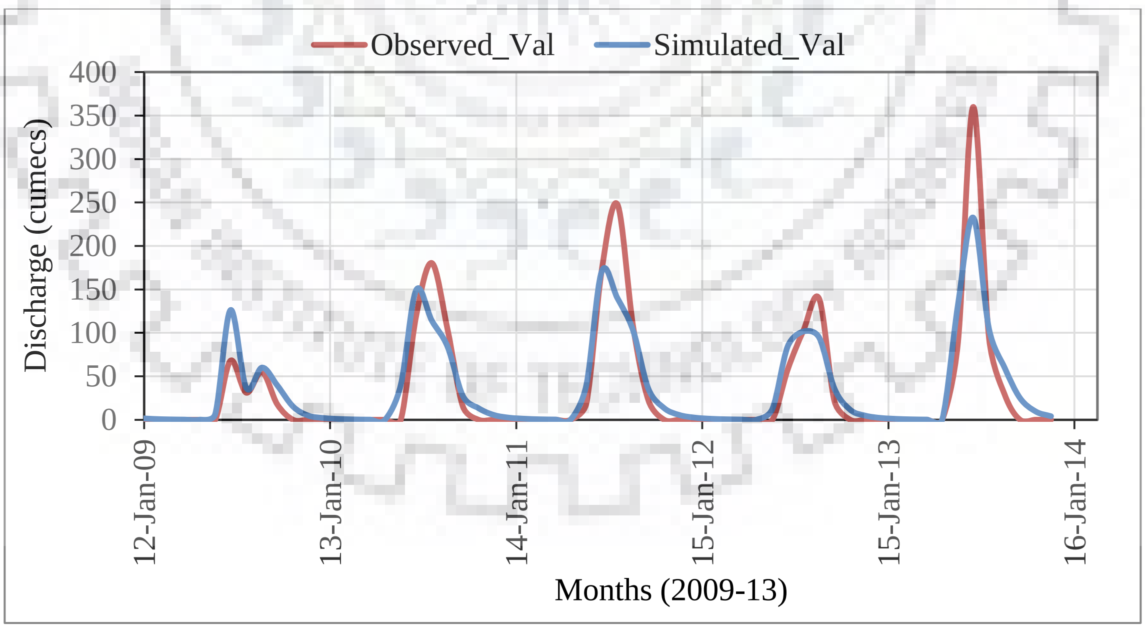

Figure 5-20: Plot between observed and the simulated surface runoff values during validation period

5.6 Concluding Remark

The neural network was properly trained. An accuracy rate of 99.98% is obtained. It stopped after performing 7370 iterations out of 10000 iterations as maximum accuracy was achieved. The entire process was executed with a skill measure of 0.9997 which is approximately equal to 1. From the model performance criteria it can be concluded that model training was performed efficiently and the predicted land use/ land cover can be considered reliable.

Regionalization method was performed for modifying the observed streamflow data from the donor catchment. Catchment characteristic similarity technique was implemented to check the similarity between the donor catchment and the study area. After simulated data was fitted in best possible way, the model performance criteria showed very good results.

6 CONCLUSION

6.1 General

From this study it can be concluded that the Land Change Modeler has been used successfully implemented for modelling and simulating the urban growth process. One of the reasons might be the use of good land use/ land cover images while the model was being trained. The results from this study can be helpful to the urban planning department, as it gives a holistic view to the growth. SWAT model was applied successfully on the urban ungauged catchment. For precipitation IMD dataset was used instead of CFSR dataset. Regionalisation using catchment similarity was done for the study which indicated very good results according to the model performance criteria.

6.2 Conclusion

The major contribution to the increase in the urban area was from the barren area and a part from the tree cover. Thus, the model also took care of the sustainability. Catchment characteristics like slope, soils, land use and area were considered. SUFI-2 algorithm was used for model calibration and validation. Sensitivity analysis was performed indicating the parameters the catchment hydrologic behaviour. The simulated streamflow for the time series has shown very good results according to performance criteria ranges of R^2, NSE, PBIAS and RSR. Based on the above study following conclusions and significant contribution can be drawn.

1) Predicting land use/ land cover for the year 2030 and 2050, which will help the urban planners for better understanding the spatio-temporal dynamics of land use change and can be incorporated while devising suitable development plans which will ensure sustainability. By the year 2030 about 48% and by 2050, 57% of Navi Mumbai will be urbanized. Major contribution to the urban class is coming from tree cover and barren class. Very less advancement is shown wetland and forest areas, which shows the predicted results are ensuring sustainability. The accuracy rate is 99.98% and calculated with a skill measure of 0.9997. It indicates that model has been trained very efficiently and can be used for understanding the spatio-temporal land use change dynamics of Navi Mumbai.
2) Prediction in an Ungauged Basins (PUBs) is quite challenging. The major contribution is the hydrologic modelling of urban ungauged catchment by adopting the regionalization technique. By regionalization the parameters are transferred from a donor catchment to the

study area. For this the similarity index was calculated and it indicated that the donor catchment is 15% similar to the study area. The calculation of the similarity index has been explained in detail. The observed data of the donor catchment was modified accordingly.

3) Moreover the calibration and validation have shown very good results, which means that the model can be used for understanding the hydrological behaviour of the catchment. During calibration period (2003-2008) and validation period (2009-2013) the R^2 values were reported as 0.79 and 0.85, the NSE values are 0.76 and 0.86, PBIAS values are +3.25% and -5.45% and the RSR values are 0.006 for both calibration and validation. These model performance criteria lie in the very good range.

6.3 Scope for Further Work

Neural networks certainly have some inherent limitations as what weight were being assigned to the variables was not made clear. It also does not consider if a specific change in the land use has occurred because of government policies. Model integrated with the effect of change in government policies should be incorporated. It is important to consider that the regionalisation techniques are a solution for analysing the ungauged watersheds. But promising regionalization techniques will show poor results at a different location. Methods of regionalization like inverse difference weighted, kriging, comparison of the flow-duration curves and other methods should be implemented to check their reliability.

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