"PREDICTING THE BUILT-UP GROWTH OF BENGALURU TO FORECAST GUIDANCE VALUES USING SATELLITE IMAGERY"

BACHELOR OF ENGINEERING

in

INDUSTRIAL ENGINEERING AND MANAGEMENT

Submitted to Ramaiah Institute of Technology (Autonomous Institute Affiliated to VTU), Belgaum, in Partial Fulfilment of the Requirements for the Degree of BACHELOR IN ENGINEERING in Industrial Engineering and Management

SUBMITTED BY:

GARGI	(1MS18IM019)
HANIYA FATHIMA	(1MS18IM020)
KV ALEKHYA	(1MS18IM023)

CARRIED OUT AT

URSC-ISRO

Bengaluru

UNDER THE GUIDANCE OF

Internal Guide	External Guide
Dr. ND Prasanna	Shri Rahul Kumar & Shri. Vivek Kumar Gautam
Head of Department	IRS-Programme Management Office
Department of IEM	URSC - ISRO
RIT	Old Airport Road
Bengaluru	Bengaluru

DEPARTMENT OF INDUSTRIAL ENGINEERING AND MANAGEMENT

RAMAIAH INSTITUTE OF TECHNOLOGY

(Autonomous Institute Affiliated to VTU)

BENGALURU- 560054

TERM: 23/03/2022 - 06/07/2022

CERTIFICATE

यू.आर.राव उपग्रह केंद्र
अंतरिक्ष विभाग
भारत सरकार
विमानपुर पोस्ट
बेंगलूरु - 560 017

इसरो isro
Indian Space Research Organisation

U. R. Rao Satellite Centre
Department of Space
Government of India
Vimanapura Post
Bengaluru - 560 017

DATE : 24-06-2022

Certificate

This is to certify that Ms. Gargi
of Ramaiah Institute of Technology *has undergone*
Project training in Program Management and Systems Group *at this Centre*
during the period from 23/03/2022 to 23/06/2022.

COURSE : B.E (Industrial Engineering and Management)
PROJECT TITLE : Predicting the Built-up Growth of Bengaluru to Forecast Guidance Values using Satellite Imagery
PROJECT MEMBERS : 1. Haniya Fathima 2. K V Alekhya
PERFORMANCE : Excellent

U.R. RAO SATELLITE CENTRE HRDD PPEG BANGALORE

(Ramesh Naidu V)
Group Director - PPEG, URSC

(Lalitha Abraham M A)
Head, HRDD - PPEG, URSC

यू.आर.राव उपग्रह केंद्र
अंतरिक्ष विभाग
भारत सरकार
विमानपुर पोस्ट
बेंगलूरु - 560 017

इसरो isro
Indian Space Research Organisation

U. R. Rao Satellite Centre
Department of Space
Government of India
Vimanapura Post
Bengaluru - 560 017

DATE : 24-06-2022

Certificate

This is to certify that Ms. Haniya Fathima
of Ramaiah Institute of Technology *has undergone*
Project training in Program Management and Systems Group *at this Centre*
during the period from 23/03/2022 to 23/06/2022.

COURSE : B.E (Industrial Engineering and Management)
PROJECT TITLE : Predicting the Built-up Growth of Bengaluru to Forecast Guidance Values using Satellite Imagery
PROJECT MEMBERS : 1. Gargi 2. K V Alekhya
PERFORMANCE : Excellent

U.R. RAO SATELLITE CENTRE HRDD PPEG BANGALORE

(Ramesh Naidu V)
Group Director - PPEG, URSC

(Lalitha Abraham M A)
Head, HRDD - PPEG, URSC

यू.आर.राव उपग्रह केंद्र
अंतरिक्ष विभाग
भारत सरकार
विमानपुर पोस्ट
बेंगलूरु - 560 017

U. R. Rao Satellite Centre
Department of Space
Government of India
Vimanapura Post
Bengaluru - 560 017

DATE : 24-06-2022

Certificate

This is to certify that Ms. K V Alekhya *of* Ramaiah Institute of Technology *has undergone Project training in* Program Management and Systems Group *at this Centre during the period from* 23/03/2022 to 23/06/2022.

COURSE : B.E (Industrial Engineering and Management)

PROJECT TITLE : Predicting the Built-up Growth of Bengaluru to Forecast Guidance Values using Satellite Imagery

PROJECT MEMBERS : 1. Gargi 2. Haniya Fathima

PERFORMANCE : Excellent

(Ramesh Naidu V)
Group Director - PPEG, URSC

U.R. RAO SATELLITE CENTRE
HRDD
PPEG
BANGALORE

Lalitha Abraham
(Lalitha Abraham M A)
Head, HRDD - PPEG, URSC

ACKNOWLEDGEMENT

The completion of this major project could not have been possible without the participation and effort of several people whose names may not all be enumerated. Their contributions are sincerely appreciated and gratefully acknowledged. The group would like to express their deep appreciation and indebtedness, particularly to the following:

The management of Ramaiah Institute of Technology for giving us the platform and infrastructure to be able to excel.

The Principal, Dr. N.V.R. Naidu, for giving us this opportunity, the Head of the Department of Industrial Engineering and Management, Dr. N.D. Prasanna, for his support and guidance as our project guide and our external guides, Shri Rahul Kumar & Shri. Vivek Kumar Gautam, for their endless support, kind and understanding spirit during our project period.

The staff and the faculty, for providing us with an opportunity to explore and learn hands on and benefit us with practical and real-world knowledge.

Our gratitude also extends out to our families and friends, for extending their support in one way or the other- morally, financially and physically.

We thank all the people who have helped us directly or indirectly in the successful completion of our project.

Team

1. Gargi
2. Haniya Fathima
3. K V Alekhya

ABSTRACT

Karnataka is one of the fast-growing states in India. With urbanisation and an increase in population, people are migrating from other states causing urban sprawl. Land use and land cover changes (LULC) are a major challenge in the Bengaluru periphery. Spatial - temporal LULC was observed over a span of twenty years (2001-2021). The level-1 data pertaining to satellite images for the years 2011, 2014, 2017 and 2021 were classified by using the supervised classification technique on ArcGIS. The multiclass maps were then leveraged with various proximity maps like distance to roads, airports, metro, etc, which were examined to have an impact on the late rate estimations and the built-up growth. The projected growth was calculated by integrating the input maps into a CA model-based software known as Terrset, which was calibrated to give high statistical accuracies between the actual and predicted layers. The model produced detailed cartography which highlighted the land-use change in key areas. Guidance value data along with built-up pixel count were obtained ward/hobli wise, with the help of which future guidance values were estimated using multiple linear regression on Minitab.

While the stock of land is fixed, its supply is not, and that vastly depends on land-use and land change patterns. Data trends required for land investment and management are unavailable to the public. One needs to apply several proxies to determine the price of land and take decisions. Through the study of urban built-up and guidance value, this project provides a comprehensive assessment of LULC and provides a forecasting model for long-term land development and real estate management.

DISCLAIMER

This project report has the following disclaimers:

1. The satellite data used in the model is available on the USGS Earth Explorer website and ISRO Bhuvan website including text, images, graphics, etc.

2. Every guidance value used in the project is an overall ward-wise and hobli-wise representation of the actual data sourced sincerely from online websites, and is not the actual value. (Refer to Table 8 for year-wise source)

3. Certain guidance values that were not available online, were estimated based on the trend observed in the available data.

4. The output of the model may or may not coincide with actuals, mainly due to fewer data points used in the prediction and forecasting models and non-accessibility of data for different constraints which may affect built-up count/guidance value.

5. The aim of the project is to have a process defined for the guidance value forecasting model using satellite imagery predictions for solely educational, non-commercial use.

6. Readers are requested to check facts, relevant laws, and contents of the project with original government data pertaining to every property of interest, prior to making any commercial decisions for which the authors assume no responsibility.

7. The trial version of ArcGIS was used to classify the satellite images and the student version of TerrSet was used for the modelling procedure.

INDEX

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS		
S. No.	**Abbreviation**	**Definition**
1	ARC-GIS	Aeronautical Reconnaissance Coverage Geographical Information System
2	ANN	Artificial Neural Network
3	BBMP	Bruhat Bengaluru Mahanagara Palike
4	BUI	Built-Up Index
5	CA	Cellular Automata
6	CBD	Central Business District
7	CRS	Coordinate Reference System
8	DF	Degrees of Freedom
9	DN	Digital Number
10	EM	Electromagnetic
11	GDP	Gross Domestic Product
12	GV	Guidance Value
13	ISRO	Indian Space Research Organisation
14	IR	Infrared
15	ISAC	ISRO Satellite Centre
16	LCM	Land Change Modeller
17	LULC	Land Use Land Cover
18	MOLUSCE	Modules for Land Use Change Evaluation
19	NASA	National Aeronautics and Space Administration
20	NDBI	Normalised Difference built-up Index
21	NDVI	Normalised Difference Vegetation Index
22	NDWI	Normalised Difference Water Index
23	OSM	Open Street Map
24	QGIS	Quantum Geographical Information System
25	RS	Remote Sensing
26	SEZ	Special Economic Zones

27	SPSS	Statistical Package for the Social Sciences
28	SRO	Sub Registrar Office
29	URSC	U. R. Rao Satellite Centre
30	UV	Ultra Violet
31	USGS	United States Geological Survey

CHAPTER 1
INTRODUCTION

Urban geography is the extensive study of cities in terms of their various aspects namely built-up environment, population concentration, and their environmental impacts. Owing to the multitude of processes that take place in urban ecosystems every day, the scope of the subject appeals to the interest of urban planners, civil engineers, administrators, policy makers, etc. Urban growth is the spatial and demographic process through which cities see an increased importance due to the concentration of population within a particular society and economy.

Bengaluru is located in South India in the state of Karnataka, India. At present, Bengaluru's urban and rural have a built-up area of 4496 sq. km. Post the industrial revolution in the 1990s and the emergence of information technology and communication sectors in the 2000s, a rapid spurt in population marked the onset of urbanisation and peri urbanisation. This has brought on a large-scale, change in the landscape of the city.

The urban dynamics of Bengaluru were analysed using remote sensing data obtained from the USGS portal for the years 2011, 2014, 2017 & 2021. Proximity maps for various factors affecting urban development were created on quantum geographic information system namely for roads, central business district, special economic zones, metro, airport. The city map with Bruhat Bengaluru Mahanagara Palike wards, and urban and rural Hobli boundaries was created. Land use analysis was carried out using imagery from Landsat 7 & Landsat 8 using a supervised classification method on ArcGIS. Five major types of land use classes were considered for the project - urban built-up, water, barren land, forest land, and agricultural land. The growth of Bengaluru is visualised for the year 2031 through TerrSet Land-use Change Modeller. The simulated land use for 2031 shows an increase in built-up of 42.42%.

Visualisation of the built-up growth patterns provides a necessary insight required for effective urban planning. The use of guidance values is the chosen basis for the application of this project. Guidance values for properties and land have been compiled for the years 2007 to present date. On the other hand, the pixel count for built up in each classified image ,for each ward was generated via quantum geographic information system. The idea was to correlate & estimate the fluctuation of guidance values with urban expansion within each Bengaluru ward/hobli. This was further examined on Minitab, a software particularly used for the statistical evaluation of data.

A simple linear regression model was used to determine the relationship between built-up, year and guidance value. Low p values and high R-squared values indicated that the data closely fits the regression lines calculated for the data of each ward and Hobli. Multiple linear regression analysis was performed with built-up and year as the continuous predictors to obtain the response of GV. Accuracies of over 90% were obtained through built-up regression equations and over 95% for GV regression equations.

For quicker calculations and better accessibility, a python program was configured to read the CSV files containing all coefficients of the linear equations and input ward/Hobli name and year of interest from the user to obtain the guidance value.

CHAPTER 2
COMPANY PROFILE

The U R Rao Satellite Center, formerly known as ISRO Satellite Center, is an ISRO centre for the design, development, and construction of Indian satellites. It was established in the year 1972 as the Indian Scientific Satellite Project in the Peenya Industrial Estate, Bengaluru. In April 2018, ISAC was renamed as U. R. Rao Satellite Centre after the former ISRO Chairman and ISAC founding director, Dr. Udupi Ramachandra Rao.

Through the 1970s and 1980s, URSC was engaged in mastering the basic skills and technologies required for the task of satellite building. Since the early 90's, numerous advanced communication, meteorological, remote sensing, navigation, and space science satellites were constructed and launched. The communication, meteorological, remote sensing, and navigation satellites launched by URSC have continued to serve the key sectors of the Indian economy like communication, agriculture, water resources, urban planning, land use, fisheries, weather forecasting, and disaster management, search and rescue, and navigation.

The Space science missions - Chandrayaan-1, Astrosat, and Mars Orbiter Mission have received worldwide acclaim and put India on the map while inspiring the next generation. More than a hundred state-of-the-art satellites built over forty years by URSC stand testimony to the technical excellence and expertise the centre has managed to scale. With over 2500 highly trained manpower, URSC today is a hub of advanced, sophisticated satellite technologies that feed into the Indian Space Programme. The centre also houses state-of-th- art design, development, building, and testing facilities for satellites.

Company Mission: Build satellites to provide satellite-based services to the common man, pursue research and development in satellite-related technologies

Company Vision: To harness space technology for national development, while pursuing space science research and planetary explorations

Company Functions:

- The primary function of URSC is to design, develop, integrate and test different categories of satellites namely - Communication, Earth observation, Navigation and Space Science Satellites
- The centre is responsible for the total spacecraft project management from the conceptualisation phase to the operationalisation phase in orbit
- To pursue research & development in the area of advanced satellite technologies and establish infrastructure and facilities for satellite building
- To actively involve private, and public-sector industries for realising satellite systems
- To promote and encourage the vast Indian student community by providing opportunities for universities, colleges, and academia in R&D activities, projects, etc.

CHAPTER 3
LITERATURE REVIEW

A literature review can be seen as an explanation of published work that is relevant to a project or dissertation. It is a thorough comment on the research that is read, and the findings of different authors, which are compared to gain supplementary knowledge related to the project work area. It is helpful to know how much research has been done in the area and to know the gaps in existing available research. It helps avoid duplication of work and presents an original.

For this project, a review of the literature available was thoroughly studied and their findings were explored in the context of the company and the scope of the project.

***Baig, M.F.; Mustafa, M.R.U.; Baig, I.; Takaijudin, H.B.; Zeshan, M.T.,* Assessment of Land Use Land Cover Changes and Future Predictions Using CA-ANN Simulation for Selangor, Malaysia (2022)**

The paper highlights the effect of anthropogenic activities on land use, land cover in the state of Selangor, Malaysia and aims to predict future trends based on the CA Artificial Neural Network technique. The input parameters considered were aspect, slope, distance from road and change map to obtain the output for land use change of different land use classes namely water, developed, barren, forest, agriculture, wetlands. A transition matrix depicting the land conversions and study of the same providing information of affecting factors. These findings may be used by decision makers to analyse the effects of socioeconomic variables and promote sustainable development plans. [1]

***Yayuan Lei, Johannes Flacke, Nina Schwarz,* Does Urban planning affect urban growth patterns? A case study of shenzhen, China (2021)**

The paper explores the effects of urban master plans on urban growth patterns in different plan periods in Shenzhen, China. Pixel based and patch-based methods were used to quantify urban growth patterns and classify the same. Elements such as planned build up zone, ecological protection zone,distances, GDP, population density, etc. were chosen from the master plan and considered as the factors in logistic regression model for land use planning. Factors affecting development were studied, pattern outliers were identified and the relationship between urban planning and urban growth patterns was tabulated.[2]

***N. S. Nalini*, Urbanisation and changing temperature patterns in the city of Bengaluru (2020)**

Rising temperature in cities, as a consequence of urbanisation, has attained greater attention world-wide. Temperature is one of the significant factors affecting guidance values of any given city. The material used for constructing buildings are directly affected by the surrounding temperature. As a result, property prices may rise or marked down depending upon the construction material that is mostly used within the area of interest identified. [3]

***Vivek Kumar Gautam, Palani Murugan, Mylswamy Annadurai,* A New Three Band Index for Identifying Urban Areas using Satellite Images (2017)**

This paper discusses the various indices that are used to classify built up areas against non-built-up areas. Each of the index formulas utilise different band combinations to obtain output and have varied accuracy. Our project deals with calculating the 7 indices given in the paper for a few years of satellite data. An accuracy assessment of the calculated indices was performed via georeferencing on google earth pro by importing that particular index image for a particular year and assigning values of 1 and 0 for accurate or inaccurate classification. The process allows us to compare and identify an index having an accuracy greater than 80%. [4]

***Dr. Narayanan Edadan*, Structural Determinants of Unregulated Urban Growth and Residential Land Pricing: Case of Bengaluru, Journal of Urban Planning and Development (2015)**

This paper examines the relationship between unregulated urban growth and residential land market pricing in the context of one of the fastest growing cities in Asia, Bengaluru. The key research points include the factors contributing to exponential growth and sprawl of Bengaluru, the structural factors determining residential land market prices and how the regulated and unregulated land development processes affect land market prices in the growing urban system of Bengaluru city. This formed the basis for study on the several distortions in the land market and provided insight into the diseconomies of urban sprawl. [5]

***Gargi Bindal, Nitin Mishra, Praveen Kalura*, Land Use Land Cover Classification Using ARC-GIS and ERDAS Tool-A Review (2017)**

This paper focuses on methods of classifying land cover on the basis of a variety of satellite image characteristics using the ARC-GIS software. Both supervised & unsupervised methods of classification are used for comparison. Supervised method is based on similarity of cases which is used to obtain predefined classes that have been characterised spectrally; which was used for our project. This was used to finalize our method for the project. [6]

***Varun Narayan Mishra, Praveen Kumar Rai, Kshitij Mohan*, Prediction of land use changes based on Land Change Modeller (LCM) using remote sensing: A case study of Muzaffarpur (Bihar), India (2014)**

This paper discusses the usage of TerrSet, a land use change model tool that supports the analysis of land change dynamics along with classification. The primary objective of this paper is to analyse the present classified layer and predict the future growth of Muzaffarpur city and its surrounding, Bihar (India)by making use of the Landsat satellite images of 1988 and 2010 (i.e., LANDSAT 5 &7). This data was then classified into 8 classes using image processing supervised classification method in a multi-temporal approach and was then predicted for the years 2025 & 2035.TerrSet, formerly, IDRISI, LCM was used to observe and analyse the land use and land cover changes between different classes during the period 1988-2008.The accuracy of the predicted maps obtained was close to 78%. [7]

***Bharath H Aithal, Vinay S and Ramachandra T V*, Modeling and Simulation of Urbanisation in Greater Bengaluru, India, Proc. of National Spatial Data Infrastructure 2013 conference, IIT Bombay (2013)**

This paper analyses the potential of the Markov chain and CA model for predicting spatio-temporal urban growth dynamics in Bengaluru. The growth of Bengaluru is visualized for the year 2020 using business as usual scenario. For simulation and validation, multi-temporal LULC information have been used, the results of which indicate that the future expansion of Bengaluru city will be in the peri- urban region, due to the current dense urbanisation at the city core. This was used to form conclusions of the scope of urban density and decide the area of study for the project. [8]

***Dr. P. K. Srimani, Mrs. Nanditha Prasad*, Land Use and Land Cover Mapping by using Remote Sensing and GIS Techniques – a Case Study of Kasaba Hobli, Hoskote Taluk, Bengaluru Rural District, Karnataka, India (2013)**

This study analyses LULC dynamics through remote sensing in Hoskote Taluk. Image processing data and field visits helped identify different classes of land use and their spatial distribution in the Kasaba area namely agricultural land, built up area, water bodies. This baseline information can be used in the formulation of policies and benefits in planning and development of the area. This formed the basis for estimation of built up area in the rural taluks of Bengaluru under our project study. [9]

***Tania Prvan, Anna Reid, Peter Petocz*, Statistical Laboratories Using Minitab, SPSS and Excel: A Practical Comparison (2002)**

This article focuses on three statistical laboratories, their descriptive statistics, statistical inference and regression models for introductory statistics. Minitab, SPSS and Excel are three software packages widely used in the field of statistics. A thorough analysis of the merits and demerits of each, including the various functions available, helped to decide and choose the most relevant and useful package, Minitab. [10]

***Kairu, Edward*, An introduction to remote sensing. GeoJournal (1982)**

This geo-journal provides an extensive insight into the topic of remote sensing i.e. the collection and interpretation of information about an area or object without physical contact. This information provided the basis to understand image processing, image resolutions, colour composites, GIS, image classification, etc.

From the literature review, various case studies using ArcGIS and Terrset were studied, which included the use of various methods of image classification and LULC modelling. An understanding on how the same can be implemented in the project dataset was achieved. It also gave an insight on the data and information required to carry out the forecasting of guidance values using Minitab in sync with the built-up growth. [11]

CHAPTER 4
METHODOLOGY

This chapter describes the framework of the project and provides a description of the methods chosen to analyse the satellite imageries and perform the land change modelling. An introduction to the fundamentals of remote sensing and image processing is key to understanding the working of the software and its tools. The flowchart below explains the project methodology in brief.

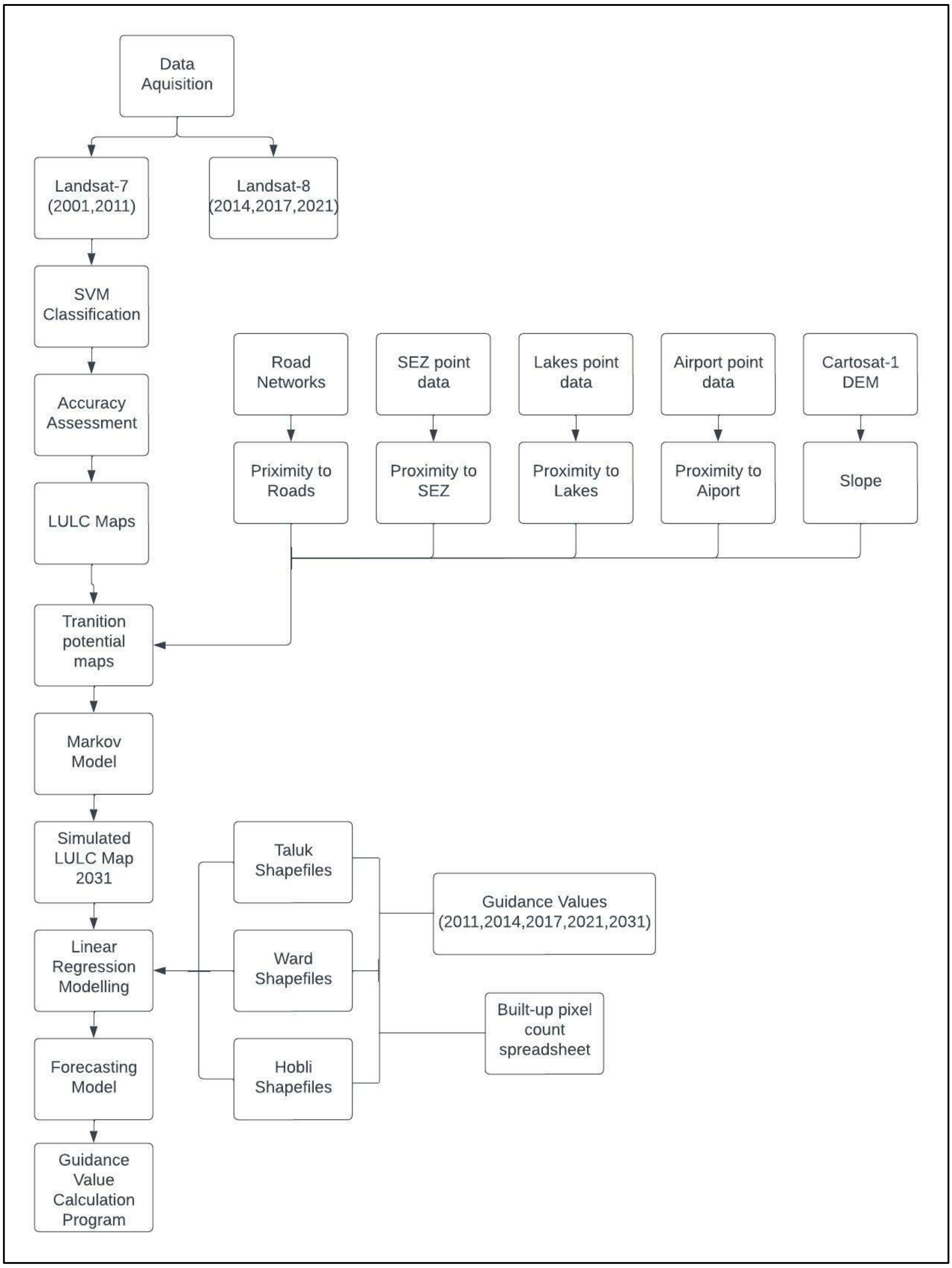


Figure 1: Project Methodology

4.1 Fundamentals of Remote Sensing and image processing

4.1.1 Introduction

The science of acquiring information on the physical and chemical properties of the earth’s surface, atmosphere and oceans, without any form of physical contact using airborne and satellite sensors is termed as remote sensing.

The data is collected in the wavelengths comprising the electromagnetic spectrum. The detectors onboard sense and record the reflected or emitted energy from the earth’s surface. The energy is then converted into a voltage, which an analogue to digital converter turns into a digital number (DN) for the energy. These values are then displayed with an appropriate colour to build images of a particular region.

Remote sensing data-enabled decision making based on the current and future state of our planet. The following are some of the many applications of remote sensing in different fields:

- Agriculture: Crop type, yield and condition estimations, mapping of soil characteristics and land management
- Environmental monitoring: Forest fire detection, Forest cover monitoring
- Hydrology: Wetland monitoring, soil moisture estimations, flood monitoring and mapping
- Land cover and land use: Natural resource management, baseline mapping for geographic information system (GIS) input, urban change detection

4.1.2 Principles of Remote Sensing

a. Electromagnetic radiation: The first requirement of remote sensing is an energy source that can illuminate the target of interest which is in the form of electromagnetic radiation. It is a form of energy propagation which can be explained using the wave concept. Electromagnetic waves are characterised by their velocity, frequency and wavelength.

b. Electromagnetic Spectrum: The electromagnetic spectrum is categorised into several sections of electromagnetic spectrum radiation varying in frequency or wavelength ranging from shorter wavelength higher frequency bands of Gamma rays, X-ray, UV-rays, Visible region, Ner-IR, Mid-IR, to longer wavelength of microwaves and radio waves.

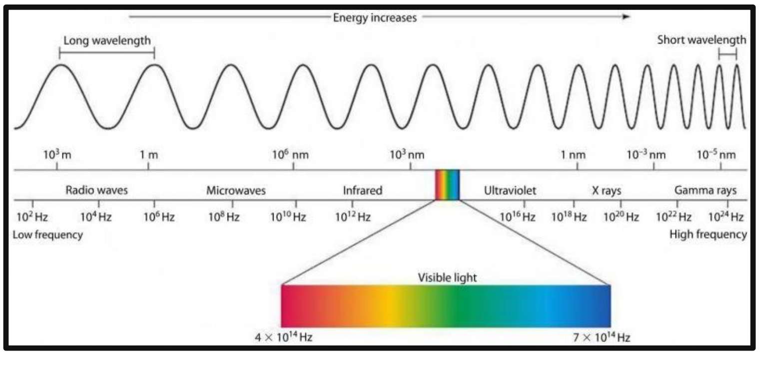


Figure 2: Electromagnetic Spectrum

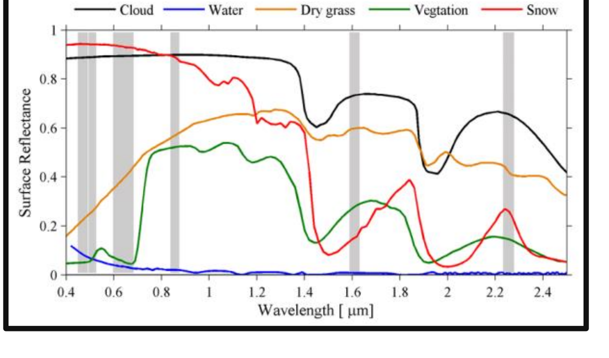


Figure 3: Spectral Reflectance Signature

Table 1: Landsat 8 Bands

Landsat 8 OLI		
Spectral region region	Wavelength range (nm)	Resolution (m)
Blue	435–451	30
Blue	452–512	30
Green	533–590	30
Red	636–673	30
NIR	851–879	30
SWIR1	1566–1651	30
SWIR2	2107–2294	30

4.1.3 Orbits

Orbit: An orbit is a curved path followed by an object around the earth's surface due to gravity. Remote sensing satellites are placed at an altitude of 700-900 km. The area imaged by the satellite is termed as Swath.

a. Sun synchronous orbits: These orbits circle earth in north to south directions, roughly passing over the poles. They are situated at an altitude of 700-900 km. They are synchronous with the sun i.e. always at a fixed position with respect to the sun. This means that the satellite will pass the same spot on the earth's surface at a constant local time of the day which enables it to collect data which is closely related and produce images that allow it to study how features change over time.

b. Geostationary orbits: They circle the equator from west to east and they are synchronous with the direction of rotation of the earth's surface. They are placed at an altitude of 35,786 km and are used by weather and communication satellites.

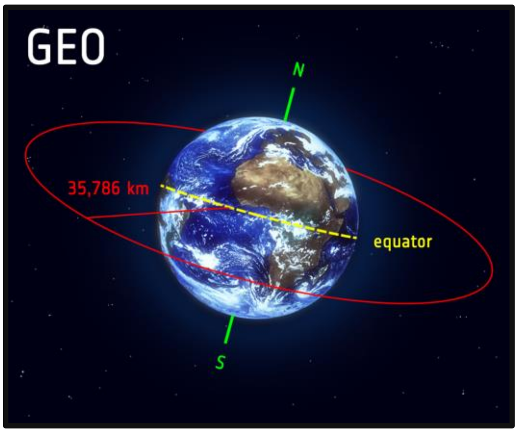


Figure 4: GEO Orbit

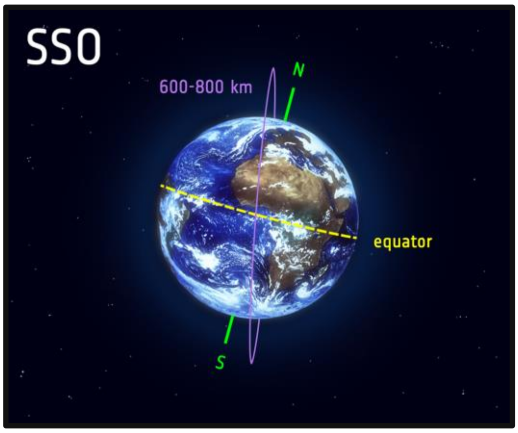


Figure 5: Sun-Synchronous Orbit

4.1.4 Satellites and Sensors

Landsat series satellite: Launched by NASA and USGS, they are the world's longest running system of sun-synchronous orbiting satellites for optical moderate resolution remote sensing of land, coastal and water bodies.

Sensors:

i. Landsat-7: Enhanced Thematic Mapper Plus

ii.Landsat-8: Operational Land Imager and Thermal Infrared sensor.

Table 2: Sentinel-2 and Landsat 8 Bands

	Landsat 7	Wavelength (micrometers)	Resolution (meters)
Enhanced Thematic Mapper Plus (ETM+)	Band 1	0.45-0.52	30
	Band 2	0.52-0.60	30
	Band 3	0.63-0.69	30
	Band 4	0.77-0.90	30
	Band 5	1.55-1.75	30
	Band 6	10.40-12.50	60 * (30)
	Band 7	2.09-2.35	30
	Band 8	.52-.90	15

- Spectral: It is the number and width of the spectral bands recorded by a sensor. Instruments detect various wavelengths along the EM spectrum which are termed as bands. The narrower the wavelength, the finer the spectral resolution.

- Temporal: It is the revisit period of a satellite.

- Spatial: It is the geographic area covered by a pixel in an image. Lesser areas account for higher spatial resolutions. The smallest unit of a remote sensing image is a pixel.

- Radiometric: It is the ability of the sensor to detect the differences between radiances of different targets. It contains the actual information content of an image.

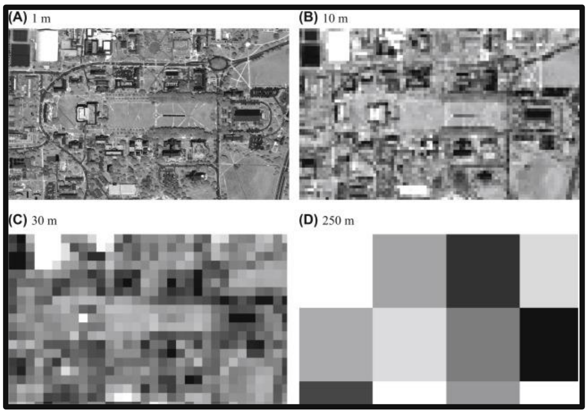


Figure 6: Spatial Resolution

4.1.5 Image classification

a. Supervised classification: Training areas are created for different classes of spectral signatures based on the analyst's knowledge of the geographical features of the land cover types. The numerical information from the pixels of the identified areas is used to train the computer to recognize the various signatures and classify all the pixels accordingly.

b. Unsupervised classification: The spectral classes are first grouped according to their numerical information and then later assigned a land cover type by the analyst.

c. Indices: Spectral index calculations involve the manipulation of various spectral bands in order to extract relevant information on specific features. Examples include vegetation indices - NDVI, water indices - NDWI and build-up indices - NDBI.

4.1.6 Image interpretation

Satellite images can be studied through composite images. These are of two types.

a. False colour composite: The displayed colour of an image does not resemble the actual colour and the colour assignment for the bands of multispectral images can be done in an arbitrary manner.

b. Natural colour composite: The spectral bands are combined in a manner so as to obtain an image that resembles a visual colour photograph which is vegetation in green, soil in brown and water in blue.

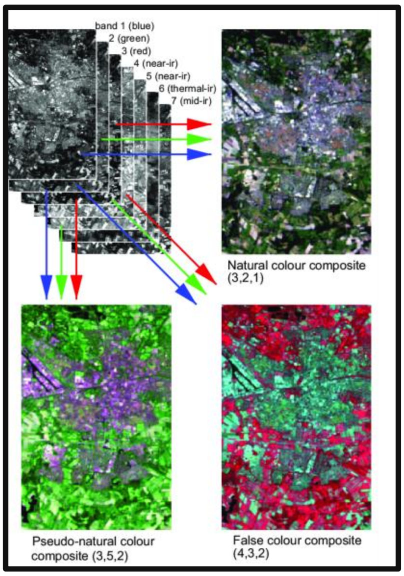


Figure 7: Colour Composites

4.2 Study Area

The study area considered for this study was the city of Bengaluru, Karnataka, India, located between the latitudes ranging from 13° 30' 08' to 12° 40' 20" N and longitudes ranging from 077° 23' 16" to 077° 43' 45" E.

The study area includes the rural and urban taluks of Bengaluru. Rural Bengaluru is divided into four taluks, namely Doddaballapur, Devanahalli, Hosakote and Nelamangala and Urban Bengaluru into five taluks: Bengaluru North, South, East, Yellahanka and Anekal, as shown in the figure.

For the purpose of obtaining accurate guidance values, the study area was further divided into urban hoblis, BBMP wards and rural hoblis.

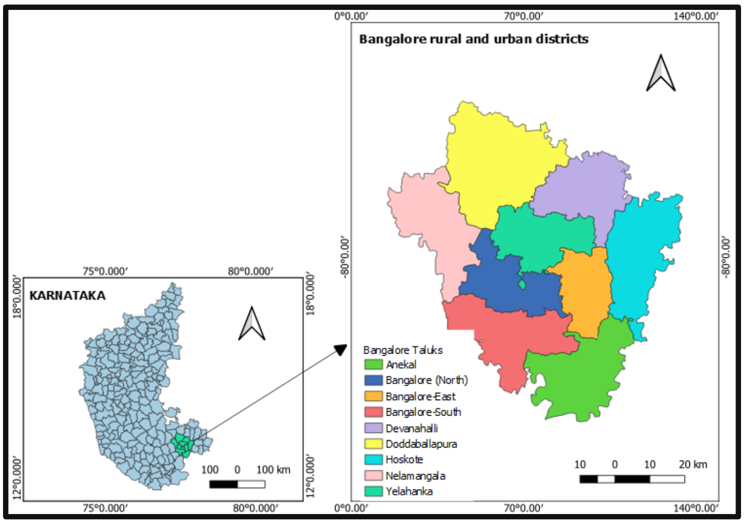


Figure 8: Study Area

4.3 Working Methodology for Satellite Imagery - Method 1

The steps to collect the satellite images from USGS are included below.

1. Satellite data was obtained from the USGS website, following which the images were clipped onto the Bengaluru shapefile by setting the right CRS on the QGIS software.
2. The satellite data was then pre-processed, making sure to consider the relevant bands along with some images requiring mosaicking as the footprints of the data obtained for the Sentinel-2 data did not comply with the study area.
3. The next step was to analyse the land use classification of 12 years. This was done by using a predefined set of formulas known as indices. It can also be stated as the difference between two selected bands normalised by their sum. These formulas were fed into the software into a raster calculator and the desired classification was obtained. In our case two classes i.e., built-up & non-built-up were obtained. There are several formulas used to calculate the built-up classification however, after an in-depth computation BUI was observed to be most suitable. Each index was calculated using a discrete set of band combinations.
4. An integral part of all these calculations was thresholding where the upper and lower thresholds of every classified image were adjusted to provide the most accurate classification.
5. An accuracy assessment was conducted manually by utilising the Google Earth Pro software for all the years considered.
6. The next step was to predict the built up for the year 2031.Tools like the MOLUSCE plugin on the QGIS software and Python via Jupyter Notebooks were used for

prediction. However, the outputs obtained were unsatisfactory owing to low accuracy and dense overestimation. Moreover, the consideration of only 2 classes using the index calculation proved to be inconvenient while predicting built-up using the TerrSet land prediction software. This led us to explore alternative methods & tools like supervised classification using ArcGIS for land change and built-up prediction.

7. The outputs obtained using the above methodology is as given below.

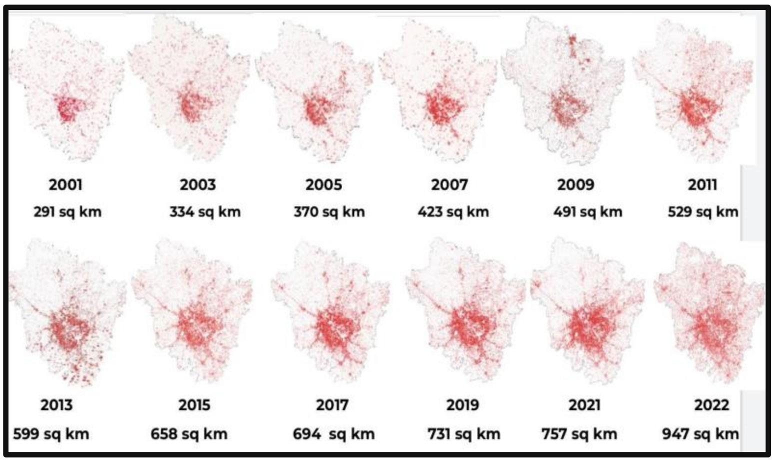


Figure-9: BUI Maps from Years 2001-2022

Figure-10: TerrSet Predicted Map

4.4 Working Methodology for Satellite Imagery - Method 2

4.4.1 Data Collection

USGS is a renowned scientific agency of the United States that provides scientific information about the impact of land-use change and climate, natural hazards, water resources, energy sources, minerals, etc. Headquartered in Reston, Virginia, USGS scientists develop methods and tools to enable timely, useful, and relevant information about the Earth and its process. The company’s mission is to monitor, analyse, and predict current and evolving dynamics of complex human and natural Earth-system interactions and to deliver actionable information at scales and timeframes relevant to decision-makers. USGS Earth Explorer is one of the largest databases of global visitation where users search catalogs and download satellite and aerial imagery.

Procedure to download imagery from USGS Earth Explorer

1. An account was created with USGS through registration.
2. Region of interest was selected by setting geographic limits or entering the coordinates of Bengaluru city.
3. Under administrative boundaries, a political entity was chosen as the area of study, based on taluks.
4. The desired time period, dates, and/or months were entered.
5. In the datasets tab, the relevant satellite - Landsat Collection 1 Level 1 (Landsat 8 OLI, Landsat 7 ETM+) was chosen.
6. Data was filtered in the additional criteria tab namely cloud cover less than 10% to obtain clean, usable images.
7. The footprint of the images was viewed to choose appropriate imagery.
8. Data was downloaded by choosing the download button for the GeoTIFF data product for Landsat.

Table-3: Selected Image Characteristics

	Landsat 7,8
Geocoding Method	Feature (GNIS)
Feature Class	Administrative boundary
Feature Type	Political Entity
Area Selected	12.9716° N, 77.5946° E
Months Selected	March, April
Dataset	Landsat Collection 1 Level 1
Additional Criteria	Cloud Cover <10%
File Type	GeoTIFF data product
Image Resolution	30m

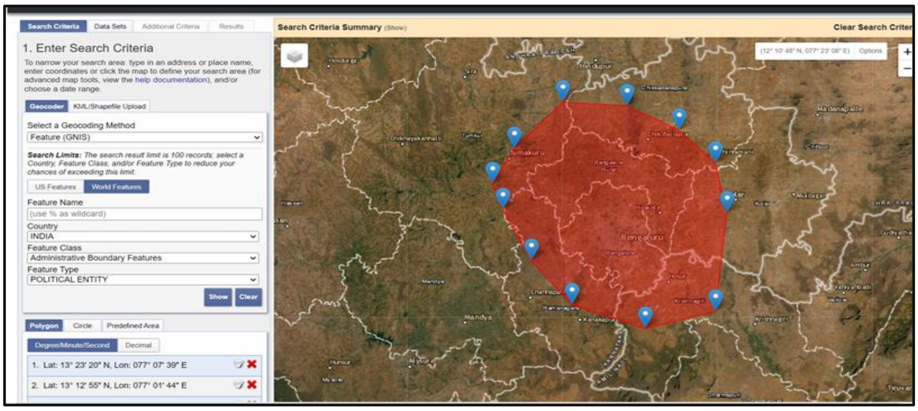


Figure-11: Data Collection from USGS

4.4.2 Software used

1. QGIS

   QGIS is an open-source geographic information system that enables editing, visualising and analysing of geospatial data. It supports raster, vector and mesh layers. It also supports georeferencing of images and composition and exporting of maps.

   One of the most user-friendly features of QGIS enables independent organisations and developers to develop plugins using the Python and C++ APIs as a reference, which act as an additional functionality for the application. QGIS was used in the project to create proximity maps and analyse the features of every ward and hobli in the study area.

2. ArcGIS

   ArcGIS is an online Geographic Information System that allows execution of several GIS processing tools such as clipping, spatial analysis, overlay etc. in addition to model building, Google Map integrated APIs, ArcMap. ArcGIS was used to analyse the satellite images for the project and perform supervised classification on the same.

3. Terrset

Terrset is an integrated geospatial software for monitoring and modelling the earth's systems for sustainable development and for the analysis and display of geospatial information. It incorporates several IDRISI Image Processing tools. The TerrSet Land Change Modeller is an innovative planning and decision support software tool that simplifies the elaborate complexities of LULC analysis, habitat assessment, and resource management. It was used in the prediction of the 2031 land change map.

4.4.3 Supervised Classification

Supervised classification is employed to segment the spectral domains of satellite data into their respective land-cover classes, which are decided by the user according to their knowledge of the ground truth.

The supervised classification of the images belonging to the years 2001, 2011, 2014, 2017, and 2021 consisted of four classes namely Urban, Water, Forest, Barren, and Agriculture. These classes were decided upon analysis of the composite raster formed and information on the area covered by the taluks under sub-categories of land types from the literature survey.

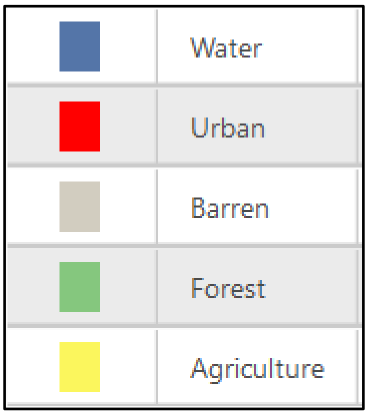


Figure 12: Land-cover classes

Working methodology for the supervised classification of satellite images

I. Creating the composite image

Colour composites are created to render individual raster data sets, which can be used to detect changes in areas, urban growth etc.

The raw data of bands 1 to 8 were loaded on ArcGIS. The bands were added to the 'Multi-value input control box' in the 'Composite Bands' tool in the Geoprocessing toolbox and then run to obtain the composite raster data-set.

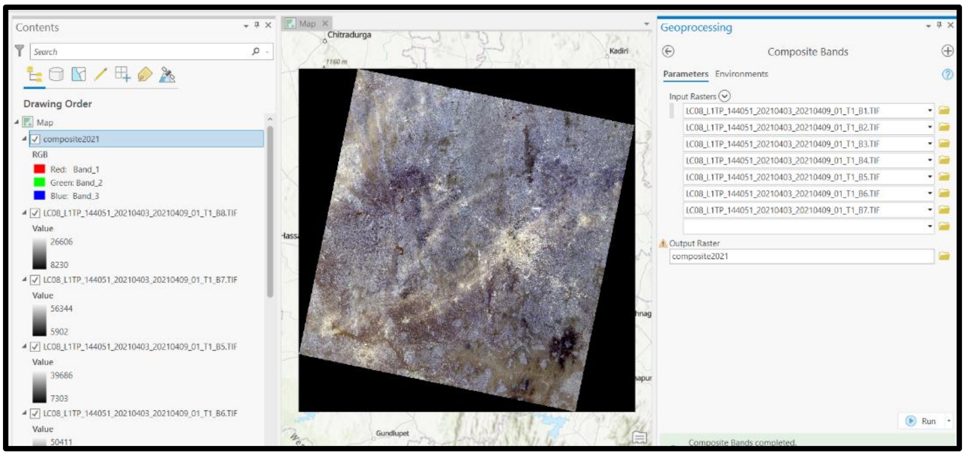


Figure 13: Composite Raster

Table 4: Band composite combinations

	SWIR 2	SWIR 1	Near IR	Red	Blue	Composite (Urban)	Composite (Agriculture)
Landsat - 8	7	6	5	4	2	7-6-4	6-5-2
Landsat - 7	7	5	4	3	1	7-5-3	5-4-1

II. Creating the Pan Sharpened raster data-set

Pansharpening is the process of combining a high-resolution raster data-set with a low- resolution multi-band raster data-set to create a high-resolution multi-band raster data-set for improved visual analysis.

The raster bands are entered accordingly in the red, green, blue, and infrared channels in the 'Create Pan Sharpened Raster Dataset' tool and the output file location is specified. Band 8 belongs to the high-resolution panchromatic band which is inputted into the tool. The tool uses various algorithms like Esri, IHS, Brovey, etc to fuse the panchromatic and multispectral bands together.

III. Classification wizard

The classification wizard offers a simplified user experience for the entire classification workflow. It is available under the 'Imagery' tab for the multiband images. It consists of the following steps.

a. Training sample manager: The training samples for the classification can be added using the training sample manager which includes the classification schema and sketch tools. The training samples are representative sites for all the classes which are saved as a polygon or point feature class. They are created based on the user's knowledge of the source data.

Procedure to collect the samples is highlighted below.

- A classification schema that determines the number and types of classes required for the classification, is created with 5 classes namely Water, Barren, Agriculture, Urban, and Forest.
- The class which requires the training samples to be added is chosen from the schema.
- The polygon or circle option under the sketch tool is chosen to create the polygons for each class.

- The individual training samples can also be grouped and removed using the ‘Delete’ button.
- The individual samples are then grouped and combined accordingly using the ‘Collapse’ button.
- The samples are saved in the specified output shapefile location.

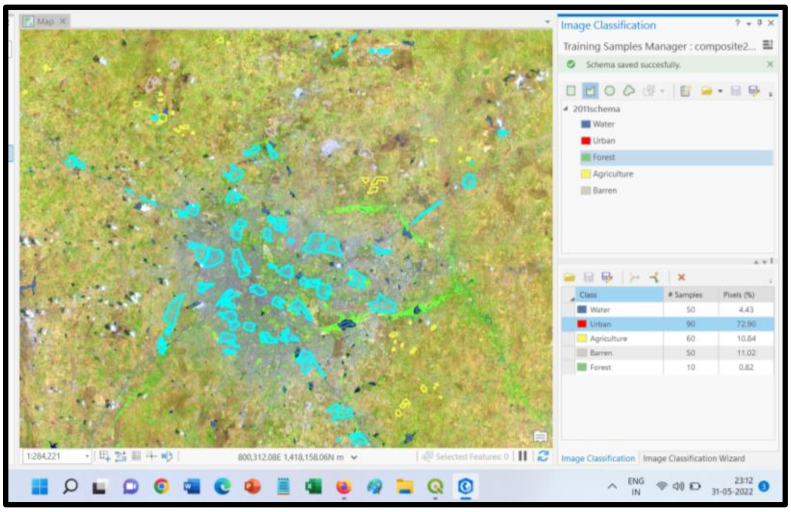


Figure 14: Training Sample Manager

b. Configure: The classification method and type can be selected under the ‘Configure’ option. ‘Pixel-based’ classification approach is chosen where the spectral characteristics of the individual pixels decide the class to which it is assigned. ‘Supervised classification’ considers the training samples provided and carries out the classification accordingly.
   Procedure to configure is highlighted below.

- ‘Supervised’ and ‘Pixel-Based’ are chosen as the classification method and type.
- The output location is specified and the training sample shapefile is entered in the training sample option.
- The composite multiband raster dataset is chosen as the reference dataset.

c. Train: The ‘Support Vector Machine’ classifier is an advanced machine learning algorithm that is not influenced by noise or unbalanced number or size of samples.
   Procedure to train is highlighted below.

- SVM is chosen as the classification method.
- The maximum number of samples is given as 120.
- The image is then trained to obtain the preview of the classification and the class definition files.

d. Classify: The results of the classification are saved to an output directory by running the classification.
   Procedure to classify is highlighted below.

- The output dataset is specified.
- The respective class definition file (.ecd) is chosen from the directory and a preview of the classification is entered under the user-specified form.
- The classifier is run to obtain a final classified dataset.

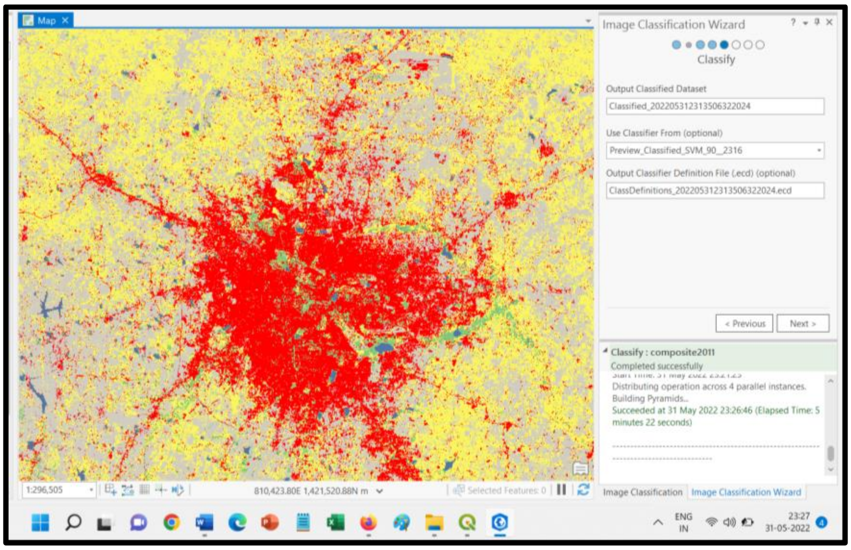


Figure 15: Classification Preview

e. Reclassification of pixels: To address the errors in the classified dataset, the reclassifier can be used to edit the areas in which the pixels are misclassified.

Procedure to reclassify is highlighted below.

- The reclassification can be carried out according to the region which creates polygons or an object which is used to create circles.
- The polygons or circles are drawn around the misclassified regions and the ‘Current class’ and 'New class’ are chosen accordingly. For example: From ‘Agriculture to Urban’ or from ‘Urban to Barren’.
- The ‘Edit Log’ is used to view, select or remove the changes.
- The reclassfier is then saved to the directory and run to obtain the reclassified dataset.

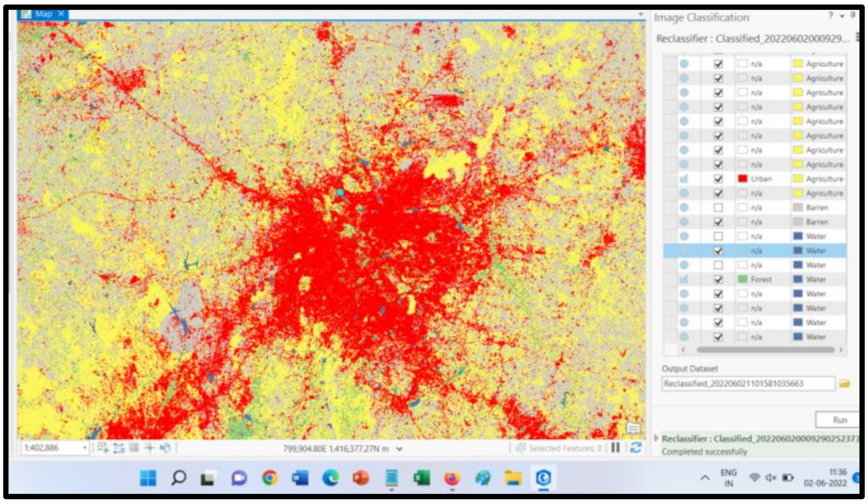


Figure 16: Reclassification of the misclassified pixels

4.4.4 Accuracy Assessment

Accuracy assessment is carried out to calculate the accuracy of the classification. A set of random points are generated for each of the classes which are evenly distributed across the map according to the specified sampling strategy. The random points are cross verified using the reference dataset to check for misclassified pixels. The output confusion matrix is calculated for the updated points.

Working methodology for the accuracy assessment of classified images

I. Clipping the classified image to an extent: The classified raster is clipped to the extent of the taluk.

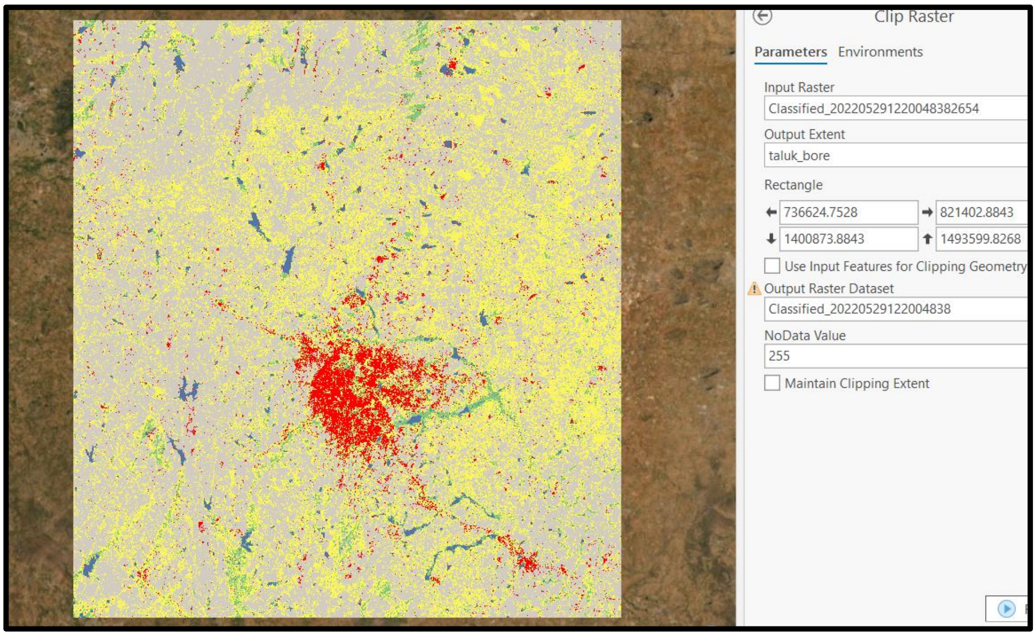


Figure 17: Clipped Classified Dataset

II. Accuracy assessment tool

a. Procedure to carry out the accuracy assessment is highlighted below:

- The clipped classified raster is entered as the input raster.
- The accuracy is carried out for 200 random points.
- 'Equalised Stratified Random' sampling strategy is chosen where an equal number of points are generated for each of the classes.
- The confusion matrix is saved to the specified output directory and the assessment is run to generate the points and the matrix.

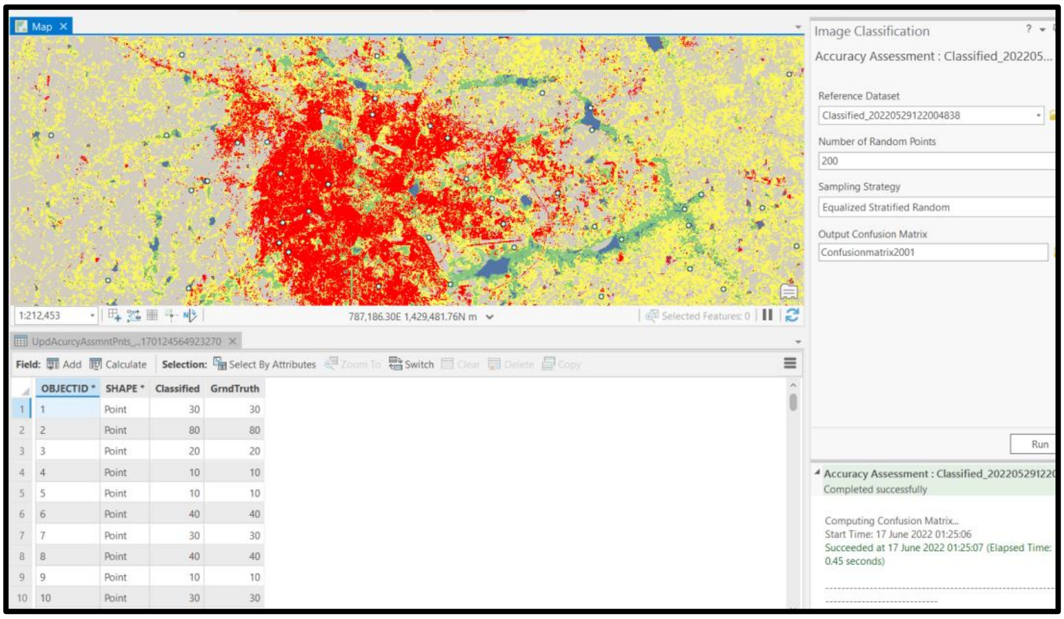


Figure 18: Accuracy Assessment Tool

b. Comparison of classified image and the ground truth

- The attribute table consists of the 'Classified' and 'Ground Truth' fields belonging to the pixels coinciding with the generated points. The classified field specifies the actual classification of the pixel and the ground truth can be edited to obtain the confusion matrix.
- Each of the random points is checked and reclassified accordingly using the reference composite dataset.
- The 'Ground Truth' from the attribute table of the 'Updated accuracy assessment table' is updated manually for any of the misclassified pixels.

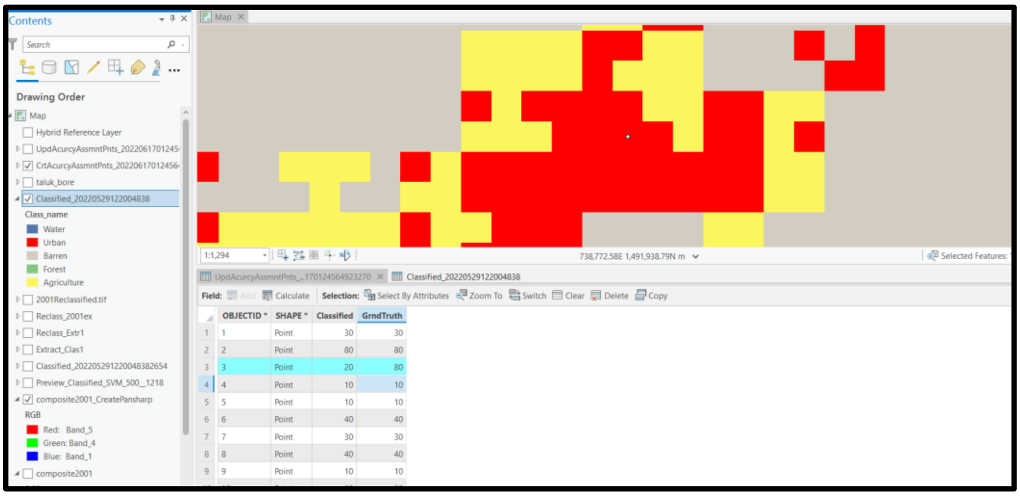


Figure 19: Random point as seen on the classified map

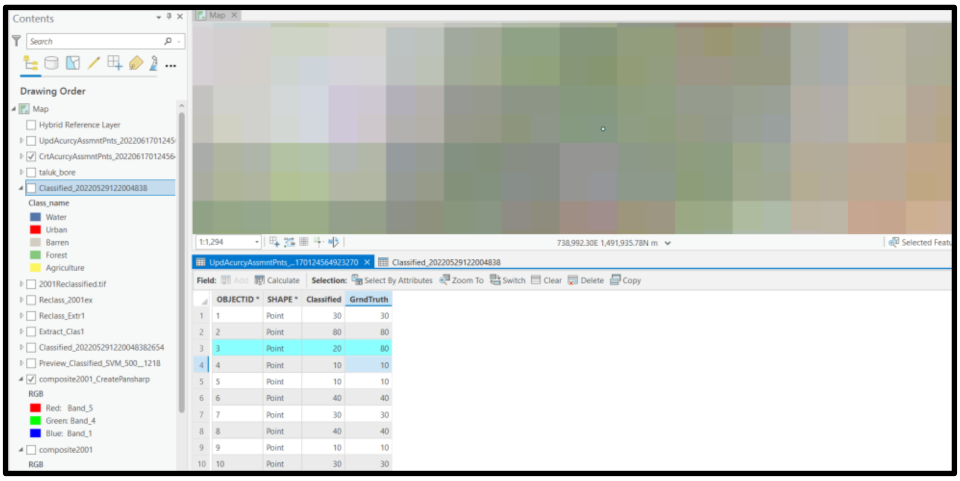


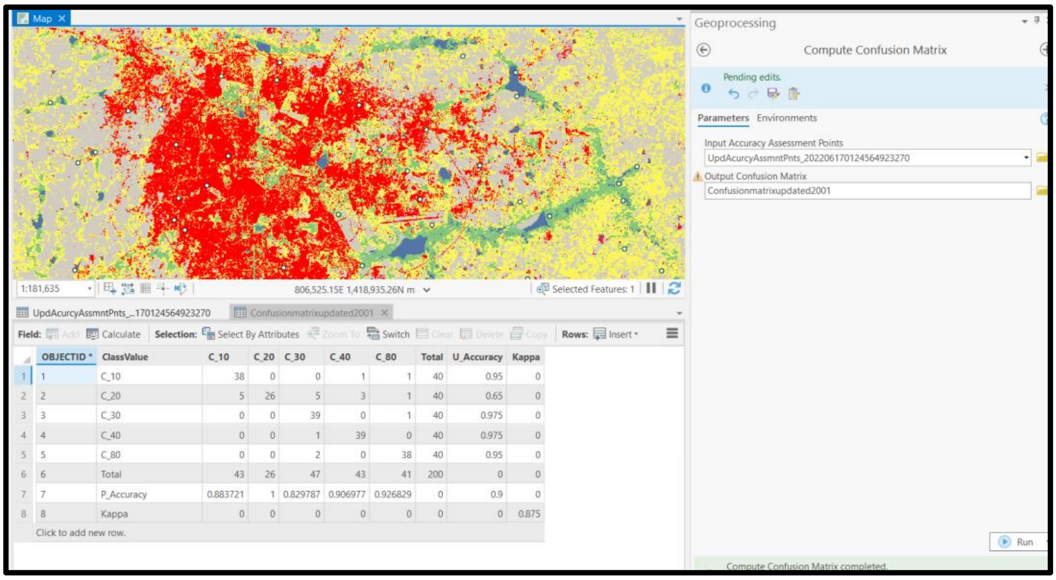
Figure 20: Misclassified pixel according to the reference dataset

c. Accuracy indicators: The output confusion matrix is created using the 'Compute Confusion Matrix' tool.
The confusion matrix is an error matrix that compares the class-by-class relationship between the results of the classification and the updated ground truth. It computes the confusion matrix for the random points, consisting of the following indicators:

- User's accuracy (Commission error): The user's accuracy specifies the false positives. This is calculated with respect to the reference dataset where the total row values specify the number of pixels that are incorrectly classified as a known class that has extra pixels when they should belong to a different class.
- Producer's accuracy (Omission error): The producer's accuracy specifies the false negatives. This indicator is calculated with respect to the classified dataset where the

total column values specify the number of pixels of a known class missing pixels, and are classified as belonging to a different class.

- Over all Kappa statistic: Kappa is the measurement of the performance of a system and gives an overall assessment of the accuracy of the classification. Its value lies between 0 and 1 where 1 represents 100 percent accuracy.



OBJECTID *	ClassValue	C_10	C_20	C_30	C_40	C_80	Total	U_Accuracy	Kappa
1	C_10	38	0	0	1	1	40	0.95	0
2	C_20	5	26	5	3	1	40	0.65	0
3	C_30	0	0	39	0	1	40	0.975	0
4	C_40	0	0	1	39	0	40	0.975	0
5	C_80	0	0	2	0	38	40	0.95	0
6	Total	43	26	47	43	41	200	0	0
7	P_Accuracy	0.883721	1	0.829787	0.906977	0.926829	0	0.9	0
8	Kappa	0	0	0	0	0	0	0	0.875

Figure 21: Confusion matrix for the updated accuracy assessment table

4.4.5 Generation of Proximity Maps

Input parameters in our case are what affect change in land cover over a period of time. These input parameters help determine the built-up expansion in the years to come. Seven parameters were considered for the growth model. The following parameters affect urban growth and may be used as inputs for the growth model.

a. Elevation - it can determine the cost of land and development as a proxy for drainage
b. Slope - it is inversely proportional to ease of building and therefore cost of construction
c. Distance to primary roads - existing main roads & highways are closely related to transportation cost and time
d. Distance to secondary roads -secondary highways & roads are connected to transportation cost and time.
e. Distance to tertiary roads - tertiary highways & roads are connected to transportation cost and time along with emphasising more on rural built up & networks.
f. Lakes - Promotes property demand.
g. Special Economic Zones & Airport - Can promote land & construction demand.

Data collection to obtain Feature Maps

Feature maps in simple terms can be defined as point, line or shape maps that are created with respect to each parameter considered. The steps involved in collecting data for the feature maps is as follows.

1. Open the QGIS software and install the plugin Quick OSM (2021 updated). This tool is used to search for specific parameters of interest and create the respective point and shape files.
2. Type in the Value & Key which are equivalent to category & subcategory of a particular

parameter. The figure given below the Value considered is highway and the Key considered is primary highway. The same process has been utilised for 4 parameters i.e., lakes, primary, secondary & tertiary roads.

3. Next, provide the layer extent i.e., of Bengaluru and run the software after which the line, point and shape layers are obtained, which will be automatically uploaded on the QGIS workspace.
4. For SEZ & airport data was not readily available on the Quick OSM plugin. Place search OSM, another plug in was used to key in the required area on the OSM map. This zooms into the specific area where a point is located alongside providing it an ID and name.
5. For the slope feature layer, data was obtained from the Bhuvan website (Cartosat-1). This had to be then merged & clipped on QGIS.

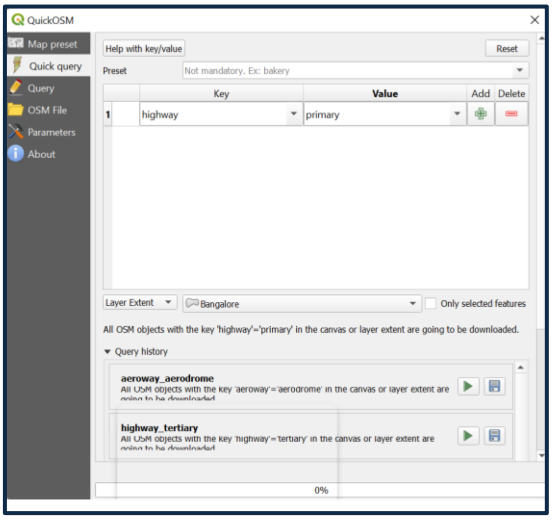


Figure 22: Loading the point files from Quick OSM

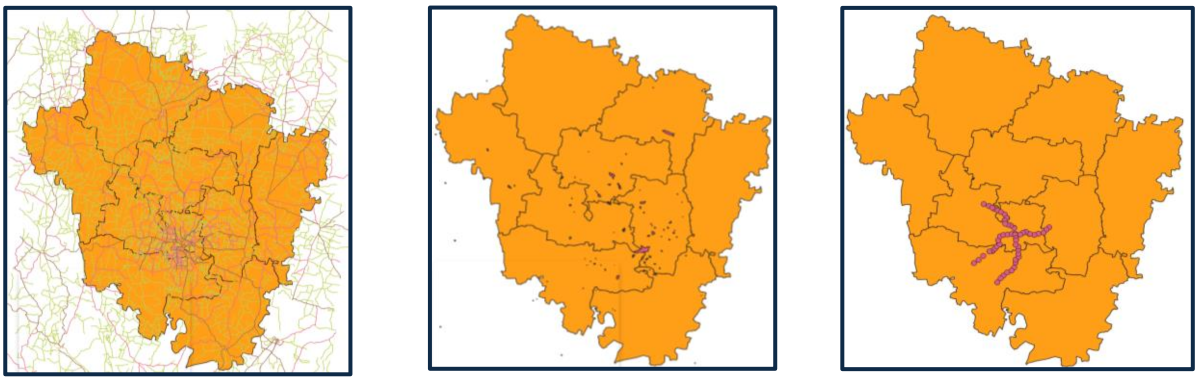


Figure 23: Line and Polygon files

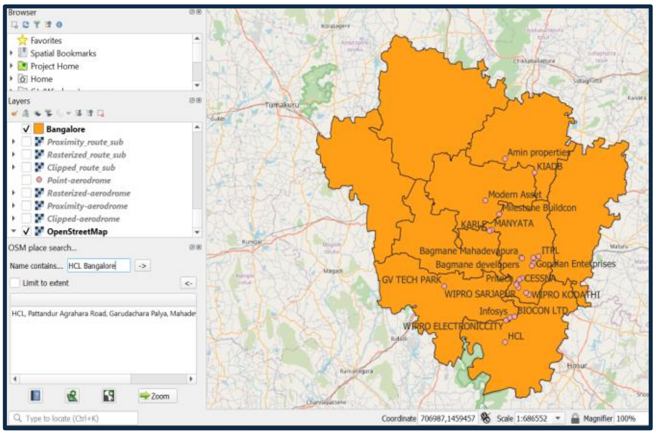


Figure 24: SEZ points created using OSM search

Conversion of Feature maps to Proximity maps

Proximity analysis involves calculating the distances of individual cells to various geographical features like roads, lakes, buildings, economic zones, etc. This is done by measuring the Euclidean distance which is the length of the line segment between two points in a Euclidean space i.e., the centre of source cells to the centre of destination cells. Open Street Map which is an open-source application that contains a repository of geographical features in the form of various shapefiles like points, polygons, lines, and polylines was used as our base layer. The procedure followed to create the proximity maps is highlighted below.

a) Euclidean distances are calculated by the 'Proximity analysis' plugin by inputting the rasterized layer.

- 'Proximity - Raster distance' option under 'Analysis' is used.
- The rasterized layer is given as the input and georeferenced units are chosen with a resolution of 15. The file is then saved before running the analysis.

b) Clipping to an extent

- 'Clip raster by mask layer' under 'Extraction>Raster' is chosen.
- The proximity map is clipped to an extent using the taluk shapefile. The no data values are given as 9999 in order to exclude the points that do not fall within the study area boundary and retain the points that include the feature.

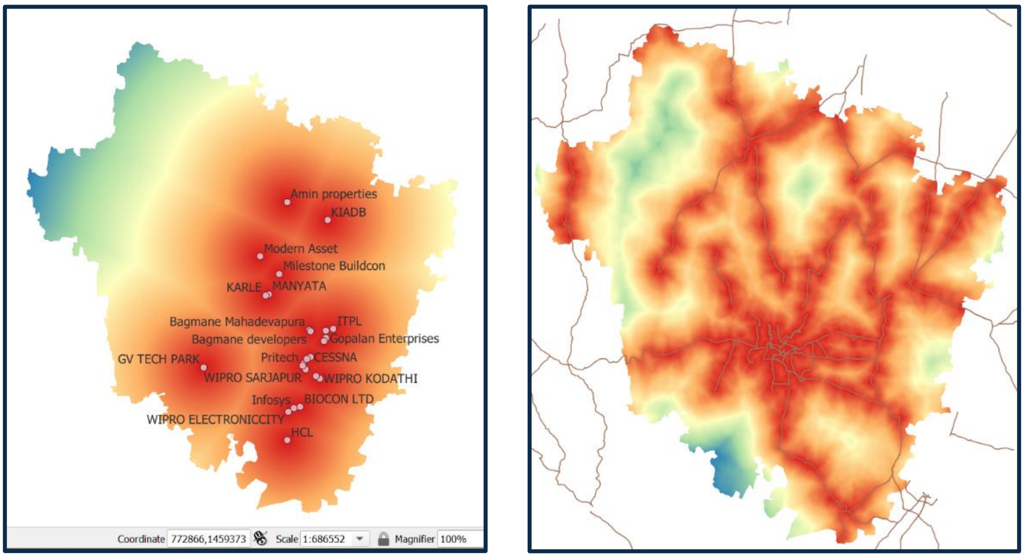


Figure 25: Distance to SEZ and Road Proximity Maps

4.4.6 Land Change Modelling

Urban growth is a complex spatiotemporal phenomenon that includes built-up activities taking place both horizontally and vertically. Urban land-use change modelling is used to show how land use varies across a city and to predict the growth pattern and extent for a future period. It can enhance one's understanding of processes and patterns of built-up that emerge from human-environment interactions. The following are important modelling techniques.

1. Cellular automata model
   Cellular automata is a common approach for urban land use change modelling that allows for discovering and analysing potential built-up pathways through scenario building. CA is a mathematical construction consisting of a row or a grid of cells in which each one has an initial value from a known and limited number of possible values and all cells are simultaneously evaluated and updated according to their internal states and the values of their neighbours.

   CA models can further be divided as:

- SLEUTH CA model - The SLEUTH model is a cellular automata-based computer simulation model that utilises historical land use/ land cover, slope, road, and hill-shade information to calibrate and simulate the land use/land cover change and built-up
- MOLUSCE CA model - MOLUSCE is a CA based model developed as a plugin for QGIS. It uses historical urban maps to calculate areas of change as a first step. One method can be selected among Artificial Neural Network, weight of evidence, logistic regression or multi criteria evaluation to estimate the transition potential in the second step following which CA uses the area of change and transition potentials to simulate the built-up.
- FUTURES CA model - FUTURES model uses past population trends and projected population to estimate per capita land demand when estimating the amount of future built-up. It uses logistic regression to estimate transition potential.

2. Regression model
   Land-use regression is a standard approach for predicting pollutant concentrations using concentration measures, GIS-derived spatial parameters, and site characteristics and allows for the characterization of exposure differentials within urban areas.

3. Fractals
   It is a geometric pattern that repeats itself at smaller scales to produce self-similar, irregular shapes and surfaces that cannot be represented using classical geometry. Fractals can be used to model complex natural shapes such as clouds and coastlines.

4. Agent based models
   They are a generic style of representation for individual-based dynamics processes, such as movement of individuals and objects.

4.4.7 Model Selected: Land Change Modelling using Markov Model

Working methodology for creating the predicted model

1. Matching the extents (Window): The rows and columns for the proximity maps were matched on the 'Window' tool to fit the extent of the land change maps.

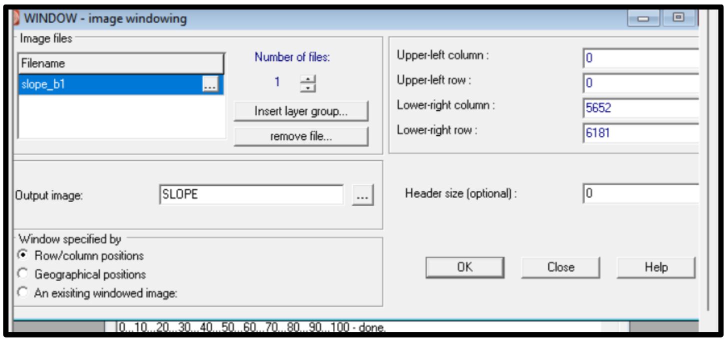


Figure 26: Matching the extent of the proximity maps

2. Conversion of tiff to rst files (GDAL conversion utility): The tiff files of the proximity maps and land change maps were converted to rst files on the 'GDAL conversion utility' tool.

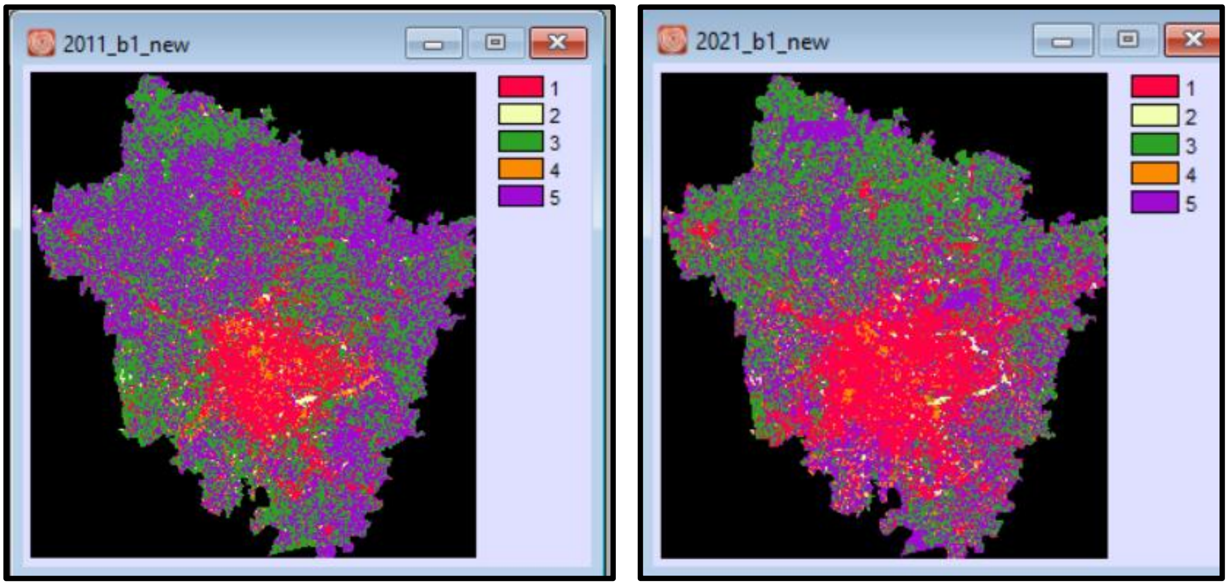


Figure 27: RST files of 2011 and 2021 LULC maps

3. Land-change modeller: Land-change modeller is a vertically integrated software environment on Terrset which allows for change analysis by exploring various transitions, analysing driver variables and employing predictive modelling techniques to quantify and visualise dynamic land-change.

I. Change Analysis Tab

- The 'Project Parameters' panel accepts two inputs that belong to the earlier and later land cover image. In this case, LULC maps of 2011 and 2021 were used for the prediction. The slope map was used as an additional input.
- The 'Change Analysis' panel is used to quantitatively assess through graphs, the gains, losses, and contributions to the change pertaining to the respective classes.

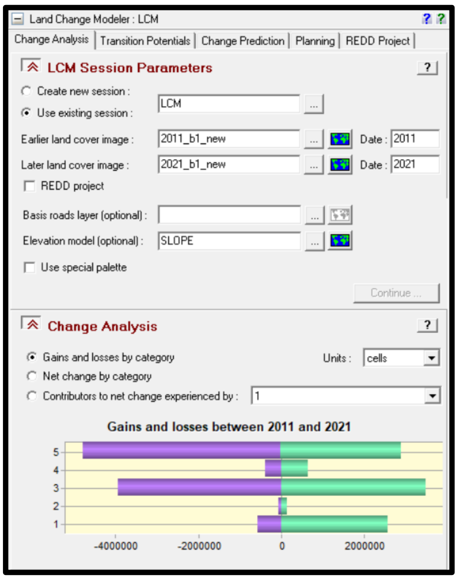


Figure 28: Session parameters and change analysis for the land change prediction

- The transition of various classes over the two time periods is assessed under the ‘Change Maps’ panel which evaluates the map changes, gains, losses, and transition patterns. Since the number of combinations between various transitions is high due to the five classes, the dominant transitions are chosen which can later be grouped and modelled under the ‘Transition Potential’ Panel. In this case, the transition from classes ‘3 to 1‘ and ‘5 to 1’ was assessed for the model.

  Transition maps for the chosen transitions were created and the areas were assessed. The area for transition ‘3 to 1’ was found to be 318.802 sq km and ‘5 to 1’ was 227.037 sq km, which notably suggests a greater contribution to growth from the former.

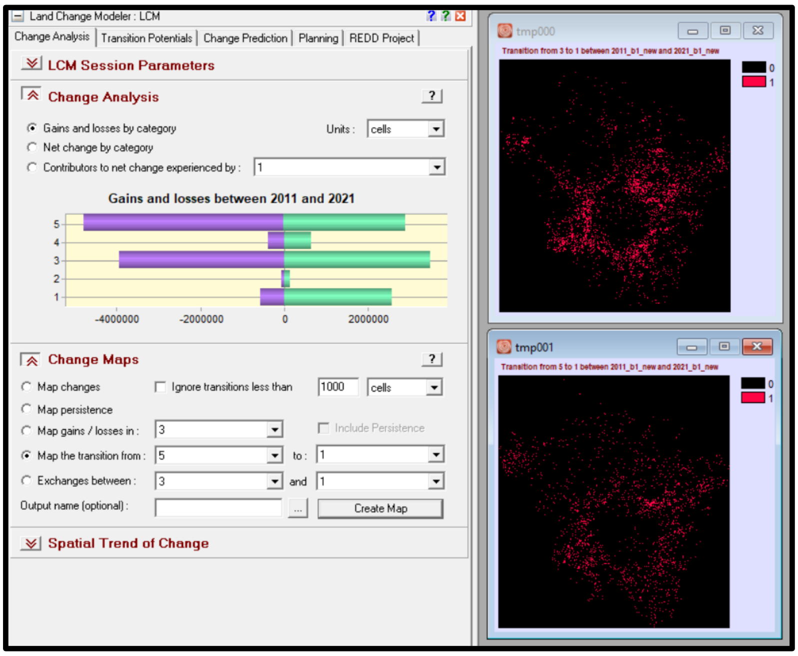


Figure 29: Change analysis and change maps representing the transition from classes 3 and 5

II. Transition Potentials Tab: The dominant transitions are grouped under sub-models which are analysed with respect to a set of driver variables namely airport, lakes, SEZ, primary secondary, and tertiary road networks. Once the driver variables are chosen, they are tested for their explanatory power. The transition sub-models are modelled using the MLP neural network model, which provides information on the contributions of each of the variables. A transition potential map is created for each of the sub-models, which is an expression of the time-specific potential for change.

- The ‘Status’ panel lists out all the potential transition combinations between the two land cover maps. The relevant transitions are grouped under sub-models. The transitions ‘3 to 1’ and ‘5 to 1’ are chosen as the change observed from the LULC maps suggests that barren and agricultural land contribute the most to urban growth.
- ‘Test and Selection of Driver Variable’ panel allows us to test for the explanatory power of the variables. The quantitative measure used to check for the association is the Cramer’s value. Drivers with Cramer's value greater than 0.15 are useful, although this does not assure a strong performance as the analysis is imprecise. An MLP analysis is a stronger test of the complexity of the relationship. The following table specifies the driver variables and their measure values:

Table 5: Driver variables and their Cramer’s V

Driver Variables	**Overall Cramer's Value**
Airport	0.0905
SEZ	0.218
Lakes	0.227
Primary road network	0.13
Secondary road network	0.107
Tertiary road network	0.107

- All the variables that need to be evaluated for the model can be added under the ‘Transition Sub-Model Structure’ panel. The variables can either be set to static i.e. variables that remain unchanged or dynamic which are variables that change with respect to time. The base layer type is set to the land use map and the class is chosen as 1 for the dynamic variables as the distance is calculated with respect to the urban class in the change prediction stage. The following table lists the driver variables and their respective role and basis layer type:

Table 6: Driver variables and their roles

Variable	**Role**	**Basis Layer Type**
Airport	Static	
SEZ	Static	
Lakes	Static	
Primary road network	Dynamic	Land cover map
Secondary road network	Dynamic	Land cover map
Tertiary road network	Dynamic	Land cover map

- The ‘Run Transition Sub-Model’ panel allows to model the transitions and the selected method is multilayer perceptron neural network model, which has a strong capability to give a detailed assessment of the relationship between the variables and the land cover maps.
  i) The pixels that have and have not undergone a transition are used as the samples for the training process. The start and end learning rates are assumed automatically by the model and all the other values are assumed as default values. Higher numbers of hidden layer nodes with respect to the variables tend to capture specific characteristics. Hence, the number of hidden layer nodes is increased to 10.
  ii) The 10000 samples include both the transition and persistence classes. The samples are randomly assigned to two groups namely training and validation pixels. Once the training samples are used to train the network in an iteration, the model tests the ability to predict the correct classes of the validation pixels which signifies the accuracy rate. A skill statistic of 1 alludes to a perfect prediction.

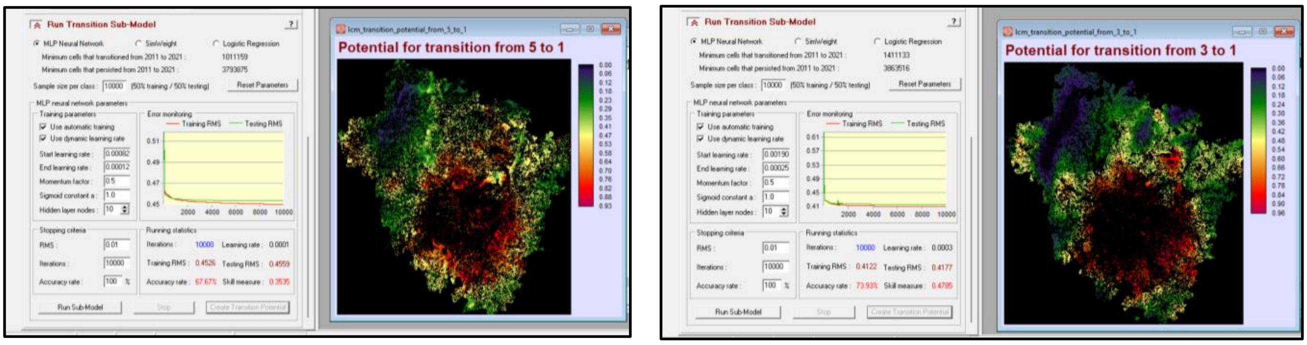


Figure 30: Transition sub-models

III. Change Prediction

- The ‘Change Demand Modelling' panel enables the prediction of land change for a user specified future time period. **2031** is selected as the desired year. Markov Chain is chosen as the model to calculate and visualise the amount of change. This model projects the transition potentials into the future and creates a transition probabilities file which specifies the probabilities of transition of each of the classes into every other. The following table specifies the transition probability file:

Table 7: Transition probabilities between all of the classes

	Class 1	**Class 2**	**Class 3**	**Class 4**	**Class 5**
Class 1	0.8084	0.0075	0.0626	0.0239	0.0976
Class 2	0.1161	0.5008	0.1003	0.1175	0.1654
Class 3	0.1807	0.0040	0.4946	0.0101	0.3105
Class 4	0.2425	0.0743	0.0653	0.2893	0.3287
Class 5	0.1179	0.0050	0.3798	0.0551	0.4422

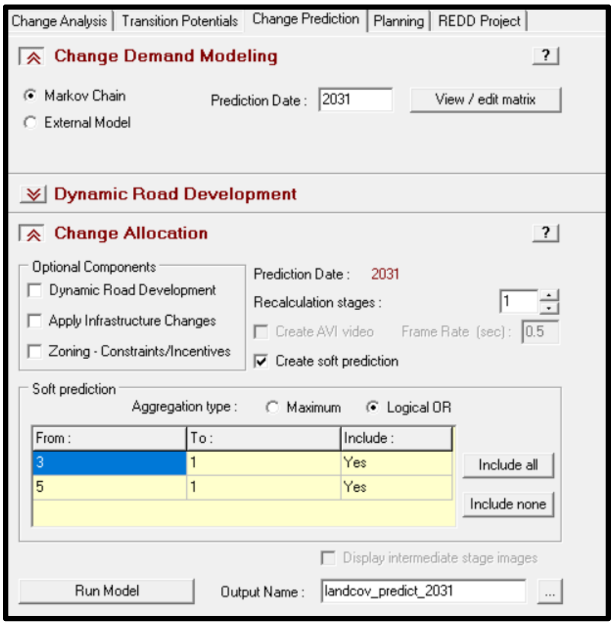


Figure 31: Change demand modelling panel

4.5 Working Methodology to obtain & compile guidance values & built-up Pixel count

4.5.1 Guidance Values

Set by the State government, guidance value is the minimum price below which a property cannot be registered. The current guidance value of the property in a particular area in a city could be received from the jurisdiction Sub-register office. The upward revision of guidance value more often witnesses decline in property registration by large numbers owing to the increase in property prices. Bengaluru has lately witnessed a surge in guidance value on property by as much as 100% in certain areas, great fluctuations have been seen over the years.

Guidance values have been collected for the year 2022 and earlier for the main areas in Bengaluru urban and rural. The trend was studied in order to forecast future values and be able to identify areas of investment and land development that are in line with the built-up model and its proxies. This can be used to effectively manage land use by both private and government organisations. Data pertaining to guidance values were obtained from several sources.

Table 8: Guidance value sources for compilation of representative values

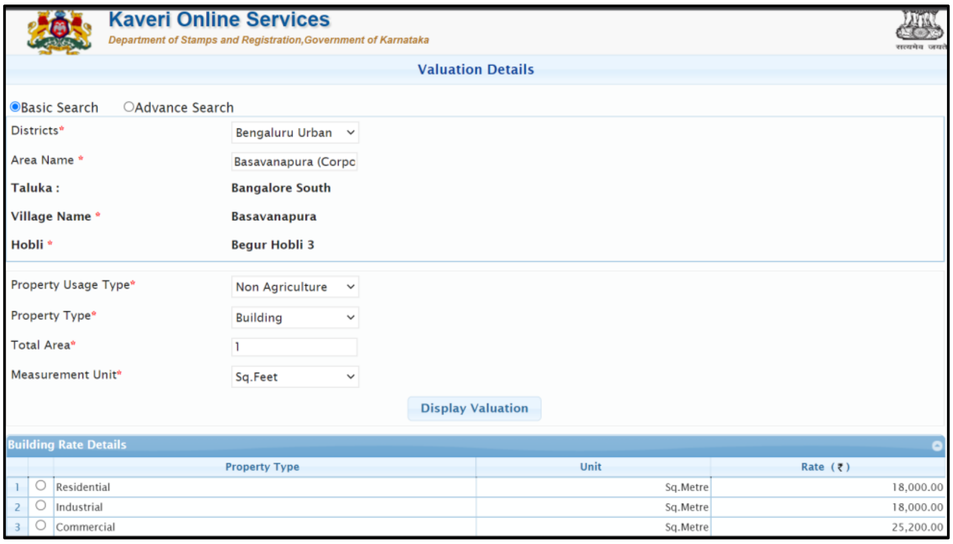
Year	Source
2011	**Estimated by following the trend observed in** https://brai.in/wp-content/uploads/2017/07/Market-Value-No.RD-325-MUNOMU-98-Bangalore-Dated-3-12-1998.pdf **and** 2014 GVs
2014	https://www.karnataka.com/real-estate/land-guidance-value-bangalore/ **and** https://www.commonfloor.com/guide/new-guidance-values-for-bangalore-announced-47183
2017	https://brai.in/must-know/
2021	https://kaverionline.karnataka.gov.in/KnowYourValuation/KnowYourValuation

- Guidance values sourced from various websites as mentioned in Table 8, were compiled and categorised based on the several wards and hoblis in Bengaluru.
- The unit considered was square metres.
- Values corresponding to BBMP were considered, and a ward/hobli wise **representation of the guidance value** was tabulated as shown in Table 9.
- Guidance value data for the years 2018 upto 2021 was collected via the Kaveri portal online by entering the required district and the name of a ward along with other criteria namely agricultural, non-agricultural land, vacant commercial & residential properties.

2017-18 Guidance value for the Immovable Properties coming under the jurisdiction of K.R.Puram Sub Registrar Office						
Sl NO	Hobli/ Village/Region/Road	Residential Sites approved by Competent Authority	Residential Sites coming under the jurisdiction of Local Organization	Villa/ Row Houses	Agricultural Property	Apartments/Flats constructed on Residential Sites approved by Competent Authority/Local Organization
		(Rupees per Square Meter)	(Rupees per Square Meter)	(Rupees per Square Meter)	(Rupees in Lakhs per Acre)	(Rupees per Square Meter For Super Built up Area)
1	2	3	4	5	6	7
59	Cheluvaiah Extension		20700			
60	Gurumurthy Reddy Layout		20700			
	Ward No. 53, Basavanapura					
	Basavanapura					
61	Basavanapura	21900	20700		127	
62	30 Feet Basavanapura Main Road	24900	23700			
63	Renaissance Nature Walk			80730		

Figure 32: Guidance value data of Basavanapura for the year 2017 obtained from Bangalore Realtors Association India

Above, is an illustration of guidance value data obtained for the ward Basavanapura, for the year 2017 in square meters. Likewise, data was obtained from the same source for the rest of the wards for the year 2017.


Kaveri Online Services
Department of Stamps and Registration,Government of Karnataka
Valuation Details

Basic Search   Advance Search

Districts*	Bengaluru Urban
Area Name *	Basavanapura (Corpc
Taluka :	Bangalore South
Village Name *	Basavanapura
Hobli *	Begur Hobli 3
Property Usage Type*	Non Agriculture
Property Type*	Building
Total Area*	1
Measurement Unit*	Sq.Feet

Display Valuation

Building Rate Details

	Property Type	Unit	Rate (₹)
1	Residential	Sq.Metre	18,000.00
2	Industrial	Sq.Metre	18,000.00
3	Commercial	Sq.Metre	25,200.00

Figure 33: 2021 Guidance value data obtained from the Kaveri Portal for Basavanapura

Above, is an illustration of how the guidance value was collected for the Ward Basavanapura that comes under the taluk Krishnarajapura. The district name was first entered following which the ward of interest was entered . Accordingly, the property usage type along with the area measurement unit were entered it. Through this, three outputs were obtained i.e., commercial, residential and industrial property and were averaged to obtain a value of 20400 for the year 2021.

Table 9: Spreadsheet containing Guidance Values

TALUK	HOBLI	WARD	Land Guidance Value (per sq m)			
			2011	*2014*	*2017*	*2021*
Bangalore East	Krishnarajapuram	A.Narayanapura	17761	24360	35500	42300
Bangalore East		Banaswadi	13993	23700	26100	40000
Bangalore East		Basavanapura	9700	14500	20700	20400

The wards for which data was not available, estimates were taken based on trends observed in other wards or for a given year. For example, considering the ward Basavanapura, **2014** data was not available online, leading us to observe a trend in the GV change in other wards within the given hobli. These differences were averaged out and the value obtained was subtracted from 2017 value of Basavanpura i.e., (20700-6700 = 14000). Since there were many other wards considered while averaging ,14500 was the actual value obtained. A similar procedure was followed for wards/years for which data was not easily available.

Likewise, the guidance values were approximated for **2011**based on the actual values from 1998 & 2014.From consultation and literature survey it was also found that there was an increase in the values by 25-70% in 2007 varying across Bengaluru, which formed the basis for estimation.

All the guidance value data obtained from a variety of sources were compiled onto a spreadsheet in the format as shown in Table 9 for further analysis.

4.5.2 Built Up Pixels

Built-up areas are regional objects that consist of abundant buildings and nonbuilding area regions, such as lawns, trees, and other green belts. Built-up pixels are required to observe the increase/decrease in built-up cover over a period of time i.e., by comparison between classified images of different years. Built-up pixels decide the size and the quality of a given image. Data for the above was collected using the QGIS software.

- First, the Bengaluru shapefile pertaining to urban BBMP wards and rural hoblis were taken into consideration and were obtained from the KGIS website.

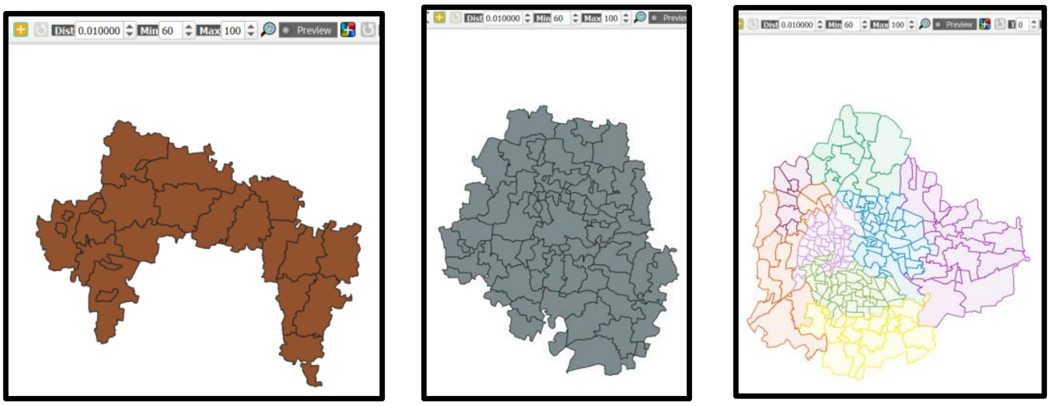


Figure 34: Individual Bengaluru urban & rural shapefiles

- The urban wards and rural hoblis were then merged using the QGIS software to obtain an aggregated image as shown in the figure below.

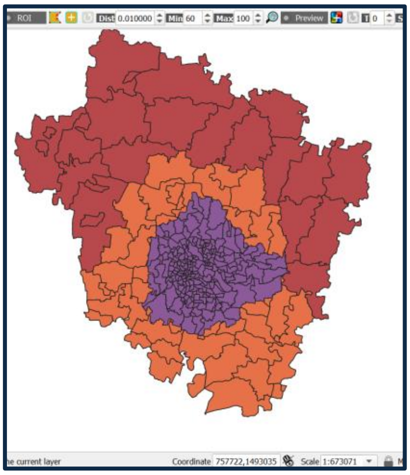


Figure 35: Merged Urban wards & Rural boblis

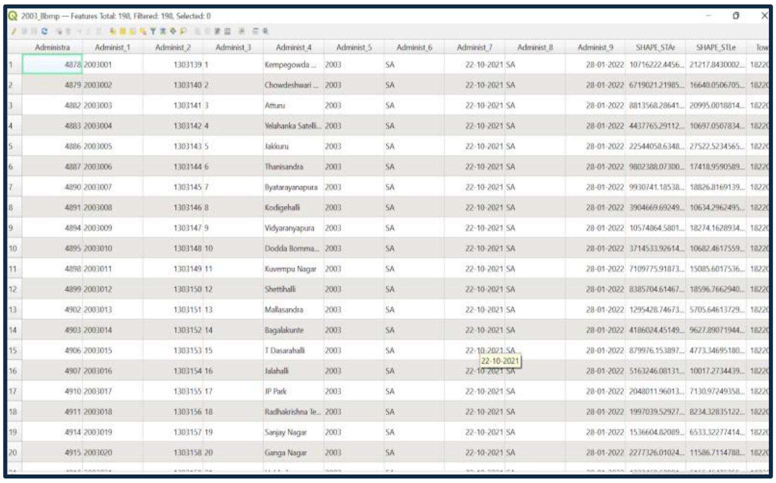


Figure 36: Attribute table

- The classified images were then exported into QGIS.
- The next step was to split the classified image into individual ward/hobli polygons based on the merged boundary shapefile.
- This was done by utilising a plugin on QGIS known as the Easy Raster Splitter. This takes in the input layer i.e., the classified image of a particular year along with the layer containing features required to split the classified image. The feature selected in this case was the column with all the wards & hoblis.

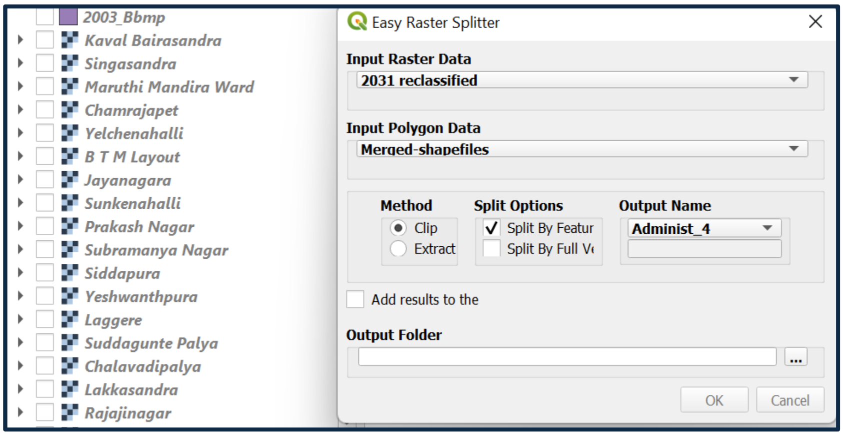


Figure 37: Easy Raster Splitter

- These steps were followed to obtain individual polygons for the rest of the classified images after which pixel count in each of these polygons had to be generated.

Figure 38: Split Polygons in the rural areas

- To generate the pixel count of each class in a given polygon a tool called r.report from the processing toolbox on QGIS was used. Here the individual ward, hobli polygons are provided as an input along with the unit c which stands for pixel count. The report generated is as shown below in the figure. The pixel count for each of the classes ranging 1-5 are generated however, the pixel count for only urban built up was taken into consideration for our analysis; in our case: Class 1.

- The image below illustrates the pixel count report generated for the urban ward Basavanapura for the year 2011 ,2014,2017,2021 & 2031, having a pixel count of 14501, 23002, 19251, 23591 & 24975 respectively for urban built-up (class 1) as shown in Figure 37.

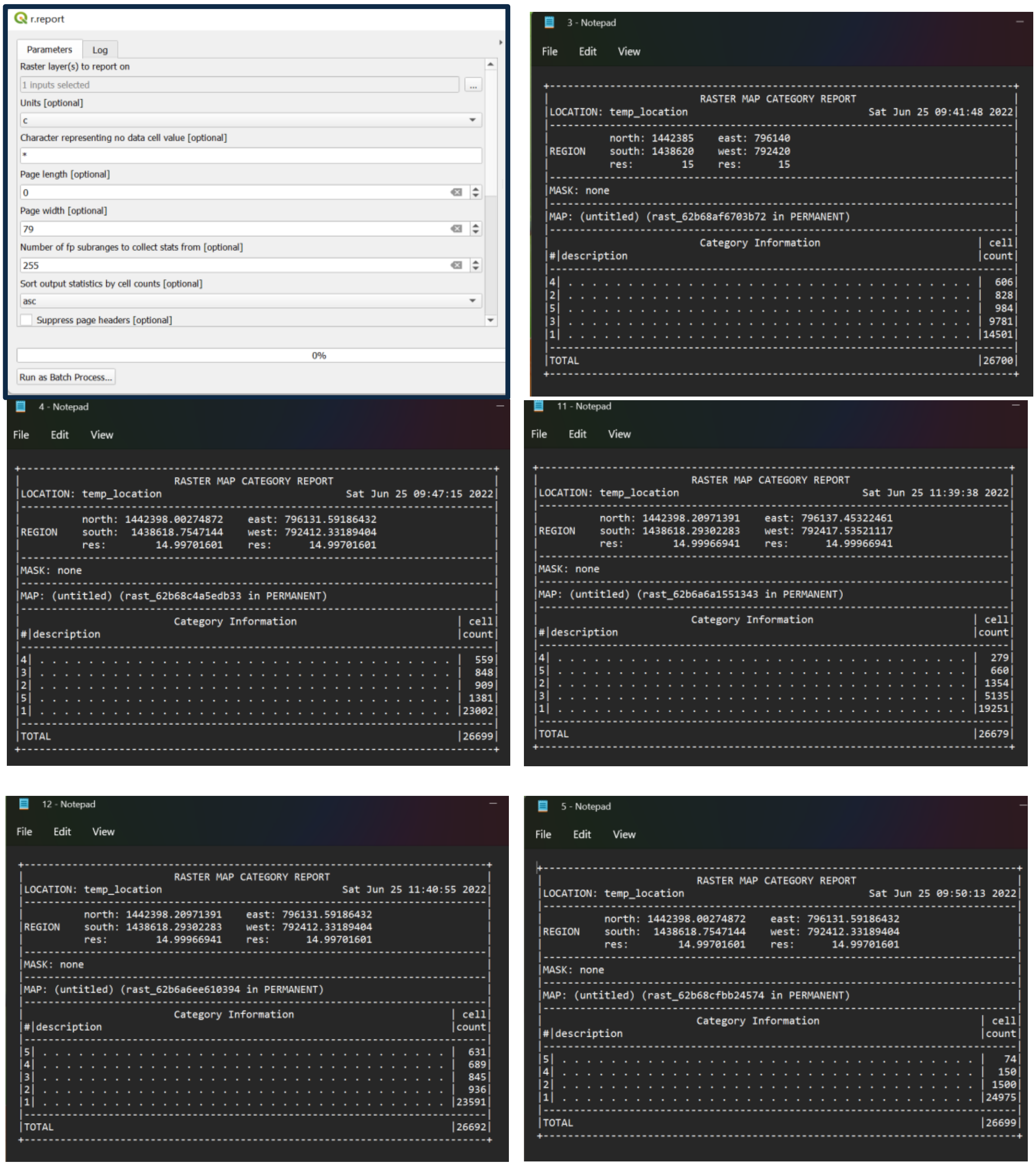


Figure 39: Pixel count reports generated on QGIS for Basavanapura (for the years 2011,2014,2017,2021 and 2031)

- Likewise, the reports were generated for all the 198 wards & for the 5 years considered, i.e, 2011,2014,2017,2021 & 2031, falling under BBMP along with the rural and urban hoblis.
- These values were entered onto a spreadsheet with a similar format as what was considered while entering year wise guidance values.

Table 10: Pixel count for each ward

TALUK	HOBLI	WARD	Built-up Growth				
			2011	2014	2017	2021	2031
Bangalore East	Krishnarajapuram	A.Narayanapura	8445	8572	8117	9263	9343
Bangalore East		Banaswadi	14846	14257	13913	14637	14975
Bangalore East		Basavanapura	14501	23002	19251	23591	24975

Table 10, illustrates the compilation of built-up growth for a few wards, for the 5 years considered in terms of pixel count on an excel sheet with a similar format as that used for compiling the guidance values. Similarly reports for other wards were generated and compiled.

4.6 Forecasting Model

In statistics, data transformation is the application of a deterministic mathematical function to every point in a data set, yi = f(zi) where each point zi is replaced with its transformed value yi which is a function of its initial value. This is applied so that data meets statistical inference procedure assumptions.

Data transformation is used to make data suitable for modelling with linear regression The simplest linear regression models assume a linear relationship between the expected value of Y and each independent variable. Linear regression analysis was used to forecast the value of a dependent variable based on the value of an independent variable. It is the most commonly used tool for predictive analysis and forecasting modelling. The primary equation used in this project is $Y = a + bX$; interpreted as a unit increase in X is associated with b units increase in Y.

4.6.1 Introduction to Minitab

Minitab is a software package that helps one analyse data. Minitab provides many statistical analyses, such as regression, ANOVA, quality tools, process improvement tools, value stream mapping, Monte Carlo simulation, process mapping, graphical analysis, design of experiments, to name a few.

The main benefits of Minitab include the numerous tools, user friendliness, simple and straightforward interface and the assistant feature.

4.6.2 Data compilation & format

Minitab requires data to be structured in columns so as to provide a versatile format from which one can rapidly analyse data through several different methods. For every ward/Hobli the data was compiled in separate columns namely year, built up pixel value and guidance value.

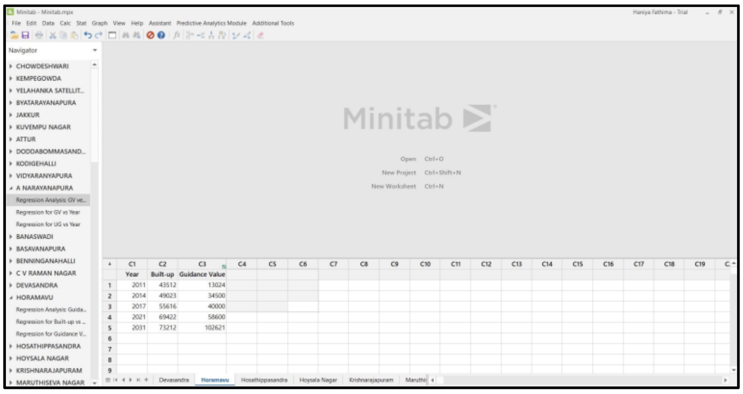


Figure 40: Minitab data format

4.6.3 Working Methodology for Forecasting

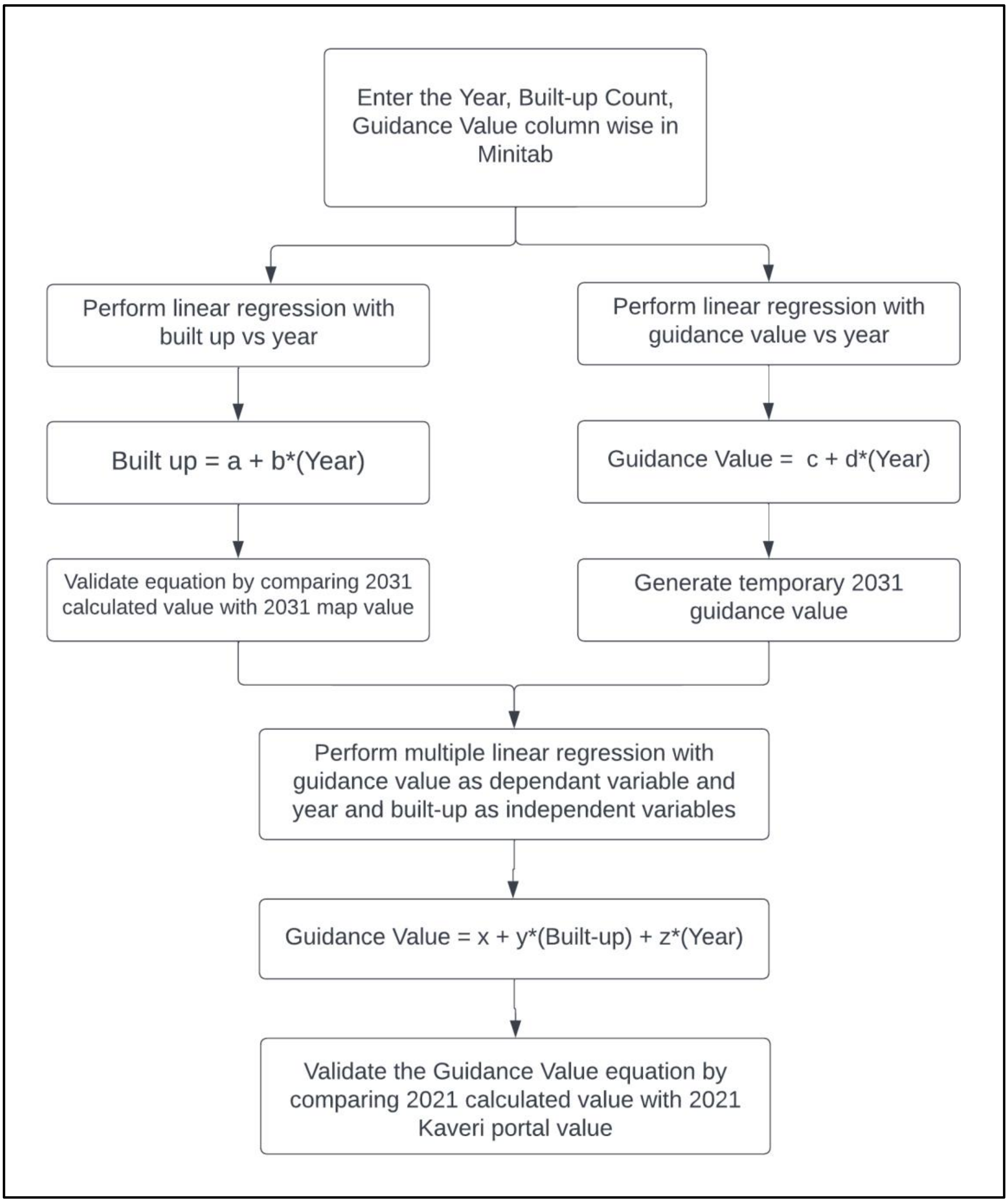
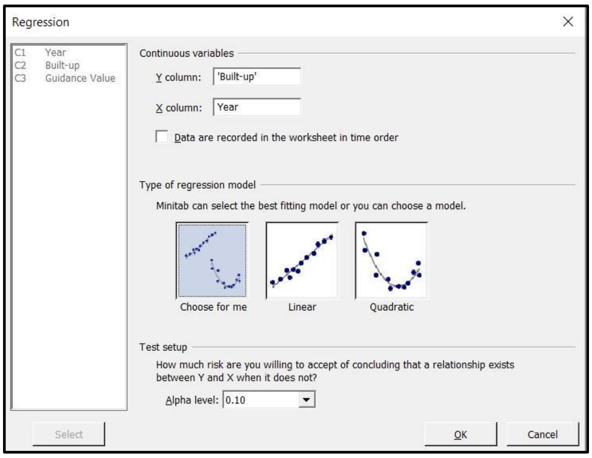


Figure 41: Procedure for 1 ward/hobli on Minitab

The flowchart in figure 39 explains the procedure followed to obtain the final multiple linear regression for each ward/hobli. It is explained in detail in the following paragraphs, the same procedure was followed for all wards and hoblis in urban and rural Bengaluru.

The data collected for each ward and Hobli was 2011,2014,2017,2021 and 2031 built up pixel values and 2011,2014,2017 and 2021 guidance values. In order to obtain the forecasted guidance value for 2031 and thereby equations that may use the same independent variables to predict any value of GV, the following procedure was followed.

1. Regression tool under the assistant feature was used to input built -up as Y variable which is dependent and year as X variable which is independent. The type of regression model was determined by Minitab by selecting the best fitting model based on standard deviation, R squared value and p value. Alpha level was set to 0.1 for testing. The majority of ward and Hobli data followed linear regression and in order to standardise the method, linear regression model was chosen for all. The resulting output is a fitted line plot and a standard linear equation of the form Y = a + bX corresponding to **Built-up = a + b*(Year)** . P value lower than 0.1, high R squared value in the form of percentage and positive r value of correlation indicated positive statistical significance.



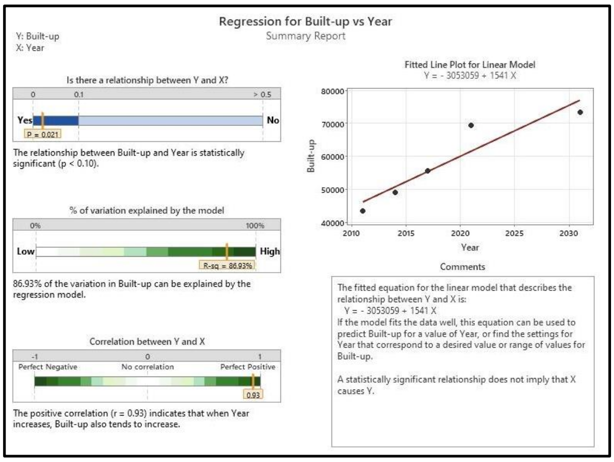


Figure 42: Minitab Simple Regression

Figure 43: Regression for built up vs Year

2. The fitted line for built-up vs year was used to calculate the value of built up for the year 2031. This was compared with the built-up value from the supervised classification map values tabulated earlier. An average percentage difference between the two was calculated as 2.39% for urban wards and hoblis and 9.49% for rural hoblis.

Table 11: Validation of built-up equation

TALUK	HOBLI	WARD	Built-up from Map 2031	Fitted line for Built-up vs Year	Fitted Line for 2031 Built-up Growth	Percentage Difference
Bangalore East	Krishnarajapuram	A.Narayanapura	9343	**Y = -98027 + 52.89 X**	9393	0.53%
Bangalore East		Banaswadi	14975	**Y = -32596 + 23.34 X**	14808	1.12%
Bangalore East		Basavanapura	24975	**Y = -804112 + 408.7 X**	25958	3.93%

3. In order to have the same number of points for both built-up and guidance values, a temporary GV was forecasted for 2031 using the same method as that for urban built up. A line was fitted for guidance value versus year through linear regression of the form Y = a + bX corresponding to, **Guidance Value = c + d*(Year)**. The 2031 calculated value from this line was entered into the Minitab column to create an equal number of rows for each column. This is crucial for the next step.

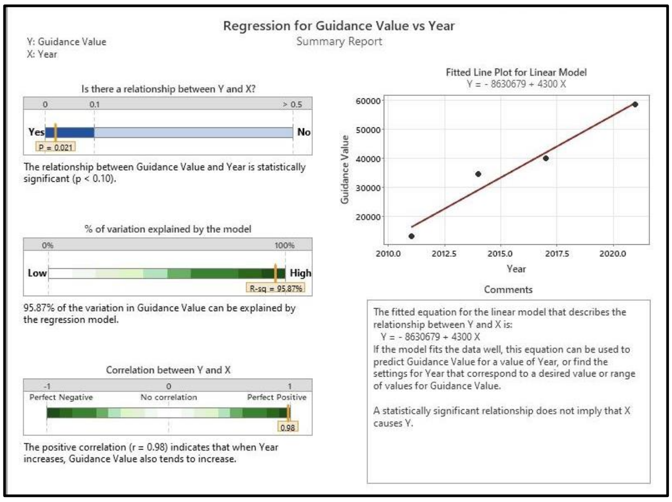


Figure 44: Regression for Guidance Value vs Year

4. Under the Stat dropdown, regression and fit regression model was selected. In order to obtain the guidance value response, the continuous predictors were set as year and built up. All other parameters were set to default.

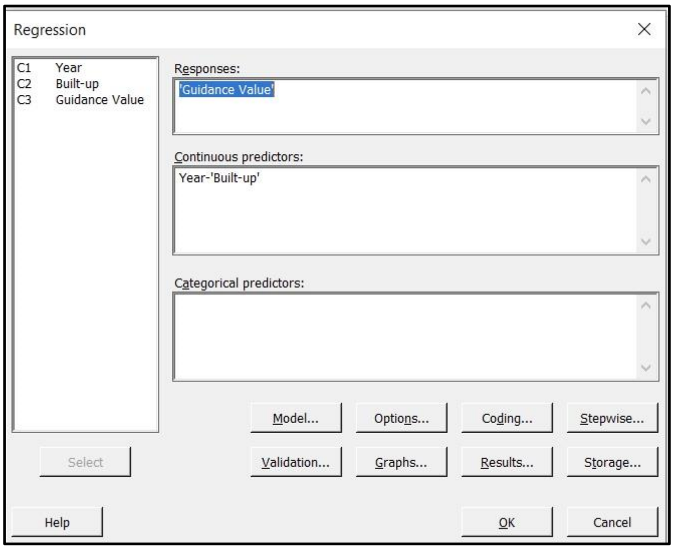


Figure 45: Fit Regression Model on Minitab

CHAPTER 5
RESULT

The details of the study carried out in equation with the project titled “Predicting the built-up growth of Bengaluru to forecast guidance values using satellite imagery” is highlighted under the headings given below.

5.1 Land-use Land Change Maps
5.2 Percentage Change in Built-up
5.3 Accuracy Assessments
5.4 Predicted Model
5.5 Area Changes in Bangalore
5.6 Forecasting Model
5.7 Guidance Value Calculation Program

5.1 Land-use Land Change Maps

- LULC maps are created for the years 2001, 2011, 2014, 2017 and 2021, as they coincide with the data that was collected on the guidance values. Five classes were considered for the classification namely Water, Urban, Forest, Barren and Agriculture. The growth increases linearly as specified by the areas given in the table given below.

Table 12: Year with corresponding built-up area in sq. km

Year	Area (square kilometres)
2001	237.728
2011	661.073
2014	673.223
2017	867.304
2021	1111.629

- Reclassification was undertaken for the classified maps of the years 2014 and 2017 due to the overestimation of urban pixels. The misclassified urban pixels belonged to the barren and agriculture class.
- Gradual growth in the urban areas was observed from the classified maps as shown in the figure 46. The growth in the rural areas seemed to increase sparsely.

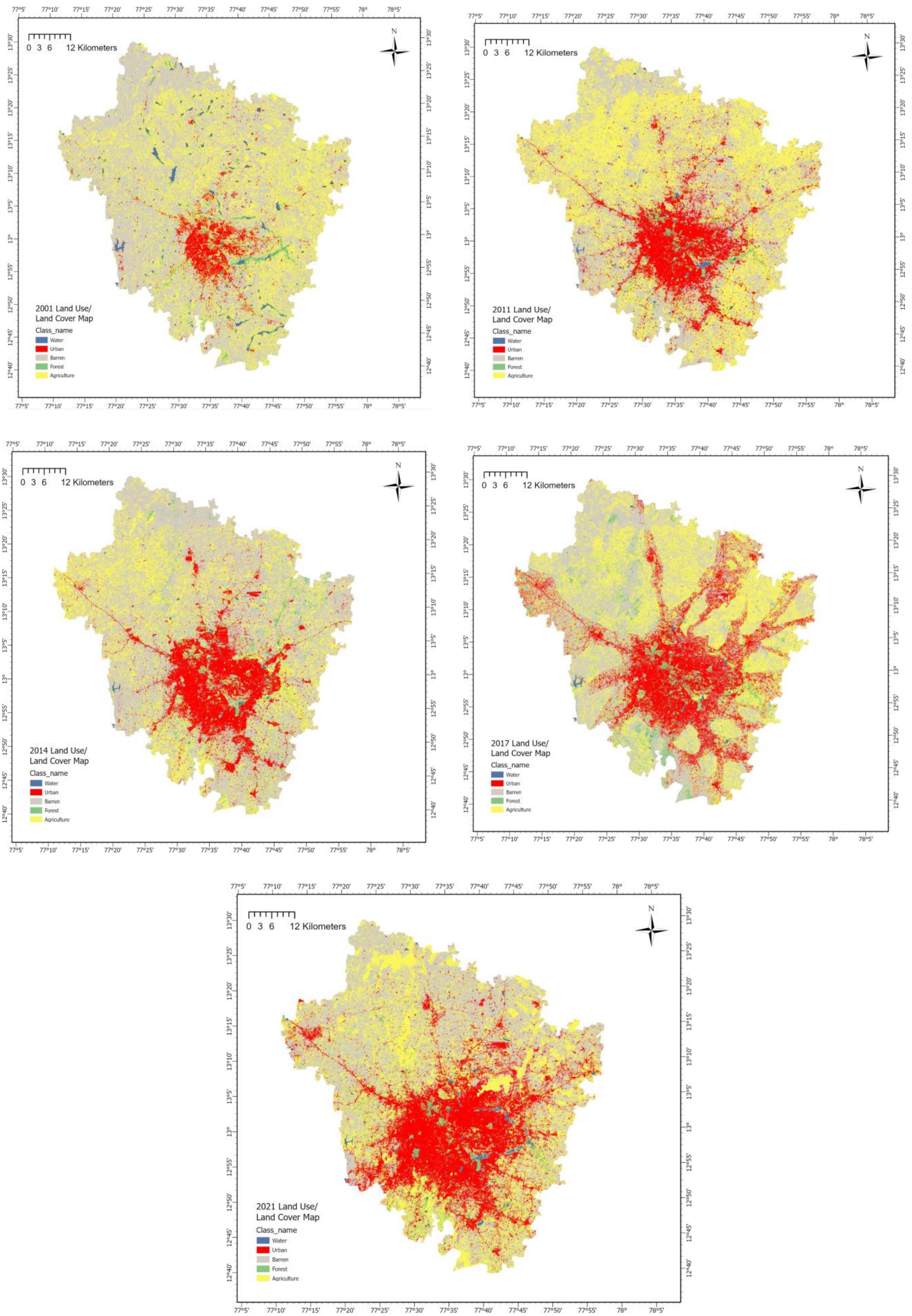


Figure 46: Temporal satellite-based LULC classified images of the years 2001, 2011, 2014, 2017 and 2021 of Bangalore rural and urban

5.2 Percentage Change in Built-up

Here, the results obtained are with regards to the fluctuation in pixel count for each of the 5 classes considered. Percentage increase is computed only for built-up as our analysis is only limited to that. Figure represents the pixel count for each of the classes; urban, water, barren land, forest & agriculture. This table was further utilised to obtain a bar graph. As observed in Figure, there is an upward trend in built-up over the 5 years considered along with the predicted year 2031.The percentage increase in built-up from 2021 to 2031 is approximately 42 %.

Table 13: Pixel count of each class over the years

Year	Urban	Water	Barren	Forest	Agriculture
2001	1056573	315660	10692428	734995	7184001
2011	2937612	110431	7827739	511861	8596014
2014	2993295	82017	10201163	980854	5729404
2017	3854855	89626	8014348	1351568	6674649
2021	4960530	178740	7355064	732824	6767540
2031	7062431	201143	6026077	791601	5912948

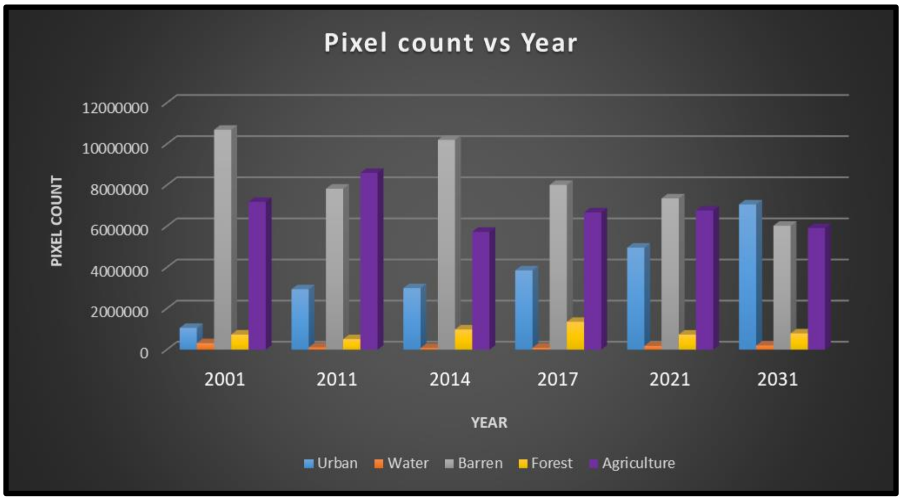


Figure 47: Pixel count fluctuation for each class vs the year

5.3 Accuracy Assessments

The results from the accuracy assessments of the classified maps are highlighted below.

- The percentage of total number of pixels in each class that are omitted is given by the first column and commission errors are accounted for in the second column of the following table. The kappa coefficient revealed an overall accuracy of 87% for 2001 map, 67% for 2011 map, 86% for 2014, 88% for 2017 and 82% for 2021 map, as given in the table 14.
- The bands which belonged to the 2011 dataset required image correction. The decrease in accuracy for the 2011 classified map is due to the gap filling procedure that was undertaken for the same, which could have affected the clarity and properties of the composite raster. Overall, the accuracies range between 45-95% which suggests that the supervised classification procedure was accurate.

Table 14: Accuracy assessment indicators for the LULC maps of 2001, 2011 and 2021

Class	**Producer's Accuracy**					**User's Accuracy**					**Over all Kappa Coefficient**				
Year	2001	2011	2014	2017	2021	2001	2011	2014	2017	2021	2001	2011	2014	2017	2021
1-Urban	0.8837	0.7692	0.8282	0.7862	1	0.95	1	0.9497	0.9896	0.9	0.875	0.6763	0.8632	0.8874	0.825
2-Water	1	0.9091	0.9986	1	0.9032	0.65	0.4545	0.7876	0.8237	0.7					
3-Barren	0.8297	0.7155	0.7982	0.8076	0.7255	0.975	0.9397	0.9867	0.9134	0.925					
4-Forest	0.9069	0.6667	0.8687	0.9124	0.8809	0.975	0.6	0.7982	0.9625	0.925					
5-Agriculture	0.9268	0.9014	0.9150	0.9180	0.85	0.95	0.7272	0.8371	0.8929	0.85					

5.4 Predicted Model

The results from the predicted model are highlighted below.

- The transition models exhibited an accuracy of around 70% indicating the fairly decent explanatory power of the driver variables. The table below signifies the same.

Table 15: Accuracy rates for the transition sub-models

Transition Sub-Model	Accuracy Rate	Skill Measure
3 to 1	73.93%	0.4785
5 to 1	67.67%	0.3535

- The output values for the transition potential maps lie in the initial areas of the barren and agricultural land classes.
- The model produces hard and soft predictions for the specified year. The hard prediction signifies what the final prediction looks like based on the transitions, host and claimant classes observed by the model. Soft prediction visualises the extent to which the areas possess the right conditions to have a causal link to change.

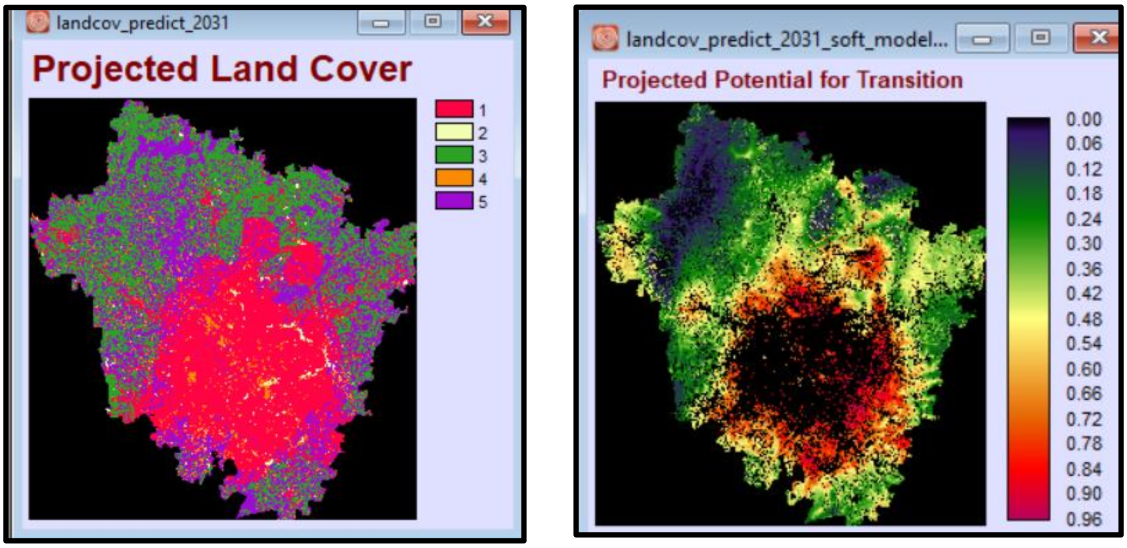


Figure 48: Hard and soft prediction of the land change for 2031

- The final model was reclassified on ArcGIS to eliminate the null values. The change is observed to have taken a course towards Devanahalli and Bangalore south possibly due to the influx of development surrounding the airport and SEZ variables, as shown in the figure 49. There is also sparse growth seen in the rural areas of Doddaballapur and Nelamangla. The area belonging to the urban class is 1588.181 square kilometres.

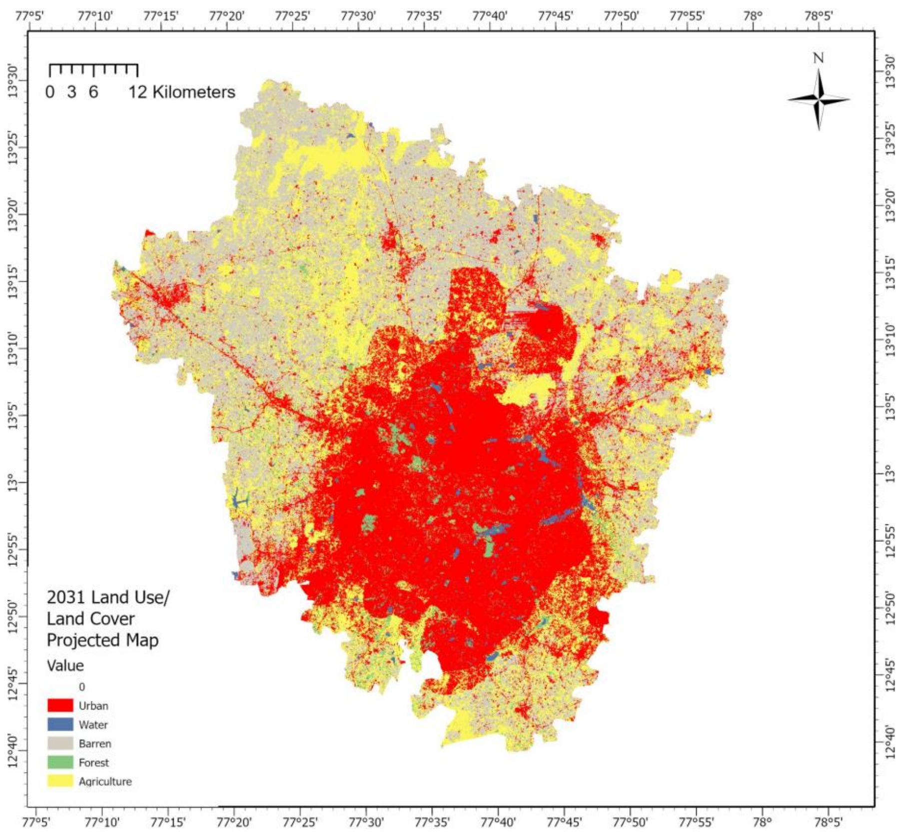


Figure 49: Reclassified projected LULC map for the year 2031

5.5 Area changes in Bangalore

The area of every class of the LULC maps for each of the six years was analyzed and it can be observed that the percentage area covered by the developed areas is exponentially increasing. The percentage distribution increased from 5% in 2001 to 35% in 2031. Most of this growth can be attributed to the steady decrease in the percentages of barren and agricultural land. The percentage area of barren land decreased from 53% in 2001 to 30% in 2031 and that of agricultural land reduced from 42%in 2011 to 29% in 2031, as highlighted under the table 16. This could conclude that a large area of barren land can contribute to urban sprawl in the future.

There is no notable change in the areas observed for water and forest land covers. The percentage area for water bodies remains constant throughout at around 1% and forest areas fluctuate between 3 and 6%. Hence these transitions were not considered during the modelling and prediction phase.

Table 16: Area covered and the percentage-area of the land-cover classes

Year	2001		2011		2014		2017		2021		2031	
LULC Classes	Area	%	Area	%	Area	%	Area	%	Area	%	Area	%
Urban	237.728	5.287	661.073	14.701	673.223	14.976	867.304	19.289	1111.629	24.721	1588.181	35.318
Water	71.024	1.580	29.377	0.653	18.446	0.410	20.165	0.448	45.242	1.006	45.242	1.006
Barren	2405.796	53.506	1757.024	39.073	2294.348	51.040	1803.148	40.102	1654.294	36.788	1355.419	30.142
Forest	165.374	3.678	119.299	2.653	220.604	4.908	304.089	6.763	178.027	3.959	178.027	3.959
Agriculture	1616.4	35.949	1930.018	42.920	1288.603	28.666	1501.729	33.398	1507.597	33.526	1329.921	29.575
Total Area	4496.322		4496.791		4495.224		4496.435		4496.789		4496.79	

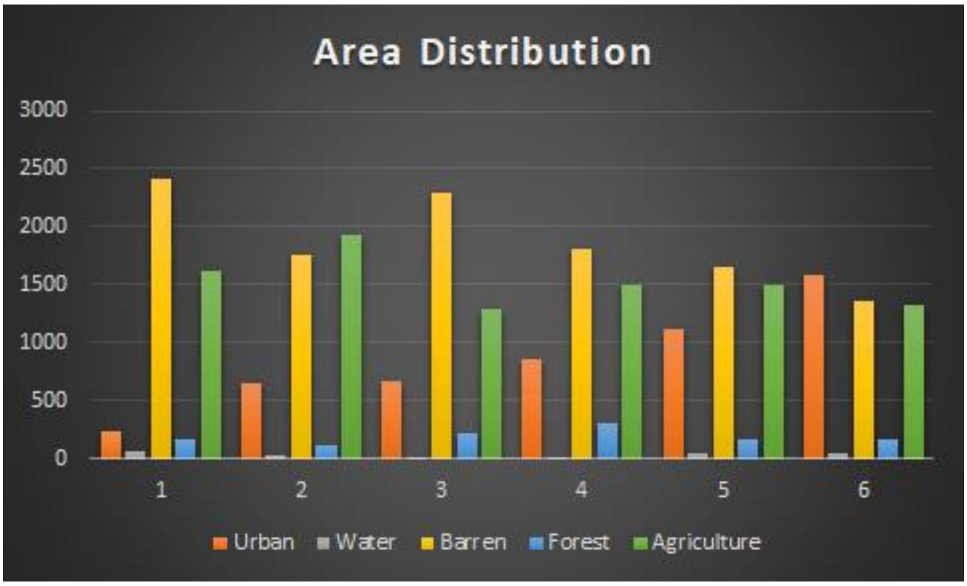


Figure 50: Area distribution of land-cover classes

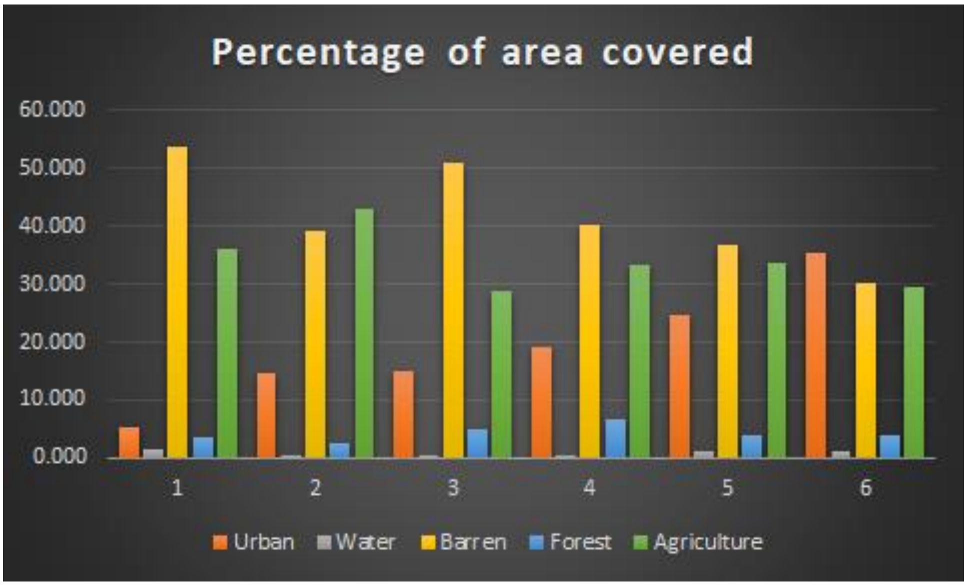


Figure 51: Percentage distribution of land-cover classes

The percentage change in areas is observed to fall from 178% in 2001 to 42% in 2031 for the developed areas, as highlighted under the table 17. There is a steep decrease in the percentages observed of barren and agricultural land which may be due to the transformation of the same into built-up areas.

Table 17: Percentage change in areas for the land-cover classes

Year	2001		2011		2014		2017		2021		2031	
LULC Classes	Area	% Change	Area	% Change	Area	% Change	Area	% Change	Area	% Change	Area	
Urban	237.728	178.080	661.073	1.838	673.223	28.829	867.304	28.171	1111.629	42.870	1588.181	
Water	71.024	-58.638	29.377	-37.209	18.446	9.319	20.165	124.359	45.242	0.000	45.242	
Barren	2405.796	-26.967	1757.024	30.581	2294.348	-21.409	1803.148	-8.255	1654.294	-18.067	1355.419	
Forest	165.374	-27.861	119.299	84.917	220.604	37.844	304.089	-41.456	178.027	0.000	178.027	
Agriculture	1616.4	19.402	1930.018	-33.234	1288.603	16.539	1501.729	0.391	1507.597	-11.785	1329.921	
Total Area	4496.322		4496.791		4495.224		4496.435		4496.789		4496.79	

5.6 Forecasting-Model

The output of multiple linear regression analysis was a standard equation of the form Y = a + b*X + c*Z corresponding to

Guidance Value = x + y*(Year) + z*(Built-up)

which can be used to calculate GV for any year of choice.

Each of the coefficients’ p-value and Variance Inflation Factor were displayed in addition to the model summary with R squared values. An analysis of the variance provided each source’s number of degrees of freedom, adjusted sum of squares, adjusted mean squares, f value and p value, further explained below.

➔ The p-value for each term tests the null hypothesis that the coefficient is equal to zero with no effect. A low p-value (< 0.1) indicates that the null hypothesis can be rejected. A predictor with a low p-value is a relevant addition to the model because changes in the predictor's value are related to changes in the response variable and vice versa. For both simple linear and multiple linear regression, the null and alternate hypothesis is:

Null hypothesis, H_0 = Coefficient of independent variable(s) is equal to zero

Alternate hypothesis, H_1 = Coefficient of independent variable(s) is not equal to zero

➔ The degrees of freedom are the amount of information in the column wise data. The regression analysis uses the same to estimate the values of unknown population parameters. The total DF is determined by the number of observations in the dataset.

➔ The adjusted sum of squares for a term is the increase in the regression sum of squares compared to a model with only the other terms. It quantifies the amount of variation in the response data, explained by each term in the model. Minitab uses this to calculate the p-value for a term. It also uses the sums of squares to calculate the R squared statistic.

➔ Adjusted mean squares measure how much variation a term or a model explains, assuming that all other terms are in the model, regardless of the order they were entered, also considering DF.

➔ F-value is the test statistic used to determine whether the term is associated with the response for the lack-of-fit test. It is used to determine whether the model is missing higher-order terms that include the predictors in the current model.

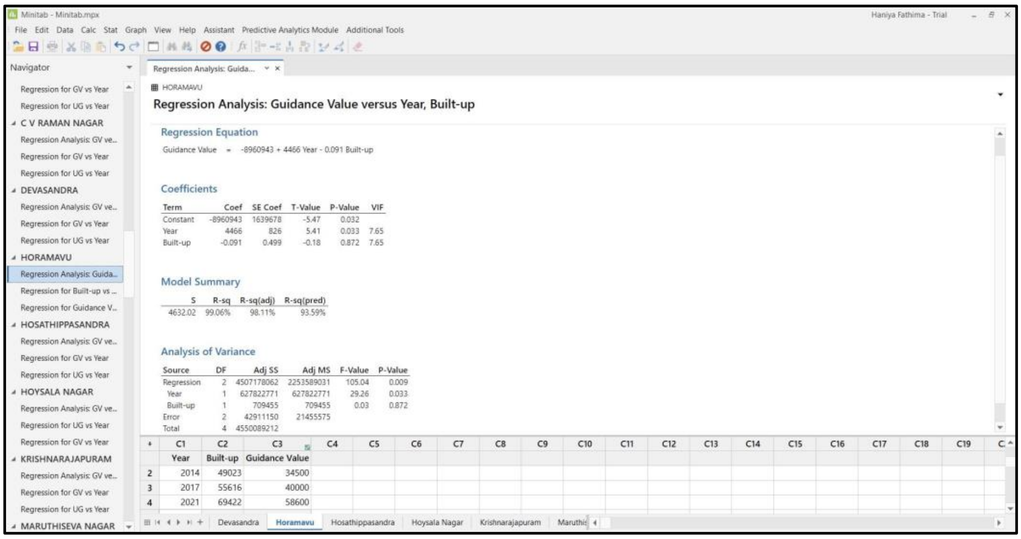


Figure 52: Regression Equation for GV on Minitab

The GV forecasting equation obtained from regression analysis was used to obtain the guidance value for 2031 by inputting the built-up value of 2031 and the year. This forecasted value was obtained for every ward and hobli for the year 2031.

Table 18: Guidance Value Regression Equation

TALUK	HOBLI	WARD	Regression Analysis Equation	Forecasted Guidance Value per sq m
				2031
Bangalore East	Krishnarajapuram	A.Narayanapura	Guidance Value = -5448012 + 2733.7*Year - 3.78*Built-up	68816
Bangalore East		Banaswadi	Guidance Value = -4873038 + 2416*Year + 2.04*Built-up	64407
Bangalore East		Basavanapura	Guidance Value = -3969553 + 1980.1*Year - 0.157*Built-up	48109

In order to validate the final GV forecasting equation, the guidance value for 2021 was calculated and compared with that obtained from the Kaveri portal. An average percentage difference of 4.39% was obtained for urban and 4.15% for rural.

Table 19: Validation of GV equation

TALUK	HOBLI	WARD	Guidance Value from Kaveri Portal	GV from Regression Analysis	Percentage Difference
			2021		
Bangalore East	Krishnarajapuram	A.Narayanapura	42300	41782	1.23%
Bangalore East		Banaswadi	40000	39557	1.11%
Bangalore East		Basavanapura	28500	32229	13.08%

The guidance value equation can be used along with the built-up equation for any year of choice.

5.7 Guidance Value Calculation Program

In order to forecast the guidance value for a ward/hobli and year of choice, a program was developed on python to analyse the data and obtain the desired outputs.

```
import pandas as pd

def hobli_guidance_value(hobli_name, year):
    df = pd.read_csv("hoblis.csv")

    df = df[df['hobli'].str.contains(hobli_name)]

    built_up = df['a'] + df['b']*year
    guidance_value_pandas = df['x'] + df['y']*year + df['z']*built_up
    guidance_value = round(guidance_value_pandas.values[0])
    guidance_value_sqft = round(guidance_value/10.764)

    print(f"{guidance_value} is the value per sq mt")
    print(f"{guidance_value_sqft} is the value per sq ft")
    return

def ward_guidance_value(ward_name, year):
    df = pd.read_csv("wards.csv")

    df = df[df['ward'].str.contains(ward_name)]

    built_up = df['a'] + df['b']*year
    guidance_value_pandas = df['x'] + df['y']*year + df['z']*built_up
    guidance_value = round(guidance_value_pandas.values[0])
    guidance_value_sqft = round(guidance_value/10.764)

    print(f"{guidance_value} is the value per sq mt")
    print(f"{guidance_value_sqft} is the value per sq ft")
    return

def main():

    val = input("Enter : hobli or ward?: ")
    if val == "hobli":
        hobli_name = input("Enter hobli name: ")
        year = int(input("Enter year: "))
        hobli_guidance_value(hobli_name, year)
    else :
        ward_name = input("Enter ward name: ")
        year = int(input("Enter year: "))
        ward_guidance_value(ward_name, year)
    return

if __name__=="__main__":
    main()
```

Figure 53: Guidance Value Forecasting Python Code

Pandas is an open-source library that is used for analysing and manipulating data with ease on Python. It provides several data structures and operations for manipulating numerical data with high performance and productivity.

The program is designed to go through the following steps

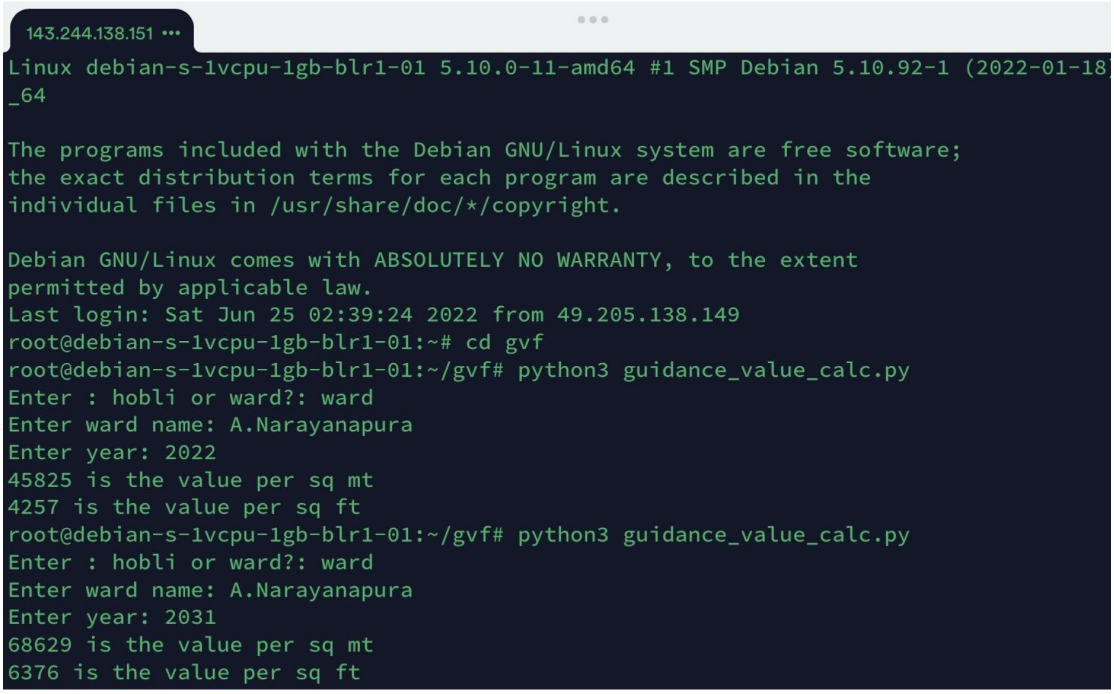
- Read the CSV files containing all the coefficients of year and built up as well as the constants, for each ward and hobli.
- Input the ward or hobli name and year as per preference of the user.
- built up growth is first calculated as built-up = a + b*year where a is the constant and b is the coefficient of year taken from the CSV files.
- This value is inputted into the guidance value forecasting equation as Guidance value = x + y*Year + z*built-up where x is the constant, y is the coefficient of year and z is the coefficient of built up taken from the CSV files.

- The guidance value is outputted in terms of per square metre and per square foot.

Table 20: Coefficients & constants of regression equations exported as CSV file input for python program

ward	a	b	x	y	z
A.Narayanapura	-98027	52.89	-5448012	2733.7	-3.78
Banaswadi	-32596	23.34	-4873038	2416	2.04
Basavanapura	-804112	408.7	-3969553	1980.1	-0.157

A sample of the working of the program is shown in Figure 51. The input has been taken as ward, A.Narayanapura and year 2022 and the output has been obtained as Rs. 45825 per square metre and Rs. 4257 per square foot. The second input has been taken as ward, A.Narayanapura and year 2031 and the output has been obtained as Rs. 68628 per square metre and Rs. 6376 per square foot.



```
143.244.138.151 •••
Linux debian-s-1vcpu-1gb-blr1-01 5.10.0-11-amd64 #1 SMP Debian 5.10.92-1 (2022-01-18
_64

The programs included with the Debian GNU/Linux system are free software;
the exact distribution terms for each program are described in the
individual files in /usr/share/doc/*/copyright.

Debian GNU/Linux comes with ABSOLUTELY NO WARRANTY, to the extent
permitted by applicable law.
Last login: Sat Jun 25 02:39:24 2022 from 49.205.138.149
root@debian-s-1vcpu-1gb-blr1-01:~# cd gvf
root@debian-s-1vcpu-1gb-blr1-01:~/gvf# python3 guidance_value_calc.py
Enter : hobli or ward?: ward
Enter ward name: A.Narayanapura
Enter year: 2022
45825 is the value per sq mt
4257 is the value per sq ft
root@debian-s-1vcpu-1gb-blr1-01:~/gvf# python3 guidance_value_calc.py
Enter : hobli or ward?: ward
Enter ward name: A.Narayanapura
Enter year: 2031
68629 is the value per sq mt
6376 is the value per sq ft
```

Figure 54: Guidance Value Forecasting Program

The above program can therefore be used to calculate any guidance value - past, present or future with high accuracy.

CHAPTER 6
CONCLUSION

From the studies carried out on "Predicting the built-up growth of Bengaluru to forecast guidance values using satellite imagery", the following conclusions are discussed.

- Guidance values provide the basis for several important land-based decision makings. While market value depends on various external factors subject to the seller, guidance value stays constant until updated by the government. At present, guidance values for Bengaluru may be accessed via the internet through the government website, Kaveri portal for the present year. However, there is an increasing demand for viewing both past data and having an understanding of the trend of the future. This is because of the importance of guidance values - it plays an important role in purchasing decisions, it helps people study land prices so they may buy and sell competitively and lucratively, it provides the basis for land valuation, registration and income tax collection.
- To keep in sync with both the company and the stream of Engineering, this project uses satellite images as well as statistics to solve the above-mentioned issue.

- Satellite images were processed to assess the study area consisting of Bengaluru urban and rural in order to identify and map the different land classes. By inputting the several factors affecting land change namely distance to airport, CBD, SEZ, etc. the predicted maps were more accurate and in sync with proxies.

- Guidance value is for properties and agricultural land and the built-up class from the classified maps was used to correlate the two. An extensive database was created for ward /hobli wise representative guidance values and corresponding built up pixel values for the study years. Linear regression equations were formulated to correlate the variables and a final regression analysis equation considering year and built up was used to forecast guidance value. For faster and more effective use of the database, a program was designed to read all data, input the year of choice for the desired ward or hobli and obtain the guidance value with high accuracy. Therefore, the vast database of linear regression equations serves as a valuable tool to quickly identify **ward/hobli wise representative guidance values** in urban and rural Bengaluru. The use cases for the following project are listed below.

* Determine ward/hobli wise representative value of land
* Compare and determine areas with high potential, considering all proxies
* Form a basis for approximate financial requirement for land registration and income tax
* Take calculative land-based decisions based on representative future guidance value
* Decide the appropriate year to buy and sell based on various input parameters considered

CHAPTER 7
SUMMARY

The project life cycle consists of five phases as defined below.

1. **Conception Phase**: Problem was identified as lack of technology-based decision-making tool for urban planning. The idea was to use satellite images to accurately classify land and predict future urban built up to forecast guidance values.

2. **Definition Phase**: The scope of idea was defined, and finalised as "Predicting the Built-up Growth of Bengaluru to Forecast Guidance Values using Satellite Imagery".

3. **Preparation and Organising Phase**: Reports & presentations were prepared to include information that was collected and accordingly planned to carry out the work.

4. **Implementation Phase**: To predict a future map, past satellite images were analysed and classified. Numeric data for guidance values was collected. Statistical analysis was used to correlate the two and obtain forecasting equations for every ward and hobli. A program was developed for quick calculation.

5. **Clean Up Phase**: Final report was prepared and handed over to the company for formal acceptance and verification of the project.

CHAPTER 8
LIMITATIONS

Limitations of the project are those characteristics that influenced the interpretation of the findings from the project, as listed below.

- **15m resolution of satellite image restricted accuracy of land classification**

Spatial resolution refers to the size of a pixel on ground and determines the preciseness of an image. For instance, if an image has a 15m resolution, it goes to say that each pixel stands for a 15m*15m area on ground. This definitely is far accurate than using a 30m*30m resolution image which is considered a medium resolution image that at most covers an entire city leading to poor distinction amongst individual objects like vehicles and types of buildings. Although the considered image is 10m*10m image, an accuracy greater than 80% has not been obtained, indicating that the resolution is still not high enough to distinguish between finer objects on ground.

- **Only two inputs used for land change forecasting model limited intervals of prediction**

The prediction of a future map is limited by the fact that only two years can be fed into Terrset and most other LULC prediction software and models. The accuracy of the map for subsequent years is limited to the features of only two inputs. Multiple details over several time periods could be considered and made more apparent in a forecasted map if more than 2 years are inputted. Hence the predicted output map of 2031 from Land Change Modeler is currently limited by the features of 2011 and 2021.

- **Less number of points considered in regression analysis**

In the project, the independent variable considered was the year and the dependent variables considered were guidance values and pixel count. The pixel count was obtained only for years corresponding to that of the guidance values. Due to limited number of years for which guidance values were obtained, the number of points considered for the regression analysis were only five. On an average, 2.39% of the fitted built up urban growth and 9.49% of fitted built-up rural growth were not in sync with the built-up growth from the 2031 classified map owing to fewer number of points considered.

- **All Guidance Values are a ward/hobli wise representation**

Owing to the fact that the project scope has been classified into wards and hoblis and Guidance value data available from SROs and Kaveri Portal pertains to a single property, the Guidance values considered for the project are a representation of the ward/hobli on the whole. In addition, guidance values are determined by the state government and remain constant until they are revised by the government. Guidance values for Bengaluru remained constant between 2007-2013, 2014-2016, 2018-2021 and hence one year has been chosen for study in these intervals and correlated with respective built-up values. Future guidance values are determined based on the proxies for built up and the chosen years for which data on guidance value was compiled. It must be noted that these representative values are subject to change based on government policies and decisions and the accuracy of the data is within project scope and limitations.

CHAPTER 9
SUGGESTIONS & SCOPE FOR FUTURE WORK

The following can be considered for the review of the guidance values and inputs in the database in the future.

- **Add revised guidance values for every year to keep up with government changes**

Guidance values are periodically updated by the government and can be viewed on the Kaveri portal for the respective year. The timely addition of these new values to the database will continually improve the quality of the project database and thereby contribute to providing more efficient forecasted values to the user.

- **Add more points to database to improve accuracy of regression equations and thereby forecasting**

Regression equations require an optimum number of points in order to obtain accurate equations. Through the addition of more points in the Minitab software, the accuracy of the regression equations can be improved. This will further reduce the gap between actual and predicted values of guidance values.

- **Use higher resolution satellite images**

The use of higher resolution satellite images would allow for more accurate supervised classification where each class, namely built up, water, forest land, agricultural land and barren land could be identified more accurately to their real extent. This would thereby provide more precise values of built up that can be used as inputs in the growth regression equation. Ultimately this would also positively affect the guidance value forecasting equation.

CHAPTER 10
REFERENCES

[1] ***Baig, M.F.; Mustafa, M.R.U.; Baig, I.; Takaijudin, H.B.; Zeshan, M.T.,*** **Assessment of Land Use Land Cover Changes and Future Predictions Using CA-ANN Simulation for Selangor, Malaysia (2022)**

[2] ***Yayuan Lei, Johannes Flacke, Nina Schwarz,*** **Does Urban planning affect urban growth patterns? A case study of shenzhen, China (2021)**

[3] ***N. S. Nalini*****, Urbanisation and changing temperature patterns in the city of Bengaluru (2020)**

[4] ***Vivek Kumar Gautam, Palani Murugan, Mylswamy Annadurai,*** **A New Three Band Index for Identifying Urban Areas using Satellite Images (2017)**

[5] ***Dr. Narayanan Edadan*****, Structural Determinants of Unregulated Urban Growth and Residential Land Pricing: Case of Bengaluru, Journal of Urban Planning and Development (2015)**

[6] ***Gargi Bindal, Nitin Mishra, Praveen Kalura*****, Land Use Land Cover Classification Using ARC-GIS and ERDAS Tool-A Review (2017)**

[7] ***Varun Narayan Mishra, Praveen Kumar Rai, Kshitij Mohan*****, Prediction of land use changes based on Land Change Modeller (LCM) using remote sensing: A case study of Muzaffarpur (Bihar), India (2014)**

[8] ***Bharath H Aithal, Vinay S and Ramachandra T V,*** **Modeling and Simulation of Urbanisation in Greater Bengaluru, India, Proc. of National Spatial Data Infrastructure 2013 conference, IIT Bombay (2013)**

[9] ***Dr. P. K. Srimani, Mrs. Nanditha Prasad,*** **Land Use and Land Cover Mapping by using Remote Sensing and GIS Techniques – a Case Study of Kasaba Hobli, Hoskote Taluk, Bengaluru Rural District, Karnataka, India (2013)**

[10] ***Tania Prvan, Anna Reid, Peter Petocz*****, Statistical Laboratories Using Minitab, SPSS and Excel: A Practical Comparison (2002)**

[11] ***Kairu, Edward,*** **An introduction to remote sensing. GeoJournal (1982)**

CONTACT DETAILS

Name: Gargi

USN: 1MS18IM019

Number: +917204743861

Email ID: gargisat00@gmail.com

Name: Haniya Fathima

USN: 1MS18IM020

Number: +919741922399

Email ID: haniyafathima11@gmail.com

Name: K V Alekhya

USN: 1MS18IM023

Number: +917619566555

Email ID: alekhyaredd20@gmail.com