Impact of Mopa airport on LULC.

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I hereby declare that the data presented in this Dissertation report entitled, "Impact of Mopa airport on LULC.". is based on the results of Analysis carried out by me in the Economics Discipline at the Goa Business School, Goa University under the Supervision of Ms Heena Subrai Gaude and the same has not been submitted elsewhere for the award of a degree or diploma by me. Further, I understand that Goa University or its authorities / College will not be responsible for the correctness of observations / experimental or other findings given in the dissertation.

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PREFACE

This study examines the relationship between urbanization, environmental change, and population dynamics in Mopa and its surrounding villages in Goa, India. Rapid urbanization has created economic opportunities and improved resource access, but it has also raised concerns about environmental issues such as deforestation, biodiversity loss, and urban heat islands. The study's goal is to provide a comprehensive analysis of the relationships between urbanization, changes in vegetation cover, variations in land surface temperature, and population dynamics within the study area.

The study will use remote sensing technologies and advanced statistical modeling techniques to uncover the intricate patterns and associations that guide these interrelated activities. Key indices such as the Normalized Difference Built-up Index (NDBI), Normalized Difference Vegetation Index (NDVI), and Land Surface Temperature (LST) are used to measure and track landscape changes over time.

The findings can help policymakers, urban planners, and stakeholders make better decisions that balance economic development and environmental sustainability. This study is an important step toward understanding the complexities of urbanization and its environmental impacts in Mopa and its surrounding villages. By uncovering these relationships, we may open the way for more informed and responsible urban planning strategies, ensuring that future development is guided by ecological preservation and community well-being principles.

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ABBREVIATIONS USED

Entity	Abbreviations
Normalized difference vegetation index	NDVI
Normalized difference built-up index	NDBI
Land surface temperature	LST
Population count	POP COUNT
Land use land cover	LULC

ABSTRACT

When the MOPA (Mopa Airport) project was launched in Goa, it had a significant impact on land use/land cover (LULC) changes in the region. The study utilized remote sensing data to analyze these impacts. Landsat data was employed to create Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-up Index (NDBI), Land Surface Temperature (LST), and population count for the study area. A panel fixed effects model was used to analyze the trade-off between built-up and vegetation areas, land surface temperature, and population.

The findings show trend of increasing built-up areas associated with rising land surface temperatures. While population density has a statistically insignificant effect, the positive relationship between LST and NDBI suggests that urban development patterns may contribute to rising temperatures. Furthermore, the negative relationship between NDBI and NDVI demonstrates the potential loss of vegetation cover due to urbanization.

CHAPTER 1

INTRODUCTI0N

1.1 Background

India's economic growth has been steadily increasing over the years, with the country's GDP growing at an average rate of around 6-7% annually in the last decade(Chatterjee et al., n.d.). This growth has led to a rise in per capita income (PCI) and improvement in various welfare indicators. However, sustaining this growth trajectory requires significant investments in infrastructure development. The share of infrastructure spending as a percentage of GDP in India is 3.3% for fiscal year 2024 [Invest India].

The concepts of economic growth and welfare expansion are related and frequently coexist (Tridico & Paternesi Meloni, 2018). The steady rise in a nation's output of goods and services over an extended period of time is referred to as economic growth, and it is commonly gauged by variations in the GDP (Kuznets, 1971). The welfare system, on the other hand, is concerned with the overall health and standard of living of people living in a community. This can be impacted by a number of variables, such as social services, healthcare, work possibilities, and money.

Economic growth frequently results in an improvement in the population's general standard of living and well-being (De Neve & Sachs, 2020) , as seen by rising welfare indicators. Increasing job and income-generating opportunities is one of the main ways that growth affects welfare. Expanding sectors and the emergence of new companies raise household incomes, lower unemployment rates, and produce jobs. As a result, people and families are better able to afford more housing, healthcare, education, and other necessities, which improves their general wellbeing.

Furthermore, technical innovation and breakthroughs are encouraged by economic expansion, which raises productivity and efficiency in a variety of industries. These developments may result in improved goods and services, more competitiveness in international marketplaces, and higher pay for those with specialized knowledge. Because of these variables, people's quality of life is improved and their living standards grow, contributing to an increase in wellbeing overall.

The state of Goa, renowned for its thriving tourism industry, has also witnessed steady economic growth in recent years. According to data from the Directorate of Planning, Statistics, and Evaluation, Goa's Gross State Domestic Product (GSDP) is estimated to be around ₹1.0 trillion (US$13 billion) for the financial year 2023-2024 . This places Goa at the 23rd rank among all Indian states and union territories.. Recognizing the importance of infrastructure development, the state government has been actively increasing its spending on infrastructure projects.

One of the major infrastructure projects in Goa is the MOPA (Mopa Airport) project, which is expected to have a significant impact on the state's economy and land use/land cover (LULC) patterns. While infrastructure development is essential for economic growth and welfare expansion, it can also have adverse environmental impacts, including habitat destruction, biodiversity loss, and changes in land surface temperature, Normalized Difference Built-up Index (NDBI), and Normalized Difference Vegetation Index (NDVI).

Remote sensing technology plays a crucial role in analyzing and monitoring these changes in LULC patterns. By utilizing satellite data and techniques like NDVI, NDBI, and Land Surface Temperature (LST) calculations, researchers can quantify and assess the impact of infrastructure development on the environment and ecosystem. These remote sensing indices provide valuable insights into changes in vegetation cover, built-up areas, and land surface temperatures, which are crucial indicators of the environmental impact of development projects.

The aim of this study is to analyse the impact of the MOPA Airport project on LULC changes in Goa using remote sensing data and techniques. The study will employ Landsat satellite data to create NDVI, NDBI, LST, and population count for the study area, and a panel fixed effects model will be used to analyze the trade-off between built-up and vegetation areas, land surface temperature, and population dynamics. By quantifying these relationships, the study aims to provide valuable insights into the environmental and ecological consequences of the MOPA Airport project, informing sustainable development strategies and mitigating measures.

"Infrastructure Development: Catalyst for Economic Growth, Innovation, and Inclusive Development"

Infrastructure is essential for stimulating economic growth because it makes a place that is favourable to enterprises, increases connectivity, and improves the general standard of living in communities. Building strong infrastructure—such as energy and transportation networks, telecommunications networks, water supplies, and sanitary facilities—not only makes it easier to move people and products around, but it also draws in investments, encourages productivity, and sparks innovation. The foundation of economies is this interconnected network of infrastructural elements, which allows them to prosper and adjust to changing opportunities and challenges.

Improved connection is one of the main ways that building infrastructure creates greater potential for economic growth. Roads, trains, ports, and airports are examples of efficient transportation infrastructure that lowers transportation costs, improves supply chain effectiveness, and increases market access for companies. For instance, a well-kept road system enables businesses to deliver goods more swiftly and affordably, reaching clients in far-off areas and growing their clientele. Similar to this, updated ports and airports promote international trade by drawing in foreign capital and increasing exports, which in turn boosts economic activity and generates job possibilities. .

Furthermore, the economy frequently benefits from infrastructure developments in multiple ways. An extensive infrastructure project, like building a high-speed rail system or a power plant using renewable energy, for instance, not only produces direct jobs during construction but also indirect jobs in industries like manufacturing, services, and supply chains. Government tax revenues rise as a result of increasing economic activity, and these gains can be further spent in social programs, healthcare, education, and infrastructure development to further boost welfare and economic growth.

Furthermore, by narrowing the gaps between urban and rural areas, infrastructure development promotes inclusive growth and regional development. Enhanced communication and availability of infrastructural services in isolated and rural regions facilitate market access, modern farming methods adoption, and revenue diversification for farmers. This encourages balanced regional development, eases the strain of migration, and supports rural livelihoods. In a similar vein, investments in social infrastructure—that is, in places like community centers, schools, and hospitals—promote social inclusion and human capital development, setting the stage for growth that is both equitable and sustainable.

However, strategic planning, prioritizing investments, and efficient governance are necessary to realize the full potential of infrastructure-led economic growth. Governments are essential in developing and carrying out infrastructure projects that tackle major development issues and optimize socio-economic gains, often working in tandem with private sector partners and international organizations. This entails carrying out feasibility studies, evaluating the effects on the environment and society, raising money, guaranteeing accountability and transparency, and encouraging involvement and interaction from stakeholders.

Furthermore, the development of infrastructure must be in line with the principles of sustainable development, which include resilience, inclusion, and environmental sustainability. Energy-efficient construction, renewable energy projects, and environmentally friendly transportation are examples of green infrastructure projects that support attempts to mitigate the effects of climate change by lowering carbon emissions and lessening their negative environmental effects. Planning for inclusive infrastructure takes into account the requirements of underserved areas, advances gender parity, and guarantees accessibility for people with disabilities, all of which contribute to the promotion of social inclusion and personal empowerment.

"Environmental Impacts of Infrastructure Development: Challenges and Sustainable Solutions"

Although infrastructure development is essential for both inclusive and economic growth, it frequently comes at a high environmental cost. Numerous negative effects on the environment, such as habitat destruction, biodiversity loss, pollution, deforestation, water scarcity, and climate change, can result from the building and expansion of infrastructure, such as transportation networks, energy facilities, urban development projects, and industrial zones. To guarantee that infrastructure development is sustainable and does not jeopardize ecosystem health or the welfare of current and future generations, these environmental costs must be carefully evaluated and minimized.

The immediate and visible environmental impacts of infrastructure development, particularly habitat destruction and fragmentation, have significant implications for land surface temperature, the Normalized Difference Built-up Index (NDBI), Normalized Difference Vegetation Index (NDVI), and population dynamics. Land clearing for infrastructure projects not only disrupts natural habitats but also alters surface properties that influence land surface temperature. The removal of vegetation and the introduction of impervious surfaces such as roads and buildings can lead to increased land surface temperatures due to reduced evapotranspiration and increased heat absorption. This phenomenon, known as the urban heat island effect, can further exacerbate climate change impacts and affect local microclimates.

Furthermore, an increase in the NDBI, which measures the size of built-up regions in satellite images, frequently coincides with the installation of infrastructure. The NDBI tends to climb, suggesting a higher share of built-up surfaces, as more land is transformed for infrastructural purposes. The process of urbanization leads to changes in the land surface temperature and other environmental changes related to urban growth.

Sustainable development, urban planning, and environmental protection must all be integrated into comprehensive approaches to address these interrelated environmental concerns. The negative effects of infrastructure development on land surface temperature, NDBI, NDVI, and population dynamics can be lessened by implementing green infrastructure, protecting natural habitats and wildlife corridors, encouraging sustainable land use practices, and implementing climate-resilient urban design strategies. In addition to promoting environmental sustainability, these tactics also help to raise resilience and general quality of life in both urban and rural regions. Lower NDVI values indicate ecological disturbance and environmental degradation. They are attributed to reduced plant cover and biodiversity loss caused by habitat destruction and fragmentation.

Significant environmental concerns associated with infrastructure projects include deforestation, land degradation, air and water pollution, and greenhouse gas emissions. In addition to causing respiratory illnesses and soil deterioration, pollutants emitted during construction, industrial emissions, vehicle exhaust, and trash disposal can also harm aquatic habitats and cause water contamination. Sustainable waste management techniques, clean energy sources, and pollution control technologies are essential to reducing these concerns.

Another major effect of infrastructure development on the environment is deforestation, which decreases the storage of carbon and interferes with ecosystem services like soil fertility, water regulation, and natural pest control. To solve these problems, reforestation initiatives, sustainable land use policies, and the preservation of vital ecosystems are necessary. Significant environmental concerns include pollution and water scarcity, particularly in areas with competing needs for water resources. For irrigation, electricity, and water supply, dams and reservoirs can change river flows, lessen the amount of water available downstream, and have an effect on fisheries and aquatic habitats. Groundwater depletion, contaminated water sources, and polluted runoff are all potential outcomes of infrastructural expansion brought on by urbanization and industrialization.

Climate change and groundwater emissions are two more important environmental effects of infrastructure expansion. The key to lowering greenhouse gas emissions and increasing climate resilience is to switch to low-carbon and renewable energy sources, encourage energy efficiency, and implement climate-resilient infrastructure designs. Increased trash production, noise pollution, visual pollution, and disturbance of ecosystems and cultural heritage sites are examples of indirect environmental effects.

Infrastructure development can present chances for environmental sustainability and conservation in spite of these obstacles. Green infrastructure projects can lessen their negative effects on the environment, encourage resource efficiency, and improve ecosystem services. Examples of these projects include green buildings, renewable energy projects, sustainable transportation systems, and ecological restoration projects. By incorporating natural solutions into infrastructure plans, communities can become more resilient to natural disasters and climate change, while also enjoying better biodiversity, water management, and air quality.

In conclusion, even while the development of infrastructure is critical to both inclusive and economic growth, it is also critical to address the risks and expenses related to infrastructure projects for the environment. Stakeholders may reduce environmental impacts, improve ecosystem resilience, and develop infrastructure that benefits people and the environment by embracing sustainable practices, encouraging environmental conservation, and incorporating nature-based solutions into infrastructure designs. Achieving sustainable development goals and guaranteeing a successful and healthy future for all depend on striking a balance between infrastructure development and environmental conservation.

1.2 Aim of the research

The aim of this research is to evaluate the impact of Mopa airport on Land use land cover in the Mopa village. .

1.3 Objectives of the research

1. To analyse the impact of Mopa airport on Land use land cover in the Mopa village.

2. To examine the associations between urbanization (measured by NDBI), vegetation health (NDVI), land surface temperature (LST), and population growth, employing panel regression models and controlling for village-specific factors.

1.4 Research Question

To what extent has the construction and operation of the Mopa airport influenced the patterns of land-use and land-cover change in Mopa and surrounding areas over the past [2013 TO 2023]?

1.5 Research gap

While urbanization and its environmental impacts have been extensively studied, there remains a gap in comprehensively understanding the interrelated dynamics between built-up area expansion, vegetation cover changes, land surface temperature variations, and population growth trends at a local scale. This study aims to bridge this gap by providing a granular analysis of Mopa and its surrounding villages, leveraging high-resolution remote sensing data and advanced statistical techniques to capture the nuanced relationships and trade-offs within this specific geographic context**.**

1.6 scope of the research

The scope of this research encompasses Mopa village and its surrounding villages in the Indian state of Goa. The study utilizes remote sensing data from Landsat satellite imagery spanning the period from 2013 to 2023, coupled with census data on population counts for the same time frame. The analysis focuses on the derivation of key environmental indicators, including the Normalized Difference Built-up Index (NDBI), Normalized Difference Vegetation Index (NDVI), and Land Surface Temperature (LST), from the satellite imagery. These indicators are then integrated with population data to investigate their interconnected relationships using regression modeling techniques, including panel data analysis. The research findings aim to provide valuable insights for policymakers and urban planners, enabling them to balance development goals with environmental conservation efforts in Mopa and neighboring regions.

CHAPTER 2

REVIEW OF LITERATURE

2.1 Introduction

The chapter comprises of scholarly articles, books, a published thesis and other sources which are relevant to the study. It provides context for the present study by identifying previous studies. The chapter shows the previous researches conducted in the field of the present study.

2.2 Review of Literature

The paper "Impact of Public and Private Infrastructure Investment on Economic Growth: Evidence from India" by (Unnikrishnan & Kattookaran, 2020) looks at how public and private infrastructure investment affects economic growth in India. The author's goal is to demonstrate, using empirical evidence, how public and private infrastructure investments contribute significantly to economic development. The study will most likely analyse data to demonstrate that strong infrastructure, whether in transportation, energy, or communication, is critical to attracting investments, increasing productivity, and fostering overall economic growth. It emphasizes the importance of balanced investments in public and private infrastructure for long-term economic growth, as well as policy implications for optimizing India's infrastructure development strategy.

Similarly The paper "Government Expenditure on Infrastructure as a Driver for Economic Growth in Nigeria" by (Chijioke & Amadi, 2020) investigates the relationship between government infrastructure spending and economic development in Nigeria ,the study presents empirical evidence demonstrating a positive relationship between infrastructure investments and economic growth, emphasizing infrastructure's critical role in attracting investment, increasing productivity, and reducing regional disparities. The study uses econometric techniques to examine the impact of infrastructure spending on key economic indicators, providing policy recommendations and advocating for strategic infrastructure investments as catalysts for Nigeria's long-term economic development. (Razzaq et al., 2022) examines the impact of inclusive infrastructure development, green innovation, and sustainable resource management in China in order to demonstrate how these factors interact to reduce environmental footprint. By examining China's trade-adjusted material footprints, the study demonstrates how inclusive infrastructure projects, combined with green innovation practices, contribute to sustainable resource utilization and environmental protection. The author emphasizes the importance of incorporating environmental considerations into infrastructure development strategies and encouraging innovation for efficient resource management, citing China's experience as a case study to draw lessons for other regions aspiring to sustainable development.

The author, Aplin, (2005), argues that remote sensing, which involves gathering data from satellites and aircraft, is a valuable tool for ecological research. This technology allows ecologists to study and monitor ecosystems across vast areas, providing insights into health, land cover changes, and potentially even animal populations.

In the survey Toth & Jóźków,(2016) study on remote sensing explores the technology used to obtain information about the Earth from a distance. They focus on two critical elements: the platforms that transport the sensors and the sensors themselves. On the platform side, they consider anything from Earth-orbiting satellites at varying altitudes to airplanes, balloons, and even ground-based stations and towers. The paper distinguishes between passive sensors, which record reflected sunlight, and active sensors, which produce energy to measure the return signal. These sensors may include cameras that capture visible and infrared light, radar systems, and LiDAR technologies.

Imagine you're an ecologist investigating a big forest, but instead of walking through dense trees, you have a powerful tool at your disposal. This technology is called biophysical distant sensing, and it functions similarly to an eagle's eye, allowing it to see beyond the surface. John R. Jensen developed this technology, which employs satellites and aircraft to study how light interacts with plants, soil, and water. It's more than just taking gorgeous images of landscapes; it's also about extracting important information. Think of it this way: different biological materials, like healthy leaves or dry soil, reflect light in unique ways. By studying these subtle variations, biophysical remote sensing can tell you a lot. It can reveal the health of vegetation, the amount of chlorophyll in leaves, the density of plant matter (biomass), and even how much moisture is in the soil. It can even measure surface temperature. This is a game-changer for ecologists, agricultural scientists, and resource managers. They can monitor the health of forests from space, track changes in vegetation over time, and even assess drought conditions. It's like having a constant pulse on the health of our ecosystems, allowing us to make informed decisions about conservation and resource management. So, the next time you look up at a satellite, remember it might not just be taking pictures; it could be revealing the secrets of our planet's life force. (Jensen, 1983)

Alexander F. H. Goetz, Barrett N. Rock, and Lawrence C. Rowan, explain the various applications of remote sensing techniques, including mineral mining, environmental monitoring, and archaeological study. The authors highlight the benefits of remote sensing, such as its capacity to cover huge areas quickly, collect multispectral data for extensive analysis, and provide significant insights into geological formations and climatic conditions. They investigate several remote sensing systems, including satellite imaging, airborne sensors, and ground-based approaches, emphasizing their importance in mapping terrain, locating mineral resources, assessing vegetation health, and monitoring land use changes. The report also discusses problems in remote sensing, such as the complexities of data interpretation and the necessity for specialist picture analysis expertise. Overall, the authors provide a comprehensive overview of how remote sensing technology enhances exploration efforts across diverse domains, making it an essential tool for researchers and professionals in the exploration and earth sciences. (Goetz et al., 1983)

(Nagendra, 2001)explores the application of remote sensing technology in assessing biodiversity. The author delves into the significance of understanding and monitoring biodiversity, emphasizing its importance for conservation efforts and ecosystem management. Nagendra discusses how remote sensing tools, such as satellite imagery and aerial surveys, can provide valuable information about various aspects of biodiversity, including species distribution, habitat types, and ecosystem health. The paper highlights the advantages of using remote sensing for biodiversity assessment, such as its ability to cover large areas, provide consistent and repeatable data, and detect changes over time. The author also discusses the challenges and limitations of remote sensing in biodiversity assessment, such as data interpretation complexities and the need for ground truth validation. Overall, the paper showcases the potential of remote sensing technology as a powerful tool for monitoring and managing biodiversity, offering insights that can inform conservation strategies and enhance our understanding of ecological systems. The author also covers the constraints and limitations of remote sensing in biodiversity assessment, such as data interpretation complications and the importance of ground truth confirmation. Overall, the article demonstrates remote sensing technology's potential as a valuable tool for monitoring and maintaining biodiversity, providing insights that can help inform conservation policies and improve our understanding of ecosystems.

The authors (Chi et al., 2016) talked about the intricate landscape of utilizing big data in the realm of remote sensing. The authors shed light on the immense potential of big data analytics in revolutionizing how we process and interpret remote sensing data, particularly from satellites and airborne sensors. They discuss the challenges posed by the vast volumes of data generated, including data storage, processing speed, and scalability issues. However, amidst these challenges, the authors highlight the opportunities that big data presents, such as enhanced spatial and temporal resolutions, improved data fusion capabilities, and the ability to extract valuable insights through advanced analytics techniques like machine learning and artificial intelligence. The paper also addresses the importance of data quality, accuracy, and validation in leveraging big data for remote sensing applications. Overall, the authors emphasize the transformative impact of big data analytics in remote sensing, offering a roadmap for overcoming challenges and harnessing the vast potential of big data to unlock new discoveries and insights in Earth observation and environmental monitoring.

(Atkinson & Lewis, 2000)proposes geostatistical classification as a crucial technique for remote sensing analysis. The authors address the significance of classification approaches in analyzing and categorizing satellite data in order to extract useful information about land cover and land use. They examine the fundamentals of geostatistical classification, emphasizing its capacity to include spatial linkages and variability into the classification process, which increases the accuracy of land cover mapping. The paper discusses fundamental topics including variogram analysis, which evaluates spatial autocorrelation, and kriging, a geostatistical interpolation approach used in classification. The authors also discuss the benefits of geostatistical classification, such as its capacity to handle uncertainty and quantify classification accuracy using error matrices and validation procedures. They also explore problems such as data preprocessing, selecting appropriate classification algorithms, and dealing with regional variation in land cover. Overall, the study is a fundamental guide to geostatistical classification methods in remote sensing, providing insights into their uses, benefits, and considerations for academics and practitioners in the field.

(Thilagam & Sivasamy, 2013) explores the usefulness of remote sensing and Geographic Information Systems (GIS) for developing land resource inventories in their study "Role of Remote Sensing and GIS in Land Resource Inventory-A Review". They suggest that these technologies are useful instruments for collecting data on land resources at various scales, ranging from local areas to entire regions and even internationally. The authors are likely highlighting the benefits of remote sensing data, which has higher resolution than older approaches, for activities such as mapping and monitoring land deterioration.

The study by (Chandrakant S et al., 2023) provides a comprehensive review of waste land development and management in Goa State, India. It explores waste land's definition, classification, and environmental issues related to mishandling. The authors emphasize the importance of sustainable waste land management strategies to reduce environmental deterioration and increase ecosystem resilience. The study also explores the socioeconomic implications of waste land, highlighting its potential for productive land uses like afforestation, agriculture, and renewable energy initiatives. The authors also examine the current state of waste land in Goa, focusing on land degradation, land use patterns, and waste land management policy frameworks. They emphasize the need for integrated approaches incorporating technology advancements, community participation, and policy interventions.

the study based on expanding use of remote sensing and Geographic Information Systems (GIS) to research coasts. (Parthasarathy & Deka, 2021) talks about the use of satellite photography to estimate coastal risk and track shoreline changes over time. Remote sensing provides useful information, allowing researchers to track changes and detect objects such as coastlines, vegetation, and water bodies. GIS, on the other hand, is critical for interpreting acquired data by combining various geographical data such as topography, geology, and wave patterns to provide a comprehensive picture of coastal risk. This combination can aid in the development of Coastal Vulnerability Indexes (CVI), which identify locations that are most vulnerable to erosion, sea-level rise, and other coastal hazards. The authors argue that remote sensing and GIS are effective tools for studying coastal processes and developing coastal management plans.

when it comes to using multispectral data to investigate mangrove ecosystems. (Thakur et al., 2020) explains the remarkable advances made in this discipline since its inception nearly four decades ago. Scientists may investigate the unique spectral features of mangroves using multispectral data, which captures information from numerous wavelengths. Effective image processing techniques are critical for retrieving this data. The authors investigate various processing techniques for mapping mangrove distribution, measuring health, and calculating attributes such as biomass. However, the paper acknowledges the challenges associated with remote sensing for mangrove studies, emphasizing the importance of careful selection of sensors, appropriate processing techniques, and considering spectral behaviour.

In The article "Three Decades of Indian Remote Sensing in Coastal Research" (Murthy et al., 2022)talks about the major impact of Indian Remote Sensing (IRS) satellites on coastal research in India over the last 30 years. IRS data, which was launched in 1988, proved to be an effective tool for researching and maintaining India's enormous coastline. IRS data's extensive coverage and regular updates have helped map and monitor coastal features such as shorelines, marshes, and vegetation. Tracking changes over time is critical for understanding coastal processes and hazards such as erosion. IRS data can also be used to manage coastal resources, analyze possible fishing grounds, identify disaster-prone locations, and create coastal development laws.

The Index-Based Built-up Index (IBI) is a new index that aims to increase the accuracy and precision of detecting built-up land features in satellite images. The author (Xu, 2008) point out the limits of current approaches and indices for reliably detecting developed areas from satellite data, such as background noise interference and limited separation between built-up and natural areas. The IBI uses thematic index-derived bands, such as the Soil Adjusted Vegetation Index (SAVI), Modified Normalized Difference Water Index (MNDWI), and Normalized Difference Built-up Index (NDBI), to depict vegetative cover, water bodies, and built-up areas. The IBI outperforms previous approaches in identifying built-up land features while suppressing background noise, as demonstrated by thorough validation using Landsat ETM+ images. The IBI is a promising tool for precise and reliable identification of built-up land features in satellite imagery, contributing to remote sensing techniques for urban analysis and environmental monitoring. (Shaginimol et al., 2023) highlights the importance of remote sensing and Geographic Information Systems (GIS) in selecting suitable locations for sustainable aquaculture in India. The authors argue that unplanned aquaculture development can have negative environmental and sectoral consequences. They propose a more scientific approach, using remote sensing and GIS to provide data on factors such as land cover, water quality, depth, salinity, tidal influence, infrastructure, and socioeconomic factors. This data helps identify areas that meet ecological and economic requirements for specific aquaculture species, ensuring the long-term viability of projects while minimizing environmental impact.

(Jain & Watve, n.d.) focuses on the Environmental Impact Assessment (EIA) of the Mopa greenfield airport project in Goa, India. The authors critically investigate the EIA through the lens of vulnerability, focusing on how it affects livelihoods. They claim that EIAs frequently underestimate the social and environmental costs of large-scale projects. The report will most likely analyze the Mopa airport scenario to demonstrate how the EIA may have overlooked the increased vulnerability of local residents reliant on traditional activities such as agriculture or fishing. The authors argue that including vulnerability evaluations into EIAs is critical. This would entail investigating how the project would effect people's access to resources, ability to deal with change, and overall well-being. By incorporating this viewpoint, EIAs can give a more fair assessment of the potential implications of development initiatives.

CHAPTER 3

METHODOLOGY

3.1 Study Area

Figure 1 map of study area

This research focuses on Mopa village and its surrounding villages in the state of Goa, India. The area has experienced rapid urbanization and development due to tourism and infrastructure projects. The study area is made up of a combination of urban settlements, farmland and natural habitats. The villages in the study area range in urbanization from densely populated cities to more rural villages. The study area offers an ideal environment to explore the relationship between built up area expansion, vegetation cover changes, land surface temperature variation and population dynamics. Furthermore, the study area plays an important role in the economy and tourism industry in Goa, making it an essential region for sustainable planning. The results of this research can be used to inform policy makers and urban planners to ensure that economic growth in Mopa and surrounding villages is balanced with environmental conservation.

The value of this research is further enhanced by the availability of the remote sensing data of the study area over the period of 2013-2023. The long-term nature of the data enables the analysis of temporal trends and patterns, which provide insight into the dynamic processes that shape the landscape of the region. The focus of this study is on Mopa and the surrounding villages.

3.2 Data Sources

To conduct a comprehensive analysis, this study leverages two primary data sources: remote sensing imagery and population data.

Remote Sensing Data:

Landsat satellite imagery from the USGS Earth Explorer was collected from 2013 to 2023. Landsat's multispectral capabilities and constant revisit intervals make it an ideal data source for long-term monitoring of land cover changes and the extraction of critical environmental indicators.

Using the QGIS open-source geographic information system software, the following remote sensing indices were derived from the Landsat imagery:

Normalized difference Built-up Index (NDBI): This index is specifically developed for focusing on built-up areas and urban structures, serving as a measure of urbanization levels in the studied area.

The Normalized Difference vegetation index (NDVI) is a commonly used indicator that measures the greenness and health of plant cover, allowing for the study of changes in vegetated regions over time.

Land Surface Temperature (LST): Using Landsat's thermal infrared bands, LST was estimated to capture spatial and temporal variability in surface temperatures across the research area.

Population Data:

To incorporate demographic factors into the analysis, village-level population counts for the study area were obtained from ORNL land scan viewer, developed by Oak Ridge National laboratory spanning the same time period (2013-2023). These data provide insights into population dynamics and their potential influence on urbanization and environmental changes.

3.3 Data Processing

Prior to analysis, the remote sensing data underwent a series of preprocessing steps within the QGIS environment:

1. Radiometric calibration: Raw digital numbers from the satellite imagery were converted to at-sensor radiance values and subsequently to top-of-atmosphere reflectance values, ensuring consistency and comparability across different image scenes.
2. Atmospheric correction: To account for atmospheric effects and improve the accuracy of surface reflectance values, atmospheric correction algorithms were applied to the imagery.

3. Cloud masking: Cloud cover can obscure land surface features and introduce noise in the data. Therefore, cloud and cloud shadow detection algorithms were employed to mask out these areas from the analysis.

After preprocessing the NDBI and NDVI indices were calculated with band algebra operations using QGIS Raster Calculator tool. The indices were obtained for each image scene over the duration of the study. The next step in the analysis was to perform zonal statistics using QGIS. The average NDBI values, NDVI values and LST values were extracted from the village boundary polygons. The remote sensing data was aggregated at the village level. Environmental indicators were combined with the population counts to create a dataset that combined zonal statistics with population data. This dataset served as the starting point for statistical analysis.

3.4 Statistical Modeling

The processed dataset was analysed using regression techniques in the R statistical software environment, enabling the exploration of relationships between urbanization, vegetation cover, land surface temperature, and population dynamics. The following models were employed:

1. Linear Regression Models:
    - Simple linear regression models were constructed to assess the relationships between the variables of interest: NDBI, NDVI, LST, and population counts.
    - Scatter plots with overlaid regression lines were generated to visualize these relationships and evaluate the linearity assumptions underlying the regression models.

- Coefficients, statistical significance, and goodness-of-fit measures (such as R-squared) were examined to interpret the strength and direction of the relationships between variables.

2. Panel Regression Model:

- To capture the temporal dynamics and account for unobserved village-specific characteristics, a panel fixed effects regression model was employed.
- In this model, the NDBI (Normalized Difference Built-up Index) was treated as the dependent variable, while NDVI, LST, and population counts were used as independent variables or predictors.
- The panel regression approach allowed for the analysis of within-village changes in NDBI concerning changes in the independent variables over the study period, controlling for time-invariant village-specific factors.
- This model provided insights into how variations in vegetation cover, land surface temperature, and population counts within each village were associated with changes in urbanization levels (as measured by NDBI) within that same village over time.

The combination of remote sensing data analysis techniques and advanced statistical modeling methods allowed for a comprehensive investigation of the relationships between urbanization, vegetation health, land surface temperature, and population dynamics in Mopa and its surrounding villages. This integrated approach provided valuable insights into the environmental impacts of development activities and the interplay between various factors shaping the landscape within this study area.

CHAPTER 4

MOPA'S DEMOGRAPHIC PROFILE

Mopa is a village in Pernem taluka, North Goa district, Goa. According to the 2011 Population Census, the settlement of Mopa is home to 243 families. Mopa's total population is 1,082, with 544 males and 538 females, for an average sex ratio of 989. Mopa village has 117 children aged 0 to 6 years, accounting for 11% of the total population. There are 56 male and 61 female children aged 0 to 6 years. Thus, according to the 2011 Census, the Child Sex Ratio in Mopa is 1,089, which is higher than the village's average Sex Ratio (989).

Mopa, a part of the state of Goa, is home to a diverse population, with a mix of rural and urban dwellers, indigenous communities, immigrants, and settlers. Demographic indicators such as population, age distribution, education, and occupational structure offer insights into the socio-economic and development needs of this region. Mopa's population size has fluctuated over the years, driven by migration trends, economic growth, and infrastructure growth. Age distribution data shows a mix of ages, with younger populations dominating due to factors such as fertility rate and migration trends. Educational attainment levels vary, and efforts are being made to improve education and skills training opportunities for residents, especially in rural areas.

This region has experienced considerable urbanization and development in recent years, owing to causes such as tourism and infrastructural construction increase. The research region has a diversified topography, comprising urban settlements, agricultural lands, and natural habitats, making it a unique and representative location for investigating the complex linkages between built-up area expansion, environmental changes, and population dynamics.

According to the 2011 census, Mopa's literacy rate is 86.6%. Thus, Mopa village has a higher literacy rate than the North Goa district's 81.1%. Mopa village has a male literacy rate of 91.6% and a female literacy rate of 81.55%. According to the Indian constitution and the Panchyati Raaj Act (Amendment 1998), Mopa village is administered by the Sarpanch (Head of Village), who is the village's chosen representative.

<u>Working Population according to Census 2011</u>

In Mopa village, 545 people out of the total population were working. 38.9% of workers identify their work as Main Work (employment or earning more than 6 months), while 61.1% are employed in Marginal activity that provides a living for less than six months. Of the 545 people working in Main Work, 52 were cultivators (owners or co-owners), and 6 were agricultural labourers.

Table 1 Mopa Demographics

PARTICULARS	**TOTAL**	**MALE**	**FEMALE**
NO. OF HOUSES	243	-	-
POPULATION	1082	544	538
CHILD (0-6)	117	56	61
SCHEDULE CAST	68	34	34
SCHEDULE TRIBE	0	0	0
LITERACY	86.63%	91.60%	81.55%
TOTAL WORKERS	545	320	225
MAIN WORKER	212	-	-

MARGINAL WORKER	333	133	200

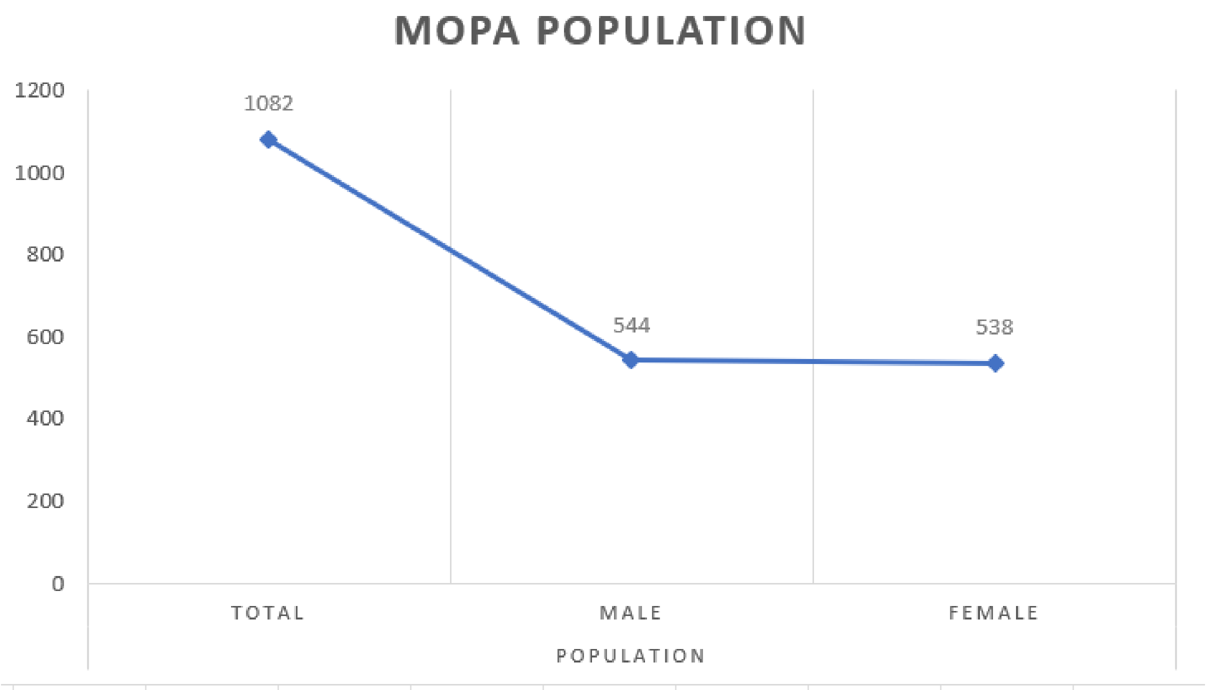

Figure 2 Mopa Population Graph

4.1 Environmental policies

Over time, Mopa, Goa, has experienced major challenges and changes in the environmental policy landscape. The region's approach to sustainable development and infrastructure growth has been affected by important events.

In October 2015, a significant change in environmental policy occurred with the Environment Ministry's acceptance of the Rs3,000 crore Mopa Airport project. The government's dedication to striking a balance between environmental sustainability and economic development was demonstrated by this permission, which came about after thorough assessments. An all-encompassing approach to environmental stewardship was reflected in its treatment of important issues like the Environmental Impact Assessment (EIA) process, mitigation strategies, regulatory compliance, and public comment.

On [29 MARCH 2019], however, the environmental policy journey faced a major obstacle when the Supreme Court suspended the environmental approval for the Mopa Airport project. This decision demonstrated the difficulties in striking a balance between infrastructure development and environmental concerns when it was later reviewed on [16 Jan 2020], when the stay was lifted. It highlighted the need for strong policy frameworks and regulatory oversight in environmentally sensitive places such as Mopa, illustrating the region's continuous efforts to strike a balance between development and preservation of the environment.

The progression of Mopa's environmental policy is narrated chronologically by these events, which range from recommendations to approvals to court decisions. They emphasize how the region's environmental policies and development are shaped by the dynamic interactions of sustainability, infrastructural development, legal justification, and regulatory compliance.

CHAPTER 5

DATA ANALYSIS

"Mapping Urbanization, Vegetation Cover, and Land Surface Temperature in Mopa and Surrounding Villages Using Remote Sensing Indices"

5.1 Normalized Difference Vegetation Index (NDVI)

Normalized Difference Vegetation Index (NDVI) is a widely used metric in remote sensing and environmental studies to quantify the presence and health of vegetation in a given area. It is calculated using spectral reflectance data captured by satellite sensors or other remote sensing platforms, typically in the red and near-infrared (NIR) bands of the electromagnetic spectrum.

The formula for NDVI is: NDVI= (NIR+RED)/(NIR-RED)

where NIR is the reflectance in the near-infrared band and Red is the reflectance in the red band.

NDVI values range from -1 to 1, with higher values indicating dense and healthy vegetation (closer to 1) and lower values representing sparse or stressed vegetation (closer to -1 or 0). A value of 0 typically corresponds to non-vegetated areas such as water bodies or urban areas.

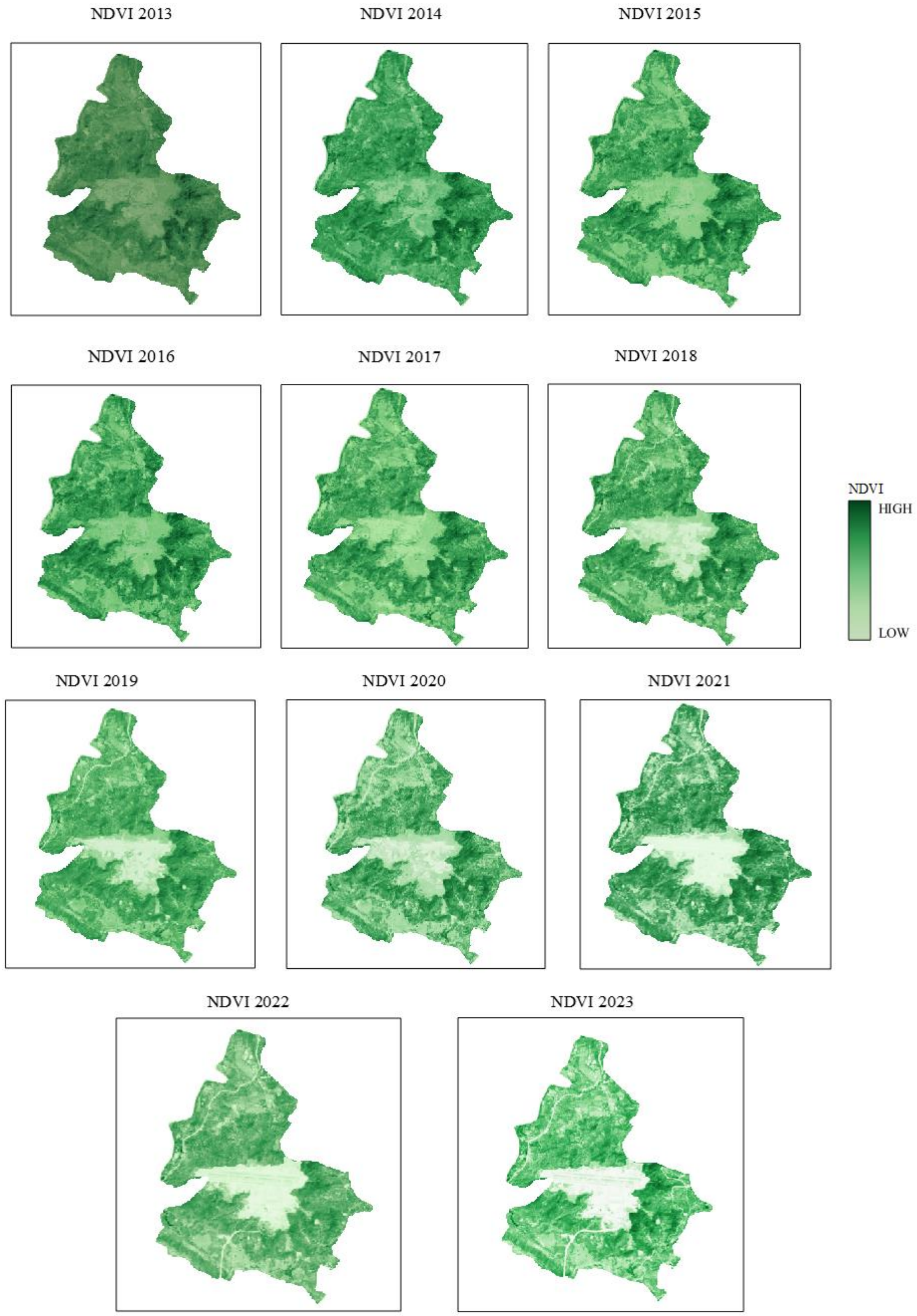

Figure 3 Mopa NDVI Maps

5.2 Normalized Difference Built-up Index (NDBI)

The Normalized Difference Built-up Index (NDBI) is a spectral index used in remote sensing to detect and quantify built-up areas or urban infrastructure in satellite imagery. It is particularly useful in land use and land cover classification, urban planning, environmental monitoring, and assessing the extent of human settlements.

NDBI is calculated using the following formula:

$$NDBI=(NIR+SWIR)/(NIR-SWIR)$$

where NIR is the reflectance in the near-infrared band and SWIR is the reflectance in the shortwave infrared band.

NDBI values typically range from -1 to 1. Higher positive values (closer to 1) indicate a higher proportion of built-up areas, such as buildings, roads, pavements, and other impervious surfaces. Lower or negative values (closer to -1) represent non-built-up areas, such as vegetation, water bodies, bare soil, and open spaces.

Overall, NDBI provides valuable insights into urbanization trends, land use changes, and the spatial distribution of built-up areas, contributing to informed decision-making in urban planning, environmental management, and sustainable development initiatives.

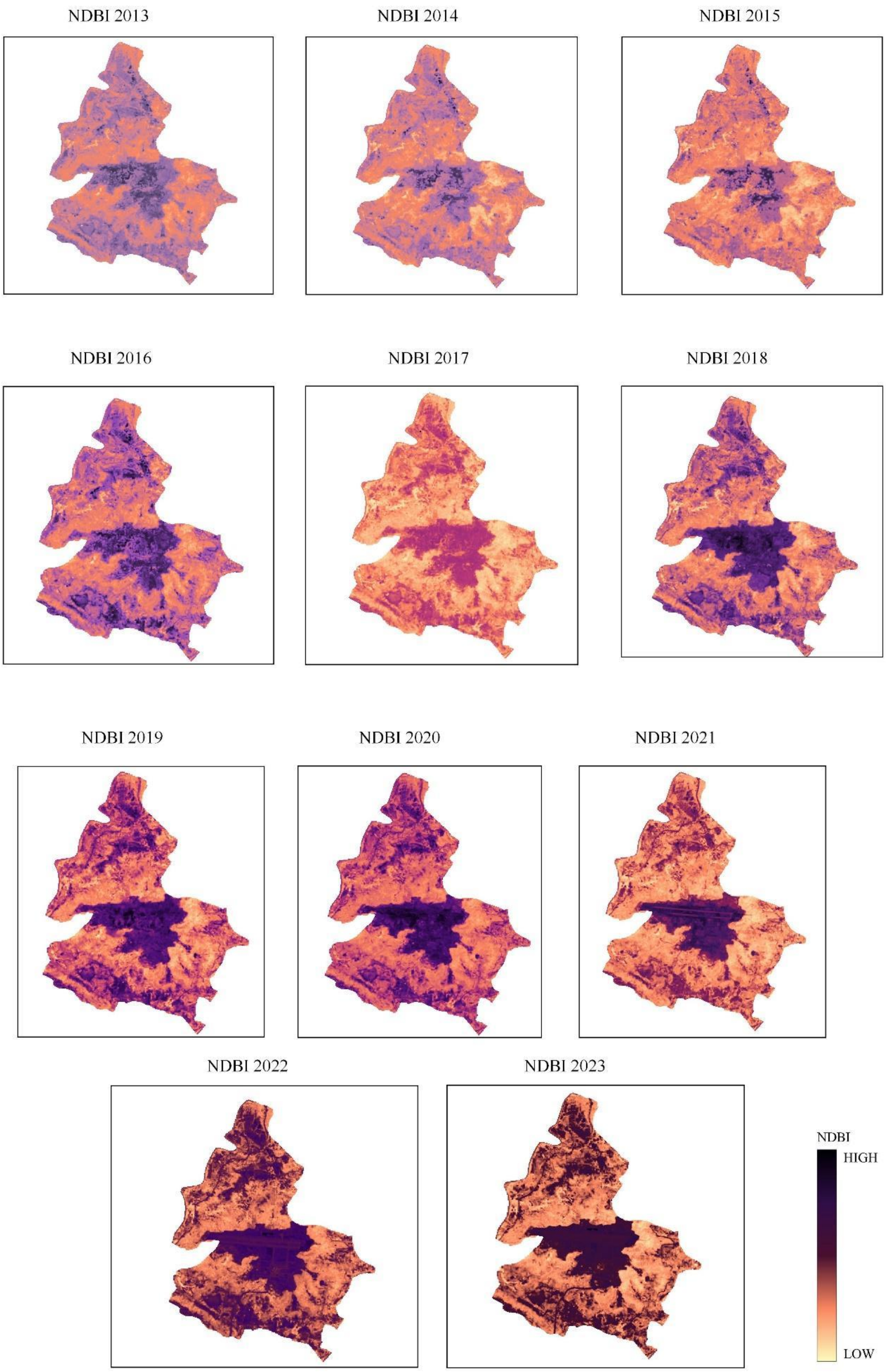

Figure 4 Mopa NDBI Maps

5.3 Land Surface Temperature (LST)

LST is a measurement of the Earth's surface temperature from space or from an aircraft. It's different from air temperature, and is affected by a variety of factors, including the amount of land cover, the type of land use, the amount of solar radiation, the amount of moisture in the soil, and the conditions of the atmosphere. Land surface temperatures (LSTs) are usually measured in degrees Kelvin (C) or degrees celcius (C). They are derived from remote sensing data (TIRs) collected by sensors on satellites. The estimation of LST involves the correction of atmospheric effects and the conversion of TIR bands radiance values into temperature values by algorithms. The accuracy and accessibility of LST information have improved with the development of satellite sensors, improved data processing methods, and improved spatial modeling. This has made LST a valuable parameter for remote sensing and environment studies, as it can be used to monitor environmental changes, understand interactions between land and atmosphere, and support sustainable development practices.

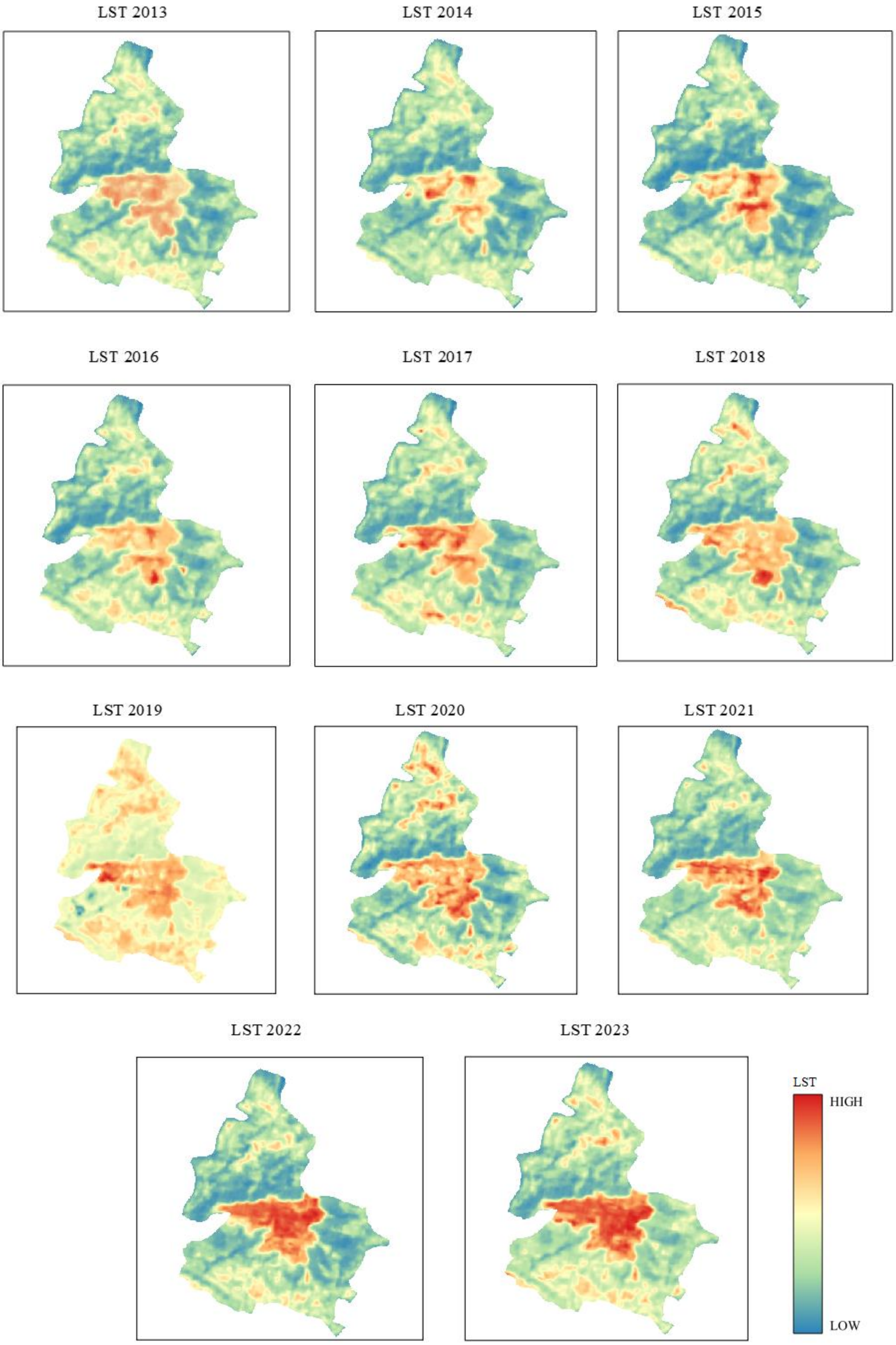

Figure 5 Mopa LST Maps

CHAPTER 6

"Statistical Analysis of Urbanization, Environmental Changes, and Population Dynamics in Mopa and Surrounding Villages"

6.1 Introduction

This chapter presents a statistical investigation into the relationship between urbanization, environmental change, and population dynamics in Mopa and its nearby villages. It analyzes the relationship between urbanization levels and changes in vegetation cover, land surface temperature, and population growth patterns using remote sensing data and various modelling tools. The analysis used linear regression models and scatter plots to investigate the relationship between these variables, providing information about the intensity and direction of the associations between urbanization, vegetation health, surface temperature, and population counts.

in addition, the study employs a panel regression approach to examine changes in NDBI, NDVI, LST, and population counts in Mopa and its neighboring villages over time. This strategy isolates the impacts of environmental and demographic factors on urbanization rates while considering unobserved time-invariant village-specific factors. The findings give a quantitative framework for evaluating the environmental consequences of development activities in the studied area. Diagnostic tests and model validation approaches are used to assure the durability and dependability of the results. The chapter concludes by analyzing how these findings affect long-term urban development and environmental conservation efforts in Mopa and its adjacent villages.

6.2 Objective 1

The first objective is to analyse the relationships between urbanization, vegetation cover, land surface temperature, and population dynamics in Mopa and surrounding villages using statistical regression modelling techniques.

The aim of this objective is to look into the links between urbanization (as measured by NDBI), vegetation cover (NDVI), land surface temperature (LST), and population trends in Mopa and nearby communities. It combines statistical regression modeling techniques, such as linear regression models for bivariate analysis and panel regression (fixed effects) models, to investigate within-village changes over time while controlling for village-specific variables. The purpose is to measure and analyze the relationships between these variables, shedding light on the trade-offs and interconnections between urbanization, environmental factors (vegetation and temperature), and population growth. The findings of these regression models can help to inform sustainable urban planning and environmental conservation efforts in the research area by identifying the probable environmental consequences of development activities.

6.2.1 Model 1 - NDVI vs. NDBI

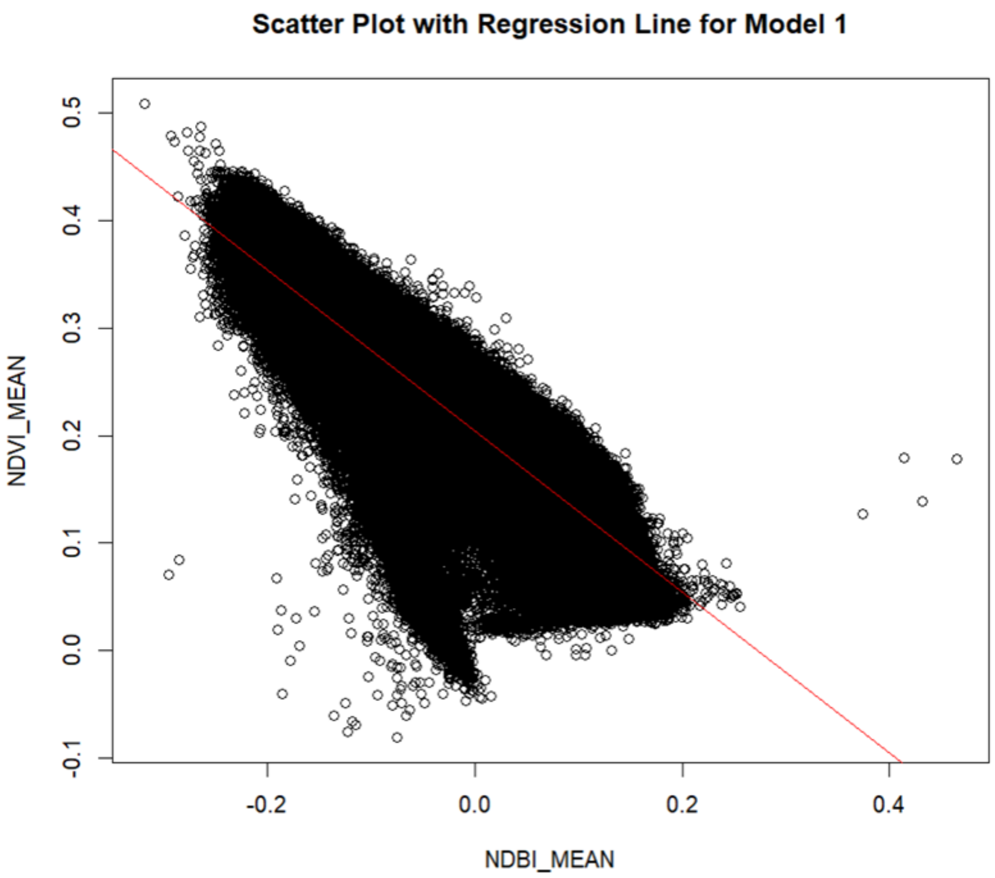

Figure 6 Scatter Plot MODEL 1

The scatter graph shows the relationship between the NDVI_MEAN (Normalized Difference Vegetation Index Mean) on the y-axis and the NDBI_MEAN (Normalized Difference Built-up Index Mean) on the x-axis. The NDVI measures vegetation density and health, whereas the NDBI assesses urbanization or built-up areas.

The data points form a triangle pattern, with a large concentration of points in the lower left corner, indicating a negative correlation between the two variables. The NDBI_MEAN grows, indicating increased levels of urbanization, whereas the NDVI_MEAN decreases, implying reduced vegetation cover and health.

The regression line, shown in yellow, has a negative slope, visually confirming the inverse link between the variables. The line fits the data reasonably well, capturing the overall pattern of decreasing vegetation index as the built-up index increases.

Overall, the scatter plot and regression line reveal a strong negative link between urbanization and vegetation cover. Higher levels of built-up areas are often associated with lower vegetation indices.

Table 2 Regression MODEL 1

	MODEL 1
CONSTANT	2.046e-01 *** (6.089e-05)
NDBI	-7.494e-01 *** (5.430e-04)
R SQUARE	0.7652
ADJUSTED R SQUARE	0.7652
OBSERVATIONS	584568

The above linear regression model shows the relationship between the dependent variable (NDVI_MEAN) and the independent variable (NDBI_MEAN).

The model shows a statistically significant negative relationship between NDVI_MEAN and NDBI_MEAN, as evidenced by the negative coefficient (-0.7494) for NDBI_MEAN. This negative coefficient indicates that when the built-up index (NDBI_MEAN) increases, the vegetation index (NDVI_MEAN) decreases on average. This inverse association is consistent with the expected pattern, as places with increased urbanization or built-up structures often have lower plant cover.

The model's coefficients are extremely significant, with p-values less than 2e-16, The residual standard error of 0.03878 represents the average amount by which the model's predictions differ from the actual NDVI_MEAN data.

The R-squared value of 0.7652 indicates that in this linear model, the NDBI_MEAN variable accounts for approximately 76.52% of the variation in NDVI_MEAN. The comparatively high R-squared value indicates that the built-up index is a good predictor of vegetation cover in the study area.

Overall, the linear regression model gives useful insight into the negative relationship between urbanization and vegetation cover.

6.2.2 Model 2 - NDVI vs. LST

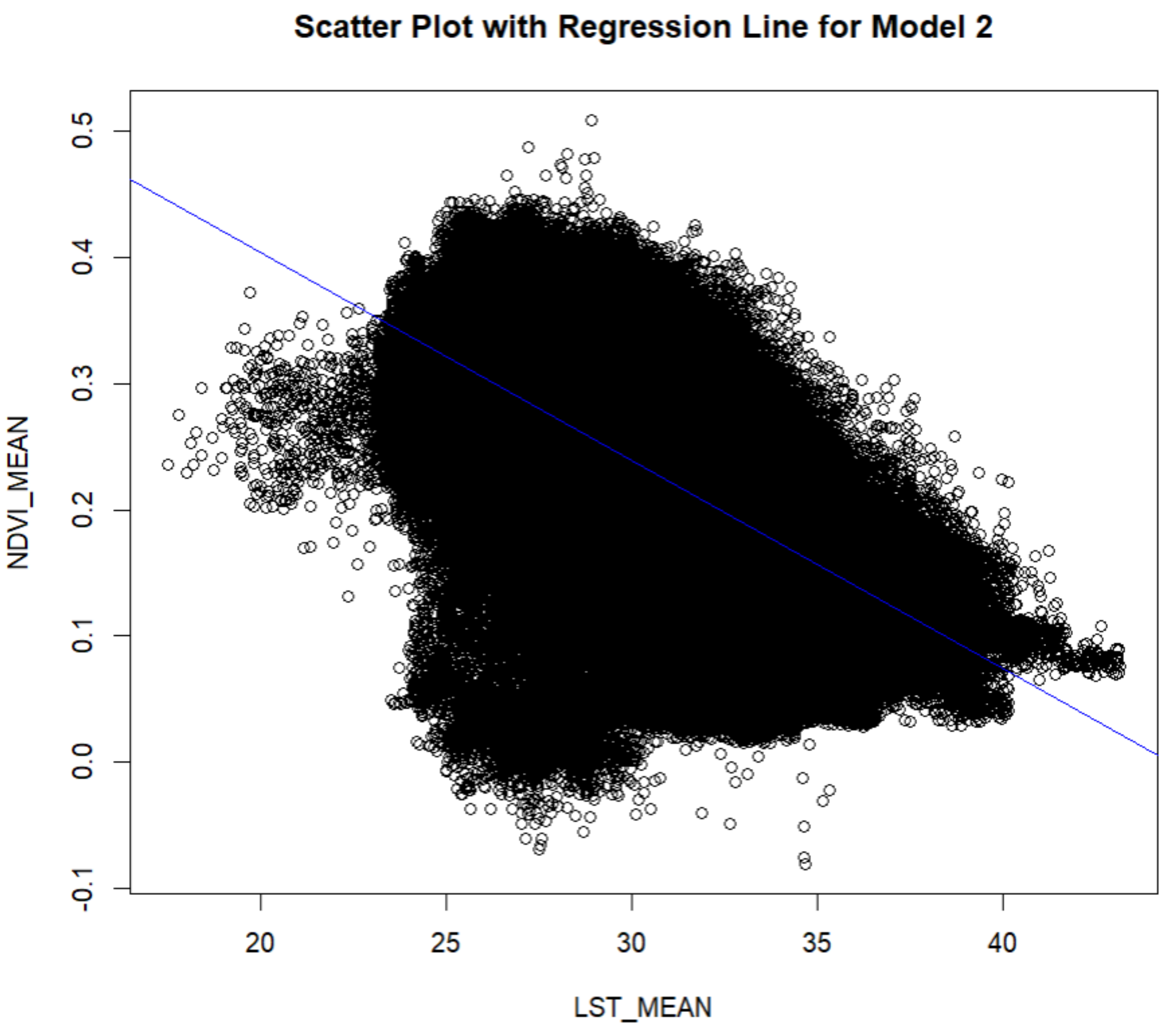

Figure 7 Scatter plot MODEL 2

This scatter plot, together with the regression line, provides insight into the relationship between vegetation and land surface temperature across Mopa and its surroudings. The graph shows two major metrics: NDVI_MEAN (average amount of green vegetation) and LST_MEAN (average concentration of land surface temperature).

The data points themselves show a negative connection. This indicates that when the NDVI_MEAN values rise, suggesting places with more lush vegetation, the LST_MEAN values fall, showing a decrease in overall temperature. This graphically confirms the assumption that locations with extensive vegetation cover usually have less land surface temperature, and vice versa.

The data points are spread around the regression line, demonstrating that the LST_MEAN alone cannot explain all of the variation in NDVI. The model only explains 35.06% of the variation in NDVI (see R-squared in the model output).

This shows that, while the negative association exists, it is not particularly strong. In other words, while there is a general trend of greater vegetation indicating less temperature, there are certainly exceptions, as well as other variables impacting both.

Overall, the scatter plot verifies the model's findings of a negative relationship between LST_MEAN and NDVI_MEAN. As the average LST rises, the average NDVI falls, which supports the hypothesis that higher temperatures are associated with less vegetation cover.

Table 3 Regression MODEL 2

	MODEL 2
CONSTANT	7.339e-01 *** (8.636e-04)
LST	-1.649e-02 *** (2.935e-05)
R SQUARE	0.3506
ADJUSTED R SQUARE	0.3506
OBSERVATIONS	584568

The linear regression model described here attempts to explain the link between the mean Normalized Difference Vegetation Index (NDVI_MEAN) and the mean Land Surface Temperature (LST_MEAN). The model's performance is evaluated using a variety of statistical indicators and coefficients.

First, the intercept term in the model is 0.7349, which means that when the mean LST is zero, the anticipated mean NDVI is 0.7349. However, because LST is unlikely to be zero in practical situations, the intercept is mostly employed mathematically within the model.

The coefficient for LST_MEAN is -0.01649, indicating a negative correlation between LST and NDVI. Specifically, for every unit rise in LST_MEAN, we expect a 0.01649 unit decrease in NDVI_MEAN, while other variables remain constant.

The p-values for both coefficients are less than 2e-16, providing strong evidence against the null hypothesis that there is no link between LST_MEAN and NDVI_MEAN.

Overall, this model indicates a significant negative relationship between land surface temperature and vegetative health as evaluated by NDVI, with LST accounting for approximately 35% of the variation in NDVI.

6.2.3 <u>Model 3 - NDBI vs. Population</u>

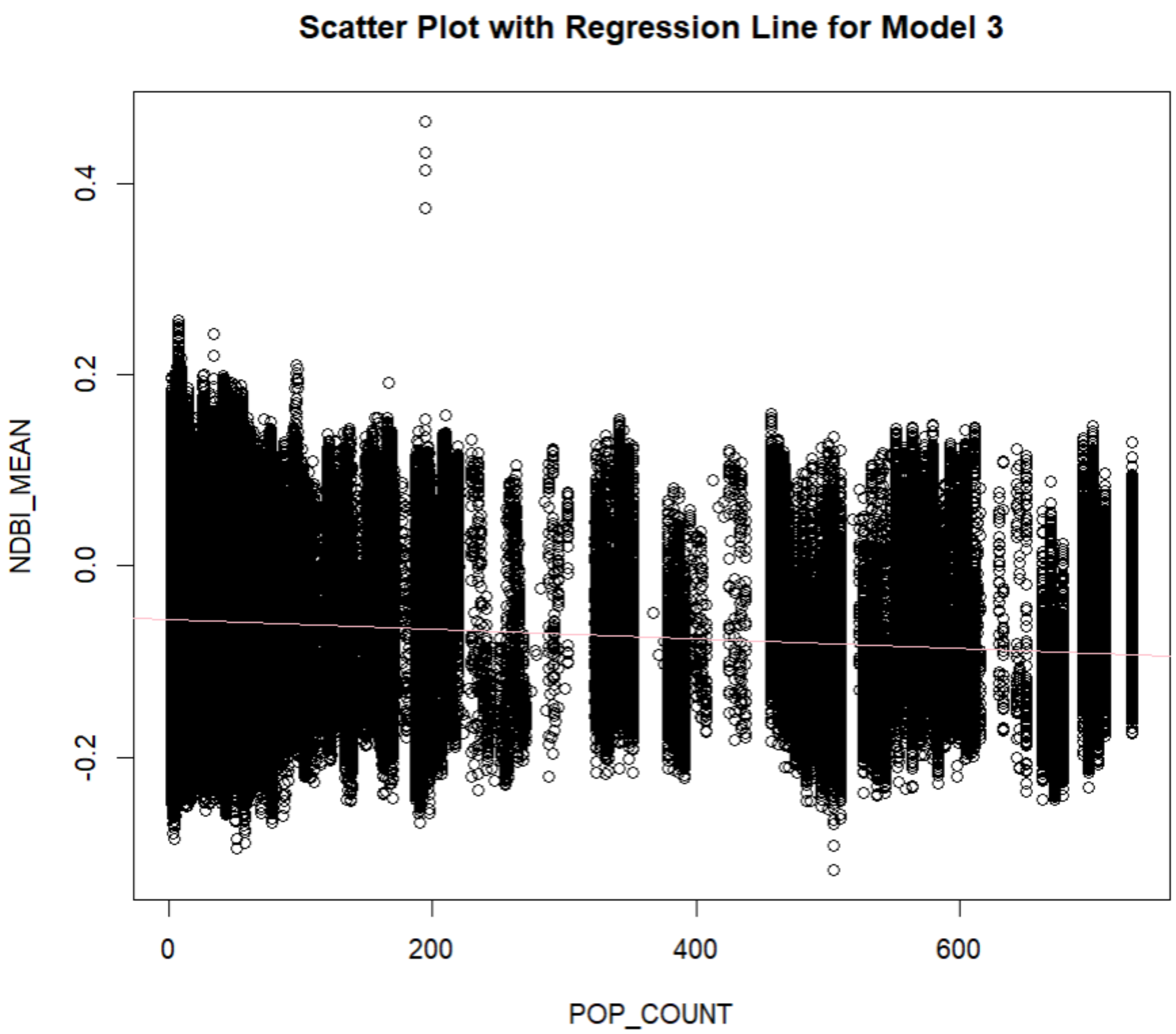

Figure 8 Scatter plot MODEL 3

The graph is a scatter plot with a regression line showing the link between the NDBI_MEAN (Normalized Difference Built-up Index Mean) on the y-axis and the POP_COUNT (Population Count) on the x-axis. The NDBI measures urbanization or built-up areas, with higher values indicating more developed or urban zones.

The scatter figure reveals a large concentration of data points at lower POP_COUNT values, with NDBI_MEAN values ranging from approximately -0.2 to 0.4. As the POP_COUNT rises, the data points get sparser, and the NDBI_MEAN values tend to fall, with some outliers exhibiting larger values.

The regression line, showing the best-fit linear connection between the two variables, has a slightly negative slope. This shows that, on average, as the POP_COUNT rises, the NDBI_MEAN falls slightly, implying an inverse link between population count and urbanization levels.

However, it is crucial to note that the scatter plot contains a significant degree of variation and outliers, implying that the relationship between population count and urbanization is not exactly linear or continuous across all data points. Other parameters that were not included in this simple linear regression model may have an impact on the NDBI_MEAN values.

Moreover, a few data points with extremely high POP_COUNT values (above 800) appear to be outliers or possible variations, which may have a disproportionate impact on the regression line.

Overall, the scatter plot and regression line provide a visual picture of the relationship between population counts and levels of urbanization.

Table 4 Regression MODEL 3

	MODEL 3
CONSTANT	-5.678e-02 *** (1.447e-04)
POPULATION	-3.708e-05 *** (7.012e-07)
R SQUARE	0.00513
ADJUSTED R SQUARE	0.005128
OBSERVATIONS	542328

The linear regression model analyzes the relationship between the mean Normalized Difference Built-up Index (NDBI_MEAN), a measure of urbanization, and the population count (POP_COUNT) in a given area. The model results indicate that there is a statistically significant negative association between these two variables.

The coefficient for POP_COUNT (-3.708e-05) shows that for every unit increase in population count, the mean built-up index falls by a little amount (0.0000037) on average. This negative correlation may appear contradictory, given that higher population numbers are typically connected with increased urbanization and built-up areas. However, it is important to note that the model only accounts for a small amount of the variability in the built-up index (roughly 0.513%), as evidenced by the low R-squared value.

The negative coefficient could be attributed to a variety of factors, including the presence of rural settlements with higher population densities but lower levels of urbanization, as well as the existence of urban areas with declining populations as a result of migration or urban renewal projects. It is also possible that the link between population and built-up index is nonlinear or impacted by variables not included in this simple linear model.

While the model is statistically significant overall, as evidenced by the F-statistic and p-value, the low R-squared value indicates that population count alone is not a good predictor of the built-up index. Other factors, such as economic development, land use rules, and geographical features, may be more important in determining the extent of urbanization in a specific location. As a result, the interpretation of this model should be approached with caution, and additional analysis integrating additional important variables may be required to better understand the drivers of urbanization and built-up areas.

6.3 Objective 2

Objective 2 is To examine the associations between urbanization (measured by NDBI), vegetation health (NDVI), land surface temperature (LST), and population growth, employing panel regression models and controlling for village-specific factors.

Objective seeks to investigate the complex relationships between urbanization, environmental conditions, and population dynamics in Mopa and its adjacent villages. This objective addresses for the longitudinal aspect of the investigation by using a panel fixed effects regression model, which controls for unobserved village-specific variables that may influence these associations.

The dependent variable in the panel regression approach is the Normalized Difference Built-up Index (NDBI), which represents the level of urbanization in each village. The primary independent variables are the Normalized Difference Vegetation Index (NDVI), which measures vegetation health, Land Surface Temperature (LST), and Population Count data.

The purpose of this panel fixed effects model is to quantify within-village variations in NDBI in relation to changes in NDVI, LST, and population increase across the research period. The fixed effects specification separates the effects of these environmental and demographic factors on urbanization levels while controlling for time-varying village-specific factors that could bias the results.

The purpose uses advanced regression modeling to provide insights into the trade-offs and interconnections between urban growth, vegetation cover, land surface temperature, and population dynamics in the study area.

6.3.1 model 4 NDBI vs NDVI, LST , POPULATION

Table 5 Regression MODEL 4

	MODEL 4
NDVI	-8.4108e-01 *** (1.3084e-03)
LST	3.0332e-03 *** (2.0940e-05)
POPULATION	-3.0255e-08 (7.3185e-07)
R SQUARE	0.49952
ADJUSTED R SQUARE	0.44391
OBSERVATIONS	488094

This model employs the plm function in R to perform a panel fixed effects regression analysis. It investigates how changes in vegetation cover (NDVI_MEAN), land surface temperature

(LST_MEAN), and population count (POP_COUNT) within villages over time (likely 2013-2023 based on previous models) relate to changes in built-up area (NDBI_MEAN).

Within Effects: The model="within" argument specifies a fixed effects model focusing on the within-village effects. This means the model isolates how changes in the independent variables (NDVI_MEAN, LST_MEAN, POP_COUNT) within a particular village over time are associated with changes in built-up area (NDBI_MEAN) within that same village. Unobserved village-specific characteristics that might influence these variables are controlled for in this approach.

Coefficients:

NDVI_MEAN: The negative and highly significant coefficient (-0.841) indicates that a decrease in vegetation cover (NDVI_MEAN) within a village over time is associated with an increase in built-up area (NDBI_MEAN) within that village. This supports the notion that development projects can lead to deforestation or conversion of natural landscapes.

LST_MEAN: The positive and highly significant coefficient (0.003) suggests that a rise in land surface temperature (LST_MEAN) within a village over time is linked to an increase in built-up area (NDBI_MEAN) within that village. This finding aligns with the concept of urban heat islands, where human development activities contribute to higher temperatures in urbanized areas.

POP_COUNT: The coefficient for population count (-3.0255e-08) is very small and statistically insignificant (p-value = 0.967). This implies that changes in population within villages over this time period are not significantly related to changes in built-up area after controlling for the effects of vegetation cover, land surface temperature, and village-specific factors.

R-squared:

The R-squared value (0.4995) is moderately high, indicating that the model explains nearly 50% of the variation in changes in built-up area (NDBI_MEAN) within villages based on the changes in vegetation cover, land surface temperature, and population count within those villages over time.

The adjusted R-squared value (0.4439) accounts for the number of explanatory variables in the model and is also considered moderately high.

Overall Interpretation

This panel fixed effects model provides valuable insights into the interplay between development, environmental changes, and population dynamics within Mopa villages. The results show that changes in vegetation cover and land surface temperature within villages are significantly associated with changes in built-up area, suggesting that development projects can have environmental consequences. Interestingly, population growth within villages doesn't seem to be a significant driver of built-up area changes after considering the other factors in the model. It's important to remember that these are within-effects, capturing the relationships within villages over time. The model doesn't necessarily tell you about the differences between villages.

CHAPTER 7

CONCLUSION

The overall study explored the intricate connections between urbanization, environmental changes, and population growth in Mopa and nearby villages. Using satellite imagery and advanced statistical models, the complex relationships in study helps to provide insights for sustainable development planning in the region.

The study analyzed satellite data to create maps showing urban growth, vegetation cover, and land surface temperature patterns over time. These maps revealed how urbanization led to loss of greenery and increased heat in urban areas, highlighting the environmental impacts of development.

Through statistical models like regression analysis, it is found that as urbanization increased (measured by built-up areas), vegetation cover decreased, and land surface temperatures rose. This inverse relationship between urban growth and environmental factors like vegetation and temperature was significant.

Interestingly, while vegetation and temperature changes were linked to urbanization within villages, population growth alone did not strongly predict urban expansion after considering other factors. This finding suggests that urbanization is driven by multiple factors beyond just population increase.

The overall research emphasizes the need for balanced development strategies that prioritize environmental conservation alongside urban growth. By understanding the trade-offs between urbanization, vegetation, and temperature, policymakers can mitigate negative impacts and promote greener, more livable communities.

Combining satellite data and statistical modeling provided a comprehensive understanding of the complex dynamics shaping the landscape, enabling data-driven decision-making for sustainable urban planning.

While the study made significant contributions, future research could explore socioeconomic drivers of urbanization, additional environmental variables, and alternative development scenarios for a deeper understanding of sustainable urban growth in the region and beyond.

Overall, dissertation represents a crucial step in unraveling the multifaceted relationships between urbanization, environmental changes, and population dynamics, paving the way for informed decision-making and the creation of resilient, eco-friendly communities in Mopa and neighboring villages.

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