ASSESSMENT OF ECOSYSTEM HEALTH OF KOCHI WITH URBANISATION AND CHNAGING CLIMATIC PATTERNS OF KOCHI

by

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(2018-20-007)

THESIS

Submitted in partial fulfilment of the requirement for the degree of B.Sc. – M.Sc. (Integrated) Climate Change Adaptation

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DECLARATION

I, Abhijith V S (2018–20–007) hereby declare that this thesis entitled **"Assessment of Ecosystem Health with urbanization and changing climatic patterns of Kochi"** is a Bonafede record of research work done by me during the course of research and the thesis has not previously formed the basis for the award to me of any degree, diploma, associateship, fellowship, or other similar title, of any other University or Society.

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Abhijith V S

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ABBREVIATIONS

1. BT – Brightness Temperature
2. CA-ANN – Cellular Automata Artificial Neural Network
3. CAP – Constructed Area Proportion
4. DTR – Diurnal Temperature Range
5. ED – Edge Density
6. EH – Ecosystem Health
7. EIA – Environmental Impact Assessment
8. ESH – Ecosystem Health
9. ESV – Ecosystem Service Value
10. FRAC-AM – Area Weighed Mean Fractal Dimension Index
11. GDP – Gross Domestic Product
12. GIS – Geographical Information System
13. LST – Land Surface Temperature
14. MLP – Multi-Layer Perceptron
15. MOAT – Morris One-at-a-Time Method
16. NGO – Non-Governmental Organisation
17. NDVI – Normalised Difference Vegetation Index

18. OLI – Operational Land Imager
19. PD – Patch Density
20. PH – Physical Health
21. POPD – Population Density
22. RBF – Radial Basis Function
23. RF – Random Forest
24. RSS – Random Subspace Selection
25. SRTM – Shuttle Radar Topography Mission
26. SVM – Support Vector Machine
27. TIRS – Thermal Infrared Sensor
28. TOA – Top of Atmospheric Spectral Radiance
29. UHIs – Urban Heat Islands
30. VORS – Vigour-Organization-Resilience-Ecosystem Services

INTRODUCTION

The ability of ecosystems to organise themselves, function independently, and withstand external perturbations is reflected by the indicator of ecosystem health (EH), which is comprehensive in evaluating the sustainability and stability of ecosystems (Costanza, 1992; Rapport, Costanza, & McMichael, 1998). The urbanisation of the world is accelerating, notably in Sub-Saharan Africa and Asia. Despite this, most of it occurs without urban planning, and even those municipalities that try to do so typically fail to do it well or to address the demands of the majority. Cities as a result are crowded, unclean, unfriendly to the environment, and disorganised, endangering the health and happiness of their inhabitants. But there is a potential for that to change. The world will construct as much infrastructure and sustainable urban development during the next 20 years as it has ever done (Artuso. M., *et al.,*2022)

India's urban agglomerations are the second largest in the world in terms of population size, trailing only China. Since independence, the urban population of India has steadily grown, with an urban growth rate that is higher than the average population growth rate (1764%). The main causes of urban development in India were industrialization, planned development, and globalisation (Sulochana, Shekhar.,2021).

The city of Kochi, which is situated in the Indian coastal state of Kerala, is rapidly urbanising, and it must deal with the difficulties brought on by shifting climatic patterns. Kochi, one of the region's major port cities and economic hubs, has experienced rapid urbanisation and population growth in recent years. Numerous environmental problems arise as a result of the relentless urban sprawl, which places great stress on the ecosystems in the area. Additionally, the city's susceptibility to environmental stressors is made worse by the constantly shifting climate patterns caused by global warming and climate change. An extensive evaluation of the ecosystem health in Kochi is necessary due to the interconnection of urbanisation and climate change, which affects not only natural habitats and biodiversity but also human livelihoods. By 2036, urbanization is predicted to account for 73 percent of overall population growth (MoHFW, 2019)

Land urbanisation is a process that transforms agricultural land into land used for building in cities and transforms rural communal land into state-owned land. Investigating how land urbanisation affects ecosystem health is crucial to halting ecological degradation and achieving regional sustainability. According to many (Cobbinah *et al.,* 2015; Elmqvist *et al.,* 2021; Hölscher & Frantzeskaki, 2021), urbanisation is a phenomenon and a process that focuses on both the act of increasing population concentration in cities caused by natural increase and in-migration and the spatial morphological changes that characterise such population growth. In this context, urbanisation is frequently categorised as rapid, where the rate of population concentration exceeds the capacity of cities for planning and management; and abnormal, where the process does not result in socioeconomic growth for city residents and where the anticipated timing and conditions of progress associated with urbanisation do not occur, impeding the ability of city managers to adequately plan for the change (World Cities Report, 2022).

Lack of public space development is one of the main problems with commercial development in Kerala's city cores in the context of rapid urbanisation (Abhilash.R.S., Ar. Nirmal., 2015). Numerous factors, such as quick population growth, rural-to-urban migration, and more plentiful economic opportunities, are driving Kochi's urbanisation. The development of infrastructure, residential areas, and industries was required by the city's population growth, which led to significant habitat loss and fragmentation. Natural landscapes that are turned into concrete jungles have their ecosystems upset, their wildlife is displaced, and their precious resources are depleted. Additionally, air pollution worsens the urban environment due to the growth of transportation networks and vehicle emissions. Protecting the delicate ecosystems and ensuring a sustainable urban development trajectory for Kochi depend on addressing the many problems that come with urbanisation.

According to reports, extensive urbanisation along the coast has a direct impact on the physical and biogeochemical makeup of near-shore waters through hydro-meteorological forcing, leading to irregularities such coastal warming (Bhattacharjee, S., Lekshmi, K. & Bharti, R., 2023). Like many coastal cities around the world, Kochi is especially vulnerable to the effects of varying climatic patterns. Several climate-related changes are brought about in the area as a result of the increase in global temperatures caused by greenhouse gas emissions. Coastal ecosystems, such as mangroves and wetlands, which are essential for preventing storm surges and providing habitat for a wide variety of species, are seriously threatened by rising sea levels. The altered precipitation patterns could lead to an increase in extreme weather occurrences like flooding and heavy rain, which could have detrimental effects on both terrestrial and aquatic ecosystems. The sustainability and resilience of Kochi's ecosystems and communities depend on an understanding of and response to these climate-related challenges.

Identification and monitoring of specific indicators that reflect the overall health and functionality of the environment are necessary for evaluating the ecosystems' health. Biodiversity levels, which reflect the variety and abundance of plant and animal species in the area, are among these indicators. Given that each species makes a distinct contribution to ecological functions and processes, species diversity is crucial for the resilience and stability of ecosystems. Additionally, it is important to monitor water quality because bodies of water are crucial resources for both people and wildlife. Aquatic life and human health may suffer from the rising pollution from industrial effluents, sewage, and agricultural runoff. The same is true for measuring the amount of air pollution brought on by industrial operations, vehicle emissions, and urban activities. Air pollution poses a serious threat to ecosystems as well as human health. Researchers and decision-makers can learn more about the current condition of ecosystem health and the potential effects of urbanisation and climate change by measuring and analysing these indicators.

In Kochi, one of the most serious effects of urbanisation and climate change is biodiversity loss. Urbanisation is encroaching on natural habitats, fragmenting ecosystems, and preventing wildlife populations from migrating freely. As natural areas get smaller, species compete more fiercely for resources, which results in declining population sizes and even local extinctions. A further effect of ecosystem change on biodiversity is the disruption of vital ecological relationships like predator-prey interactions and pollination networks. Ecosystem stability is significantly impacted by biodiversity loss because it reduces ecosystems' capacity to respond to and adapt to changing environmental conditions. As a result, preserving Kochi's biodiversity is essential for ensuring the sustainability and adaptability of its ecosystems. For instance, the mangrove forests that offer vital services to both human populations and the ecosystems they support are facing deforestation and degradation over the past 50 years and 20–35% of the global mangrove extent has been lost. Mangroves have experienced a dramatic loss in the past few decades as a result of inadequate representation of the value of the mangroves in decision-making (Joshy, S., Shukla, J., Dhyani, S., 2022).

The combined effects of urbanisation and climate change pose serious problems for water bodies in and around Kochi. One of Kerala's largest lakes and a crucial ecosystem in the area, Vembanad Lake, is being degraded by pollution, sedimentation, and encroachments. Over the past two decades, unregulated sand mining has caused the riverbed in the storage zone to decrease at a rate of 7 to 15 cm each year. As a result, the physical and biological habitats of these river systems suffer serious harm (Padmalal, D., Maya, K., Sreebha, S. *et al.,*2008). In addition to harming aquatic life and posing health risks to people who depend on these water resources, industrial discharge, untreated sewage, and agricultural runoff all contribute to the deterioration of water quality. Like how emissions from vehicles, businesses, and construction projects have a negative impact on air quality. Residents of the city may experience respiratory issues and other health problems as a result of fine particulate matter and air pollutants. Urgent action must be taken to address the deteriorating water and air quality through strict pollution control measures and sustainable urban planning.

Designing successful adaptation strategies necessitates a thorough understanding of the Kochi ecosystems' susceptibility to urbanisation and shifting climatic patterns. Vulnerability assessments help to set priorities for conservation and restoration efforts by identifying areas most at risk of ecological degradation. Scales and vulnerability assessments are closely related, both in terms of technical application and conceptualization, which calls for further scientific advancement (Fekete, A., Damm, M. & Birkmann, J.,2009). These evaluations consider both anthropogenic and natural factors, such as land use patterns, pollution levels, and the resilience of ecosystems to environmental stressors. Natural factors taken into consideration include habitat type and biodiversity. With this knowledge, stakeholders can create tailored adaptation strategies to safeguard delicate ecosystems and strengthen their resistance to future changes. To achieve a harmonious balance between urban development and ecological preservation, such measures may include habitat restoration, green infrastructure development, and sustainable urban planning.

A comprehensive strategy is needed to reduce the negative effects of urbanisation and shifting climatic patterns on Kochi's ecosystems. Maintaining ecological connectivity and boosting biodiversity can be achieved by implementing sustainable urban planning strategies that give priority to green spaces, cut down on urban sprawl, and safeguard natural habitats. The city can lessen the impact of the urban heat island effect and enhance air quality by incorporating green infrastructure into the urban landscape, such as parks, green roofs, and urban forests. In addition, implementing smart transportation strategies, encouraging the use of electric vehicles, and promoting public transportation can help lower emissions and lessen air pollution.

LST is a crucial characteristic that affects the Earth's surface's radiative energy budget and is crucial in determining turbulent heat fluxes and outgoing longwave radiation at the land-atmosphere interface. It is used as an input in land-surface models for a variety of purposes, including monitoring droughts, estimating soil moisture, and estimating evapotranspiration.

LST is a significant component of the climate system that influences how energy is divided between latent and perceptible heat fluxes and acts as a trend indicator for surface warming brought on by climate change (Glynn, *et al.,*2019). Several Earth science research projects have made use of LST data, including those that track the consequences of global warming, measure the urban heat island effect, and comprehend the spatial dynamics of heatwaves. It can be observed that the lowest surface temperature is seen in green areas, especially parks with lots of trees, which also have the greatest mean normalised difference vegetation index (NDVI) values of roughly 0.5. The highest surface temperature, however, is found in built-up or sparse areas, where it is 36.1 °C (Sarah, *et al.,*2017). A decline in plant cover and an increase in urban built-up area are linked to higher surface temperatures, the study finds, establishing a clear negative association between surface vegetation and surface temperature.

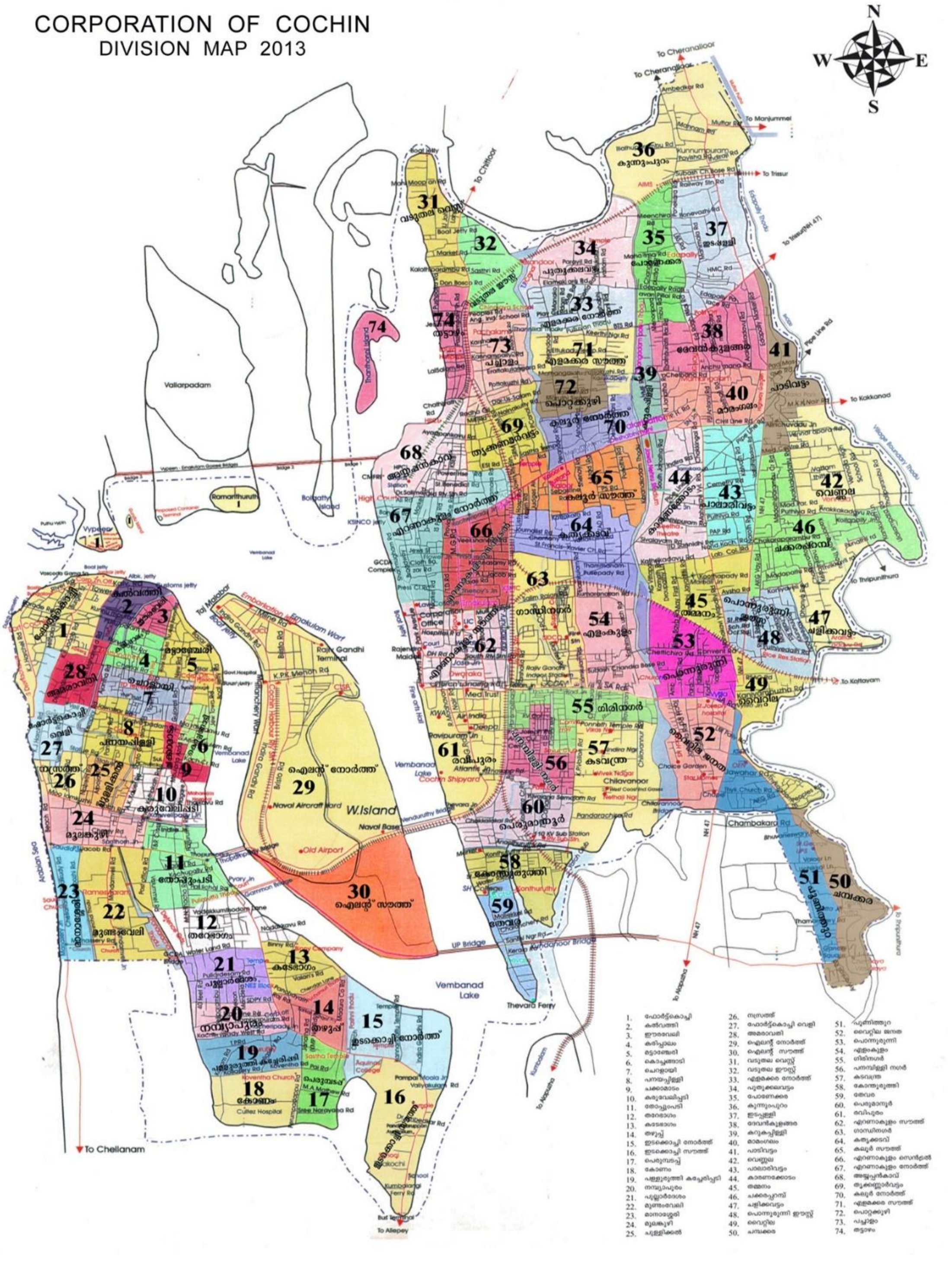
In order to maintain the health of Kochi's aquatic ecosystems, water pollution must be addressed. To improve water quality, it is crucial to put in place effective sewage treatment systems and reduce industrial discharge into waterways. Additionally, reducing the use of harmful chemicals and promoting sustainable agricultural methods can lessen agricultural runoff and its negative effects on water resources. Wetlands and mangroves can be restored and conserved to serve as vital habitat for a variety of species as well as natural barriers against storm surges and coastal erosion. Various aspects of freshwater fish reproduction, such as spawning timing, pattern, and habitats, as well as the endocrine (HPG) axis, sexual maturation, gamete generation, sex differentiation, embryonic development, and hatching, have been reported to be impacted by changing climatic trends. Acute temperature variations that can upset the endocrine system and hamper reproduction are the main causes of phenological shifts in freshwater fish reproduction. Freshwater fish adjust their distribution range, timing of migration, and spawning behaviour in response to change climatic patterns (Manish, *et al.,*2020).

Working together with different stakeholders, such as governmental organisations, non-profit organisations, researchers, and local communities, is necessary to maintain and restore the health of Kochi's ecosystem. Governmental organisations are essential in establishing and upholding laws that support sustainable growth and the preservation of natural resources. Given the long-term effects on the environment and human well-being, local authorities should give priority to green spaces and sustainable infrastructure projects. NGOs and research organisations can contribute by conducting studies to pinpoint vulnerable areas and offering their expertise in creating conservation and adaptation plans. The effective implementation of these strategies depends on active community engagement. Solutions can be more efficient and inclusive if local communities are involved in decision-making processes, environmental issues are brought to light, and sustainable practises are promoted.

Kochi must concentrate on adaptation tactics in the face of shifting climatic patterns. Ecosystem-based approaches can help ecosystems become more resilient to stressors caused by the climate. For example, by restoring damaged coastal ecosystems like mangroves and coral reefs, shorelines can be kept from eroding and vital habitat for marine biodiversity can be provided. Farmers can adapt to shifting rainfall patterns by implementing climate-resilient agricultural practises like crop diversification and water conservation. A culture of environmental stewardship can also be fostered by educating local communities about the effects of climate change and promoting sustainable practises, encouraging both individual and group efforts to conserve ecosystems.

It was discovered that over the years 2009 to 2011 the Cochin estuary's depth has decreased. The temperature of the water was rising. The estuary's salinity was oligo-mesohaline in nature. The relationship between conductivity and river discharge was highly positive. Due to increased primary production in the surface layers, there was a higher oxygen content throughout the post-monsoon period. The ecology was under stress, as evidenced by elevated CO_2 and an alkaline pH. High BOD readings have been linked to nutrient enrichment and organic contamination. Ammonia-N_2 concentrations on average rose. High silicate values in surface waters were caused by the monsoon's intense rainfall and enhanced surface runoff. The Cochin estuary had a nitrogen shortage, according to Redfield ratio study (Thasneem, T.A. *et al.,*2018).

The evaluation of Kochi's ecosystem's health considering urbanisation and shifting climatic patterns is a crucial first step in tackling the environmental issues the city is currently facing. Understanding the complex interactions between these phenomena is essential as urban areas continue to grow and the threat of climate change increases. Stakeholders can work together to develop adaptation strategies to support sustainable urban development and protect the city's delicate ecosystems by using a variety of indicators to assess ecosystem health, assessing the impacts on biodiversity, water, and air quality, and identifying vulnerabilities. To ensure the welfare and prosperity of Kochi's citizens while preserving the region's natural heritage for future generations, it is crucial to place a high priority on the health of its ecosystems.



Source: Kochi Municipal Corporation

Fig. 1: Ward map of Kochi

We can see global and regional changes in maximum and minimum temperatures as well as the diurnal temperature range (DTR) using data from monitoring stations all around the world. The average surface air temperature rose by about 0.5°C throughout the 20th century. This rise was significantly influenced by variations in the daily minimum temperatures. The decline in DTR in numerous regions, including the United States, was caused by rising cloud cover and falling insolation. Urbanised areas frequently showed a narrower DTR when compared to the nearby rural areas, demonstrating how urbanisation affects temperature patterns. (David R. Easterling *et al.,* 1997).

Kochi with its municipalities and corporations makes a great study area since it is a unique microcosm of the coastal ecology. Kochi is situated at the meeting point of the Arabian Sea and the Lakshadweep Sea. A range of varied landforms, such as mountains, woods, and wetlands, may be found in the city, which offer a variety of habitats for plants and animals. With over 3,000 types of plants and animals reported in the area, Kochi is home to a thriving biodiversity. A significant breeding habitat for whales, dolphins, and sea turtles is the city. Due to Kochi's status as a significant industrial and commercial hub, it faces numerous pollution-related risks. These dangers include pollution of the air, water, and land. Kochi is also a vulnerable city to the effects of climate change. Rising sea levels and more severe weather are already affecting the city. We can learn more about how to mitigate and adapt to the effects of climate change in other parts of the world by researching the effects of climate change in Kochi. With excellent transit connections, a steady supply of electricity, and several academic and research institutes, Kochi has a developed infrastructure. This makes it an accessible and convenient location to carry out environmental studies.

REVIEW OF LITERATURE

Assessing the health of urban ecosystems is a crucial step in ensuring their long-term sustainability and the well-being of the humans who depend on them. Urban ecosystems provide several important services to humans, such as air and water purification, carbon sequestration, and regulation of climate. These services are essential for human health and survival, and a healthy urban ecosystem is crucial for the long-term sustainability of urban areas.

However, urban ecosystems are also particularly vulnerable to the impacts of climate change, and the increasing pressure of urbanization can also have negative effects on their health. Assessment of ecosystem health in urban areas can help identify and address any changes in biodiversity, as well as the effects of changing weather patterns and the impacts of urbanization. This information is valuable for urban planners and managers, as it provides a basis for informed decision-making about the management and development of urban areas. By ensuring the health of urban ecosystems, we can support their continued ability to provide the resources and services necessary for human survival and well-being. Understanding the spatial distribution characteristics of ecosystem service value (ESV) and their underlying driving factors is critical for ecosystem service management (Luo *et al.,*2020). In the process of urbanization, due to human living and production activities, land use and cover has been changing, including conversion of ecological land into construction land, and conversion of forestland, grassland, and other land into agricultural land (MEA, 2005), which will directly lead to changes in the ESVs. Accelerated urbanization has changed land use patterns, leading to the deterioration of ecosystems. Assessments of ecosystem health (ESH) during the urbanization process are used to determine the reasons and mechanism for this, and to uncover negative factors and the results indicate that urbanization had a negative impact on ESH, of which the dominant factor was the proportion of construction land from 1990 to 2005 (Xiao,2020). Urbanization, along with economic development, population increase, and land use change, is the main path to social development. Nowadays, about 55% of the world's population lives in cities and the global urbanization rate is expected to reach 68% by 2050. Urban expansion can cause great changes in ecosystem structure and function. During the process of urbanization, the flow of material, energy, and information is influenced, and the structure and function of ecosystems are affected (Xiao,2020).

Land use and land cover classification is a critical process that involves the identification and mapping of different types of land use and land cover within a specific area. This information is vital for planning and managing land resources, monitoring changes in the environment, managing natural resources, and mitigating the effects of climate change. By understanding the distribution and extent of different land cover types, planners and policymakers can make informed decisions about the best use of land, such as identifying areas suitable for agriculture, forestry, urban development, or conservation. Additionally, land use and land cover classification help in monitoring changes in the environment, such as deforestation or urban sprawl, which can have a significant impact on natural resources, such as water, soil, and biodiversity. Finally, land use and land cover classification are crucial for studying and mitigating the effects of climate change, as changes in land use can have a significant impact on the global carbon cycle and regional climate patterns. Overall, land use and land cover classification are an essential tool for ensuring sustainable land management practices and protecting the environment.

1.1 Ecosystem Health Assessment

Ecosystem health assessment is the process of evaluating the overall condition and function of an ecosystem in order to determine its level of health or sustainability. It involves the measurement and analysis of a wide range of ecological factors, such as biodiversity, nutrient cycling, energy flow, and habitat quality, as well as the interactions between these factors. Toro and Iodice (2018) proposes a framework for assessing the health of ecosystems in urban areas, using the Metropolitan Area of Naples as a case study. The assessment considers three perspectives: vigour, organization, and resilience, and uses a system of indicators to classify the territory. The evaluation is carried out using Geographic Information System and Multi-Criteria Decision Analysis, resulting in a subdivision of the metropolitan area into different zones with varying degrees of risk and vulnerability. The overall objective of the paper is to provide an assessment of the urban health of the Metropolitan Area of Naples for improving its resilience. This study focuses on the Metropolitan Area of Naples in Italy, which is a densely populated urban area with over 3.5 million inhabitants.

The study area is vulnerable to climatic hazards due to its high concentration of population and economic activities, and improper urban development. Despite its problematic context, the Metropolitan Area of Naples has potential for development due to its rich cultural, environmental, and economic resources. Assessing the health of the environment in urban areas involves identifying potential issues, collecting data, analysing the data, engaging with stakeholders, developing solutions, implementing solutions, and monitoring and evaluating the impact of the solutions. The process starts with identifying environmental health issues such as air and water quality, noise pollution, access to green spaces, waste management, and climate change. Data collection involves monitoring and analysing the various environmental factors to determine the extent of the issues. Engaging with stakeholders, including residents, community groups, and government officials, is essential to ensure that the assessment is comprehensive and inclusive. Based on the data collected and analysis conducted, solutions can be developed to address the environmental health issues in the area, which may include developing policies and regulations, reducing noise pollution, increasing access to green spaces, improving waste management practices, and reducing the impact of climate change. Once solutions have been developed, they need to be implemented and monitored and evaluated to ensure their effectiveness and sustainability. Ecosystem health assessment that emphasizes the importance of identifying and addressing the underlying causes of ecosystem stress and degradation and a holistic, ecosystem-based approach to management is necessary to promote long-term ecosystem health (Cormier and Slade,1998). Ecosystem health assessment can help to quantify the value of ecosystem services and promote the sustainable use of natural resources (Costanza *et al.,* 1997).

Achieving sustainable growth and supplying enough resources depend on maintaining ecosystem health at a high level. Monitoring ecosystem health and analysing the effects of urbanisation on ecosystems are crucial for managers and decision-makers when it comes to land use planning and the formulation of scientific eco-environmental policies. Despite the large number of research that have been done, it is still difficult to quantify the linkages between urbanisation and ESH because of how complex the ecosystem is. Ecologists have used a variety of methodologies, including the vigour, organisation, and resilience framework, to evaluate ESH. Three characteristics—vigour, organisation, and resilience—can be used to measure an ecosystem's health. Vigour indicates the functioning of ecosystems as represented by their metabolism or primary productivity, whereas Organization represents the number and variety of linkages between system components, which are often quantified by the landscape pattern index. Resilience is the capacity of a system to maintain its structure and function in the face of stress, and it is often assessed using the kind of land use.

A way of evaluating ESH that considers both natural ecosystems and human well-being is provided by an ESH theory that integrates vigour, organisation, resilience, and ecosystem services. Using these four factors, this technique gives thorough measurement and spatialization of ESH levels. Moreover, the strategy incorporates socioeconomic data, landscape patterns, and changes in land use. This approach is used in certain research regarding the evaluation of regional ecosystem health. Urbanization levels can be investigated from several respects: (1) population growth, which is the main feature of the development of a modern city; (2) economic development, which is the main means of urban development; (3) the expansion of constructed land, which links directly to population growth and economic development and (4) living standards improvement, which is the result of urbanization. Ecosystem health assessment as a tool for promoting sustainable ecosystem management and ecosystem health assessment can help to identify underlying causes of ecosystem stress and degradation, and can inform management decisions aimed at improving ecosystem health (Slade and Cormier,1995). Ecosystem health assessment can help to inform adaptive management strategies and promote resilience in the face of environmental change (Biggs *et al.,*2012). Ecosystem health assessment can help to improve the effectiveness of EIA by providing a more holistic and integrated understanding of environmental impacts and their potential long-term consequences (Robinson *et al.,*2015). Ecosystem health assessment can also help to identify key stressors and inform management decisions aimed at improving water quality and ecosystem health (King *et al.,* 2018).

1.2 Ecosystem Health Assessment in India

The concept of ecosystem health was first mooted by Aldo Leopold in 1941. He defined that ecosystem health can be understood as a management concept that contributes to solve environmental problems. Rapport *et al.,* popularized the word "ecosystem health." They characterized it as a form of biological system dependability and maintainability, which has the capacity for keeping up its organisational structure as well as natural regulating and recuperation capacity after resilience. In a study conducted in the Murshidabad district of West Bengal (Das *et al.,*2020), India is home to a floodplain wetland system consisting of natural wetlands, oxbow lakes, and human-made ponds. Anthropogenic activities such as agricultural expansion, urbanization, and industrialization have put immense pressure on this ecosystem. The Pressure-State-Response (PSR) model was used to assess the health of the wetland ecosystem by analysing the impact of these anthropogenic pressures on the state and response of the ecosystem. Data on water quality, land use, and land cover were collected, and the results showed a significant decline in the state of the wetland ecosystem. Reduced water quality, loss of vegetation cover, and changes in land use were identified as the primary indicators of this decline. Several responses by the ecosystem to these pressures were also identified, including changes in hydrology, soil erosion, and reduced biodiversity.

The Ganga River system is facing significant environmental degradation, including pollution, habitat loss, and biodiversity loss for that a holistic, ecosystem-based approach to managing the river system to promote its long-term health must be taken. The ecosystem health of a semi-arid region in India was found to be facing significant environmental stressors such as land degradation, water scarcity, and declining biodiversity and sustainable land management practices must be promoted and conservation efforts in order to improve ecosystem health (Rajeevan *et al.,* 2018). The ecosystem health of the Himalayan ecosystem in India is facing a range of environmental stressors such as deforestation, land degradation, and climate change (Dhiman *et al.,* 2018). Like these it can also be seen that Western Ghats and the wetlands of India are also facing significant environmental stressors such as deforestation, land degradation, habitat loss, pollution and habitat fragmentation (Singh *et al.,*2019 & 2021).

1.3 Land Use and Land Cover

Land use could also cause massive changes in ESH largely, and many studies have discussed the influence of the relationship between land use changes and ESH (Cui,2019). First, there is a need to examine the clustering patterns between ESH and urbanization, especially at the local scale. Spatial correlations are commonly found between ESH and their drivers (Including urbanization), leading to biases in the results obtained by ordinary least squares (OLS) and geographically weighted regression. Therefore, other statistical techniques dealing with spatial autocorrelation must be employed. Second, previous studies have focused on the regional scale, with administrative districts as the usual unit of spatial analysis. Additionally, remote sensing images are also instrumental in assessing and investigating ESH across space and time at temporal and spatial scales in an area. The urbanisation can be measured using 3 indicators like Gross Domestic Product (GDP), Constructed Area Proportion (CAP), and Population Density (POPD). With the rapid development of urbanization, human activities including industrial emissions, waste, transportation, chemical fertilizers, and pesticides have changed the physical, chemical, and biological properties of urban soil, which leads to the sharp decline of urban soil quality and the typical heavy concentrated, heterogeneous, and cumulative pollution. Urban soil closely contacts dense urban population and affects not only life health and food safety through food chain but also the quality of urban environment through water and air. Land use and land cover change in tropical regions can have negative impacts on ecosystem services such as water resources, carbon storage, and biodiversity and the impacts can vary depending on the type and intensity of land use change, as well as the characteristics of the specific ecosystem (Law and Ling, 2018). The conversion of forests to other land uses has led to significant losses in ecosystem services, particularly those related to water regulation and carbon storage (Lovato *et al.,*2020). The land use and land cover change in South Asia has had significant negative impacts on biodiversity, particularly through habitat loss and fragmentation and these impacts are driven by a range of factors, including deforestation, agricultural expansion, urbanization, and infrastructure development (Singh *et al.,* 2021)

Ecosystem health refers to the ability to self-organization, self-maintenance, and recovery to stress in temporal scale, and maintaining healthy ecosystems is fundamental to guarantee the achievement of sustainable development of metropolitan regions, as healthy ecosystems can provide material basis and ecological services for human survival. As a huge and complex system, ecosystem is a network of multiple interactive relationships, and it is always assessed through establishing evaluation models. Different models can give different views in assessing ecosystem health, and a great quantity of evaluation factors which can be conducted at different scales should be focused. Nevertheless, many frameworks, including subsystem model, PSR (Pressure-State-Response) model, natural-economic-social model etc., have been used to establish evaluation factors of the ecosystem from aspects of social, economic, and human beings, ignoring the importance of land use/land cover change and its related transformation of landscape patterns, which not only affects ecosystem provisioning to meet the basic demands of consumption by society, but also impairs the buffering capacity of ecosystem. Under such circumstances, assessing and analysing ecosystem health from directions of land use/cover change and landscape pattern should provide deeper spatial insights into the dynamics and ecological consequences of ecosystem health development. The mechanism of ecosystem operation is complicated and can be influenced by environmental and human factors. Assessment of ecosystem health was based on mathematical statistics or empirical equations to express the temporal variation in a "top-down" analysis process, which ignored the spatial and temporal differences in ecosystem change and evolution. With the development of remote sensing technology, which provide critical data source, the geographical information system (GIS) spatial analysis tools have been widely used to monitor ecosystem health in metropolitan regions and the combination method uses a "bottom-up" simulation process, which can be integrated with other models. Considering the comprehensive health status and the detailed factors of ecosystems in metropolitan region, the general framework of ecosystem health assessment integrating the two aspects (top-down) needs to be established (Xiao *et al.,*2018).

The weights assigned to these indicators of VORS model have a determining effect on the assessment results. Since assessing ecosystem health involves humans making subjective judgments that should consider human needs of ecosystem functional services, using subjective methods to determine the weights to be assigned to the indicators is one way of highlighting the relative importance of the different indicators. This is both scientifically reasonable and a widely accepted practice in EHA (Wang *et al.,*2020).

1.4 Impact of LULC on Ecosystem Health

Urbanization is regarded as one of the major environmental problems and the primary cause of landscape fragmentation and LULC change. Urbanization alters the spatial arrangement and functioning of ecosystems as well as increasing impermeable surfaces and accumulating wastes and toxic substances in urban environments. In one sense, natural and human-induced spatiotemporal change is one of the constant and inevitable characteristics of urban ecosystems but the rapid changes experienced by the Earth ecosystems over the past century raised the concerns that natural ecosystems are being depleted day by day and, accordingly, raised the need for analysing the state of ecosystems and their health to mitigate the adverse effects of urbanization (Atak and Tonyaloglu, 2020). Whilst gradual changes and occasional abrupt disturbances are considered as normal in all ecosystems, the LULC change dynamics should be investigated with care where urbanization and human-induced factors threaten the nature and biodiversity. In the twentieth century, researchers have paid close attention to the environmental issues from an ecological point of view and raised questions about the effects of human societies on ecosystems as well as the ways of sustaining them. Recent evidence suggests that the ecosystem health approach is one of the main diagnostic indicators of ecosystem condition. Deforestation and conversion of natural vegetation to agriculture and pasture land have negative impacts on ecosystem health, including reduced biodiversity, increased carbon emissions, and altered nutrient cycling (Ribeiro *et al.,*2016). Land use changes, such as urbanization, agriculture, and mining, have negative impacts on ecosystem health, including reduced biodiversity, altered hydrological cycles, and increased soil erosion (Maitre *et al.,*2018).

1.5 Urbanization

The most important anthropogenic influences on climate are the emission of greenhouse gases and changes in land use, such as urbanization and agriculture. But it has been difficult to separate these two influences because both tend to increase the daily mean surface temperature. The impact of urbanization has been estimated by comparing observations in cities with those in surrounding rural areas, but the results differ significantly depending on whether population data or satellite measurements of night light are used to classify urban and rural areas (Kalnay and Cai, 2003). Urbanization is seen as an effect of the current globalization phenomenon, with social aspects as well as the economic ones, representing the migration process of the population organizing in urban areas, areas considered to be true centres of progress that offer multiple options to residents. Substantial expansion of urban areas is due population migration to these areas, the identification of new feature options that can ensure the raising of welfare levels of individuals and improve their conditions of life. Intense global urbanization is required to adopt the measures and conditions to provide strategic planning and sustainable long-term space measures considering the principles of sustainable development and the impact of environmental condition on the quality of life. States have different levels of development, thus facing the urbanization impact differently, less developed states being the most affected by the impact of urbanization-regarding water resources, or wealth (Dociu and Dunarintu, 2012). India is currently experiencing one of the fastest rates of urbanization in the world, India's urban transition has been shaped by factors such as economic growth, changing patterns of migration, and government policies and the implications of urbanization in India, which include social inequality, environmental degradation, and urban poverty thus there is a need for effective urban planning and policy to manage the impacts of urbanization and promote sustainable and equitable urban development in India (Zachariah and Rajan, 2003). Urbanization can have both positive and negative impacts on health, depending on factors such as the availability of healthcare facilities, exposure to environmental hazards, and the social and economic determinants of health (Florida and King, 2003).

1.6 Changes in Temperature Distribution

Land surface temperature (LST) is an important factor in global climate change studies, in estimating radiation budgets, in heat balance studies and as a control for the climate dynamics and modelling frame. The remote sensing technique is used to detect the land use changes, its impact on the land surface temperature and variation in mean LST from these hot spots. Thermal infrared remote sensing proved its capability in monitoring temperature and affecting microclimate in urban areas. It was observed that the LST of different land use differs significantly (Kayet *et al.,*2016). LST depends on the different LULC categories. LST is entirely related to the physical process of surface energy. It provides information on time-to-time variation of earth surface energy change. It is an important factor for monitoring vegetation, climate change, and change in the built-up area. Now a day it becomes a serious environmental issue (Sahoo *et al.,*2016) The research conducted by Scherrer *et al.,*(2005) analysed changes in temperature distribution across Europe, both observed and projected under different climate change scenarios. The findings indicate that the observed changes in temperature distribution over the last few decades are consistent with the anticipated effects of global warming, with a shift towards more extreme high temperature events. Furthermore, the study highlights regional variations in temperature changes, with northern and eastern Europe expected to experience the largest changes. These findings emphasize the need for effective adaptation strategies to mitigate the potential impacts of these changes on human health, ecosystems, and infrastructure.

Studies conducted by Brunner *et al.,* (2019) showed that extreme heat events are becoming more frequent and intense, while extreme cold events are becoming less frequent and less intense in Europe and it was also found that warming is occurring more rapidly in the northern parts of Europe compared to the southern parts. Temperature increases are likely to lead to reduced crop yields, particularly for maize, sorghum, and millet it can also be found that there will be an increase in heat stress on livestock, which may lead to reduced productivity and health problems (Nkonya *et al.,*2017). Heat-related mortality is projected to increase in the future, particularly in urban areas, while cold-related mortality is projected to decrease and the changes in temperature distribution may exacerbate existing health disparities (O'Neill *et al.,* 2018). Results have shown that changes in temperature distribution are altering the timing and magnitude of snowmelt, leading to earlier peak flows and reduced water availability in summer months and the changes in temperature distribution are exacerbating water scarcity in regions that are already water-stressed. For the temperature changes in permafrost, permafrost temperatures are increasing, leading to degradation of permafrost and increased greenhouse gas emissions and the changes in temperature distribution are altering the balance of carbon storage and release in the Arctic (Romanovsky *et al.,* 2016).

1.7 Urbanization and Temperature Change

Urban areas experience higher temperatures than rural areas, which is known as the urban heat island effect, while urbanization has led to higher temperatures in urban areas, this effect has not significantly influenced the overall temperature trend over the past few decades but its impact on regional climate is quite large (Goddard *et al.,*2019). Researchers found that the urbanization of the city had a significant impact on temperature readings, with an increase of 0.15°C per decade due to urbanization effects. It was also found that site changes had an impact on temperature readings, with an increase of 0.06°C per decade due to the relocation of weather stations (Guo *et al.,*2010). Urbanization requires the promotion of the study of the urban environment, to find ways to integrate urban development and eco-environment processes for sustainable cities and a sustainable city is one that supplies sustainable welfare to its people and has the capacity to maintain and improve its ecosystem services (Zhao,2010). Urbanization has a significant warming effect on surface temperatures, with a stronger impact in the urban core compared to the surrounding suburban and rural areas (Zhang *et al.,*2017). Urbanization is contributing to an increase in night-time temperatures, which can exacerbate the urban heat island effect (Shepherd *et al.,* 2017).

1.8 Impact of Climate Change on Ecosystem

Ecosystems have a critical role to play in addressing climate change, but that their potential is often overlooked in climate change policy and the importance of protecting and restoring ecosystems, and calls for greater recognition of their role in mitigating climate change (Smith *et al.,*2014). The potential for climate change to cause significant disruptions to ecosystems and the services they provide, and emphasizes the need for integrated management approaches that account for the interactions between different ecosystems and their responses to climate change (MEA,2005).Several adaptations must be taken to reduce the impact of urbanisation on ecosystem health like increasing vegetation cover in cities can help to reduce the surface temperature, cool the air, and improve air quality, thereby mitigating the impact of urbanization on climate change development (Akbari *et al.,*2009) and ecosystem-based approaches can provide a cost-effective and sustainable means of addressing climate change impacts, while also supporting economic and social (Tadross *et al.,* 2017). Climate change is likely to have significant impacts on ecosystem services, including water supply, soil fertility, and carbon sequestration, and that effective adaptation measures will require the integration of ecosystem-based approaches into national and regional climate change policies (Midgley *et al.,*2019). Global warming has the potential to cause significant and often unpredictable impacts on terrestrial ecosystems, and that there is a need for a multi-disciplinary approach to studying these interactions in order to better understand and predict the complex feedbacks and tipping points that may occur (Harte,2015).

Climate change is already having significant impacts on ecosystems and that these impacts are likely to intensify in the coming decades, with potentially catastrophic consequences for biodiversity and ecosystem function (Lovejoy and Hannah,2005). Understanding the interactions between climate change and other environmental stressors such as land use change and pollution is important and an integrated, multidisciplinary approach is necessary to fully understand the impacts of climate change on ecosystems and to develop effective management strategies. Warming temperatures, ocean acidification, and sea level rise are already having significant impacts on marine biodiversity and ecosystem function and there is a need to reduce greenhouse gas emissions and promote the resilience of marine ecosystems through targeted management interventions (Guldberg *et al.,* 2019). Climate change is already having significant impacts on terrestrial invertebrates, with potentially far-reaching consequences for ecosystem processes such as nutrient cycling and pollination (Diamond *et al.,* 2020). Warming temperatures and changing sea ice patterns are already having significant impacts on the distribution and behaviour of Arctic marine mammals and seabirds and there is need to monitor and manage Arctic ecosystems in the face of climate change to promote the resilience of these species and the ecosystems they inhabit (Leclerc *et al.,* 2021).

1.9 Need for Ecosystem Health Assessment

Ecosystem health index is an important tool for measuring the health and functioning of ecosystems. The VORS (Vigour-Organization-Resilience-ecosystem Services) model is one approach to measuring ecosystem health, and several studies have examined its effectiveness. One area that requires attention is the standardization of methods when applying the VORS model. It is crucial to develop guidelines for selecting indicators, collecting data, and analysing results to improve the reliability and comparability of ecosystem health assessments. Studies such as Lazzari *et al.,* (2018) emphasize the importance of standardizing methods to enhance the quality of research and make the results more useful for decision-making.

Further validation of the VORS model is necessary to assess its reliability and validity. While the model has been applied in several studies, more validation is required to confirm its effectiveness. For instance, Moilanen *et al.,* (2018) applied the VORS model to assess the health of forest ecosystems in Finland and compared the results with other measures of ecosystem health. The study found that the VORS model was a useful tool for assessing the health of forest ecosystems. Similarly, Marques *et al.,* (2020) applied the VORS model to assess the health of coastal lagoons in Portugal and found that the model was reliable and valid for assessing ecosystem health. However, further studies are necessary to validate the model in other types of ecosystems.

More studies are required to apply the VORS model in different types of ecosystems. While the VORS model has been applied in various ecosystems, most studies have focused on terrestrial ecosystems. It is necessary to apply the model in aquatic and marine ecosystems, as well as in urban ecosystems. Studies such as Jiao *et al.,* (2019) and Klauco *et al.,* (2020) have applied the VORS model to assess the health of wetlands and grassland ecosystems, respectively. However, more studies are necessary to apply the model to a broader range of ecosystems.

Lastly, more research is necessary on the use of the VORS model in decision-making and management. While the model provides a way to measure ecosystem health, it is essential to understand how the results can be used to inform decision-making and management. Studies such as Vitousek *et al.,* (2019) and Bhatti *et al.,* (2021) have applied the VORS model to assess the health of coral reef and agricultural ecosystems, respectively, and found that the results could be used to guide management decisions related to sustainable development. However, further studies are necessary to explore the effectiveness of the VORS model in guiding management decisions in different contexts.

In summary, while there have been some studies on the use of the VORS model for assessing ecosystem health, further attention is required to address the areas identified earlier. Standardizing methods, validating the model, applying it to different ecosystems, and exploring its effectiveness in decision-making and management are crucial areas for future research.

RESEARCH GAP

Ecosystem health assessment is a critical area of research that has significant implications for environmental management and conservation in India. Several studies have attempted to address some of these gaps. For instance, the Forest Survey of India has conducted a series of forest health assessments across the country, providing valuable data on the health of Indian forests (FSI, 2019). Similarly, studies such as Singh *et al.,* (2017) have used various models and frameworks to assess the health of wetlands and grasslands in India. However, more comprehensive assessments that consider multiple ecosystems and the interactions between them are necessary.

Efforts are also underway to develop standardized methods for ecosystem health assessment in the Indian context. For instance, the Indian Council of Forestry Research and Education (ICFRE) has developed a Forest Health Monitoring System that uses standardized indicators to assess the health of forests across the country (ICFRE, 2021). However, more research is necessary to evaluate the effectiveness of these methods and to identify the most appropriate approaches for assessing ecosystem health in India.

Finally, studies such as Nautiyal *et al.,* (2013) and Maitra *et al.,* (2018) have explored the links between ecosystem health and human well-being in the Indian context, highlighting the importance of considering social and cultural factors in ecosystem management and conservation.

In summary, while there have been some efforts to assess ecosystem health in India, there is still a significant research gap in this area. Addressing this gap requires a more coordinated and comprehensive approach that considers multiple ecosystems, develops standardized methods for ecosystem health assessment, and integrates ecosystem health and human well-being in policy and decision-making processes.

MATERIALS AND METHODS

Description of Study Area:

The study area taken for the thesis work is the area falling under Greater Cochin Development Authority, GCDA was constituted by the State Government in 1976 with a view to mastermind an orderly and planned development within the Greater Cochin Region comprising Kochi Corporation, 6 municipalities & 33 panchayaths having an area of 732 sq. km. The extend of the GCDA area is from 8°52'25.05"N to 9°53'46.48"N, 76°10'10.35"E to 76°24'30.29"E.

Kochi is a resourceful city at the northern tip of a land that is not more than 19 kms long and its width in some areas is even less than 1.6 kms. The city is separated from India's landmass by estuaries of rivers of Western Ghat and inlets from Arabian Sea and this feature makes Kochi a natural harbour. The area of the entire city is approximately 88 square kilometres and a major portion of Kochi lies at the sea level. It has a rich history, a diversity of ethnic populations, and an old-world elegance in addition to being Kerala's burgeoning cosmopolitan and commercial centre. Kochi stands out from the rest of the state in terms of lifestyle, dressing, variety, market, and opportunities thanks to its distinctive style statement. By 2031, the city region's population is projected to grow to 2.27 million. In order to ensure that Kochi can meet the requirements of a smart city, this significant increase necessitates an urgent review of several important components of the city infrastructure. The city's location at the confluence of various ecosystems must be taken into consideration in order to ensure the quality of urban development. Hence there also arises the need for the assessment of ecosystem health and compare it to the probable future and past ecosystem health to get an idea of how anthropogenic activities are affecting the same.

Datasets Used:

For the calculation of Land Surface temperature (LST) we make use of the satellite data available from USGS Earth Explorer website. We make use of the Landsat 5-7 and Landsat 8-9 of the years 2000,2010 and 2022. Landsat 5-7 was taken since the latest 8-9 had only been released after 2013. Landsat 7 ETM+ images consist of eight spectral bands with a spatial resolution of 30 meters for bands 1 to 7. The panchromatic band 8 has a resolution of 15 meters. The Landsat 8 satellite payload consists of two science instruments - the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS). These two sensors provide seasonal coverage of the global landmass at a spatial resolution of 30 meters (visible, NIR, SWIR); 100 meters (thermal); and 15 meters (panchromatic). The satellite data were taken between October and November to get the least amount of cloud cover possible. For extracting the parameters required for ecosystem health assessment and future Land Use Land Cover Prediction, the Shuttle Radar Topography Mission (SRTM) void filled data was obtained from the USGS Earth explorer. The Shuttle Radar Topography Mission (SRTM) database contains global elevation data with 3 arc-second (90 m) spatial resolution.

	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

	Bands	Wavelength (micrometers)	Resolution (meters)
Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) Launched February 11, 2013	Band 1 - Coastal aerosol	0.43 - 0.45	30
	Band 2 - Blue	0.45 - 0.51	30
	Band 3 - Green	0.53 - 0.59	30
	Band 4 - Red	0.64 - 0.67	30
	Band 5 - Near Infrared (NIR)	0.85 - 0.88	30
	Band 6 - SWIR 1	1.57 - 1.65	30
	Band 7 - SWIR 2	2.11 - 2.29	30
	Band 8 - Panchromatic	0.50 - 0.68	15
	Band 9 - Cirrus	1.36 - 1.38	30
	Band 10 - Thermal Infrared (TIRS) 1	10.60 - 11.19	100
	Band 11 - Thermal Infrared (TIRS) 2	11.50 - 12.51	100

Fig. 2: Band sets of Landsat 7 and Landsat 8, Source: USGS

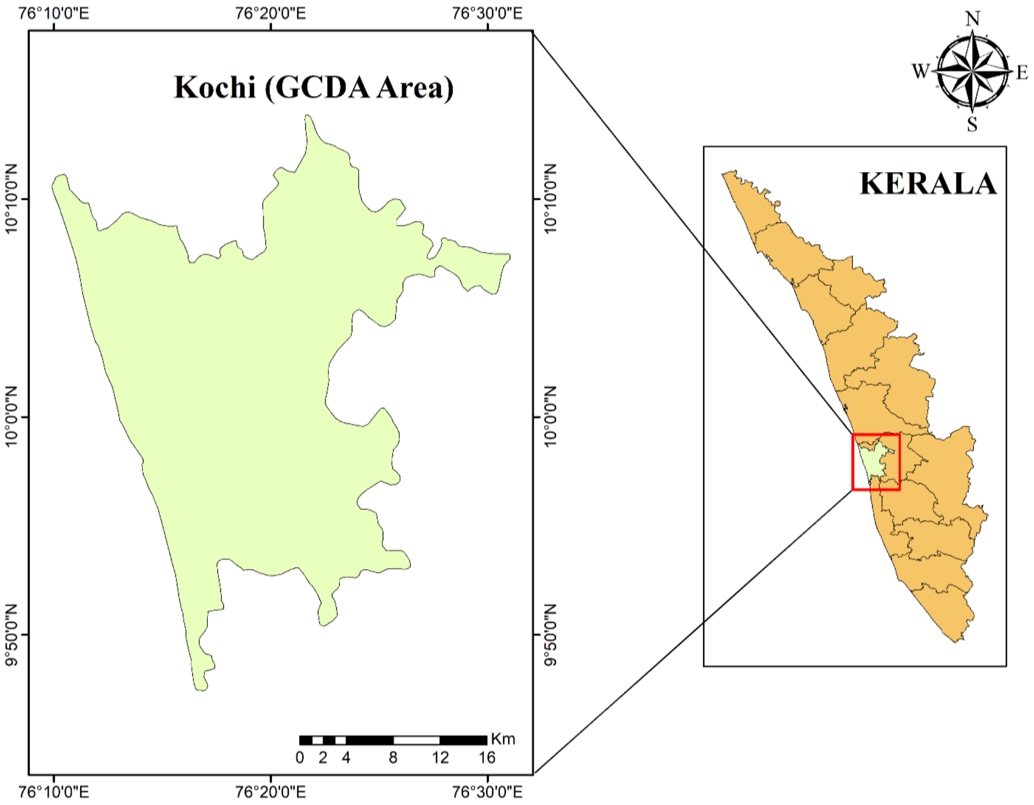


Fig 3: Study Area map

Land Surface Temperature (LST):

A crucial factor in both ecology and climatology, land surface temperature (LST) has an impact on species and ecosystems on a range of scales. identified by NASA and other international organisations as one of the most significant Earth System Data Records (King, 1999). LST measures the emission of thermal radiance from the land surface, where the incoming solar energy interacts with and heats the ground, or the surface of the canopy in vegetated areas. LST is sensitive to changes in surface conditions due to this property, which makes it a good indicator of energy partitioning at the land surface-atmosphere boundary (Nemani *et al.,* 1996; Wan *et al.,* 2004; Lambin and Ehrlich, 1995; Mildrexler *et al.,* 2009). LST is one of the most crucial parameters in the physical processes of surface energy and water balances because of the information it provides on the redistribution of energy into latent and sensible heat fluxes at spatial scales ranging from the leaf level to the landscape and In order to study the thermal heterogeneity of the Earth's surface and the effects of both natural and man-made changes on surface temperatures, its retrieval from remotely sensed thermal-infrared (TIR) data offers spatially continuous LST measurements with global coverage (Jin and Dickinson, 2010; Li *et al.,* 2015).

The Land Surface Temperature can be estimated or calculated using the Landsat 8 thermal bands. It simply requires applying a set of equations through a raster image calculator, which was done using ArcMap in our study. The first step is to download the Landsat 8 image for a Kochi city, unzip it, and check certain information needed (that can be obtained from the metadata file in the downloaded file) for the calculation. For the calculation of LST, we must calculate Top of Atmospheric spectral radiance (TOA), Brightness temperature (BT), Normalized Difference Vegetation Index (NDVI), Proportion of Vegetation (P_v), and emissivity (ε) of Kochi city.

To calculate the LST, we make use of the USGS formulas, for which we first calculate the Top of Atmospheric (TOA) spectral radiance through the formula,

$$\mathbf{TOA\ (L) = M_L * Q_{cal} + A_L}$$

where:

ML = Band-specific multiplicative rescaling factor from the metadata

Qcal = corresponds to band 10.

AL = Band-specific additive rescaling factor from the metadata

From the TOA spectral radiance, we calculate the Brightness Temperature (BT) of Kochi city using

$$\mathbf{BT = (K_2 / (\ln (K_1 / L) + 1)) - 273.15}$$

where:

K1 = Band-specific thermal conversion constant from the metadata

K2 = Band-specific thermal conversion constant from the metadata

L = TOA

For calculating the Normalized Difference Vegetation Index (NDVI), that is essential for calculating proportion of vegetation (P_v), which is highly related to the NDVI, and emissivity (ε). We make use of band 4 and band 5 for Landsat 8 and for Landsat 7 we use the band 3 and band 4 as they correspond to Near Infrared (NIR) and Red.

$$\mathbf{NDVI = (NIR-Red)/\ (NIR+ Red)}$$

For Landsat 8, it is

$$\text{NDVI} = (\text{Band } 5 - \text{Band } 4) / (\text{Band } 5 + \text{Band } 4)$$

For Landsat 7, it is

$$\text{NDVI} = (\text{Band } 4 - \text{Band } 3) / (\text{Band } 4 + \text{Band } 3)$$

Afterward, we calculate the Proportion of Vegetation (P_v), using the formula,

$$\mathbf{P_v = Square\ ((NDVI - NDVI_{min}) / (NDVI_{max} - NDVI_{min}))}$$

The minimum and maximum values of the NDVI image can be displayed directly in the image or can be obtained from the properties tab of NDVI

Then we calculate the emissivity (ε), using the formula

$$\boldsymbol{\varepsilon = 0.004 * P_v + 0.986}$$

where the value of 0.986 corresponds to a correction value of the equation. And finally for calculating the Land surface temperature (LST), we use:

$$\mathbf{LST = (BT / (1 + (0.00115 * BT / 1.4388) * Ln(\varepsilon)))}$$

Land Use Land Cover Classification using Support Vector Machine:

Land use and land cover classification is a scientific endeavour that leverages remote sensing technology to systematically categorize and delineate the Earth's surface based on discernible attributes. As primary cues for this classification, spectral signatures—distinctive electromagnetic energy patterns—displayed by various surface materials are used. Spatial data is examined for patterns, features, and relationships that denote different land cover types using a range of classification algorithms, including supervised, unsupervised, and machine learning techniques. These algorithms represent a crucial computational step in the broader field of geospatial analysis because they accurately assign pixels or segments to classes by encapsulating complex decision boundaries. Following classification, post-processing techniques reduce noise, identify coherent patches, and improve the accuracy of the output. Through validation procedures that compare the classified data with actual reference data, the veracity of the classification is assessed, quantifying the precision and dependability of the classification scheme. This classification framework also plays a key role in change detection analyses, making it possible to identify and track changes in land use and land cover configurations over time. As a result, it is a crucial tool for disciplines like environmental assessment, urban planning, agricultural management, and disaster mitigation.

Understanding the distribution and dynamics of different land types requires understanding the classification of land use and cover. This classification evaluates spectral, spatial, and temporal characteristics to distinguish between urban, agricultural, natural, and other land categories using remote sensing technologies like satellites and aerial imagery. These meticulous maps of land use and cover changes are essential for determining how human activity affects the environment, tracking deforestation, tracking urban growth, and even forecasting potential ecological shifts. These insights are used by researchers and decision-makers to create successful plans for biodiversity conservation, disaster response, and land management.

In our study, we make use of the Support Vector Machine (SVM) classifier available in ArcGIS, for the classification of LULC. A machine learning algorithm called a Support Vector Machine (SVM) is made for both classification and regression tasks. When dealing with intricate and nonlinear data distributions, it is especially helpful. Finding the ideal decision boundary, or hyperplane, that divides data points from different classes in a way that maximises the margin between them is the central concept of SVM.

A thorough methodology using field surveys, Google Earth images, and topographical maps from the years 2022, 2010, and 2000 is used to create training and testing data. A total of 500 to 600 sample sites were carefully chosen to act as training and testing samples, laying the groundwork for the subsequent land use and land cover (LULC) classification procedure. The training and testing datasets for 2022 were created using a two-pronged strategy. To directly gather pertinent data, initial field surveys were conducted on the ground. In order to ensure accurate and representative training and testing data, this also involved physical assessments, measurements, and data recording at specific locations. Parallel to this, spatial data from a larger geographical context was extracted using Google Earth images, enhancing the dataset with remote sensing knowledge.

Considering the temporal context, the data collection strategy was modified for the years 2010 and 2000. The training and testing samples were primarily drawn from secondary data because there was no field data available for those years. The creation of spatial data was greatly helped by the historical perspectives provided by Google Earth images. Topographical maps, which record historical data on land use and land cover, were also used as additional sources of data for these two years, giving a snapshot of the landscape's characteristics at those points in time.

The choice of two crucial SVM parameters, C and γ, is crucial. A low value indicates underfitting because there are not many support vectors defining the decision boundary, while a high value indicates overfitting because there are more samples that become support vectors, resulting in a wider decision boundary. The ideal C value maximises generalisation potential while minimising training error. The distance between the decision boundary and the closest support vectors is represented by the γ parameter. While high γ values only include the closest points, low γ values also include points that are farthest from the decision boundary. As a result, a desirable value of γ is essential for accurately defining the decision boundary.

We used a radial basis function (RBF) to get around the restrictions related to the classification of multi-class Land Use and Land Cover (LULC) datasets. The RBF kernel is frequently used in this context due to its high generalisation capability. The formulation of the RBF kernel is:

$$\mathbf{K\ (x, y) = exp(-\gamma \cdot \|x-y\|^2)}$$

and where $\gamma = 1/2\sigma^2$, with σ being a positive parameter governing the radius of the data given.

For our study in the Assessment of the ecosystem health of Kochi, we take h the following parameters and kernel RBF:

A kernel width gamma (γ) of 0.143, a penalty parameter (C) of 100, and a classification probability threshold of 0.3, as

Validation and accuracy assessment of LULC map obtained via SVM:

The validation of the LULC map is important for the overall accuracy of the project itself. Any classification project must include an accuracy assessment. A different data source that is thought to be accurate or ground truth data is compared to the classified image. Fieldwork can be used to gather ground truth, but it takes time and money. The interpretation of existing classified imagery, high-resolution imagery, or GIS data layers can also yield ground truth data.

Making a set of random points from the ground truth data and comparing them to the classified data in a confusion matrix is the most popular method for evaluating the accuracy of a classified map, which was employed in our project. The accuracy assessment methodology in ArcGIS uses a structured process to assess the accuracy of a classification of land use and land cover. Getting reference data that accurately depicts the actual ground conditions through field surveys or high-resolution imagery is required as the first step. These benchmarks—reference points or polygons—are used to evaluate our classification accuracy. In our case, we take random points in Google Earth Pro use it as the reference point for the LULC classified map of 2010 and 2000. For the 2022 year, we conduct field surveys and make use of GPS receivers to pinpoint the several classes mentioned in our study.

The "Confusion Matrix" tool in ArcGIS is helpful once reference data is available. This tool creates a matrix that shows how the classes determined by the classification and those from the reference data correspond. While columns represent the classified classes, rows represent reference classes. The values in this matrix represent the number of reference points or polygons that are associated with various combinations of reference and categorised classes.

ArcGIS provides functionalities to compute a range of accuracy metrics as a result. In addition to "Overall Accuracy," which measures the proportion of correctly identified pixels or points to the total count, these metrics also include "Producer's Accuracy" and "User's Accuracy." Regarding the total number of reference pixels or points for a given class, the former speaks of the percentage of pixels or points that were correctly classified within that class. The latter, on the other hand, shows the percentage of pixels or points correctly classified for a given class relative to the overall number of classified pixels or points assigned to that class. Additionally, evaluating classification performance is aided by the "Kappa Coefficient," a statistical measure that considers both agreement and chance.

The formula required for calculation and accuracy assessment is mentioned below,

Overall Accuracy = ((Total Number of Correctly Classified Pixels (Diagonal)/ (Total Number of Reference Pixels)) ×100

Users Accuracy= ((Number of Correctly Classified Pixels in each Category)/ (Total number of Classified Pixels in that Category (The Row Total)) ×100

Producer Accuracy= ((Number of Correctly Classified Pixels in each Category)/ (Total Number of Reference Pixels in that Category (The Column Total)) ×100

Kappa Coefficient (T)=((TS×TCS)-∑ (Column Total × Row Total))/ (TS^2-∑ (Column Total x Row Total))

A sample of the accuracy assessment table is as follows:

	Water Body	Sparse Vegetation	Dense Vegetation	Built up	Bare soil	Total (User)
Water Body	X	X	X	X	X	X
Sparse Vegetation	X	X	X	X	X	X
Dense Vegetation	X	X	X	X	X	X
Built up	X	X	X	X	X	X
Bare soil	X	1	X	X	X	X
Total (Producer)	X	X	X	X	X	X

Table 1: Sample Table of accuracy assessment

Prediction of the future Land Use Land Cover using Cellular Automata Artificial Neuro Network (CA-ANN):

Predicting Land Use and Land Cover (LULC) changes plays a pivotal role in diverse disciplines due to its capacity to illuminate evolving land utilization patterns. This predictive ability is extremely important for managing and monitoring the environment. Ecological shifts like deforestation, urbanisation, and agricultural expansion can be detected by observing changes in LULC, assisting in the preservation of ecosystems, biodiversity, and natural resources. Additionally, LULC forecasts provide invaluable insights for urban planning, allowing for the informed resource allocation and infrastructure development decisions necessary for sustainable urban growth.

Achieving accurate LULC predictions is essential for efficient natural resource management. For resources like water, soil, and forests to be preserved, it is crucial to monitor changes in land cover. This makes it possible to develop proactive conservation strategies, facilitating the sustainable use of resources. In the assessment and management of disaster risk, the predictive analysis of LULC alterations also plays a crucial role. Pre-emptive actions can be taken to strengthen disaster preparedness and response mechanisms by identifying areas that are vulnerable to natural disasters, such as floods and landslides.

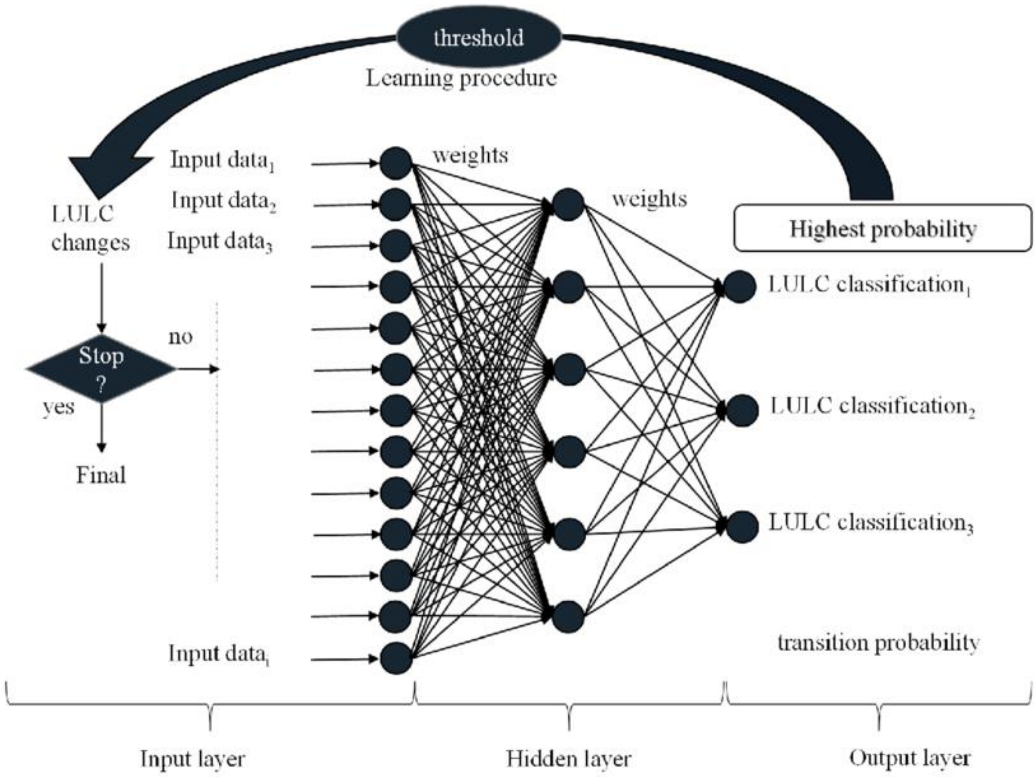
The capacity to foresee LULC changes is of utmost significance in the field of biodiversity conservation. This forecasting aids in identifying habitats that are in danger of extinction and makes it easier to implement specific conservation measures. Additionally, LULC prediction provides a solid framework for well-informed economic planning. It identifies opportunities for sustainable growth, investments, and job creation in a variety of industries, including forestry, tourism, and agriculture. These forecasts also shed light on the range of ecosystem services related to various types of land cover, from carbon sequestration to pollination, helping to inform policymaking and influencing sustainable land use practises.

In our study, we make use of the Cellular Automata Artificial Neuro Network (CA-ANN) for the prediction of the Land Use Land Cover of Kochi. We make use of QGIS 2.18 for the prediction as the MOLUSCE plugin required is only compatible with the earlier version of QGIS i.e., the QGIS 2.18 version. The artificial neural network (ANN) method was used in the cellular automata (CA) model because it has been shown to produce better results than other techniques such as linear regression.

An artificial neural network (ANN) is a machine learning technique that can record and visualise intricate interactions between inputs and outputs. The brain's simplification of its neurons served as the model for the ANN, a network of nodes. It is made up of several neurons or nodes that function concurrently to transform input data into output categories. Input, hidden layers, and output are the typical three layers of an ANN. Depending on the application, a network has several neurons in each layer. Each neuron has a direct connection to another neuron in the layer below it. According to Varoonchotikul (2003), these links have a weight that reflects the strength of the outgoing signal. The most effective network type to use in an ANN will depend on the problem at hand and the data at hand. According to Govindaraju (2000), the multi-layer perceptron (MLP) is possibly the most widely used neural network.

The CA model is a hybrid that combines the ideas of Markov Chains and Cellular Automata. Cells and other identical components are arranged in a predictable and discrete space to form the CA. The fundamental idea behind CA is that any LULC transition cell or pixel can be studied using both its current circumstances and advancements in the cells or pixels around it. This incorporates transformation rules based on neighbouring cells using the Markov model. To illustrate transition rules, original and later conditions' probabilities are used. Based on a cell's or pixel's initial state, its neighbours' conditions, and a set of transformation rules, the CA-Markov model generates the situation for that cell or pixel. The proximity principle, which states that regions close to current areas of the same class are more likely to transition to different LULC classes, is used to illustrate the complexity of transition in this case. Using a set of transformation rules, the CA-Markov model is renowned for its capacity to predict the intricate dynamics of spatiotemporal patterns. By acting on transition probabilities and using ANN-based suitability maps for each LULC category to produce precise future predictions, the model addresses the issues with LULC transformations.

In our study, ANN-MLP was used to forecast the transitional probability model by combining land-use change conditioning variables. The 2010 and 2022 LULCs maps were used to extract information about elevation, slope, proximity to the urban area, waterbody, sparse vegetation, dense vegetation, and bare soil. The Euclidean distance method was then applied to the derived data in ArcGIS software to produce proximity parameters.



Source: Saputra, M Hadi.,2019

Fig. 4 – Illustration of CA-ANN

For checking the calibration of the model, we primarily run it with the LULC data of the years 2000 and 2010 to get the map of 2022 which can be compared to the actual 2022 map and thus validating the accuracy of the CA-ANN model in predicting LULC of our region. When a reasonably accurate map was obtained, we move forward for prediction of LULC of 2032.

The steps involved in the CA-ANN modelling involves:

Data collection: The first step entails gathering historical information about past land use and land cover changes of 2000,2010 until 2022. This information may consist of satellite images, aerial pictures, demographic data, and other pertinent spatial data. The data should cover a sizable enough area to include different land use classes and their alterations. The data must be cleaned, georeferenced, and transformed into a format that can be used for analysis after it has been collected.

Selection and Extraction of Relevant Features: From the gathered data, appropriate features must be extracted for the modelling procedure. These characteristics involves elevation, slope, proximity to the urban area, waterbody, sparse vegetation, dense vegetation, and bare soil were extracted from the 2000 and 2018 LULCs maps. In order to extract more useful information from the raw data and improve the model's ability to recognise underlying patterns, feature extraction techniques may also be used.

ANN Model Training: Using the pre-processed data, an Artificial Neural Network (ANN) must be created and trained. The complexity of the issue and the features picked would determine the ANN architecture. It is important to choose the network's hidden layers, activation mechanisms, and optimisation algorithms wisely. To ensure accurate model evaluation, the training data should be divided into training, validation, and possibly testing sets. To understand the connections between the selected features and changes in land use, the ANN learns from previous LULC data.

Setup for Cellular Automata (CA): A framework for Cellular Automata (CA) must be created simultaneously. The CA grid cells represent various land areas, and the state of each cell identifies a particular land use class. Based on previous LULC data, transition rules should be developed that show how cells change their states over time in response to neighbouring cells' states and other variables.

Combining CA and ANN: The predictive ability of the ANN can improve the transition rules of the CA model. The transition rules of the CA model can be updated or modified using the ANN predictions. For instance, the CA's decision-making process may be influenced by the ANN's predictions about the likelihood that a particular area will change from being forest to urban.

Training of CA-ANN model: The CA-ANN model is trained using historical data that is current as of the year in question. The CA transitions are guided by the ANN's predictions, producing a more accurate simulation of changing land use. To ensure precise predictions and a better representation of real-world scenarios, the combined model is refined iteratively.

Future Scenario Simulation: Future scenarios can be simulated using the trained CA-ANN model. The model produces forecasts for 2032's land use and land cover based on inputs for that year, including elevation, slope, proximity to the urban area, waterbody, sparse vegetation, dense vegetation, and bare soil. The iterative simulation process considers both the intricate relationships learned by the ANN and the local interactions modelled by CA.

For the classification of Land Use and Land Cover (LULC), the CA-ANN (Cellular Automata-Artificial Neural Network) model offers several advantages over traditional models. The CA-ANN model excels at capturing complex relationships in LULC data by fusing the spatial and temporal dynamics of cellular automata with the nonlinear pattern recognition of artificial neural networks. Superior predictive accuracy is obtained because of considering neighbourhood influences and local interactions, as well as the adaptability of the ANN component, especially for scenarios with complicated, nonlinear changes. This integrated approach is a flexible tool for decision-making in urban planning, environmental management, and sustainable development because it not only better manages data uncertainty but also makes scenario testing and policy evaluation easier.

Validation of the predicted LULC using Random Forest:

The validation of predicted Land Use and Land Cover (LULC) maps holds immense significance due to its multifaceted benefits. When compared to actual observed data, it provides a reliable mechanism for evaluating the precision and veracity of the model's projections. This procedure allows for the identification of potential errors, biases, and inconsistencies in the model's performance, ensuring the accuracy of the outcomes. By providing trustworthy insights for urban planning, disaster management, and resource allocation, validated predictions not only increase trust among stakeholders and decision-makers but also make it easier for them to make well-informed decisions. Validation directs changes to the model's methodology and parameters by highlighting the biases and limitations of the model, which ultimately leads to predictions that are more accurate and trustworthy. Future LULC cannot be validated, so the performance of the model needs to be examined for dependability and robustness. Sensitivity analysis has therefore been applied in this study.

Breiman (Breiman, 2001) created Random Forest, one of the popular and effective ensemble supervised learning algorithms. This algorithm can be applied to unsupervised learning, classification, and regression problems. It has been extensively used in a variety of fields, including hydrology, LULC classification, natural hazard modelling, and finance (Salam and Islam 2020; Chen *et al.,*2019; Talukdar and Pal 2020).

The Random Subspace Selection (RSS) and bagging are combined to form the RF (Chen *et al.,* 2019). The main benefits of the RF are its lower sensitivity to the multicollinearity test and its ability to handle missing and unbalanced data. The RF model functions as follows: It first creates subphases from the old data using the bootstrap resampling tool, which is equivalent to zero sizes in the old dataset, then uses the subphases to create decision trees. Finally, it creates the output by combining the predictions from all the decision trees (Ntree) similarly. According to Chen *et al.,* (2020), the Ntree count and the data's features, which included subsets of the data, have a significant impact on the RF algorithm's performance. When Ntree is large, modelling takes longer, while when it is small, there are more errors. The "Random Forest" package in R Studio 3.2 was used to perform RF in this work. The probability of fragmentation was modelled using the RF. All decision trees (Ntree) predict outcomes in a similar way.

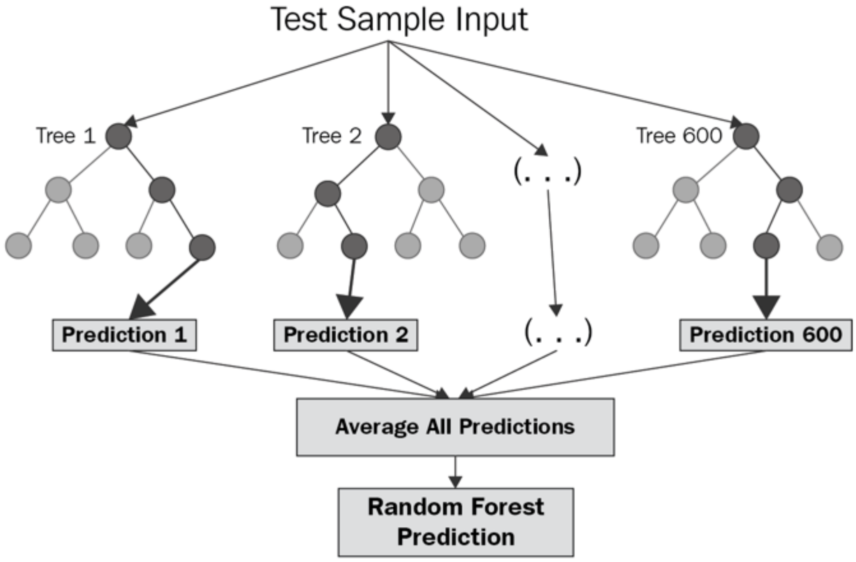


Fig. 5 – Illustration of Random Forest, Source: Corporate Finance Institute

When conducting a sensitivity analysis for Land Use and Land Cover (LULC) data, Random Forest (RF) stands out from other techniques with several benefits. It is a priceless asset because it can deliver accurate variable importance measurements. The straightforward quantification of each feature's impact by RF makes it easier to identify the variables that have the greatest influence in the context of LULC, where many different factors influence changes. Furthermore, RF's skill at capturing intricate nonlinear relationships is essential for comprehending complex LULC dynamics. By removing noise and concentrating on the most important factors, the method's resistance to unimportant variables improves the accuracy of sensitivity analysis. Insights into how different factors interact to drive LULC changes are provided by the seamless capture of interaction effects between variables. The analysis gains credibility because of RF's resistance to data perturbations, which guarantees consistency in variable importance scores. The ability of RF to handle such situations without overfitting is particularly advantageous because LULC data can frequently be high-dimensional. RF's role in accurate sensitivity analysis is further cemented by its robustness to outliers, simplicity of interpretation through importance scores, and efficient generalisation. By incorporating these advantages, RF develops into a powerful tool for figuring out the complex relationships and motivating factors behind LULC changes, ultimately assisting in the making of well-informed decisions in urban planning, environmental management, and sustainable development.

Assessment of the Ecosystem Health using Vigor-Organisation-Resilience-Ecosystem Service (VORS) model:

We employ the VORS model to assess the health of Kochi's ecosystem, through which a careful examination of Ecosystem Services (ES), a crucial factor that includes the benefits enjoyed by communities as a result of ecosystems, is especially important. This aspect entails a multi-dimensional analysis that is distinguished by two different criteria. The first criterion focuses on a complex assessment of the ecosystem's physical state. This in-depth analysis of three clearly defined indicators sheds light on the underlying ecological processes and the functionality of the ecosystem.

The scope of our assessment extends beyond local boundaries and encompasses Kochi City's ES evaluation. The importance of Ecosystem Services (ES) is highlighted in this context. An elevated ES value is a sign of the ecosystem's strong ability to supply material resources and materials, which has a significant impact on the wellbeing of the community it supports. This elevated value highlights the ecosystem's exceptional ability to maintain equilibrium at the same time, demonstrating the successful balancing act between anthropogenic needs and ecological stability.

Due to its inherent advantages over competing models, the adoption of the VORS (Vigor-Organization-Resilience-Services) model for the evaluation of ecological health and ecosystem services in Kochi presents a well-justified choice. Notably, the model stands out for its thorough approach, which includes a wide range of important indicators. The VORS model provides a multidimensional perspective that fully captures the dynamics of the ecosystem by assessing not only the provisioning of ecosystem services but also the aspects of vigour, organisation, and resilience. The VORS model's holistic analysis offers a more nuanced understanding of the ecosystem's health and functioning than models that might focus on a single indicator.

The explicit inclusion of ecosystem services in the assessment process is crucial to understanding its significance. The VORS model acknowledges the intricate symbiosis between ecological health and the benefits derived by human communities from ecosystems, in contrast to some models that may overlook the crucial role of ecosystem services. In the case of Kochi, where the interdependence between natural systems and societal well-being is of utmost importance, this integration is particularly pertinent.

The ability of the VORS model to achieve synergy among its various indicators is another distinctive feature. A complex web of interactions that shape the ecosystem's condition is created by the interdependence of vigour, organisation, resilience, and ecosystem services. The VORS model offers a more accurate and comprehensive representation of the ecosystem's functioning by capturing these intricate relationships.

The model's inclusion of both urban dynamics and ecosystem health is extremely pertinent given Kochi's urban setting. It acknowledges the complex interplay between human endeavours, urban growth, and the provision of ecosystem services. Due to its compatibility with urban environments, the VORS model can be used as an effective tool to inform sustainable development policies in Kochi and elsewhere.

The model's results also have application for policymakers and decision-makers. The VORS model gives them the knowledge they need to make well-informed decisions that strike a balance between societal needs and environmental concerns by providing a comprehensive perspective on ecological health and ecosystem services. Its integrative methodology aids in the development of policies that protect ecological integrity while fostering human progress, supporting the larger sustainability agenda.

In our study, EH values are classified into five categories:

Very good (80–100%)

Good (60–80%)

Moderate (40–60%)

Very poor (20–40%) and

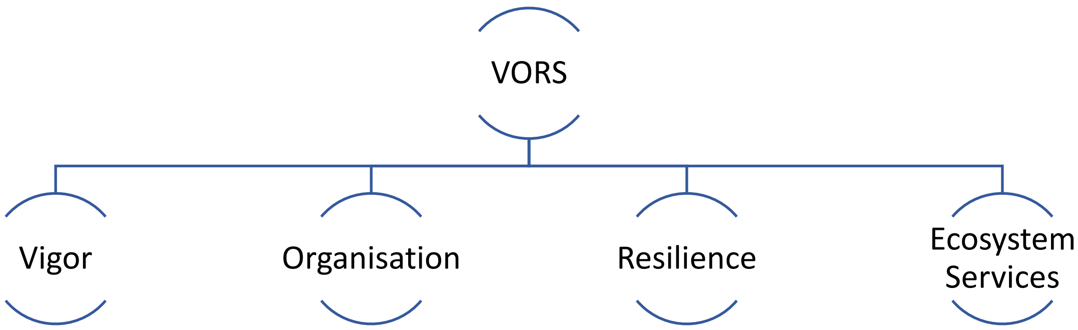
Poor (0–20%)

We make use of Physical Health (PH) and Ecosystem Health (EH) in our study, and as mentioned, we know the relationship between the PH and EH is positive. Physical health involves the biophysical components of the ecosystem in contrast to the ecosystem health which also include the ecosystem services provided by the ecosystem along with its physical health. The formula for obtaining Physical health and ecosystem health is as follows:

$$\mathbf{PH = \sqrt{3}\ (V \times O \times R)}$$

$$\mathbf{H = \sqrt{\ } (PH \times ES)}$$

where H denotes the EH level of the units being appraised in Kochi City and PH denotes the ecosystem’s physical health. ES is the ecosystem service value of the urban ecosystem of Kochi with respect to various land use land cover types.



Vigor (V) – It is a crucial indicator that assesses the overall vitality, health, and energy of an ecosystem. This indicator assesses the biophysical health of the ecosystem, including the vegetation, soil, and water resources. The ecosystem's capacity for growth, reproduction, and regeneration is referred to as vigour, and it reflects the strength of its plant and animal populations. It also considers the ecosystem's capacity to withstand stress and bounce back after them. The model's key component, vigour, offers a fundamental perspective on the ecosystem's overall health and well-being by providing insights into the ecological robustness, vitality, and functional capacity of the ecosystem. In our study, the Vigor of Kochi is taken from the Normalized Difference Vegetation Index (NDVI) of the same.

For calculating the NDVI of we make use of the Landsat imagery that can be obtained from the USGS Earth Explorer website. From the downloaded Landsat imagery, we make use of band 5 and band 4 for NDVI calculation for Landsat 8 that can be applied in the 2022 year. Since the Landsat 8 was only launched after 2013, we make use of Landsat 7 for the remaining 2010 and 2000 year, for which we take the band 4 and band 3. The formula for calculating NDVI that was applied in to raster calculator of ArcGIS is as follows:

NDVI = (NIR-Red)/ (NIR+ Red)

For Landsat 8, it is

NDVI = (Band 5 – Band 4) / (Band 5 + Band 4)

For Landsat 7, it is

NDVI = (Band 4 – Band 3) / (Band 4 + Band 3)

In general, NDVI values range from -1.0 to 1.0, with negative values indicating clouds and water, positive values near zero indicating bare soil, and higher positive values of NDVI ranging from sparse vegetation (0.1 - 0.5) to dense green vegetation (0.6 and above). The value of NDVI will be standardised to 0-1, using the fuzzy membership function of ArcGIS for running of the model

Organisation (O) - Organization is a significant indicator that assesses the structural complexity, spatial arrangement, and interconnectedness of the components within an ecosystem. The ability of an ecosystem to support a variety of biological interactions is reflected in the arrangement and distribution of various species, habitats, and ecological niches. This indicator considers elements like species diversity, trophic relationships, ecosystem structure, and the presence of vital ecological connectors like buffer zones and corridors.

The VORS model aims to capture the complex web of interactions that contribute to the stability, adaptability, and overall health of an ecosystem by examining how an ecosystem is organised. A highly organised ecosystem is more likely to have a wide range of species, clearly defined niches, and symbiotic relationships, all of which increase the ecosystem's resistance to disturbances and environmental changes. Together with the other VORS indicators, organisation contributes to a thorough understanding of an ecosystem's health, informing conservation initiatives, land management plans, and sustainable development strategies.

The value of organisation was obtained mainly from the fragmentation characteristics of the Land Use Land Cover type and the respective year. The fragmentation characteristics we consider include:

- **COHESION Index**: The value range of COHESION index indicate several characteristics of the land. Pertaining to the cohesion index (COHESION), An indicator of total fragmentation and a lack of connectivity between patches is a value of 0. This indicates that patches are separate from one another and do not have boundaries in common. A value of 1 denotes high patch cohesion and connectivity. This indicates that patches are interconnected and have a lot of shared boundaries. In other words, a landscape with a higher COHESION value is one that is more connected and cohesive, and one with a lower value is one that is more dispersed and disconnected. The context and study objectives may influence the precise interpretation of COHESION values.
- **Patch Density**: Depending on the landscape characteristics, the data resolution, and the size of the study area, patch density (PD) can vary significantly. Patch Density values depend on the degree of spatial heterogeneity or fragmentation in the landscape and can range from 0 to relatively high values.
- **Edge Density**: For ED, or edge density, a landscape without any edges or distinctions between different land cover types has a value of 0. This might indicate a landscape that is entirely uniform and has only one type of land cover. Greater amounts of edge or boundary length per unit area are indicated by higher values, which represent increasing edge density. Greater edge densities indicate a more fragmented landscape with a variety of nearby land cover types.

- **Contagion (CONTAG) Index:** The Contagion Index (CONTAG), which measures the degree of spatial contagion or aggregation within a land use/land cover pattern, typically ranges from 0 to 1. Patches of the same land cover type are dispersed and isolated from one another in a pattern with a CONTAG value of 0, which represents a completely fragmented pattern. There is no spatial aggregation or contagion in this situation. When the CONTAG value is 1, the pattern is entirely contagious or aggregated, with no gaps or other land cover types in between the patches of the same land cover type.
- **Area Weighed Mean Fractal Dimension (FRAC-AM) Index:** A value of 0 for the Area Weighed Mean Fractal Dimension Index denotes a landscape that is entirely uniform, smooth, and free of any fractal patterns or heterogeneity. A landscape with a value of 2 is highly complex and fragmented, with the most fractal patterns and heterogeneity possible.

All the values of the indexes were obtained from the FRAGSTATS 4.2 software, which is a spatial pattern analysis program for categorical maps representing the landscape mosaic model of landscape structure. The landscape under analysis can represent any spatial phenomenon and is user-defined. The spatial heterogeneity of the landscape as depicted by the categorical map is simply quantified by FRAGSTATS.

The value obtained for each of the Index are standardised using the fuzzy membership logic and for obtaining the value of organisation, we overlay the indexes using the fuzzy overlay function of ArcGIS. The resultant raster image has the value range for organisation.

Resilience (R): Resilience is a critical indicator that measures an ecosystem's ability to absorb and recover from disturbances, shocks, or environmental changes while maintaining its fundamental structure and functions within the framework of the VORS (Vigor-Organization-Resilience-Services) model. An ecosystem's resilience is measured by its capacity to withstand or adapt to disturbances, maintaining its integrity and offering ongoing ecological services.

The VORS model's resilience indicator assesses several important factors, such as the species diversity, the presence of keystone species, the ecosystem's capacity to adapt to changing conditions, and its ability to recover from disturbances. Even in the face of disruptions, an ecosystem with high resilience can continue to provide its essential services.

The VORS model sheds light on an ecosystem's capacity for adaptation and its potential to overcome difficulties like climate change, habitat fragmentation, and human activities by analysing resilience. Making wise decisions for ecosystem conservation, restoration, and sustainable management with an understanding of resilience helps to ensure the long-term health and functionality of ecosystems for both ecological and human well-being.

For calculating the Resilience in our study, we make use of the formula,

$$\mathbf{R} = \sum_{i=1}^{n} \boldsymbol{Ai} \times \boldsymbol{Ri}$$

Where A_i is the area under the specific land use land cover type and R_i is the coefficient of resilience of the specific land use land cover type.

The table below shows the resilience coefficient of the various LULC classes adopted in our study

Table 2: different LULC types and their corresponding coefficient values

LULC Type	Waterbody	Dense Vegetation	Sparse Vegetation	Built-up	Bare soil
Resilience Coefficient value	0.8	0.8	0.6	0.2	0.2

Source: (Xie *et al.,* 2008; Peng *et al.,* 2015; He *et al.,* 2019)

Ecosystem Services (S): Ecosystem services is a key element of the VORS (Vigor-Organization-Resilience-Services) model, which emphasises the value and advantages that ecosystems offer to both human societies and the environment. Ecosystem services include a variety of direct and indirect benefits that ecosystems provide, such as provisioning services (such as providing food, water, and raw materials), regulating services (such as controlling the climate), purifying services (such as water filtration), supporting services (such as soil formation and nutrient cycling), and cultural services (such as providing leisure activities and aesthetic value).

The evaluation of ecosystem services within the VORS framework entails determining how well an ecosystem promotes and maintains ecological integrity as well as human well-being. This evaluation typically considers the range, quality, and quantity of ecosystem services as well as their interactions with resilience, organisation, and vigour indicators.

It is possible to quantify the concrete advantages that ecosystems provide to communities, such as clean air, clean water, and fertile soils, by analysing ecosystem services within the VORS model. The reciprocal relationship between an ecosystem's health and the welfare of the human populations that depend on these services is also considered in this assessment. The VORS model's practical relevance is ultimately increased by the inclusion of ecosystem services because it links ecological health with societal values and priorities, enabling more informed and comprehensive decision-making for sustainable resource management and conservation strategies.

The Ecosystem services are calculated using the formula,

$$\mathbf{ESV} = \sum_{i=1}^{n} \boldsymbol{Ai} \times \boldsymbol{Pi}$$

Where A_i denotes the area of LULC type i, n denotes the number of LULC types, and Pi denotes the values per unit area of LULC type i.

The table below represents the coefficient of ecosystem services taken for various land use land cover classes is as follows:

Table 3: Different LULC types and their corresponding ESV values

LULC Type	**Equivalent Biome**	**Costanza *et al.,* (1997), 1994 US $ ha^{-1} Yr^{-1}**	**Costanza *et al.,* (2014), 1997 US $ ha^{-1} Yr^{-1}**
Cropland	Cropland	92	5567
Sparse Vegetation	Grassland/rangelands	232	4166
Mangroves	Wetland/Tidal marsh	9990	193843
Waterbodies	Mangroves Lakes/Rivers	8498	12512
Sandy Coast	Desert	0	0
Urban built-up	Urban	0	6661

Source: Costanza *et al.,*1997

Validation of the VORS model using Morris Method:

The Morris one-at-a-time method (MOAT), which Morris (1991) introduced, is a potent tool for performing global sensitivity analysis on model parameters. This strategy's fundamental step is to assess how different parameters interact with one another to affect model results. MOAT provides information on parameter sensitivity by quantifying the overall and inter-parameter effects.

The fundamental idea behind MOAT is to generate r MOAT paths by perturbing all input parameters to the same relative extent throughout a series of model simulations. These routes include modified parameter values while maintaining constant values for others. Calculating gradients based on these paths' mean (m) and standard deviation (s) is the method's key step. The effects of parameter changes on model results are shown by these gradients.

The Morris method stands out due to its focus on thoroughly examining the impact of each parameter's perturbation across numerous simulations runs. This methodology sets MOAT apart from traditional one-at-a-time (OAT) analyses, where each parameter is changed independently without considering the overall impact. A more comprehensive understanding of sensitivity patterns is produced by MOAT's systematic parameter modification and the interactions that result from it, which improves the ability to recognise important factors and complex parameter interactions.

RESULTS

Land Surface Temperature:

In most of India's divisions, there has been a tendency towards less annual and monsoon rainfall, which has been accompanied by reported temperature variations across the country. Particularly during the winter and post-monsoon seasons, temperatures have increased significantly, including minimum, maximum, and mean values. Notably, a significant range of fluctuation was seen for the minimum temperature. In most regions of India, there is a trend towards less annual and monsoon rainfall, and temperature variations are seen everywhere.

The land surface temperature of each of the year 2000,2010 and 2022 were analysed and it was found that over the years, the overall LST have been increased with variations of 2^0C for both the maximum and minimum temperatures. Several hotspots were identified that has increasing temperatures. Most of the high temperate regions were observed at centre of cities and build-ups.

From the change map generated by comparing the LST maps of 2000 and 2010, we can see that a net cooling had occurred with most of the area reducing their LST by 2^0C and the increase in LST was at maximum of around 5^0C which was at the core of cities and at the Cochin airport that had been operational since 1999 but the extensive number of flights and solar panels were observed after the 2010, leading to increased amounts of LST over the region comparatively.

For the change map concerning 2010 to 2022, we see a greater change than the one that was observed for the 2000 and 2010. An average of 2^0C was again observed as the average increase in the maximum and minimum temperatures. The maximum increase in temperature was around 9^0C and the maximum decrease in temperature was around 7^0C.

From the year 2000, there had been a steady increase in the amount of LST hotspots present in Kochi. Primarily the hotspots were based in Eramam (10°04'35.3"N 76°17'51.9"E), Marine drive (9°58'46.5"N 76°16'35.9"E), Kochi refinery (9°58'16.3"N 76°22'37.8"E), Perumanoor (9°57'13.1"N 76°17'18.9"E), Willington Island (9°57'56.1"N 76°16'06.2"E), Cochin airport (10°09'15.2"N 76°23'30.3"E).

In the year 2010, it had been increased by four, while maintaining the previously observed ones. The newly added ones include Kalamassery (10°03'30.2"N 76°20'53.4"E), Mochamkulam (10°03'11.2"N 76°22'45.8"E), Irumpanam terminal (9°59'09.5"N 76°21'12.9"E), lakeshore (9°55'04.8"N 76°19'18.0"E).

By 2022, there had been an increase of five hotspots, which includes Kakkanad (10°00'12.6"N 76°20'35.4"E), Brahmapuram (9°59'29.2"N 76°21'59.6"E), Vallarpadam Island (9°58'44.7"N 76°15'07.0"E), Kaloor Stadium (9°59'47.4"N 76°18'04.2"E), Nalam mile (10°05'20.6"N 76°24'14.6"E).

In addition to the increase in hotspots, there had been greater increase in regions having high temperature that were changed from low temperate regions, which can especially be observed from the changes in 2010 and 2022 LST maps

The rendered maps of LST hotspots, Land Surface Temperature and Absolute Change Maps are as follows:

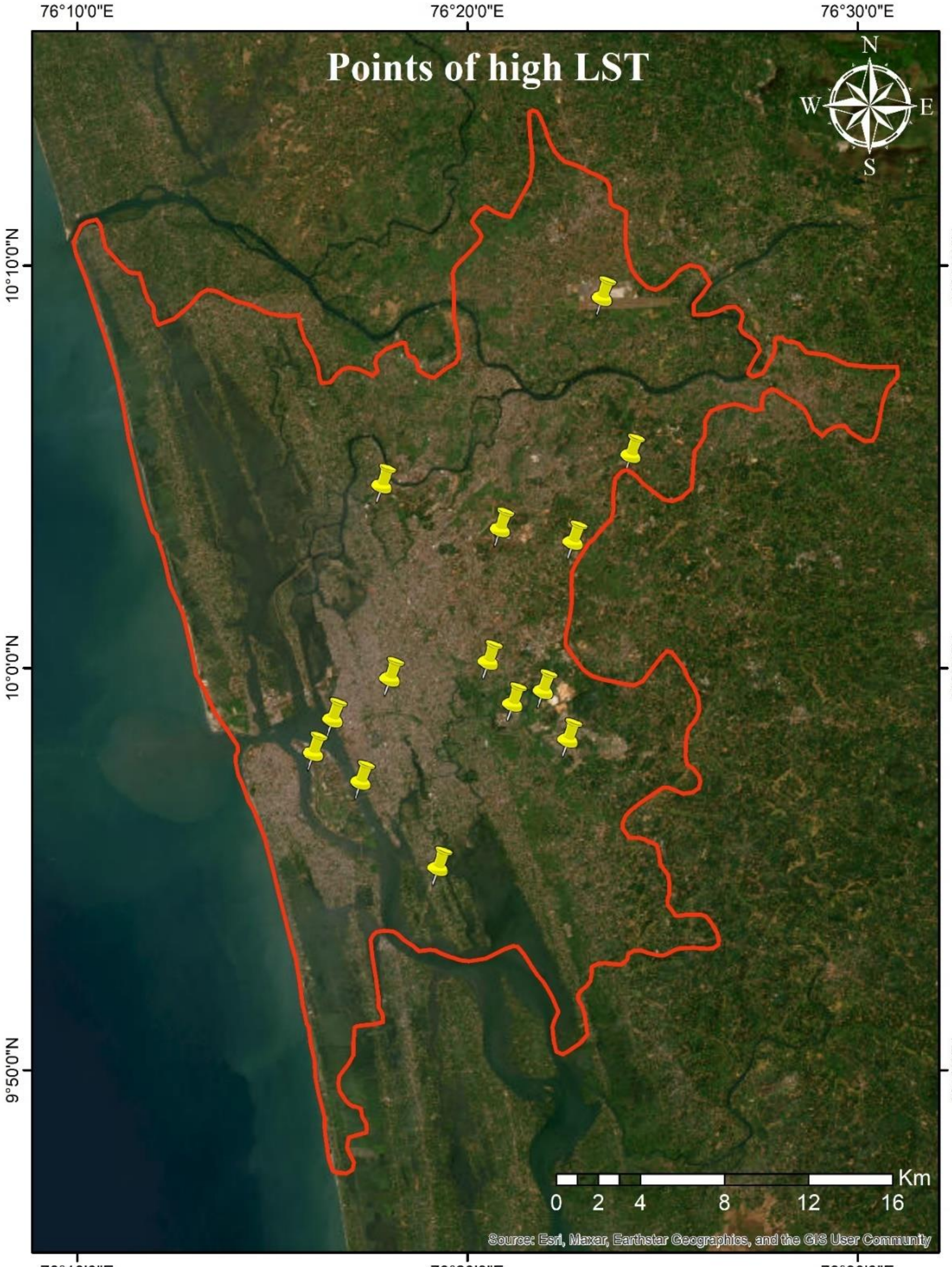


Fig 6: Points showing areas of high LST plotted using Google Earth Pro

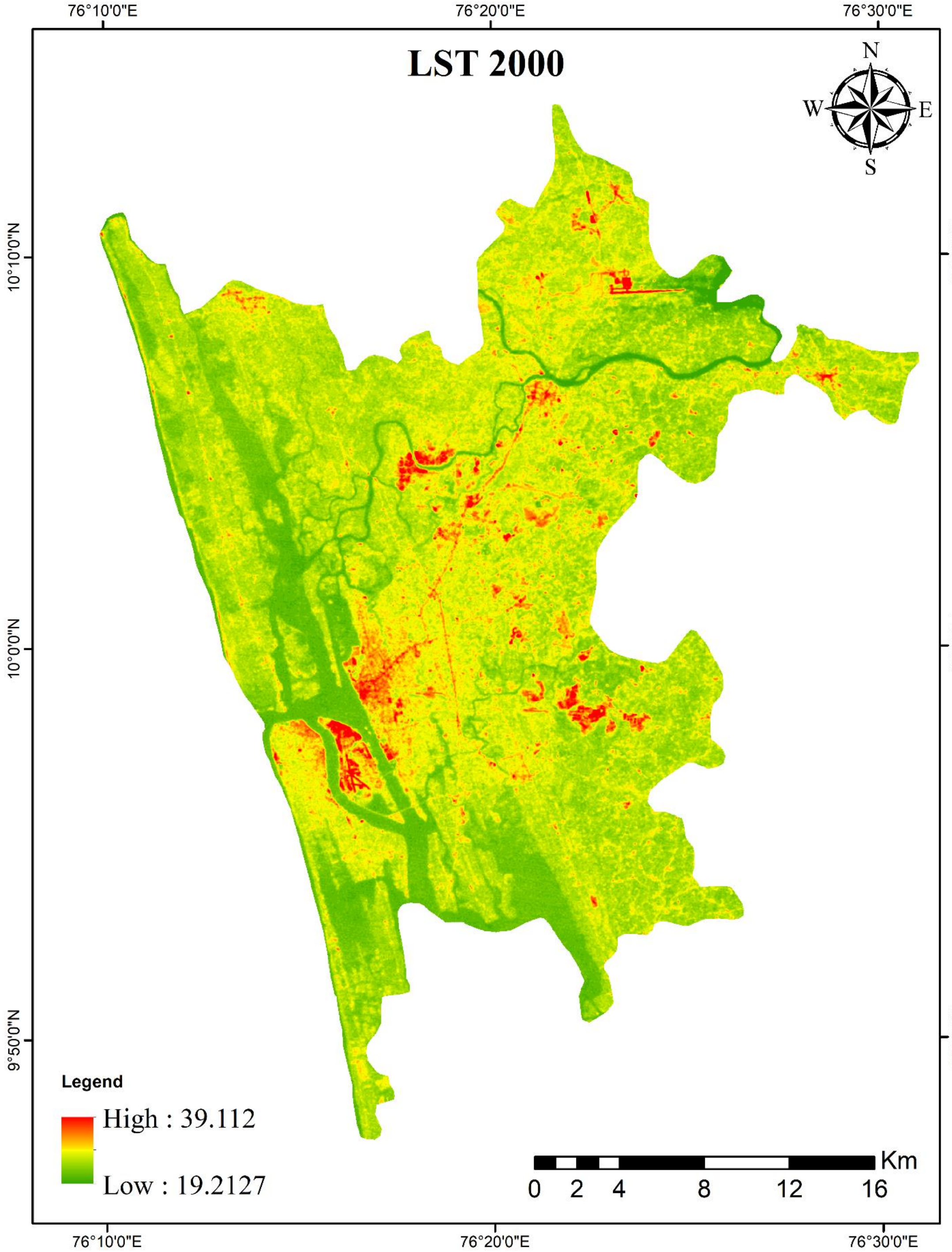


Fig 7: Land Surface Temperature of 2000

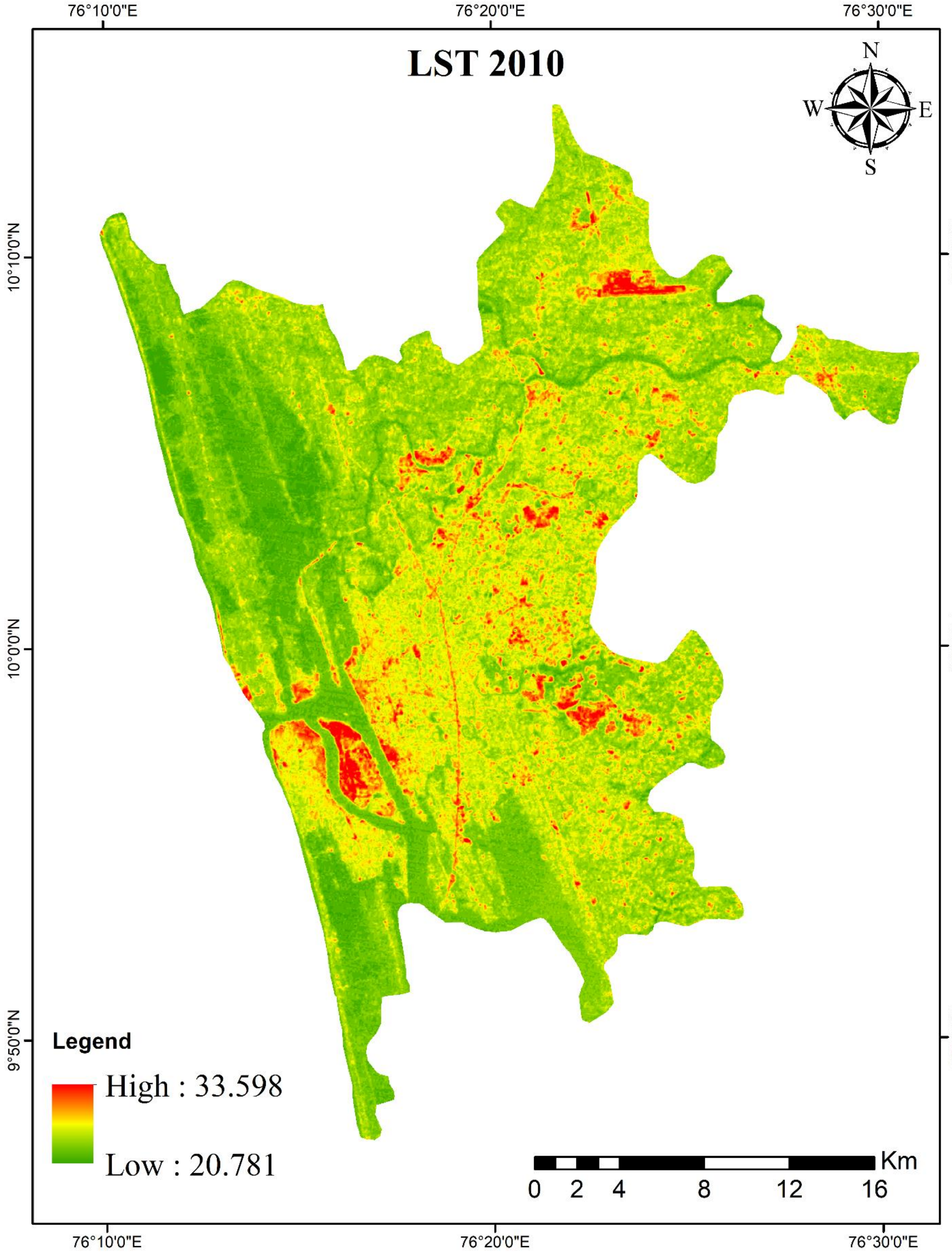


Fig 8: Land Surface temperature of 2010

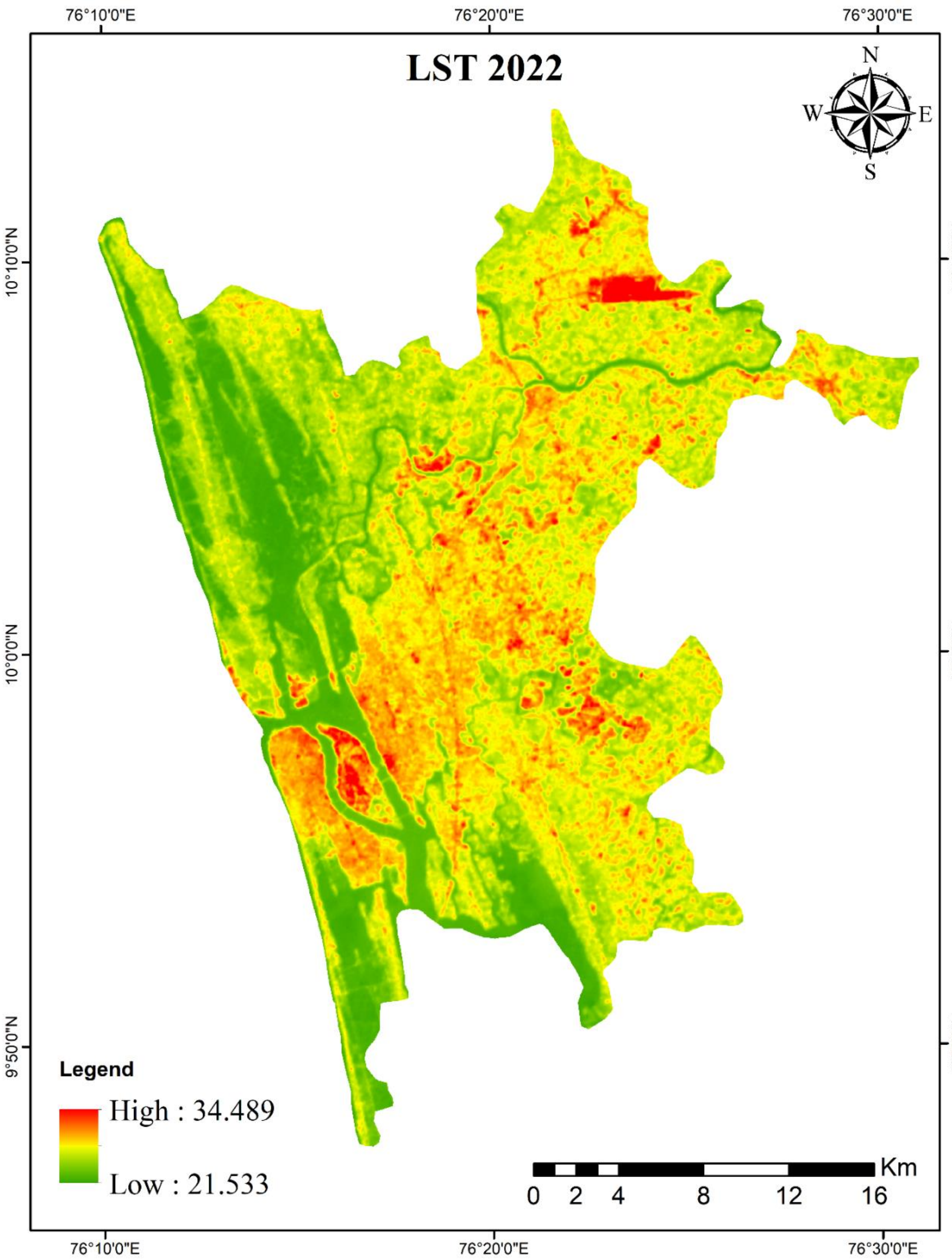


Fig 9 : Land Surface Temperature 2022

From the LST changes that can be observed, most of it was in areas having rapid urbanisation. From the absolute change map obtained in 2010, there can be seen only slight variations in increase of temperature, but the decrease in temperature is high since some of the land that was occupied were taken up by rising water levels, leading to decreased temperature in that region. The process of fast urbanisation is directly linked to the changes in Land Surface Temperature (LST), especially in locations where major urban expansion is taking place. Rapid urbanisation is the process through which rural or natural landscapes are transformed into urban regions with developed infrastructure, increased population density, and modified land use patterns. The local ecosystem is significantly impacted by this phenomenon, which also causes fluctuations in the land surface temperature. Compared to natural landscapes, urban settings often feature a higher density of structures, roads, and other heat-absorbing surfaces. Urban heat islands (UHIs), where temperatures in urban areas are greater than in neighbouring rural regions, are created as a result of this. Urbanisation may consequently result in a rise in LST in places which were mentioned above.

The drop in temperature in areas where urbanisation and rising water levels are a problem has numerous effects: While a drop in temperature may appear to be beneficial in reducing the heat island effect, it can also signal possible hazards, such as an increase in a region's susceptibility to extreme cold events. Additionally, the loss of land due to rising water levels indicates probable environmental changes and flooding concerns, which might have serious ramifications for ecosystems and populated areas in these areas.

The increase in LST near air ports is due to the solar cell heat island effect. The LST kept on increasing to date near the Cochin international Airport, which is evident in the absolute change maps of both timelines. On the plus side, solar energy systems play a significant role in the production of renewable energy, which helps to fight climate change by lowering greenhouse gas emissions. They support a greener, more sustainable energy future by using the sun's energy to produce electricity. The use of renewable energy must increase in order to reduce air pollution, combat climate change, and improve energy security. Therefore, even though solar panels may cause localised heat, this effect must be compared to their overall environmental advantages.

The impact of the heat island effect from solar cells is not all positive. The possibility for increasing energy use for cooling in regions with high solar panel densities is one of the main worries. Buildings and spaces near solar panels may need more energy-intensive cooling to maintain suitable indoor temperatures when solar panels increase the ambient temperature. This may result in increased electricity use and, in certain situations, reverse some of the energy savings brought about by solar power generation. Higher electricity costs for consumers and companies can result from increased cooling energy demand, which can put a strain on regional electrical infrastructures.

Environmental concerns may result from increased temperatures in locations with concentrated solar panels. It might disturb regional ecologies, affecting plants and animals that are susceptible to temperature variations. For instance, some plant and animal species may find it difficult to adjust to warmer climates, which could change biodiversity and cause habitat loss.

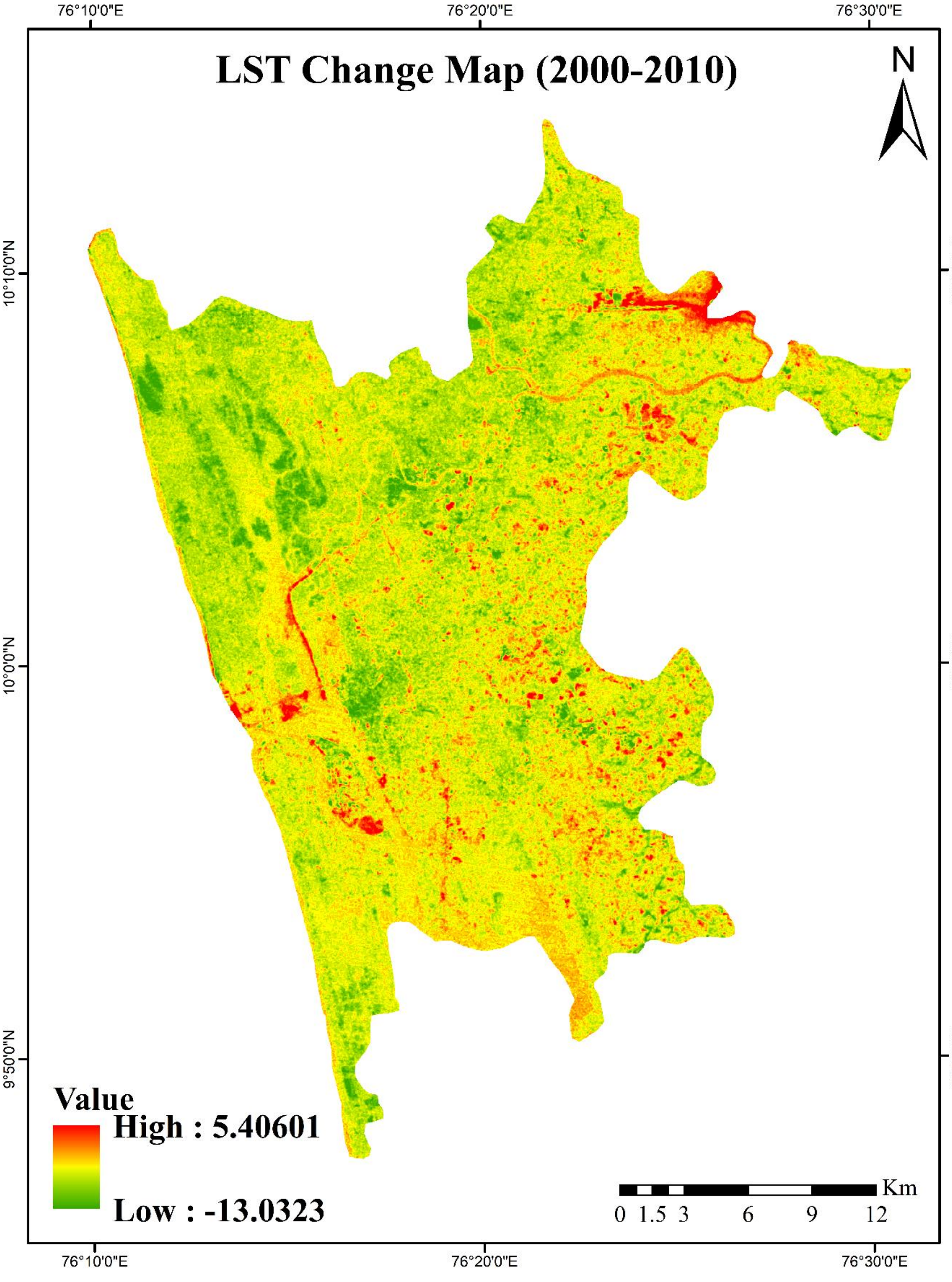


Fig 10: Land Surface Temperature Change Map from 2000 - 2010

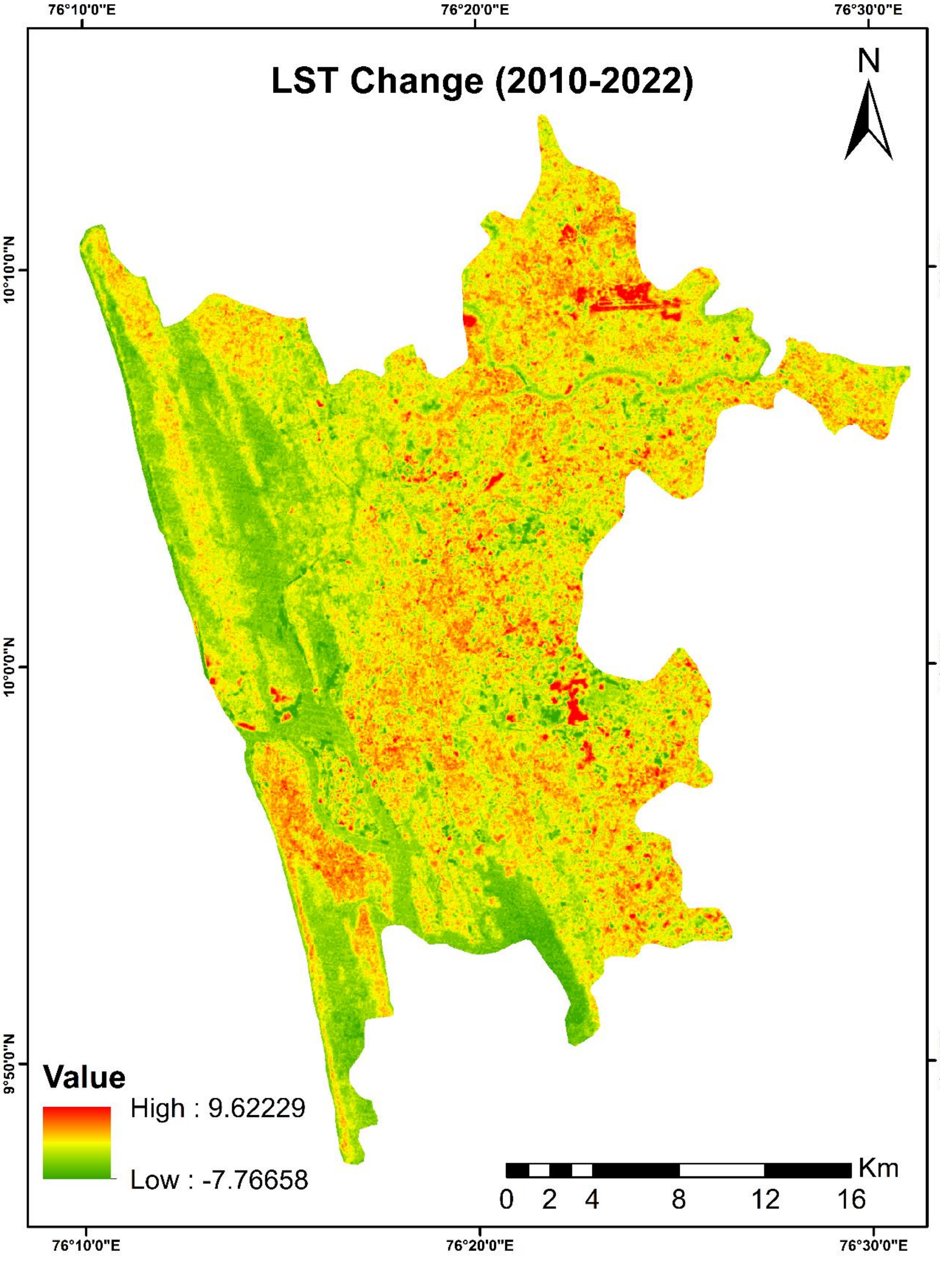


Fig 11: Land Surface Temperature from 2010 to 2022

Land Use Land Cover Classification

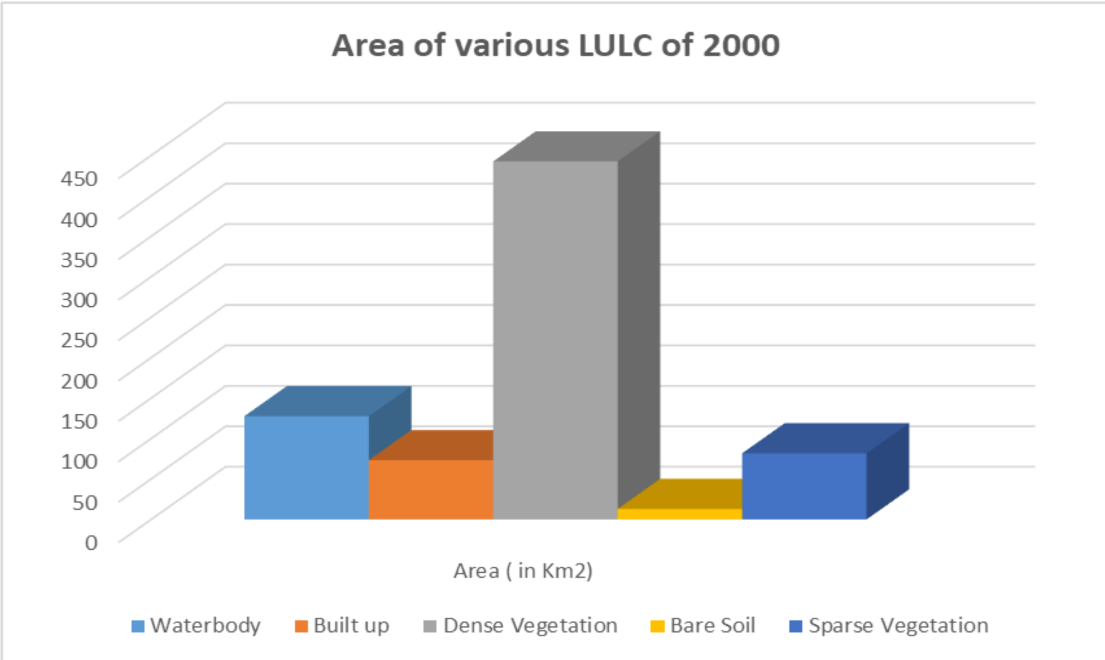
As mentioned, we make use of the support vector machine classifier for the classification of Land Use and Land cover of Kochi. We took training samples of an amount of 500 – 600 for each year among the various land use classes identified. From the figures and charts that were obtained we can see a clear variation between the 2000, 2010 and 2022 years. the existence of two significant and opposing trends were observed in Kochi, the first is the intensification of land use activities, which is occurring at a rate of 1.37% per year and is primarily driven by urbanisation and infrastructure developments, and the second is the fallowing and abandonment of land, which is occurring at a rate of 0.21% per year and is primarily caused by the rising cost of farming. The urban grids are approaching saturation, taking up about two-thirds of the land with urban features at the price of vegetation, and the rates of change are more pronounced in the rural areas.

LULC changes of the year 2000:

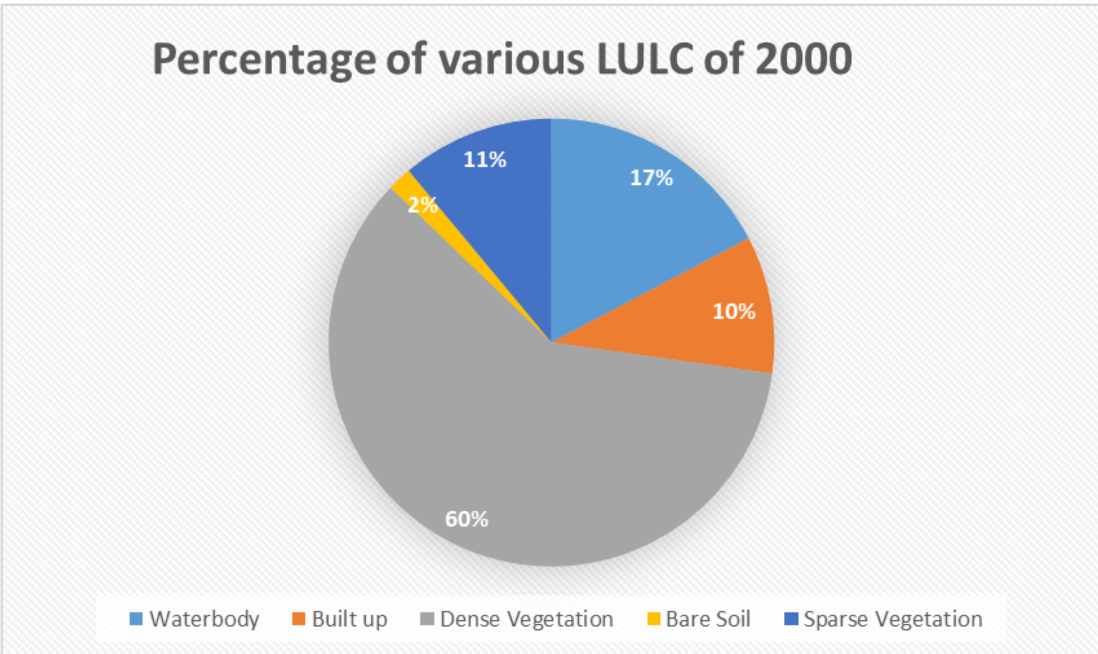
The LULC of the year 2000 mainly consists of dense vegetation that covers about 60% of the total percentage. The high rate of dense vegetation can be accounted for the agricultural activities that can be observed and had been drastically decreased over the last 20 years. Dense vegetation is followed by waterbody, sparse vegetation, built up and lastly bare soil in order of their relative percentage. It can be observed that the area under bare soil was consistent throughout the years.

Table 4: Relative area and percentage under each LULC classes of 2000

Land Use Land Cover Classes	***Total Pixel Count***	***Area (in Km^2)***	***Percentage occupied by said LULC***
Waterbody	141945	127.75	17.29
Built up	81471	73.32	9.926
Dense Vegetation	491906	442.71	59.93
Bare Soil	14468	13.02	1.76
Sparse Vegetation	90925	81.83	11.07



(a)



(b)

Fig 12 : (a) Bar graph showing area under each LULC of 2000, (b) Pie chart showing percentage of LULC of 2000

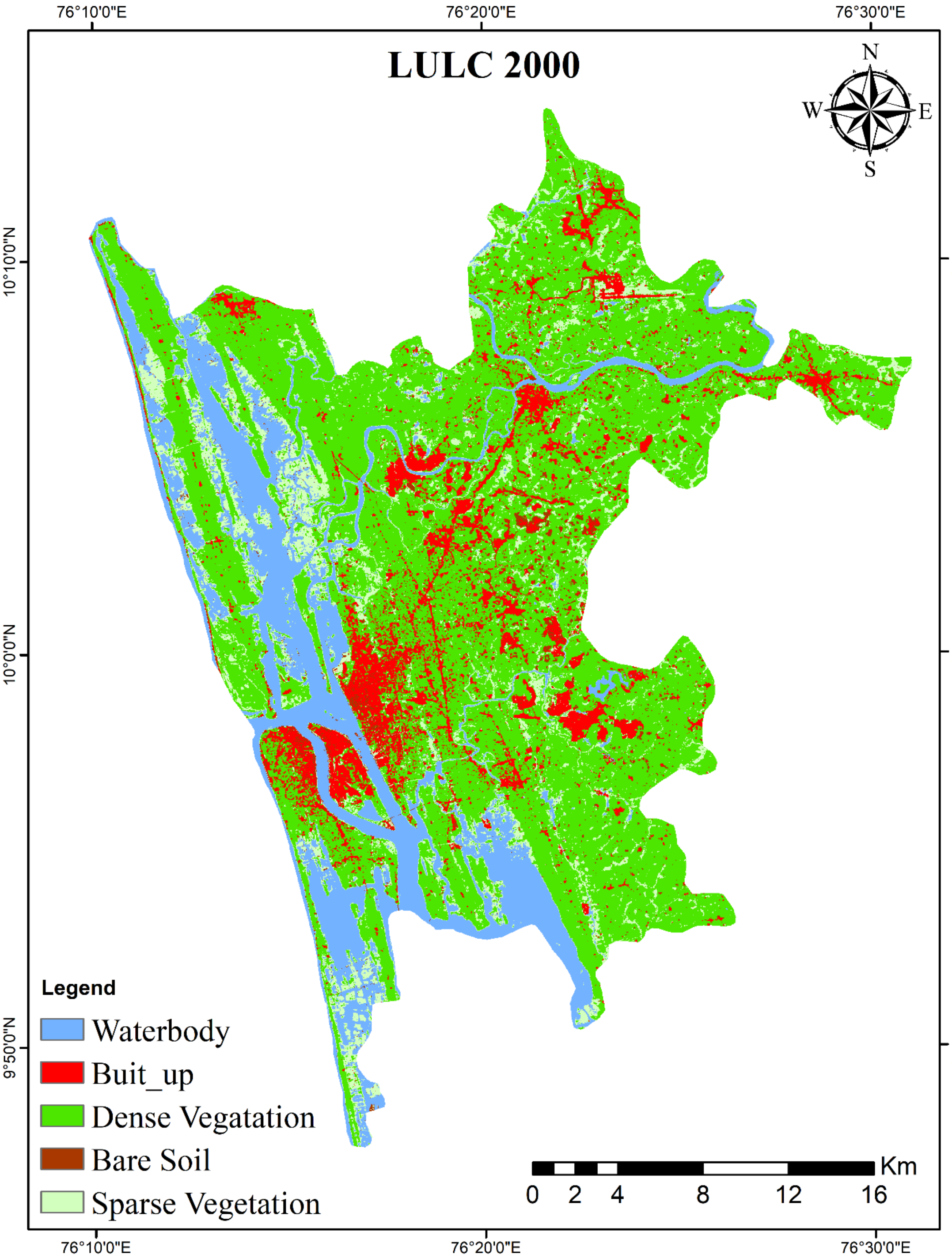


Fig 13: Map of LULC of 2000

Table 5: Accuracy Assessment of LULC of 2000

	Water Body	Sparse Vegetation	Dense Vegetation	Built up	Bare soil	Agricultural Land	Total (User)
Water Body	9	0	0	0	0	0	9
Sparse Vegetation	0	6	1	1	0	0	8
Dense Vegetation	0	0	15	0	0	0	15
Built up	0	1	0	14	0	0	15
Bare soil	0	1	0	0	5	0	6
Agricultural Land	1	1	1	0	0	4	7
Total (Producer)	10	9	17	15	5	4	60

Overall Accuracy = 88.33 %

Users Accuracy for:

Waterbody = 100 %

Sparse Vegetation = 75%

Dense Vegetation = 100%

Built up = 93.33%

Bare soil = 83.33%

Agricultural land = 57.14%

Producer Accuracy for:

Waterbody = 90 %

Sparse Vegetation = 66.67%

Dense Vegetation = 88.24%

Built up = 93.33%

Bare soil = 100%

Agricultural land = 100%

Kappa Coefficient (T) = 0.8551

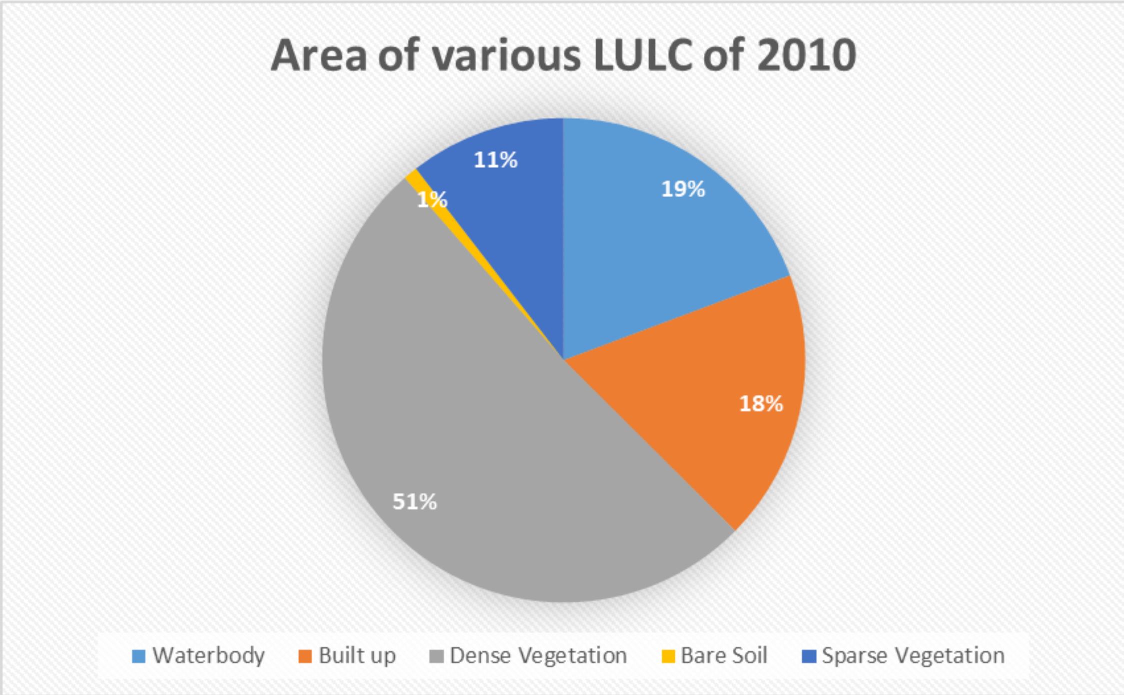
From the set of equations done, the resultant overall accuracy was 88.33% and the resultant Kappa Coefficient was 0.8551, which are both well above the required minimum accuracy for accepting the LULC map obtained

LULC changes of the year 2010:

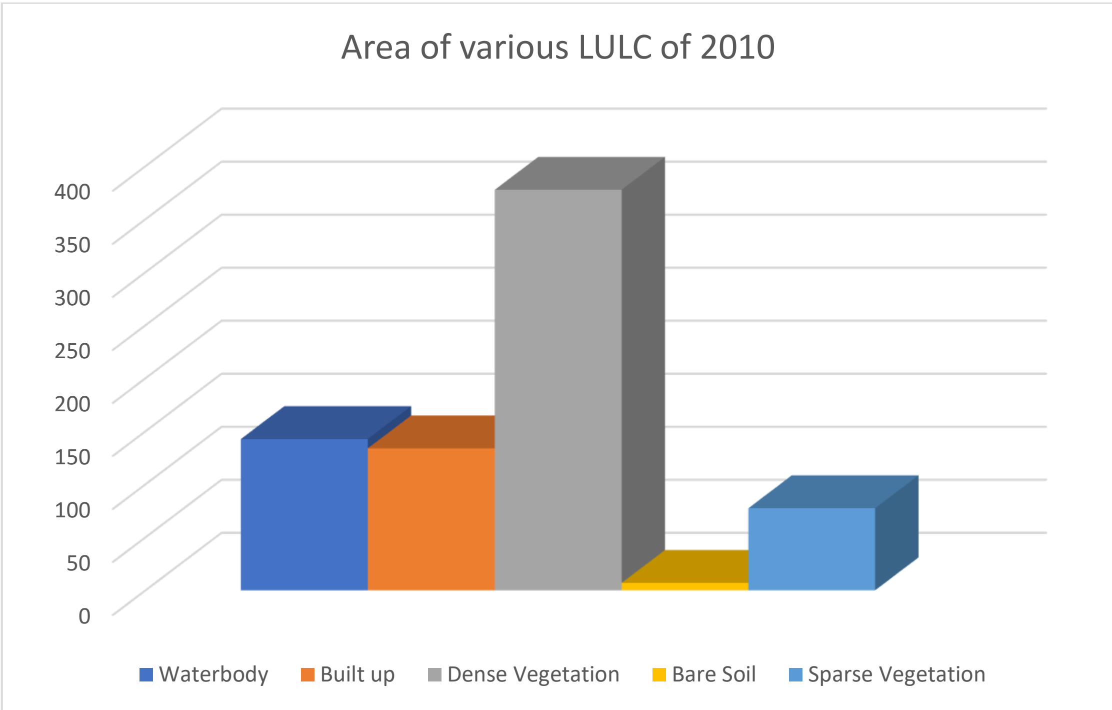
We can see an increase in the built-up area from that of the year 2000. The dense vegetation had decreased by 9% and the built-up had increased by 8%, i.e., most of the lost vegetation had been turned into built-up which can be accounted by the increased levelling of paddy fields around the time

Table 6: Relative area and percentage under each LULC classes of 2010

Land Use Land Cover Classes	***Total Pixel Count***	***Area (in Km^2)***	***Percentage occupied by said LULC***
Waterbody	158462	142.61	19.30
Built up	148756	133.88	18.12
Dense Vegetation	419698	377.72	51.13
Bare Soil	7807	7.02	0.95
Sparse Vegetation	85992	77.39	10.47



(a)



(b)

Fig 14 : (a) Bar graph showing area under each LULC of 2010, (b) Pie chart showing percentage of LULC of 2010

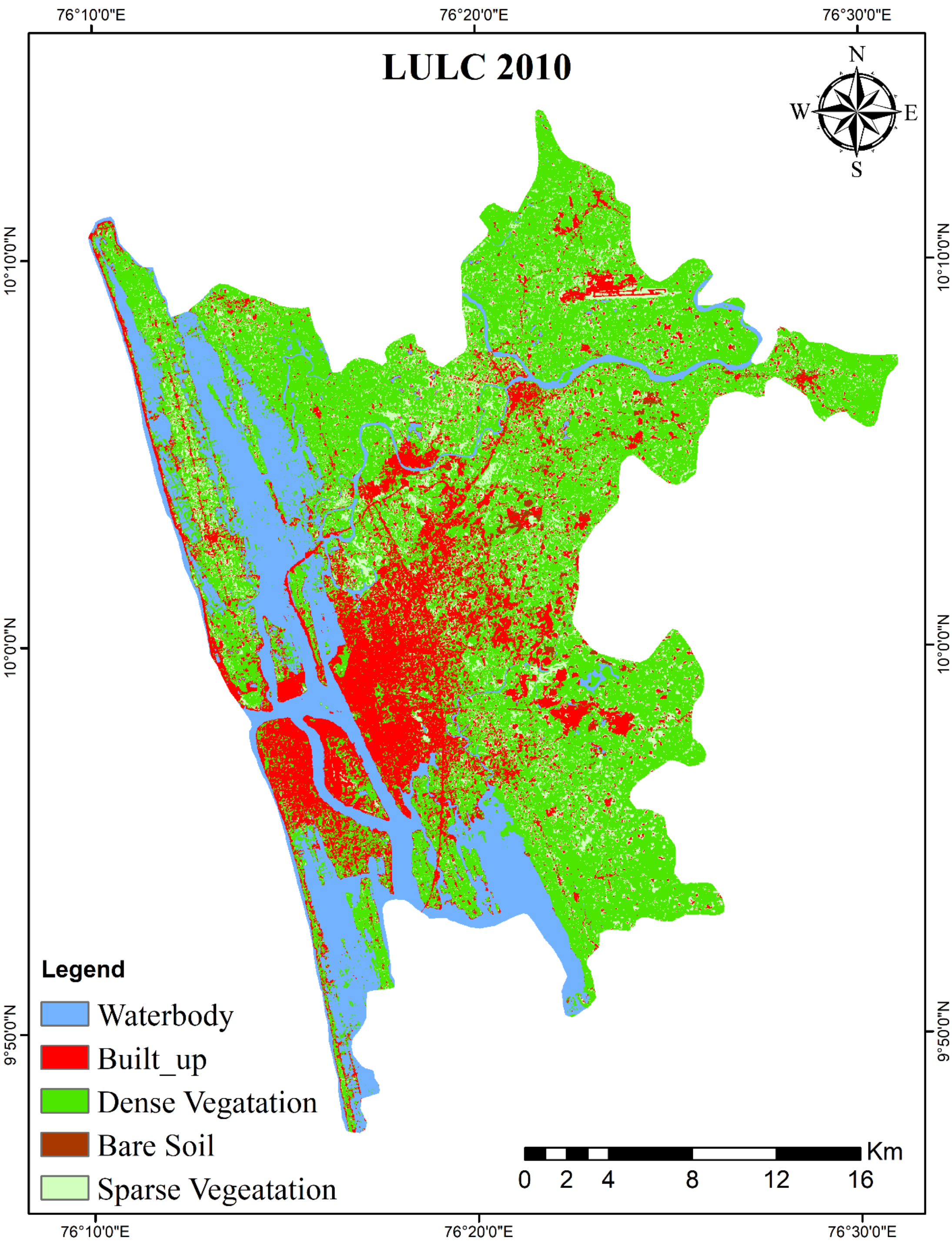


Fig 15: Map of LULC of 2010

Table 7: **Accuracy Assessment of LULC of 2010:**

	Water Body	Sparse Vegetation	Dense Vegetation	Built up	Bare soil	Total (User)
Water Body	12	0	0	0	0	12
Sparse Vegetation	0	12	0	0	0	12
Dense Vegetation	1	1	11	0	0	13
Built up	0	0	1	10	1	12
Bare soil	0	2	1	1	7	11
Total (Producer)	13	15	13	11	8	60

Overall Accuracy = 86.67 %

Users Accuracy for:

Waterbody = 100 %

Sparse Vegetation = 100%

Dense Vegetation = 84.62%

Built up = 83.33%

Bare soil = 63.64%

Producer Accuracy for:

Waterbody = 92.31 %

Sparse Vegetation = 80%

Dense Vegetation = 84.62%

Built up = 90.91%

Bare soil = 87.5%

Kappa Coefficient (T) = 0.8330

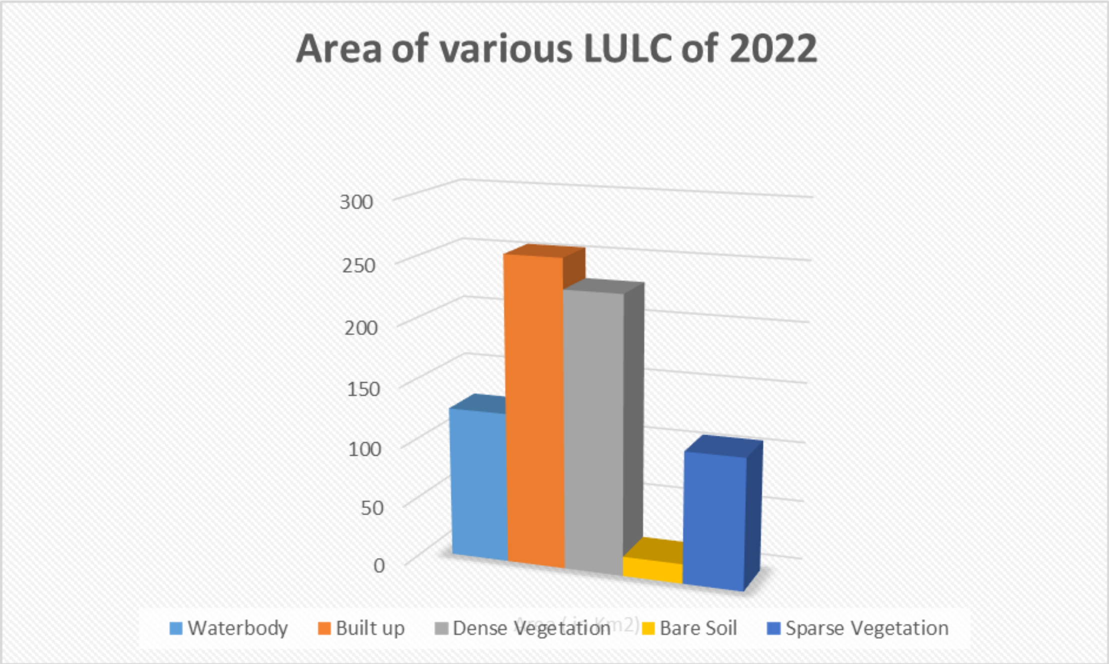
From the set of equations done, the resultant overall accuracy was 86.67% and the resultant Kappa Coefficient was 0.8330, which are both well above the required minimum accuracy for accepting the LULC map obtained

LULC changes of the year 2022:

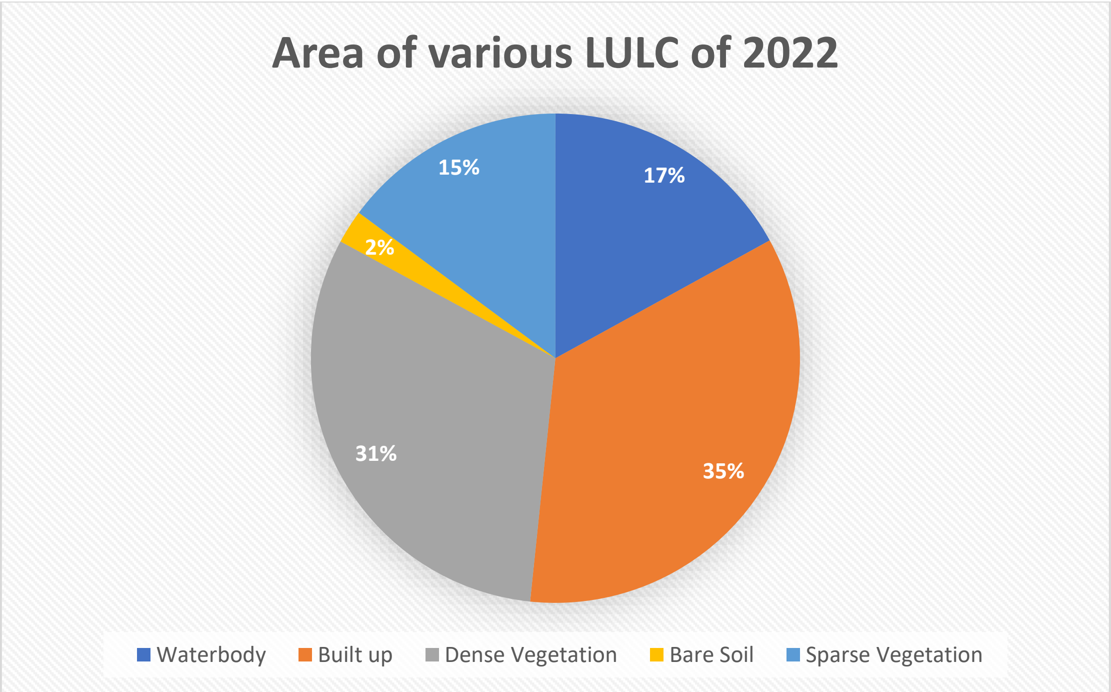
Apart from the previous years, we can see a huge variation in the area of built up and dense vegetation. The amount of built up had increased nearly two-fold from 18% to 35% and the amount of dense vegetation had decreased by 20%. The amount of sparse vegetation had also increased by 3%. Most of the converted dense vegetation had been occupied by built-up, which can be authorised by the sudden increase in population of Kochi which is 3,406,000 in 2023 when compared to 2,063,000 in 2010 (www.macrotrends.net/cities /21305 /cochin / population)

Table 8: Relative area and percentage under each LULC classes of 2022

Land Use Land Cover Classes	*Total Pixel Count*	*Area (in Km^2)*	*Percentage occupied by said LULC*
Waterbody	139556	125.60	17.004
Built up	284365	255.92	34.64
Dense Vegetation	256614	230.95	31.26
Bare Soil	18224	16.40	2.22
Sparse Vegetation	121956	109.76	14.85



(a)



(b)

Fig 16: (a) Bar graph showing area under each LULC of 2022, (b) Pie chart showing percentage of LULC of 2022

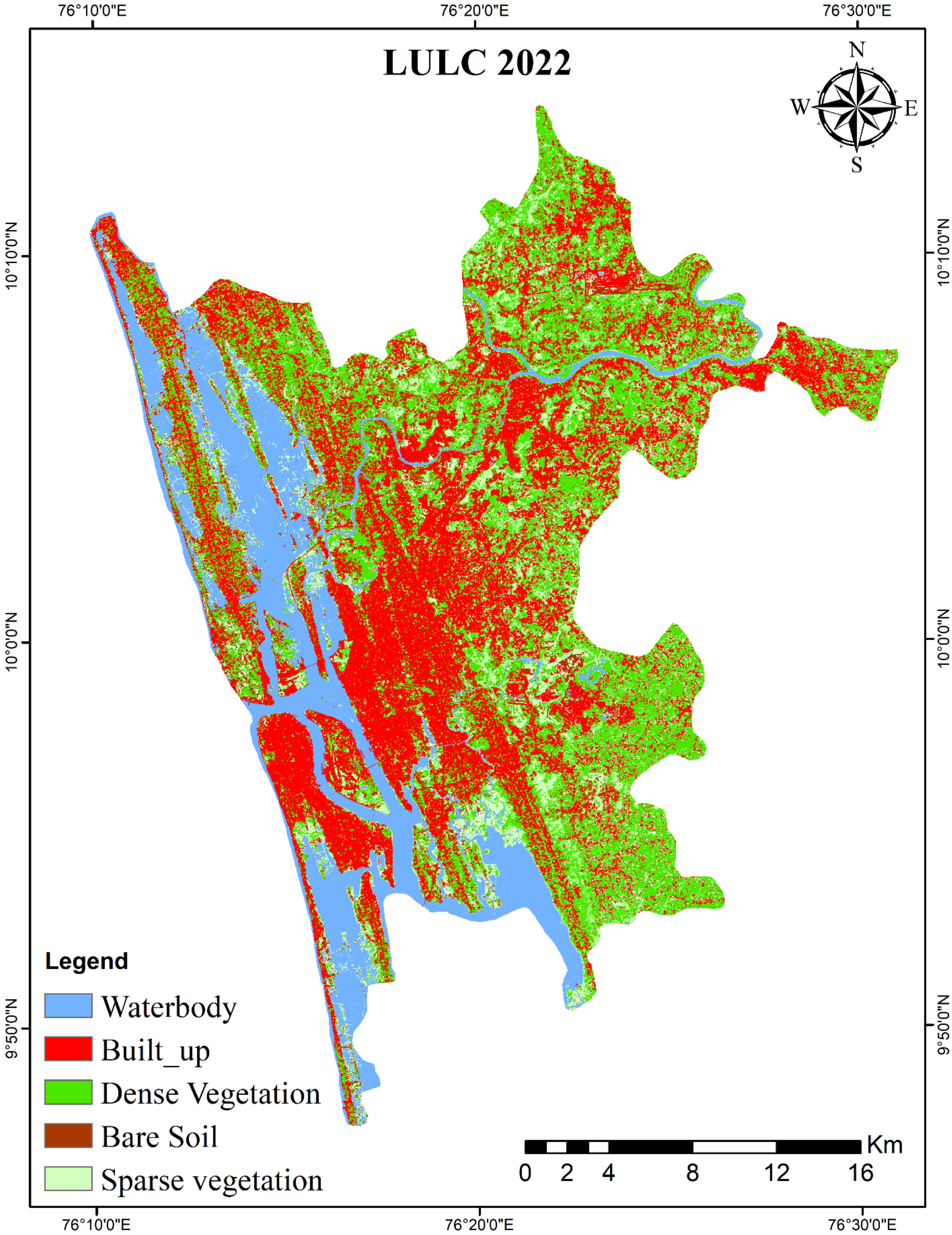


Fig. 17: Map of LULC of 2022

Table 9: Accuracy Assessment of LULC of 2022

	Water Body	**Sparse Vegetation**	**Dense Vegetation**	**Built up**	**Bare soil**	**Total (User)**
Water Body	12	0	0	0	0	12
Sparse Vegetation	2	11	0	0	0	13
Dense Vegetation	0	1	8	0	0	9
Built up	0	0	1	19	0	20
Bare soil	0	1	0	0	5	6
Total (Producer)	14	13	9	19	5	60

Overall Accuracy = 91.67%

Users Accuracy for:

Waterbody = 100 %

Sparse Vegetation = 84.62%

Dense Vegetation = 88.89%

Built up = 95%

Bare soil = 83.33%

Producer Accuracy for:

Waterbody = 85.71%

Sparse Vegetation = 84.62%

Dense Vegetation = 88.89%

Built up = 100%

Bare soil = 100%

Kappa Coefficient (T) = 0.8917

From the set of equations done, the resultant overall accuracy was 91.67% and the resultant Kappa Coefficient was 0.8917, which are both well above the required minimum accuracy for accepting the LULC map obtained.

Ground Truth Validation of LULC of 2022

For the validation of LULC, we made use of both accuracy assessment using randomly generated points along with the ground truth data obtained from the field using the LOCUS android app. A total of 60 points were taken randomly with respect to the classes for determining the accuracy. The points obtained were taken and evaluated in coordination with the map of Google Earth pro.

Table 10: Accuracy table for the ground truth of 2022

	Waterbody	**Sparse Vegetation**	**Dense Vegetation**	**Built up**	**Bare Soil**	**Total (User)**
Waterbody	10	0	2	0	0	12
Sparse Vegetation	0	10	0	0	0	10
Dense Vegetation	0	0	14	0	0	14
Built up	0	0	3	14	0	17
Bare Soil	0	0	0	0	7	7
Total (Producer)	10	10	19	14	7	60

Overall Accuracy = 91.67%

Users Accuracy for:

Waterbody = 83.33 %

Sparse Vegetation = 100%

Dense Vegetation = 100%

Built up = 82.35%

Bare soil = 100%

Producer Accuracy for:

Waterbody = 100%

Sparse Vegetation = 100%

Dense Vegetation = 73.68%

Built up = 100%

Bare soil = 100%

Kappa Coefficient (T) = 0.8939

From the set of equations done, the resultant overall accuracy was 91.67% and the resultant Kappa Coefficient was 0.8939, which are both well above the required minimum accuracy for accepting the LULC map obtained.

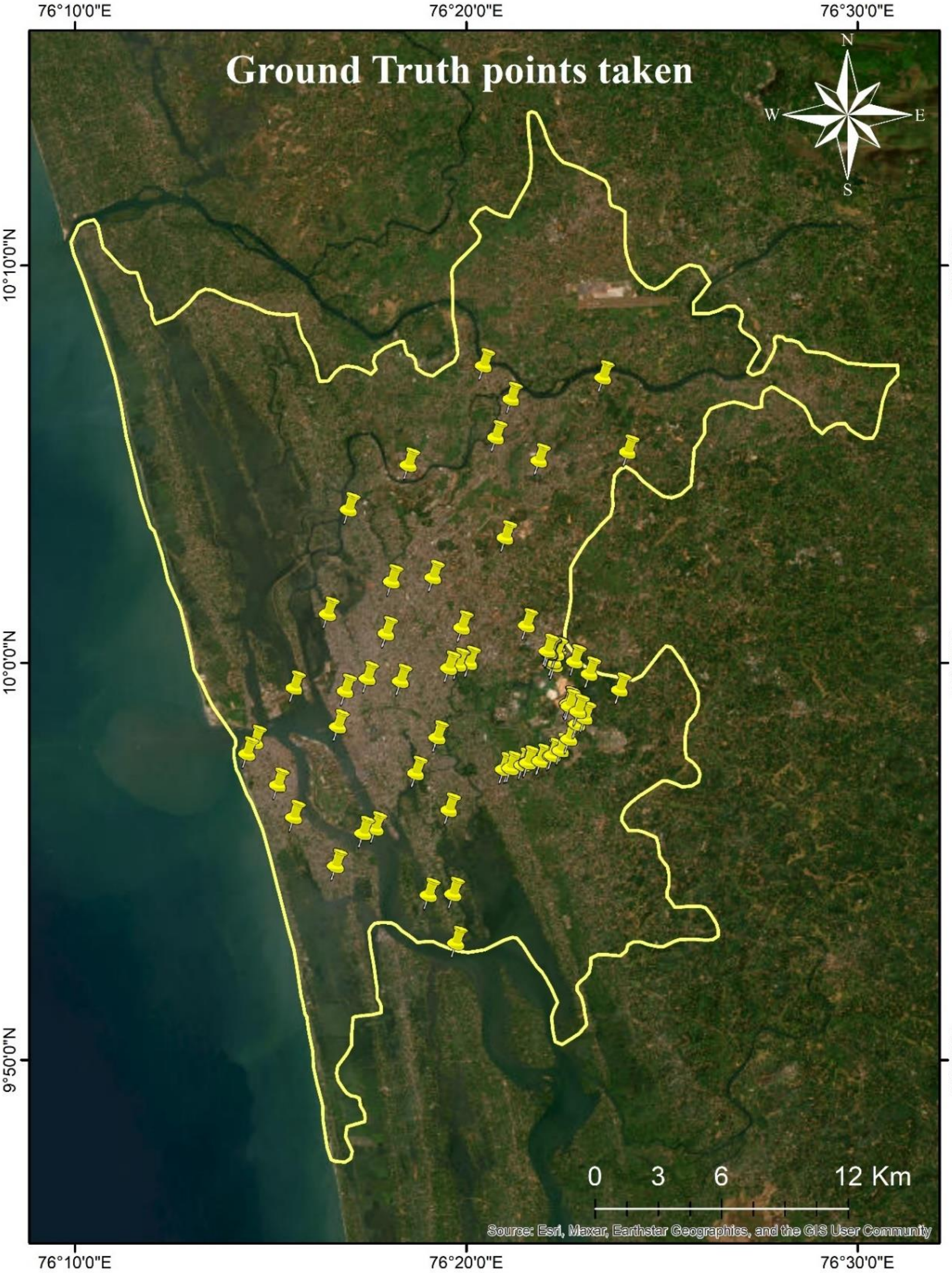


Fig 18: Groud truth points taken for 2022

Fig 19 : Figures of Built_up near Marine Drive, Kochi

Prediction of the Future LULC using CA-ANN

For the prediction of Future LULC we made use of the MOLUSCE plugin of QGIS 2.18. The MOLUSCE plugin makes use of artificial neural network (ANN) method in the cellular automata (CA) model because it has been shown to produce better results than other techniques such as linear regression. In our study, seven LULC change conditioning factors were identified for 2022 and 2032, which includes

- elevation
- slope
- proximity to an urban area
- agricultural land
- scrubland
- sparse vegetation
- water bodies

Prior to being used to anticipate future LULC maps, the model's performance has been assessed by simulating the current LULC and optimising the model's parameters. Otherwise, the upcoming LULC map would not be reliable. As a result, the 2022 LULC map was initially simulated, and in the current study, the model's performance was evaluated. After the model demonstrated good performance, it was used for the 2032 LULC map.

After acquiring change maps and transition probabilities between the LULC periods of 2000-2010 and 2010-2022 using QGIS, the ANN model was utilised to integrate the conditioning factors for forecasting the LULC transitional suitability map. There is a system for acquiring training and test datasets included in the QGIS MOLUSCE plug-in.

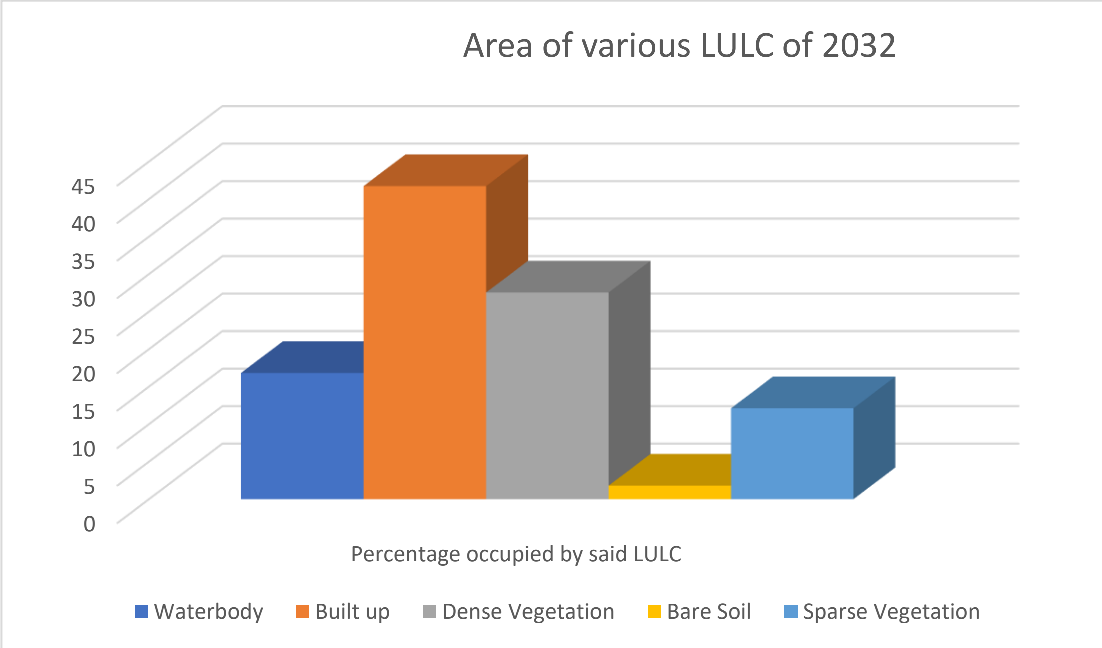
The LULC transitional suitability model was created using a multi-layer perceptron architecture with a back-propagation method. The input data for this stage are a change map (obtained by doing a change analysis between the initial layer (2000) and the most recent LULC,2022) and are anticipated to have an impact on the likelihood of changes taking place.

The model's output values are the component weights that it has chosen. Each factor is given one or more weights as a result of fine-tuning the model, depending on how much it contributes to the likelihood that changes will occur. Weight can be positive (feedback—if the factor is present, changes are unlikely) or negative (close association between the factor and the likelihood that changes will occur). Following that, the CA model's output from the ANN model was combined.

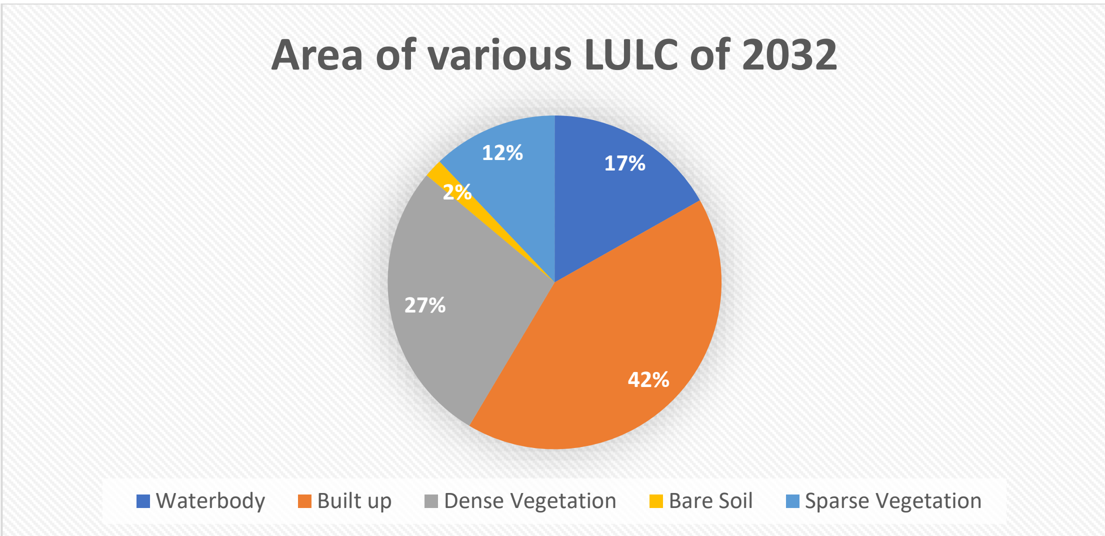
During the ANN model's training, several model parameters were optimised to produce better outcomes. The parameters of the ANN model were optimised by a process of trial and error. The following are the optimised parameters: 1000 iterations, 0.001 learning cycles, 0.02 momentum cycles, 10 pixels in the neighbourhood, and 10 in the hidden layer. Numpy.tanh sigmoid function is the activation function. After obtaining the land-use probability or suitability model by ANN, the LULCs were predicted using CA simulation. The CA model was further optimised. The model was initially set to one iteration (10 years), which corresponds to the forecast for the following ten years i.e., for 2032 from 2022.

Table 11: Relative area and percentage under each LULC classes of 2032 is as follows:

Land Use Land Cover Classes	***Total Pixel Count***	***Area (in Km^2)***	***Percentage occupied by said LULC***
Waterbody	138027	124.22	16.81
Built up	342473	308.22	41.72
Dense Vegetation	226086	203.47	27.54
Bare Soil	14753	13.27	1.79
Sparse Vegetation	99376	89.43	12.10



(a)



(b)

Fig 20: (a) Bar graph showing area under each LULC of 2022, (b) Pie chart showing percentage of LULC of 2022

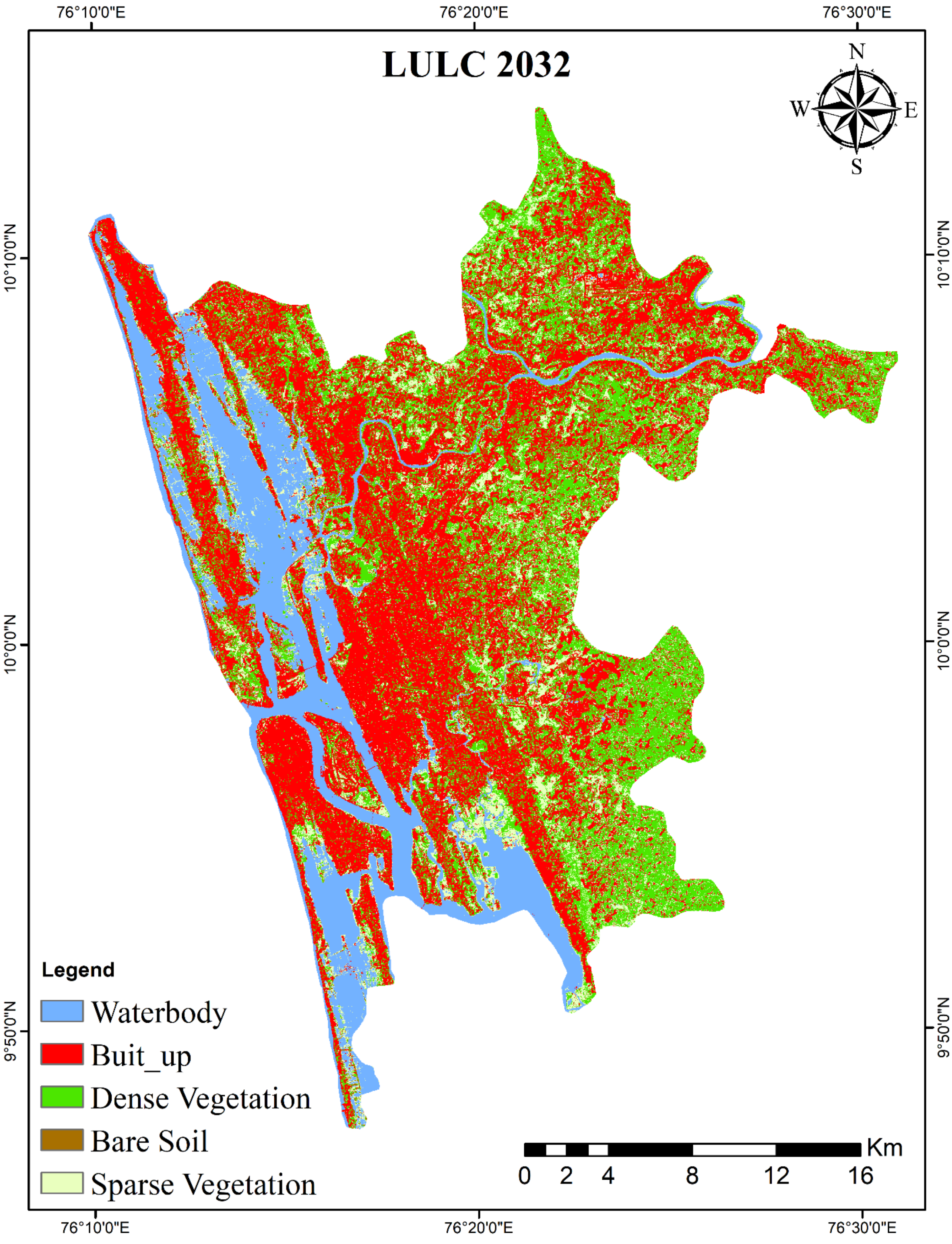


Fig. 21: Predicted LULC map of 2032

Computational models known as cellular automata are widely utilised in geography, urban planning, and environmental research. Each cell in a grid or lattice used by these models serves as a single spatial unit. CA models update the state of each cell depending on established rules and the states of its neighbouring cells as they proceed through discrete time steps. Because of this quality, CA models are very effective at capturing local interactions and spatial interdependence, two crucial elements in LULC changes.

The ANN model's outputs serve as the starting point for the integration procedure. These results show the suitability or likelihood of LULC changes occurring in each grid cell. These probabilities are calculated by combining transition probabilities from the ANN, conditioning factors from historical data, and historical data. Then, the rule set for the CA model is established, describing how suitability values and the surrounding area affect LULC changes. A cell's movement from one land-use category to another is determined by these rules based on the probability the ANN provides. The strength of the CA model lies in its ability to capture spatial interactions and feedback mechanisms, considering not only the suitability of a cell but also the state of its neighbouring cells. For example, if a cell exhibits a high suitability for urban development and its neighbouring cells are also transitioning to urban areas, this local influence is considered in the model's predictions.

Our approach combines data-driven modelling (ANN) with a spatial simulation technique (CA) to forecast future LULC maps based on historical data and conditioning factors. It involves multiple steps of data processing, model training, and parameter tuning to achieve accurate predictions of land-use changes. Even while comparing to the LULC of 2022, we see a staggering increase in the amount of area covered under the built-up category. The percentage of built-up had increased to 42% in the predicted LULC model of 2032. The dense vegetation had decreased by 4% and the spare vegetation had also decreased by 3%. The amount of area lost from the vegetation types is reflected in the total built-up area of 2032.Seven factors were identified for having influence on the Land use Land Cover Change dynamics, most which are proximity to said LULC classes along with the slope and elevation of the study area. Following are the various parameters that were identified to influence the LULC change of our study area:

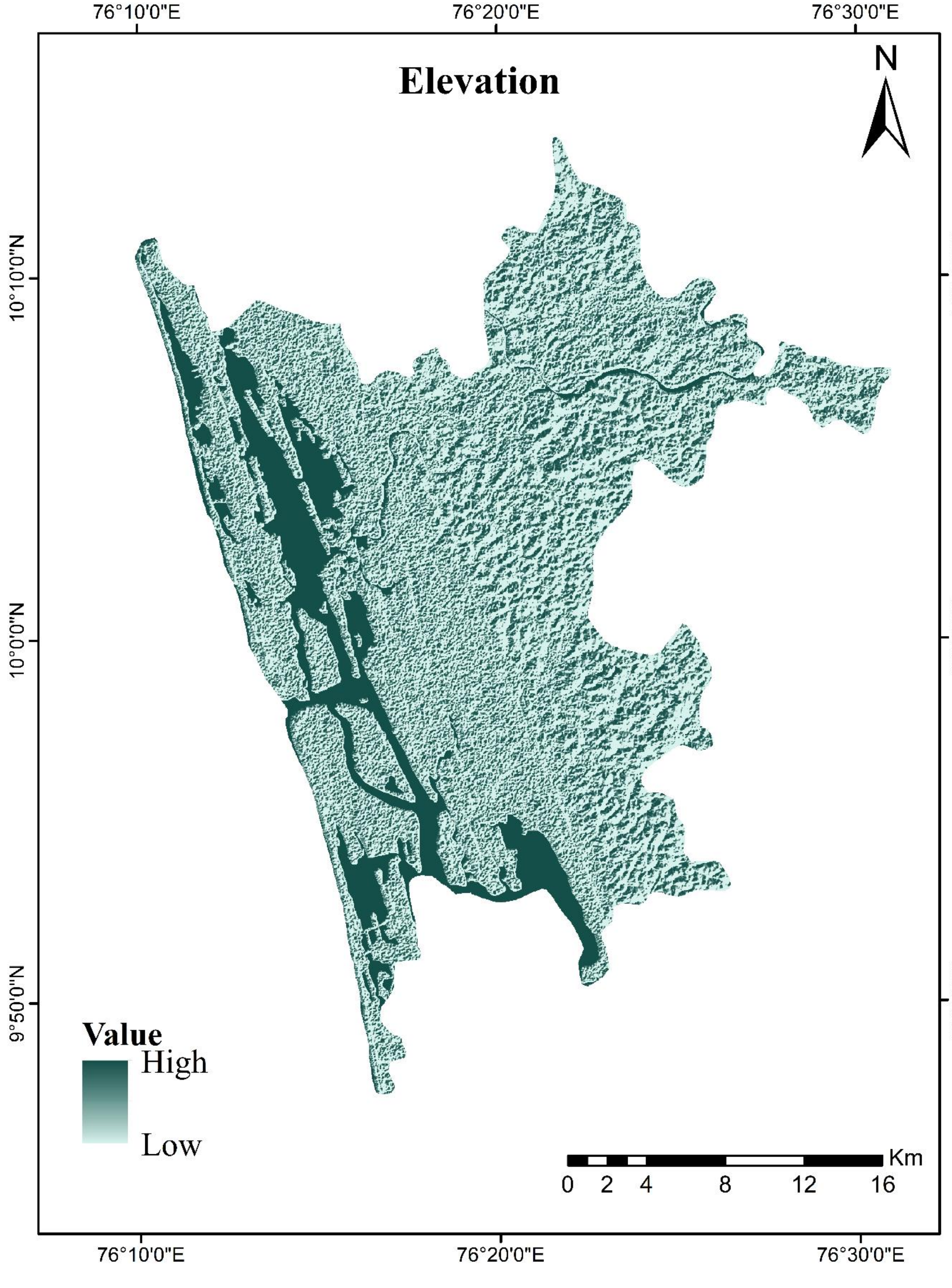


Fig. 22 – Elevation map of Kochi

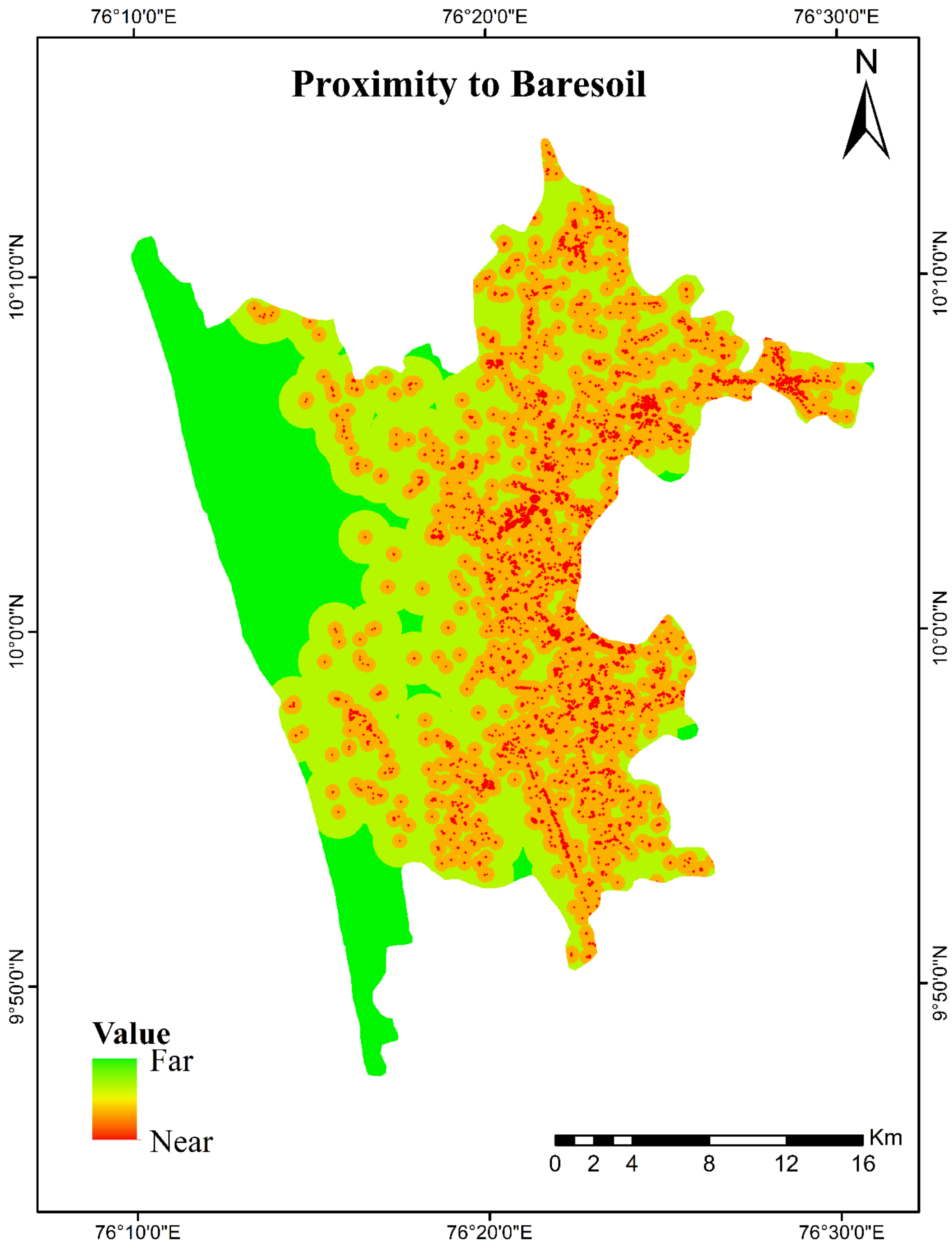


Fig 23: Proximity to Bare Soil

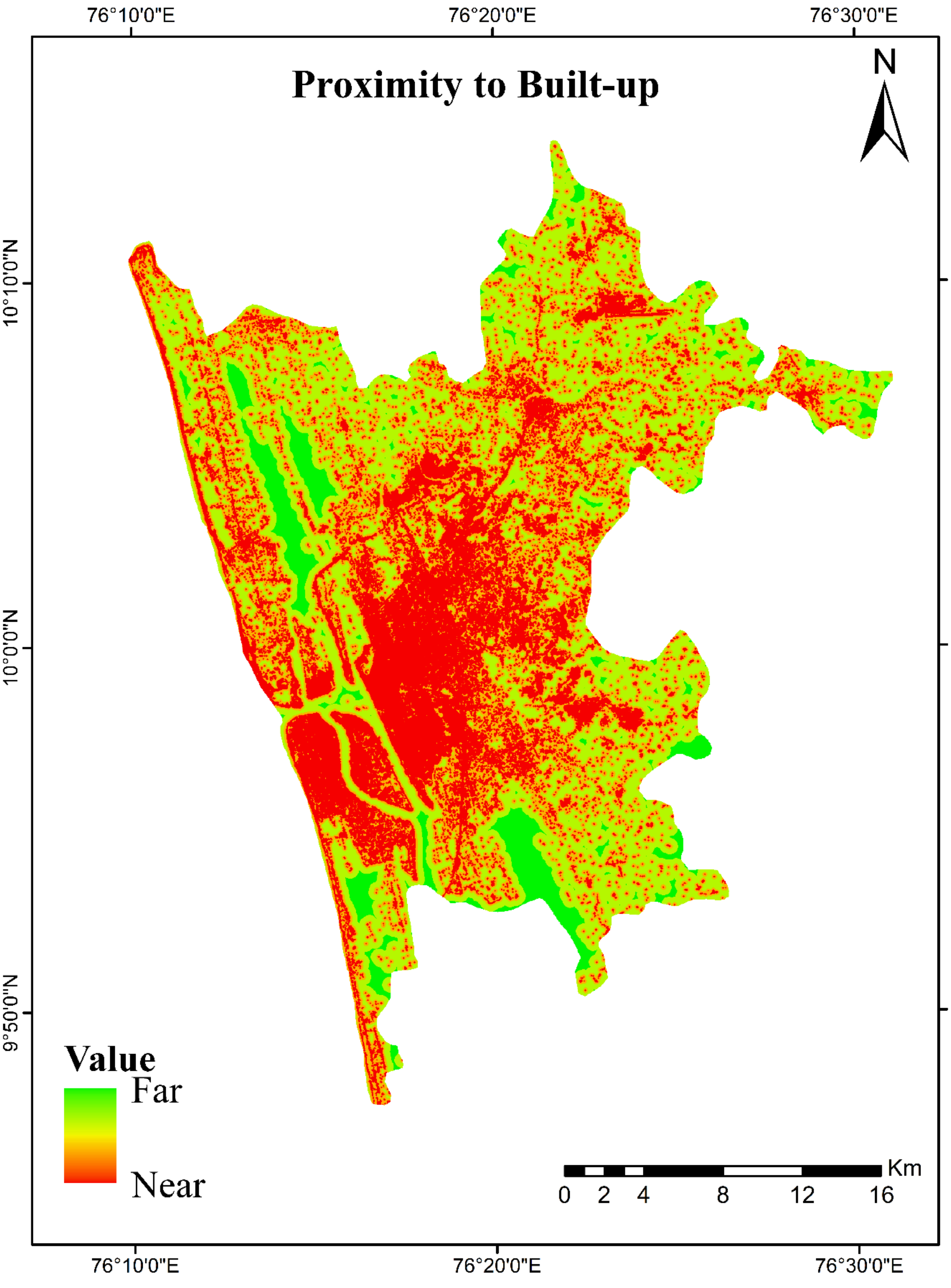


Fig 24: Proximity to Built-up

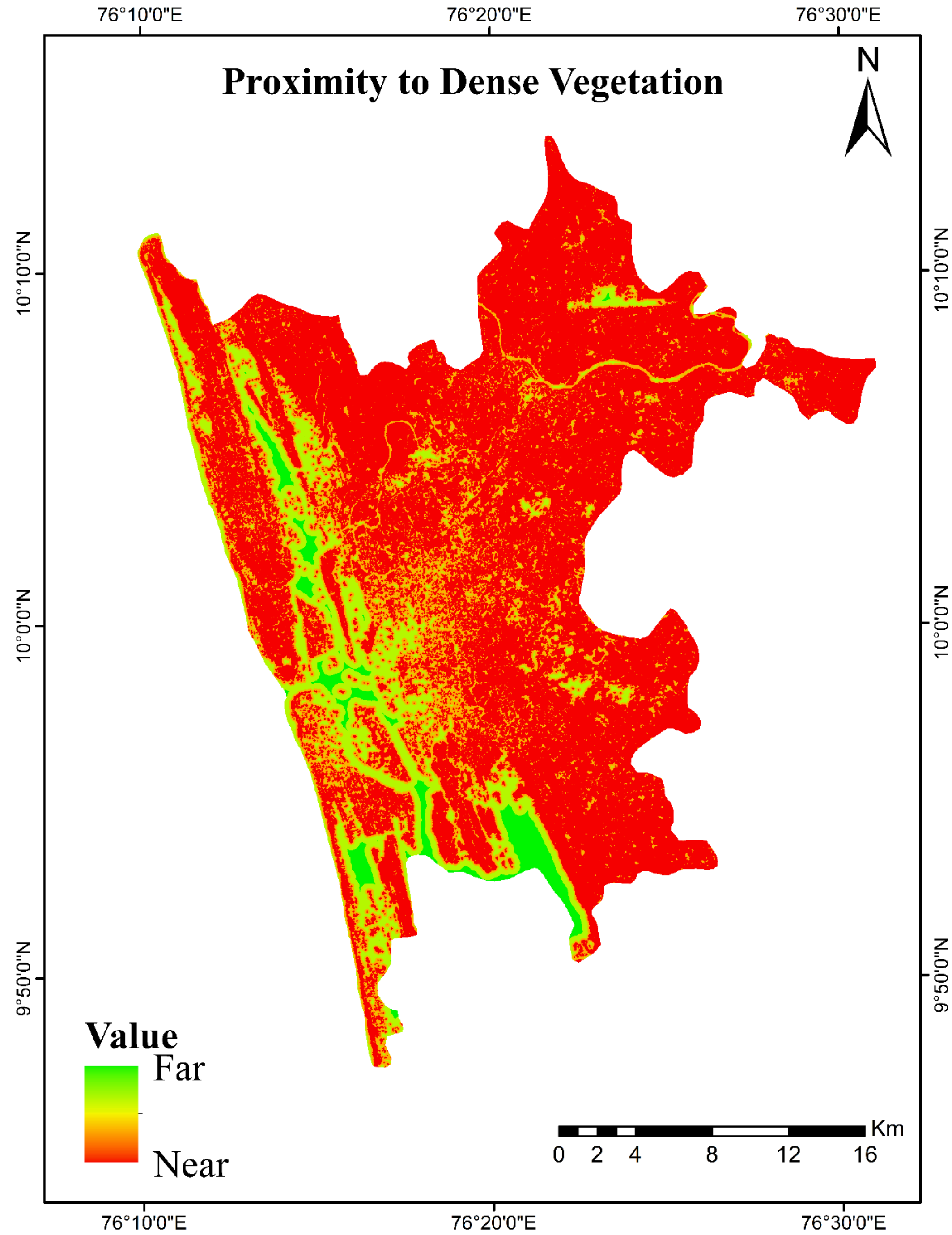


Fig 25: Proximity to Dense Vegetation

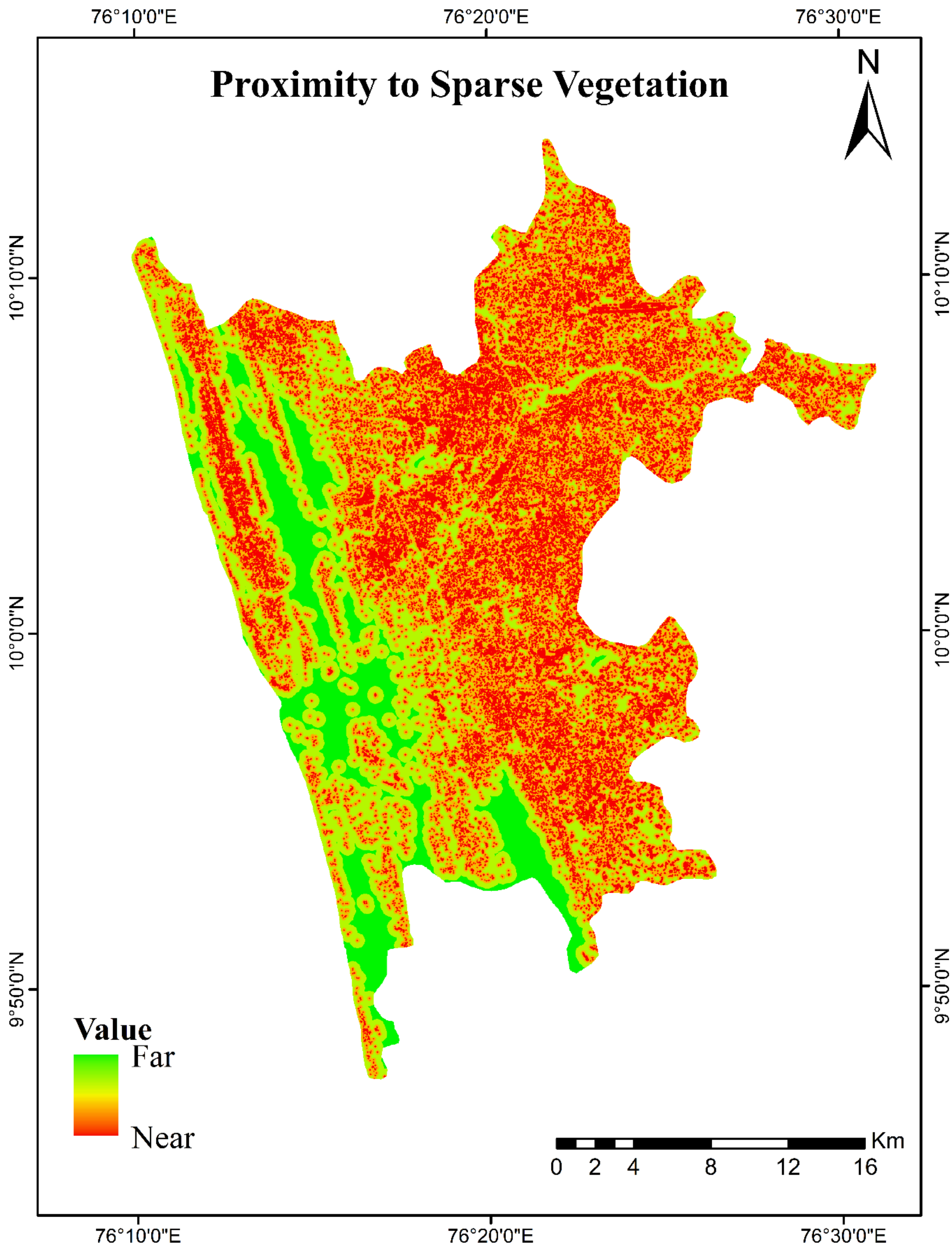


Fig 26: Proximity to Sparse Vegetation

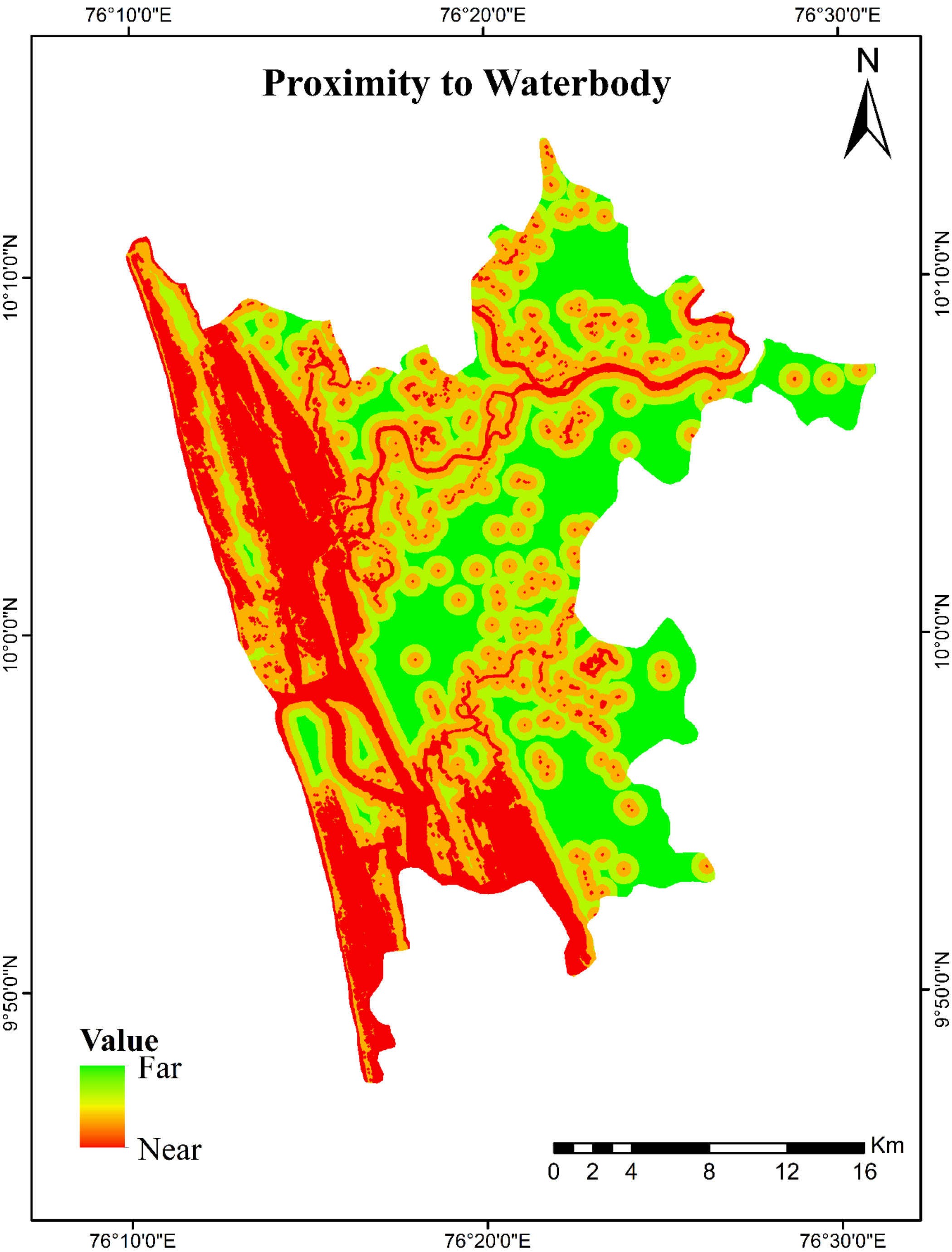


Fig 27: Proximity to Waterbody

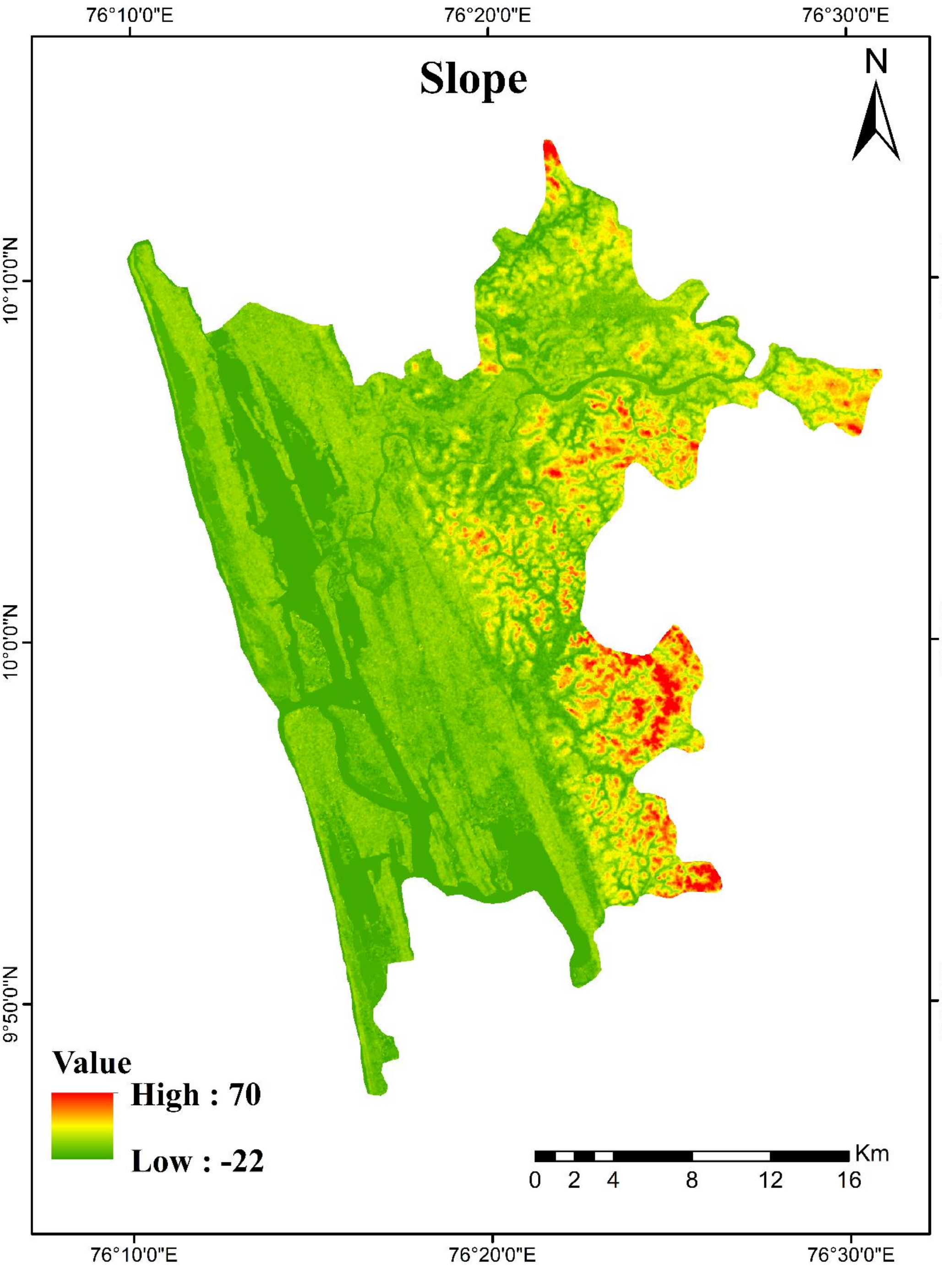


Fig 28: Slope of Kochi

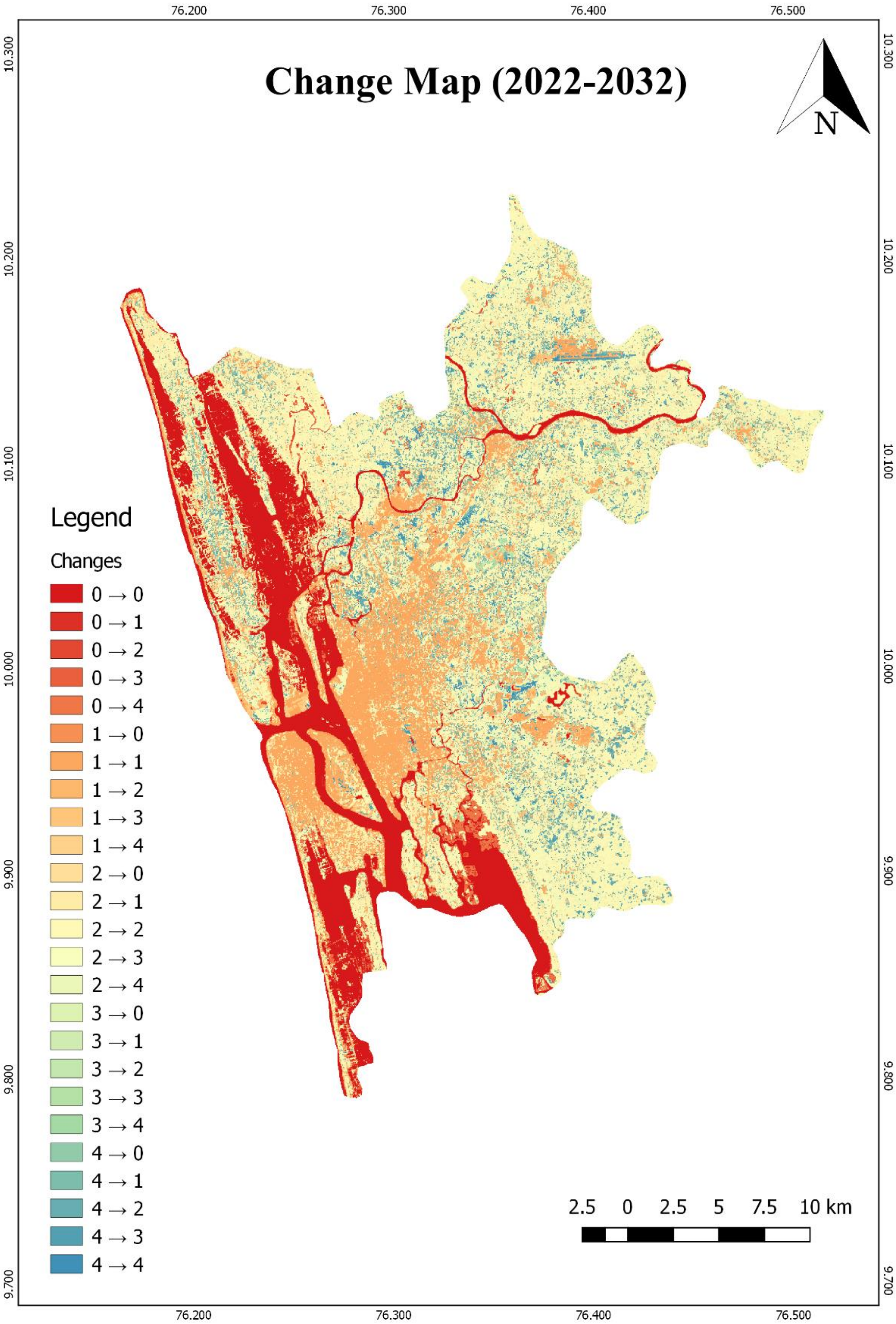


Fig 29: change map that gives us the changes or transition probability from one LULC to another.

The map above shows the change simulated with respect to the LULC of 2010 and 2022. The change from one LULC to another is given through the colour code. 0 represents the waterbody, 1 represents the built-up, 2 represents the dense vegetation, 3 represents the bare soil, 4 represents the sparse vegetation.

For the stimulated map, the Kappa coefficient was found to be 0.79, the correlation coefficient was found to be 0.814 and the overall correctness of prediction was 75.3%. The process had been repeated and only when a passable correctness was obtained, the result was added. The successful result was obtained under optimized parameters as follows: Iteration rate: 1000, Learning rate: 0.001, Momentum: 0.02, Neighbourhood: 10 px, Hidden layer: 10, Activation function: numpy. tanh sigmoid function.

Changes in LULC over the years:

There has been a large change in the LULC over the years especially from dense vegetation to built-up. A high LULC change, in terms of the environment, denotes significant alterations to ecosystems and natural landscapes. This frequently entails turning natural environments like woods, marshes, or grasslands into cities or fields of agriculture. As many species struggle to adapt or locate adequate habitats, these changes may result in the loss of biodiversity and a reduction in ecosystem services including pollination, water purification, and climate regulation. High LULC change may also exacerbate existing environmental problems by increasing soil erosion, altering regional climatic patterns, and interfering with water cycles. Increased greenhouse gas emissions are frequently a result of rapid LULC change, particularly because of deforestation and the growth of urban areas. By releasing carbon dioxide that has been held in the atmosphere, the destruction of forests, which serve as carbon sinks, can hasten climate change. Urbanisation can also result in higher energy use, pollution, and heat island effects, all of which can exacerbate environmental problems. It is clear when the natural landscape has been significantly altered into an urban or man-made environment when there is a transition from thick vegetation to built-up regions. Habitat loss and fragmentation are shown by the transition from areas of dense vegetation to built-up areas. By providing homes, food, and breeding grounds for numerous plant and animal species, dense vegetation, such as forests or lush greens, is essential for sustaining biodiversity. The native ecosystem is harmed when these places are turned into built-up areas, which lowers the diversity of animals. Many wildlife species find it difficult to adapt to urban settings, and some could potentially go extinct locally as a result of the destruction of their native habitats.

We can say an overall change of 0.48% of waterbody from the LULC of 2000 to that of the predicted model of 2032. The total built-up was projected to increase by 31.8% from the LULC of 2000, which is the highest among the others. The dense vegetation had been project to decrease by 32.39% from the total that was available at 2000. There is little to no variation of 0.3% increase to the bare soil and a variation of 1.03% of the level that was in 2000 year.

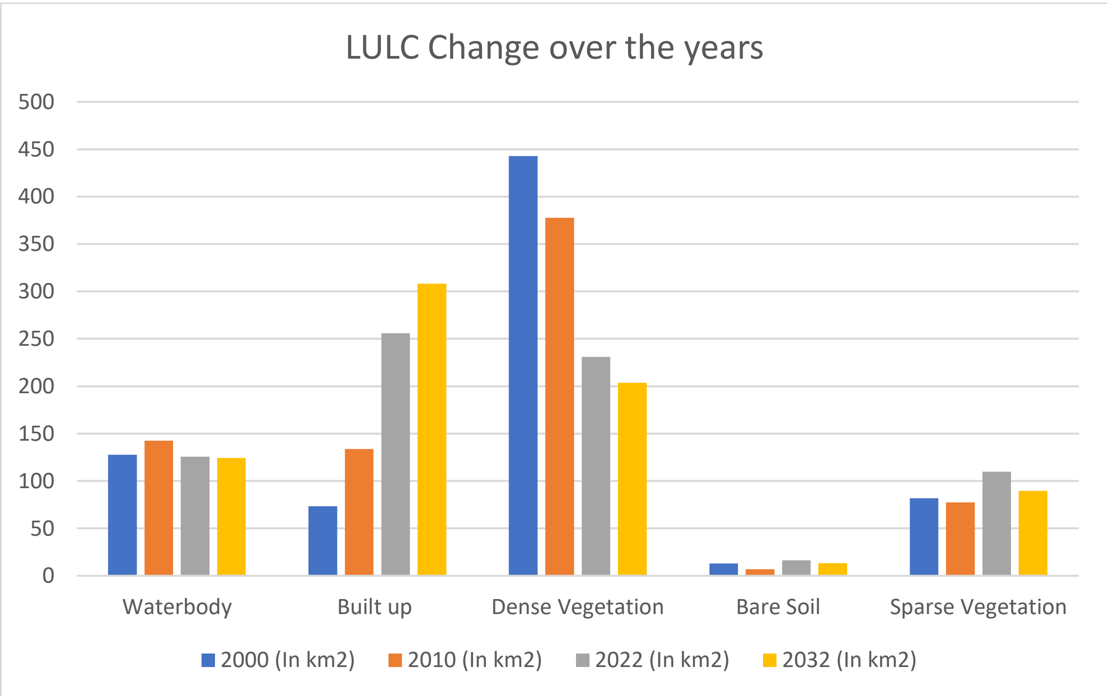


Fig 30: Chart showing various classes and their changes over the years

Table 12: Relative change of LULC over the years

Land User Types	*2000.00* (In km^2)	*2010.00* (In km^2)	*2022.00* (In km^2)	*2032.00* (In km^2)	Δ*Change* (2000-2010) in %	Δ*Change* (2000-2010) in km^2	Δ*Change* (2010-2022) in %	Δ*Change* (2010-2022) in km^2	Δ*Change* (2022-2032) in %	Δ*Change* (2022-2032) in km^2
Waterbody	127.75	142.62	125.60	124.22	2.01	14.87	-2.30	-17.02	-0.19	-1.38
Built up	73.32	133.88	255.93	308.23	8.20	60.56	16.52	122.05	7.08	52.30
Dense Vegetation	442.72	377.73	230.95	203.48	-8.80	-64.99	-19.87	-146.78	-3.72	-27.48
Bare Soil	13.02	7.03	16.40	13.28	-0.81	-5.99	1.27	9.38	-0.42	-3.12
Sparse Vegetation	81.83	77.39	109.76	89.44	-0.60	-4.44	4.38	32.37	-2.75	-20.32

Land User Types	Δ*Change* (2000-2032) in %	Δ*Change* (2000-2023) in km2
Waterbody	-0.48	-3.53
Built up	31.80	234.90
Dense Vegetation	-32.39	-239.24
Bare Soil	0.03	0.26
Sparse Vegetation	1.03	7.61

Analysis using RF:

The error and fragmentation probability of the 2032 LULC was analysed by using the RandomForest package in R. It was performed for finding out the Mean Absolute Error (MAE), Mean Squared Error (MSE) and the Root Mean Squared Error (RMSE). The result showed value ranges of:

Mean Absolute Error (MAE): 0.2679229

Mean Squared Error (MSE): 0.3715336

Root Mean Squared Error (RMSE): 0.6095355

Which shows relatively less error, and thus the predicted LULC was taken for further analysis.

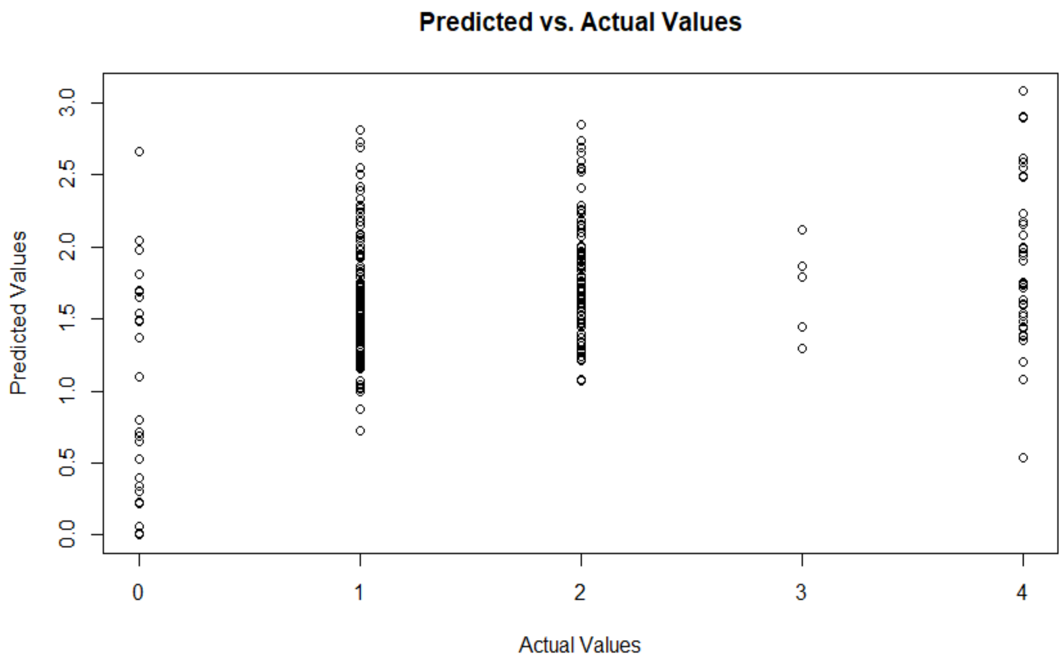


Fig 31: Plot obtained from RandomForest of the actual values and predicted values of classification

VORS Ecosystem Health Model

We make use of the VORS ecosystem health model for the assessment of ecosystem health in Kochi. The Model is divided into several components and sub-categories within itself. The major categories are Vigour, Organisation, Resilience and Ecosystem services. Each component is calculated via different methods but each are significant for calculating the ecosystem health. The foundation of the VORS model is the notion that an ecosystem is healthy if it can sustain its vitality, organisation, resilience, and services across time. It can be applied to evaluate the condition of ecosystems at various sizes, from specific locations to large regions. A set of indicators is chosen for each dimension in the VORS model to measure the ecosystem's health. An overall health index is created by scoring and weighting the indicators. The index values can be used to compare the condition of several ecosystems or to chart the evolution of an ecosystem's condition through time.

Vigor

For extracting the data of Vigor, we make use of the NDVI of the respective years 2000, 2010 and 2022, as they can be extracted from Landsat data. The NDVI for 2032 was predicted using CA-ANN, until an accurate result was obtained. NDVI ranges between -1 and +1, where NDVI readings between -1 and 0 that are low or negative frequently indicate non-vegetated surfaces. These places could be bodies of water, deserted land, or urban areas with little to no vegetation. NDVI readings that are close to 0 indicate scant or stressed vegetation, such as crops grown during dry spells or during the winter when there is less vegetation. Areas with scant or stressed vegetation often have moderate NDVI values between 0 and 0.2. This category covers a range of landscapes, including semi-arid areas, croplands, and shrublands that may be under moderate stress.

Healthy and dense vegetation is indicated by high NDVI values, between 0.2 and 0.5. These values cover a wide range of land cover types, such as thriving croplands, lush grasslands, and various kinds of woods, all of which exhibit vigorous vegetation development. Healthy and dense vegetation cover is represented by NDVI values greater than 0.5. This group comprises regions with vibrant, green flora, active cropland,

and deep woodlands. Such numbers imply that the assessed area has an abundance of flourishing plant life.

In our study, we standardise the NDVI value using the fuzzy logic function available in ArcGIS 10.8 for normalising the value to every component. The initial NDVI values were -0.5789 to 0.5737. Negative NDVI readings, like -0.5789, often indicate the existence of unvegetated surfaces or surfaces with severely constrained or stressed vegetation. Places like lake bodies, arid land, urban settings, or regions where vegetation is either completely absent or under severe stress in this range. In our case, it is the presence of waterbodies and built-up. NDVI values between 0 and 0.5 imply vegetation that is reasonably healthy and thick. These numbers can be used to represent a variety of land uses, such as croplands, shrublands, and grasslands with differing levels of vegetative health, which in our case corresponds to sparse and dense vegetation classes. NDVI values greater than 0.5, like 0.5737, are a sign of robust and dense vegetation. This implies that there is likely a lot of lush vegetation in the area, which may include woods, crops that are developing quickly, or regions covered in brilliant green foliage, in our case it is the presence of Mangalavanam Bird sanctuary.

When standardized, the ranges become 0 – 0.658, where most of the high values were observed to be at core of dense vegetation and the lower values in the waterbody and near built-up areas. The acquired standardized map is further used for the analysis of the VORS ecosystem model of 2000.

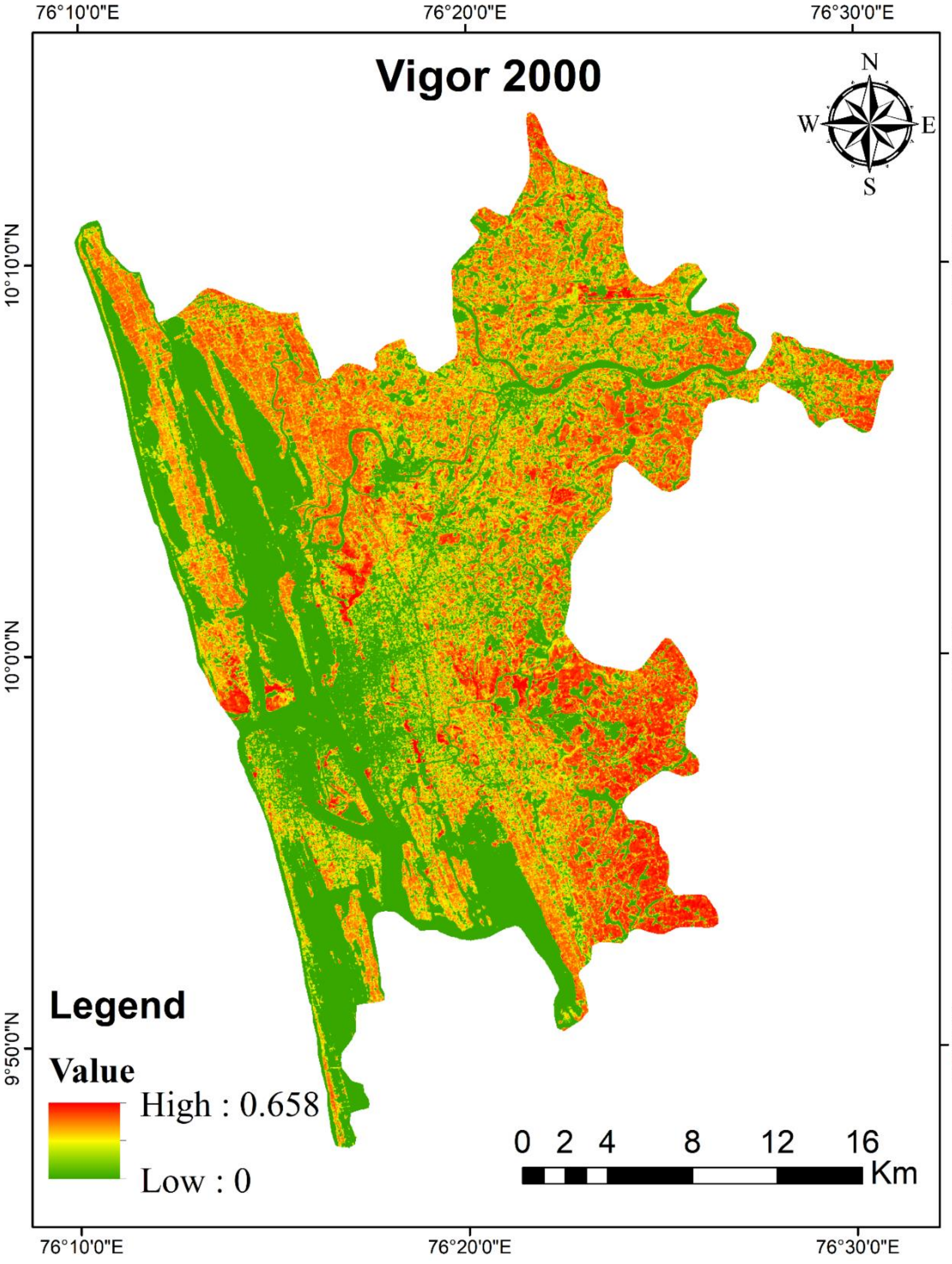


Fig 32: Vigor Map of 2000

Organisation:

As mentioned in the methodology, we make use of the Fragstats 4.2 software for obtaining the components required for calculating the organization parameter of VORS. In our study we make use of Patch Density (PD), Edge Density (ED), Area Weighed Mean Fractal Dimension Index, and COHESION index. We make use of the MS small membership function for the analysis of organization hence the value range will be between 0 and 1.

The value ranges for the many indices utilised throughout the model, such as the cohesiveness index, represent several land features (COHESION), An indicator of total fragmentation and a lack of communication across patches is a value of 0. This indicates that patches are separate from one another and do not have borders in common. A score of 1 denotes good patch cohesiveness and connection. This indicates that patches are interconnected and have a lot of shared borders. To put it another way, a higher COHESION value denotes a more connected and cohesive landscape, whilst a lower value denotes a more dispersed and disconnected terrain. For the Cohesion of the LULC of 2000, we obtained the standardized value range of 0.639 to the maximum value of 1.

For the Patch density (PD), it can vary widely depending on the landscape characteristics, the resolution of the data, and the size of the study area. In general, Patch Density values can range from 0 to relatively high values depending on the level of fragmentation or spatial heterogeneity in the landscape. In our study, the standardized ranges varied between 0.3002 to a maximum value of 1.

For the Edge density (ED), A value of 0 indicates a landscape with no edges or boundaries between land cover types. This could imply a completely homogeneous landscape with a single land cover type. Higher values represent increasing edge density, indicating a greater amount of edge or boundary length per unit area. Higher Edge Density values suggest a more fragmented landscape with multiple land cover types in proximity. In our study, the standardized ranges varied between 0.6414 to the maximum value of 1.

For the Area Weighed Mean Fractal Dimension Index (FRAC-AM), A value of 0 indicates a completely smooth and homogeneous landscape with no fractal patterns or heterogeneity. A value of 2 indicates a highly fragmented and complex landscape with maximum fractal patterns and heterogeneity. The value range for FRAC-AM for our study ranges from 0.6396 to the maximum value of 1. The maximum value of 1 was seen for built-up and bare soil and the low value range of the indicators were seen for dense and sparse vegetation. The indicators were combined using the fuzzy overlay function to obtain the final organization parameter which ranges from 0.3002 to 0.7058.

Table 13: Table showing values of various indices inside organisation parameter

LULC class	***ED***	***FRAC_AM***	***CONNECT***	***COHESION***	***PD***
Waterbody	*20.2539*	*1.2961*	*0.1015*	*99.5452*	*2.4112*
Built-up	*36.9442*	*1.215*	*0.0229*	*96.0611*	*6.4754*
Dense Vegetation	*73.6488*	*1.3426*	*0.0996*	*99.7992*	*1.5082*
Bare Soil	*14.7956*	*1.08*	*0.0155*	*61.2472*	*10.0847*
Sparse vegetation	*56.0743*	*1.1944*	*0.0211*	*91.1822*	*6.6108*

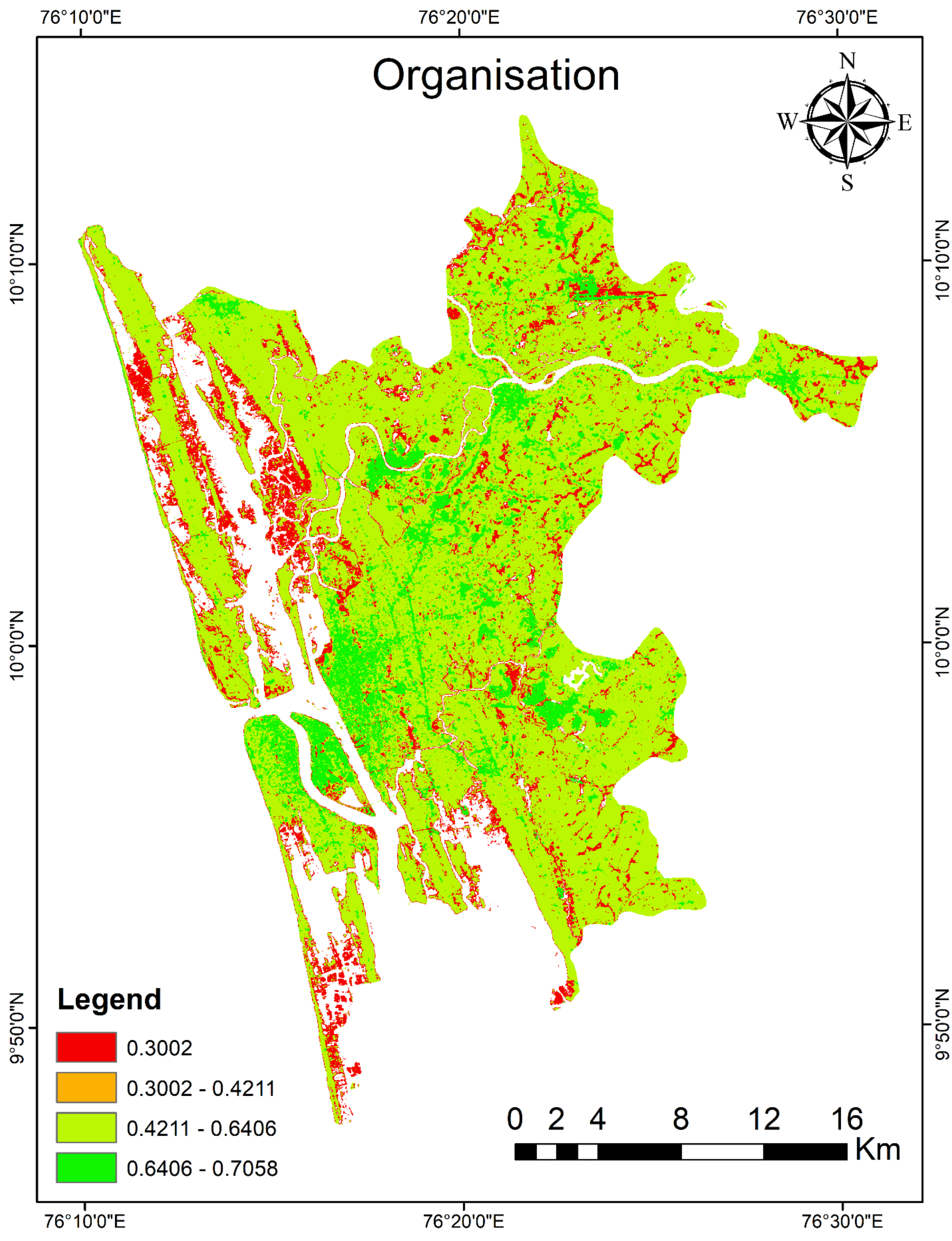


Fig 33 – Organisation Map of 2000

From the map, it can be observed that the value of organization parameter was least for sparse vegetation and most for the built-up. In VORS, it is typical for the organisation parameter to be higher for densely populated areas and lower for sparsely vegetated areas. This is because densely populated places often have a wider variety of buildings and uses than locations with little vegetation. The diversity of structures and functions is often smaller under sparse vegetation. For instance, a solitary species of plant might predominate in a sparse desert terrain.

Built-up environments frequently feature a wider variety of animal and plant species. This is so that various species can have a diversity of habitats. The presence of trees, bushes, flowers, and grasses in a park, for instance, can serve as a habitat for a variety of birds, insects, and other animals. A single species of plant may be present in a barren desert setting, which supports a significantly lesser number of species. Ecological processes are frequently more diverse in built-up environments. This is so that they can accommodate a wide range of various land uses. For instance, a built-up region could include parks, shops, businesses, and industries. Since Kochi has close to 70 parks, it would provide evidence for the high level of organization parameter for built up in the 2000 year.

Resilience

For obtaining the resilience value of the LULC we multiply the coefficient of resilience with the area under the respective classes. The amount obtained is normalized using the fuzzy operator and the resultant resilience factor is used for further analysis. A high value of Resilience was seen for Dense Vegetation and a low value was seen for Built-up, Bare soil and Sparse Vegetation

Table 14: Resilience Value table of each class

Land Use Land Cover Classes	***Coefficient of Resilience***	***Area (in Km^2)***	***Resilience value***
Waterbody	*0.8*	*127.75*	*102.2*
Built up	*0.2*	*73.32*	*14.664*
Dense Vegetation	*0.8*	*442.71*	*354.168*
Bare Soil	*0.2*	*13.02*	*2.604*
Sparse Vegetation	*0.6*	*81.83*	*49.098*

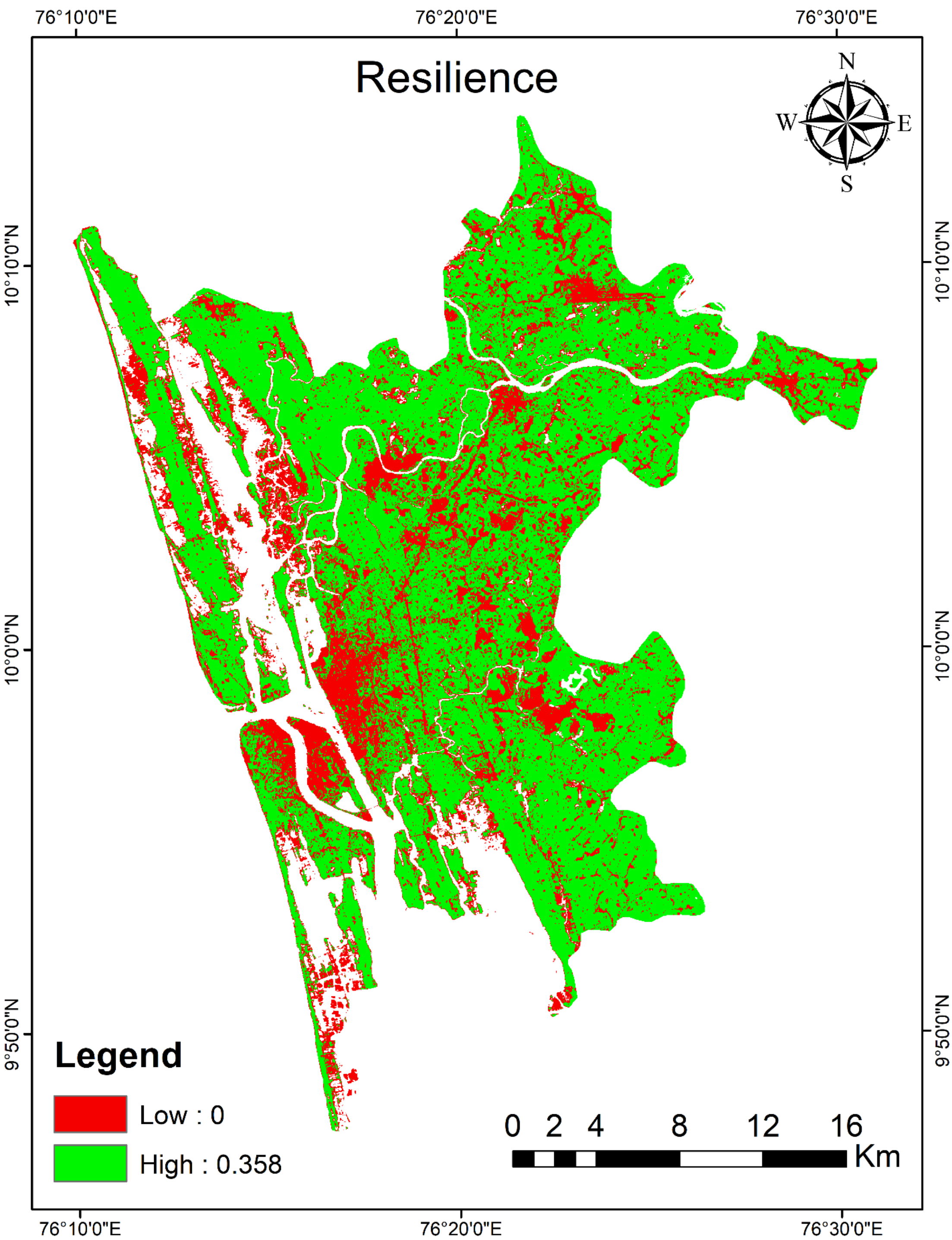


Fig 34: Resilience Map of 2000

Ecosystem Services

Like resilience, we make use of the coefficient of ecosystem services for calculating the ecosystem services for the LULC types. The coefficient is multiplied to the respective LULC classes. Unlike the resilience coefficient, some LULC classes does not have any value since they do not provide any ecosystem services. Since urban settings are frequently heterogeneous and complicated, it can be challenging to create precise coefficients for all the environmental services that they offer. In addition, certain ecosystem services provided by metropolitan regions, such cultural and aesthetic qualities, may be arbitrary. Many people believe that bare land has a damaged ecosystem and provides few ecological services. But some ecosystem services, including carbon sequestration and water infiltration, can still be provided by bare land. The Ecosystem services were seen higher for dense vegetation, sparse vegetation and waterbody, but null for both built-up and bare soil.

Table 15: The table shows the ecosystem service value

Land Use Land Cover Classes	*Coefficient of Ecosystem Services*	*Area (in Km^2)*	*Resilience value*
Waterbody	*8498*	*127.75*	*1085619.5*
Built up	*0*	*73.32*	*0*
Dense Vegetation	*9990*	*442.71*	*4422672.9*
Bare Soil	*0*	*13.02*	*0*
Sparse Vegetation	*232*	*81.83*	*18984.56*

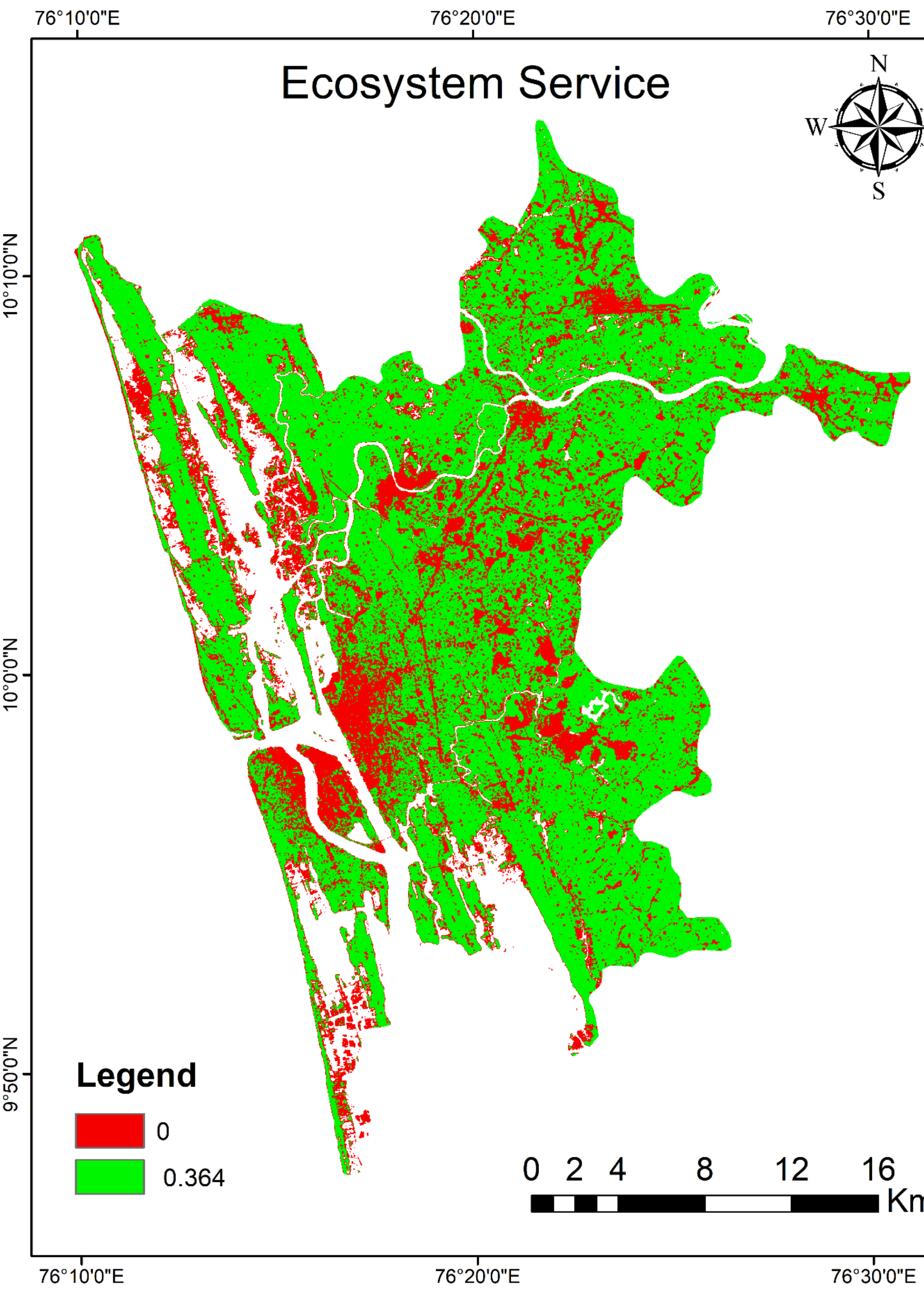


Fig 35: Ecosystem Service Map 2000

From combining all the indices in the raster calculator by applying the formula we can obtain the VORS ecosystem model of 2000. The resultant ecosystem health model had a range of 0 to 0.4877. The model was then divided into 5, where:

Very good = 80 – 100% of the total range

Good = 60 - 80% of the total range

Moderate = 40 – 60 % of the total range

Bad = 20 – 40% of the total range

Very Bad = 0 - 20% of the total range

Table 16: Area under each VORS class:

Ecosystem Health Condition	*Area under each class (in km^2)*	*Percentage under each class*
Very Bad	*218.493*	*35.766*
Bad	*50.058*	*8.194*
Moderate	*71.260*	*11.664*
Good	*96.763*	*15.839*
Very good	*174.317*	*28.534*

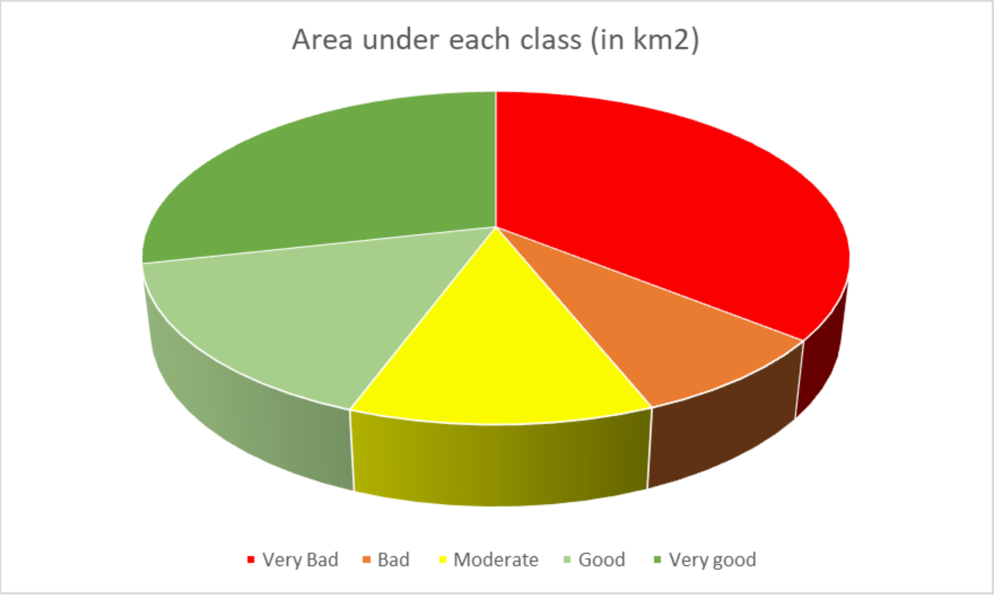


Fig 36: Chart showing area under each VORS class

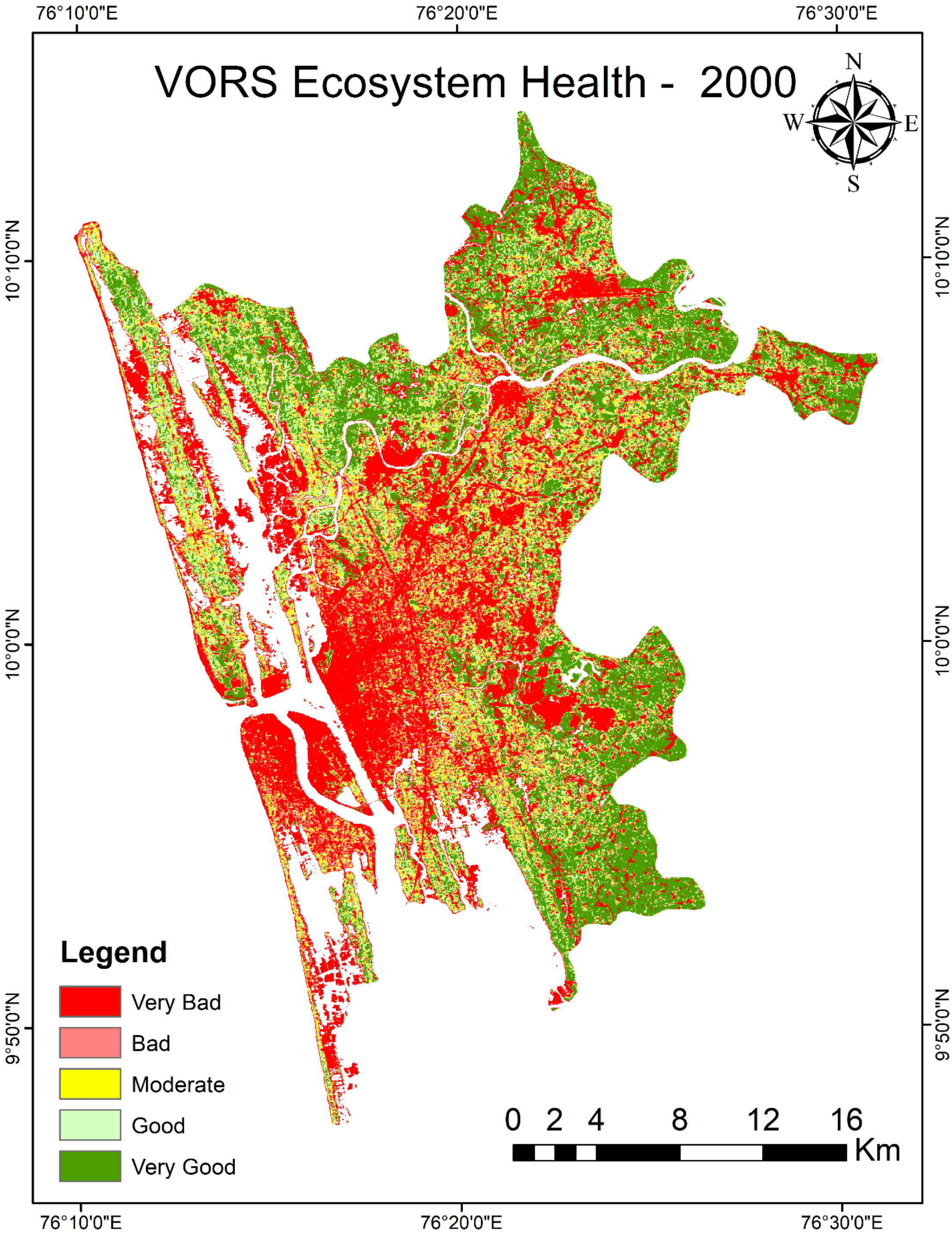


Fig 37: VORS Ecosystem Health Map - 2000

From the ecosystem model, we can see that about 35% or 218 km^2 of the area is considered as having bad ecosystem health, followed by 28% having good ecosystem health, which is 174 km^2 of the whole Kochi. The area having bad ecosystem health are those that are at the core of built-up and bare soil and the areas that have the good ecosystem health are concentrated at the cores of dense and sparse vegetations. The areas having moderate ecosystem health involves the boundary or transition zones between built up and dense vegetation. The ecosystem health of Kochi is relatively low when compared to other cities since it has a high compactness between build-ups as development is concentrated rather than diverse.

VORS Ecosystem Health – 2010

Vigor

In our study, we standardise the NDVI value using the fuzzy logic function available in ArcGIS 10.8 for normalising the value to every component. The initial NDVI values were -0.3684 to 0.5586. Negative NDVI readings, like -0.3684, often indicate the existence of unvegetated surfaces or surfaces with severely constrained or stressed vegetation. Places like lake bodies, arid land, urban settings, or regions where vegetation is either completely absent or under severe stress in this range. In our case, it is the presence of waterbodies and built-up. NDVI values between 0 and 0.5 imply vegetation that is reasonably healthy and thick. These numbers can be used to represent a variety of land uses, such as croplands, shrublands, and grasslands with differing levels of vegetative health, which in our case corresponds to sparse and dense vegetation classes. NDVI values greater than 0.5, like 0.5586, are a sign of robust and dense vegetation.

When standardized, the range becomes 0 – 0.676, where most of the high values were observed to be at core of dense vegetation and the lower values in the waterbody and near built-up areas. The acquired standardized map is further used for the analysis of the VORS ecosystem model of 2010. When compared to the previous year, the vegetation had seen to be decreased overall and the maximum vegetation had also been decreased. The minimum range of vegetation had increased, signifying the presence of shelter trees along built-up areas.

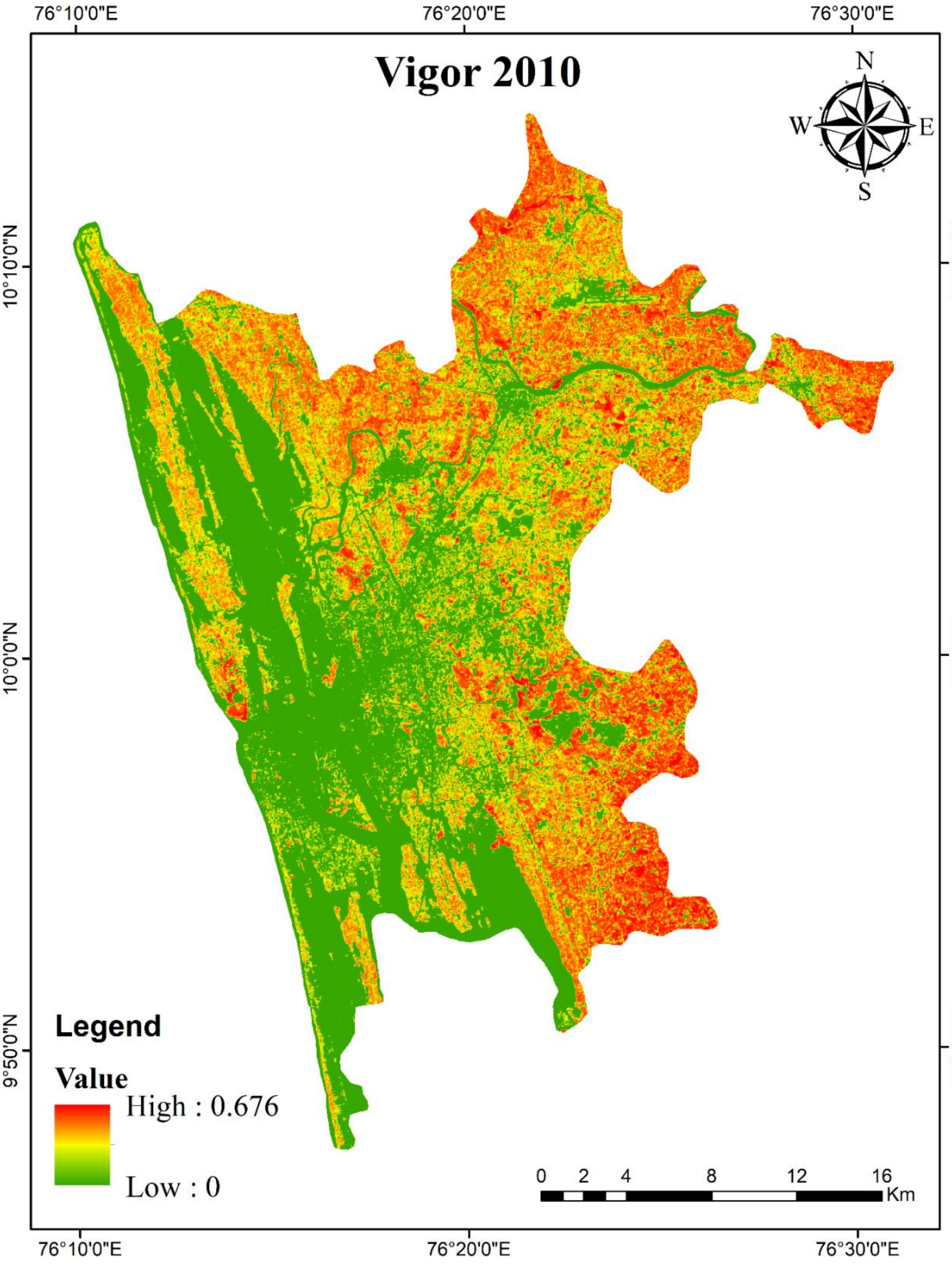


Fig. 38 – Vigor Map 2010

Organisation:

Like the previous year, we make use of the COHESION, Patch Density, Edge Density, and the Area Weighed Mean Fractal Dimension Index for the evaluation of the Organisation parameter. Each of the indexes were standardized between 0 and 1 using the MS small membership function and the resultant values were used for the fuzzy overlay for finding the organisation parameter. While comparing to the previous year, the edge density had decreased, the patch density had slightly increased, the fractal dimension index and a decrease in the cohesion index, which implies fragmentation of habitats, change in LULC, change in climate and loss of habitats.

There had been an increase in the overall organisation parameter from 0.3002 to 0.3232, which would imply the increase in the connectivity of built up and the increase of built-up.

Table 17: Values of various indices inside organisation parameter

LULC class	*ED*	*FRAC_AM*	*CONNECT*	*COHESION*	*PD*
Waterbody	*19.3502*	*1.3034*	*0.1396*	*99.6425*	*1.0939*
Built-up	*59.3527*	*1.2722*	*0.0187*	*98.5627*	*10.063*
Dense Vegetation	*115.4684*	*1.3947*	*0.053*	*99.7689*	*5.5372*
Bare Soil	*6.9927*	*1.0878*	*0.0383*	*67.4425*	*2.7605*
Sparse vegetation	*79.6107*	*1.1355*	*0.012*	*75.9289*	*23.4525*

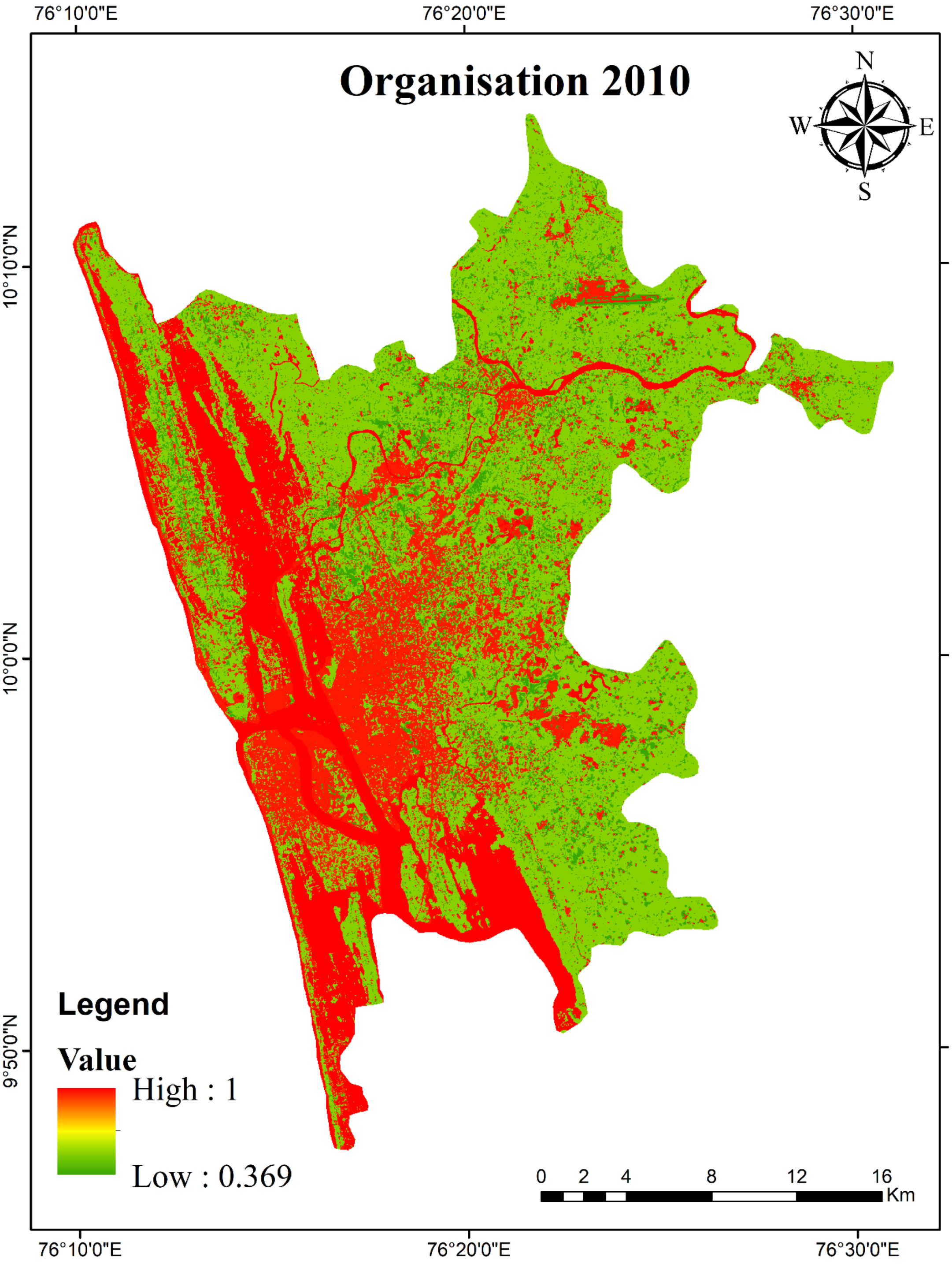


Fig 39: Organisation Map 2010

Resilience:

The Coefficient of resilience was used for obtaining the Resilience parameter, by multiplying the same with the total area under each LULC. Compare to the previous year the resilience value had been increased, but the area having low resilience had increased drastically.

Table 18: Resilience Value table of each class

LULC class	***Coefficient of Resilience***	***Area (in km²)***	***Resilience Value***
Waterbody	*0.8*	*142.61*	*114.088*
Built-up	*0.2*	*133.88*	*26.776*
Dense Vegetation	*0.8*	*377.72*	*302.176*
Bare Soil	*0.2*	*7.02*	*1.404*
Sparse vegetation	*0.6*	*77.39*	*46.434*

Ecosystem Services:

Like the resilience value, the coefficient of ecosystem services was used for calculating the ecosystem services value. Compared to the previous year, the area under dense vegetation had decreased dramatically, leading to decreased levels of areas having high ecosystem health.

Table 19: Ecosystem service Value table of each class

LULC class	***Coefficient of Ecosystem Services***	***Area (in km²)***	***Ecosystem service Value***
Waterbody	*8498*	*142.61*	*1211899.78*
Built-up	*0*	*133.88*	*0*
Dense Vegetation	*9990*	*377.72*	*3773422.8*
Bare Soil	*0*	*7.02*	*0*
Sparse vegetation	*232*	*77.39*	*17954.48*

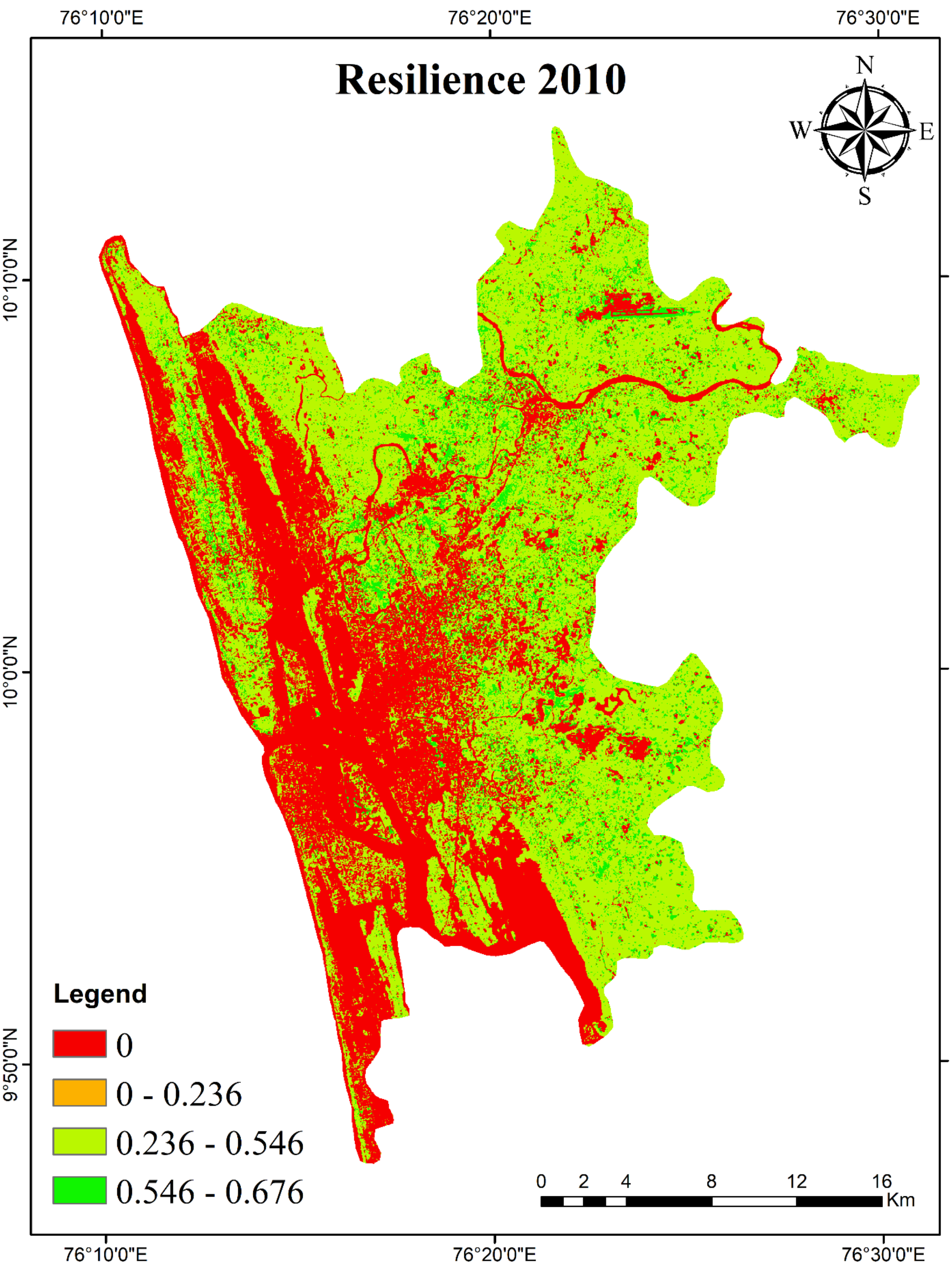


Fig 40: Resilience Map 2010

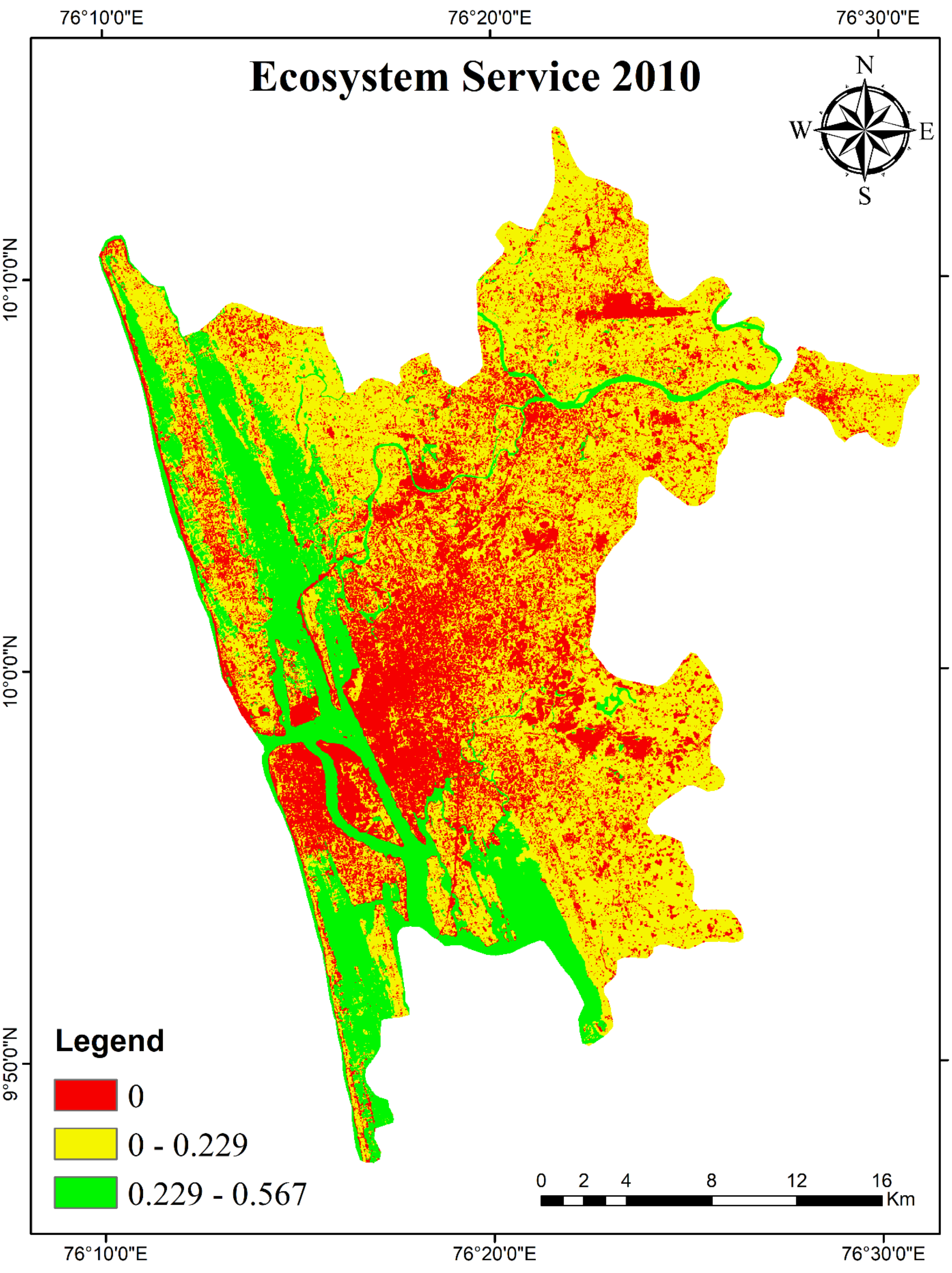


Fig 41: Ecosystem Service Map 2010

VORS Ecosystem health of 2010:

From the ecosystem model of 2010, we can see that the area under bad ecosystem health was increased from 218 km^2 to 245 km^2 leading to an overall increase of bad ecosystem health by 6%. The area under good ecosystem health had drastically been reduced from 28% to 13%. Like the previous year, the area having bad ecosystem health are those that are at the core of built-up and bare soil and the areas that have the good ecosystem health are concentrated at the cores of dense and sparse vegetations. The areas having moderate ecosystem health involves the boundary or transition zones between built up and dense vegetation. Most of the area that had been lost from the good ecosystem health had manifested in the moderate and bad ecosystem health, signifying transition phase towards urbanisation.

Table 21: Area under each VORS class of 2010

Ecosystem Health Condition	*Area (in m2)*	*Percentage under each class*
Very bad	*245.852*	*41.248*
Bad	*42.831*	*7.186*
Moderate	*93.564*	*15.697*
Good	*131.081*	*21.992*
Very Good	*82.699*	*13.875*

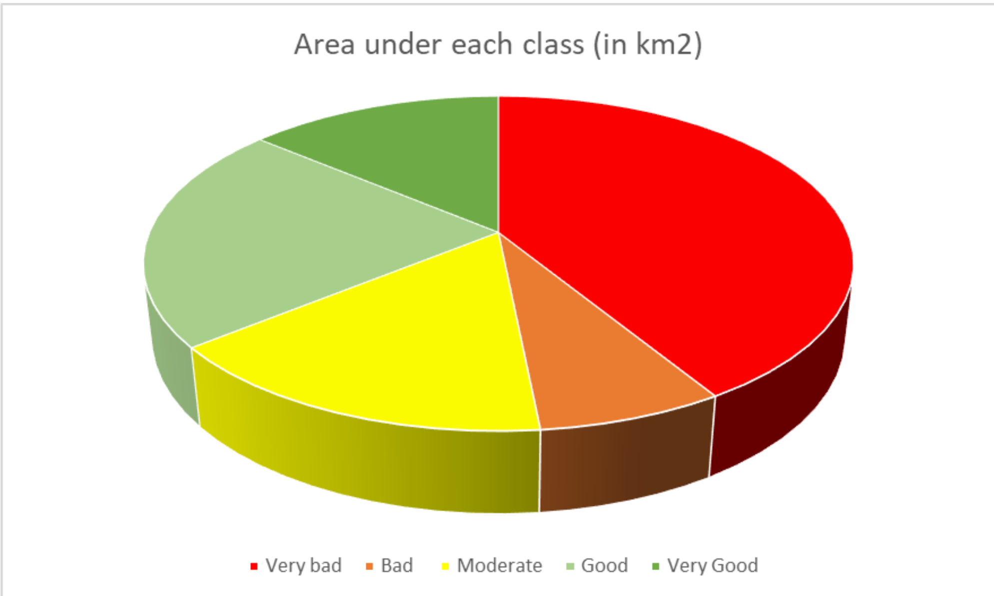


Fig 42: Chart showing area under each VORS class

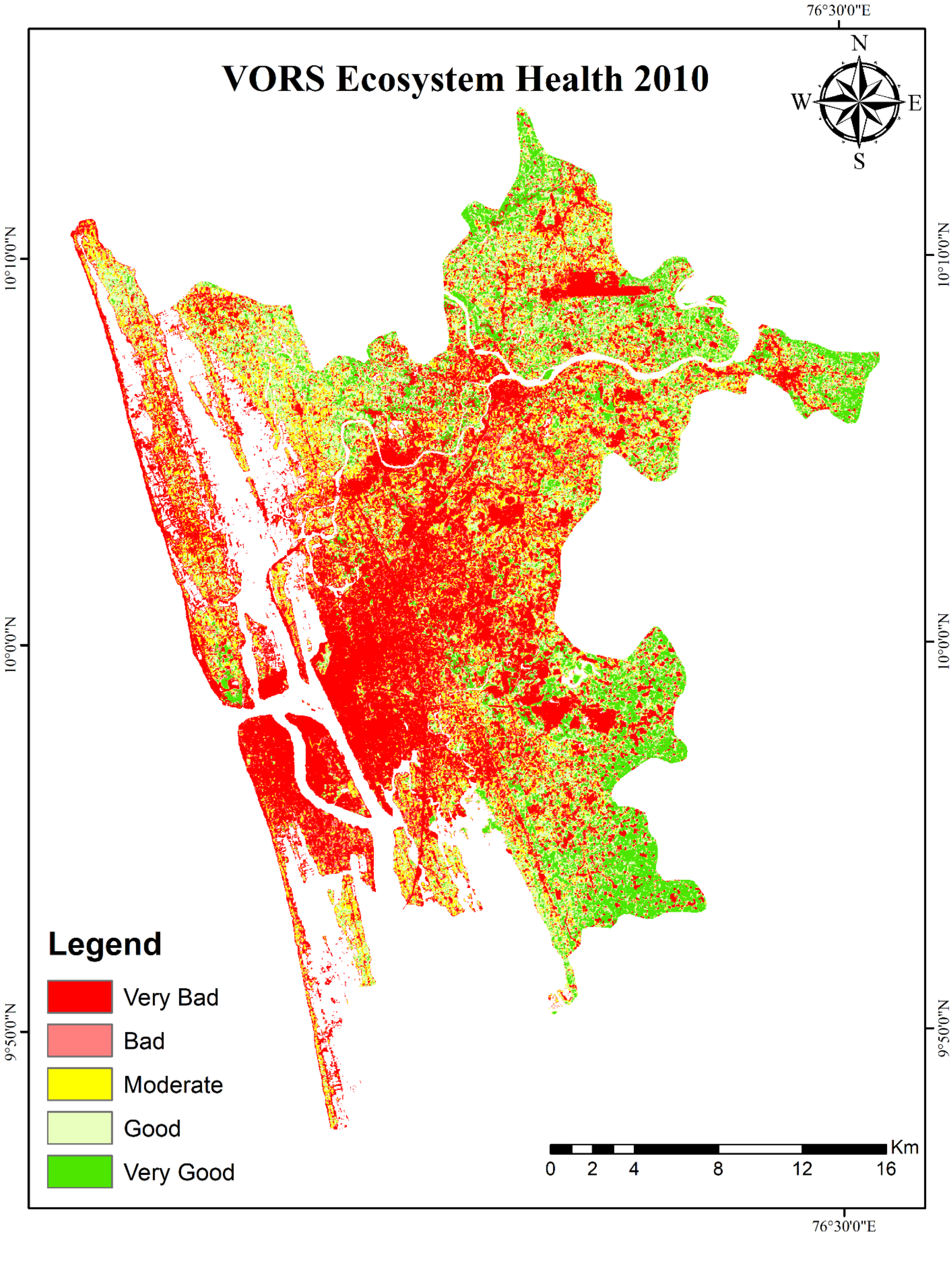


Fig 43: VORS Ecosystem health Map 2010

VORS Ecosystem health 2022

Vigor:

The initial NDVI values were -0.1186 to 0.5093. Negative NDVI readings, like -0.1186, often indicate the existence of unvegetated surfaces or surfaces with severely constrained or stressed vegetation. Places like lake bodies, arid land, urban settings, or regions where vegetation is either completely absent or under severe stress in this range. In our case, it is the presence of waterbodies and built-up. NDVI values between 0 and 0.5 imply vegetation that is reasonably healthy and thick. These numbers can be used to represent a variety of land uses, such as croplands, shrublands, and grasslands with differing levels of vegetative health, which in our case corresponds to sparse and dense vegetation classes. NDVI values greater than 0.5, like 0.5093, are a sign of robust and dense vegetation.

There has been a decrease in the range of NDVI over the years, i.e., both the maximum and minimum is decreasing that indicates a significant decrease in the overall greenness of the area. This could be caused by several factors, including deforestation, drought, pollution, or climate change. The decrease in the minimum is a sign of increase in vegetation that can be due to climate change. It is evident when we compare the LULC maps of 2000,2010 and 2022, the sparse vegetation had increased, which can be the reason why there is a decrease in the minimum range of NDVI.

The standardized Vigor ranges from 0 -0.707. The area having high NDVI had decreased, but the overall maximum had been increased slightly. The standardized Vigor map is as follows:

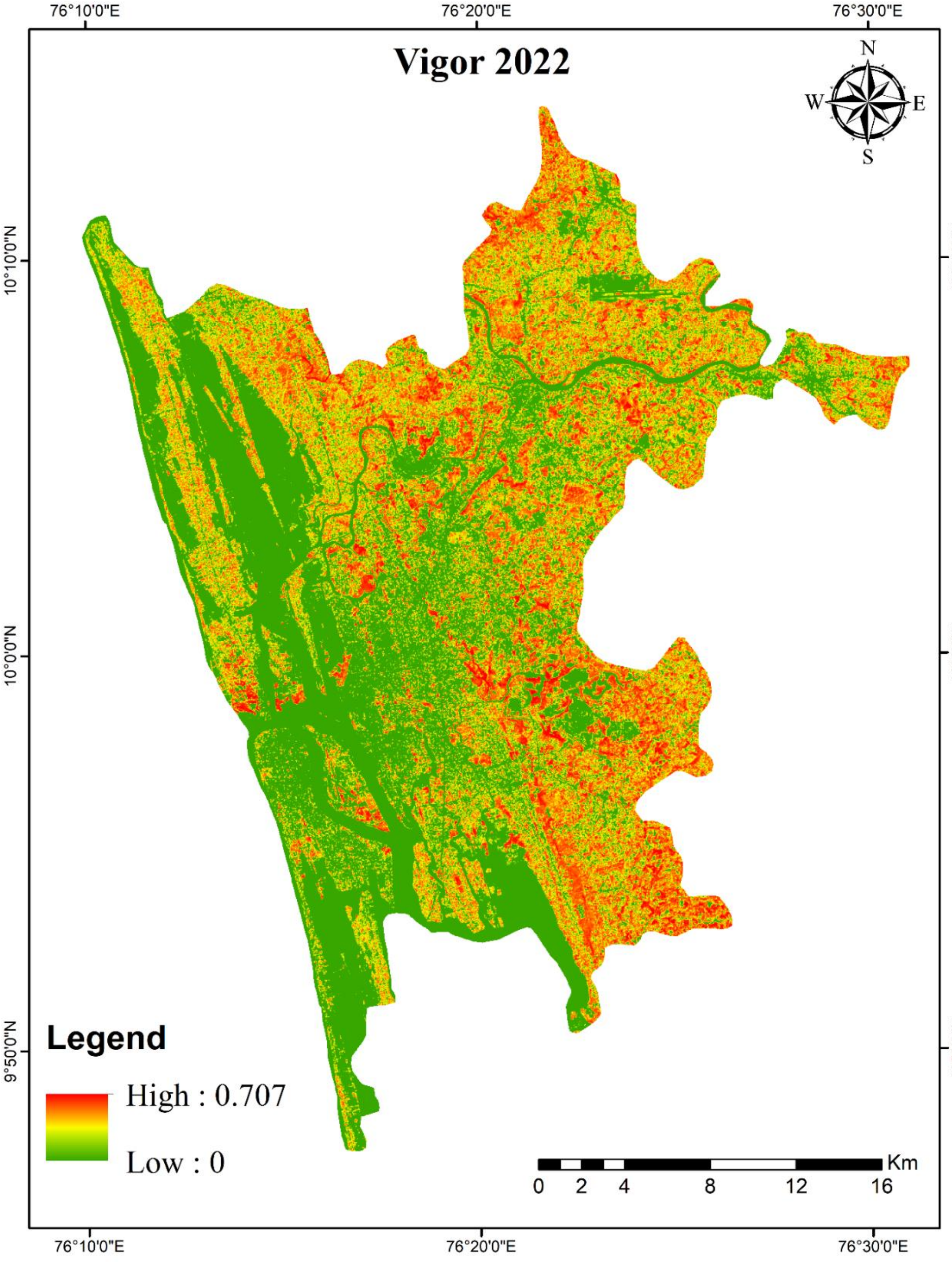


Fig 44: Vigor Map 2022

Organisation:

Like the previous year, we make use of the COHESION, Patch Density, Edge Density, and the Area Weighed Mean Fractal Dimension Index for the evaluation of the Organisation parameter. Each of the indexes were standardized between 0 and 1 using the MS small membership function and the resultant values were used for the fuzzy overlay for finding the organisation parameter. While comparing to the previous year, the edge density had decreased, the patch density had slightly increased, the fractal dimension index and a decrease in the cohesion index, which implies fragmentation of habitats, change in LULC, change in climate and loss of habitats.

The waterbodies showed the least cohesion index and the highest was by the Dense Vegetation. Patch density was seen highest for sparse vegetation and lowest for water. The edge density was highest for dense, sparse and built-up and low for bare soil and waterbody. For the fractal dimension Index was around 1.07 to 1.34 for all classes indicating a moderate fractal pattern and heterogeneity.

There had been an increase in the overall organisation parameter from 0.3232 to 0.378, which would imply the increase in the connectivity of built up and the increase of built-up area. The lower organization parameter is seen for spare vegetation.

Table 21: Value of various organisation indices inside organisation parameter

LULC class	*ED*	*FRAC_AM*	*CONNECT*	*COHESION*	*PD*
Waterbody	*19.961*	*1.307*	*0.0909*	*99.589*	*1.82*
Built-up	*113.921*	*1.342*	*0.0293*	*99.1982*	*10.5*
Dense Vegetation	*148.295*	*1.3408*	*0.0212*	*98.7496*	*16.2*
Bare Soil	*20.435*	*1.079*	*0.0115*	*59.322*	*10.1*
Sparse vegetation	*110.163*	*1.163*	*0.0098*	*82.698*	*32.7*

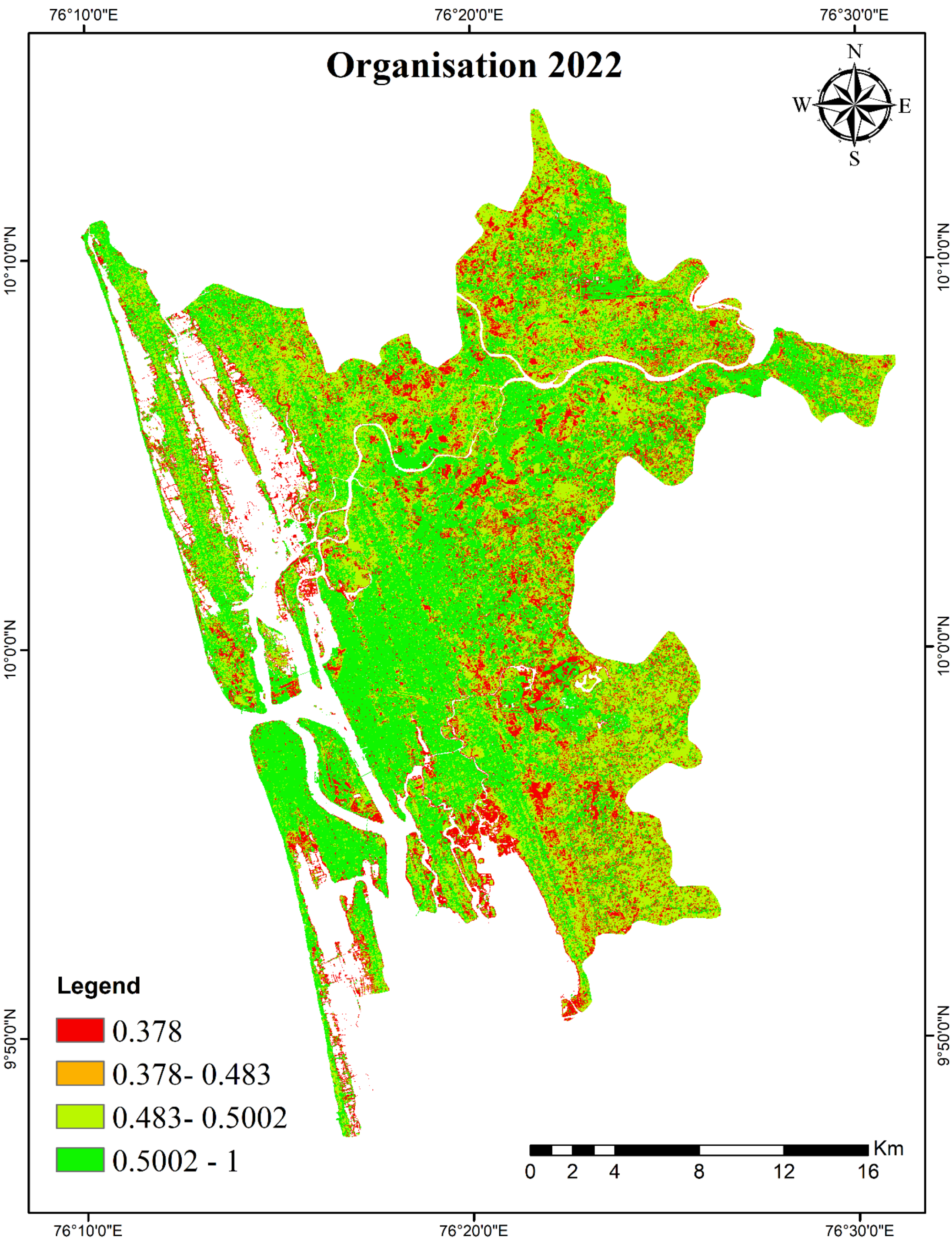


Fig 45: Organisation Map 2022

Resilience:

By multiplying the resilience coefficient by the total area under each LULC, the resilience parameter was obtained. The resilience rating had increased from the year before, but the area with low resilience had grown significantly. The maximum range had somewhat shrunk.

Table 22 : Resilience Value of LULC classes of 2022

Land Use Land Cover Classes	*Coefficient of Resilience*	*Area (in Km^2)*	**Resilience Value**
Waterbody	*0.8*	*125.6*	*100.48*
Built up	*0.2*	*255.92*	*51.184*
Dense Vegetation	*0.8*	*230.95*	*184.76*
Bare Soil	*0.2*	*16.4*	*3.28*
Sparse Vegetation	*0.6*	*109.76*	*65.856*

Ecosystem Services :

The coefficient of ecosystem services was utilised to calculate the ecosystem services value, same like it did for the resilience value. The area covered by dense vegetation had drastically dropped from the previous year, which resulted in a decrease in the percentage of regions with a healthy ecology.

Table 23 : Ecosystem service value of LULC classes of 2022

Land Use Land Cover Classes	*Coefficient of Ecosystem Services*	*Area (in Km^2)*	*Ecosystem Service Value*
Waterbody	8498	*125.6*	*1067348.8*
Built up	0	*255.92*	*0*
Dense Vegetation	9990	*230.95*	*2307190.5*
Bare Soil	0	*16.4*	*0*
Sparse Vegetation	232	*109.76*	*25464.32*

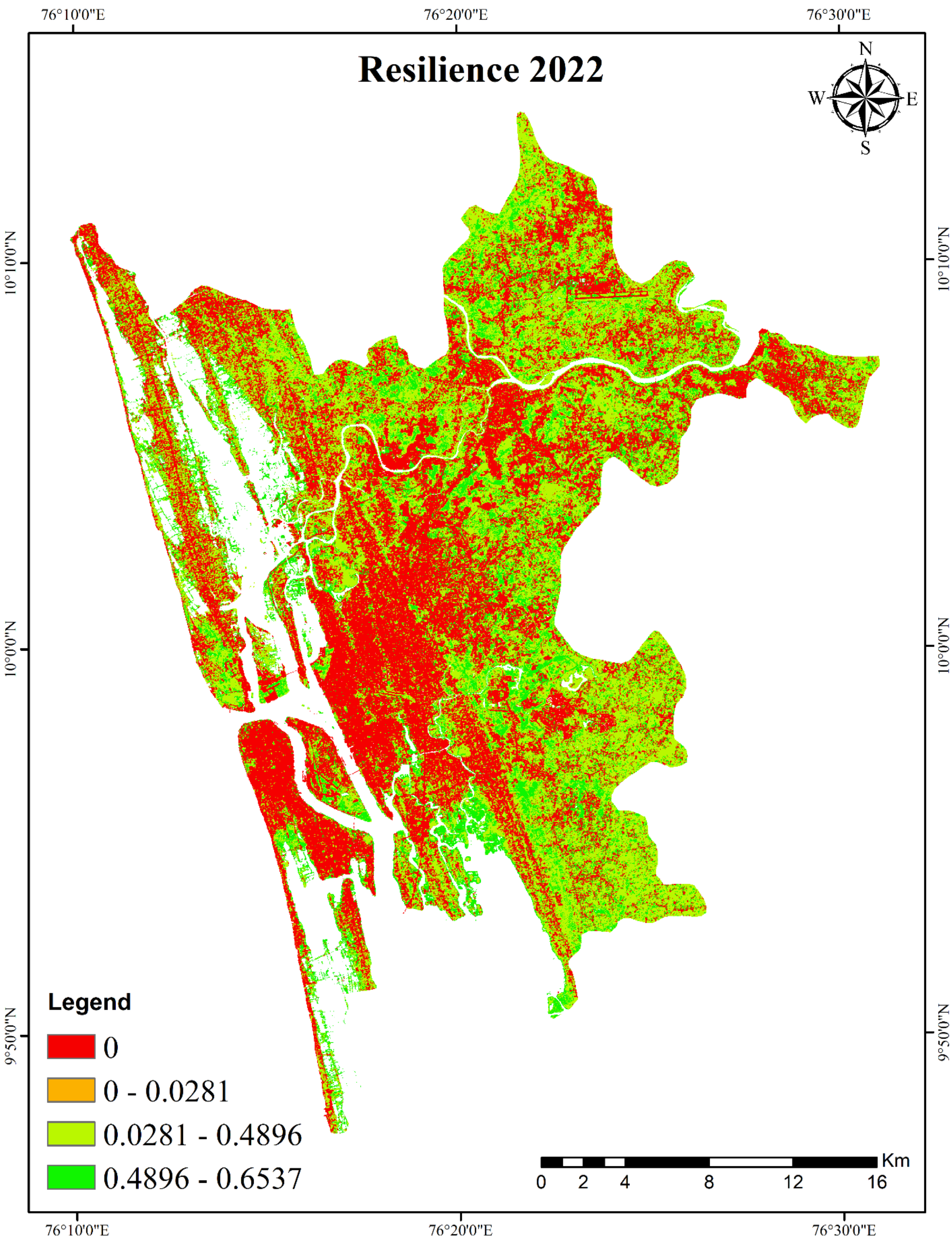


Fig 46: Resilience Map 2022

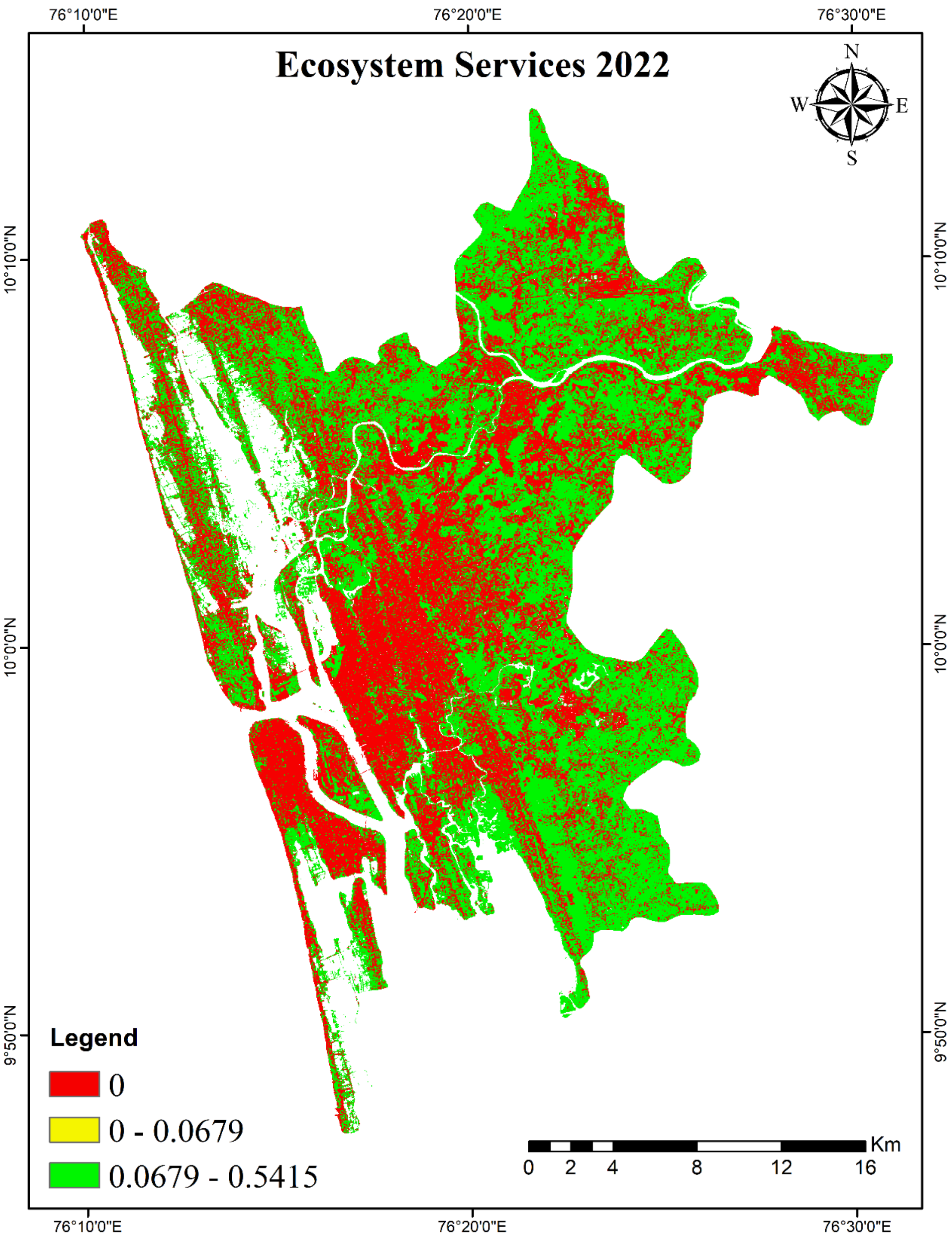


Fig. 47: Ecosystem Service Map 2022

VORS Ecosystem Health of 2022:

The result was obtained as a value range from 0 to 0.519, which was divided with equal intervals into 5 categories being, very good (80-100%) , good (60-80%), moderate (40-60%), bad (20-40%) and very bad (0-20%).From the result obtained it can be seen that 366 km^2 of the area is listed as being very bad, 25 km^2 of the area has bad ecosystem health, 22 km^2 of area has moderate ecosystem health, 97 km^2 of area falls under good ecosystem health, and 101 km^2 of the area is marked as being very good. The area falling under very bad ecosystem health is the highest with about it being 59% of the total area of Kochi. The classes falling under the very bad ecosystem health primarily includes built up and bare soil. The area under very good ecosystem is second highest with it being 16% of the total area. It mainly consists of area near dense and sparse vegetation. The area under very good ecosystem health involves area that has high density of vegetation and are core areas of the respective classes.

Compared to the previous years, there had been a drastic change in the ecosystem health of Kochi. Most of the ecosystem health classes had decreased and all of it had been transferred over to being bad ecosystem health. Only the very good ecosystem health had slightly increased by 3%. It can be due to the focus for construction of parks and conservation of biodiversity initiatives by local governments. But most of the areas having moderate ecosystem health, at least 12%, was converted over to very bad ecosystem health. It can be due to the ever-increasing urbanisation in Kochi. The bad ecosystem health has increased by 18%, i.e., about 110km^2 of the total area. The EH obtained from the predicted LULC of 2032 map to get an idea of the future EH condition.

Table 24: Area under each VORS health class

Ecosystem Health Condition	***Area (in m2)***	***Percentage under each class***
Very bad	*366.723*	*59.820*
Bad	*25.524*	*4.1636*
Moderate	*22.369*	*3.648*
Good	*97.145*	*15.846*
Very Good	*101.279*	*16.520*

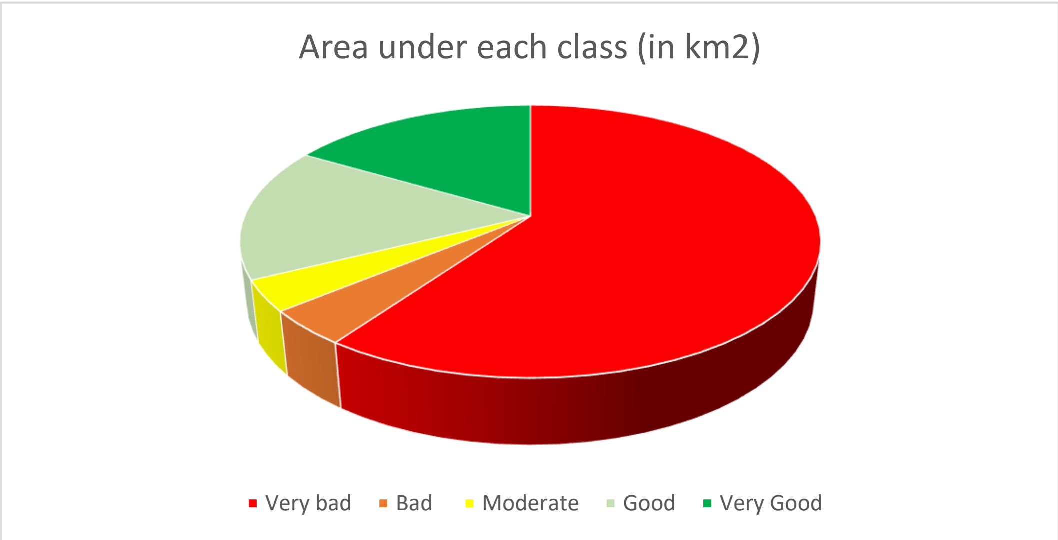


Fig 48: chart showing area under each VORS class of 2022

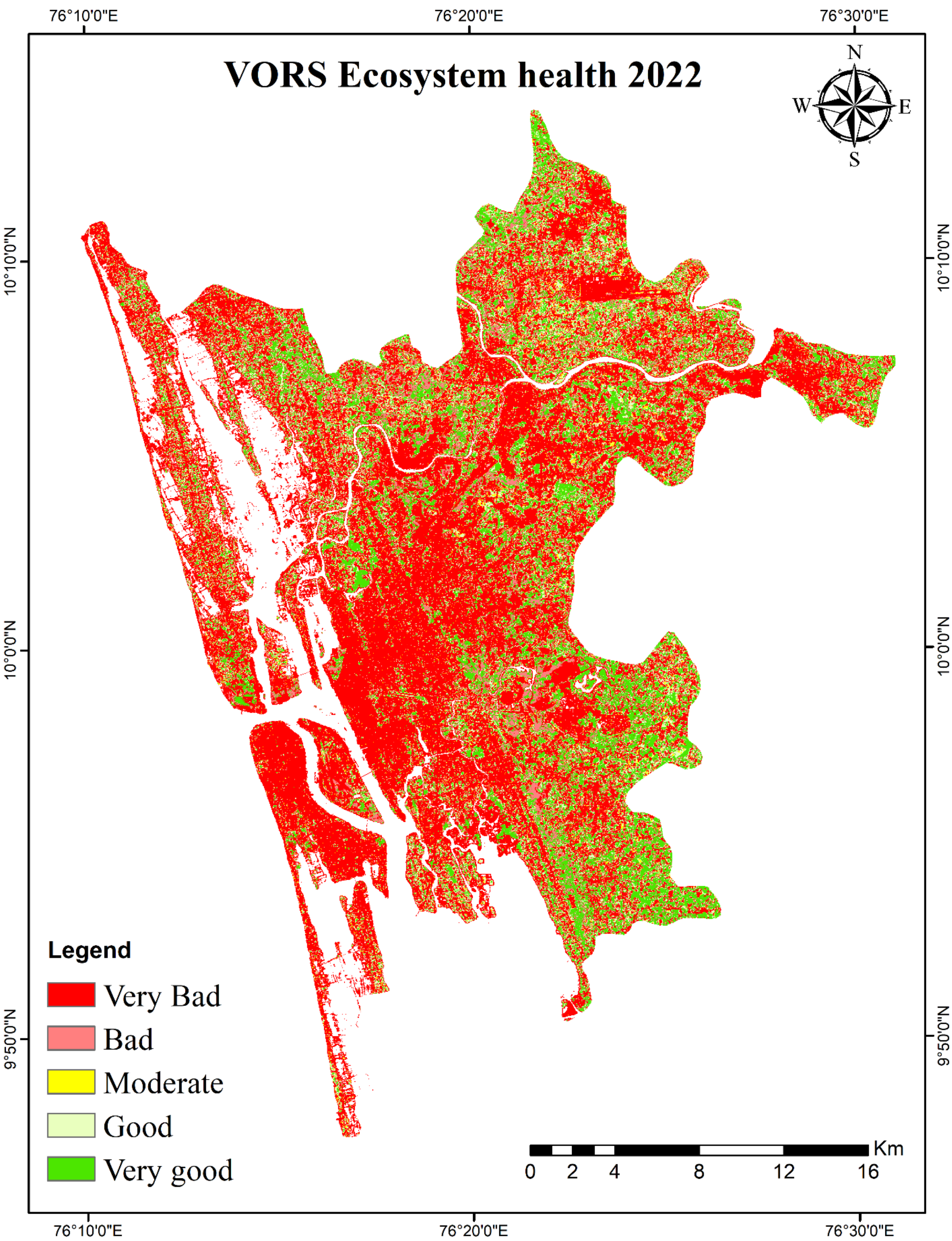


Fig. 49: VORS ecosystem health Map 2022

VORS Ecosystem Health 2032:

Vigor:

For the vigor parameter we make use of NDVI parameters obtained from the Landsat data. The NDVI was predicted via the CA-ANN model with the parameters like elevation and slope given as the input parameter. The maps given for reference were the NDVI maps of 2010 and 2022 and the iteration was given, i.e., for 10 years.

The initial NDVI values were -0.2282 to 0.5263. Negative NDVI readings, like -0.2282, often indicate the existence of unvegetated surfaces or surfaces with severely constrained or stressed vegetation. Places like lake bodies, arid land, urban settings, or regions where vegetation is either completely absent or under severe stress in this range. In our case, it is the presence of waterbodies and built-up. NDVI values between 0 and 0.5 imply vegetation that is reasonably healthy and thick. These numbers can be used to represent a variety of land uses, such as croplands, shrublands, and grasslands with differing levels of vegetative health, which in our case corresponds to sparse and dense vegetation classes. NDVI values greater than 0.5, like 0.5263, are a sign of robust and dense vegetation

There had been an increase in the overall maximum and minimum range of the NDVI value, but the area under the maximum range had decreased significantly and the area under the minimum had increased significantly when compared to the previous years.

The standardized Vigor ranges from 0 - 0.617. The area having high NDVI had decreased, and the overall maximum had also decreased. Most of the regions now have decreased NDVI and like previous years only the areas that are at the core of dense vegetation were seen to have high levels of NDVI. There is a trend of decrease in the area under high NDVI values and an increase in area under low NDVI values are increasing rapidly.

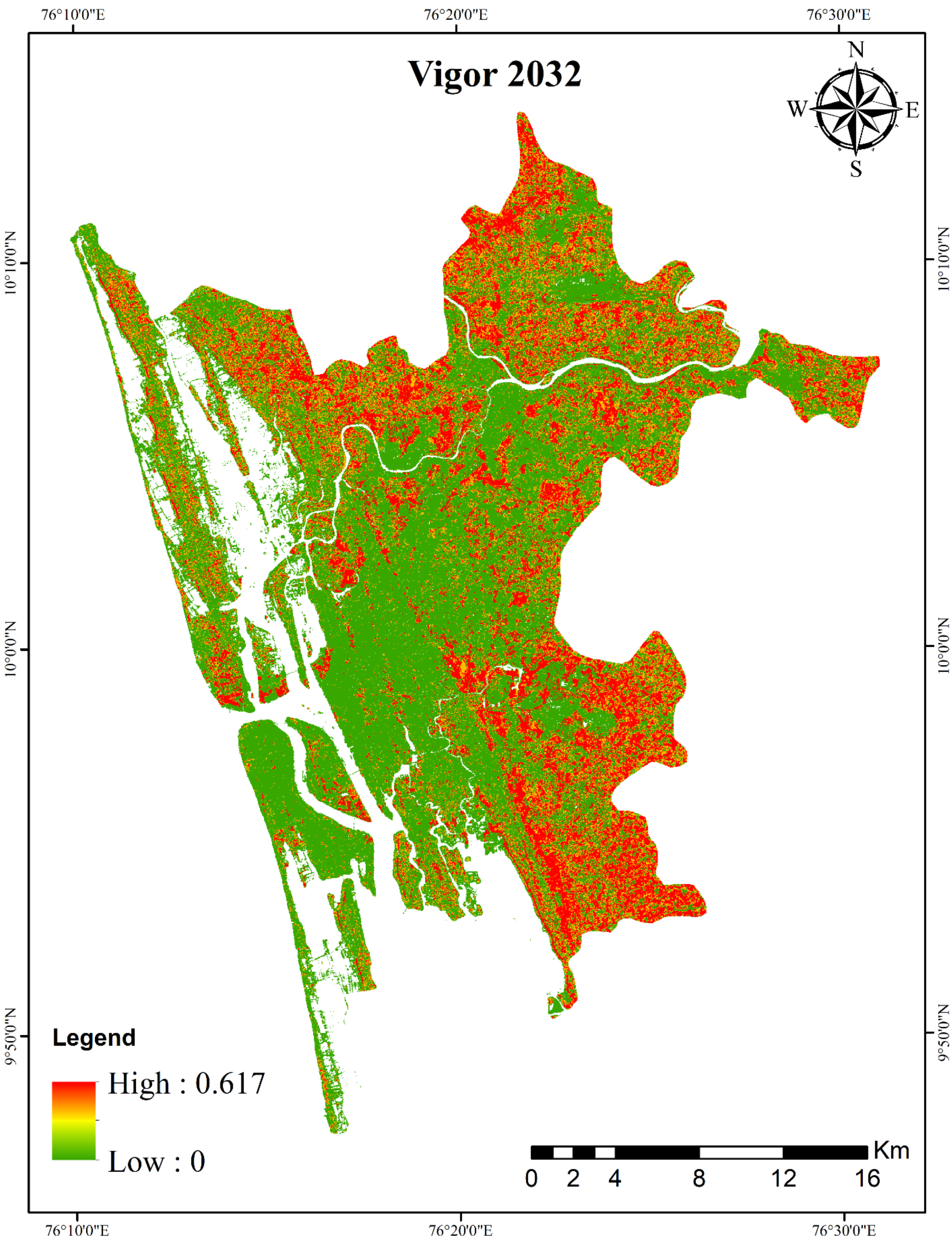


Fig 50: Vigor Map 2032

Organisation:

Like last year, we evaluate the Organization parameter using the COHESION, Patch Density, Edge Density, and the Area Weighed Mean Fractal Dimension Index. The MS tiny membership function was used to normalise each index between 0 and 1, and the resulting values were then used in the fuzzy overlay to determine the organisation parameter. From the analysis, we can see that the edge density, fractal dimension, Connectance and cohesion indices had increased for Built-up and reduced for Dense vegetation. The Patch density had remained same for Built up, but had increased for Dense vegetation, signifying growth of vegetation at only its core spaces. The transition zones had been changes to built-up and the Connectance for sparse vegetation had also decreased, that symbolises a decrease in connectivity between spare vegetation, and ultimately the reduction in sparse vegetation.

There had been a slight decrease in the overall organisation parameter from 0.378 to 0.351, which would imply the increase in the connectivity of built up and the increase of built-up area and the decrease in connectivity between sparse vegetation, causing the overall reduced value.

Table 25: Values of indices in the organisation parameter of 2032

LULC class	*ED*	*FRAC_AM*	*CONNECT*	*COHESION*	*PD*
Waterbody	*19.57*	*1.307*	*0.1005*	*99.593*	*1.726*
Built-up	*127.985*	*1.381*	*0.036*	*99.578*	*9.291*
Dense Vegetation	*148.128*	*1.3158*	*0.018*	*98.348*	*20.207*
Bare Soil	*17.208*	*1.072*	*0.013*	*53.164*	*8.704*
Sparse vegetation	*91.516*	*1.154*	*0.009*	*80.529*	*28.774*

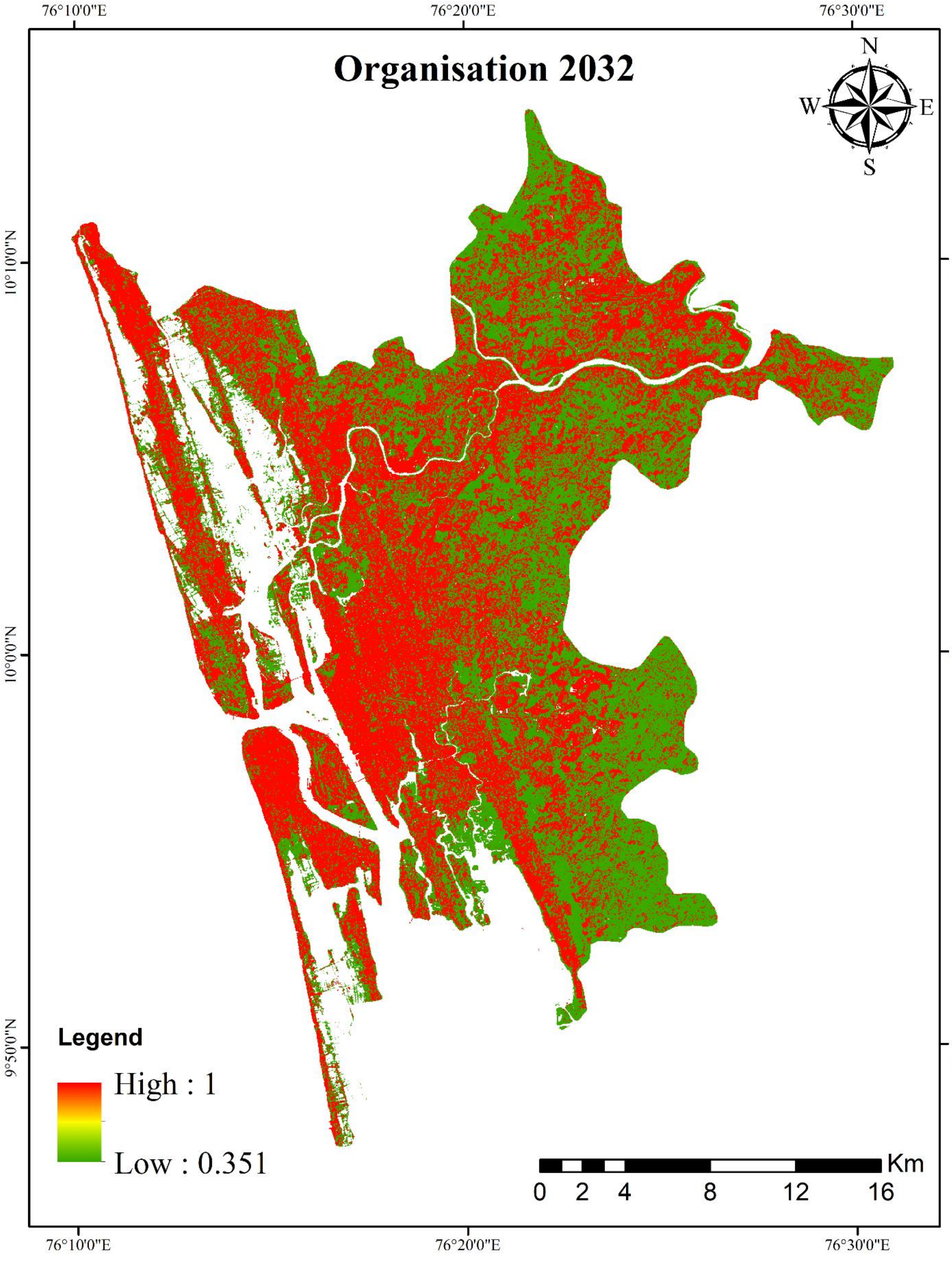


Fig 51: Organisation Map 2032

Resilience:

By multiplying the resilience coefficient by the total area under each LULC, the resilience parameter was obtained. The resilience rating had increased from the year before, but the area with low resilience had grown significantly, and there had been a considerable increase in the area under the moderate range, which can be due to increased edge density between urban area and its intrusion into vegetation types.

Table 26: Resilience Value of 2032

Land Use Land Cover Classes	***Coefficient of Resilience***	***Area (in Km^2)***	***Resilience Value***
Waterbody	*0.8*	*124.22*	*99.376*
Built up	*0.2*	*308.23*	*61.646*
Dense Vegetation	*0.8*	*203.48*	*162.784*
Bare Soil	*0.2*	*13.28*	*2.656*
Sparse Vegetation	*0.6*	*89.44*	*53.664*

Ecosystem Services:

The coefficient of ecosystem services was utilised to calculate the ecosystem services value, same like it did for the resilience value. Since it was projected that the area under built-up will rise drastically by 18%, it is certain that there will be a huge decrease in the Ecosystem service values of 2032.

Table 27: Ecosystem service value of 2032

LULC class	***Coefficient of Ecosystem Services***	***Area (in km2)***	***Ecosystem service Value***
Waterbody	*8498*	*124.22*	*1055621.56*
Built-up	*0*	*308.23*	*0*
Dense Vegetation	*9990*	*203.48*	*2032765.2*
Bare Soil	*0*	*13.28*	*0*
Sparse vegetation	*232*	*89.44*	*20750.08*

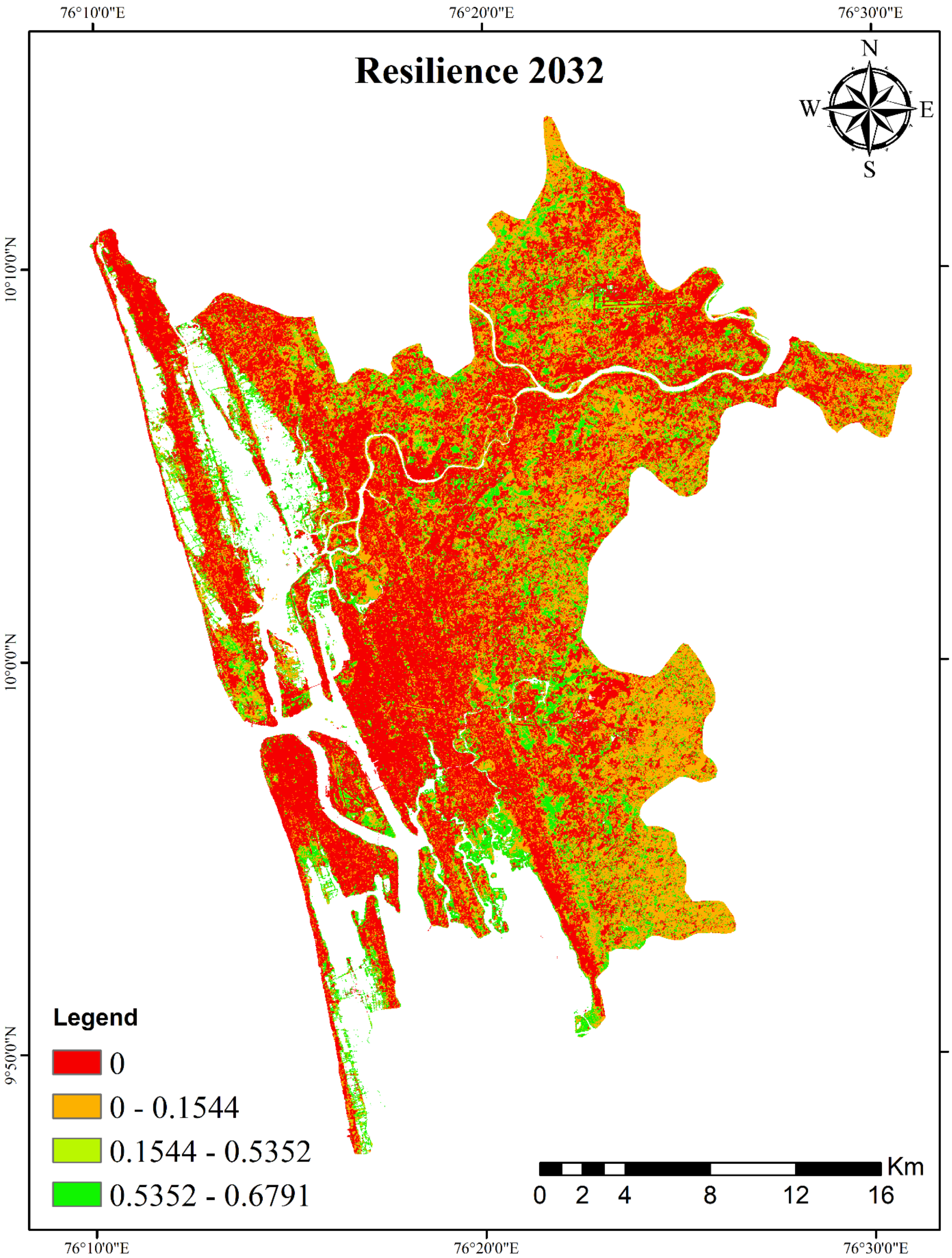


Fig. 52 – Resilience Map 2032

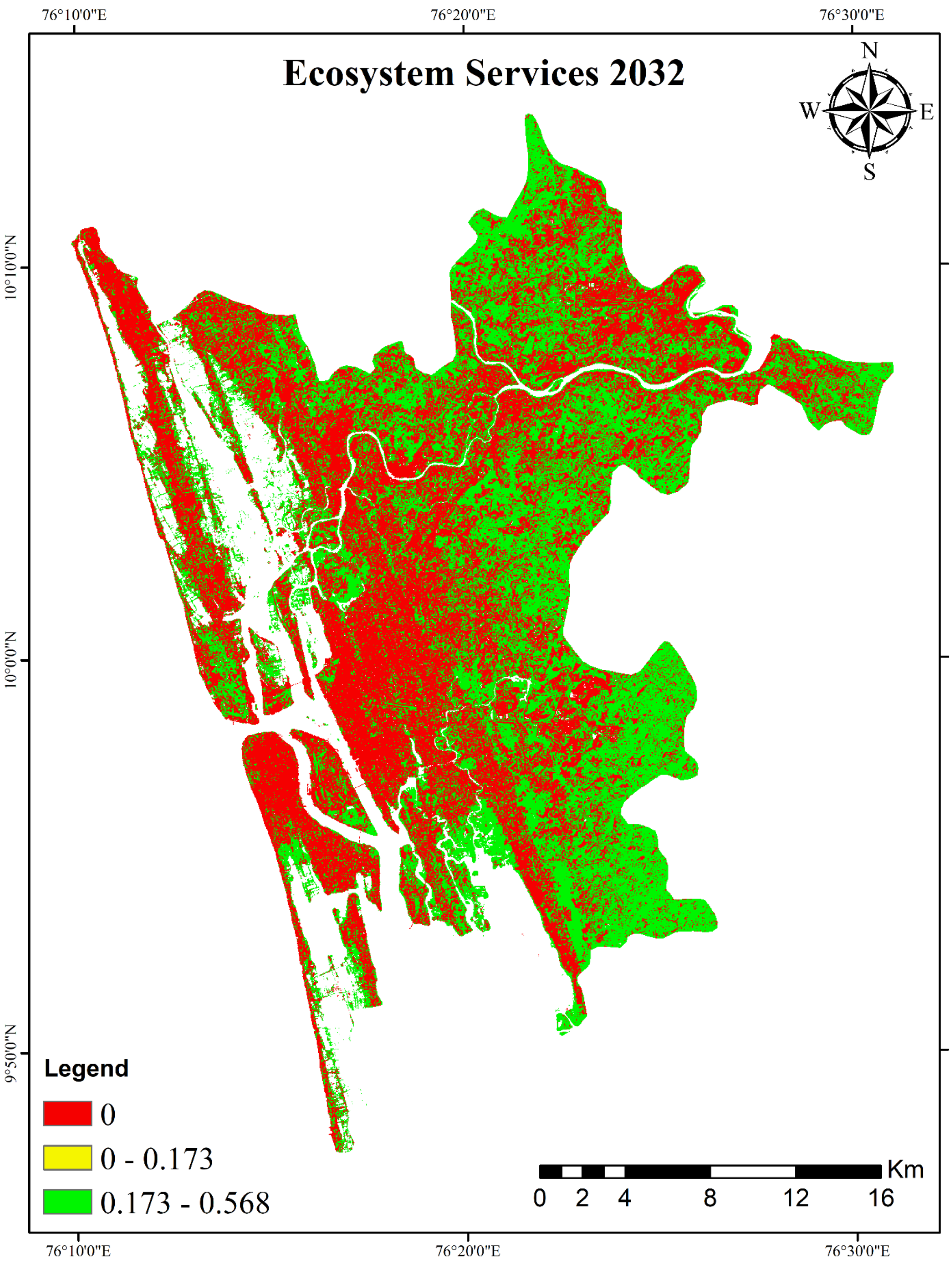


Fig 53: Ecosystem Service Map 2032

VORS Ecosystem health: 2032

The result was obtained as a value range from 0 to 0.543, which was divided with equal intervals into 5 categories being, very good (80-100%), good (60-80%), moderate (40-60%), bad (20-40%) and very bad (0-20%). From the result obtained, 440 km^2 of the area is listed as being very bad, 37 km^2 of the area has bad ecosystem health, 51 km^2 of area has moderate ecosystem health, 64 km^2 of area falls under good ecosystem health, and 19 km^2 of the area is marked as being very good. There are significant differences between the 2022 and 2032, as the very bad ecosystem health had an increase of 12 % and the very good ecosystem health on the contrary had decreased by 13%. The amount of moderate ecosystem health had increased significantly when compared to the previous years.

The area falling under very bad ecosystem health is the highest is predicted to be about 74% of the total area of Kochi. The classes falling under the very bad ecosystem health primarily includes built up and bare soil. The area under good ecosystem is second highest with it being 10% of the total area. It mainly consists of area near dense and sparse vegetation. The area under very good ecosystem health involves area that has high density of vegetation and are core areas of the respective classes, but most of it had been lost by 2032.

Compared to the previous years, there had been a drastic change in the ecosystem health of Kochi. Most of the ecosystem health classes had decreased and all of it had been transferred over to being bad ecosystem health. The CA-ANN model predicted the future LULC by considering the trend that had been observed from 2000,2010 and 2022. It is a clear indication of the future, if no measures are taken.

Table 28: Area under each VORS classes of 2032

Ecosystem Health Condition	***Count***	***Area under the class***	***Percentage under each class***
Very Bad	*489886*	*440.897*	*71.758*
Bad	*41692*	*37.522*	*6.107*
Moderate	*57551*	*51.795*	*8.430*
Good	*71722*	*64.549*	*10.505*
Very Good	*21837*	*19.653*	*3.198*

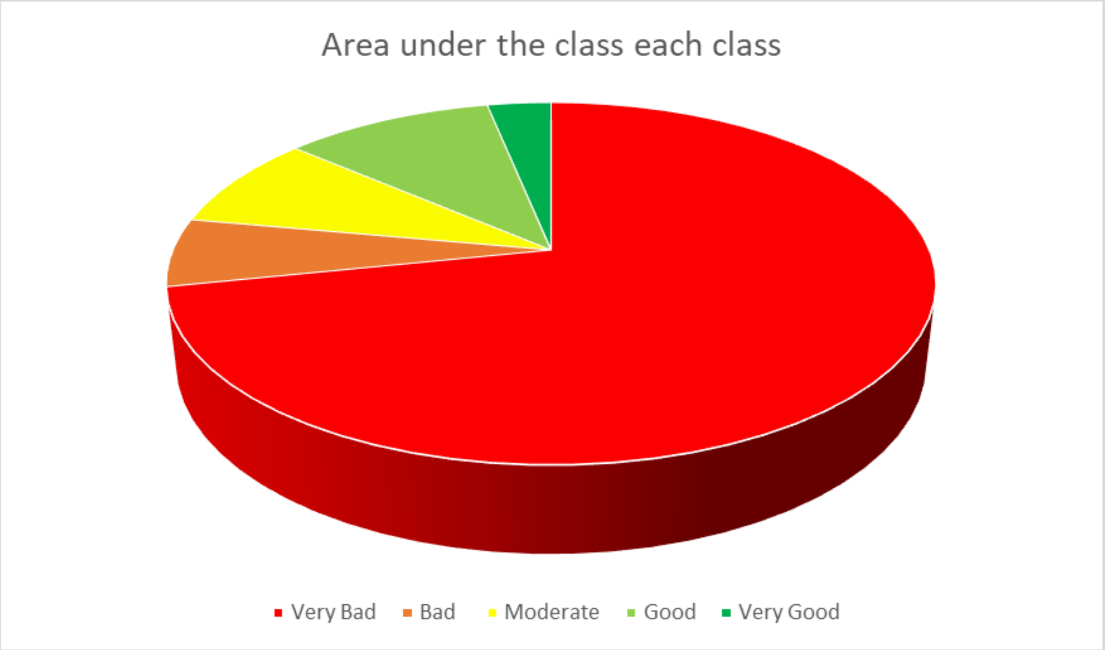


Fig 54: Chart showing area under each VORS classes of 2032

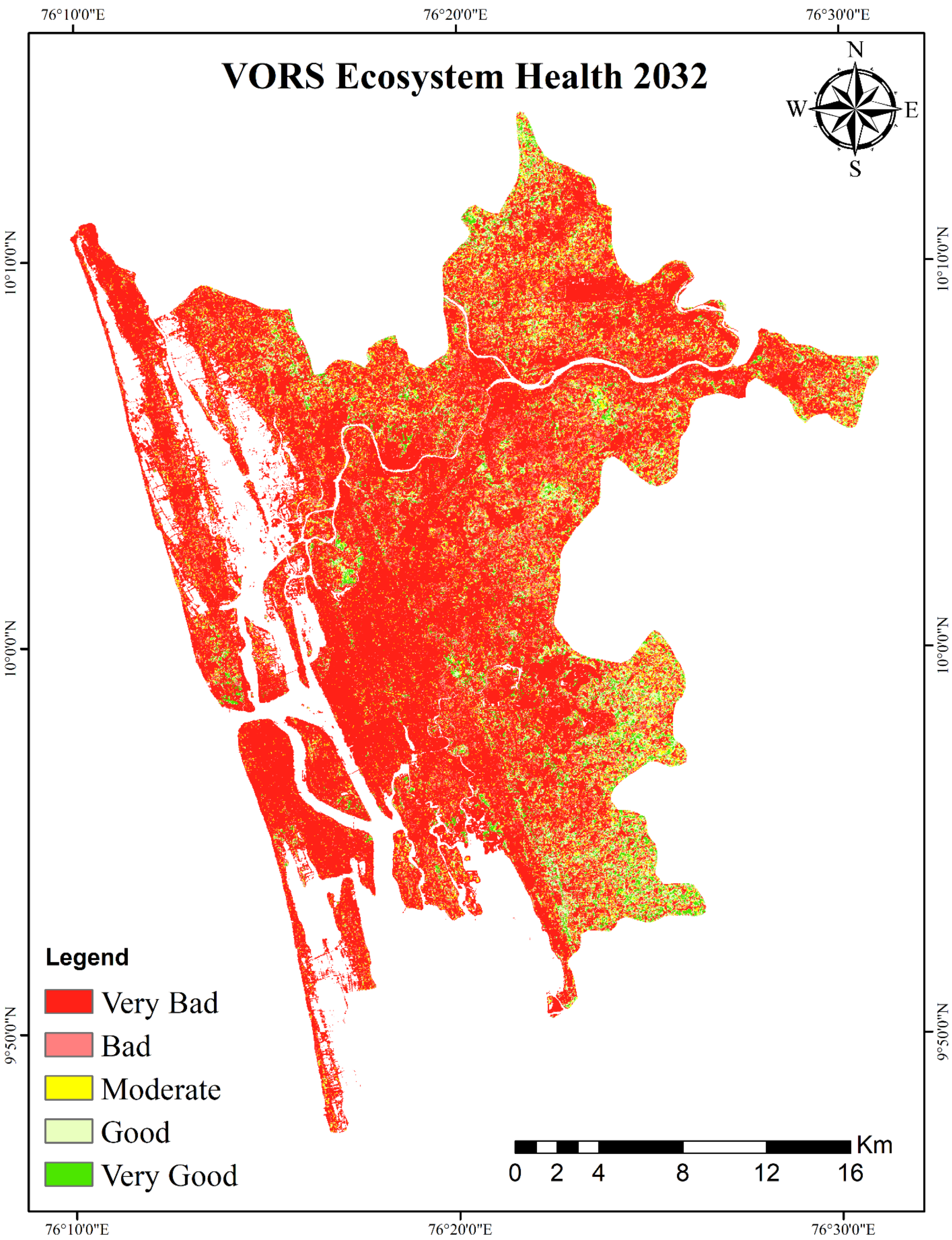


Fig 55: VORS Ecosystem Health 2032

Table 29: Change in VORS Ecosystem Health over the years

Ecosystem Health Condition	***2000***	***2010***	***2022***	***2032***
Very Bad	*218.494*	*245.852*	*366.724*	*440.897*
Bad	*50.058*	*42.831*	*25.5249*	*37.5228*
Moderate	*71.2602*	*93.564*	*22.3695*	*51.7959*
Good	*96.7635*	*131.081*	*97.1451*	*64.5498*
Very Good	*174.317*	*82.699*	*101.28*	*19.6533*

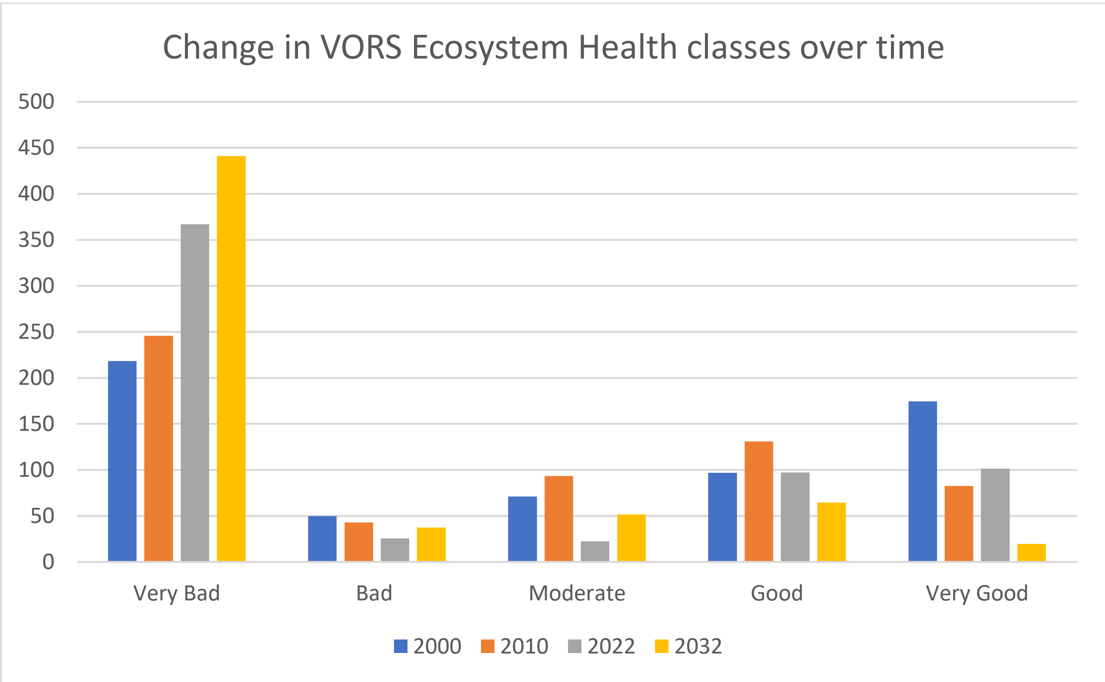


Fig 56: graph showing Change in VORS classes over time

DISCUSSION

We had analysed several characteristics that can influence climate and our earth, involving Land Surface Temperature, Land Use Land Cover Changes and Ecosystem Health condition. After analysing each factor, we see a deteriorating ecosystem and ever-increasing Land Surface Temperature, that can be accounted to the rising industries and oil refineries in Kochi. Even though development is necessary, for a better tomorrow, a sustainable and green approach to development practices and using public transport systems are the most basic method that can be adopted.

For the case of LST, we can see a high value at 2000, of 39 ^{0}C, it is believed to be the value of a single pixel and most of the areas showed a maximum of 32.62 ^{0}C. It can be seen steadily increasing after 2000 and the area under high temperature had drastically increased by 2022. The presence of solar panels at the Cochin Airport is also a major cause for the increasing LST near the area.

To reduce the negative effects of urban heat islands and improve the general standard of living for people, it is crucial to lower Land Surface Temperature (LST) in metropolitan areas. To do this, a variety of tactics might be used. Increased urban vegetation is one practical strategy. Through a process known as evapotranspiration, planting trees and developing green areas can offer shade, absorb sunlight, and release moisture. This reduces LST and aids in cooling the neighbourhood. Local governments can put laws into place that promote the establishing and upkeep of parks and trees in urban settings. By supplying natural insulation and cooling effects, green roofs and walls on buildings can also help reduce LST.

Additionally important is improving urban planning and architecture. Compact urban designs with numerous tall, densely populated buildings can trap heat, aggravating LST. Enhancing air circulation and reducing heat concentration can be accomplished by encouraging diverse land use, fostering green corridors, and introducing open areas. To do this, zoning restrictions that support eco-friendly urban planning practises can be implemented.

The decrease of LST is significantly aided by energy-efficient construction. Building heat production can be reduced by promoting the use of energy-efficient construction techniques, insulation, and HVAC (Heating, Ventilation, and Air Conditioning) systems. Lower LST can also result from the usage of cool roads and pavements that reflect sunlight rather than absorbing it.

While considering the LULC, we can see a huge decline in the area of dense vegetation, and an exponential increase in the built-up classes. The prediction for LULC was based on previous trend and the LULC can change differently when put under an economic scene, as areas like Kakkanad can grow drastically, which was projected to have only small variations. Maintaining ecological balance and protecting green spaces in urban settings depend on reducing the loss of dense vegetation and reducing the rise in built-up areas. To deal with this problem, several tactics might be used.

First and foremost, thorough urban planning is necessary. Cities should implement land use regulations that place a high priority on preserving open space and dense vegetation. Creating protected spaces, greenways, and zoning laws that limit excessive development in ecologically sensitive places are some examples of how to do this. As an alternative to expansive urban expansion, urban planners should promote compact, sustainable development patterns that emphasise infill construction and adaptive reuse of pre-existing buildings.

Another important strategy is to incorporate green infrastructure into urban development. In order to make up for the loss of vegetation at ground level, cities might encourage the incorporation of parks, green roofs, and green walls into building design. Incorporating green infrastructure not only improves the appearance of cities but also improves air quality, lessens the effects of heat islands, and creates habitat for wildlife.

Additionally, encouraging green building methods can aid in the preservation of thick vegetation. Developers who include green elements into their projects may be eligible for tax incentives, density bonuses, or expedited permitting from local governments. Mandates for tree planting, the creation of green buffers, and the use of native plant species in landscaping are a few examples of such. Our effort's key components are community involvement and public awareness. Citizens can make better decisions if they are taught about the advantages of keeping dense greenery and the drawbacks of unrestrained urbanisation. Participating in conservation efforts, community gardening, and tree-planting campaigns can encourage a sense of ownership and accountability for sustaining green places.

Lastly, effective policies and programmes can be developed and implemented through joint efforts involving government agencies, environmental organisations, and corporate sector partners. Together, these organisations can more effectively and thoroughly combat the reduction of dense vegetation and the rise in built-up areas by combining their resources, knowledge, and money.

For the decreasing ecosystem health that is evident from our VORS model, certain measures must be taken to increase ecosystem health in our region. The VORS model is based on the vegetation parametrises and make use of fragmentation statistics of the land, that was analysed for obtaining the ecosystem health of Kochi. The worsening state of Kochi's environment owing to fragmentation has been a serious problem in recent years. Ecological equilibrium has been thrown off by unregulated growth and rapid urbanisation, which have fragmented natural ecosystems. A comprehensive strategy is required to reverse this worrying trend. This essay describes a diverse approach to improving Kochi's failing ecosystem's health, with a particular emphasis on reducing the effects of fragmentation.

The implementation of strict land-use planning and zoning restrictions is one of the key approaches to address the problem of fragmentation. Environmental protection and sustainable development must be given top priority under these policies. To stop increasing fragmentation, it is crucial to designate green belts, wildlife corridors, and protected areas inside the urban landscape. Protecting vital natural ecosystems and migratory pathways. In order to stop the degradation of the ecosystem, it is essential to promote sustainable urban development practises. Compact, diversified land-use patterns that reduce Kochi's ecological imprint should be encouraged. Planning for effective public transit networks, controlling urban sprawl, and encouraging the growth of green, walkable areas are all necessary to achieve this. Kochi may lessen the negative consequences of fragmentation by planning urban areas with nature in mind. A well-informed and active populace is essential for the recovery of ecological health. To instil a sense of environmental responsibility among its citizens, Kochi should launch community participation and awareness programmes. These activities can be educational campaigns, workshops, or other projects that promote resource conservation, recycling, and trash reduction.

To strengthen Kochi's ecology, it is essential to invest in green infrastructure. This entails establishing parks, green areas, urban gardens, and green roofs. Such projects not only improve the aesthetic appeal of the city but also offer habitats for local species and vegetation. The creation of interconnected pockets of biodiversity inside the urban environment is made possible by green infrastructure, which acts as a barrier against fragmentation. Diverse parties must work together to address Kochi's fragmentation and environmental degradation. To properly fund and carry out the suggested projects, local government, non-governmental organisations (NGOs), and private sector companies must cooperate. Coordination makes ensuring that resources are used effectively and that various viewpoints are considered when making decisions. Kochi should set up a system of constant monitoring and study into the condition of its ecosystem in order to modify tactics and guarantee long-term sustainability. This will assist the city in adjusting its conservation efforts and staying ahead of new environmental concerns. Kochi's ability to make decisions that encourage environmental resilience is facilitated by ongoing data collection and ecosystem research.

A critical issue that necessitates immediate attention and coordinated action is Kochi's deteriorating ecological health condition as a result of fragmentation. A thorough plan is necessary to stop this tendency. Kochi can work towards reviving its ecosystem and minimising the effects of fragmentation on its environmental health by enacting strict land-use planning and zoning regulations, fostering sustainable urban development, engaging the community, investing in green infrastructure, fostering collaboration, and carrying out ongoing research. Kochi has the potential to become a model for sustainable urban development in India and abroad if it works hard and persistently.

SUMMARY

Land Surface Temperature (LST) is an essential part of the Earth's climate system and has major effects on the world at large, especially in terms of sustainability. LST is the term used to describe the temperature of the Earth's surface as measured from space or through other remote sensing methods, and it has several significant consequences for the long-term sustainability and health of our planet. Rising LST is a crucial sign of rising global temperatures, which are mostly brought about by human activities like the burning of fossil fuels and deforestation, which intensify the greenhouse effect. Scientists and decision-makers can better grasp the scope and pace of global warming by monitoring LST. Making wise actions to prevent climate change and prepare for its effects requires this information.

LST has significant effects on urban planning and growth as well. Understanding and managing LST in cities is essential as urbanisation and global population growth both continue. We observed an average increase of 1^0C, every 10 years, i.e., the LST was 32^0C in 2000, 33^0C in 2010, 34^0C in 2022. Even though it does not seem like much, it can have great impacts on urban planning, thermal comfort and the flora and fauna in the region.

Ecosystem health is of paramount importance in the global concept because it directly affects human well-being, supports biodiversity and resilience, and is essential for achieving sustainability. For the long-term survival and development of our planet and future generations, it is not only morally necessary to acknowledge the value of ecosystems and to take action to conserve and restore them. Ecosystem health is a key idea in the global context since it is essential to preserving our planet's health and ensuring the long-term viability of life on Earth. The health of ecosystems, which consist of a diverse range of interrelated living creatures and their physical habitats, is crucial for several reasons.

From the assessment of ecosystem health via VORS in our study, we can see a decreasing trend of ecosystem health, with the very bad ecosystem health increasing from 35% in 2000 to a staggering 59% by 2022. The predicted LULC showed an

ecosystem health of 71%, which was done using trend analysis of the previous years. Even though it was done using fragmentation characteristics, we can see the direction in which the ecosystem health of Kochi is heading.

First and foremost, there is a clear connection between environmental health and human wellbeing. Ecosystems provide crucial functions like the production of food, clean water, and the control of the temperature. In addition to providing habitat for pollinators that support agriculture, healthy ecosystems can filter water, control climate by absorbing and storing carbon dioxide, and purify air. These essential functions are disrupted when ecosystems are threatened or degraded, which has detrimental effects on human health and way of life. Furthermore, ecological resilience depends on biodiversity, a crucial element of ecosystem health. Ecosystems with a wide variety of species are more likely to be able to adapt to disturbances and changing environmental conditions. Additionally, a high biodiversity offers genetic resources that are important for biotechnology, medicine, and agriculture. Ecosystems are more susceptible to disease outbreaks and extreme weather conditions when biodiversity is lost because of habitat destruction or pollution, which ultimately jeopardises the sustainability of the planet, and humans as a whole.

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ASSESSMENT OF ECOSYSTEM HEALTH OF KOCHI WITH URBANISATION AND CHNAGING CLIMATIC PATTERNS OF KOCHI

by

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ABSTRACT OF THE THESIS

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ABSTRACT

Ecosystem health, which encompasses the delicate balance of ecological processes and the welfare of various species within ecosystems, is crucial to sustainability. preserving key services like clean air, clean water, and climate regulation—all of which support human well-being and economic stability—requires preserving the health of ecosystems. Furthermore, robust ecosystems foster biodiversity, which increases their resistance to environmental change and capacity for adaptation, assuring their long-term viability. Recognising the inherent relationship between ecosystem health and sustainability, we place a high priority on good environmental stewardship, promoting the peaceful coexistence of people and the environment.

By contributing to the urban heat island effect, a phenomenon where urban regions experience hotter temperatures than their surrounding rural areas, land surface temperature (LST) plays a crucial role in urban cities. The main cause of elevated LST in cities is heat absorption and retention by structures, asphalt, and other man-made surfaces. The health, energy use, and general well-being of urban dwellers may be significantly impacted by this increasing heat. From our analysis on the LST of Kochi city through the decade, we see an increase of 1^0C from 2000, with higher amounts of high temperature hotspots.

Our work employs a novel fuzzy-VORS (vigour, organisation, resilience, ecosystem services) model that combines fuzzy logic and a VORS model to forecast the past, present, and future health of the ecosystem in Kochi (Greater Cochin Development Authority Area), India. In this work, the land use and land cover (LULC) maps for the years 2000, 2010, and 2022 were classified using a support vector machine (SVM) classifier. Using delta change, the LULCs dynamics for the years 2000–2010, 2010–2022, and 1990–2022 were calculated. Using the cellular automata-artificial neural network model, the LULC map for 2032 was anticipated (ANN-CA). Sensitivity analysis was carried out using the random forest (RF) machine learning technique. The VORS model and the fuzzy inference system were combined to predict the ecosystem health conditions for the years 2000 through 2032. Urban areas grew by 349 percent between 2000 and 2022, according to LULC maps. The rapid and ongoing urbanisation

process has resulted in a severe reduction in all natural resources and ecosystem services. According to a LULC map from the year 2032, the built-up area would be 308.23 km^2. All sensitivity study methodologies revealed that vegetation, scrubland, and closeness to urban areas are quite sensitive to land suitability models to simulate and forecast LULC maps for 2022 and 2032.