PREDICTION OF LAND SURFACE TEMPERATURE FOR MITIGATING URBAN HEAT ISLAND EFFECTS

A Case Study of Dar es Salaam

By

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A Dissertation Submitted to the Department of Geospatial Sciences and Technology in Partially Fulfilment of the Requirements for the Award of Bachelor of Science in Geoinformatics (BSc.GI) of Ardhi University

CERTIFICATION

The undersigned certify that they have read and hereby recommend for acceptance by the Ardhi University dissertation "**Prediction of Land Surface Temperature for Mitigating Urban Heat Island Effects** "in partial fulfillment of the requirements for the award of degree of Bachelor of Science in Geoinformatics at Ardhi University.

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Dr. JOSEPH HAYOLA

(Supervisor)

Date ……………………….

DECLARATION AND COPYRIGHT

I, WILLIAM, ERICK A. hereby declares that, the contents of this dissertation are the results of my own findings through my study and investigation, and to the best of my knowledge they have not been presented anywhere else as a dissertation for diploma, degree or any similar academic award in any institution of higher learning.

………………………………..

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Am forever grateful.

DEDICATION

I dedicate this dissertation to my beloved family; Mrs. Georgina Fidel and Mr. Aloyce Ngassa, whose unwavering support and belief fuelled my academic journey. This dissertation reflects the values you instilled - perseverance, dedication, and love. Grateful for your sacrifices and life lessons. To my entire family, your collective encouragement and understanding were vital. This work honors each of you who contributed to my growth. With my guidance, I complete this milestone carrying your lessons and love.

ABSTRACT

Dar es Salaam is one of the fastest-growing and most affected cities by urban heat island (UHI) in Africa. UHI is a phenomenon that causes higher temperatures in urban areas than in rural areas, which has negative impacts on the environment, the economy, and the well-being of the residents. To mitigate the urban heat island effect, urban planners need to have accurate and reliable information on the future changes in land surface temperature and the areas that will be most vulnerable. However, previous studies have not been able to provide such information for Dar es Salaam. Therefore, this study aims to develop a predictive model for Dar es Salaam's LST based on urban development and climate change scenarios. This model will enhance our understanding of the issue and support urban planning and management strategies to reduce the UHI effect.

Landsat images from 2014, 2018, and 2022 were employed to generate key variables, including the Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-up Index (NDBI), and Land Surface Temperature (LST). This study explores the current state of LST distribution and the implications of the UHI effect on urban planning and management. Predictive models, including Artificial Neural Networks (ANN) and Cellular Automaton (CA), are employed to forecast LST scenarios for 2026. The validation of the CA-ANN model confirms its accuracy in predicting LST with an accuracy of 86.98%.

The findings reveal a consistent upward trend in LST, with higher temperatures expected in the central areas of Dar es Salaam, primarily characterized by extensive built-up development. Urbanization, coupled with declining vegetation coverage, exacerbates the UHI effect, intensifying energy consumption, greenhouse gas emissions, and health risks.

This research emphasizes the need for proactive measures to address UHI effects, sustainable urban development, and climate mitigation. It provides crucial insights for urban planners, policymakers, and stakeholders to shape a more resilient and sustainable future for Dar es Salaam, mitigating the challenges posed by rising LST and fostering a healthier urban environment.

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ACRONYMS AND ABBREVIATIONS

ANN- Artificial Neural Network

CA- Cellular Automata

LST -Land Surface Temperature

NDBI - Normalized Difference Vegetation index

NDVI -Normalized Difference Vegetation index

UHI -Urban Heat Island

USGS - United State Geological Survey

CHAPTER ONE
INTRODUCTION

1.1 Background

Dar es Salaam is the main commercial city of Tanzania and a gateway for many landlocked countries (TIC, 2017). It is also one of the fastest-growing cities in Africa, with a population of about 6.7 million in 2020 (World Population Review, 2020). As Tanzania progresses to be one of the best-performing and most stable economies in Africa, with the improvement and increase in trade and industries, the city is rapidly expanding. However, this urban development also brings environmental challenges, such as the urban heat island (UHI) effect. The UHI effect occurs when urban areas are warmer than the surrounding rural areas due to the alteration of the natural land cover by human activities. Roads, rooftops, and other artificial surfaces absorb more solar radiation and emit more heat than vegetation and soil, resulting in higher land surface temperatures (LST) in urban areas (Golden; 2004; Taha et al, 1992). The UHI effect can have negative impacts on the local climate, such as increasing the frequency and intensity of heat waves, altering precipitation patterns, reducing air quality, and possibly contributing to global warming.

Dar es Salaam is one of the most affected cities by UHIs in Africa. According to Kabanda (2019), the average UHI intensity in Dar es Salaam was 3.5°C during the day and 2.5°C during the night in 2018. Another study by Li et al. (2018) showed that SUHI intensity increased with urbanization and reached a peak value of 2.8°C in 2015. These high temperatures pose serious threats to the well-being of urban dwellers and the sustainability of urban systems. For instance, heat waves have become more frequent and severe in Dar es Salaam, causing discomfort, dehydration, heat exhaustion, and heat stroke among residents. Moreover, UHIs increase the demand for cooling devices, such as air conditioners and fans, which in turn increase energy consumption and greenhouse gas emissions. Furthermore, UHIs reduce soil moisture and evapotranspiration, which affect water availability and quality in the city.

Various methods have been employed to study UHIs in Dar es Salaam, such as remote sensing and statistical analysis. These approaches have revealed the spatial and temporal patterns, driving factors, and mitigation strategies of UHIs in the city. However, these studies have not been able to predict the future changes in land surface temperature and identify the specific areas within the city that will be most affected by the UHI effect. Therefore, there is a need for a predictive model of LST for Dar es Salaam, which is a fast-growing city with a complex urban environment. Such a model would enable us to forecast how the UHI effect might change under different scenarios of urban expansion and climate change. This would provide valuable insights for city planning and management, as well as for enhancing thermal comfort, reducing health risks, and saving energy and water resources in the city.

This study aims to develop a predictive model for Dar es Salaam's Land surface temperature By doing so, it will offer valuable insights into how the UHI effect might progress and affect the city in the future, and provide urban planners with critical information to support their decision-making processes and improve their strategies to mitigate the UHI effect.

1.2 Problem Statement.

Dar es Salaam is undergoing rapid urbanization that affects its land surface temperature and creates an urban heat island effect. This phenomenon has negative impacts on the environment, the economy, and the well-being of the residents. To mitigate the urban heat island effect, urban planners need to have accurate and reliable information on the future changes in land surface temperature and the areas that will be most vulnerable. However, previous studies have not been able to provide such information for Dar es Salaam. Therefore, this study aims to develop a predictive model for Dar es Salaam's land surface temperature based on urban development and climate change scenarios. This model will enhance our understanding of the issue and support urban planning and management strategies to reduce the urban heat island effect

1.3 Research Objectives

1.3.1 Main Objective

The main objective of the study was to forecast the spatiotemporal distribution of land surface temperature (LST) in a rapidly urbanizing Dar es salaam city for mitigating of urban heat island (UHI) .**1.3.2 Specific Objective**

- To generate LST maps from Landsat 8 images for the years 2014, 2018, and 2022.
- To predict the LST map for the year 2026 for Dar es salaam city.

1.4 Research Questions

- What are the spatial and temporal patterns of LST in the study area and how do they vary across different years?
- How effective is the developed LST prediction model in estimating and forecasting the UHI effect in Dar es Salaam City?

1.5 Significance of the Research

This study can inform urban planning and development policies aimed at mitigating the negative effects of UHIs, promoting sustainable urban development, and improving the well-being of urban residents. It can also contribute to the broader discourse on the relationship between urbanization and local climate, and inform international policies and programs aimed at promoting sustainable urbanization.

1.6 Beneficiaries of the research

- Urban planning and development

Studying of UHI can help in urban planning and development by identifying areas that are more vulnerable to heat stress. This knowledge can be used to develop urban green spaces, increasing vegetation cover and plan for strategic placement of building to reduce the impact of UHI.

- Health sectors

High temperature in urban areas can lead to various health problem, such as heat exhaustion, dehydration and heatstroke .by predict the extent and intensity of urban heat island in cities, authorities can take appropriate measure to mitigate the heat-related health risks**.**

- Policy makers

Policymakers can utilize the research outcomes to develop evidence-based policies aimed at reducing urban heat island effects. This may involve implementing regulations on building materials, encouraging green infrastructure and incentivizing sustainable practices. such policies can enhance overall environmental sustainability and resilience

- Residents and communities

Local communities can benefit by gaining insight into how to adapt to and mitigate rising temperature. accessible information about predicted land surface temperature can empower residents to make informed decision such as choosing suitable housing location and engaging in community initiatives to enhance green spaces.

1.7 Description of the study area

Dar es Salaam is located at range of (0°58’31”- 11°45’44”) S, and (29°22’48’’ - 40°26’50’’) E on a natural harbor on the coast of East Africa, with sandy beaches in some areas. Climate condition of Dar es salaam is tropical climate with relatively high temperature, high humidity and annual rain fall over 1000 mm. Dar es Salaam is the most important city for both business and government. The city contains high concentrations of trade and other services and manufacturing compared to other parts of the country; Dar es salaam has a population of about 5,383,728 people according to the 2022 census report.

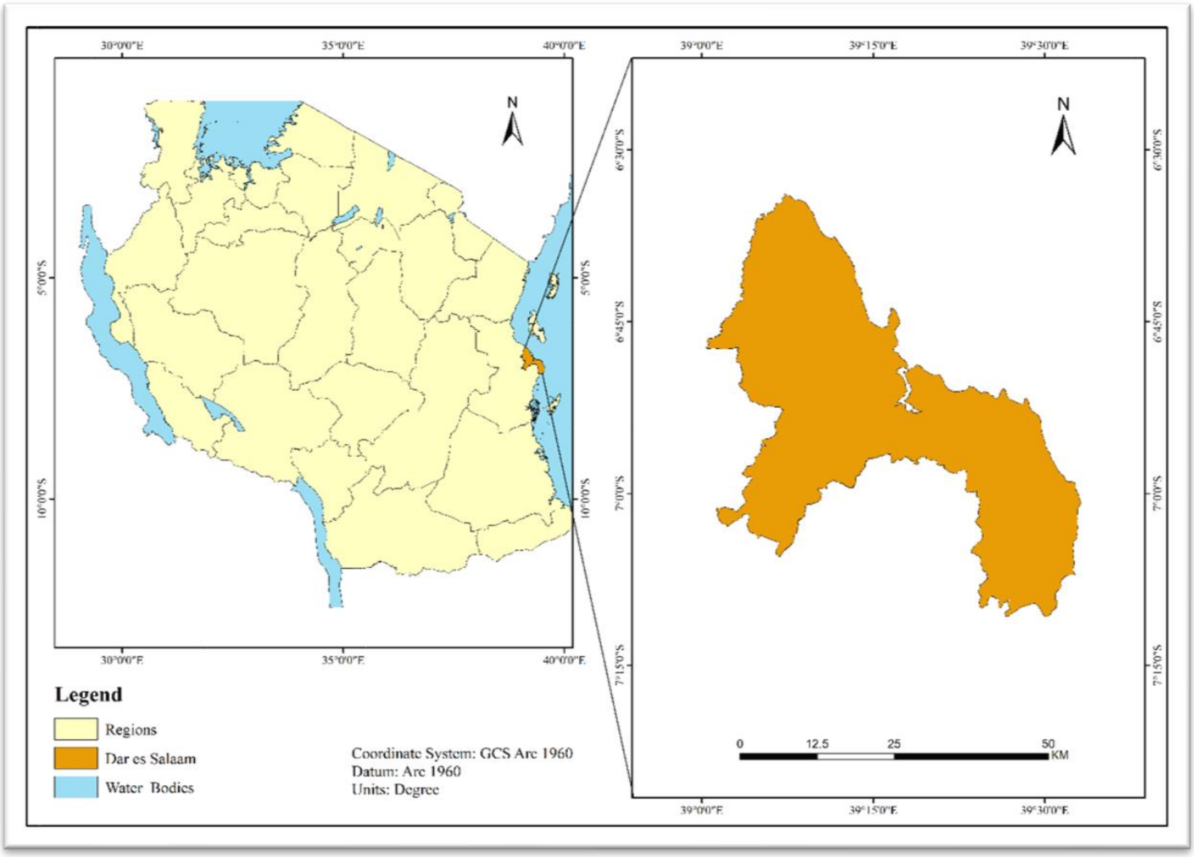

Figure 1.1 Location map of Dar es Salaam

CHAPTER TWO

LITERATURE REVIEW

2.1 Remote Sensing concept

Remote sensing is a scientific and technological field that involves obtaining information about Earth’s surface features or phenomena without direct contact. It uses sensors mounted on satellites or aircrafts that capture electromagnetic radiation emitted or reflected by the Earth. This data can be used to monitor and analyse various aspects of the Earth, such as its land, atmosphere, oceans, and ecosystems (Paul, 2004). Remote sensing consists of two main processes: data acquisition and data analysis using different electromagnetic energy sensor systems. One of the commonly used sensor systems is Landsat 8 OLI, which captures detailed images of the Earth’s surface in various spectral bands, including visible, near-infrared, and short-wave infrared. Landsat 8 OLI provides moderate-resolution imagery, with pixel sizes ranging from 15 to 100 meters. Landsat 8 OLI data is used for applications such as land cover mapping, agriculture, forestry, and environmental monitoring (Li et al., 2021). This study uses spectral indices derived from Landsat 8 OLI images obtained from remote sensing technique to predict land surface temperature for future estimation of urban heat island.

2.1.1 Satellite Imagery

These are pictures of the Earth captured by imaging satellites operated by governments and businesses worldwide. Numerous satellite missions have been launched into space, with the earliest space images taken in 1946. The initial Landsat program commenced in 1972. These images have diverse applications, including agriculture, forestry, geology, education, cartography, and planning (NASA, 2020).

Landsat is the oldest continuous satellite program dedicated to observing the Earth, providing imagery at a resolution of 30 meters. Currently, the Landsat 7, Landsat 8, and Landsat 9 satellites are in orbit.

2.1.2 Landsat 8 OLI

Landsat 8 OLI (Operational Land Imager) is an instrument aboard the Landsat 8 satellite, launched in 2013. OLI captures detailed images of Earth's land surface in various spectral bands, including visible, near-infrared, and short-wave infrared. It provides moderate-resolution imagery, with pixel sizes ranging from 15 to 100 meters.

OLI's data is used for applications such as land cover mapping, agriculture, forestry, and environmental monitoring and the Thermal Infrared Sensor (TIRS), which are utilized for studying Earth's surface temperature and investigating global warming (Li et al., 2021).

Table 2.1 Landsat 8 bands

Band No	**Colour**	**Wavelength (nm)**	**Spectral resolution (m)**
Band 1	Blue	433 – 453	30
Band 2	Blue	450 – 515	30
Band 3	Green	525 – 600	30
Band 4	Red	630 – 680	30
Band 5	NIR	845 – 885	30
Band 6	Sswir	1560 – 1660	30
Band 7	Lswir	2100 – 2300	30
Band 8	Pan	500 – 680	15
Band 9	Cirrus	1360 – 1390	30
Band 10	TIR	10300 – 11300	100
Band 11	TIR	11500 – 12500	100

2.3 Land cover indices

Land cover indices are quantitative measures derived from remote sensing data that provide valuable information about the composition and distribution of different land cover types within a given area. These indices are derived by analyzing the spectral characteristics of satellite imagery, particularly in the visible, near-infrared, and short-wave infrared wavelengths.

Common land cover indices are the Normalized Difference Vegetation Index (NDVI) and Normalized Difference Vegetation Index (NDBI) (Zha et al., 2003).

2.3.1 Normalized Difference Vegetation Index (NDVI)

The Normalized Difference Vegetation Index (NDVI) is a commonly used remote sensing index for evaluating the health and biomass of vegetation. It is derived from the reflectance values captured in the red and near-infrared (NIR) bands of the electromagnetic spectrum.

These reflectance values are typically obtained through sensors mounted on satellites or aircraft. NDVI values range from -1 to 1, with values close to 1 indicating dense and healthy vegetation, values close to -1 indicating bare soil or water, and values close to 0 indicating sparse or non-vegetated areas.

NDVI is highly favoured as a vegetation index due to its sensitivity to the chlorophyll content in leaves, which serves as a reliable indicator of vegetation health and biomass. It can be applied to monitor vegetation growth, identify changes in land cover, and detect regions experiencing drought or desertification (Rehna and Natya, 2016).

The formula for NDVI is represented as

$$NDVI = \frac{NIR-RED}{NIR+RED} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (2.1)$$

For Landsat 8 OLI (Mallinis, et al., 2018)z

$$NDVI = \frac{band\ 5 - band\ 4}{band5 + band4}$$

Where:

NIR = reflectance in the near-infrared band

Red = reflectance in the red band

2.3.2 Normalized Difference Built up Index (NDBI)

NDBI identifies the extent of impervious areas and highlights the built-up areas. Urban areas have more reflectance in the shortwave infrared (SWIR) band than the near-infrared (NIR) band The higher values of NDBI show areas of high-density built-up while the lower values indicate non-built-up areas (Zha et al., 2003). The resulting NDBI values range from -1 to 1. Higher positive values indicate a higher likelihood of built-up areas, while lower or negative values indicate a higher presence of non-built-up areas such as vegetation or water.

NDBI can be Calculated from the Short-wave Infrared Band and near-infrared by using the following formula (Zha et al., 2003).

$$NDBI = \frac{SWIR-NIR}{SWIR+NIR} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (2.2)$$

For Landsat 8 OLI

$$NDBI = \frac{band\ 6 - band\ 5}{band\ 6 + band\ 5}$$

Where:
SWIR-Short Wave Infrared band and
NIR-Near-Infrared Band

2.4 Land surface temperature

Land surface temperature (LST) refers as the temperature felt when the land surface is touched with the skin or temperature of the ground (Aydan, 2016). Involves the Measurement of how hot or cold the surface of the earth would feel to the touch of particular location. The main factors that affect land surface temperature are vegetation and bare land, because they respond rapidly to changes in incoming solar radiation due to cloud cover.

There are different algorithms used to calculate Land surface temperature. These algorithms have been specified for different thermal sensors on satellites, such that the algorithm use for one thermal sensor (or combination of thermal sensors) cannot be used for another thermal sensor (Juan, 2004).

These algorithms are;

- Single channel
- Split window
- Dual angle

To apply split window or Dual angle algorithms at least two thermal channels are required. A single channel algorithm is used to retrieve LST from sensors that have single thermal band, the main advantage of this algorithm compared with split window and dual angle method is that it can be applied to different thermal sensors using the same equation. As well-known Landsat 4-5 (TM) and 7 (ETM+) have single thermal bands each but Landsat 8 (TIRS) there are two Thermal bands. Due to the high contamination of stray light in band 11 for Landsat 8, a single channel algorithm is used to estimate Land Surface Temperature.

2.5 Urban Heat Island

Urban heat island (UHI) is a phenomenon where urban areas have much higher temperatures than the rural areas around them (Oke, 2014). This happens because of the changes in land surfaces and human activities in cities. UHI is caused by many factors, such as urbanization, more hard surfaces, less green spaces, heat from buildings and vehicles, and different wind patterns. Cities like Dar es Salaam has many buildings, roads, and concrete surfaces that soak up and keep heat during the day and release it at night. This makes the night time temperatures higher, which is called the nocturnal UHI effect. Also, the loss of vegetation and trees in cities reduces the cooling effect of evaporation and shade, which makes the temperatures even higher (Streutker, 2003). The UHI effect has many impacts on cities and people's well-being. It can lead to more energy use for cooling, lower air quality, and higher health risks from heat. People who are more vulnerable, such as the elderly and those with health problems, are especially at-risk during heatwaves in cities (Stone Jr et al.,2012).

2.6 Prediction of land surface temperature

Prediction in remote sensing refers to the process of using historical or current remote sensing data to make informed estimates or forecasts about future conditions, changes, or attributes of a specific area or phenomenon on the Earth's surface (Rahmani et al., 2019). One specific and crucial application of remote sensing prediction is in the realm of predicting land surface temperature (LST), an essential environmental parameter.

LST prediction involves applying various analytical techniques, statistical methods, and machine learning algorithms to the collected remote sensing data, including satellite-based data from Landsat and MODIS sensors, in order to generate meaningful predictions (Rahmani et al., 2019; Chen et al., 2017). This process is particularly important for gaining insights into how LST, a key factor in climate studies and urban heat island analysis, will evolve over time and space.

Various modelling techniques are applied to predict future LST conditions. These techniques can range from simple linear regression to more complex machine learning algorithms like Random Forest, Support Vector Machines, and Artificial Neural Networks (Chen et al., 2017). Integration of meteorological data, such as temperature and humidity, is often critical to improving the accuracy of LST predictions (Jin et al., 2019).

The overarching goal of predicting LST using remote sensing is to contribute to fields such as urban planning, agriculture, and climate science by providing accurate estimates of how land surface temperatures will change in the future, allowing for informed decision-making and environmental management (Grossard et al., 2018). As remote sensing technology and modelling techniques continue to advance, the accuracy and precision of LST predictions are expected to improve, thereby enhancing our understanding of the Earth's surface temperature dynamics and their impact on various environmental processes.

2.7 CA Markov model

Cellular Automata (CA) is a spatial dynamics model extensively utilized in the examination of land use transformations. It is a well-liked simulation model that treats time and location separately, with interactions occurring locally.

The CA model represents a natural landscape as a grid, where each cell is updated at time stage T + 1 based on the neighbouring cell states at time t and predefined transition rules. By employing cellular automation, it becomes possible to simulate changes along a two-dimensional axis, making it a valuable approach for studying spatial dynamics. This method finds widespread application in various geographical domains, particularly in forecasting urban development and changes in land use. (Sabree Ali et al., 2020).

2.8 Artificial Neural Network

Artificial Neural Networks (ANNs) are a class of machine learning models inspired by the structure and function of biological neurons in the human brain. ANNs are widely used for various tasks, including prediction and classification, due to their ability to learn complex patterns and relationships in data.

When it comes to predicting land surface temperature (LST), ANNs can be applied to capture the intricate interactions between various environmental factors that influence LST, such as vegetation cover, urbanization, and atmospheric conditions.

Several studies have used different types of ANNs to predict LST using satellite data, such as Landsat, MODIS, and Sentinel. For example (Ranjan et al. 2018) used ANN in conjunction with geoinformatics technology to predict LST changes in Jodhpur city, India . They used maximum value composite technique to derive seasonal LST from MODIS data, and applied ANN to forecast LST for future years. (Gholami et al. 2018) used ANN to estimate LST in urbanized landscapes in Isfahan, Iran They used Landsat 8 OLI imagery to derive LST and green cover spatial patterns, and explored the effects of urbanization on LST.

CHAPTER THREE

METHODOLOGY

3.1 Methodology work flow

The methodology section explains the step-by-step plan used to carry out the study. It lays out important aspects like who took part, how information was collected, and the methods used to analyse the data. In this particular approach, Landsat satellite image data were obtained from the USGS database. After that, these images went through necessary pre-processing steps to fix problems caused by the atmosphere. Then, the improved images were used to figure out Land Surface Temperature (LST), which is a really important factor when we're trying to understand Urban Heat Island (UHI) effects.

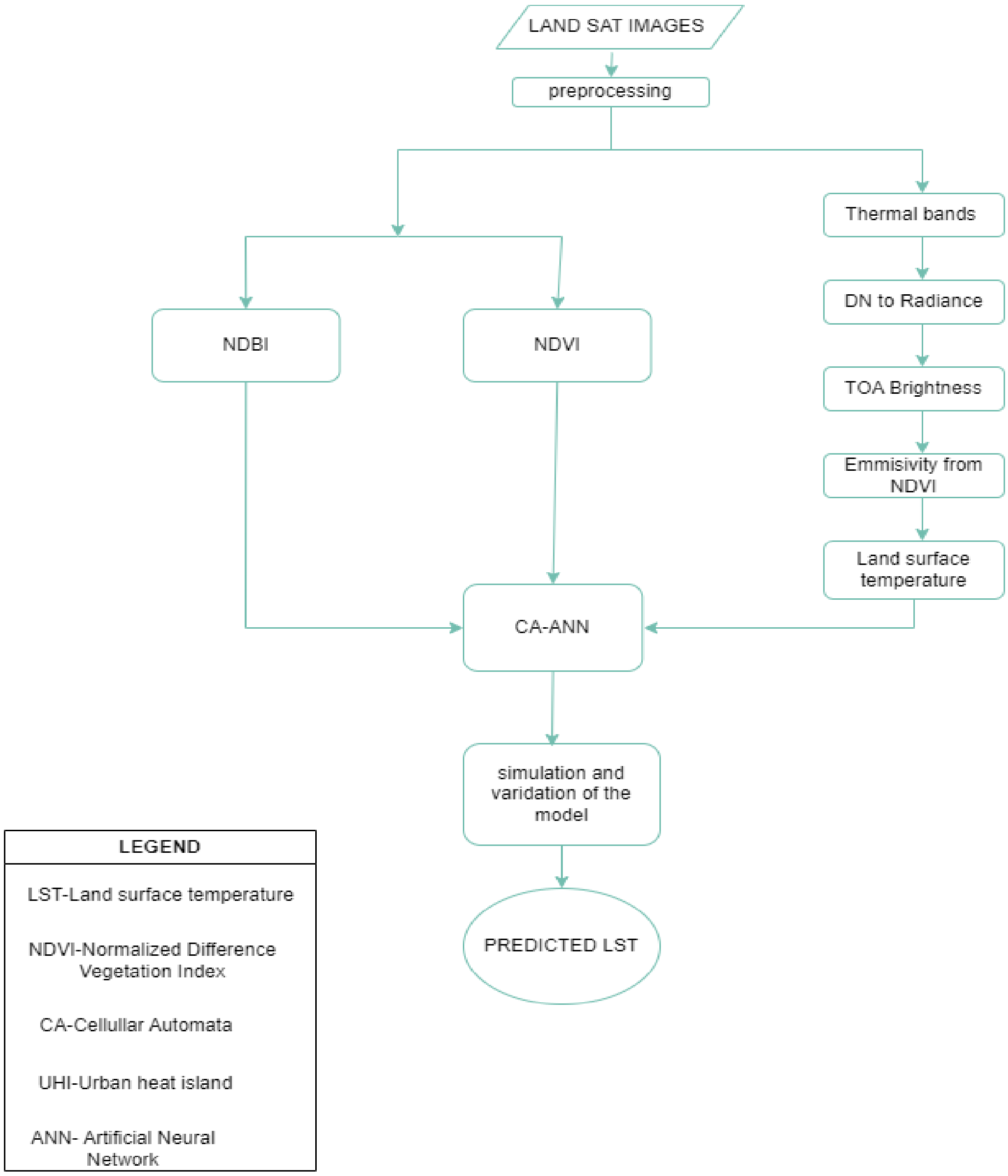

Figure 3.1 Methodology flowchart

3.2 Data and Data source

The data used in this study include Landsat 8 OLI images, active SRTM DEM and study areas boundary as summarized in table 3.1 Landsat 8 data were downloaded from the USGS Earth explorer website, three images of path and rows 166/065 collectively cover our study area. These images were acquired in June of 2014 and June of 2018 and June of 2022.

Table 3.1 data collected and its source

DATA TYPE	SOURCE OF DATA	SPATIAL RESOLUTION
Landsat 8	USGS	30m
Dar es salaam administrative boundary	DIVA GIS	

3.3 Image Pre-processing

Image pre-processing involves image preparation before undertaking further procedures to obtain the required information from satellite images. In this study, pre-processing of Landsat images was performed as follows;

3.3.1 Re projection

Landsat scenes were re-projected from the default image coordinate system used in the Landsat archive which is a Projected Coordinate System (UTM) to Geographical Coordinate System, World Geographical coordinate system (WGS 1984). This was done to all images so that they could be referenced to a common coordinate system. The purpose of re-projecting data from UTM to Geographic Coordinate System was to avoid datum confusion.

3.3.2 Atmospheric correction

The measured radiance from the earth's surface is subjected to clouds and other particles in the atmosphere. Atmospheric correction was applied to remove the noises in the atmosphere by applying Dark Object Subtraction (DOS1) method under the pre-processing tool in Q GIS 3.16. Landsat images were imported in the Q GIS environment in which Downloaded and installed the Semi-Automatic Classification Plugin (SCP) were selected.

The SCP is a QGIS plugin that provides tools for various remote sensing tasks, including atmospheric correction. The dark Object Subtraction (DOS1) method is used to remove noise from the Landsat image

3.4 Computation of land cover indices

Two LCIs (NDVI, and NDBI) were computed to examine their relationship with LST.NDVI is used to identify the vegetation characteristics (Baloloyet al., 2018). Since the characteristics of the soil and the coverage of vegetation varies in the study area and NDBI are used to identify the urban features from RS data, having extra indices increases the choice of variables that best predicts LST.

3.4.1Normalized differences vegetation index

NDVI is commonly used to extract coverage of green vegetation in which serves as a reliable indicator of vegetation health and biomass. It can be applied to monitor vegetation growth and identify changes in land cover (Rehna and Natya, 2016).

It is used as one variable to compute LST from RS data (Omran, 2012). The RED and NIR portion of the spectrum is used for the derivation of NDVI.NDVI values range from -1 to 1, with values close to 1 indicating dense and healthy vegetation, values close to -1 indicating bare soil or water, and values close to 0 indicating sparse or non-vegetated areas. NDVI was computed by the equation 2.1 (Tucker, 1979).

$$NDVI = \frac{NIR-RED}{NIR-RED} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2.1)$$

Where:

NIR-Near-Infrared Band

RED- Red Band

3.4.2 Normalized Differences Built-up Index

NDBI can be Calculated from the Short-wave Infrared Band (SWIR) and near-infrared band (NIR). The r NDBI values range from -1 to 1. Higher positive values indicate a higher likelihood of built-up areas, while lower or negative values indicate a higher presence of non-built-up areas such as vegetation or water.

NDBI was calculated by the equation 2.2 (Zha et al., 2003):

$$NDBI = \frac{SWIR-NIR}{SWIR+NIR} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2.2)$$

Where:

SWIR-Short Wave Infrared band and

NIR-Near-Infrared Band

3.5 Land surface temperature estimation

Land surface Temperature map was produced by utilizing satellite images. Four LANDSAT 8 thermal bands were downloaded from USGS. Each image was processed individually in R studio software to produce land surface temperature. LST was extracted from the thermal bands of Landsat images acquired in 2014, 2018, and 2022. It was computed from the thermal band in the Landsat 8 using a Single channel algorithm. Firstly, the images were re-projected then the following procedures.

Step 1: Conversion of digital numbers (DN) to Top of Atmosphere (TOA) Radiance:

The conversion of digital number to top of atmosphere radiance computed by using equation 3.1

$$\mathrm{L}\lambda = ML * \mathrm{Qcal} + \mathrm{AL} \qquad \ldots\ldots\ldots\ldots\ldots (3.1)$$

Where,

$\mathrm{L}\lambda$ -Top of Atmosphere.

ML-Radiance Multiplicative Band (No).

AL-Radiance Add Band (No).

Qcal-Quantized and Calibrated Standard product pixel values.

ML and AL values are found in the metadata file of the Landsat 8 OLI images where by the values were 0.00033420 and 0.1 respectively and Qcal is the thermal band in which we chose band 10 from the Landsat 8 OLI images.

Step 2: Conversion to Brightness Temperature (BT):

Brightness temperature was calculated from the spectral radiance of thermal bands by the equation 3.2 (Weng et al., 2004)

$$BT = K2/In\,(K1/\,L\lambda\, + 1) - 273.15. \qquad \ldots\ldots\ldots\ldots (3.2)$$

Where,

BT- Brightness temperature.

$\mathrm{L}\lambda$ -Top of Atmosphere.

KI- Constant Band (No).

K2 Constant Band (No).

K1 and K2 values are provided in the metadata file of the Landsat images as shown in table 3.2

Table 3.2 showing k value for Landsat 8

K1_CONSTANT_BAND_10	774.8853
K2_CONSTANT_BAND_10	1321.0789

Step 3: Calculating Normalized Difference Vegetation Index (NDVI)

NDVI was calculated using Near Infrared Band and Red Band. In this case the bands used in calculating the NDVI for Landsat 8 OLI were band 5(NIR) and band 4(RED).

$$NDVI = \frac{NIR-RED}{NIR-RED} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2.1)$$

Where,

NIR=DN values from Near Infrared band.

RED-DN values from Red band.

Step 4; Calculating the Proportional Vegetation (PV).

The maximum and minimum values of the NDVI were used to calculate the fractional vegetation cover equation 3.3 used in calculate proportional vegetation.

$$PV = Square\ ((NDVI - NDVImin)/\ (NDVImax - NDVImin)) \quad \ldots\ldots\ldots\ldots (3.3)$$

Step 5: Calculating land surface emissivity.

Emissivity is controlled by many factors including atmospheric water content and roughness of the surface. Emissivity has a strong association with NDVI and is computed from it by using equation 3.4 (Weng and Larson).

$$E = 0.004\ PV + 0.986 \qquad \ldots\ldots\ldots\ldots\ldots\ldots (3.4)$$

Where,

E= Land Surface Emissivity.

PV= Proportional Vegetation

Step 6; Land surface temperature (LST).

The land surface temperature of all the images was computed by using equation 3.5:

$$LST = (BT/(1 + (0.00115\ BT/1.4388)\ In\ (E))) \qquad \ldots\ldots\ldots\ldots\ldots (3.5)$$

Where;

BT - Brightness temperature

E - Land surface emissivity

3.6 Prediction of future LST

A key aspect of the study is forecasting LST distribution. Using several models, including ANN and CA, the spatiotemporal distribution of LST is predicted (Mansouri et al., 2016). MOLUSCE plugin tool in the QGIS software for this study was used to forecast the 2026 LST distribution, which is considered to be among the best prediction models. It incorporates conventional algorithms like CA, ANN, Logistic Regression, Multi-Criteria Evaluation, and Weights of Evidence. The input module for this study contains dependent variable LST distribution and independent variables NDVI and NDBI for LST prediction. LST maps for 2014, 2018 and 2022 were used in simulating 2026 LST map. Since visible, SWIR and thermal bands used in LST and NDVI, and NDBI estimation, all the images are converted in the 30 m × 30 m spatial resolution using standardization approach before performing prediction analysis. Analysis of area change calculates LST variations between two time periods and created transition matrices and mapped the LST change distribution. The ANN model was used to predict LST transition potential in the modelling methods stage setting the maximum iteration at 1000. Transition potentials prompt the probability of future LST change using a neural network and include detailing of the descriptive power of driver variables. The pixel for the neighbourhood was set to 9 cells (3 × 3) to set maximum iterations and pixels for the model. Based on the CA modelling approach, predicted LST maps were generated, the validation stage generated different kappa statistics like percent of correctness, standard kappa, kappa histogram, and kappa location

3.7 Validation of the predicted LST

The CA-ANN model was first used to predict the LST for 2022 to ensure the acceptance of prediction result. With the help of the QGIS-MOLUSCE Plugin software, a comparison of the predicted and the estimated maps was established using different kappa parameters. The comparison showed excellent results as all the kappa parameters, percentage of accuracy and overall kappa value.

3.8 UHI intensity

The UHI intensity is calculated by the relative LST as Equation 3.6 (Weng, 2004)

$$Tr = (Ts - Ts) / Ts \text{ ....} (3.6)$$

where: Tr is the relative LST, Ts is the LST (°C), Ts is the mean LST (°C).

Table 3.4 classification of urban heat island intensity

Relative LST	UHI intensity
< 0	non-UHI
≥ 0	UHI

CHAPTER FOUR

RESULT AND DISCUSSION

4.1 Normalized Difference Vegetation Index

After the transformation of DN values to spectral radiances, NDVI index of each dataset is calculated The NDVI index outputs values between −1 to +1. with values close to 1indicating dense and healthy vegetation, values close to -1 indicating bare soil or water, and values close to 0 indicating sparse or non-vegetated areas. The range of NDVI value of Dar es salaam was (-0.59 -0.91), (-0.73 – 0.91) and (-0.71 - 0.93) for year 2014,2018,2022 respectively, as shown in the figure 4.1show distribution of ndvi in Dar es salaam

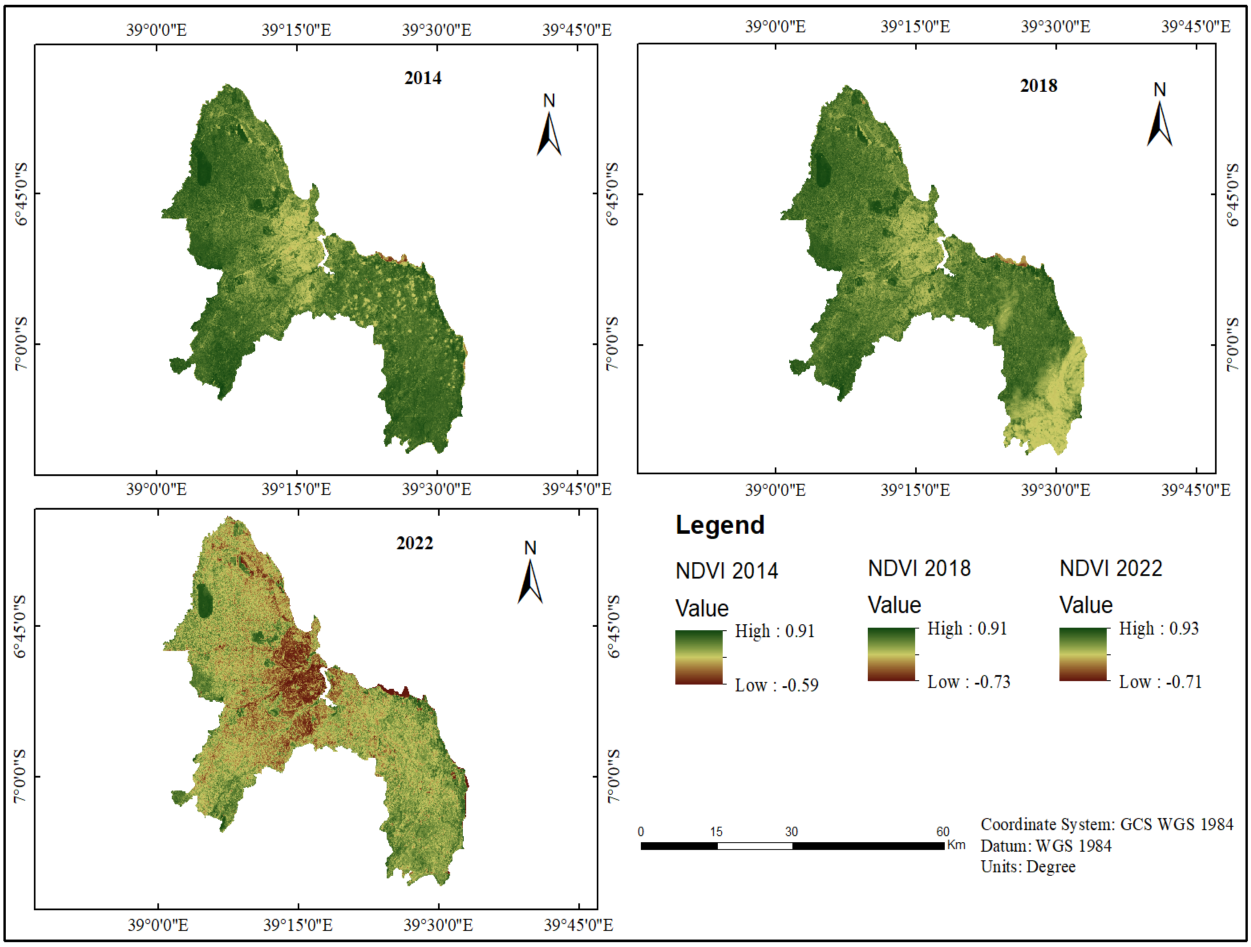

Figure 4.1: NDVI distribution maps

4.2 Normalized Difference Built-Up Index

The range of NDBI value of Dar es Salaam was (-0.89 - 0.57), (-0.9 – 0.68) and (-0.89 -0.50) for years 2014, 2018, and 2022 respectively, the resulting NDBI values range from -1 to 1. Higher positive values indicate a higher likelihood of built-up areas, while lower or negative values indicate a higher presence of non-built-up areas such as vegetation or water. The analysis of the NDBI index allows for an examination of the impact of vegetation coverage and urban areas on the urban heat island (UHI).

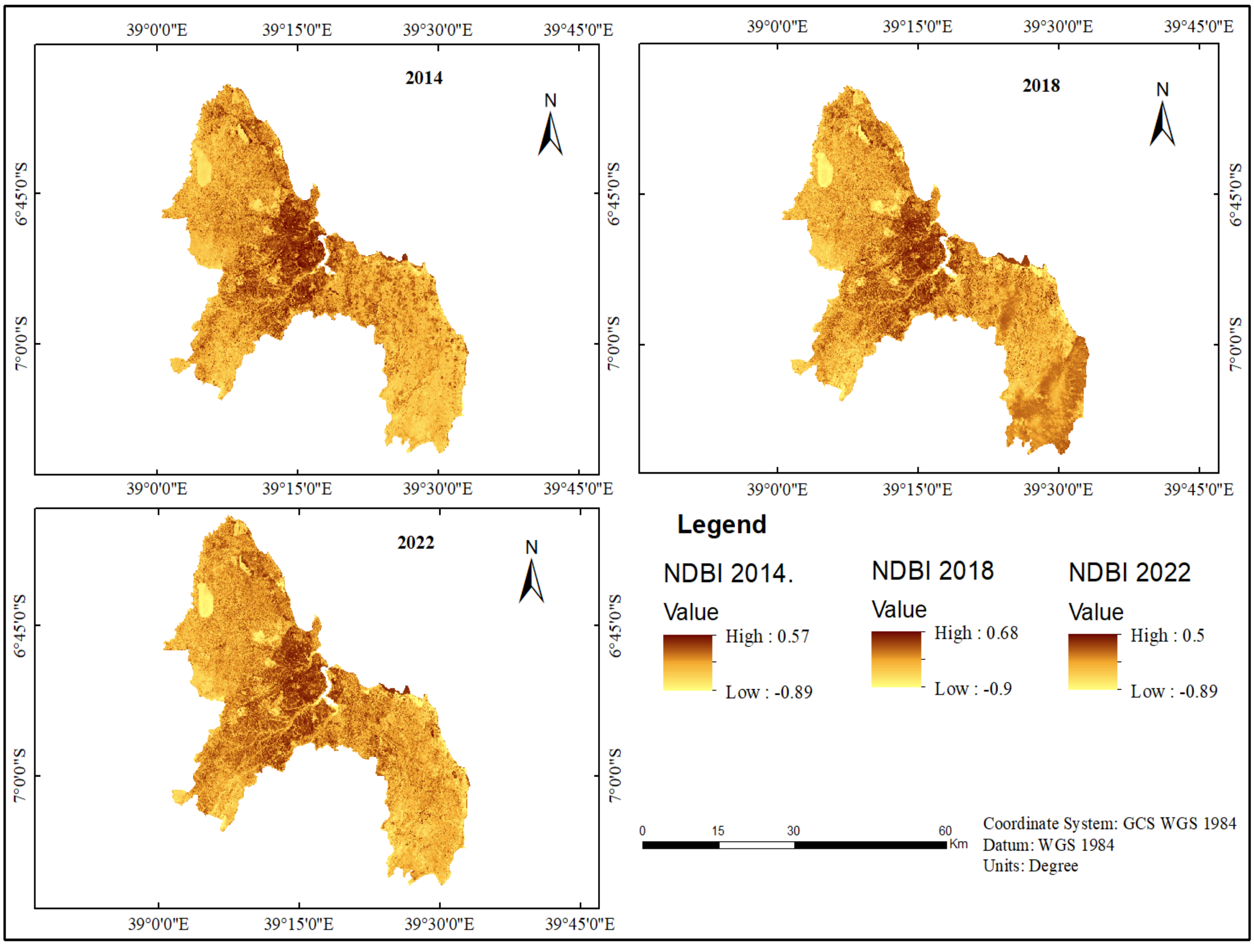

Figure 4.2: NDBI distribution maps

4.3 Land surface temperature distribution

For year 2014, the Dar es Salaam region experienced an average land surface temperature (LST) of 23.49°C. The temperature range during this month spanned from a minimum of 11.6°C to a maximum of 30.33°C as shown in figure 4.3. This data indicates a relatively moderate temperature profile for the region during that year. The lowest temperature recorded reflect cooler end of spectrum, likely occurring during might or early morning, while highest temperature suggests warm daytime conditions

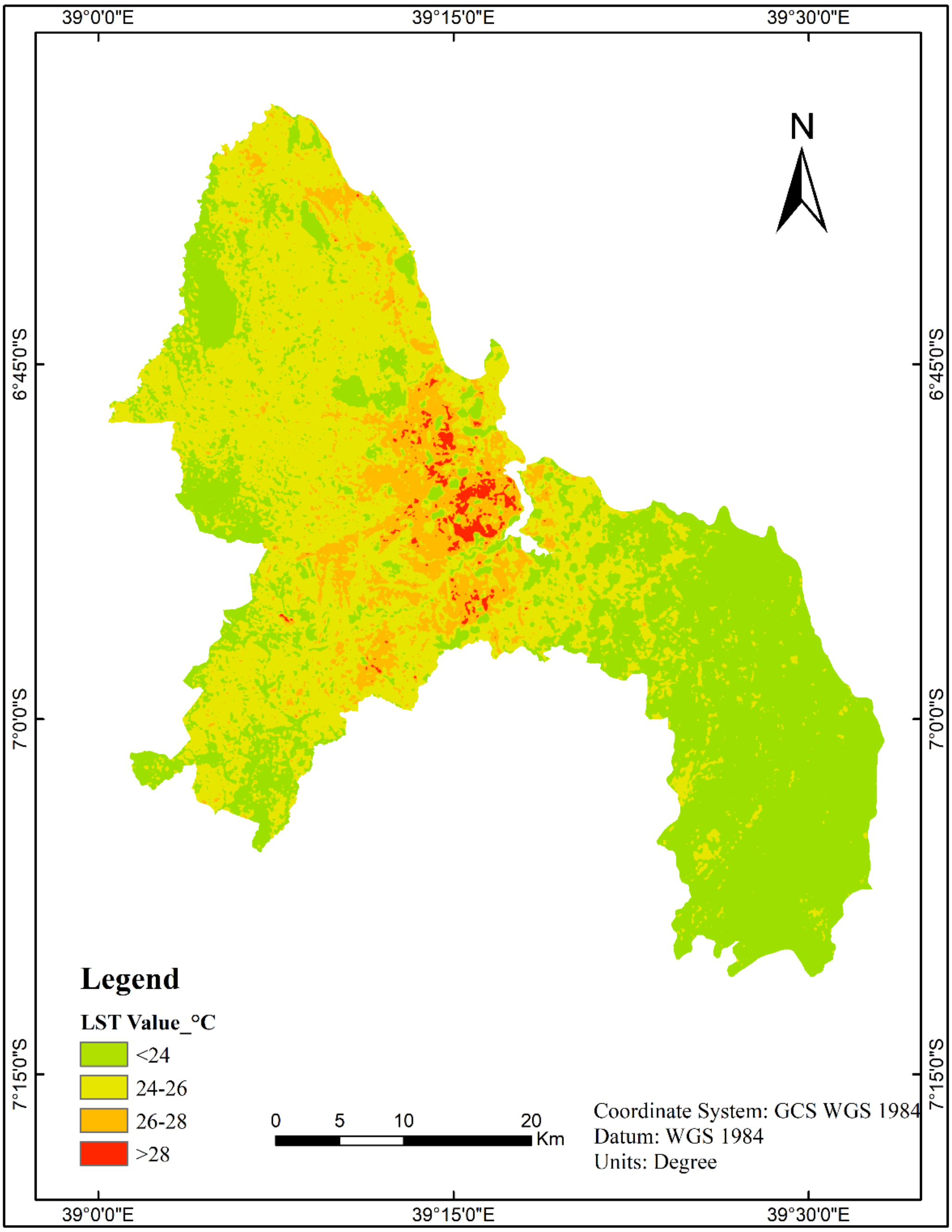

Figure 4.3: Dar es salaam distribution of land surface temperature for year 2014

For year 2018, there was a noticeable increase in land surface temperature compared to 2014. The lowest recorded temperature for this year was 15.21°C, while the highest temperature reached 32.06°C. This range indicates a broader temperature spectrum compared to 2014, with both the lowest and highest values experiencing an upward shift. The average LST for 2018 stood at 24.27°C, indicating a significant warming trend compared to the previous year.

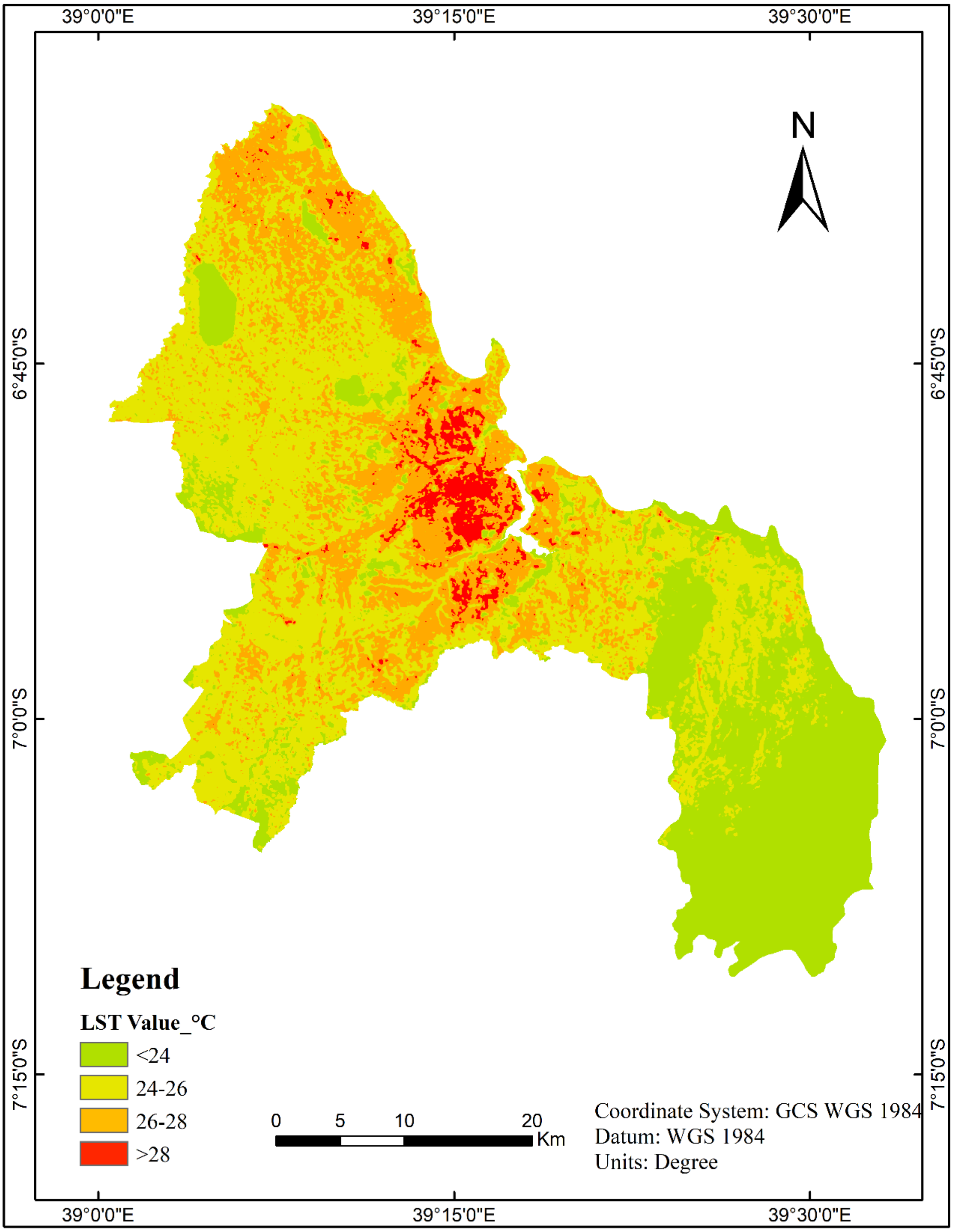

Figure 4.4 Dar es salaam distribution of surface temperature year 2018

June 2022, the trend of increasing land surface temperature continued, reaching even higher levels compared to both 2014 and 2018. The lowest temperature observed during this year was 21.48°C, while the highest temperature reached 32.09°C. These figures reflect a progressive warming trend over the years, particularly evident in the higher recorded minimum temperature. The average LST for 2022 was 26.15°C, indicating a substantial increase in comparison to the previous years. This upward trend in land surface temperature is indicative of a warming trend in the Dar es Salaam region, which could have far-reaching implications for the local environment, ecology, and community livelihoods.

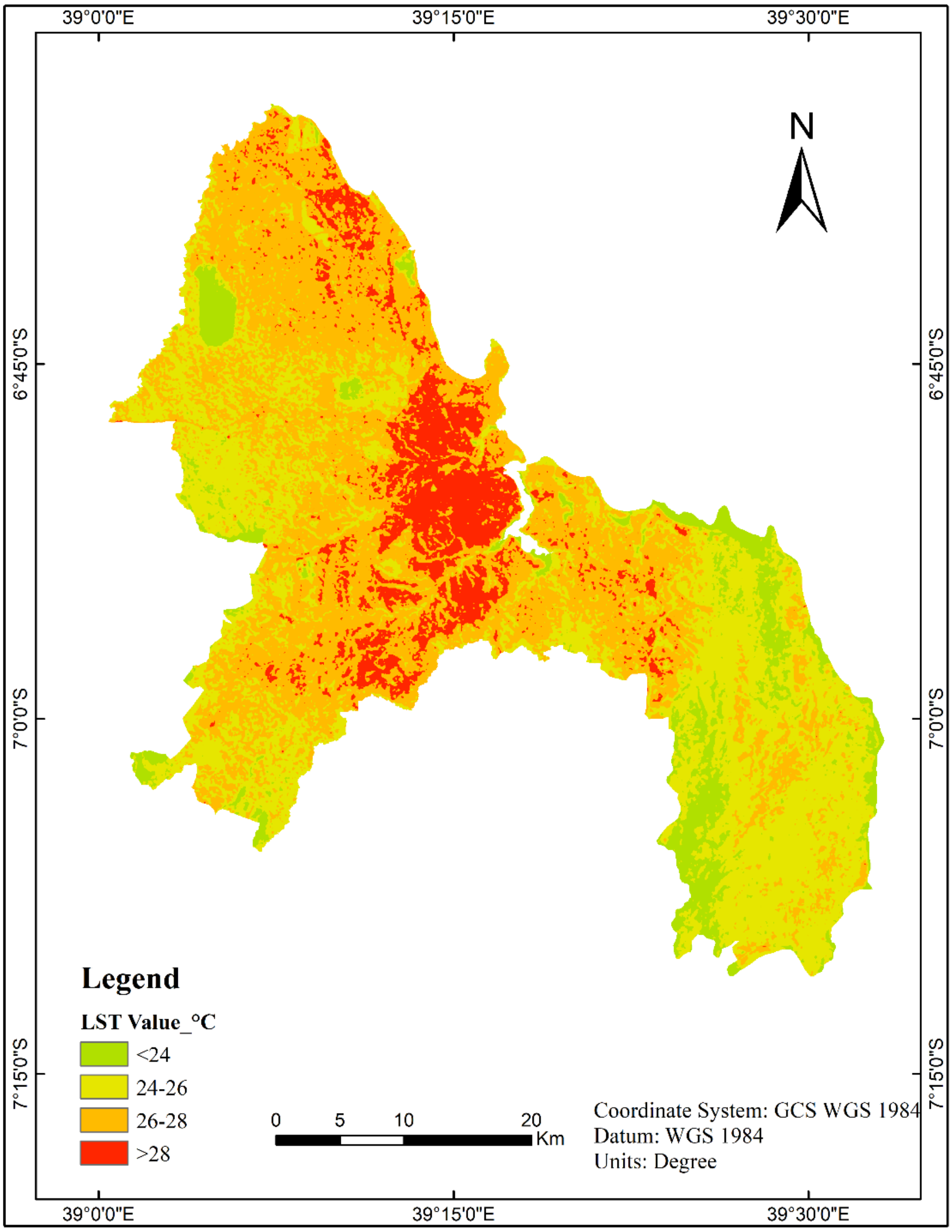

Figure 4.5 Dar es salaam distribution of surface temperature of year 2022

The analysis of land surface temperature distribution over the years 2014 to 2022 clearly illustrates a consistent and gradual increase in temperatures for the Dar es Salaam region. This trend, marked by rising average temperatures and higher recorded maximums and minimums, points to a warming pattern that warrants attention as shown in a figure 4.6. The consistent rise in both average temperatures and temperature extremes points to an increasing prevalence of UHI characteristics, Factors such as urban development, land use changes, and broader climatic shifts could all contribute to the observed changes in land surface temperature

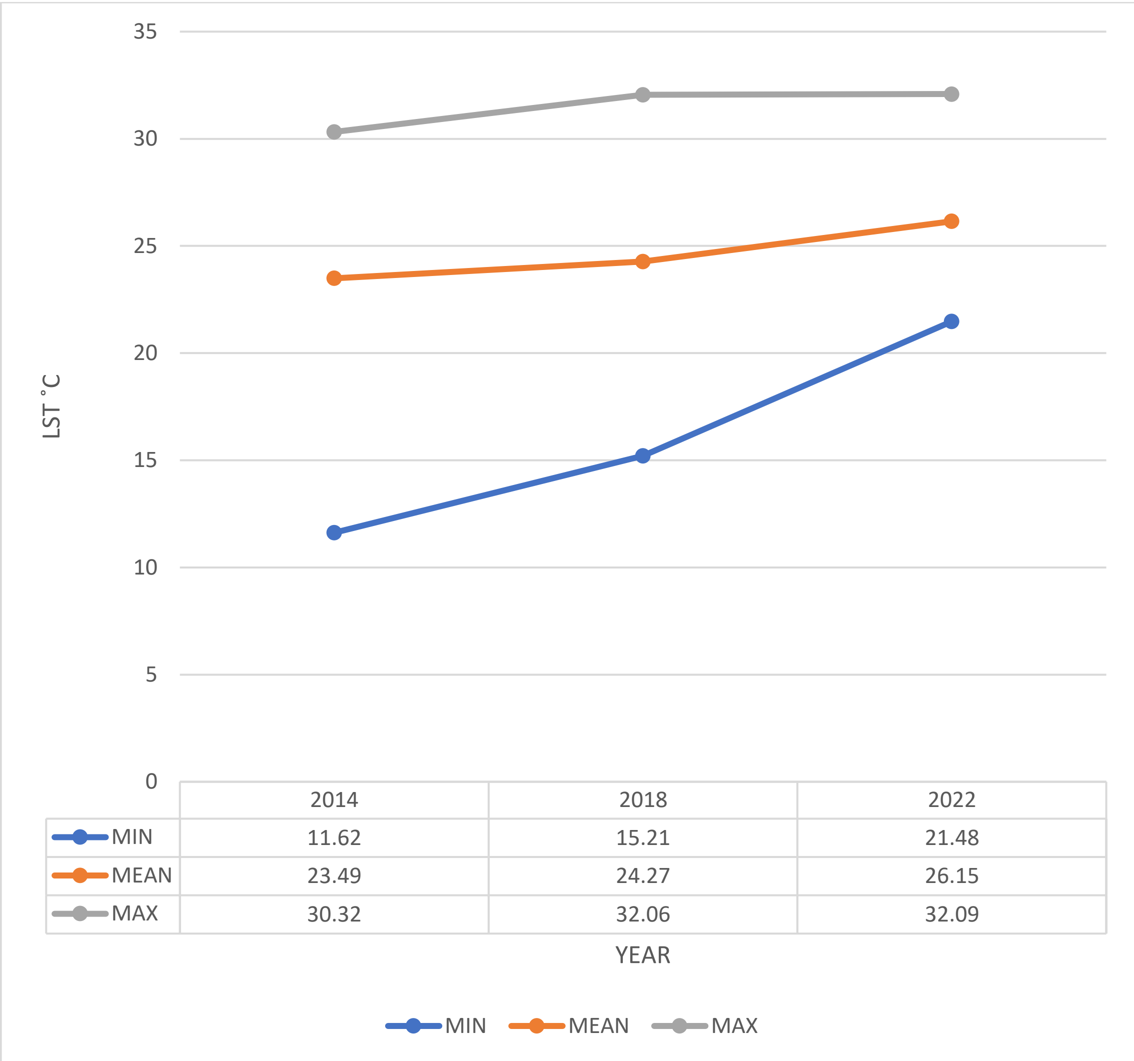

Figure 4.6 Graph of land surface temperature trend

Table 4.1: Area coverage of LST categories from 2014 to 2022

LST area coverage (ha) in different years			
	2014	2018	2022
<24°C	53276.2006	38673.7302	14504.686
24-26°C	57741.6882	50407.8582	27118.8736
26-28°C	34110.4582	48354.3858	71773.7496
>28°C	17845.653	25538.0258	49576.6908
Total	162974	162974	162974

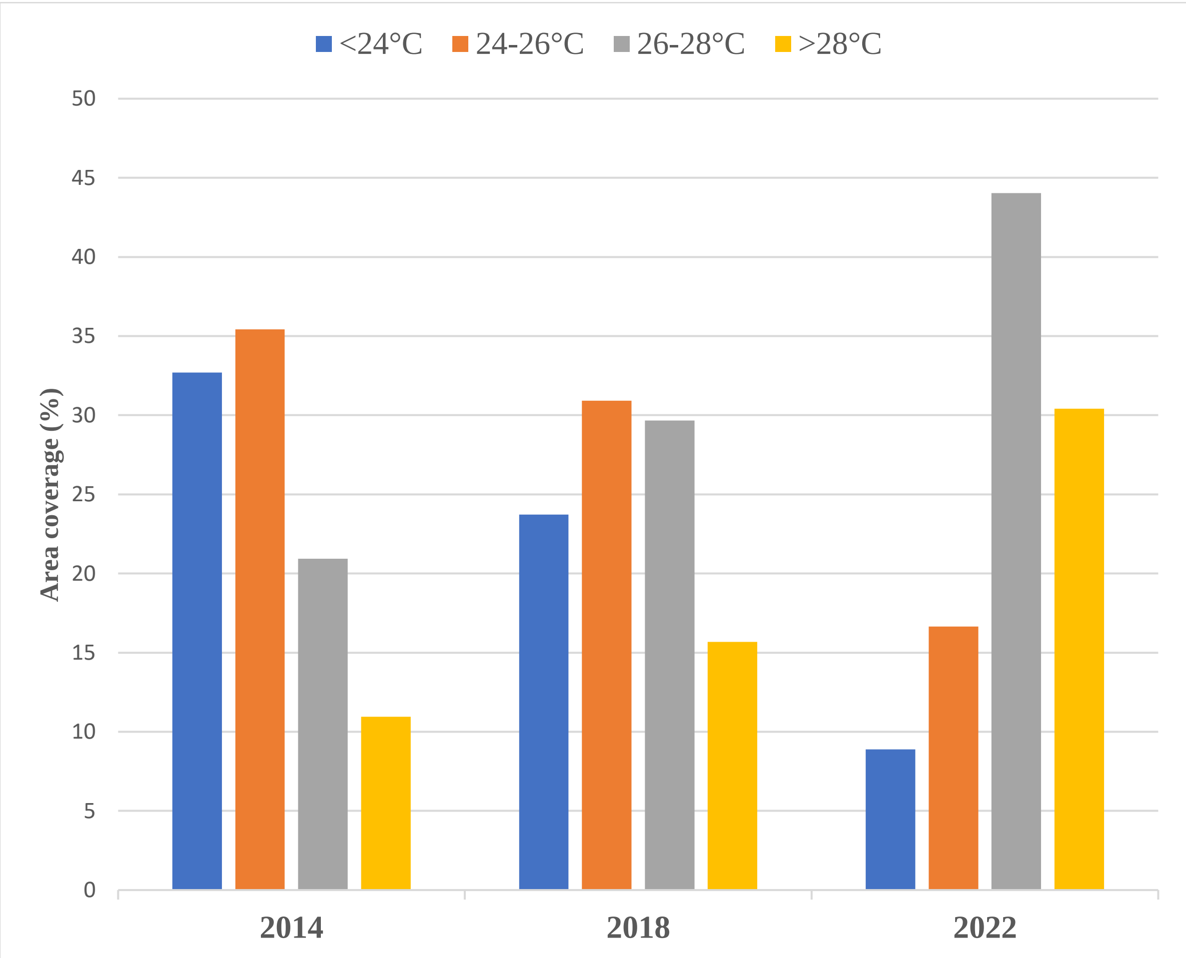

Figure 4.7: Area coverage (%) of LST categories in different years

4.6 Urban heat island intensity

The analysis of land surface temperature distribution in Dar es Salaam indicates a consistent upward trend. In 2022, the highest recorded temperature was 32.09 ºC, while the lowest recorded temperature was 21.48 ºC identifies the urban heat island (UHI) phenomenon, and highlights the implications of higher temperatures in urban areas (Zeng, 2018). By classifying the magnitude of UHI, we can distinguish between areas with and with non UHI effects. In this classification, areas with values below 0 are considered to have non UHI area as shown in figure 4.8, while areas with values above 0 indicate the presence of UHI area.

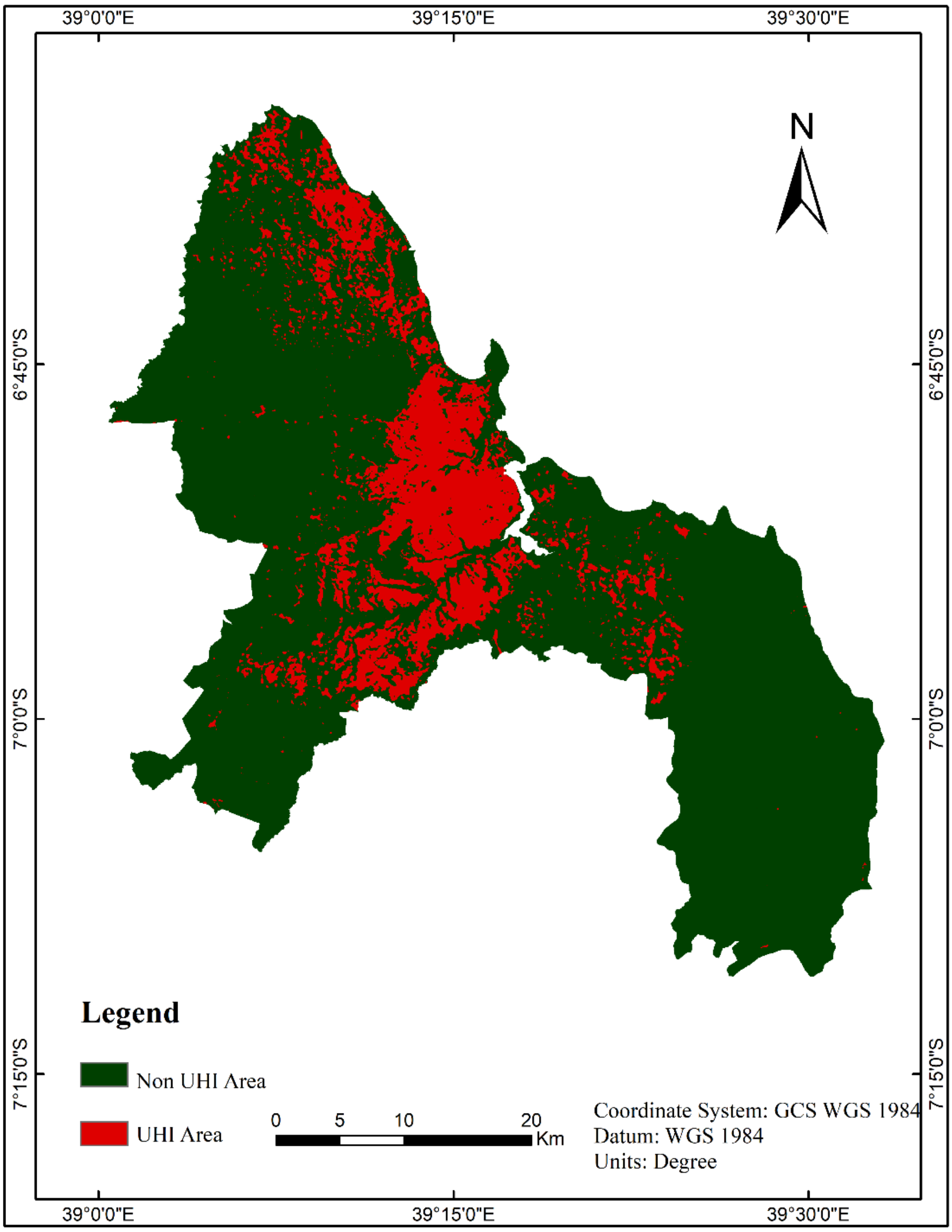

Figure 4.8: Urban Heat Island intensity of Dar es Salaam 2022

4.7 Simulation and Validation of predictive model

The CA-ANN model was first used to predict the LST for 2022 as shown in figure 4.9 and the LST generalate from Landsat image were used as reference to validate the prediction to ensure the acceptance of prediction result in table 4.1 With the help of the QGIS-MOLUSCE Plugin software, a comparison of the predicted and the estimated maps was established using different kappa parameters. The comparison showed excellent results as all the kappa parameters, percentage of accuracy and overall kappa value.

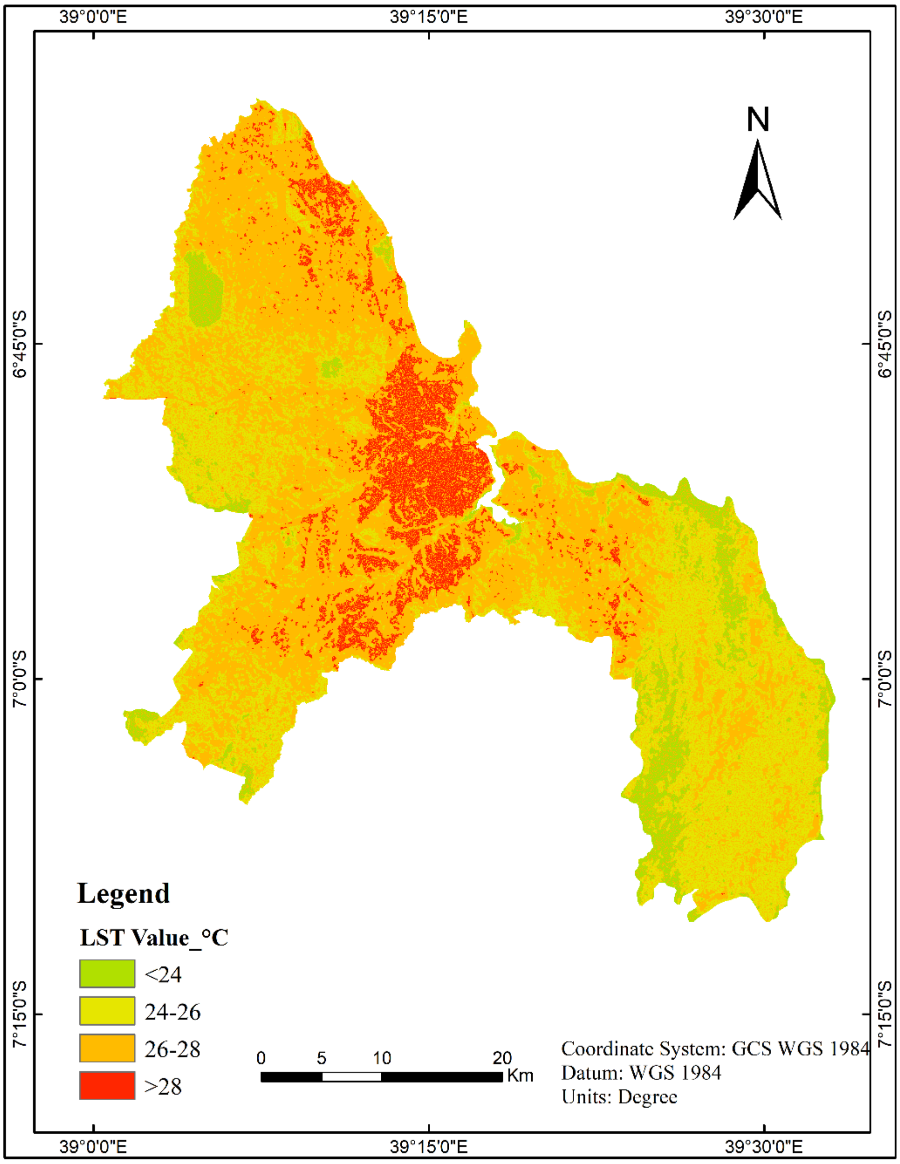

Figure 4.9 the predicted land surface temperature of year 2022

Table 4.1: ANN model validation for predicted LST

Kappa statistics	Kappa location	Kappa histogram	Overall kappa	Percentage of accuracy
LST 2022	0.9	0.79	0.79	86.98%

The parameters—Kappa statistics, Kappa location, Kappa histogram, Overall Kappa, and Percentage of accuracy assess an Artificial Neural Network (ANN) model's performance in predicting Land Surface Temperature (LST). Kappa statistics gauge agreement between predicted and observed values, factoring in chance agreement possibilities. Ranging from -1 to 1, a higher value signifies better agreement. Kappa Location evaluates spatial prediction accuracy, while Kappa Histogram measures agreement in distribution patterns. Overall Kappa combines these aspects for an overall assessment, and Percentage of Accuracy shows the correctness in predictions as a percentage. While no fixed minimum exists for acceptance, higher Kappa values closer to 1 and a greater accuracy percentage are preferred.

The ANN model validation for predicted LST shows fair agreement for kappa location and kappa histogram, and moderate agreement for overall kappa. The percentage of accuracy is 86.98%, which means that 86.98% of the cells in the predicted and the estimated maps have the same category. A higher percentage of accuracy indicates a better prediction model.

4.8 Prediction of land surface temperature

Figure 4.10 shows the predicted LST map of the study area for the year 2026. The area covered by the lower LST category (< 24 c), (24-26 c) was predicted to decrease while the area covered by the LST category (26 - 28 c) and LST highest category (>28 c) was predicted to increase. The area covered by the first two LST categories (<24 c, and 24 – 26 c) was predicted to decrease by 1.2 %, and 3.91 % respectively. Contrary to the lower categories, the area covered by the LST category (26 - 28 c) and highest LST category (>28 c) was predicted to increase by 4 %, and 1.1 % respectively from 2022 to 2026. These changes reflect a shift in the LST distribution towards higher temperatures, which could have negative impacts on the environment and human well-being. Figure 4.11 show the comparison of the area covered by each LST category between 2022 and 2026.

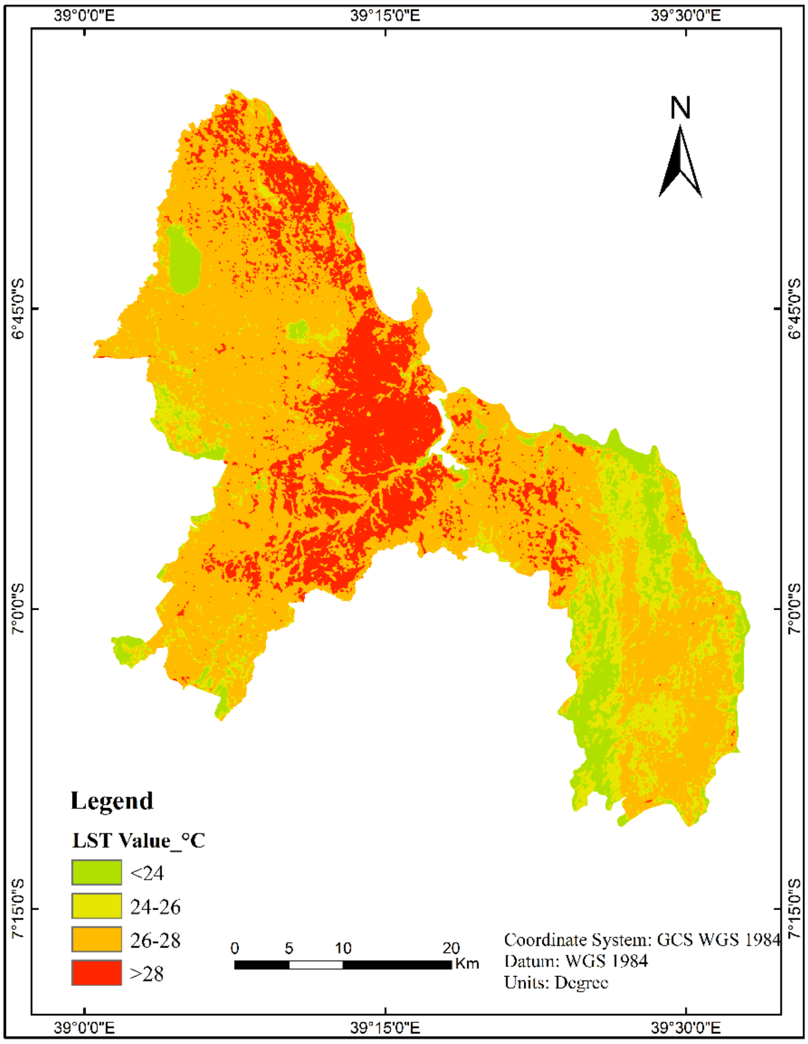

Figure 4.10 the predicted land surface temperature of year 2026

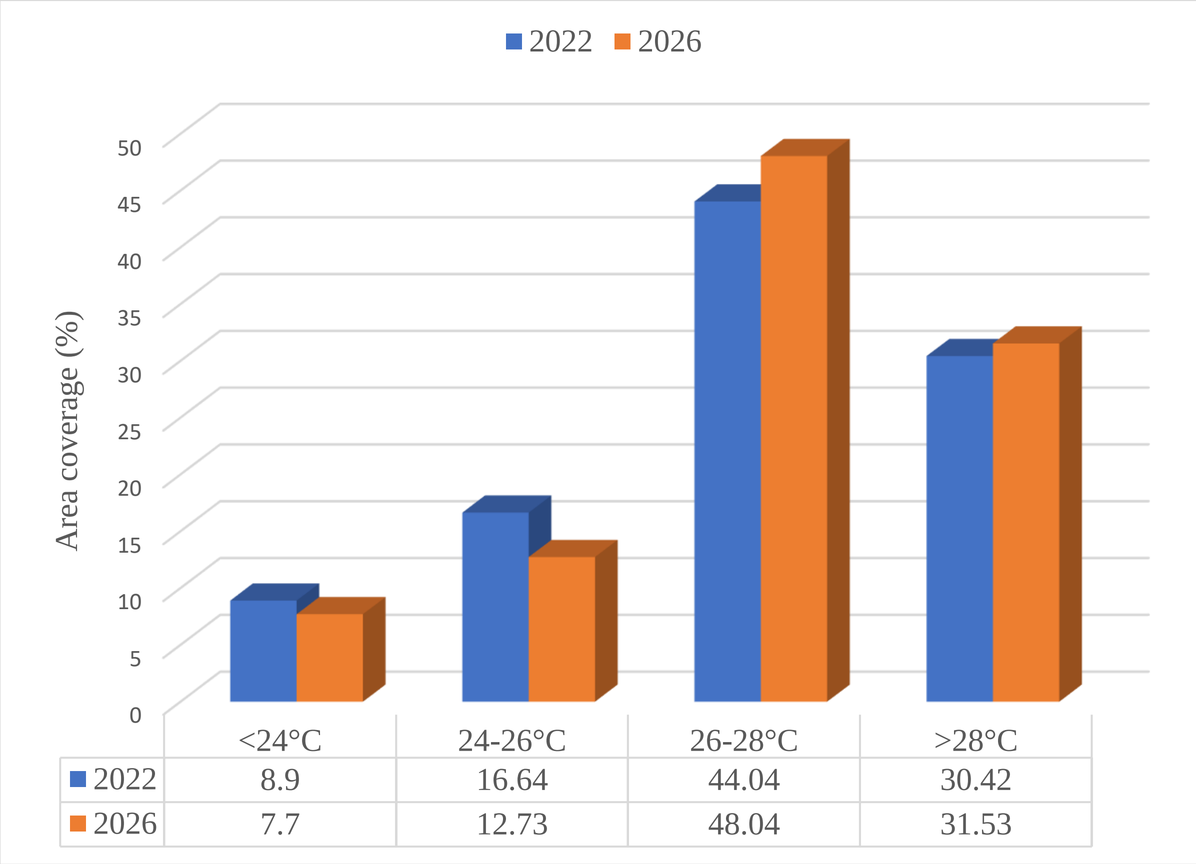

Figure 4.11: Comparison of area coverage of LST categories between 2022 and 2026

4.9 Discussion of the results

The predicted LST map for 2026 shows a significant increase in the area covered by the higher LST categories (26 - 28 c and >28 c), and a corresponding decrease in the area covered by the lower LST categories (<24 c and 24 - 26 c). This indicates a continuous warming trend in the Dar es Salaam region, which is consistent with the previous LST maps from 2014, 2018, and 2022.

The predicted LST map for 2026 also shows that the higher temperature areas are mostly concentrated in the central part of Dar es Salaam, where the built-up areas are dominant. This suggests that urbanization and land use changes are the main drivers of the LST increase and the UHI phenomenon in the region. The urban areas tend to have higher LST than the surrounding rural areas, due to the higher absorption and emission of solar radiation by the artificial surfaces, the lower evapotranspiration and albedo of the vegetation, and the heat sources such as vehicles and industries.

The implication and warning for a sustainable environment in Dar es Salaam are that the increasing LST and UHI phenomenon could pose serious challenges for the urban ecology, climate, and health. The higher LST and UHI could lead to increased energy consumption, greenhouse gas emissions, air pollution, water scarcity, heat stress, and infectious diseases. These could affect the quality of life, productivity, and resilience of the urban population, especially the vulnerable groups such as the elderly, the poor, and the children.

To mitigate the adverse effects of the LST increase and the UHI phenomenon, some possible strategies are to promote urban greening, increase the use of renewable energy, improve the urban planning and design, enhance the public awareness and participation, and implement the adaptive and preventive measures. These strategies could help to reduce the LST and UHI, improve the urban microclimate, conserve the natural resources, and protect the human health and well-being.

CHAPTER FIVE

CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

This research has developed a predictive model for Dar es Salaam's land surface temperature (LST) using Landsat images and a combination of Cellular Automaton (CA) and Artificial Neural Networks (ANN). The model has shown high accuracy in forecasting LST scenarios for 2026, revealing a significant increase in the urban heat island (UHI) effect and its associated challenges for urban planning and management. The study has also highlighted the importance of incorporating future LST projections into urban planning and management processes, as well as adopting mitigation strategies to reduce the UHI impact and enhance urban resilience. The study findings reveal a consistent upward trend in LST, with higher temperatures expected in the central areas of Dar es Salaam, primarily characterized by extensive built-up development. Urbanization, coupled with declining vegetation coverage, intensify the UHI effect, intensifying energy consumption, greenhouse gas emissions, and health risks. The study contributes to provides a useful tool for decision-makers and stakeholders in Dar es Salaam to plan for a more sustainable and resilient urban future.

5.2 Recommendation

research suggest that there is a need for effective urban planning strategies that prioritize green infrastructure within built-up areas. Integrating vegetation and green spaces can help mitigate the urban heat island effect by providing shade, evaporative cooling, and reducing surface temperatures which can help create a more comfortable and sustainable urban environment.

Study recommends further research to conduct long-term monitoring of land surface temperature and urban heat island dynamics can provide valuable insights into temperature trends and variations over time. studies can help assess the effectiveness of mitigation measures and capture the impacts of urban development and climate change on the urban heat island effect.

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