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MSc Dissertation

Use of GIS and Remote Sensing Techniques to Evaluate the Wetland Degradation in the Wami Ruvu River Basin

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USE OF GIS AND REMOTE SENSING TECHNIQUES TO EVALUATE THE WETLAND DEGRADATION IN WAMI RUVU BASIN

Dissertation Submitted to Sokoine University of Agriculture in Partial Fulfillment of the Requirements for the Degree of Master of Science in Land Use Planning and Management

By

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EXTENDED ABSTRACT

Wetlands are crucial ecosystems that provide numerous ecological services, including water purification, flood control, and habitat for diverse plant and animal species. During the last decade, around 50% of the earth's wetlands have already been converted to industrial, agricultural and residential use and these lands continue to disappear at a shocking rate without their values being understood. Wami Ruvu river basin in Tanzania is rich in wetlands, a total of 2482 km^2 of the area is covered by wetlands both floods plain, marsh and swamp. Little information on wetland degradation on extent, condition, trend and drivers on wetland degradation is available Wami Ruvu river basin. However, the aim of the study was to assess Historical wetland degradation and prediction of future Wami-Ruvu Basin wetland change pattern.

Multi-temporal Landsat satellite data including thematic Mapper Landsat (TM and ETM+) and Operational Land Imager (OLI) images were used for land use/cover (LULC) mapping in the assessment of wetland degradation and their distribution pattern based on the LULC by the years 2000, 2010 and 2020. A Random Forest Classification (RFC) approach was employed to classify the Landsat images into different land use/cover classes which included wetlands, water bodies, agriculture, urban areas, bush lands, bare lands, woodlands, and forest. The future wetland map of the study area was developed using hybrid CA- Markov in Land Cover modeler.

The study observed the trend based on the spatial dynamics during the two decades Which showed a progressive decrease in the collection of wetlands coverage throughout the region, although the degradation rate varies in time coverage area as it was found to be about 1209.0753Km^2, 949Km^2, 521.33Km^2 and 213Km^2 of wetland was lost, for the year 2000, 2010, 2020 and 2050 for the individual pixel values respectively. On the other hand, the studies revealed that -34.41Km^2/y of wetlands potentially are degraded annually due

to human and natural stressors in 20 years of our study. Thus this gradual decrease in wetland area is contributed mainly by the increase of human activities within and surrounding the wetland boundaries which is well observed in classified land use/cover images with kappa statistics above 75%.

The results of this study will contribute to a better understanding of wetland degradation in the Wami-Ruvu River Basin and facilitate informed decision-making for wetland conservation and restoration efforts. The findings will help identify priority areas for targeted interventions and provide a baseline for monitoring future changes in wetland condition and trend to attain the Sustainable Development Goals.

IKISIRI KUU

Ardhi oevu ni mfumo ikolojia muhimu ambao hutoa huduma nyingi za ikolojia, ikijumuisha utakaso wa maji, udhibiti wa mafuriko, na makazi ya aina mbalimbali za mimea na wanyama. Katika muongo uliopita, karibu 50% ya ardhi oevu ya dunia tayari imegeuzwa kuwa matumizi ya viwanda, kilimo na makazi na ardhi hizi zinaendelea kutoweka kwa kasi ya kushangaza bila umuhimu wake kueleweka. Bonde la Mto Wami Ruvu nchini Tanzania lina utajiri mkubwa wa ardhi oevu, jumla ya kilomita 2482 za eneo hilo zimefunikwa na ardhi oevu. Taarifa chache kuhusu uharibifu wa ardhi oevu kuhusu kiwango, hali, mwenendo na vichochezi kuhusu uharibifu wa ardhi oevu zinapatikana katika bonde la mto Wami Ruvu. Hata hivyo, lengo la utafiti lilikuwa ni kutathmini uharibifu wa kihistoria wa ardhi oevu na utabiri wa mabadiliko ya baadaye wa ardhi oevu katika Bonde la Wami-Ruvu.

Data za setilaiti za Landsat za vipindi mbalimbali ikiwa ni pamoja na picha za anga za Landsat (TM na ETM+) na Operational Land Imager (OLI) zilitumika kuandaa ramani za matumizi ya ardhi/uoto (LULC) katika tathmini ya uharibifu wa ardhi oevu kwa miaka ya 2000, 2010 na 2020. Mbinu ya Uainishaji wa uoto/ matumizi ya ardhi yaani (Random Forest Classification) ilitumika kuainisha picha za anga yaani Landsat katika madaraja tofauti ya matumizi ya ardhi ambayo yalijumuisha maeneo oevu, maeneo ya maji, kilimo, maeneo ya mijini, misitu, ardhi tupu, pori na vichaka. Ramani ya baadaye ya ardhi oevu ya eneo la utafiti ilitengenezwa kwa kutumia hybrid CA-Markov modeli

Utafiti huu ulizingatia mwelekeo kulingana na mienendo ya anga katika miongo miwili ambayo ilionyesha kupungua kwa kasi kwa maeneo oevu katika eneo lote, ingawa kiwango cha uharibifu kinatofautiana katika eneo hilo kwa vile iligunduliwa kuwa 1209.0753Km^2, 949Km^2, 521.33Km^2 na 213Km^2 za ardhi oevu zilipotea, kwa mwaka wa 2000, 2010, 2020 na 2050. Kwa upande

mwingine, tafiti zilifichua kuwa -34.41Km^2/y ya ardhi oevu huharibiwa kila mwaka kutokana na shughuli za kibinadamu na asili katika miaka 20 ya utafiti wetu. Kwa hivyo kupungua kwa eneo la ardhi oevu kunachangiwa zaidi na ongezeko la shughuli za kibinadamu za ndani na zinazozunguka mipaka ya ardhi oevu ambayo inaonekana vizuri katika ramani za matumizi ya ardhi / uoto zenye takwimu za kappa zaidi ya 75%.

Matokeo ya utafiti huu yatachangia katika kujenga uelewa mzuri juu ya uharibifu wa ardhi oevu katika Bonde la Mto Wami-Ruvu na kuwezesha kufanya maamuzi sahihi kwa juhudi za uhifadhi na urejeshaji wa ardhi oevu. Hata hivyo, utafiti utasaidia kutambua maeneo ya kipaumbele kwa sehemu zinazolengwa na kwa kutoa msingi wa ufuatiliaji wa mabadiliko ya ardhi oevu na mwelekeo wa kufikia Malengo ya Maendeleo Endelevu ya dunia.

DECLARATION

I, **Kimario, Edina Pius**, do hereby declare to the Senate of Sokoine University of Agriculture that this dissertation is my own original work done within the period of registration and that it has neither been submitted nor being concurrently submitted in any other institution.

Kimario, Edina Pius Date
(MSc Candidate)

The above declaration is confirmed by;

Prof. Boniface Mbilinyi Date
(Principal Supervisor)

Dr. Proches Msigula Date
(Co-supervisor)

LIST OF MANUSCRIPTS

1. Assessment of Wetland Degradation Condition and Trend Based on Land Use/Cover in Wami-Ruvu River Basin Using Multi-Temporal Landsat Images

2. To evaluate future wetland degradation from 2020 to 2050 using remote sensing imagery and hybrid CA- Markov model the case of Wami-Ruvu river basin

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I would like to express my thankfulness to the Almighty God for blessing me with the strength and courage to complete this difficult mission. Various personalities have extended great support to me during the development of this thesis. In this regard, I would like to express my gratitude to Dr. Proches Msigula and Prof. Boniface Mbilinyi, my supervisors, for their efforts and constructive support that led to the successful competition of this research. I also would like to thank the lecturers and other Sokoine University staff members who took their responsibilities seriously and helped me complete my master’s degree studies.

My, family, my husband Sospeter Mugashe, Daughters and Son deserve many thanks for their support and encouragement during the hard times they played a very important role in making this possible. Last but not least, I would like to pass my appreciation to my friends and colleagues including Johannes Muhimbula and Seja Simon Msami for their contributions reviews and lessons learned.

DEDICATION

I dedicate this dissertation to my mother Yasinta Lymo, husband Sospeter Mugashe and children Deborah, Danielah, Davinah and Daaron for their love and support throughout my studies.

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LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
Arc GIS	Aeronautical Reconnaissance Coverage Information
CA	Cellular Automobile
Dem	Digital Elevation Model
GIS	Geographical Information System
LCM	Land change Modeler
LULC	Land Use/Land Cover
OLI	Operational Land Imager
USAID	United States Agency for international Development

CHAPTER ONE

1.0 INTRODUCTION

1.1 Background Information

Wetlands are among the most significant, multi-functional, and productive ecosystems on the earth (MEA, 2005). Primarily, wetlands can provide essential environmental services, including storing floodwater, reducing peak runoff, recharging groundwater, filtering impurities in water, carbon storage, and also ecologically serve as breeding grounds and critical habitat for several species of plant communities, invertebrates, fish, and wildlife (Ramsar, 2016).

In recent decades, wetlands have faced unprecedented threats from urbanization, agricultural expansion, climate change, and various human activities. As critical ecosystems, wetlands play a crucial role in maintaining biodiversity, regulating water resources, and mitigating the impacts of climate change (Davidson, 2014).

In Africa, where wetlands are particularly vital for sustaining livelihoods and conserving biodiversity, the evaluation of wetland degradation has become a matter of great importance. The degradation of African wetlands is a multifaceted issue influenced by various factors, including urbanization, agricultural expansion, infrastructure development, and climate change. However, despite the environmental degradation faced by wetlands, there is an increasing demand for ecosystem services they provide (Miraji *et al.,* 2019; Ngondo *et al.,* 2021).

In view of their importance in terms of location and ecological functions and their rapid transformation under increasing pressure, there is a need for mapping wetlands for their proper monitoring and effective management (Munishi *et al.,* 2019).

The integration of Geographical Information System (GIS) and Remote sensing techniques has now become the most costeffective method for monitoring and managing wetlands, can quantify wetland loss, identify the drivers of degradation, and develop strategies for conservation and sustainable management (Sahel *et al.,* 2017). These tools enable the assessment of key wetland parameters such as extent, land cover changes, water quality, and habitat fragmentation. Several noteworthy studies have successfully applied GIS and remote sensing techniques to evaluate wetland degradation in Africa. For example, Otukei and Blaschke (2010) employed remote sensing and GIS to assess wetland changes in the Lake Victoria Basin, highlighting the impact of land use changes on wetland health. Additionally, Adamo *et al.* (2018) utilized Landsat imagery and GIS to monitor wetland dynamics in the Niger Delta, revealing the consequences of oil exploration and urbanization on wetland ecosystems.

Wetlands in Tanzania encompass a diverse range of ecosystems, including swamps, marshes, lakes, and riverine systems. They are critical for the country's biodiversity, providing habitat for numerous species of flora and fauna, including endangered and migratory birds. Moreover, wetlands are essential for regulating water resources, acting as natural reservoirs that store and release water, which is crucial for agriculture, fisheries, and overall water security in the country (Nindi & Shayo, 2017). Over the past few decades, Tanzania has witnessed a rapid increase in population, urbanization, agriculture, and infrastructure development (URT, 2022). These human activities have led to wetland degradation, including habitat loss, water pollution, and altered hydrology. Climate change-induced impacts such as altered rainfall patterns and increased temperatures further exacerbate the vulnerability of wetlands (Munishi *et al.,* 2020). Several studies have demonstrated the successful application of GIS and remote sensing in assessing wetland degradation in Tanzania. For instance, research conducted in the Rufiji Delta utilized Landsat satellite imagery and GIS to monitor changes in land cover and land use patterns over a 30-year period, revealing significant wetland losses due to agriculture expansion

(Njana *et al.,* 2020). Another study in the Kilombero Valley employed remote sensing techniques to track changes in the extent of floodplains, which are vital wetland ecosystems, and assess their vulnerability to degradation (Mwandosya *et al.,* 2019).

Wetlands are often located in remote and sensitive sites and cannot be accessed easily due to their delicate habitat conditions providing shelter for dangerous animals, flooded conditions and thick vegetation (Mwita, 2016). The need for information supporting wetland management is multi-scalar worldwide, and the challenge demands urgent and consistent wetland monitoring mechanism assessments to guide policy making.

1.2 Problem Statement and Justification

Globally more than half of wetlands have been lost in the past 100 years (Davidson, 2014). The degradation and shrinkage of wetlands seriously threaten the security of the ecological environment and biodiversity (Mooney, 2005). Wetland ecosystems in Tanzania have been under constant threat of degradation, mainly due to anthropogenic pressure driving changes in land use patterns (Mombo *et al.,* 2011; Mwakaje, 2009; Ntongani *et al.,* 2014). Wetlands in Wami ruvu basin is one of the most important wetlands in Tanzania. Human populations in and around the Wami ruvu basin are heavily dependent on this river for various socio-economic activities and the influence of these populations has left its mark on the river's ecosystem (USAID, 2014). Human activities carried out along the basin have continued to alter the natural flow regimes of the Wami and Ruvu rivers and have major consequences to wetland ecosystems and the community that depend on them (Kashaigili *et al.,* 2006; Ngana *et al.,* 2010).

Little information on wetland degradation is available in Wami ruvu basin, suggesting needs to have detailed information on wetlands degradation (Gritzner & Jemison, 2009). Detailed information on the trends, patterns and drivers of wetland degradation will help to better monitor, manage and conserve wetland resources. Therefore, this study will identify the extent of wetland degradation in Wami-Ruvu basin and assess the trend of degradation.

The findings of this study will inform decisions and policy makers on the current situation and the severity of wetland degradation along with the drivers for degradation. The study findings will assist policy makers to make informed, immediate plans and efforts for managing and protecting the wetland resources. Furthermore, this study will draw attention to the community in the achievement of several Sustainable Development Goals (17 SDGs) specifically on No poverty, Clean Water & Sanitation, Reduced Inequality and Life on Land respectively.

1.3 Objectives

1.3.1 Main objective

The main objective of this study was to assess Historical wetland degradation and prediction of future Wami-Ruvu Basin wetland change pattern.

1.3.2 Specific objectives

The specific objectives of this study are;

(i) To assess wetland degradation condition and trend based on land use/cover /using multi-temporal Landsat images
(ii) To evaluate future wetland degradation from 2020 to 2050 using remote sensing imagery and hybrid CA- Markov model

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CHAPTER TWO

Manuscript One

2.0 Assessment of Wetland Degradation Condition and Trend Based on Land Use/Cover in Wami-Ruvu River Basin Using Multi-Temporal Landsat Images

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Abstract

The understanding of wetlands' distribution and their level of susceptibility is important to enhance management and conservation efforts. The study aimed to map wetlands and assess their distribution pattern and their degradation based on the LULC by the years 2000, 2010 and 2020. Wetland types i.e., marshes, ponds, lakes, fens, rivers, floodplains, swamps, and open water bodies with other land use such as agriculture land, built-up and natural vegetation land were classified and mapped using random forest algorithm in Arc Map. Multi-temporal Landsat satellite data including thematic Mapper Landsat (ETM+) and Operational Land Imager (OLI) images were used for LULC mapping. The random forest classifier technique is used to analyse the satellite imagery for detecting the LULC changes during the whole study period. To assess the wetland area degradation three aspects were used in this study for the analysis; wetland area change rate, annual land cover change and annual land cover change rate. The study found about -34.41Km^2/y of wetlands potentially are degraded annually due to human and natural stressors in 20 years of our study however the basin experienced a higher rate of wetland degradation in the second epoch of 2010-2020 where the basin experience -42.8Km^2/y degradation which results to the total loss of -687.75 km^2 total coverage of wetland area in the basin. This information could be used to improve wetland planning and management by wetland managers and other stakeholders.

Keywords: Land use/cover, Remote sensing, Wetland degradation, GIS, Driving factors.

2.1 Introduction

Wetlands are ecosystems that arise when inundation by water produces soils dominated by an anaerobic process and forces the biota, particularly rooted plants to exhibit adaptations to tolerate flooding (Davidson *et al.,* 2018). Wetlands are areas where water is at, near, or above the surface of the ground often enough for hydric soils to form and/or for wetland plants to grow. The wet conditions make wetlands the most biologically productive ecosystems (Thawe, 2008). Wetlands are not only vital mechanisms of the global system only about 6% of the earth's surface area is covered by them but are also one of the most important living environments for humans (Beuel *et al.,* 2016). Wetlands have a multitude of unique ecological functions including water conservation, wastewater purification and climate regulation such that they are referred to as the "kidney of the earth" (Lefebvre *et al.,* 2019; Islam *et al.,* 2021). In addition, the wetland is one of the important carbon pools nearly 35% of the total carbon stock of the terrestrial ecosystem, which plays a significant role in the global carbon cycle (Twumasi & Merem, 2006).

During the last decade, around 50% of the earth's wetlands have already been converted to industrial, agricultural and residential use (Davidson, 2014; Gardner *et al.,* 2015). These lands continue to disappear at a shocking rate without their values being understood. Numerous studies around the globe including India, china and north America have been conducted using remote sensing and GIS on wetland mapping to detect temporal land use/land cover changes (Guo *et al.,* 2017; Jamal & Ahmad, 2020; Mao *et al.,* 2021).

Numerous studies have conducted and reveal that climate change, human economic development, population growth, are the main challenges that have changed the natural hydrologic management in most of Africa's river basins, including the Sokoto Rima River basin the Didessa Sub-basin the Ouémé River basin the Draa basin and the Mara River Basin (Beuel *et al.*, 2016; Assefa *et al.,* 2021; Kogo *et al.,* 2021; Thamaga *et al.,* 2022).

Wetland ecosystems in Tanzania have been under constant threat of degradation, mainly due to anthropogenic pressure driving changes in land use patterns (Mwakaje, 2009; Mombo *et al.,* 2011; Ntongani *et al.,* 2014; John Mwita, 2016; Mugo *et al.,* 2020; Ngondo *et al.,* 2021).

Wami Ruvu river basin in Tanzania is rich in wetlands, a total of 2482 km^2 of the area is covered by wetlands both floods plain, marsh and swamp which make up approximately 4% of the total area of the Wami-Ruvu river basin (NLUFP Volume III, 2009). The Large size of wetlands is found in the central part of the Basin in Kilosa and Mvomero districts. Due to climate change, social and economic development, and irrational utilization, the total area of wetlands has been decreasing (Hu, 2020), leading to increasingly severe degradation, desertification and salinization, decreased river runoff and declined biodiversity (Twisa & Buchroithner, 2019; Keshta *et al.,* 2022; Ngondo *et al.,* 2021).

Several studies have been conducted in the Wami-Ruvu river basin been exploring on dynamic of LULC change for various times and its implication on coastal water resources caused by rapid population increase (Twisa & Buchroithner, 2019; Ngondo *et al.,* 2021) also a study has been conducted in the Ruvu riverine on analysing the drivers and economic consequence of wetland degradation (Liberath, 2017) but details on area extent magnitude and rate of change of wetland in the whole Wami ruvu river basin is still not well known. Which drivers are the dominant influencing the degradation of wetland degradation in the basin and to what extent rate are causing the degradation is also still not well known hence more information on wetland degradation is needed to be explored in Wami-Ruvu river basin.

This aim of the study was to identify the extent of wetland degradation in the study area. Specifically, (i) to assess the condition and trend of Land use Land cover and (ii) to identify the driving factors of wetland degradation.

2.2 Materials and Methods

2.2.1 Description of the study area

The Wami-Ruvu Basin is located in 6 regions and 21 districts making it one of the largest river basins in the country, the basin includes the country's largest city of Dar es Salaam and the relatively larger city of Morogoro, Kibaha, dakawa, Gairo, and Dodoma. Located within 5°S-7°S and 36°E-39°E, The basin covers an area of approximately 66 294.5 km^2 made by seven sub-catchments of which are Kinyasungwe, Mkondoa, Ngerengere, Wami, Upper Ruvu, Lower Ruvu, and the Coast it consists of two major rivers flowing its water to Indian ocean which are Wami river flowing its water from the mountain Chenene Hills, north to north-east of Dodoma, Ukaguru Mountain north of Wami., Rubeho Mountain west of Kilosa, and Nguru Mountains north of Kilosa, and Ruvu river flowing its water from Uluguru Mountains in West Part of Ruvu River (Nhamo *et al.,* 2017). According to Shen *et al.* (2019), the current population of the Wami/Ruvu Basin can be estimated at approximately 62 million based on the 2022 national population census. The average rainfall in the basin is approximately 500–780 mm per year in the western semi-arid highlands near Dodoma, and 900–1300 mm in the central areas near Morogoro and the estuarine and coastal regions. Most of the rain in the basin falls between March and May with a shorter rainy season from October to December. The annual mean temperature ranges from 12 to 32 ◦C. the basin was established in July 2002, and it operates under the Wami/Ruvu Basin Water Board. Wami-Ruvu river basin was selected as the study area as one of the largest river basins in the country to propose a new method for wetland loss identification to the other river basin in the country and another river basin in the continent.

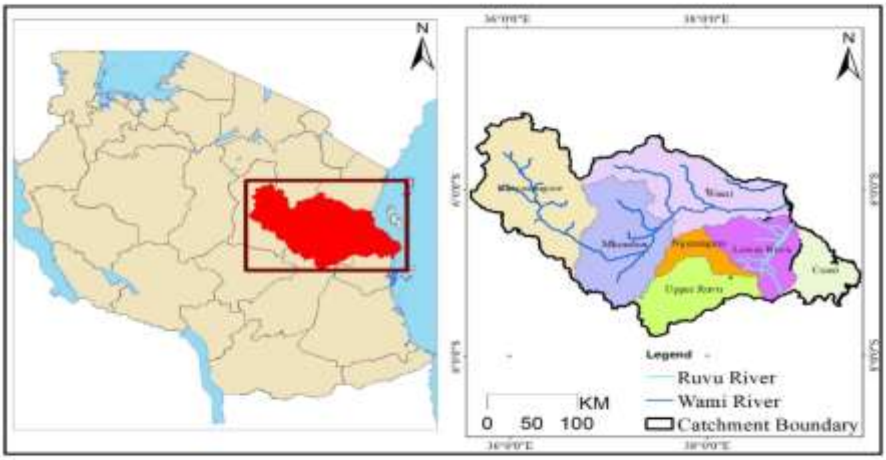

Figure 2.1: **Location of the study area, Wami–Ruvu Basin (WRB), Tanzania**

2.2.2 Data sources

The analysis of the study was conducted using Landsat satellite imagery data. The analysis was developed for two decades in the study area, covering two epoch periods which are 2000, 2010, and 2020. At a spatial resolution of 30 m and were acquired in the same season of the year (July–September) with minimal cloud cover (<10%). The datasets downloaded were surface reflectance for Landsat 5 TM images acquired in 2000, Landsat 7 ETM + for 2010 and Landsat 8 OLI images for 2020 (Table. 2.2). These Landsat images were acquired along WRS-2 paths 166 to 168 and row 64 and 65, downloaded from Earth Explorer (usgs.gov) (Table .2.3). A total of 18 Landsat scenes covering the study area were collected. Thereafter, the corrected Landsat images were mosaicked into a single composite image and subset to study the area boundary (figure. 2.2). Detailed information on the Landsat images is presented in the Table below.

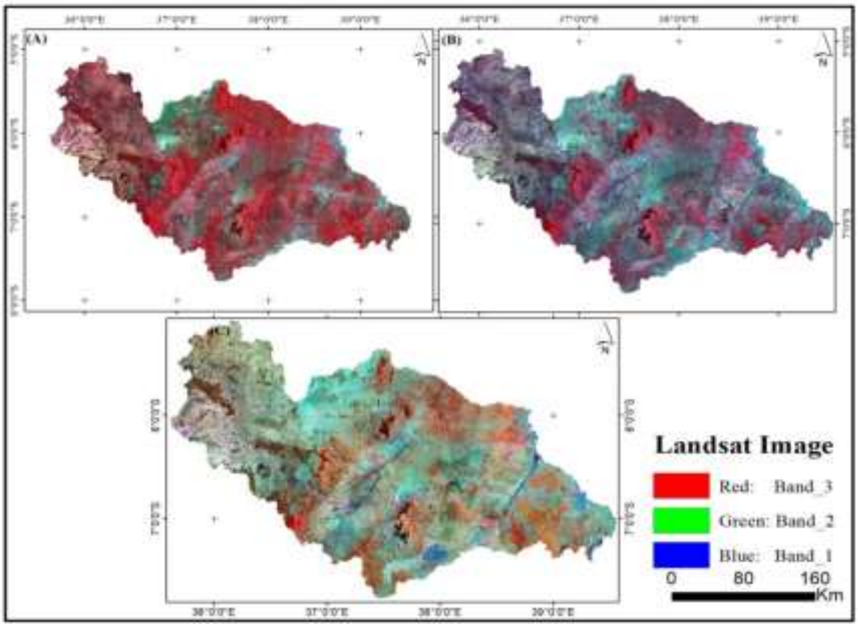

Figure 2.2: Composite Landsat images of 2000, 2010 and 2020 for the Wami Ruvu river basin

Table 2.1: Description of LULC classes used in the study

S/N	LULC Classes	Description
1	Built-up Area	Urban settlements, Rural/Trading centers, transportation networks, commercial and industrial areas
2	Water	Perennial water bodies, lakes, ponds and other water reservoirs, and flowing water confined in a channel
3	Bare land	Exposed field of land and sand fill area
4	Bush land	Shrubs, scrub and bushed
5	Agriculture land	Agriculture fields
6	Woodland	Open Crown trees
8	Forest	Evergreen and semi-evergreen forest cover.
9	Wetland	Covered with shallow water

Table 2.1 demonstrates the classification performed in the Wami-Ruvu river basin consist of eight major classes of land use/cover

were identified which are forest, agricultural land, water body, forest, bare-land, bush-land, woodland, built-up area and wetland. To develop the accurate result of classification from Landsat images we applied an integrated image classification method which involves the combination of both spectral bands and various indexes approach. The common indices used are the normalized difference vegetation index and modified normalized difference water index which are widely used indices to retrieve the vegetation and water information from satellite image bands.

Table 2.2: Details description of Landsat images used

Sensor	Date of acquisition	Path	Row	Resolution	Clouds Cover (%)
Landsat 5TM	11-07-2001	166	64	30m	0.0
	11-07-2001	166	65	30m	0.0
	07-07-2001	167	64	30m	<5
	07-07-2001	167	65	30m	<1
	06-07-2001	168	64	30m	0.0
	10-10-2001	168	65	30m	0.0
Landsat 7 ETM +	07-10-2011	166	64	30m	0.0
	07-10-2011	166	65	30m	0.0
	14-10-2011	167	64	30m	0.0
	17-05-2011	167	65	30m	0.0
	14-10-2011	168	64	30m	0.0
	17-05-2011	168	65	30m	0.0
LANDSAT 8-OLIS	10-10-2021	166	64	30m	<3
	06-07-2021	166	65	30m	<5
	10-10-2021	167	64	30m	<3
	06-07-2021	167	65	30m	<5
	14-08-2021	168	64	30m	0.0
	14-08-2021	168	65	30m	0.0

The research framework consisted of four parts: data preparation, classification of time series imagery, and wetland degradation analysis and wetland degradation driving factors analysis, initially remote sensing images, ancillary datasets, and reference datasets were collected and pre-processed. time series classification maps from 2000 to 2020 were produced through visual interpretation methods using Landsat imagery. Then, the historical dynamics of the different wetland types were analysed dataset used in the study and their sources are shown in the table below.

Table 2.3: Details description of the dataset used and their sources

S/N	Dataset used	Data source
1	Landsat TM/OLI	Earthexplorer.usgs.gov
2	Google Earth images	http://earth.google.com
3	Study area Boundary	the national bureau of statistics (NBS)
4	Population data	the national bureau of statistics (NBS)
5	Weather data	Climateengine.com/data

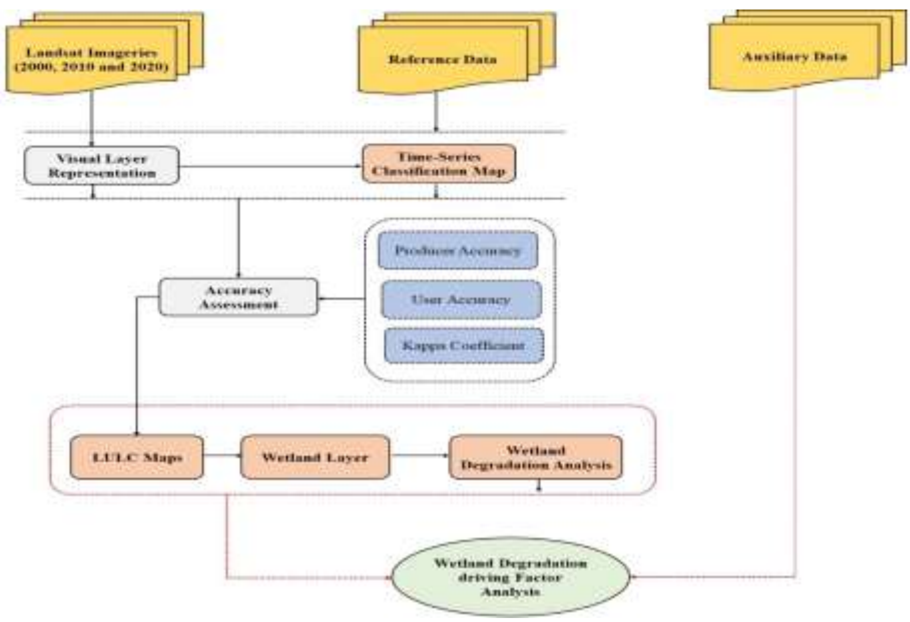

Figure 2.3: A general framework for the study design

2.2.3 Reference datasets

Reference data for the two epochs years for this study were derived from visual interpretation of Google Earth historical images (http://earth.google.com). Through the above methods, the reference datasets for 2000, 2010 and 2020 were successfully established as shown below in Figure 2.4.

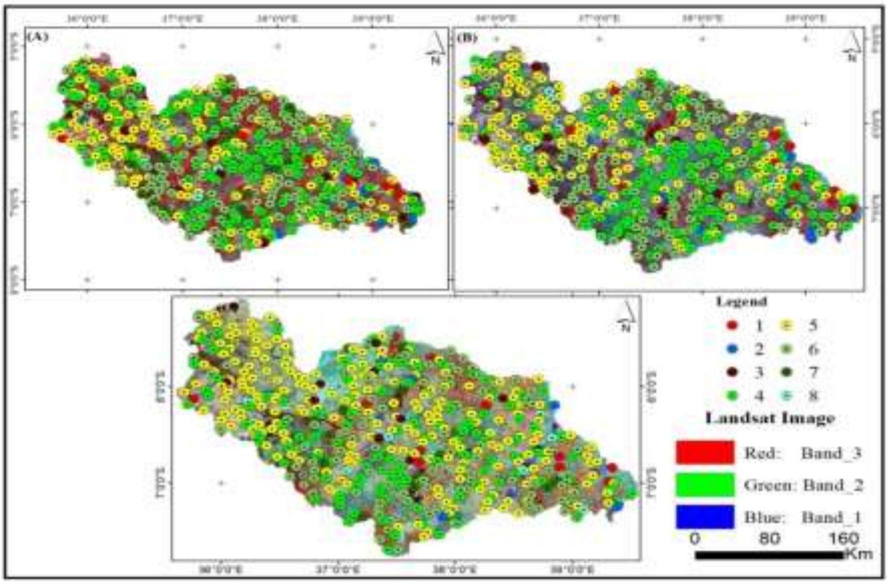

Figure 2.4: Ground truthing point for accuracy assessment of LULC

Key: Where by 1-built-up, 2-water, 3-bare-land, 4-bushland, 5-agriculture, 6-woodland, 7-forest and 8-wetland

2.2.4 Land use/cover classification system

To better understand the wetland distribution in the Wami-Ruvu river basin, a land use/cover classification system was established based on the Ramras Convention and the results of the National Land Use Framework Plan Volume I, 2009 wetland survey. Considering the importance of vegetation growth and water content in wetland classification, the normalized difference vegetation index (NDVI), and modified normalized difference water index (MNDWI) were, used as rule layers to characterize vegetation and Water background, respectively in addiction Normalized Difference Built-up Index (NDBI) was used to separate and define the developed and bare land in the basin in our classification system.

Wami-ruvu river basin classification was determined using three steps, the first step is the development of training datasets for various land use/cover the second one is classifiers selection and running of the model and the final stage is manual classification refinements. Each training dataset for existing cover for the study area was trained on a sample of 1 000 permanent pixels for 2 000, 2010 and 2020 from Landsat data and Google Earth images. Therefore, the training datasets were randomly selected.

In this classification system developed in the Wami-ruvu river basin, the Random Forest classification technique was adopted for Landsat images in R software. Random Forest is a supervised classification technique method which is a non-parametric ensemble machine-learning algorithm developed by Breiman. The RF algorithm has been widely applied for solving environmental problems, like water resource management and natural hazard management. It can handle a variety of data, like satellite imagery, and numerical data. It is an ensemble learning method based on a decision tree, which combines with massive ensemble regression and classification trees.

An integrated classification method was used in this classification by incorporating three satellite indices which include normalized differential vegetation index (NDVI), modified normalized difference water index (MNDWI) and normalized differential built-up index (NDBI), which were calculated for this purpose. Each index was added as a single band in addition to the satellite bands to have a single complex composite image. The formulas for calculated indices are shown below. Where *NIR, Red and SWIR* are the spectral reflectance values in the TM ETM+ and OLI. These equations both produce values in the range from -1 to 1.

NDVI = (NIR – Red) / (NIR + Red) …………………………………..(1)
NDBI = (SWIR – NIR) / (SWIR + NIR) ……………..……………....(2)
MNDWI = (Green – SWIR) / (Green + SWIR) …………………......(3)

Several previous studies have reported that the different band combinations can be a crucial factor for identifying different land cover types hence the above indices result and the combination can be very useful for classification in the Wami-Ruvu river basin.

2.2.5 Analysis system for the wetland ecological degradation process

Wetland degradation forms the theoretical basis for the study and by using remote sensing techniques; the analysis of this study for the Wami Ruvu River Basin Wetland degradation process was constructed based on three different aspects (area degradation rate, annual land use/cover area change and land use/cover change rate).

2.2.6 Area change rate

The reduction in wetland area is the most direct index of wetland ecosystem degradation. The Wetland area change rate reflects the degree of change in wetland area across the enter basin across different years and describes the change in area as a percentage of the original wetland area, which can therefore reflect the wetland degradation rate (Shen *et al.,* 2019). Therefore, this study selected this index for the wetland area change rate to characterize the area degradation of the Wami-Ruvu river basin Wetlands. The Wetland area change rate is calculated as;

$$RAC = \frac{EA - IA}{IA} * 100$$

Where by
RAC Is wetland area change rate
EA is the end wetland area

IA is the initial wetland area that refers to the year with no or little change in the wetland area compared to the other years.

Two other indices were being annual land cover change area (ALCA) and annual land cover change rate (ALCR), were used to calculate the dynamic degree of land cover types changes. And were determined through the use of below formula;

$ALCA = (LC1 - LC0) * 1/T$…………………….....…….. Equation 1
$ALCR = (LC1 - LCO)/LCO * 1/T) * 100\%$........................Equation 2

Where LC1 and LC0 represent the area of each land cover type at the beginning and the end of the study period, and T is the number of years. In the study, the time interval was divided into two stages (2000–2010) and (2010–2020).

2.3 Results

2.3.1 Spatial-temporal changes of land use/ cover types in Wami-ruvu river basin (2000-2020)

The LULC of the Wami Ruvu river basins were prepared through the interpretation of multispectral remote sensing satellite data of the years 2000, 2010 and 2020 (Figure. 2.5 and Figure. 2.6). Knowledge about the spatial distribution of LULC and the rate of change over some time is essential in the planning and management of land resources at local and regional levels (Akumu & Henry, 2018). The LULC changes in the Wami-Ruvu river basin were studied using historical Landsat imagery data from 2000, 2010, and 2020. The area under various land use/land covers, rate of change and per cent change during the periods of (2000–2010 and 2010–2020) were generated using thematic change analysis workflow in Envi 5.3 (Table.2.4).

Table 2.4: Random Forest classification ALCA and ALCR analysis results of 2000 2010 and 2020 in the Wami-Ruvu river basin

LULC_Classes	Area (Km^2)	Area (Km^2)	Area (Km^2)	ALCA(Km^2)			ALCR (%)		
Year	2000	2010	2020	2000-2010	2010-2020	2000-2020	2000-2010	2010-2020	2000-2020
Built up	468.3	1 184.0	2 012.6	71.6	82.9	77.2	15.3	7.0	16.5
Water	279.1	235.8	227.2	-4.3	-0.9	-2.6	-1.6	-0.4	-0.9
Bare land	1675.6	1 463.5	2 029.4	-21.2	56.6	17.7	-1.3	3.9	1.1
Bush land	21 636.7	19 752.8	17 143.1	-188.4	-261.0	-224.7	-0.9	-1.3	-1.0
Agriculture	19 748.1	22 003.3	28 499.5	225.5	649.6	437.6	1.1	3.0	2.2
Woodland	19 648.1	19 491.0	14 651.1	-15.7	-484.0	-249.9	-0.1	-2.5	-1.3
Forest	2 757.1	2 102.8	1 944.8	-65.4	-15.8	-40.6	-2.4	-0.8	-1.5
Wetland	1 209.1	949.0	521.3	-26.0	-42.8	-34.4	-2.2	-4.5	-2.8
TOTAL	**67 182**	**67 182**	**67 182**						

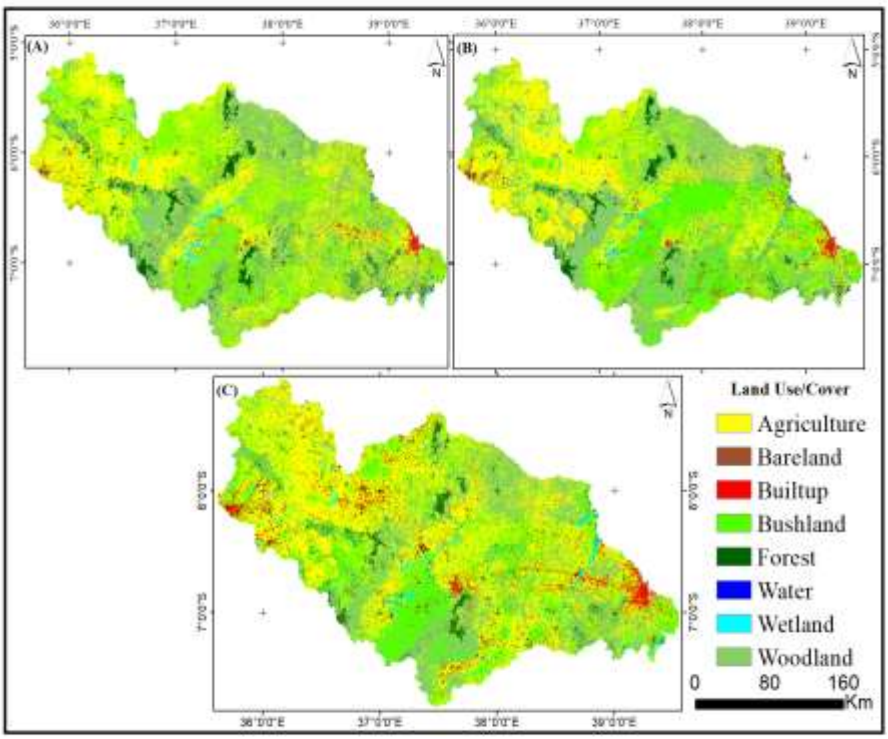

Figure 2.5: Classified image of Landsat of (A) 2000, (B) 2010 and (C) 2020

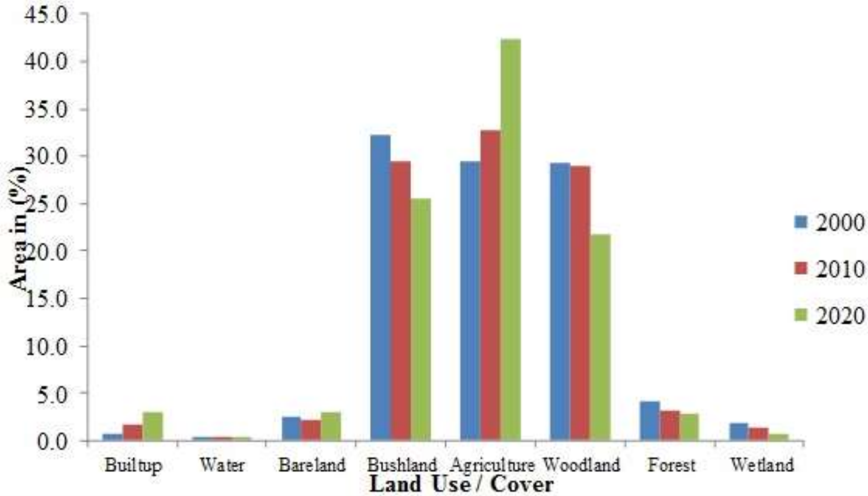

Figure 2.6: Area percentage of land use/cover for the Wami-Ruvu river basin in 1990, 2000 and 2020

2.3.2 Classification accuracy assessment

Accuracy assessment plays an important role in image classification to validate the LULC. Many pixels remain misclassified because of the uneven distribution of the data. In this study, an accuracy assessment was conducted by summarizing and quantifying the data using an error matrix. Four different accuracy results were produced including producer accuracy, user accuracy, overall accuracy, and kappa coefficient index from overall accuracy assessment which provide a better understanding of the classification accuracy. The kappa values greater than 0.75 suggested that the maps agree reasonably with the reference data (Singh *et al.,* 2020). The overall assessment results of each classified image from 2000 to 2020 are shown in the Table. 2.5.

Table 2.5: Summary of LULC classification accuracies (%) from 2000 to 2020

LU/LC Classes		2000		2010		2020
						Producer
Accuracy	**User**	**Producer**	**User**	**Producer**	**User**	
Built-up	70.0	77.8	60.0	66.7	71.4	83.3
Water	100.0	53.8	70.0	63.6	68.8	84.6
bare land	50.0	100.0	45.5	71.4	58.8	83.3
bush land	93.2	84.0	94.8	88.8	92.7	90.1
Agriculture	86.5	90.8	92.9	92.9	91.6	92.9
Woodland	96.8	94.9	96.2	94.9	96.0	92.4
Forest	85.7	100.0	83.3	93.8	88.2	83.3
Wetland	100.0	100.0	72.7	72.7	75.0	60.0
Overall Accuracy		89.3		89.8		90.2
Kappa		85.7		86.5		87.0

2.3.3 Land cover/use temporal changes analysis

Land cover/use temporal changes of the Wami-Ruvu basin between 2000-2020 were analysed through annual area land cover change and Annual land cover change rate analysis as illustrated in the table above. The results show that the basin experience a gradual high rate of annual depletion of the wetland of a total area -26.01(km^2/y) to -42.8(km^2/y) between 2000-2010 to 2010-2020 with an annual land cove change rate of -2.15(%/y) to -4.51(%/y).

Other Land Use/Cover also experience gradual degradation such as Forest degraded from -65.4(km^2/y) to -15.8(km^2/y) with ALCR of -2.37(%/y) to -0.75(%/y) of loss, Bush land decrease by -188.4 (km^2/y) to -261.0 (km^2/y) in area of coverage with ALCR of -0.87 (%/y) to -1.32 (%/y), woodland loses -15.7(km^2/y) to -484.0(km^2/y) with -0.08(%/y) -2.48(%/y), bare land changed into other land uses by -21.2(km^2/y) to 56.6(km^2/y) with ALCR of -1.27 (%/y) to 3.87(%/y), open water in lakes and river within the basin degraded in area coverage from -43.3(km^2/y) to -4.3(km^2/y) with ALCR of -1.55(%/y) to -0.37(%/y) the degradation of these land cover occurred due to increase of various human activities such as human settlement (built-up) which increase in area coverage from 71.6

(km^2/y) to 82.9(km^2/y) with ALCR Of 15.28(%/y) to 7.00 (%/y) the increase of human dominance in the basin result to the expansion of agriculture activities coverage area from 225.5(km^2/y) To 649.6(km^2/y) with ALCR of 1.14(%/y) to 2.95(%/y) .

2.3.4 In sub-basin level

2.3.4.1 Wami sub-basin

Figure. 2.7 and Table. 2.6 in the study illustrates that Wami sub-basin covering 64% of the whole basin has experienced a high increase in human activities between 2 epochs of the study area, the sub-basin experience increase of built-up area from 141km^2 in 2000 to 650km^2 in 2020 with ALCA (km^2/y) of 25.8 (km^2/y) to 25.1 (km^2/y) with ALCR of 18.4(%/y) to 6.3(%/y) between 200-2010 to 2010-2020, agriculture expand from 14432km^2 in 2000 to 20477km^2 in 2020 with ALCA of 278.5(km^2/y) to 3026.0 (km^2/y), open water increase from 70km^2 in 2000 to 139km^2 in 2020 with ALCA of 3.3 (km^2/y), to 3.6(km^2/y), a bare-land increase from 780km^2 to1451km^2 with ALCA of 1.3 to 65.9 with ALCR Increase of 0.2 (%/y) to 8.3(%/y). Bush land and woodland land cover experience increase and decrease within 2 epochs of the study, as a bush land decrease in the area of coverage from 13867km^2 in 2000 to 10728 km^2 in 2010 while increased in 2020 to 11025km^2 the loss between 2000 to 2010 is equal to -313.9 km^2/y with the rate of -2.3(%/y) and increase of 29.7(km^2/y) with the rate of 0.3(%/y) between 2010 to 2020.

And woodland increased from 11761km^2 in 2000 to 12511km^2 in 2010 with ALCA of 75.0(km^2/y) with a rate of increase of 0.6(%/y) while experiencing degradation of -418.5(km^2/y) at the rate of -3.3(%/y) between 2010 to 2020.

Wetlands in the Wami sub-basin experienced gradual degradation in area coverage from 840km^2 in 2000 to 513km^2 in 2020 with ALCA of -30.0(km^2/y) to -2.7(km^2/y) and with ALCR degradation of -3.6(%/y) to -0.5(%/y) between 200-2010 to 2010-2020, the same scenario happens to the forest which degraded from 1852km^2 to 1161 km^2

between 2000-2020 with ALCA loss of -40.0(km^2/y) to -29.1(km^2/y) with ALCR of -2.2-3.6(%/y) to -2.0-3.6(%/y) in 2000-2010 and 2010-2020.

2.3.4.2 Ruvu sub-basin

In the Ruvu sub-basin, the situation is the same it experienced gradual degradation of various land cover comparisons due to the increase of various major human activities. Agriculture as a dominant human activity in the basin expands twice between the study period of 2000 to 2020 it increased from 21.4% to 35.9% of coverage within the sub-basin which include expansion of both irrigation and rain-fed farms and become one of the dominant land uses in the basin. In Ruvu sub-basin Built-up experienced a gradual increase from 0.7% to 2.4% between 2000 to 2020 during the first epoch of ten years between 2000-2010 the built-up area increases higher in the other epoch period with ALCR and ALCA of 11.1(%/y) and 13.9(km^2/y).

Wetland, Open water, forest, bare land and woodland were the major degraded land use/cover affected in the basin as Wetlands experienced a degradation rate of ALCR of -0.7(%/y) to -3.8(%/y) between 2000-2010 to 2010-2020, forest experience degraded with ALCA of 16.4 (km^2/y) to 5.0(km^2/y) where it marks the high rate of degradation in the between 2000-2010 with ALCR loss of -2.3(%/y), open water found in river and dam within Ruvu river sub-basin experience slowly gradual change between the study period as it degraded its coverage area from 0.4% to 0.3% degraded from 2000-2020 with ACLA of -1.1 (km^2/y) to -1.4(km^2/y) between 2000-2010 and 2010-2020 also bare land experience steady degradation by 1.0% between 2000- 2010 with ALCA of -18.9 (km^2/y) and degradation rate of -3.0 (%/y).

While 2010-2020 the area for bare land increased by 0.5% with an ALCA of 9.1 (km^2/y) with a rate of increase of 9.1(%/y). Woodland experience severe conversion/degradation in this sub-basin as it degraded from 6259.9 km^2 to 4960.2 with ACLA loss of -72.1(km^2/y) to -57.9(km^2/y) between 2000-2010 to 2010-2020.

2.3.4.3 Coastal sub-basin

In the coastal sub-basin, built-up and agriculture experienced an increase annually and become the major human activities in the basin, built-up increased in the basin by 7% between 2000-2020 with a major increase between 2010- 2020 where the major expansion of urban area occurred by 5% of land use in the basin with ALCA of 23.5(km^2/y) and rate of (8.2 km^2/y). While agriculture increased by 11.5% within the study period with ALCA of 10.7(km^2/y) to 44.3(km^2/y) and ALCR of 1.0(%/y) To 3.8(%/y), the major increase was noticed in second epoch of 2010-2020 where the increase rate was 3.8(%/y) with ALCA of 44.3(8.2 km^2/y). Bush land experienced a gradual increase of area coverage where woodland and forest were converted to bush land hence it increases its area by 11.5% of the total area with ALCA of 10.7(km^2/y) to 44.3(km^2/y) between 2000-2010 to 2010-2020.

The Coastal sub-basin experienced major degradation of other major land use/cover found in the basin. During 2000-2010 wetlands degraded by -9.3 (km^2/y) with a rate of -6.6(%/y) with slow degradation in the second epoch of 2010-2020 with ALCA of -1(km^2/y) And ALCR of -2.1(%/y). Open water degraded by 1% within the study area with an ALCA of -2.8(km^2/y) to -1.7(km^2/y). Woodland and forest experienced major area reduction in the coastal sub-basin whereby forest area degraded by half of its coverage area from 4.0% in 200o to 2% in 2020 while woodland experienced a small conversion by 9.9% of its area into other land use/cover in 2020 agriculture and built increase result to deduction of bare land by 2.2% of total coverage area between 2000-2020 with ALCA of -0.6(km^2/y) To -9.8(km^2/y) and ALCR of -0.3(%/y) To -4.3(%/y).

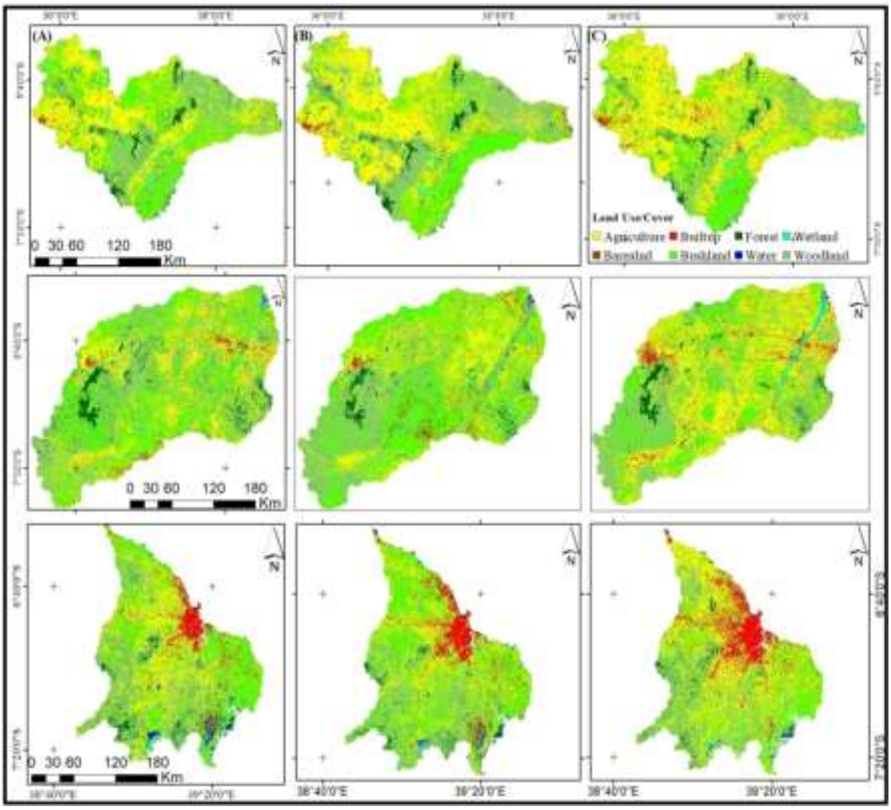

Figure 2.7: The classification results in sub-basin levels A (2000), B (2010), and C (2020)

Table 2.6: Spatial-Temporal Changes of Land Cover Types

Wami Sub Basin									
			Coverage	ALCA (km^2/y)					ALCR(%/y)
LULC	2000(Km^2)	2010(Km^2)	2020(Km^2)	2000-2010	2010-2020	2000-2020	2000-2010	2010-2020	2000-2020
Built-up	140.70	399.03	650.12	25.83	25.11	25.47	18.36	6.29	18.10
Water	70.01	103.44	139.28	3.34	3.58	3.46	4.77	3.47	4.95
Bare land	779.67	792.24	1 450.87	1.26	65.86	33.56	0.16	8.31	4.30
Bushland	13 866.96	10 728.04	11 025.02	-313.89	29.70	-142.09	-2.26	0.28	-1.02
Agriculture	14 432.42	17 217.09	20 477.11	278.47	326.00	302.23	1.93	1.89	2.09
Woodland	11 760.62	12 510.52	8 325.24	74.99	-418.53	-171.77	0.64	-3.35	-1.46
Forest	1 852.11	1 451.95	1161.07	-40.02	-29.09	-34.55	-2.16	-2.00	-1.87
Wetland	839.84	540.01	513.00	-29.98	-2.70	-16.34	-3.57	-0.50	-1.95
Total	**43 742.3**	**43 742.31**	**43741.72**						

Ruvu Sub basin									
	Coverage			ALCA (km^2/y)			ALCR(%/y)		
LULC	2000(KM^2)	2010(KM^2)	2020(KM^2)	2000-2010	2010-2020	2000-2020	2000-2010	2010-2020	2000-2020
Built-up	125.2	263.8	422.2	13.86	15.84	14.85	11.1	6.0	11.9
Water	79.2	68.3	56.8	-1.09	-1.14	-1.12	-1.4	-1.7	-1.4
Breland	631.1	442.0	533.2	-18.91	9.12	-4.89	-3.0	2.1	-0.8
Bushland	5963.1	6392.9	4802.9	42.98	-159.00	-58.01	0.7	-2.5	-1.0
Agriculture	3799.1	4330.3	6389.6	53.12	205.92	129.52	1.4	4.8	3.4
Woodland	6259.9	5539.1	4960.2	-72.08	-57.89	-64.98	-1.2	-1.0	-1.0

Forest	708.9	545.2	494.9	-16.37	-5.04	-10.70	-2.3	-0.9	-1.5
Wetland	222.6	207.1	129.3	-1.55	-7.78	-4.66	-0.7	-3.8	-2.1
Total	**17789.2**	**17788.8**	**17789.1**						

	Coastal Sub basin								
	Coverage			**ALCA (km^2/y)**			**ALCR(%/y)**		
LULC	**2000**	**2010**	**2020**	**2000-2010**	**2010-2020**	**2000-2020**	**2000-2010**	**2010-2020**	**2000-2020**
Built-up	189.3	287.0	521.9	9.8	23.5	16.6	5.16	8.19	8.79
Water	85.4	57.4	40.1	-2.8	-1.7	-2.3	-3.29	-3.00	-2.66
Bare land	232.9	227.1	128.7	-0.6	-9.8	-5.2	-0.25	-4.33	-2.24
Bush land	1420.8	1558.1	1120.5	13.7	-43.8	-15.0	0.97	-2.81	-1.06
Agriculture	1051.1	1158.4	1601.0	10.7	44.3	27.5	1.02	3.82	2.62
Woodland	1452.3	1321.2	1218.8	-13.1	-10.2	-11.7	-0.90	-0.77	-0.80
Forest	190.0	106.4	94.1	-8.4	-1.2	-4.8	-4.40	-1.16	-2.52
Wetland	141.3	47.9	37.9	-9.3	-1.0	-5.2	-6.61	-2.09	-3.66
Total	**4763.1**	**4763.4**	**4763.1**						

2.3.5 Wetland area degradation process

The result of the wetland area change rate for the years 2000, 2010 and 2020 for the Wami-Ruvu river basin was well calculated and the results are shown in Table 2.7 respectively. The negative values indicate that the wetland area was degraded and it was observed that the Wami-Ruvu river basin experienced a severe rate of wetland degradation in the year between 2010-2020. The wetland area change rate was negative for all periods of study in the basin. Only the Wami sub-basin shows a decrease in wetland area change in the year between 2010-2020 the wetland area for other sub-basin gradually increased in degradation across the study period concerning the temporal aspect, the most severe wetland degradation occurred in 2010 in the basins.

However, Figure. 2.8 demonstrates the spatial distribution in degradation rate Ruvu sub-basin, the second largest in terms of the area of coverage experienced a larger degradation rate in all two epochs. Followed by the Coastal sub-basin with a highly moderate rate of wetland degradation. Wami-sub-basin experienced a low rate of wetland degradation except for the year between 2000-2010 when it experiences a higher rate of degradation than the Ruvu sub-basin.

Table 2.7: Statistical results of wetland area degradation rate (%)

Sub-basin	2000	2010	2020
Coastal	-27.68	-75.45	-80.58
Ruvu	-61.46	-64.14	-77.61
Wami	-11.94	-43.38	-46.21

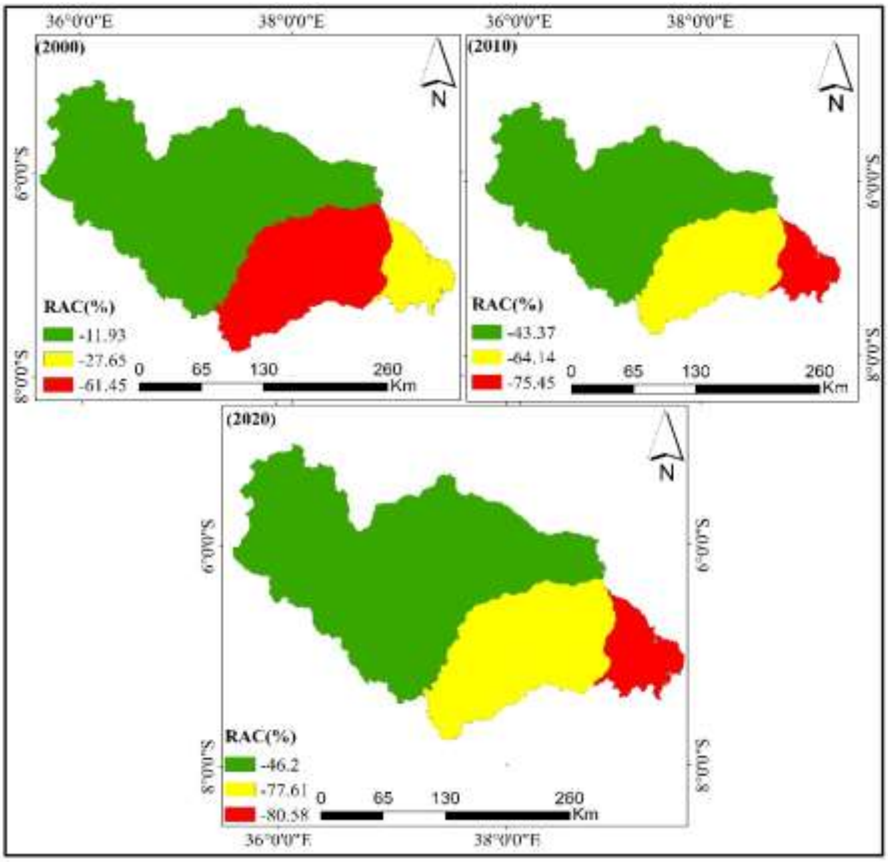

Figure 2.8: Wetland area change rate in Wami-Ruvu river sub-basins

2.3.6 Driving forces of wetland degradation in the Wami-Ruvu basin

According to the spatial-temporal classification analysis, the driving factors for dynamic wetland degradation were mainly caused by rapid economic development and natural environmental factors. To reach a well sympathetic of the drivers of wetland degradation, relationships between various driving factors both climate change, socioeconomic factors and land use change are analysed. The relationships were established Through the use of the quantitative correlation between wetland areas and each factor contributing to wetland degradation. Agriculture and settlement area increase is an important factor in the analysis of driving forces in the Wami-Ruvu river basin.

Urban expansion (urban population growth) and the increase of other social economic activities in the basin such as the increase of expansion of agricultural land were the main drivers' factors for wetland degradation from 2000 to 2020. Annual mean precipitation and temperature were selected because they have a direct impact on biomass productivity, which determines the development of vegetation and were considered natural factors causing wetland degradation. Linear correlation was established between wetlands and above mention factor and used to examine their relationship. According to the linear correlation of socio-economic factors, both human settlement and agricultural activities have a greater impact on wetland degradation than climatic factors (Table 2.9).

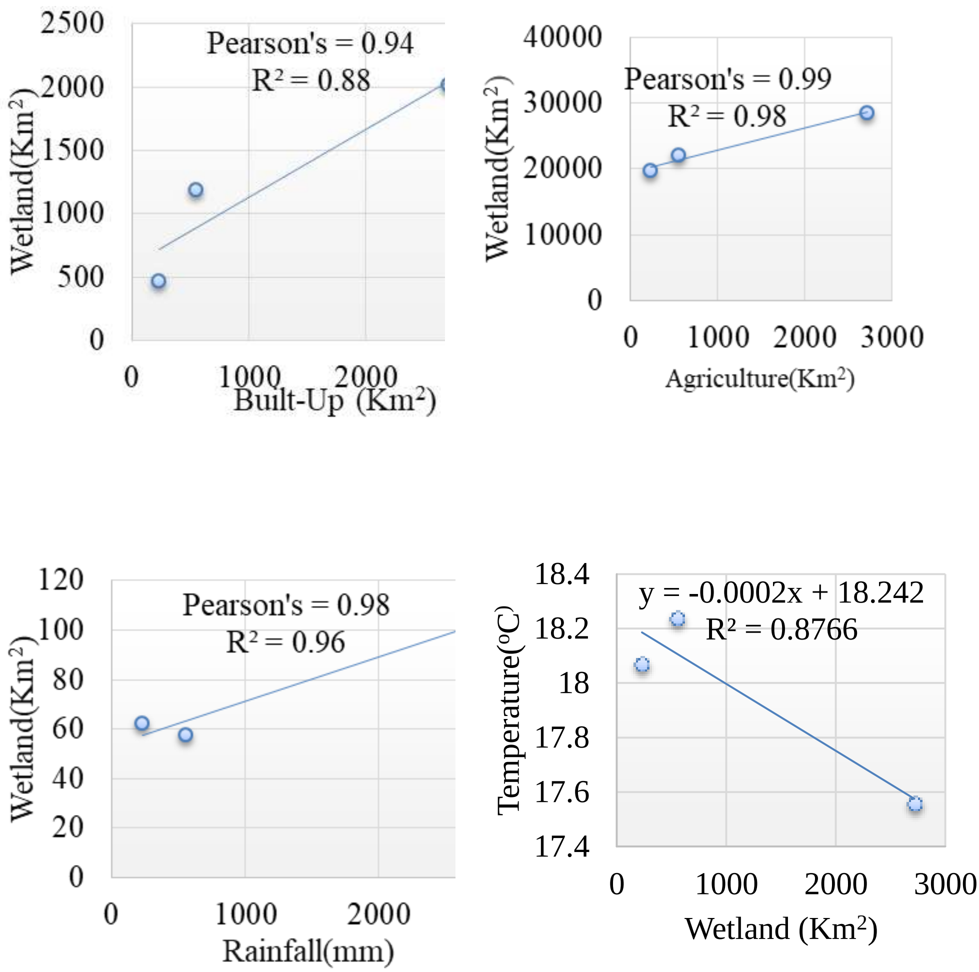

Figure 2.9: The relationship between the wetland and four variables (Total precipitation, Mean temperature, Built-up, population Size, Agriculture

2.4 Discussion

This study aims to assess and map the extent, condition and trends of wetlands found in Wami Ruvu river basin using land use/cover changes as an indicator factor for influencing wetlands degradation.

Through the results of study, a trend of land use/cover changes is showing annual shrinking of wetlands and it is identified that the wetlands, bush land and woodland are the most affected by anthropogenic activities. mainly because they provide the most arable land in the basin for cultivation and for human settlements, due to the fact that these areas have secure water annually and provide security to farmers especially who depend on rainfall cultivation. Through the analysis of land use/cover changes between 2000-2010 it shows larger changes where by the basin experience extremely increase of human agriculture activities and hence mark a higher level of agriculture land expansion. While between 2010-2020 the basin experience extremely urban sprawl with expansion and conversion of various land use/cover into urban land in all urban and village centre.

Generally, between the period of 2000-2020 the basin undergoes major transformation cause by human activities especially agriculture by almost half percentage coverage of the whole basin hence making the dominant land use. Through the analysis of land use/cover changes between the study period Vegetation land cover such as woodland, bush land, forest and water were the dominant affected through the expansion of human development activities. The worsen is that 34.4km^2 of wetland is lost every year in wami-ruvu river basin which is equal to 680km^2 for 20 years have been lost. And 515.2km^2 of vegetation cover have been converted to human activities.

In this study, we use RAC, ALC and ALCR the results obtained using these methods, for an assessment of basin wetland degradation was established, and a picture of annual wetland degradation status has been realized. Hence The applicability of a model is fundamental to its wide application for other basins at national and regional (Lu *et al.*, 2019; Shen *et al.,* 2019).

Wetlands degradation increase has been observed in other several wetlands in other basins in the country such as in Eastern Usangu, which experience a higher rate of degradation due to human development without taking any efforts by the government to protect the wetland it could have been completely depleted by now,(John Mwita, 2016). Also, Lake Victoria wetlands, have suffered significantly from degradation. Infestation of water hyacinth since the 1990s, resulting from increased nutrients due to pollution from various sources in the lake, illegal fishing practices, farming in the fringes of the wetland and the ever-growing needs of the population continue to threaten the lake ecosystem (Mkanda, 2002; Mugo *et al.,* 2020; Verschuren *et al.*, 2002).

The laws and policies governing environmental resource use and management are in place but are not in practice, the government should enforce them, there is Poor enforcement of policies and laws in the Wami - ruvu basin with political interference and hence accelerated the degradation of resources in the basin. Also lack awareness on proper usage of wetlands by local people become a key factor for the increase of wetland degradation and jeopardizing their future existence. Awareness creation on wetlands through various media such as radio and Television programs, newspapers and the use of extension officers to educate farmers and livestock keepers can also contribute to active involvement and greater public participation in issues related to the conservation and management of wetlands (Hu, 2020).

2.5 Conclusions

This study has been carried out to assess and analyse the spatial and temporal changes in wetland areas and land use/cover in the Wami-Ruvu basin using GIS and Remote sensing techniques. The results show that the area for built-up, agriculture and bare lands has been gradually increasing at the expense of a decrease of open water, wetland, forest, woodland, and bush land between the years 2000-2020. This gradual decrease in wetland area is contributed mainly by the increase of human activities within the wetland and surrounding the wetland boundaries which is well observed in classified land use/cover images with kappa statistics above 75%.

This study demonstrates successfully that remote sensing and geographical information system techniques that we used are useful as baseline scaling up to the regional and continental level in assessing the loss and degradation of wetlands and other land use/cover loss. The methods and results from this study can help our understanding of wetland changes and their driving forces in a wide area. These conclusions can be used as a guide for the bilateral government policymakers in formulating the conservation and rehabilitation plans for these wetlands for effective protection and management of wetlands for sustainable development.

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CHAPTER THREE

Manuscript Two

3.0 To Evaluate Future Wetland Degradation from 2020 To 2050 Using Remote Sensing Imagery and Hybrid CA- Markov Model the case of Wami-Ruvu river basin

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Abstract
In current industrialized world, extremely increase of urbanization, Agriculture land expansion and climate change have led to increase of degradation of wetland in many basins and coastal area, which result to the malfunction of its ecosystem services. However, there are few studies have been conducted to analyse how the historical degradation of wetland will continue in the future especially in most of the developing countries. In this study will use historical land use/cover maps of 2000,2010 and 2020 to develop land use simulation model to predict the spatial degradation of wetland in Wami-Ruvu river basin for coming 30 years (2020-2050) under different scenarios using land change modeller (LCM) in Idris-TerrSet. Future land use/cover map of the study area was developed using Markov chain and artificial neural network (ANN) Analysis in LCM modeller.

The study found of about 1209.0753Km^2 (2%), 949Km^2 (1.4%), 521.33Km^2 (0.78%) and 213 (0.32%) of wetland was decreasing, which was equal to 1339999, 1055066, 578584and 237199 for the year 2000, 2010, 2020 and 2050 for the individual pixel values respectively, which made a half of the total simulated wetland to have been lost that is 50% of the land in the study region.

Keywords: *Land change modeler, Markov chain, wetland, Cellular Automobile (CA), Remote Sensing.*

3.1 Introduction

Wetland degradation is known as the loss of a wetland area or weakening of wetland functions, due to anthropogenic land uses, it's a process which involves conversion of wetland to non-wetland areas. Substantial wetland degradation leads to yield decreases, habitat loss, and landscape fragmentation, which negatively affects human well-being, regional climate and ecological instability (Mao *et al.,* 2018). Intensive agriculture activities, climate change and urban expansion in the Wami-Ruvu basin resulted in a significant loss of wetlands in the catchment. Inappropriate and unpracticed policy and plan for the basin has resulted in the loss and degradation of wetlands since the 1990s. Hence for proper land use planning and management urgent measure is needed to quantify the extent, pattern and direction of land use/cover change to predict the future wetland degradation and other LULC dynamic which is still unknown. The majority of the study is based on LULC mapping and change detection in the basin.

In recent years there has been an increase of interest in using explicit models to predict various variables using remote sensing and Geographical information systems (GIS) as powerful and effective tools which have been used widely and intensively for detecting LULC changes and forecasting future LULC changes. Predicting land use/cover changes will enable in proper land use planning and management (Aavikson 1995).

Few models have been used in the study of wetland dynamic and their processes according to João Paulo (2018) suggest the performance of the Markov-CA model in the LULC prediction in the environmental protection area of the Banhado Grande and reveals the potential and worthiness of using this approach to design future land use changes, (Mariana Tiné *et al.,* 2019) examined and projected the spatiotemporal trends of change in open wetlands by coupling logistic regression, Markov chain methods and a multi-objective land allocation model into a hybrid geo simulation model, by using multi-temporal land cover information interpreted from Landsat images.

Chilagane *et al.* (2020) applied Remote Sensing and GIS techniques to assess the historical long-term changes in land use and land cover of the Little Ruaha catchment using Landsat satellite images of 1990, 2005 and 2015 and modeled the future change in land use and land cover up to 2040 using the stochastic CA-Markov chain. Another study by Canute Hyandye.et (2017) in the Usangu basin use Markov Chain and Cellular Automata Analysis for simulating historical land use/cover from 2000, 2006 and 2013 for projecting land use/cover of 2020 for analyzing crop intensification in the basin. Markov Chain analysis is used as a descriptive tool to predict land-use change projection on a wide range and is commonly used with cellular automata (CA) models. It's a probabilistic method which estimates the probability of change of one piece of land into other classes of LULC.

Hence, the goal of the study was to forecast future wetland degradation using the Remote Sensing images and hybrid CA – Markov model. Specifically, (i) to identify the land cover changes and transition probability and (ii) to assess the simulated wetland cover changes.

3.2 Materials and Methods

3.2.1 Study area

The Wami-Ruvu Basin is located in 6 regions and 21 districts making it one of the largest river basins in the country, the basin including the country's largest city of Dar es Salaam and the relatively larger city of Morogoro, Kibaha, dakawa, Gairo, and Dodoma. Located within 5°S-7°S and 36°E-39°E, The basin covers an area of approximately 66 294.5 km^2 made by seven sub-catchments of which are Kinyasungwe, Mkondoa, Ngerengere, Wami, Upper Ruvu, Lower Ruvu, and the Coast it consists of two major rivers flowing its water to Indian ocean which are Wami river flowing its water from the mountain Chenene Hills, north to north-east of Dodoma, Ukaguru Mountain north of Wami., Rubeho Mountain west of Kilosa, and Nguru Mountains north of Kilosa, and Ruvu river flowing its water from Uluguru Mountains in West Part of Ruvu River (Nhamo, 2017). According to Shen *et al.* (2019), the current population of the Wami/Ruvu Basin can be estimated at approximately 10.6 million based on the 2012 national population census. The average rainfall in the basin is approximately 500–780 mm per year in the western semi-arid highlands near Dodoma, and 900–1300 mm in the central areas near Morogoro and the estuarine and coastal regions. Most of the rain in the basin falls between March and May with a shorter rainy season in October to December. The annual mean temperature ranges from 12 to 32 ◦C. the basin was established in July 2002, and it operates under the Wami/Ruvu Basin Water Board.

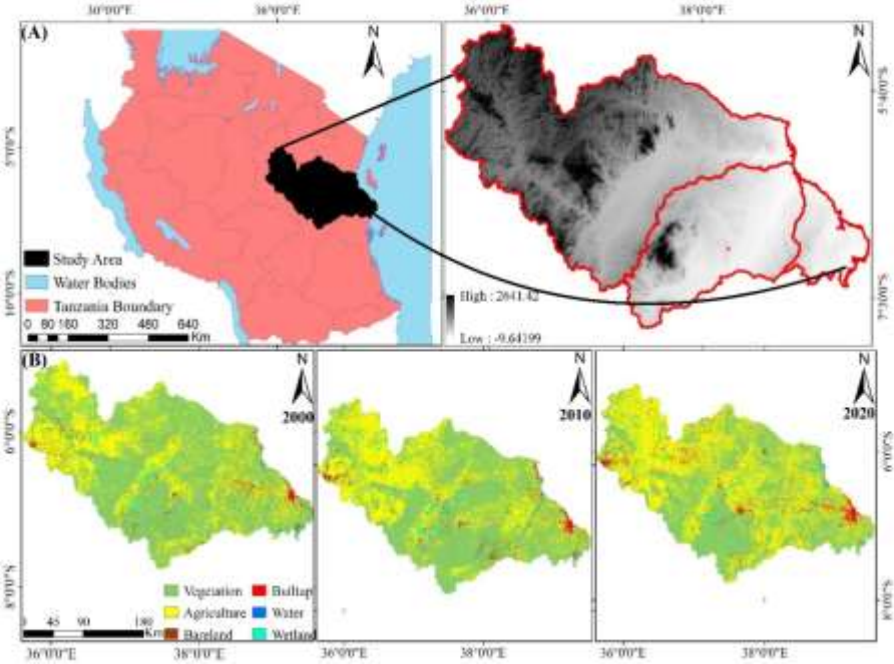

Figure 3.1: (A) Administrative boundary of Tanzania country showing the location of Wami-Ruvu basin, (B) location of study area in topographical map and land use/cover for previous study years of 2000, 2010 and 2020.

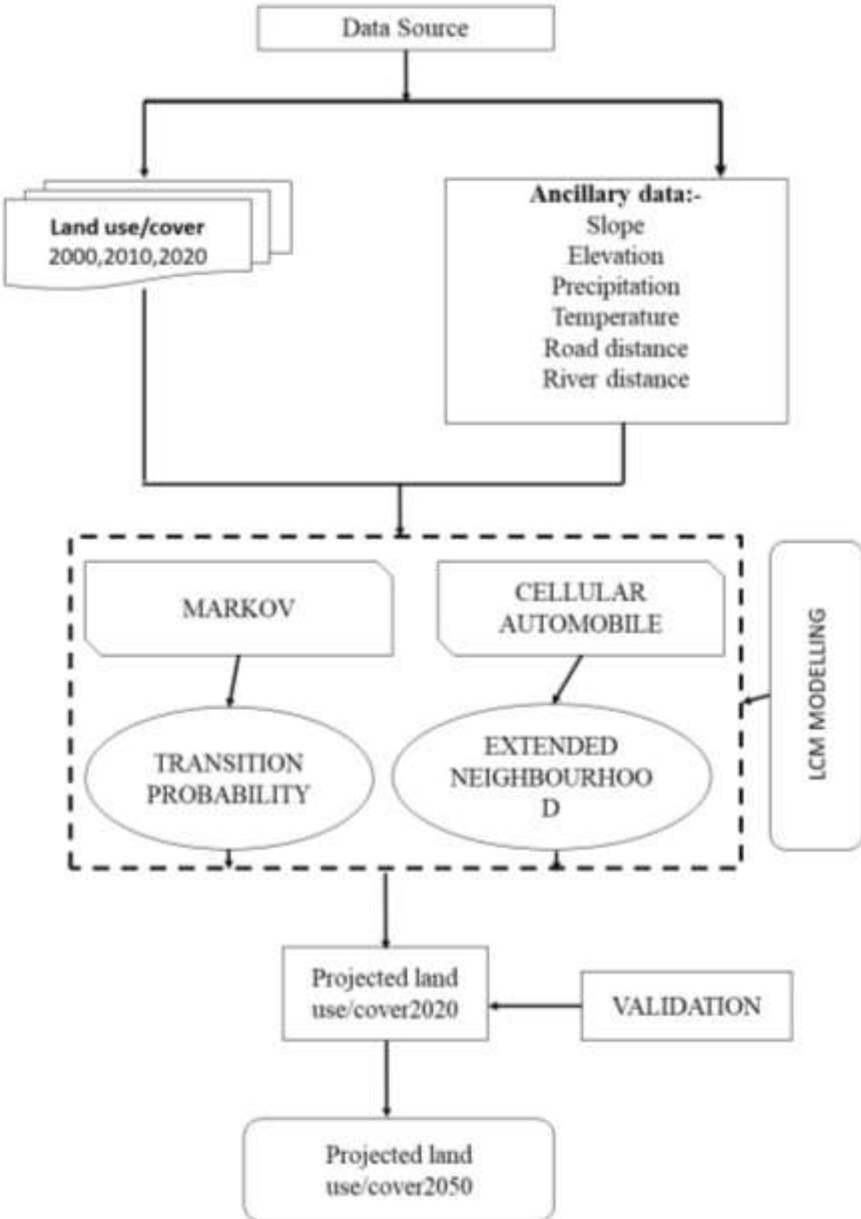

Figure 3.2: Flowchart of application of the CA-Markov model used in the study

3.2.2 Remote sensing data acquisition and preparation

The model data input used for this study include remote sensing LULC maps covering Wami-Ruvu basin for 2000, 2010 and 2020 derived from the study of (Kimario *et al.,* 2022) with spatial resolution of 30m which were acquired in the same season of the year (July–September) dry season. These LULC maps were generated use supervised random forest classifier and each LULC map were reclassified into 5 major LULC class due to their relevance in existence of wetland, the classes such as bush land, woodland and forest were grouped into one class of vegetation and hence enable us to have only five major LULC classes in our LULC maps.

in additional to that digital elevation model for topological analysis were used and arc-sec with spatial resolution of 30m, were downloaded from Earthexplorer.usgs.gov website and variable such as slope and elevation and aspect were calculated from it. Other GIS data such as road, river and population were obtained from Tanzania national bureau of statistics (NBS), climate data (precipitation and temperature) were downloaded from NASA climate engine website (Table . 3.1). All data used in the study were pre-processed, projected, resample into 30m resolution and reclassified into same number of classes for further model simulation.

Table 3.1: Details of dataset used in the study

Dataset used	Data source	Resolution(m)
LULC maps	Derived though supervised classification technique by using random forest Classifier Algorithm (RFCA)	30
Digital Elevation Model	United States Geological Survey (USGS) Earthexplorer.usgs.gov	30
Study area Boundary	The national bureau of statistics (NBS)	30
Population data	The national bureau of statistics (NBS)	30
Weather data	NASA Climateengine.com/data	30
Road proximity and GIS database Converted to raster format	The national bureau of statistics (NBS)	30
River Proximity GIS dataset converted to raster format	The national bureau of statistics (NBS)	30
Population density, converted to raster format	Population data from National bureau of statistics	30km

Table 3.2: Descriptions of the land use/cover classes

S/N	Old Class Name	New Class Name	New ID
1	Built-up Area	Built-up Area	1
2	Water	Water	1
3	Bare land	Bare land	1
4	Wetland	Wetland	2
5	Bush land	Vegetation	1
6	Woodland	Vegetation	1
7	Forest	Vegetation	1
8	Agriculture land	Agriculture land	1

Two new reclassified classes of land use/cover namely non wetland (built up, water, bare land, vegetation, and agriculture) and wetland were developed. Accuracy assessment was performed on each produced map using ground truthing points derived from Google earth pro. Change detection for produced map was lastly performed (Table. 3.2).

Based on our LULC map output of past 20 years, future land use of 30 years was simulated using land change modeller of TerrSet 18.30, land change modeller has Markov chain and artificial neural network analysis used for land use/cover change analysis. Slope, elevation, precipitation, temperature, population density, road distance and river distance were used as a driving factor in the model, predicted LULC of 2020 was produces so as to validate with the actual LULC of 2020 for the purpose of accuracy assessment (Figure 3.3, 3.4). The accuracy > 80% obtain between predicted and produced LULC of 2020 gave a way for simulation of LULC of 2030, 2040 and 2050.

3.2.3 Land use/cover change analysis

The study was carried out with the Land Change Modeller (LCM) planning decision tool provided by the TerrSet Geospatial Monitoring and Modelling software (Ding & Siqi, 2016), Which allows to detect and perform change analysis in land use/cover maps, including determining change trends as a drive of location, computing transition probabilities between land use/cover classes and predicting future land use/cover maps (Zhang *et al.,* 2015; Tang, 2017;). We used the LCM to implement a cross land-cover change model in particular, to perform change analysis, calculate transition potentials between land covers and simulate future changes in the spatial distribution of land covers(Chang-Martínez & Mas, 2021). There are other types of hybrid models in the literature that can also be applied to land-cover change studies (Chang-Martínez *et al.,* 2015). The Land Change Modeller tool was chosen mainly due to its ability to combine several methodological approaches to study spatiotemporal dynamic process.

3.2.4 Hybrid/cross land use/cover change model

Different model method of complex systems has merit and demerit, which determine its suitability for spatiotemporal modelling a specific problem. Thus why hybrid models emerged with the need to integrate two or more techniques, making it possible to gain strengths and overcome weaknesses from independent used approaches, in order to make more accurate predictions of land use/cover changes (Hyandye & Martz, 2017).

The present hybrid model for projection of land use/cover provided by Idris TerrSet integrates approaches including logistic regression (LR), Markov-chain (MC) and multi-objective optimization, into a single model (Jokar *et al.,* 2015). Linear Regression measures the probability of a dichotomous variable, determined from the influence of one or more independent variables hence for this study we need to applying LR to study changes in wetlands, and mainly to find the probability of changes of different land covers into wetland cover in the study area (Arsanjani, Helbich *et al.,* 2015; Mooney *et al.,* 2015), however LR does not take into account the influence of the neighbouring pixels into the probability calculation. For this, we added neighbour-based explanatory variables to the LR regression using Markov-chain techniques and the multi-objective land allocation algorithm to study the spatial-temporal dynamics of wetlands cover change.

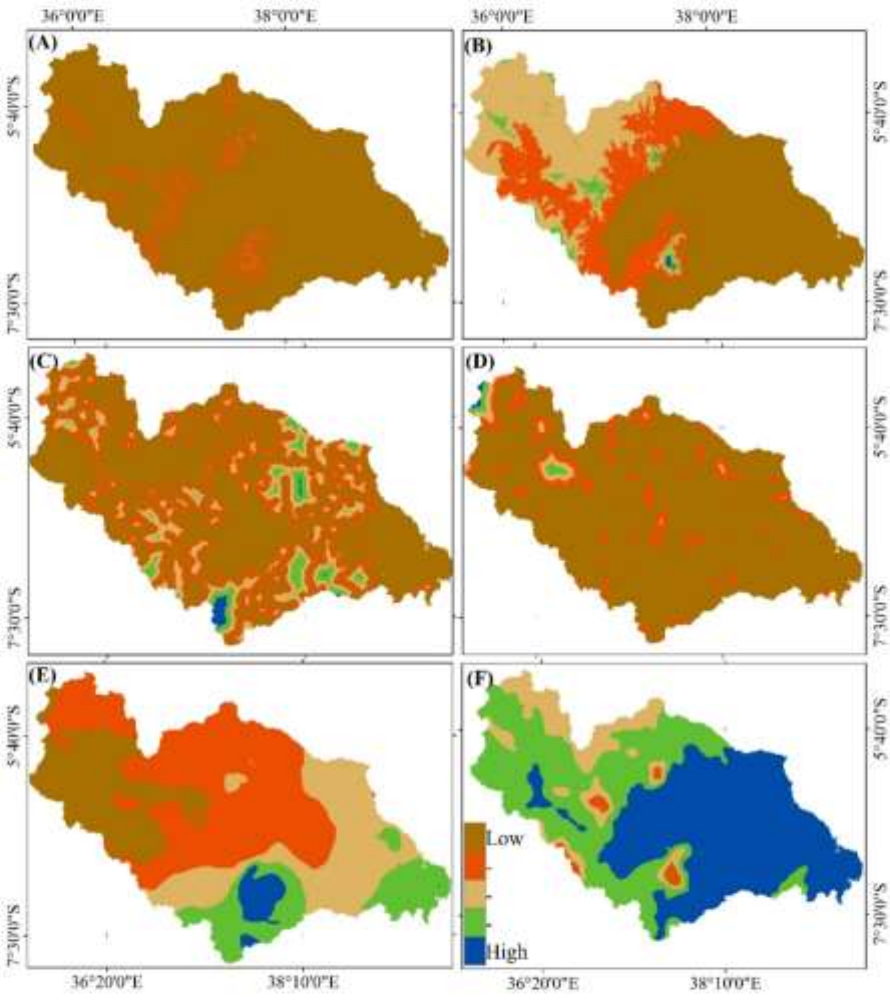

Figure 3.3: Predictor variables (a) Slope, (b) Elevation, (c) Distance from road, (d) Distance from river, (e) Precipitation and (f) Average temperature

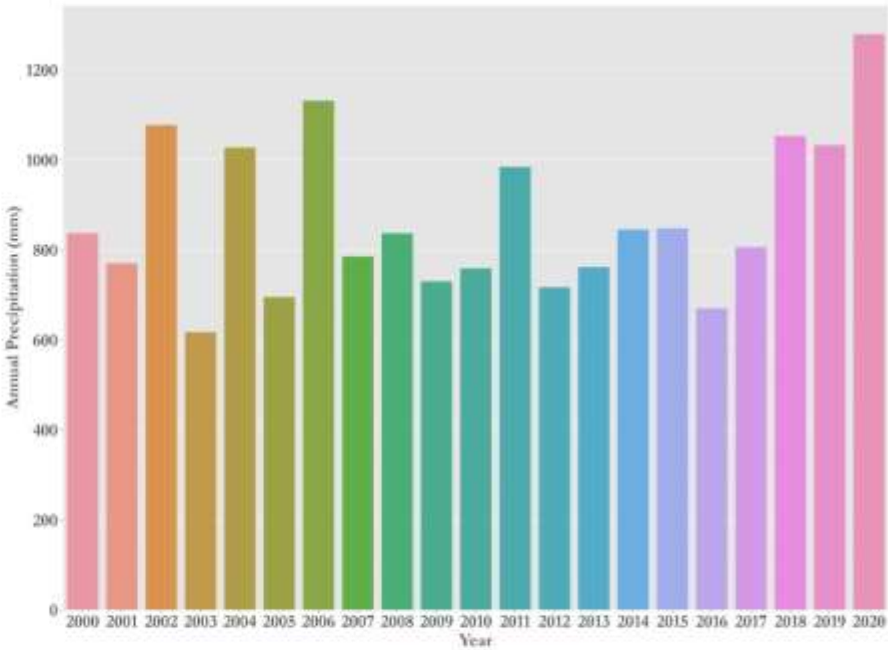

Figure 3.4: Average Annual rainfall in the Wami-Ruvu river basin, between 2000 and 2020

3.2.5 Cellular automation (CA)-Markov Chain (MC) Model

CA-MARKOV chain (MC), gives the total area (in pixels) that changes between any two land-cover classes in a given time interval. The MC matrix termed “transition area matrix table”, gives the probability that a pixel with a given land-cover class will change to any other class in a time interval. The LCM makes use of a multi objective land allocation (MOLA) algorithm to assign new land-cover transitions and to predict changes (Ding & Siqi, 2016). The MOLA uses the Logistic Regression suitability maps to help partition the MC-predicted amount of change into the different land cover classes. Land partitioning and allocating in the multi-objective model is an iterative process, which also admits unequal weighting of the different sub-objectives (Anand & Oinam, 2020).

The Markov model considers the conversion from one class to another (class transition) (Kumar *et al.,* 2014). Being *P* the transition probability of the current class in another class next time, the expression is as in the formula below,

$$P = Pij \begin{bmatrix} P1 & P2 \ldots \ldots. & Pn \\ P10 & P11 \ldots \ldots & Pnn \\ P20 & P21 \ldots \ldots & Pnnn \end{bmatrix}$$ ………………………..…….Equation (1)

Where by;

$(0 \leq Pij \leq 1)$…………………………………………..……..Equation (2)

Where by,

Where *P* is the transition probability *Pij* stands for the probability of transforming from present state *i* to another state *j* in succeeding time, *Pn* is the state probability of any time such as high transition has probabilities near (1) and the low transition will have a probability near (0). Markov Chain concludes precisely how much land would be estimated to change from the latest date to the predicted date. Which hence means transition probabilities file is the result of this process, which is a matrix that registers the probability of each land use/land cover class that which will change to all other class.

The simulation of land-cover change in LCM is an empirically driven process that moves in stages. In our analysis, we first perform an in-depth change analysis to identify valid class transitions and discard those that are irrelevant; second, we determine and create the predictor maps to be used by the Logistic Regression analysis. Third we Calculate Logistic Regression transition potential maps between cover classes, fourth and the last step is we Compute predictions with transition potential maps.

3.2.6 Logistic regression

Logistic regression analysis is a widely used approach for analytical land use/cover changes (Mas *et al.,* 2014). In our study, we model the probability of change from one single land use/cover class to another, within a predefined time interval, by assuming a binomial response (0/1, i.e. no-change/change) whose probability was determined by a logistic function (i.e. a type of sigmoid curve). A carefully chosen set of continuous predictor variables or drivers such as elevation, slope and proximity distance were used to evaluate that probability of land use/cover class change. The LR procedure consists of maximizing the logarithm of a binomial likelihood ʅ such as:

$log ʅ (y = 1/X)$ =Σ_i (y_i*logp_i-(1-y_i).log (1-p_i))……………………………….……..Equation (3)

Where;

X is a matric with rows and columns representing the observation such as land cover classes at various spatial location and predictor variables, respectively and ¥ is (0/1) response of the i observation furthermore p_i is the probability of the response variable y_i=1 for observation i and is specified through logistic function.

$pi(yi = 1) = \frac{e^{\beta * xi}}{1+e^{\beta * xi}}$……………………………..…….... Equation (4)

Whereby

The function pi represents the probability of a binary response, and β is the row vector containing the unknown regression parameters, the maximization of log L is carried out by varying the parameters ***β***.

Hence the Linear regression approach in this lcm model provide us with a sub-model that yield the probability of change for a single transition between two cover classes (i.e. wetland and non-wetland).

The output of linear regression analysis for our model in this study was a transition potential maps that indicates the degree of appropriateness of a spatial pixel for a given transition to take place.

3.2.7 Model validation

A deep validation of the projected land use/cover for Wami-Ruvu river basin is performed as important step to ensuring the accuracy of a model. We validated the results from the Linear Regression analysis, and from the projected land use/cover maps.

3.2.8 Linear Regression validation

For the LR results we used the area under the Receiver Operating Characteristic index in LCM modeller in TerrSet calls it the ROC-statistics, while very often it is also known in the literature as (AUC), area under the-curve implemented in the LCM module, which measures the explanatory power of a binary classifier and evaluates the agreement between predicted and true events (Mas et al., 2014). A ROC-statistic value above 0.7 is considered good, while values beyond 0.9 are considered excellent, as it points to a classifier with a very high performance (Lin et al., 2011). We carried out the LR by using the LCM default sampling of 10% of all available map pixels hereafter known as 10%, training set. Validation of LR predictions within LCM was then performed by computing the ROC index with those same 10% sampled points, as LCM does not permit using an independent set of points for validation.

3.2.9 Land-cover projection validation

The accuracy of the projected land use/cover map was evaluated by comparing the predicted map versus real map of the same year in the study area. Validation testing of the model was carried out by running a simulation of land cover change from 2000 to 2010, for predicting a land use/cover map of 2020 and comparing its output with the reality classified map of 2020. The validation process should evaluate the ability of the modelling procedure to accurately produce quantities and locations of categories of grid cells in a map Pontius *et al.* (2001), the objective of the model is to simulate the changes in land use/cover, the validation process should not give credit to the correct simulation of persistence. Rather, it should assess the model based on observed and simulated change. This means that in addition to the two maps of observation and simulation of the more recent time, the map of initial observation should be considered in the evaluation of the model Pontius *et al.* (2008), Alo and Pontius, (2008), hence the agreement between two maps is calculated in terms of the number of cells in each category (quantity) and the spatial location of the cells in each category (location).

According to Pontius *et al.* (2001) calculated the location and quantity agreements proposed a set of alternative Kappa indices that accounted for discrepancies between two categorical land maps. And then introduced other statistics related to the agreement and disagreement between the maps, as a substitution for the Kappa indices. In this study, we calculate both set of indices to best measure agreement or disagreement between observed and simulated map of land use/cover maps of Wami-Ruvu basin.

Likewise, we assessed the accuracy of the model using the number of excellence (Pontius *et al.,* 2008). The calculation of the number of excellence accounts for observed change and simulated change, as it is the ratio of the number of pixels in the intersection of the above two sets (2000 and 2010) to that of their union, which includes the correctly predicted change as well as errors due to prediction of change as persistence, prediction of change as change to the wrong category, and prediction of persistence as change (Pontius *et al.*, 2008; Hyandye & Martz, 2017).

The Kappa indices defined by Pontius *et al.* (2001) are linear functions and have values on a scale of 0 to 1, where 1 means perfect agreement, and 0 means total disagreement. In our study analysis we used 3 different indices for the validation: $\mathbf{K}_{standard}$, $\mathbf{K}_{no}$ and $\mathbf{K}_{location}$ as described in Pontius *et al.* (2001). $K_{standard}$ measures the ability of a simulation to achieve a perfect classification given a fixed marginal distribution of cells in a category in the simulation map. It represents the usual Cohen's Kappa index, K_{no} indicates the proportion of agreement without specifying precisely the location, and. $K_{location}$ is a measure of spatial precision associated with correct assignment of values, regardless of quantification error. And their calculated using the formula below,

$K = \frac{(M(m)N(n)}{P(p)-N(n)}$……………………………………………………..Equation (5)

Where by

Where no of information is defined by N *(n), medium grid cell level information by M (m), and perfect grid cell-level information across the landscape by P (p).*

3.3 Results

3.3.1 Land use/cover change analysis and transition probability

Through land use/ cover changes of three different dates of satellite images, showed that among the six reclassified land use cover classes, the ones corresponding to agriculture, built up, and bare land areas presented an increase in extent, whereas the classes of water, wetland and vegetation showed a decrease, with emphasis on the agriculture zones, and built-up land for human settlement which presented the largest relative increase in land use categories and vegetation cover which represented the highest land cover classes with highest decrease rate , which are well shown in the table 3.3 below.

Table 3.3: Showing Area (km^2) per land class and relative area increment (+) or decrement (−) in 2020 compared with 2000

LULC	**Area (Km^2)**	**Area (Km^2)**	**Area (Km^2)**	**Change Rate (Increment+/-Decrement)**
Year	2000	2010	2020	
Built-up	468.2709	1041	1 469.6478	68.13720267
Water	227.1681	279.1152	235.7928	3.657745275
Bare land	1675.606	1 463.4567	2 029.3992	17.43341576
Bush land	21 636.66	19 752.759	17 143.1469	-26.21173071
Agriculture	19 748.12	22 003.2873	28 499.5116	30.7071778
Woodland	19 648.12	19 491.0003	14 651.0784	-34.10700403
Forest	2 757.14	2 102.7931	1 944.7632	-41.7725356
Wetland	1 209.1	949.0	521.3	-18.38286158
Total	**67 182.41**	**67 182.4116**	**67 182.4152**	

Land use/cover change assessment between 2000 and 2020

The wetland covers in Wami-Ruvu river basin, represented 2% of the total area in 2000 while in 2020 it became 0.78 %, decreasing more than half in area coverage during a period of 20 years. Meanwhile the wetland cover, which had an area of 1 209.07 km^2 in 2000, while in 2020 the wetland area decreases to 521.33km^2 cover decrease. From 2000 to 2020 represented 50% decrease in area. By using land cover maps from 2000 and 2020 a transition probability matrix was obtained.

The transition potential maps (Table 3.4), calculated with the LR module, show the transition probabilities at each spatial location.

Table 3.4: ROC statistics of transition sub-models' probability

SUB_MODEL	ROC
built-up to water	0.16
built-up to bare land	0.23
built-up to agriculture	0.51
built-up to wetland	0.05
built-up vegetation	0.17
water to built-up	0.73
water to bare land	0.7
water to agriculture	0.8
water to wetland	0.71
water to vegetation	0.68
bare land to built-up	0.65
bare land to water	0.72
bare land to agriculture	0.68
bare land to wetland	0.79
bare land to vegetation	0.74
agriculture to built-up	0.69
agriculture water	0.73
agriculture to bare land	0.78
agriculture to wetland	0.83
agriculture to vegetation	0.72
wetland to built-up	0.72
wetland to water	0.75
wetland to bare land	0.81
wetland to agriculture	0.9
wetland to vegetation	0.73

Other validation indices calculated for the simulation of wetland in study include $K_{standard}$, K_{no}, $K_{location}$, QD and AD. The overall agreement provided by $K_{standard}$ have shown higher values as its >80% (Foody, 2002, 2004), Table 3.5 K_{no} shows a higher value too, indicating that our model correctly quantified the number of pixels of each class in both the actual and the simulated change maps. Likewise, the value of $K_{location}$, reinforces the ability of our simulation model to simulate specific localities of change found in the same locality in both the actual and the simulated change maps reasonably

Table 3.5: Kappa results from comparing the real and simulated change in land cover of 2020

Kappa indices	Results
$K_{standard}$	0.8723
K_{no}	0.95
$K_{location}$	0.81

3.3.2 Projection maps of wetland cover changes

After the model validation, wetland map was simulated; the model simulates the wetland change for years, from 2020 to 2050. In order to understand the results in terms of past spatiotemporal dynamics of wetlands in the region, we calculated the total degradation of wetlands from the remote sensing data. The observed pattern of degradation captured by the Landsat imagery indicated a decrease in wetlands land cover of over 50 percent in 2020. Likewise, our simulation outputs based on the spatial dynamics during the two decades showed a progressive decrease in the collection of wetlands coverage throughout the region, although the degradation rate in varies in time (Table 3.6). Table 3.7 and Figure 3.5, 3.6 summarize the observed and simulated changes in wetlands land cover for the Wami-Ruvu river basin. Simulated land cover map for the year 2050 shows a decrease in area extent of wetland in almost 50 percent of recorded in 2020, which means loss of 307.25 Km^2.

Table 3.6: Transition Probability

Matrix Classes	Wetland	Non-Wetland
Wetland	1	0.1396
Non-Wetland	0.1229	0.9944

Table 3.7: Metrics of observe and simulated wetland changes in Wami-Ruvu river basin

Year	Observed wetland (Pixels Values)	Observed Wetland (Km2)	Area (%)
2000	1 339 999	1 209.0753	2
2010	1 055 066	949.5594	1.4
2020	578 584	520.7256	0.78
2050	237 199	213.4791	0.32

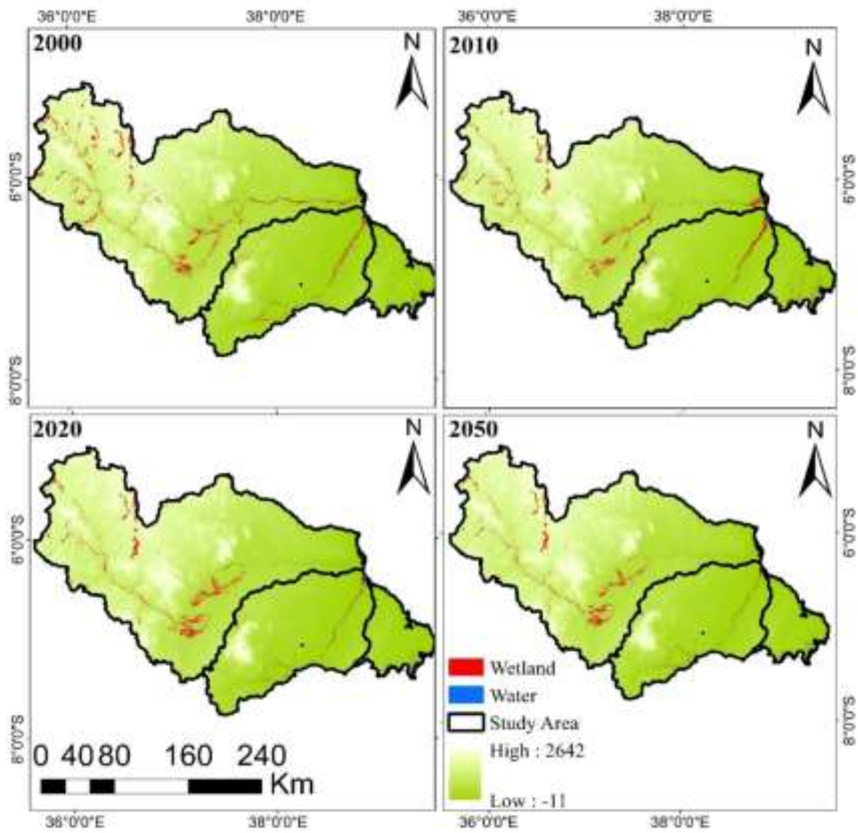

Figure 3.5: Distribution of wetland cover in observed year of 2000, 2010 and 2020 and simulated wetland cover in 2050

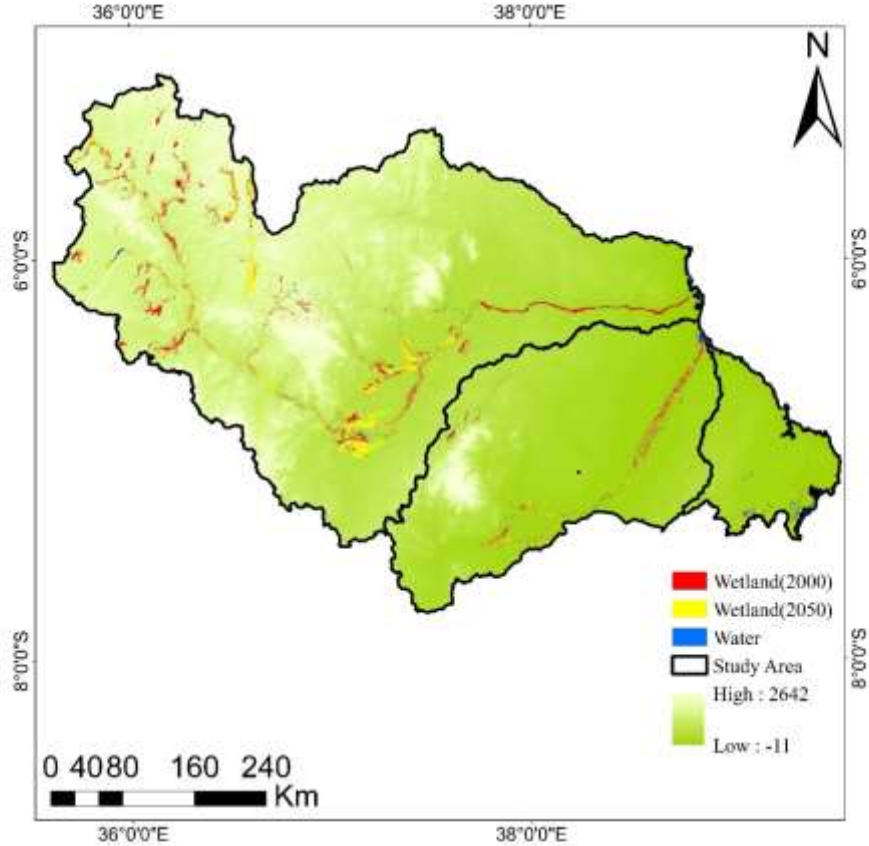

Figure 3.6: Wetland spatial change between observed year 2000 and simulated in 2050 in Wami-Ruvu river basin

3.4 Discussion

The current analysis shows a gradual decrease of the existing wetlands in the Wami-Ruvu river basin. By considering other works carried out in other wetland regions worldwide such as, Brazil (Yu *et al.,* 2010; Maeda *et al.,* 2011; Zhu and Gong, 2014; Arsanjani *et al.,* 2015; Gong *et al.,* 2015), it has been witnessed that Wami-Ruvu basin simulation results of wetland areas have shown a positive correlation trend as observed in other area.

One of the major identified threat or driver of wetland degradation in Wami-Ruvu basin and even in other study observation is uncontrolled expansion of human activities in the area, and it is assumed that it will continue to be so in the predicted time frame, due to observed expansion of human activities such as urban expansion and agriculture.

Given that our area of study consists of heterogeneous land use/cover with diversity of topographical characteristics of the studied region, hence the hybrid method used in projection in this study demonstrated useful work in recognizes the complex dynamics of wetlands distribution and gradually changes within the basin. By using a logistic regression, the model transition probabilities were automatically computed from the observed datasets, rather than being deterministically defined a priori by the model developer. Also, the MOLA algorithm employed by LCM in TerrSet have been successfully applied in the past to model the spatial-temporal dynamics of wetland cover changes (e.g. Nagabhatla *et al.,* 2012; Nghiem *et al.,* 2013; Uddin *et al.,* 2015).

Hence the use LCM model in TerrSet consist of hybrid models combining LR, MC is multi-objective optimization techniques show great promise to model wetland dynamics and other land use/cover changes in general. When studying the wetlands of Wami-Ruvu river basin we must take into account Table 14 Comparison of observed and simulated changes of wetland cover in the Wami-Ruvu river basin between 2000- 2050. Wetlands Observed from Landsat image classification in 2000, 2010, and 2020 which enable the model to further simulate the wetland coverage extent in 2050, a total area of 1209.075km^2, 949.5594km^2 and 521.3 km^2 for observed and 213.4791 691km^2 for simulated respectively.

Overall accuracies and kappa coefficient values were attained by both Landsat TM, ETM+ and OLI-TIRS were > 85% for the years 2000, 2010, and 2020 as shown on the table12 indicate that the classification performance and results are satisfactory and hence were suitable for simulation of wetland cover in 2050.

The dispersal and variety of wetlands in Wami-Ruvu river basin is mainly defined by physical factors such as topography, climate, and anthropic factors which influence the distribution (Gingras *et al.,* 2017). Secondly, the accuracy of the data used may be crucial in the results. Wetlands in the study area are composed of marshland, paddy fields and open water difficult to classify using only single data such as Landsat images. As illustrated in Table 3.1, the Only usage of LANDSAT bands -based land-cover classification detected a relatively low percentage of open wetland in the study area, the main reason for this explanation for those low percentage detection of wetland could be that there were pixels misclassification due to closeness of pixel digital number to some land use/cover and hence those areas that should have been classified as open wetlands such as swallowed water, mashed area, would have been remotely detected and classified as water and vegetation cover .hence the usage of **Green**-band and **SWIR-**bands in calculating **MNDWI** is useful used in this study as additional bands able to correctly identify wetlands (Leboeuf and Vaillancourt, 2015), the best classification option would therefore be to combine normal satellite bands products i.e. (SR_B1…..SR_B7) and spectral indices .

Various studies have shown and give out the main reason for the massive degradation of change of wetland area. The major reason could be the influence cause by the population increase from 2000 to 2020 (Lafond and Pilon, 2004; Hood and Bayley, 2008; St-Pierre *et al.,* 2017), in the basin which hence influence spatial expansion of built-up area and other human activities such as agriculture in the regions within Wami-Ruvu river basin. This is well evidence from national bureau of statistics data of population census of (2022) which stipulates the increase of population to 62 million.

Climate change influence changes in wetland extent and distribution in Wami-Ruvu river basin this was state by (Nelson *et al.,* 2014) in the influence of changes of Boreal Forest of Canada which influence the transformation of it due climatic changes. Hence it is important also to include and understand the influence of climate changes in causing the dynamic and degradation of wetland in study area, hence we include climate data both precipitation and temperature in simulation model for better understating the dynamic of wetland.

Open wetland suffers from water imbalances cause by global and micro climatic changes cause by extremely evapotranspiration caused by long dry season and increase of rainfall.

3.5 Conclusion

This study aims to assist in the decision making regarding the management plan of the Wami-Ruvu river basin for sustainable development and habitat conservation. Furthermore. This study intended to show out the methodological approach to use in determine the presence and future of land use/cover in a big area such as our study area. Hybrid CA Markov chain model was the model proposed which allow us to generate and execute past and projected scenarios of LULC. The transition probability maps and land cover change projection were successful validate by using several kappa indices. Driver for wetland changes influence such as topographical and climatic drivers were successful included in the model.

The rapid increase in population and urbanization in the basin without proper planning and management of land cover such as wetland and forest own an extremely threat to the environmental system. Proper wetland conservation policies and land use planning are required to minimize the negative impacts due to these changes. The models like LCM can be used to predict the future changes, to model growth scenarios of various land use/cover. Predicting the future wetland cover enables us to figure out proper policies for the protection and preservation of the wetland environment and sustainable use of these resources. This study also shows that the valuable spatial information can be obtained from remote sensing data which can be used for formulating proper planning and sustainable development.

CHAPTER FOUR

4.0 General Discussion

4.1 Wetland Degradation Condition and Trend Based on Land Use Land Cover Changes in the Study Area

According to the study of Vicky Anand and Bakimchandra Oinam (2019), in the Loktak sub-basin, the effects of LULC change have changed base flows, altered hydrology, increased flooding, mudslide damage, increased soil erosion, decreased aquifer recharge due to increased runoff in the Loktak sub-basin with the result of loss of diversity, and decrease in biodiversity.

Through GIS and remote sensing satellite imagery of 2000, 2010 and 2020, this study has successfully assessed wetland degradation conditions and spatial trends due to LULC change in the Wami-Ruvu River basin in Tanzania, which reveals positive and significant changes in wetland degradation conditions and increase in wetland degradation caused by the increase of human activities in the basin, especially settlement and agriculture activities expansion respectively. The study result and analysis shows that not only wetland is affected due to these human activities increase but also other biodiversity such as vegetation cover (Forest, woodland and bushland) and Open water have also experienced the effects of human activities expansion.

Based on various studies conducted on wetland degradation reveal various drivers for wetland degradation in various basins (Mwita, 2016; Mwakaje, 2009; Mugo *et al.,* 2020; Ngondo *et al.,* 2021). In this study, we have tested through the use of linear correlation it has been observed that built land, agriculture encroachment towards wetland areas and rainfall have a positive correlation on wetland degradation in the Wami-Ruvu River basin.

Through study findings, it's pure that uncontrolled and unplanned human activities increase in the basin and have immeasurable effects. Wetlands Observed from Landsat classified images of 2000, 2010, and 2020 which enabled the model to further simulate the wetland coverage extent in 2050, a total area of 1209.07 km^2, 949 km^2, 521.33 km^2 and 213 km^2 for simulated respectively.

When facing such severe and rapid land-cover changes, one requirement for decision-making is to be able to project future changes under certain assumptions. Such projections also contribute to increased awareness of the ecological and biodiversity consequences of growing pressures.

4.2 To Evaluate Future Wetland Degradation at Wami-Ruvu River Basin from 2020 to 2050 Using Remote Sensing Imagery and Hybrid Ca-Markov model

The use of models for projections of land use and occupation in future scenarios is a fundamental tool for Land planners and managers since it allows an understanding of the dynamics of human activities as well as the main threats to which the ecosystem will be subjected (Halmy *et al.*, 2015; Lathuilli Ere *et al.,* 2017).

The study uses The CA-Markov model in land change modeler found in Idris TerrSet which allows addressing issues of how the LULC will be in the Wami-Ruvu river basin hereafter whether planning measures are not taken. The lack of a Sustainable plan makes the agricultural activities within the Basin continue to progress rapidly, jeopardizing the marsh areas and the biodiversity present in the basin.

However, in recent years, Built-up expansion has also shifted to uncultivated ecosystems, including wetlands in the basin. The presence of major cities with extremely urban sprawl in the basin such as Dar es Salaam City, Dodoma City, and Morogoro municipal have been observed as the major threat to the wetlands found in the basin.

The findings of the study show the impact of changes in biodiversity on wetlands in the basin. The CA-Markov model shows that the wetlands in the Ruvu and Coastal sub-basins are a potential threated in the basin and are expected to perish in 30 years to come since there are extremely threatening activities conducted in these sub-basins with uncomfortable measures. This fact can result in a significant loss of biodiversity present in wetlands.

CHAPTER FIVE

5.0 General Conclusion and Recommendations

5.1 Conclusions

The study uses Remote sensing data in assessing a significant reduction in wetland extent over the study period. The analysis indicates that substantial portions of the wetlands have been degraded or converted for other land uses. By analysing the remote sensing data, urban expansion, agriculture, or infrastructure development, were identified as the main source for wetland degradation in our study area. Understanding the primary causes is crucial for implementing targeted conservation strategies.

Also, the study was able successfully identified specific regions within the Wami-ruvu River Basin where wetland degradation has been particularly severe. These areas mayhence became the focal points which require immediate conservation and restoration mediations.

The study intends to use remote sensing and GIS techniques in determine how land use/cover in the study area changes over 20 years of the study period and use the same data to foreseeing the future wetland degradation in the basin. The simulated wetland of 2050 of the basin revealed the continuing of degradation of wetland in the basin due either increase of human development in agricultural activities and settlement. As the main aim of the study is to spotlight the extent of wetland degradation in Wami-ruvu river basin.

Remote sensing data from multiple time allowed for the observation of temporal trends in wetland degradation. Understanding how degradation has evolved over time helps to evaluate the effectiveness of past conservation measures and to plan for the future.

5.2 Recommendations

It's well known that Conservation of wetlands is crucial as they provide essential ecosystem services, including water purification, flood control, carbon sequestration, and habitat for diverse plant and animal species. Hence Human activities, such as urban development, agriculture, pollution, and climate change, which endanger wetlands should be well regulated and monitored. Though establish strong legal protection for wetlands through local, national, and international regulations. Develop and enforce zoning laws that restrict harmful activities near or within wetlands.

Raise awareness about wetland importance and the threats they face. Engage with local communities, stakeholders, and decision-makers to promote sustainable land use practices and wetland conservation efforts.

Establish buffer zones around wetlands to protect them from potential pollution sources and to minimize the impact of human activities on these sensitive ecosystems. Promote sustainable agricultural practices that minimize wetland encroachment and reduce the use of harmful chemicals that can adversely affect wetland ecosystems. By implementing these recommendations and engaging in ongoing research and adaptive management, it is possible to mitigate the impact of human activities on wetlands and safeguard these critical ecosystems for future generations.

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