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To evaluate future wetland degradation at wami ruvu river basin from 2020 to 2050 using remote sensing imagery and hybrid ca-markov model

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ABSTRACT

Context and background:

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 analyze how the historical degradation of wetland will continue in the future especially in most of the developing countries.

Goal and objectives:

The overall objective of the study intents to provide an integrated method which includes GIS, remote sensing and CA-Markov Chain modelling to analyse the influence of LULC dynamic into wetland degradation. Specifically, is to use historical land use/cover maps of 2000,2010 and 2020 to develop land use simulation model to predict the spatial degradation of wetland for three decades.

Methodology:

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 modeler (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 modeler.

Results:

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

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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 its yield decreases, habitat loss, 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 Wami-Ruvu basin result to significant loss of wetland in the catchment. Due inappropriate and unpractised policy and plan to the basin has result to loss and degradation of wetland since 1990s. Hence in order for proper land use planning and management urgent measure is needed to quantify the extent, pattern and direction of land use/cover change so as to predict the future wetland degradation and other LULC dynamic which is still unknown. Majority of the study base on LULC mapping and change detection in the basin.

In recent years there is increase of interest of using explicit model for predict various variable using remote sensing and Geographical information system (GIS) as a 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 study 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 (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.

Markov Chain analysis is used as a descriptive tool to predict land-use changes projection on 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. A CA model is dynamic model with local interaction to reflect evolution of system where space and time are considered as discrete unit and space is represented as a regular lattice of two dimension.

Hence this study will provide an integrated method which includes GIS, remote sensing and ca Markov chain modelling to analyse the influence of LULC dynamic into wetland degradation in Wami-Ruvu river basin in Tanzania.

2.0 MATERIALS AND METHODS

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 66294.5 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 (G. 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.

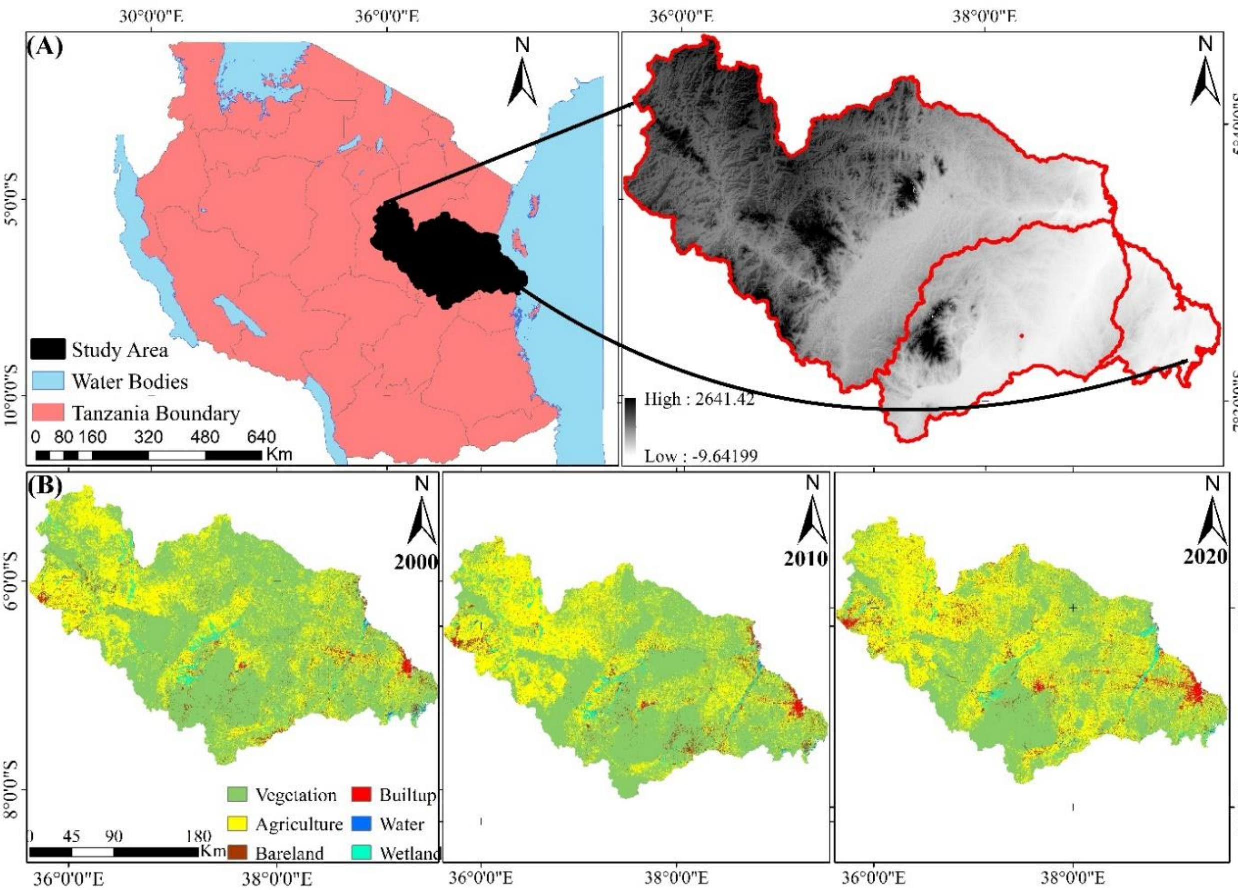

Figure 1. (A) Administrative boundary of Tanzania country showing the location of Wami-Ruvu basin, (B) location of study area in topographical map and land use/cover for previous study years of 2000, 2010 and 2020.

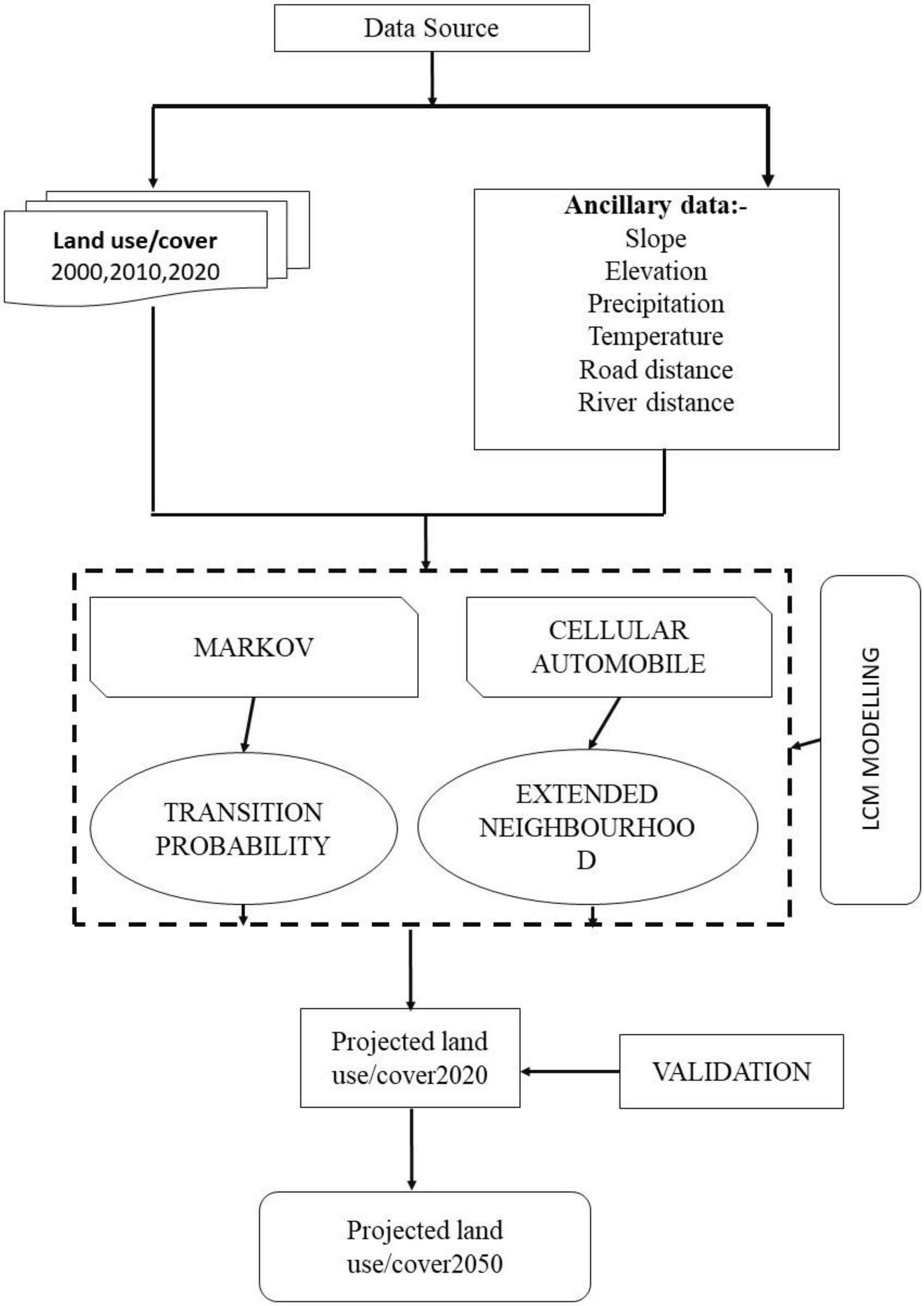

Figure 2. Flowchart of application of the CA-Markov model used in the study

2.2.1 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 https://doi.org/10.35410/IJAEB.2023.5800 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 bushland, 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. 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.

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 1. Details of dataset used in the study

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

Table *2*. Descriptions of the land use/cover classes

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.

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. The accuracy > 80% obtain between predicted and produced LULC of 2020 gave a way for simulation of LULC of 2030, 2040 and 2050.

2.3 Land use/cover change analysis

The study was carried out with the Land Change Modeler (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 (Tang, 2017; Zhang et al., 2015). 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.

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 (J. Jokar Arsanjani, Zipf, 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.

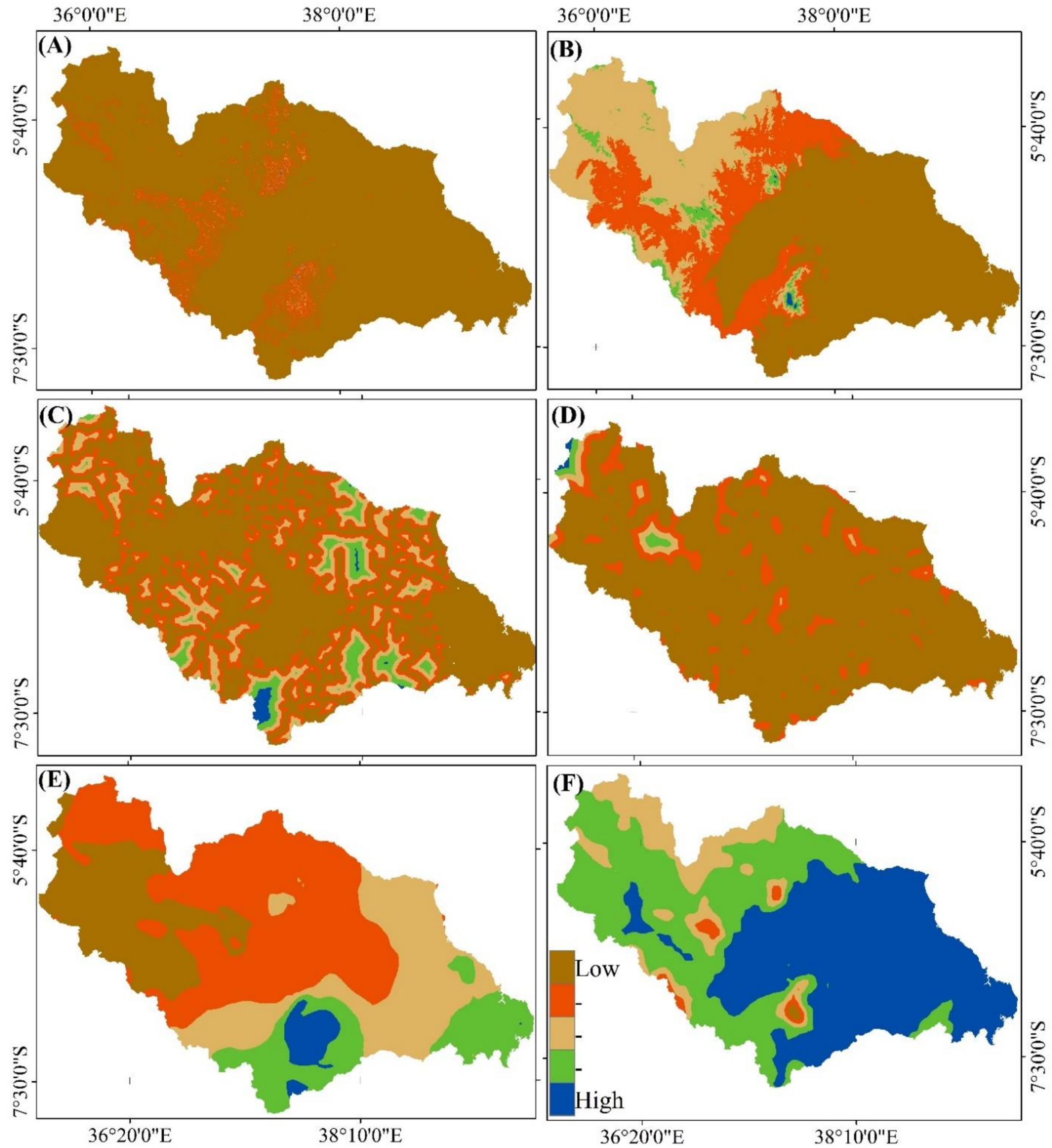

Figure 3. Predictor variables (a) Slope, (b) Elevation, (c) Distance from road, (d) Distance from river, (e) Precipitation and (f) Average temperature

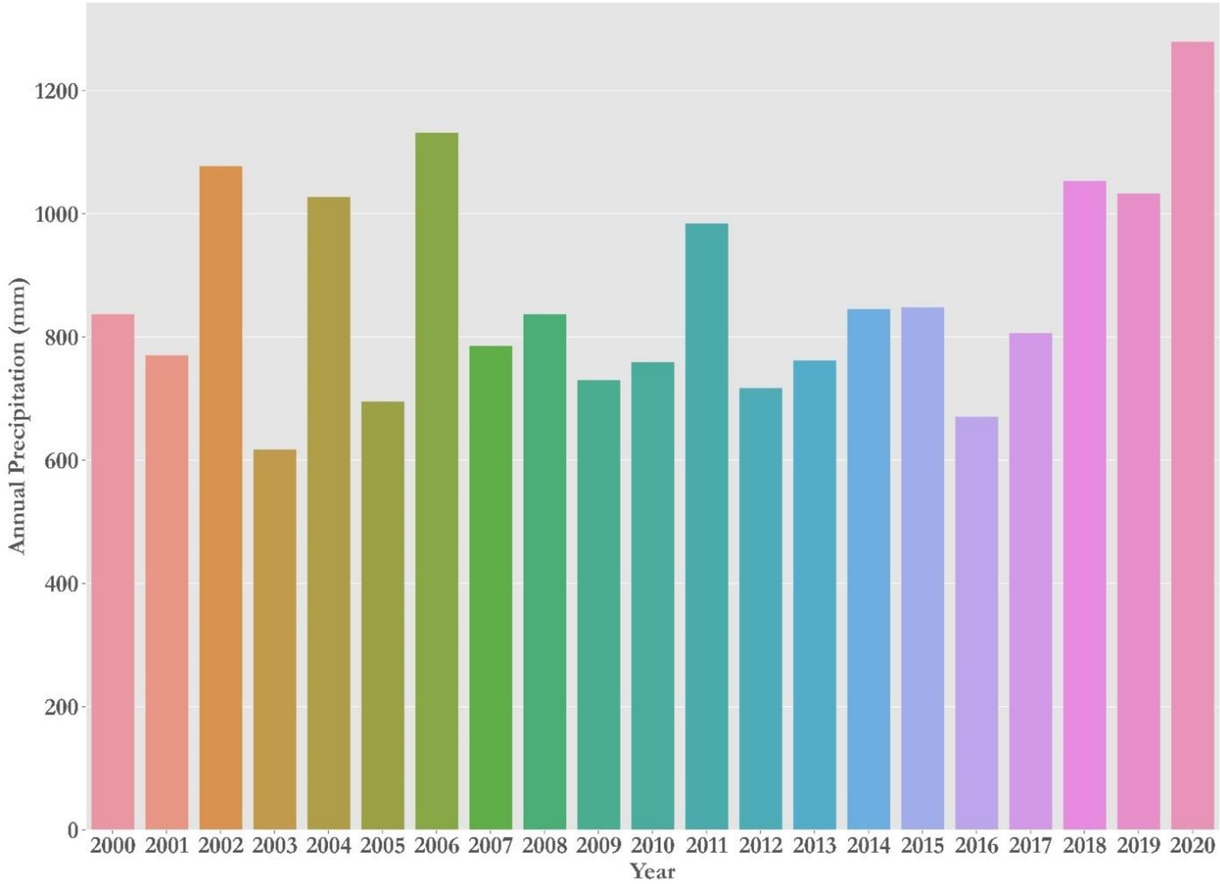

Figure 4. Average Annual rainfall in the Wami-Ruvu river basin, between 2000 and 2020

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,

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

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.

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:

$log ʅ\,(y = 1/X) = \Sigma_i\,(y_i * \log p_i - (1-y_i).\log\,(1-p_i))$ ....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)

Where by

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.

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.

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.

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,

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

Where by

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

3.0 RESULTS

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, urban, 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 below.

LULC	AREA(Km²)	AREA(Km²)	AREA(Km²)	CHANGE RATE (increment+/-decrement)
Year	2000	2010	2020	
Built-up	468.2709	1041	1469.6478	68.13720267
Water	227.1681	279.1152	235.7928	3.657745275
Bare land	1675.606	1463.4567	2029.3992	17.43341576
Bushland	21636.66	19752.759	17143.1469	-26.21173071
Agriculture	19748.12	22003.2873	28499.5116	30.7071778
Woodland	19648.12	19491.0003	14651.0784	-34.10700403
Forest	2757.14	2102.7931	1944.7632	-41.7725356
Wetland	1209.1	949.0	521.3	-18.38286158
TOTAL	**67182.41**	**67182.4116**	**67182.4152**	

Table 3. Showing Area (km2) per land class and relative area increment (+) or decrement (−) in 2020 compared with 2000.

3.2 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 1209.07 km2 in 2000, while in 2020 the wetland area decreases to 521.33km2 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 (see Appendix A), calculated with the LR module, show the transition probabilities at each spatial location.

Table 4. ROC statistics of transition sub-models' probability

SUB_MODEL	ROC
built-up to water	0.76
built-up to bare land	0.73
built-up to agriculture	0.71
built-up to wetland	0.75
built-up vegetation	0.77
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, 2004, 2002), 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 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 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 7 summarizes 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 6. Transition Probability Matrix

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

Table 7. Metrics of observe and simulated wetland changes in Wami-Ruvu river basin

Year	Observed wetland (Pixels Values)	Observed Wetland (Km2)	Area (%)
2000	1339999	1209.0753	2
2010	1055066	949.5594	1.4
2020	578584	520.7256	0.78
2050	237199	213.4791	0.32

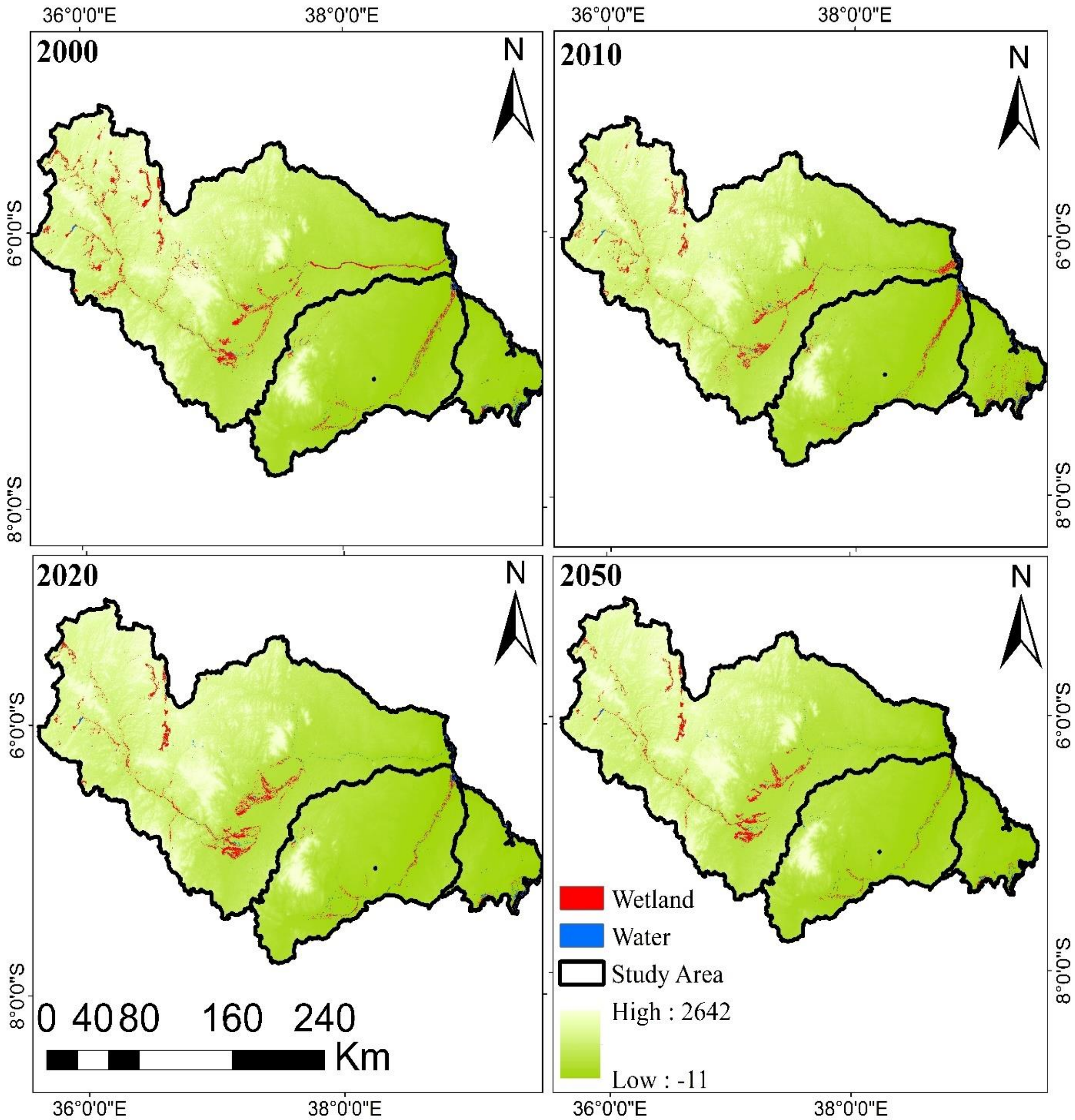

Figure 5. Distribution of wetland cover in observed year of 2000, 2010 and 2020 and simulated wetland cover in 2050

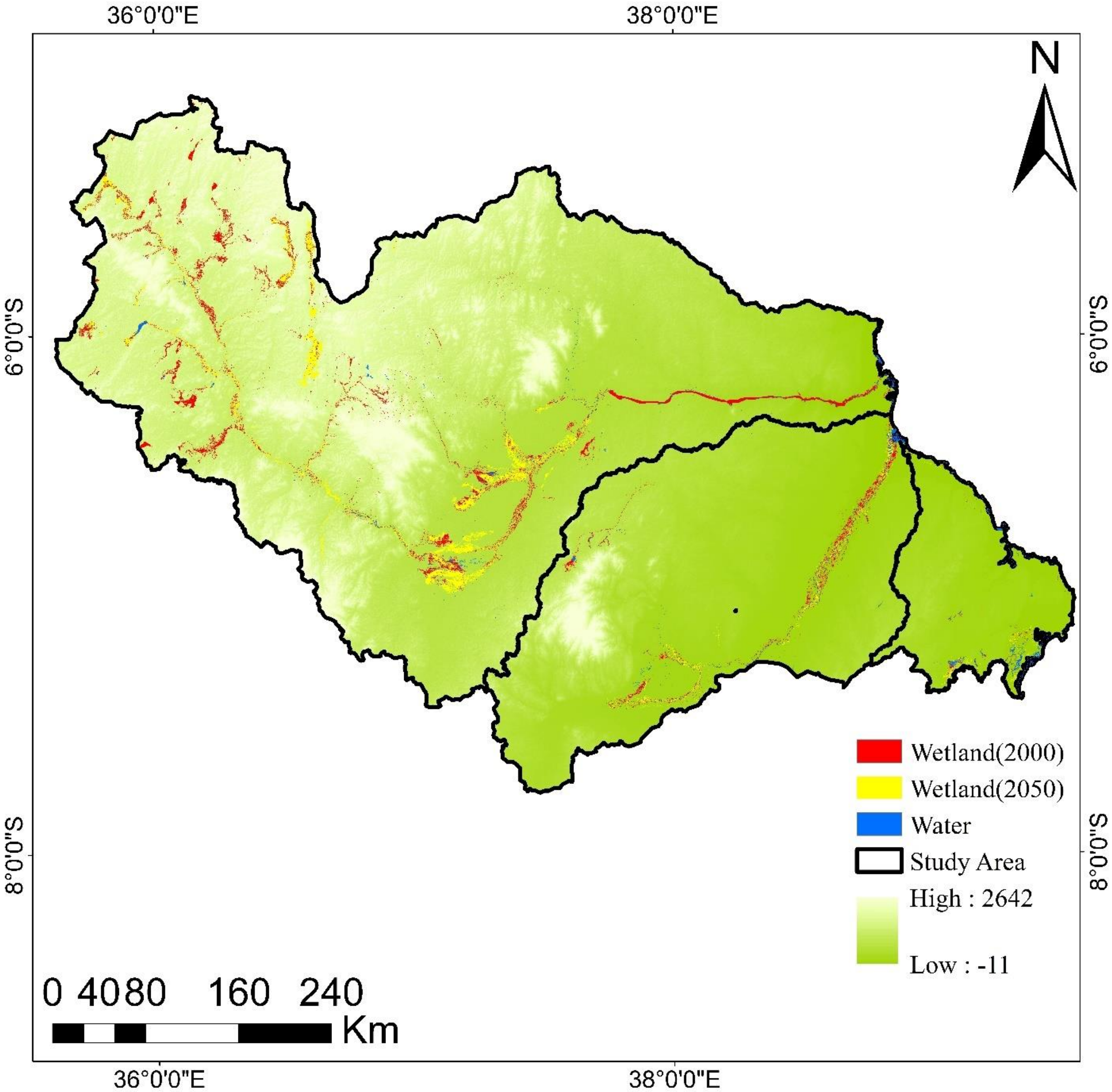

Figure 6. Wetland spatial change between observed year 2000 and simulated in 2050 in Wami-Ruvu river basin.

4.0 CONCLUSIONS

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 (Gong et al., 2015; Arsanjani et al., 2015; Maeda et al., 2011; Yu et al., 2010; Zhu and Gong, 2014), 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 km^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 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 (Hood and Bayley, 2008; Lafond and Pilon, 2004; 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 (2002-2022) which stipulates the increase of population from 1.6 million to 2.6 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.

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. Markov chain CA 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.

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9.0 KEY TERMS AND DEFINITIONS

Land Change Modeler: Refers to the use of computational models and geographic information systems (GIS) to analyze and predict changes in land use and land cover over time.

A Markov chain: A mathematical concept and a stochastic process that describes a sequence of events where the outcome of each event depends only on the state of the system at the current event, and not on the system's previous history.

Wetland: Is a distinct ecosystem characterized by the presence of water, which influences the soil, vegetation, and overall ecological conditions.

Cellular Automata (CA): It refers to a discrete, grid-based model for simulating complex systems, often used to study dynamic processes and rule-based systems.

Remote Sensing: It involves the collection of data without direct physical contact with the subject of interest.