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Quantitatively Assessing the Future Land-Use/Land-Cover Changes and Their Driving Factors in the Upper Stream of the Awash River Based on the CA–Markov Model and Their Implications for Water Resources Management

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Abstract: Despite the rapid economic and population growth, the risks related to the current dynamics of land use and land cover (LULC) have attracted a lot of attention in Ethiopia. Therefore, a complete investigation of past and future LULC changes is essential for sustainable water resources and land-use planning and management. Since the 1980s, LULC change has been detected in the upper stream of the Awash River basin. The main purpose of this research was to investigate the current dynamics of LULC and use the combined application of the cellular automata and the Markov chain (CA–Markov) model to simulate the year 2038 LULC in the future; key informant interviews, household surveys, focus group discussions, and field observations were used to assess the consequences and drivers of LULC changes in the upstream Awash basin (USAB). This research highlighted the importance of remote sensing (RS) and geographic information system (GIS) techniques for analyzing the LULC changes in the USAB. Multi-temporal cloud-free Landsat images of three sequential data sets for the periods (1984, 2000, and 2019) were employed to classify based on supervised classification and map LULC changes. Satellite imagery enhancement techniques were performed to improve and visualize the image for interpretation. ArcGIS10.4 and IDRISI software was used for LULC classification, data processing, and analyses. Based on Landsat 5 TM-GLS 1984, Landsat 7 ETM-GLS 2000, and Landsat 8 2019 OLI-TIRS, the supervised maximum likelihood image classification method was used to map the LULC dynamics. Landsat images from 1984, 2000, and 2019 were classified to simulate possible LULC in 2019 and 2038. The result reveals that the maximum area is covered by agricultural land and shrubland. It showed, to the areal extent, a substantial increase in agricultural land and urbanization and a decrease in shrubland, forest, grassland, and water. The LULC dynamics showed that those larger change rates were observed from forest and shrubland to agricultural areas. The results of the study show the radical changes in LULC during 1984–2019; the main reasons for this were agricultural expansion and urbanization. From 1984 to 2019, agriculture increased by 62%, urban area increased by 570.5%, and forest decreased by 88.7%. In the same year, the area of shrubland decreased by 68.6%, the area of water decreased by 65.5%, and the area of grassland decreased by 57.7%. In view of the greater increase in agricultural land and urbanization, as well as the decrease in shrubland, it means that the LULC of the region has changed. This research provides valuable information for water resources managers and land-use planners to make changes in the improvement of future LULC policies and development of sub-basin management strategies in the context of sustainable water resources and land-use planning and management.

Keywords: land-use/land-cover dynamic; CA–Markov model; geographic information system; remote sensing; water resource; upper stream Awash basin
1. Introduction

Land cover refers to natural structures such as vegetation and water surfaces, as well as manufactured structures that cover a certain region, whereas human activities that are related to the soil are called land use [1]. Change in land use and land cover (LULC) is an important factor in global environmental change, and it is crucial for regional development and land-use management to achieve sustainable development [2]. Due to rapid global economic and population growth and globalization, LULC is accelerating in many developing countries around the world [3]. As a result, land is being affected by competing demands and limited resources due to anthropogenic land degradation that severely disrupts various services and functions of the land [4].

Anthropogenic (human activity) affects the natural environment to a large extent through the dynamics of change (LULC). Consequently, the entire global ecosystem has been degraded due to the impact of human activities on natural resources [5]. Globally, in addition to population growth and global warming, the current dynamics of LULC are also of concern. For example, in East African countries and other regions strongly affected by population growth and climate change, human activities have greatly altered the natural landscape [6]. Future projections suggest that the world population will reach 9.1 billion by 2050, 34% higher than today, and agricultural production systems are expected to produce food for a growing global population [7,8]. Agriculture is a very important economic sector in many developing countries [9]. African forests play an important role in the development and transformation of a green economy, mitigating climate change and achieving the Sustainable Development Goals (SDGs) and the industrialization of the continent [10]. Ethiopia’s economy is dominated by agriculture and is therefore highly sensitive to climate change [11]. Agriculture, forestry, and landscapes can significantly mitigate various aspects of sustainable development, including addressing the challenges of climate change, by increasing resilience and reducing vulnerability [12].

In Ethiopia, LULC has changed dramatically over the past few decades due to population growth, agricultural expansion, urbanization, and overgrazing. Similar to most other countries in sub-Saharan Africa, Ethiopia’s population is rapidly expanding, with an estimated growth rate of around 2.8%, to a current population size of 108 million [11]. The service industry and agriculture are the main contributors to Ethiopia’s GDP, both accounting for about 40%, and the industrial sector contributes the remaining 20% [11]. Smallholder farmers in Ethiopia face widespread problems of improper planting, overgrazing, and deforestation, leading to soil erosion and loss of soil fertility, water scarcity, lack of pasture and livestock feed, and a firewood crisis [13]. The main problem of deforestation is the overexploitation of natural resources; the clearing of agricultural land to meet the food needs of a growing population and the demand for fuel and building materials leads to a continuous reduction in forest area [14]. The rapid change in LULC is due to rapid population growth requiring more arable land, more trees for household firewood consumption, and more settlement area [15,16].

LULC changes have a significant impact on hydrology and water resources by affecting the hydrological cycle [17–20]. LULC and climate change are two major factors that are inherently anthropogenic and thus affect hydrological processes. Consequently, changes in hydrology and water components caused by climate change and anthropogenic activities, such as LULC, lead to many environmental problems [21,22]. LULC and climate change are the main drivers of land degradation by promoting soil erosion, especially heavy rainfall that accelerates soil erosion and bare vegetation cover [23]. Therefore, assessing LULC dynamics is important for effective environmental management, including effective water management practices.

In Ethiopia, due to changes in the environment and land use, soil erosion and consequent land degradation are considered major constraints to agricultural productivity and food security [24–26]. Likewise, water scarcity is increasingly common due to increased water demand, urbanization, economic development, land degradation, and climate change [27]. Climate and LULC changes are some of the main drivers of land
degradation, which in turn will greatly affect water resources [19,23]. Therefore, LULC and climate-related natural disasters will affect people’s lives, livestock, and economic development, which, in turn, will lead to water shortages in communities with different needs [28]. In Ethiopia, more than 350 million trees were planted in one day to minimize the above problems. This is part of the country’s green legacy initiative to combat climate change and environmental degradation.

The main problem of the Awash River basin is land degradation, high population density, natural water degradation salinity, and wetland degradation [29]. This basin is the most important, intensively used, and environmentally vulnerable basin in Ethiopia [27,30–32]. In addition to incorporating anthropogenic and natural changes in existing land degradation, new natural resource management strategies must be designed to address uncertainties associated with land use, land degradation, and climate change [33,34]. Any effort to address and reduce uncertainty in LULC and climate change assessments must support more effective adaptation and mitigation strategies for sustainable natural resource management [35]. A detailed and useful method for developing land-use classification maps is to use GIS and RS geospatial techniques [36]. GIS and RS are used to study LULC variation and mapping [37–40] and predict soil loss in agricultural watersheds [41,42], as well as in urban management [43], fire risk assessment [44], and hydrology and water resources management [45–48]. The cellular automata (CA) model can integrate remote-sensing and geospatial data, quantitative data (driving factors), and socioeconomic data [49]. Furthermore, a Land Change Modeler (LCM)–Markov chain model was applied to parameterize future land change predictions across multiple disciplines in different geographic regions. It has been evaluated and applied to simulate land-use change, and it has also been used in an Eastern Europe post-socialist land-use change model [20,21,50–53], deforestation and forest monitoring [54,55], habitat and biodiversity [56,57], and extensively used in REDD+ project planning [58,59].

Ethiopia has fertile land and great agricultural potential; however, agriculture is still underdeveloped, and poverty persists, especially in rural areas [9]. Let us consider the current research portion of the USAB located within the Awash basin. Several studies have been conducted in the Awash River basin, but less attention has been paid to the assessment of changes in LULC in the study area. Thus, there is insufficient research in the USAB to identify and detect the role of specific types of LULC change and its drivers. In this context, there is an urgent need to estimate changes in LULC timing and predict future scenarios in the study area [60]. Currently, the sub-basin is particularly confronted with rapid population growth, land degradation, agricultural expansion, urbanization, and degradation of natural water bodies. Therefore, the main goal of this study was to analyze LULC dynamics and predict land in 2038 using spatial modeling (Markov chains and cellular automata) in the USAB’s Land Change Modeler [61] by applying GIS and RS. The findings of this study provide useful information for water resource managers and land-use planners to develop sub-basin management strategies and improve future land-use policies within the framework of sustainable water resource management and land-use planning [62]. In addition, the results of this study can be used for future hydrological assessments of sub-catchments, with particular emphasis on surface runoff and river response.

In this study, it was hypothesized that the large changes in the LULC in the upper Awash River are associated with rapid population growth and human activities that meet the food security needs of the rapidly growing population through unplanned and inappropriate natural resource management practices.

2. Materials and Methods

2.1. Description of the Study Area

The Awash River is the second-largest river in Ethiopia and the main source of water for the rift valley in central Ethiopia. The study area is located in the upper part of Awash River basin, between 8°16′ and 9°18′ north latitude and between 37°57′ and 39°17′ east
longitude with altitude varying between 1580 to 3396 m above mean sea level [63]. It lies upstream of the Koka dam and covers a total area of 9510 km², which is considered as the major area where rapid population growth, urbanization, and industrialization expansion take place that force change in the LULC from time to time. The study area shares its boundaries with the rift-valley and upper-valley basins in the south, upper Blue Nile basin in the northwest, Omo Gibe in the west, and middle Awash River sub-basin in the east (Figure 1). The basin received an annual mean rainfall of 1055 mm through the period of 1980–2017. Mean minimum, maximum, and average values of temperatures recorded at the basin during the season were 25.44 °C, 10.16 °C, and 17.80 °C, respectively [64]. Water in the sub-catchment area is mainly domestic water, mainly due to population growth and industrial expansion, and the demand for water has been increasing. Common types of land use in the upper reaches of the Awash River basin are cultivated land, shrubland, grassland, and woodland. Agriculture is the main land use in the study area. The main crops planted in this area are wheat, thrush, corn, sorghum, beans, and soybeans. Onions, tomatoes, and garlic are also some horticultural crops grown along river valleys and lake banks. In addition to growing crops, the livelihoods of communities in this area also depend on raising livestock, including cattle, sheep, goats, and poultry. The sub-basin also consists of different soil types. The predominant soil texture of the investigated area is sandy and silt clay loam. The most common soil types are Cambisols and Vertisols [65].

Figure 1. Study area location in upper Awash River basin of the central rift valley of Ethiopia.

2.2. LULC Data Sources

Modeling of future LULC in the upper Awash River basin was based on baseline LULC data for the sub-basin (1984–2019). To model and evaluate the dynamics of LULC, multi-temporal and spatial data were collected. Digital elevation models (DEMs) and multi-temporal satellite imagery were used to develop future LULC thematic maps of the watershed based on historical LULC change patterns. Remote-sensing and geospatial data are reliable sources for identifying and understanding the dynamic drivers of LULC in any landscape [66]. Multiple cloud-free scenarios were obtained from the Global Land Cover Facility (GLCF) website (https://geog.umd.edu/ (accessed on 13 July 2020)) and the United States Geological Survey (USGS), website (https://earthexplorer.usgs.gov/ (accessed on 13 July 2020)). A basic summary of the multi-temporal satellite data used is shown in Table 1. The spatial resolution (30 × 30 m) of 1984, 2000, and 2019 Landsat imagery was used to create LULC maps and determine changes in the study area. In addition, various ground-truth data, document reviews, aerial photographs, and field observations were collected from the Ethiopian Survey and Mapping Agency (EMA), Ethiopian Ministry of Water and Energy (MoWE), and socioeconomic survey images from the validation satellite Landsat.
Table 1. Historical LULC data of Landsat satellite images used for classification.

| Satellite | Sensor | Path/Row | Date of Acquisition | Resolution (m) | Source |
|-----------|--------|----------|---------------------|----------------|--------|
| Landsat 5 | TM     | 168/054  | 21 November 1984    | 30             | GLCF   |
|           | TM     | 169/054  | 22 November 1984    | 30             | GLCF   |
| Landsat 7 | ETM+   | 168/054  | 5 December 2000     | 30             | GLCF   |
|           | ETM+   | 169/054  | 5 December 2000     | 30             | GLCF   |
| Landsat 8 | OLI    | 168/054  | 16 January 2019     | 30             | USGS   |
|           | OLI    | 169/054  | 7 January 2019      | 30             | USGS   |

2.3. Landsat Data Acquisition

The Landsat TM, ETM+, and OLI images of 1984, 2000, and 2019 were selected, and GIS and IDRISI were used to analyze and process the changes in LULC, as shown in Figure 2. Remote-sensing image data of 1984, 2000, and 2019 were used, and atmospheric correction and radial calibration were performed. Relative geometric corrections were performed on the three images in order to remove geometric distortions caused by the Earth or sensor rotation [67]. Multi-temporal Landsat satellite imagery was used to analyze temporal and spatial changes to understand the dynamics of LULCs in the study area. Satellite imagery is geo-referenced using ground control points (GCPs) and projected using the Universal Transverse Mercator (UTM) system with WGS84 N 37 zones. In this study, false-color composite bands from Landsat images provided better visualization of surface features for further image processing (Figure 2).

Figure 2. Landsat satellite images of the upstream Awash River sub-basin: (a) 1984, (b) 2000, and (c) 2019.

In ArcGIS 10.4 software (Environmental Systems Research Institute (ESRI), Redlands, CA, the image subset setting process was performed using the image masking tool extraction based on the study area. The classification of LULC classes is based on using ground-truth validation data, Google Earth imagery, and visually interpreted detailed topographic maps to delineate and identify sample training locations. By defining a signature file and assigning the number of LULC classes, ArcGIS is used to apply the LULC classification through a supervised classification method (maximum likelihood algorithm), and then the geo-referenced terrain is used to verify that the LULC class map thus defined passes the ground-truth method. Supervised classification technique is more accurate than other existing image classification methods. Furthermore, it is the most commonly used pixel-wise method, which takes into account the spectral information of land-cover classes [68].

2.4. LULC Accuracy Assessments

In the process of image processing, accuracy evaluation is considered an important method for accurate image classification [69,70]. The verification/accuracy assessment of RS data is the final and one of the most essential steps to find the information value of the result data for the end user [40,71]. Using various statistical procedures to evaluate
the accuracy of LULC classification can help understand the confidence of the results and determine whether the research goals have been achieved [40]. In this study, in order to verify the classification accuracy of LULC data in Google Earth, the most usually accepted stratified random point method was used. The accuracy of LULC is evaluated by comparing the classification map based on maximum likelihood classification with different ground-truth verification data. Map accuracy evaluation can be divided into user accuracy, producer accuracy, and overall accuracy and Kappa coefficient. Accuracy evaluation can be derived from various statistical processes of the error matrix, including user accuracy, producer accuracy, and the percentage (%) of the overall accuracy for resolving accidental errors [72]. Producer accuracy refers to the measurable map accuracy, which is used to indicate the probability that the reference pixel as the ground-truth feature is correctly displayed on the classified map or the probability that a certain land cover in a certain area of the ground is classified. The accuracy of the user is a measure of the commission error, which is calculated by dividing the number of correctly classified pixels in each category by the total number of pixels classified in that category. This represents the probability that the pixels classified on the map represent the ground category [73–75]. The accuracy of producers and users is based on the confusion matrix generated for accuracy evaluation using classified maps and ground-truth reference point data sources. The Kappa coefficient is a statistical measure of reliability or consistency between evaluators. It is a discrete multivariate technique used to present map accuracy evaluation research [74,76] and the Kappa statistics computed by the following Equation (1):

$$ K = \frac{N \sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r} (x_{i+} \times x_{+i})}{N^2 - \sum_{i=1}^{r} (x_{i+} \times x_{+i})}, \quad (1) $$

where $K$ is Kappa coefficient, $N$ is the total number of observations, $r$ is the number of rows and columns in the error matrix, $x_{ii}$ is the number of observations in row $i$ and column $i$, and $x_{i+}$ and $x_{+i}$ are the marginal totals of row $i$ and column $i$, respectively [76–78].

The LULC transition matrix: The land-use transition matrix is widely used to evaluate the quantitative altering pattern of the transition of LULC changes particularly for RS and GIS studies [79]. The land-use transition error matrix refers to the LULC change into three stages, for instance, from 1984, 2000, and 2019 in this research. The transition matrix is computed using the following Equation (2) [80].

$$ P = \begin{bmatrix} p_{11} & p_{11} & \cdots & p_{1j} \\ p_{21} & p_{21} & \cdots & p_{2j} \\ \vdots & \vdots & \ddots & \vdots \\ p_{i1} & p_{i2} & \cdots & p_{ij} \end{bmatrix} \quad (2) $$

where $p_{ij}$ specifies the area in transition from landscape $i$ to $j$, and each element in the transition matrix is categorized supposing (1) $p_{ij}$ is non-negative and (2) $\sum_{j=1}^{n} p_{ij} = 1$.

2.5. LULC Change Detection

The area of the classified LULC map is calculated in square kilometers ($km^2$) and quantifies the change between each prescribed period. In addition, the absolute and relative changes of the classified LULC class are calculated by considering the difference between two consecutive LULC maps. The LULC change matrices between each prescribed period were developed to understand the temporal and spatial changes of LULC classes. In addition, the rate of change of LULC over time ($km^2$/year) is calculated by dividing the area difference between the two time periods by the length of the year. Furthermore, the following Equation (3) is used to estimate the relative change in the LULC categories classified between each successive period:

$$ \text{Percent of change} (X\%) = \left( \frac{X_2 - X_1}{X_1} \right) \times 100, \quad (3) $$
Rate of change ha/year = \( \frac{(X_2 - X_1)}{X_3} \) \( \tag{4} \)

where \( X(\%) \) is a relative change of LULC classes between earlier period \( X_1 \) and later period \( X_2 \) in km\(^2\), and \( X_3 \) is a time interval between \( X_2 \) and \( X_1 \). The positive values imply an increase in area coverage of LULC class whereas the negative values indicate a decrease in area extent.

This research adopted the post-classification change detection technology implemented in ArcGIS 10.4. The method framework for LULC classification and change detection is shown in Figure 3.

**Figure 3.** Methodological framework for LULC classification and change detection.

### 2.6. Prediction of Future Land Use/Land Cover

Long-term (2038)-scale changes in the LULC categories of the watershed were predicted based on the historical changes of the watershed from 1984 to 2019. To simulate future watershed LULC maps, the Land Change Modeler (LCM) module in IDRISI was used. TerrSet (formerly IDRISI) is an integrated remote-sensing software and geographic information system (GIS) developed by the Clark Laboratory at Clark University for the display and analysis of digital geospatial information [81]. We used LCM networks for predicting future LULC maps using Markov chains (MCs) and multilayer perceptron neural networks (MLPNNs) to determine historical transitions of LULCs developing in the basin from multi-temporal Landsat imagery. Based on past historical conversion potential, MC quantifies the LULC categories that are likely to transition from \( t_2 \) to the expected forecast period \( t_3 \). The simulation process for future LULC classes is based on a transition probability matrix that shows the probability of each LULC class transitioning to other LULC classes. Let \( Y_1 \) and \( Y_2 \) be the states of the LULC classes at period \( t_1 \) and \( t_2 \) be the change matrix with elements \( T_{ij} \) (ith row and jth column) which shows the transition \( Y_1 \) to \( Y_2 \) during \( t_1 \) and \( t_2 \) [82]. Then, the transition probability matrix can be obtained as:

\[
\text{Transition probability matrix} = \frac{T_{ij}}{\sum T_{ij}} \tag{5}
\]
If $t_3$ is an even multiple of the time duration between $t_1$ and $t_2$, then the transition probability matrix for $t_3$ can be found by powering the past transition probability matrix. If $t_3$ is not an even multiple of the periods between $t_1$ and $t_2$, the transition probability matrix can be obtained by the interpolation technique [82].

The simulated LULC map can be used to quantify and visualize future LULC classes in the basin. The ability of LCM to predict future LULC maps in the study area was validated by both 2019 forecasts and historical LULC maps. The disagreement between the predicted and historical LULC maps was measured in terms of two parameters, viz., allocation disagreement and quantity disagreement [83]. Quantity difference calculates the area difference of LULC categories in historical and forecast LULC maps. The spatiotemporal allocation differences of the LULC classes were measured by using the parameter allocation divergence. The quantity and spatial disagreement space vary within [0, 1]. The sum of allocation disagreement and the spatial disagreement signifies the overall disagreement of the predicted LULC maps with the historical maps [82].

2.7. CA–Markov Model Approach

The Land Change Modeler (LCM) was built as an empirical parametric land-change prediction tool to support a wide range of planning activities [84]. In this study, the CA–Markov model in IDRISI was used to simulate future LULC in the upper Awash River basin. CA–Markov is one of the best tools for predicting future changes in land-use parameters [85]. The CA–Markov model combines Markov chains and cellular automata to predict trends and characteristics of LULC over time [86]. Furthermore, CA–Markov is one of the design support tools to analyze the spatial distribution and temporal variation of LULC [87]. In addition, the model is widely used to describe LULC dynamics, urban sprawl, plant growth, watershed management, and forest-cover modeling. Based on the analysis of historical LULC changes, this model develops an empirical model of the association between LULC transitions and a set of explanatory variables [62,86].

Markov chains have good statistical power to predict change probabilities, and cellular automata are considered to be a powerful method for reading spatial patterns of change [88–91]. The Markov chain model refers to the change of LULC from one time to another to predict future changes [91,92]. The prediction of land-use changes can be obtained as:

$$ S(t, t + 1) = P_{ij} \times S(t) $$

(6)

where $S(t)$ is the system status at the time of $t$, $S(t + 1)$ is the system status at the time of $t + 1$, and $P_{ij}$ is the transition probability matrix [80,92]. The methodological framework applied for the CA–Markov model is shown in Figure 4.

Transition suitability maps for each LULC category are derived using a series of factors and constraints. This is done through an expert’s understanding of the interactions and effects of factors and a LULC-based multi-criteria analysis (MCA) [91]. Constraints, represented in the form of Boolean images, are criteria (0 to 1) that limit the variation of LULC, with a value of “1” representing the area suitable for suitability analysis, and “0” representing the area that controls the suitability analysis (e.g., water bodies) [62]. In contrast, the factor is usually a distance criterion that provides a degree of applicability to regional variation [93], for instance, distance to rivers, urban areas, or roads [62,94–96]. Other factors include elevation (which is a good predictor of agricultural areas) and slope, which determine the usefulness of land to humans [49]. The constraints and factors used in this study are shown in Figure 5.
Figure 4. CA–Markov model framework for LULC changes simulation.

Figure 5. Factor and constraint maps—elevation (a); slope (b); roads (c); distance to rivers (d); distance to urban areas (e); distance to roads (f).

2.8. Model Calibration and Simulation

The scenario-driven CA–Markov model method was adopted and then calibrated and verified to simulate future LULC changes. Based on the Markov cellular automata model, the LULC changes were simulated under two different historical business-as-usual (BAU) scenarios. The images of 1984 and 2000 were used for the calibration and optimization of the Markov chain algorithm, and the images of 2019 were used to verify CA–Markov’s predictions [97]. The LULC change between two time periods \( t_1 \) and \( t_2 \) was modeled using real-land-cover maps to predict the land-cover map at \( t_3 \) and verify the model. We checked
the simulated land-cover map ($t_3$) against the real map [98]. In addition, the land-cover map in 1984 is the earliest image ($t_1$), and the latest land-cover map in 2000 ($t_2$) was used to simulate the projection map of 2019 ($t_3$) and was checked against the real map in 2019. Compare the simulated LULC map with the actual map to verify the accuracy of the model. In order to predict the LULC maps in 2019 and 2038, the transition probability matrices for 1984–2000, 2000–2019, and 1984–2019 were calculated. The Markov and CA–Markov models were used to predict the LULC map in 2038.

2.9. CA–Markov Model Validation

Model validation is the main part of the CA–Markov model. It consists of test models on data not used to build the model [2]. The predicted LULC is considered consistent only when it is validated using existing ground data sets. Using the CA–Markov model and the verification model in the cellular automata, two LULC raster’s were verified; the first was the actual LULC in 2019, and the second raster was predicted. The same process was applied when predicting the LULC map in 2038, but in this case, the iterations were given in order for the time difference between 1984 and 2000. In this study, the accuracy of the CA–Markov model was evaluated using Kappa statistics, including Kappa location ($K_{\text{location}}$), Kappa standard ($K_{\text{standard}}$), and Kappa for no information ($K_{\text{no}}$) [95,99], and Equations (7)–(9) [100] were used to calculate them. The level of the Kappa index is usually between 0 and 1. Therefore, the consistency level $r$ of the Kappa index is as follows: $K < 0.5$ indicates a rare agreement; $0.5 < K < 0.75$ indicates a moderate level of agreement; $0.75 < K < 1$ indicates a high degree of agreement; and $K = 1$ indicates complete agreement [99,101]. We used the “validate” module to compare the 2019 classified LULC with the 2019 simulated LULC. Under acceptable Kappa statistics, the CA–Markov model is suitable for simulating the future LULC map in 2038, using the transition probability from 2000 to 2019 and the classification map in 2019 as the base map.

\[
K_{\text{no}} = \frac{M_{m}N_{n}}{P_{p} - N_{n}} \tag{7}
\]

\[
K_{\text{location}} = \frac{M_{m}N_{m}}{P_{m} - N_{m}} \tag{8}
\]

\[
K_{\text{standard}} = \frac{M_{m}N_{n}}{P_{p} - N_{m}} \tag{9}
\]

where $N_{n}$ is no information; $M_{m}$, $N_{m}$, and $P_{m}$ are medium grid-cell level information; and $P_{p}$ is perfect grid-cell level information across the landscape. However, when compared with the actual classification raster and the LULC prediction raster, the Kappa statistics give the degree of agreement between the raster and its probability.

2.10. Investigating the Drivers and Consequences of LULC Changes

In addition to remote-sensing data, sub-basin socio-economic data were collected and analyzed through key informant interviews, household surveys, and focus group discussions (FGDs) to verify the accuracy of the classification of LULC and further understand the possible main driving forces and consequences of watershed land use change. In this study, the multi-stage sampling method was used to select kebeles purposefully first because they represent three agro-ecological regions (Dega, Weyina Dega, and Kolla). FGD was made up of groups of elders, community leaders, women, and youth, who deliberately chose to participate in discussions to provide information related to current and past changes in LULC and to support the reliability of the survey. The socio-economic characteristics of the interviewees are shown in Table 2.
We used a questionnaire with semi-structured questions to assess the local community’s perception of LULC changes, their driving forces, and consequences. This study identified a total of 1800 households and determined a sample size of 10%, with 95% confidence and 10% accuracy. Therefore, a total of 180 sample households were selected from the list using the systematic random sampling technique [102]. Of the 180 households included in the sample, 80% were men, and the remaining 20% were women. The age of the head of the household interviewed was between 25 and 75 years old. In this study, the community’s perception of the driving force of LULC changes focused on socio-economic characteristics, the reasons for LULC changes, and the impact of LULC changes requiring households to use “agree”, “disagree”, and “uncertainty”, as well as “increase”, “decrease”, and “change”, to assess the level of family perception. The interviewees were asked to explain how they viewed the LULC changes in the sub-catchment during the different time periods evaluated. In addition, qualitative data collection methods (personal observations, focus group discussions, and key informant interviews) were used to collect data on the local residents’ views on the proximate and root causes of changes in LULC in their area. Finally, the main driving force, consequences, and direction of the LULC change were determined.

3. Results
3.1. Land Use/Land Cover (LULC) Classification

The maximum likelihood classification algorithm in IDRISI17.02 was used for supervised classification, and the spatiotemporal pattern of LULCs in the sub-watershed was assessed. According to the LULC classification system of the Food and Agriculture Organization [103], six main types of LULC (agricultural land, forest, shrubland, grassland, water body, and urban) were identified. From 1984 to 2019, the supervised classification method (maximum likelihood algorithm) LULC classification analysis showed that the study area covered various land features (agricultural land, shrubs, forests, grassland, cities, and water bodies). Agricultural land refers to the area of cultivated land used to grow various crops such as corn, sorghum, teff grass, beans, barley, millet, and wheat. Shrubland types include...
dwarf tree species; sparsely located forest and multi-stem woody vegetation are considered as shrubland. Forest is a large area of land, covered with trees and plants, which have a closed canopy cover and appear greener throughout the year. Grassland is mainly composed of grassland, wetland, and non-herbous plants. Urban refers to built-up areas that include residential cities, towns, suburbs, commercial, industrial, transportation, and roads. Water bodies are areas covered by rivers, reservoirs, lakes, dams/ponds, streams, and seasonal waterlog areas. The obtained LULC maps for the three time periods of 1984, 2000, and 2019 are shown in Figure 6. The LULC classification map shows that the total land area of the upper reaches of the Awash River is 9510 km$^2$, and the individual area coverage in 1984, 2000, and 2019 is shown in Table 3. The results show that agricultural land accounted for the largest share in 1984, 2000, and 2019, with 51.86% (4934.17 km$^2$), 60.79% (5784.05 km$^2$), and 84.07% (7999.88 km$^2$), respectively, of the total LULC class allocated. The second-largest share in the study area is shrubland. In 1984, 2000, and 2019, this category accounted for 34.32% (3265.41 km$^2$), 32.22% (3065.54 km$^2$), and 10.79% (1026.79 km$^2$), respectively. Small areas were covered by urban land with 0.26% (24.32 km$^2$) in 1984, water with 0.38% (36.49 km$^2$) in 2000, and water with 0.23% (21.51 km$^2$) in 2019 of the total sub-basin areas. In 1984, 7.31% (695.11 km$^2$) of the area was covered by forest which decreased to 2.58% (245.59 km$^2$) in 2000 and substantially decreased to 0.82% (78.25 km$^2$) in 2019.

Figure 6. The spatial LULC change of study area in the years (a) 1984, (b) 2000, and (c) 2019.

Table 3. Area statistics and percentage of the LULC in (1984–2019).

| LULC Class | 1984 (km$^2$) | Area (%) | 2000 (km$^2$) | Area (%) | 2019 (km$^2$) | Area (%) |
|------------|--------------|----------|---------------|----------|---------------|----------|
| Agriculture| 4934.17      | 51.86    | 5784.05       | 60.79    | 7999.88       | 84.07    |
| Shrubland  | 3265.41      | 34.32    | 3065.54       | 32.22    | 1026.79       | 10.79    |
| Forest     | 695.11       | 7.31     | 245.59        | 2.58     | 78.25         | 0.82     |
| Grassland  | 533.84       | 5.61     | 280.50        | 2.95     | 225.71        | 2.37     |
| Water      | 62.36        | 0.66     | 36.49         | 0.38     | 21.51         | 0.23     |
| Urban      | 24.32        | 0.26     | 103.06        | 1.08     | 163.08        | 1.71     |

3.2. Accuracy Assessment

The accuracy evaluation of the classified LULC map, especially the producer accuracy, user accuracy, overall accuracy, and Kappa coefficient, were derived from the statistical process of the error matrix. Table 4 shows the LULC map accuracy evaluation results in the three periods of 1984, 2000, and 2019. The overall map accuracy of using the error (confusion matrix) is 85%, 88%, and 90%, respectively. We calculated the Kappa coefficient of the LULC map for each category to measure the accuracy and confidence of the results. The Kappa index of the LULC classification map results in the three periods was 0.77, 0.79, and 0.89, respectively. This showed quite good overall accuracy and was accepted for subsequent change and detection analysis [104].
Table 4. The LULC maps accuracy assessment for 1984, 2000, and 2019 time periods.

| LULC Classes | LULC 1984 | LULC 2000 | LULC 2019 |
|--------------|-----------|-----------|-----------|
|              | UA        | PA        | UA        | PA        | UA        | PA        |
| Agriculture  | 84.94     | 89.04     | 86.92     | 94.06     | 86.92     | 95.34     |
| Shrubland    | 82.01     | 88.07     | 87.25     | 89.00     | 87.25     | 93.64     |
| Forest       | 86.07     | 77.78     | 87.63     | 75.89     | 87.63     | 80.61     |
| Grassland    | 83.02     | 73.33     | 84.75     | 71.43     | 84.75     | 70.49     |
| Water        | 94.2      | 95.59     | 88.37     | 97.44     | 88.37     | 88.46     |
| Urban        | 90        | 94.74     | 95.89     | 95.89     | 95.89     | 95.31     |
| Overall accuracy | 85.23 | 87.94 | 90.12 |
| Kappa coefficient | 0.77 | 0.79 | 0.89 |

3.3. CA–Markov Model Validation

The LULC changes along the upper reaches of the Awash River are not uniform. In order to be able to use the CA–Markov model to simulate the future LULC in the upper reaches of the Awash River and validate the ability of the model, we first used the transition probabilities and the transition area between the LULCs of 1984–2019 to simulate the LULC in 2019 (Figure 7). Kappa variables were used to compare simulated and classified LULC in 2019. The simulation shows that the Kappa variation evaluation is as follows: 0.76 for \(K_{no}\), 0.88 for \(K_{location}\), and 0.78 for \(K_{standard}\), showing a high level of agreement. This shows the strength and reliability of the model in simulating future LULC changes in the upper reaches of the Awash River. In addition, visual analysis shows that the LULC category in the 2019 simulated LULC is more consistent with the 2019 classified LULC category. The calculated LULC change differences between the classified LULC and the simulated LULC in 2019 are shown in Table 5. The results show that the shrubland and urban areas were seriously overestimated, while the agricultural and grassland classification showed slightly lower results than the simulation. The calculated difference between the classified and simulated LULC shows that the agricultural, grassland, and water body categories are underestimated by approximately 28.06%, 26.65%, and 7.06%, respectively. On the other hand, the CA–Markov model proved to overestimate LULC categories, such as shrubland (222.23%), forest (23.50%), and urban (4.89%).

![Figure 7. The classified and simulated LULC maps for 2019.](image-url)
Table 5. The calculated LULC changes between the classified and simulated LULCs for 2019.

| Classified LULC 2019 (km$^2$) | Classified LULC 2019 (km$^2$) | LULC Differences (km$^2$) | LULC Differences (%) |
|--------------------------------|--------------------------------|--------------------------|----------------------|
| Agriculture                    | 7996.18                        | 5752.20                  | -2243.98             | -28.06               |
| Forest                         | 78.14                          | 96.51                    | 18.36                | 23.50                |
| Grassland                      | 225.43                         | 165.35                   | -60.08               | -26.65               |
| Shrubland                      | 1025.64                        | 3304.88                  | 2279.25              | 222.23               |
| Water                          | 21.50                          | 19.98                    | -1.52                | -7.06                |
| Urban                          | 163.08                         | 171.05                   | 7.97                 | 4.89                 |
| Total                          | 9509.97                        | 9509.97                  |                      |                     |

3.4. LULC Changes and Markov Probability Transition Matrices

This study identified six LULC categories in 1984, 2000, and 2019, namely, agricultural land, forest, grassland, shrubland, water body, and urban. The area and relative change of the LULC category on the temporal scale are shown in Figure 8a,b. Temporal analysis of the LULC map of the basin shows that the accelerated development activities implemented have led to a complex and violent LULC transition.

In 2019, agricultural land accounted for the largest proportion, with 84.05% in the upper Awash River basin. LULC changes, as can be seen from Figure 8b, in the agricultural area increased significantly from 1984 to 2000 (17.22%) and from 2000 to 2019 (38.31%). The results show that the urban area, including housing, transportation, and public buildings, increased by 570.5% from 1984 to 2019, and agricultural land increased by 62%. Significant changes have taken place in the urban category. From 1984 to 2000, the urban LULC category increased by 323.73% (78.74 km$^2$) and 58.23% (60 km$^2$), respectively. Water bodies
accounted for 0.26% of the total area in 1984, but the water area decreased by 41.52% between 1984 and 2000 and 41.03% from 2000 to 2019; on the other hand, it decreased by 65.51% from 1984 to 2019. Another LULC category that faced deterioration during the study period was forest and grassland areas. In 1984, 7.31% of the total area was covered by forest; however, the forest area decreased by 64.67% between 1984 and 2000 and 68.14% between 2000 and 2019. The change in the grassland class was not as significant compared to other LULC classes. It was decreased during the study periods, and the share in the total area was 0.66% (533.84 km$^2$), 2.95% (280.50 km$^2$), and 2.37% (225.71 km$^2$) in 1984, 2000, and 2019, respectively. From 1984 to 2000, it decreased by 47.46%, and from 2000 to 2019, it decreased by 19.53%. In general, it is worth noting that in the past 36 years, nearly 68.56%, 88.74%, and 57.72% of shrubland, forest, and grassland have been converted into agricultural land and urban areas, respectively.

The post-classification change matrix comparison technique clearly shows the area that has undergone a transition from one LULC class to another LULC class between $t_1$ and $t_2$. Table 6 shows the Markov transition probabilities for the period 1984–2038, showing each category in the LULC map within that period (for example, 1984–2000, 2019–2019, and 2019–2038). That is, a given LULC category may change from one LULC category to any other category at any given time [62]. The LULC change matrix represents the transition between each LULC category during the time intervals $t_1$ and $t_2$ [49]. The change matrix in the vertical column is the area lost from one particular LULC class to another during $t_1$ and $t_2$ [105]. The area under each LULC class is represented by a diagonal line, and the area under each LULC class is the sum of the elements in the row at $t_1$. The values on the diagonal represent the transition probability matrix of each land-use category that remains unchanged from time 0 to time 1 [106]. For instance, urban and agricultural land categories are highly resistant to changes in other categories, and the probability of remaining unchanged during 1984–2000, 2000–2019, and 2019–2038 is more than 70%. Between 2019 and 2038, the highest percentage (>85%) of the urban category that remains unchanged is observed. Classifications such as shrubland and grassland also show resistance, and more than 51% of the classifications may remain unchanged in the next period, while other classifications show less resistance, and thus they are more likely to change to other LULC classes in the following period. These include forests, grasslands, and water bodies, of which less than 38% and less than 60% remain unchanged for a period of time. On the contrary, the water body category showed a low probability and a high probability of remaining unchanged during the 36-year period, and more than 60% of the category remained unchanged during the period 1984–2000. Compared to showing persistence, the Markov transition probability matrix shows how each LULC class becomes another class [62]. For example, during the period 2019–2038, 45% of the water body category may be changed to the agricultural category. In addition, between 2000–2019 and 1984–2000, approximately 39% of grassland and 40% of shrubland are likely to be converted to agricultural land, which indicates that they are less likely to continue to exist during these periods.
Table 6. Markov probability transition matrices for 1984–2000, 2000–2019, and 2019–2035 LULCs in the upper stream of the Awash River basin.

| Transition Years | Agriculture | Forest | Grassland | Shrubland | Water | Urban |
|------------------|-------------|--------|-----------|-----------|-------|-------|
| 1984–2000        | 0.7345      | 0.0021 | 0.0147    | 0.0534    | 0.0007| 0.1945|
| 2000–2019        | 0.7587      | 0.0008 | 0.0299    | 0.0492    | 0.0011| 0.1602|
| 2019–2038        | 0.7050      | 0.0004 | 0.0115    | 0.0560    | 0.0002| 0.2268|
| 1984–2000        | 0.3078      | 0.5070 | 0.0508    | 0.1310    | 0.0014| 0.0020|
| 2000–2019        | 0.2598      | 0.4276 | 0.0128    | 0.2940    | 0.0001| 0.0057|
| 2019–2038        | 0.2805      | 0.4448 | 0.0180    | 0.2518    | 0.0007| 0.0042|
| 1984–2000        | 0.3665      | 0.0264 | 0.5563    | 0.0480    | 0.0005| 0.0023|
| 2000–2019        | 0.3901      | 0.0043 | 0.5053    | 0.0964    | 0.0002| 0.0037|
| 2019–2038        | 0.3597      | 0.0039 | 0.5426    | 0.0888    | 0.0002| 0.0047|
| 1984–2000        | 0.3952      | 0.0125 | 0.0216    | 0.5470    | 0.0013| 0.0225|
| 2000–2019        | 0.2482      | 0.0033 | 0.0211    | 0.7102    | 0.0013| 0.0160|
| 2019–2038        | 0.3464      | 0.0023 | 0.0193    | 0.6108    | 0.0006| 0.0206|
| 1984–2000        | 0.2675      | 0.0045 | 0.0105    | 0.1070    | 0.0013| 0.0225|
| 2000–2019        | 0.3859      | 0.0016 | 0.0032    | 0.0429    | 0.0002| 0.0037|
| 2019–2038        | 0.4490      | 0.0006 | 0.0090    | 0.1720    | 0.0074| 0.0000|
| 1984–2000        | 0.0468      | 0.0003 | 0.0012    | 0.1566    | 0.0006| 0.7886|
| 2000–2019        | 0.0740      | 0.0000 | 0.0016    | 0.0829    | 0.0000| 0.8414|
| 2019–2038        | 0.0497      | 0.0000 | 0.0000    | 0.0910    | 0.0048| 0.8546|

3.5. Simulation of Future LULC Dynamics

Using the 2019 LULC as the base map, the transition suitability images and Markov transition probabilities generated from 2000 to 2019 simulated the LULC changes in the upper reaches of the Awash River basin in 2038, and the results are shown in Figure 9. Table 7 shows the dynamics of LULC changes in the spatiotemporal and area from 2019 to 2038. The results of the LULC change show that in 2019, 84% of the total land area of the sub-watershed was agricultural land, and it is expected to reach 78% by 2038. It is estimated that the level of shrubland will increase from 1025.64 km$^2$ (10.78%) in 2019 to 1524.54 km$^2$ (16.03%) in 2038. Similarly, the percentage of urban land is expected to double, intensifying from 163.08 km$^2$ (1.71%) in 2019 to 341.11 km$^2$ (3.59%) in 2038. The analysis results further indicate that the classification of agricultural land, forests, grasslands, and water bodies is expected to decrease in the next three decades. In particular, forest areal coverage will decrease by 59.79 km$^2$ (76.52%), and water bodies will decrease by 10.97 km$^2$ (51%). Similarly, grassland and agriculture have decreased by approximately 571.33 km$^2$ (7.14%) and 34.76 km$^2$ (15.42%), respectively.

Table 7. The LULC changes distribution from 2019–2038.

| LULC Type | 2019      | 2038      | LULC Changes (2019–2038) |
|-----------|-----------|-----------|--------------------------|
| Agriculture | 7996.18   | 7424.86   | -571.33 (−7.14)          |
| Forest    | 78.14     | 18.35     | -59.79 (−76.52)          |
| Grassland | 225.43    | 190.67    | -34.76 (−15.42)          |
| Shrubland | 1025.64   | 1524.54   | 489.91 (48.64)           |
| Water     | 21.50     | 10.53     | -10.97 (−51.01)          |
| Urban     | 163.08    | 341.11    | 178.03 (109.17)          |

Table 7. The LULC changes distribution from 2019–2038.
Figure 9. LULC distribution in the upper stream of the Awash River basin for classified 2019 and simulated 2038.

3.6. Driving Forces of LULC Changes in the Upper Stream of the Awash River Basin

LULC dynamic analysis uses the views of local communities to accompany the interpretation of remote-sensing data. The results of key informant interviews, household surveys, focus group discussions, and field observations show that both natural processes and man-made LULC have changed. From a series of different driving factors, interviewees believe that nine activities related to natural and man-made processes are the main driving factors of LULC changes in the study area (Table 8). Therefore, more than 87.8% of the interviewees stated that the rapid growth of population pressure is one of the main driving forces for changes in the LULC in the study area. Similarly, approximately 92.8%, 67.8%, 70.0%, 80.6%, and 85.6% of the respondents argued that increasing agricultural activities, reduction of soil fertility, use of trees for firewood, charcoal, and construction, wood extraction, and settlement and urban expansion, respectively, were some of the perceived environmental consequences that caused LULC changes. Therefore, the driving force of LULC change in the sub-watershed is essentially related to human influence. Thus, the driving forces of LULC changes in the sub-basin are essentially linked to human-induced influences. The results show that between 1984 and 2019, the area of agricultural land and urban/built-up areas gradually increased, while forests, shrubs, and grasslands decreased. It is supposed that the impact of human activities such as forest clearing for agriculture and demand for house construction and firewood had a greater contribution to LULC changes in the socio-economic context of Ethiopia [102]. As shown in Table 8, 73.9% of the respondents indicated that overgrazing (livestock pressure) and the advantages of free-grazing systems are the main driving forces of LULC change and land degradation. In addition, 83.3% of the interviewees believe that the increases in drought and climate change are other factors leading to changes in LULC.

Changes in LULC were determined by local communities, and their responses are shown in Table 9. The perception of changes in LULC highlights that a large number of interviewees are aware of the long-term dynamic process and driving forces of LULC and its influence over the past three decades. Perception results confirm that 86.7% and 90.6% of the respondents believe that the area of farmland and urban land has increased since the 1980s. On the other hand, the respondents believe that the areas of forest (84.4%), shrubs (81.1%), grassland (69.4%), water bodies (78.9%), swamps (88.3%), and grassland (69.4%) have declined in the upper Awash River sub-basin. Thus, the indigenous knowledge perceived from the local interviewees confirmed the LULC change information extracted from the interpretation of the remote-sensing data set.

Therefore, understanding the causes and consequences of land-use changes is crucial for scholars, decision makers, and water and land managers, as it helps to take appropriate actions for future water management.
Table 8. The main driving forces of LULC changes in the upper Awash River sub-basin according to the local land users’ perception.

| Drivers of LULC Changes                                      | Agree | Disagree | Uncertain |
|---------------------------------------------------------------|-------|----------|-----------|
| No. | %   | No. | %   | No. | %   |
| Agricultural activities                                      | 167   | 92.8   | 7   | 3.9 | 6   | 3.3 |
| Population growth                                            | 158   | 87.8   | 13  | 7.2 | 9   | 5   |
| Use of trees for firewood, charcoal, and construction         | 154   | 85.6   | 19  | 10.6| 7   | 3.9 |
| Drought and climate variability                              | 150   | 83.3   | 24  | 13.3| 6   | 3.3 |
| Settlement and urban expansion                               | 145   | 80.6   | 13  | 11.7| 14  | 7.8 |
| Overgrazing (livestock pressure)                             | 133   | 73.9   | 16  | 8.9 | 31  | 17.2|
| Wood extraction                                              | 126   | 70     | 22  | 12.2| 32  | 17.8|
| Reduction of soil fertility                                  | 122   | 67.8   | 46  | 25.6| 12  | 6.7 |
| Road and market accessibility                                 | 118   | 65.8   | 37  | 20.6| 25  | 13.9|

Table 9. Perceived LULC changes over the past three decades in the upper Awash River sub-basin.

| LULC            | Increased | Decreased | Unchanged |
|-----------------|-----------|-----------|-----------|
| No. | %   | No. | %   | No. | %   |
| Farmland        | 156       | 86.7   | 18  | 8.9  | 8   | 4.4 |
| Forest          | 19        | 10.5   | 152 | 84.4 | 9   | 5.0 |
| Shrubland       | 27        | 15.0   | 146 | 81.1 | 7   | 3.9 |
| Grassland       | 34        | 18.9   | 125 | 69.4 | 21  | 11.7|
| Urban Land      | 163       | 90.6   | 14  | 7.8  | 3   | 1.8 |
| Plantations     | 136       | 75.6   | 29  | 16.1 | 15  | 8.3 |
| Marshy area     | 4         | 2.2    | 159 | 88.3 | 18  | 9.4 |
| Irrigated Land  | 128       | 71.1   | 39  | 21.7 | 13  | 7.2 |
| Bare land       | 104       | 57.8   | 67  | 37.2 | 9   | 5.0 |
| Water bodies    | 26        | 14.4   | 142 | 78.9 | 12  | 6.7 |

4. Discussion

4.1. Validation of CA–Markov Model

The CA–Markov model was used to simulate the future LULC in the upper reaches of the Awash River basin. Model verification was conducted by comparing the classified and simulated LULC in 2019 to test the performance of the model in simulating future LULC changes. It is observed that the Kappa index estimate is between 0.76 and 0.88, which represents a high level of consistency [83,99] and the applicability of CA–Markov, which can accurately simulate the future LULC of the upstream Awash River watershed. However, the CA–Markov model proved to overestimate shrubland and urban areas while underestimating the LULC categories of agricultural land, forests, grasslands, and water bodies. Several researchers reported an acceptable CA–Markov model Kappa index [65,67–114]. Therefore, the CA–Markov model simulation is suitable for accurately predicting future changes in LULC in the upper reaches of the Awash River basin.

4.2. LULC Changes Observed from 1984 to 2019

The temporal LULC maps of the USAB were obtained by supervising maximum likelihood classification. The generated map helps to identify the dynamic pattern of visual LULC changes and quantify current and future changes. The study area sub-basin was categorized into six LULC classes, namely, agriculture land, forest, grassland, shrubland, water bodies, and urban. From the results of the above-mentioned LULC changes, it can be found that agriculture and urban areas have undergone great changes from time to time. The total area of urban and agricultural land from 1984 to 2019 was 3065.72 and 138.76 km², respectively. Therefore, about 80–85% of Ethiopians are engaged in
agriculture, mainly in self-sufficient and rain-fed agriculture and livestock production, and the country’s agricultural land has increased [11,107]. The results show that during 1984–2019, agricultural area and urbanization increased significantly at the expense of other LULC types. From the results, it was found that agricultural land is the predominant land type of the sub-basin. In the past 36 years, the total area of forest cleared between 1984 and 2019 reached 616.85 km². This means that about 88.7% of the existing forest coverage in 1984 was cleared. The largest expansion of agriculture and urbanization occurred between 1984 and 2019 and is estimated to be 62% and 570%, respectively. The results of the study show that the area of shrubland has dropped from −6% in 1984 to −68.6% in 2019. Similarly, grassland dropped from −47.5% in 1984 to −57.7% in 2019, and water bodies dropped from 41.5% in 1984 to 65.5% in 2019. It was found that the main driving forces of this transition were rapid population growth and urbanization, which led to deforestation, rainfall shortages, and farmland, which in turn exacerbated food security issues. The ever-increasing population has been driving the increase of agricultural land nationwide [5].

From 1984 to 2019, the drastic changes in the watershed were the expansion of agriculture and urbanization and the shrinking of forests, shrubs, grasslands, and water bodies. This shows that agriculture is expanding on a large scale. In Ethiopia, population growth has led to agricultural expansion, urbanization, and overgrazing; LULC has undergone tremendous changes in the past few decades [50,51,108–110]. Similarly, in the past 36 years, the LULC of this sub-basin has undergone major changes. The results show that between 1984 and 2019, the urban area increased significantly. This shows that the LULC of the urban area category has undergone tremendous changes, exerting incredible pressure on non-urban areas, especially agricultural land. Through the construction of residential units, industrial and commercial units, road networks, sidewalks, ports and leisure facilities, and other impervious surfaces, the rapid expansion of urban areas has led to the continuous expansion of building surfaces in different corners of the city [36].

The change detection results show that the extent of LULC changes that occurred in shrubs, forests, and grasslands was concentrated in agricultural land. These changes indicate that the intensification of agricultural land is the result of population growth. Rapid population growth, human migration to urban areas, and detailed agricultural farming systems are the main drivers of changes in agricultural land use in the entire sub-catchment [16,38,115–119].

Changes in land use from non-urban to urban or from forest to agricultural land have resulted in the loss of land cover for many different types of vegetation. The most serious consequence of changing land use through urbanization and agriculture expansion is the reduction of natural and expansion of agricultural land and the increase of hard surfaces in built-up areas [111]. This leads to soil erosion and loss of soil biodiversity, which leads to a decline in soil fertility, which in turn reduces agricultural productivity [112]. Changes in LULC are driven by human actions, which in turn drive changes that change the availability of human and livestock products and services [113].

4.3. Future LULC Changes for 2038

It is expected that the LULC in the upper reaches of the Awash River basin will continue to change, and the reduction and expansion of different LULC classifications may have an impact on the environment, mainly water resources. It is expected that by 2038, the types of shrubland and urban land will expand, while the types of agricultural land, forest land, grassland, and water bodies are expected to decrease. Agricultural land will be reduced and transformed into industries and urban areas if the current rate of industrialization and urbanization continues, which will have an impact on the water resources and environmental integrity of the sub-basin [67,116–124]. In addition, from 2019 to 2038, urban and shrubland are expected to increase significantly to 109% and 49%, respectively. The growth of urban areas in the sub-watershed is a sign of population growth, mainly
from rural to urban migration to Addis Ababa, because settlements in nearby towns and cities tend to promote urbanization, which is also observed in some countries [16,114–117].

LULC losses are mainly due to the expansion of agriculture and urban areas. It is observed that the types of water bodies in the upper reaches of the Awash River basin are decreasing [60]. Changes in the water level of the sub-basin have been observed, and it is reported that the Koka dam has decreased water levels, which has exacerbated the shortage of hydropower and irrigation water supply in the surrounding communities [118,119]. Thus, LULC changes in the upper stream of the Awash River basin may disturb water resources such as runoff and streamflow [120] and could reduce the dam water levels [32]. As the population increases and LULC is expected to change in the next few decades, this sub-basin will face a high demand for water resources. Thus, there is a need for well-organized and environmentally friendly industrialization and urbanization planning in both rural and urban areas.

4.4. Driving Forces of LULC Changes

As shown by the remote-sensing LULC change analysis, in the past 36 years (1984–2019), agricultural land and urban land in the upper reaches of the Awash River basin have increased significantly. Similarly, a large number of respondents believe that the main reasons for the changes in LULC are human disturbances mainly due to agricultural expansion (92.8%) and population growth (87.8%). Thus, the direction of LULC changes perceived by the respondents was consistent with the result obtained from remote-sensing image interpretation [121]. The driving force of LULC changes in the basin is essentially related to man-made influences. The results show that between 1984 and 2019, the area of agricultural land and urban/built-up areas gradually increased, while forests, shrubs, and grasslands decreased. Population growth has led to a substantial increase in the demand for food and the expansion of agricultural land by affecting the area of uncultivated forest land. It is speculated that in the socio-economic context of Ethiopia, the impact of human activities, such as agricultural deforestation and the demand for firewood and housing construction, will make a greater contribution to the changes in LULC.

Understanding the patterns and driving factors of LULC change is essential for the rational and specific planning of sustainable land management [122]. LULC is a complex and dynamic process that can be caused by many cooperative processes ranging from various natural factors to socio-economic dynamics [123]. Due to different driving factors, major LULC changes occurred in the study area (reduction of grassland, expansion of farmland and settlements, expansion of degraded land, and reduction of shrubland) [33]. Demographic drivers are part of the reason for the expansion of farmland and settlements, reduction of grassland, reduction of shrubs, and expansion of degraded land [33].

Population increase seems to be the main driving force of LULC changes, which is mainly manifested by expanding cultivated land at the expense of vegetation cover [124]. This has led to the expansion of cultivated land, charcoal, fuelwood extraction, and other wood products (such as housing construction products related to population growth) as the main direct drivers of the loss of natural vegetation in the study area [124].

4.5. LULC Change Implications for Water Resources Management

The majority of sub-Saharan Africa (SSA) countries are susceptible to LULC changes. LULC change is increasingly burdening the future water bodies. The gradual deterioration of water bodies can lead to landscape component degradation (flora, soil, and fauna), leading to desertification, which in turn leads to health problems, poverty, and loss of biodiversity [125]. Deforestation is one of the changes in LULC, which is considered to be the main cause of changes in hydrological processes such as surface runoff, sediment production, evapotranspiration, groundwater, infiltration, lateral flow, and rainfall interception [126–130]. Changes in LULC are driven by human interaction, which in turn will drive changes that change the availability of water resources. Under various circumstances, natural systems have become agricultural land to feed a growing population [131]. It has
been noted that changes in LULC will have an impact on natural resources, especially water resources in semi-arid areas [62]. Land-use and climate change are the two main driving forces that affect the hydrological processes of the watershed [125]. However, the impact of LULC changes on the hydrological system is a complex process, depending on the size of the affected area, the type of land use, and its landscape. The availability of future water resources depends, to a large extent, on land-use planning and management in a constantly changing environment. On the other hand, continued human behavior continues to modify LULC to meet increased demand, especially due to the significant increase in population and the development of better facilities [21].

The intensification of agricultural land and urban areas is related to the reduction of vegetation cover in most areas [124,132], which leads to soil compaction in farmland and an increased resistant surface in urban areas [133,134]. Since the time interval of crop evapotranspiration is relatively short compared with forest or shrubland, it is well known that agricultural land will reduce evapotranspiration However; these LULC classes exhibit low water absorption and release large amounts of water to the outlet of the sub-basin, resulting in high water production. LULC loss also indicates reduced infiltration, which means low base flow and groundwater recharge [135], high surface runoff and peak flow, and low evapotranspiration [136,137]. However, semi-arid areas such as the upper reaches of the Awash River basin have a lot of rainfall and high temperatures, and surface water evaporation is still relatively high. For example, during the period 1970–2008, the surface water evaporation in the Koka basin was estimated to be $1.37 \times 10^9$ m$^3$ [27], which is almost the same as the annual rainfall of $1.97 \times 10^9$ m$^3$, which leads to a low level of the water available in the basin area. Therefore, high evapotranspiration leads to a decrease in base flow and groundwater, which leads to a decrease in water production and flow; reduced water output may lead to water shortages and extreme water supply anxiety [62].

Assessment of river basins requires LULC change assessment to explore ecological and hydrological conditions for future sustainable water resources management. Several studies have studied the impact of LULC on water resources in many countries around the world. For instance, in eastern and southern Africa, changes in LULC are the main driver of reducing river flow and surface runoff [138], leading to water shortages. Similarly, the study reported by [139] showed that LULC changes are one of the key drivers of hydrological changes in the watershed. LULC change is a complex source of pressure that threatens the sustainability and management of water resources [136,140]. The impact of the LULC change pattern on the sub-basins connecting coastal areas and highland areas has led to economic, social, political, and environmental problems at the national, regional, and local levels in many countries. LULC changes have serious consequences for the natural environment because LULC is directly related to land degradation and leads to environmental changes. Therefore, understanding and paying attention to the existing LULC changes is very important for the policy decision making and regulatory action formulation of future LULC activities.

Changes in LULC not only affect water quality but also affect the quality of water resources through different mechanisms. Changes in LULC, such as the fragmentation and degradation of terrestrial landscape, adversely affect the quality of aquatic ecosystems. Freshwater ecosystems are some of the most threatened ecosystems on the planet, facing human and environmental pressures [141]. For example, due to the increasing pressure and scarcity of freshwater resources, the pollution of freshwater resources is attracting global attention [142]. River water quality is affected by rapid urbanization [143], and agricultural chemicals may leak or seep into the soil due to the expansion of farmland, causing pollution of nearby water sources [62]. In addition, water pollution is common in rapid urbanization, especially in developing countries, because of the lack of proper sanitation and waste treatment facilities (industrial and household). Studies have shown that there is a positive correlation between LULC changes and water quality parameters, indicating that LULC changes contribute to water quality changes, and thus, frequent water quality monitoring and LULC planning and management are recommended to curb
watershed pollution [142]. With the predicted changes in LULC in the upper Awash River basin, water resources are expected to continue to be affected; therefore, appropriate actions must be taken to reduce the impact of LULC changes on water resources, especially in these water-scarce sub-basins.

The CA–Markov model showed great efficiency in simulating LULC changes in the upper reaches of the Awash River basin, indicating that the region is vulnerable to changes and requires extensive water resources management and land-use planning in the future. To confirm the capabilities of the model, key informant interviews, household surveys, field observation, and focus group discussions were used to determine the consequences and driving factors of LULC changes in the study area. Thus, the LULC driving factors evaluated through local community surveys showed the applicability of the CA–Markov model in simulating future changes in LULC.

Therefore, the LULC changes caused by urbanization and agricultural intensification have a huge impact on the water resources of the river basin and should be considered in future water resources management.

5. Conclusions

This study utilized reliable historical data to analyze the dynamics and magnitude of LULC changes in the upstream Awash basin (USAB) and used the CA–Markov model to predict future LULC changes, contributing to a better understanding of possible LULC changes and their driving factors. To confirm the results of remote-sensing image interpretation, the consequences and drivers of change in USAB LULC were assessed through key informant interviews, field observations, household surveys, and focus group discussions. Assessment of historical LULC dynamics is critical for future agricultural and water resources management under agricultural intensification and urbanization. This research plan examined the application of RS and GIS to the dynamic characteristics of LULC in a sub-watershed and showed that LULC in the region changed significantly during the reference years of 1984, 2000, and 2019. This study showed that the CA–Markov model can simulate future changes in USAB LULC by providing a reliable 2038 historical LULC model.

The results show that the most significant changes occurred in the spatiotemporal scale of LULC dynamics. From 1984 to 2019, basin-wide agricultural and urban cover increased significantly, while shrub and forest cover decreased slightly. The USAB is expected to continue to experience LULC changes in the future, primarily the expansion of urban land and agricultural land categories. It is estimated that by 2038, the area of shrub and urban sub-watersheds will be about 1524.54 km$^2$ (16.03%) and 341.11 km$^2$ (3.59%), respectively, while the coverage area in 2019 will be about 1025.64 km$^2$ (10.78%) and 163.08 km$^2$ (1.71%), respectively. However, LULC categories such as agricultural land, forest, grassland, and water bodies are expected to decrease. Population growth and urbanization (mainly from rural-to-urban migration to Addis Ababa) are expected to lead to urban expansion, and the reclamation of agricultural land to meet the food needs of a growing population will lead to expansion of agricultural land; as a result, forest areas continue to reduce. The rapid expansion of agricultural land and urban areas, as well as the reduction of shrubland, forests, and grasslands, is evidence of the human impact of LULC dynamics. Extensive LULC dynamics are human-driven, which in turn affects humans and alters the availability of natural resources, including water, vegetation, soil, and livestock. Therefore, the extent of LULC variation perceived by local community respondents is consistent with the interpretation of remotely sensed LULC images.

Changes in LULC projected in the USAB will have an implication on water resources, such as reductions in water production (surface and groundwater), river flow and water quality, and evaporation in the watershed. The future availability of water resources depends, to a large extent, on the planning and management of land use in this changing environment. Therefore, it is necessary for water resource managers and land-use planners to understand the impact of changes in land use in sub-basins on water resources in order to improve future water resource management. LULC dynamics are caused by population
pressures that lead to urbanization and agricultural expansion through unplanned and inappropriate resource management practices to meet the food security needs of a rapidly growing population. Therefore, proper planning needs to be implemented to minimize land-use dynamics; especially in developing countries, whose resource bases are deteriorating and should be strengthened to feed their growing populations.

Agriculture-related LULCs are unavoidable for developing countries such as Ethiopia whose economies depend on agriculture, as most of their arable land is located in large river and lake basin areas. Thus, in the wake of the 2030 Sustainable Development Goals (SDGs), this study draws attention to the need for immediate action to measure sustainability indicators of land and water resources across the upper Awash sub-basin. Evidence of LULC changes and drivers of change are essential for future planning projects, as they provide more information about LULC. More encouraging results on LULC changes and their drivers were obtained using long-term coverage data. The results of this study can be used for future hydrological impact assessments in the sub-basin to contribute to the sustainability of the Koka dam. This study provides water resources managers and land-use planners with valuable information to improve future LULC policies and develop sub-watershed management strategies in the context of sustainable water resources and land-use planning and management. More research using high-resolution multi-temporal satellite imagery is needed to better estimate the dynamics of LULCs and plan for land-use, natural, and environmental resources in sub-watersheds.

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References
1. De Paulo Rodrigues da Silva, V.; Silva, M.T.; Singh, V.P.; de Souza, E.P.; Braga, C.C.; de Holanda, R.M.; Almeida, R.S.R.; de Assis Salviano de Sousa, F.; Braga, A.C.R. Simulation of stream flow and hydrological response to land-cover changes in a tropical river basin. *Catena* 2018, 162, 166–176. [CrossRef]
2. Das, S.; Sarkar, R. Predicting the land use and land cover change using Markov model: A catchment level analysis of the Bhagirathi-Hugli River. *Spat. Inf. Res.* 2019, 27, 439–452. [CrossRef]
3. Iizuka, K.; Johnson, B.A.; Onishi, A.; Magcale-Macandog, D.B.; Endo, I.; Bragais, M. Modeling future urban sprawl and landscape change in the Laguna de Bay Area, Philippines. *Land* 2017, 6, 26. [CrossRef]
4. Gessesse, B.; Bewket, W.; Bräuning, A. Model-based characterization and monitoring of runoff and soil erosion in response to land use/land cover changes in the Modjo watershed, Ethiopia. *Land Degrad. Dev.* 2015, 26, 711–724. [CrossRef]
5. Rai, R.; Zhang, Y.; Paudel, B.; Acharya, B.; Basnet, L. Land use and land cover dynamics and assessing the ecosystem service values in the trans-boundary Gandaki River Basin, Central Himalayas. *Sustainability* **2018**, *10*, 3052. [CrossRef]

6. Twisa, S.; Buchroithner, M.F. Land-Use and Land-Cover (LULC) Change Detection in Wami River Basin, Tanzania. *Land* **2019**, *8*, 136. [CrossRef]

7. Wise, T.A. Can We Feed the World in 2050? A Scoping Paper to Assess the Evidence. Global Development and Environment Institute Working Paper. 2013. Available online: https://ciaotest.cc.columbia.edu/wps/gdae/0029266/f_0029266_23757.pdf (accessed on 11 December 2021).

8. Le Mouël, C.; Forslund, A. How can we feed the world in 2050? A review of the responses from global scenario studies. *Eur. Rev. Agric. Econ.* **2017**, *44*, 541–591. [CrossRef]

9. Agidew, A.-M.A.; Singh, K. The implications of land use and land cover changes for rural household food insecurity in the Northeastern highlands of Ethiopia: The case of the Teleyayen sub-watershed. *Agric. Food Secur.* **2017**, *6*, 56. [CrossRef]

10. Oyewole, S.; Ishola, B.; Aina-Oduntan, O. Maximizing the Role of African Forest for Climate Change Mitigation and Socioeconomic Development. *World News Nat. Sci.* **2019**, *27*, 11–21.

11. Andrew, V.O.; Anouk, D.V.; Sebastiana, O.; Adinda, V.D.W.; Amerens, J.; Eva, P.M.; Helena, A.; Isabella, V.D.G.; Jessica, S.; Kevin, V.L.; et al. The Future of Work for Smallholder Farmers in Ethiopia. Policy Paper By The West Wing Think Tank for the Dutch Ministry of Foreign Affairs. 2019. Available online: file:///C:/Users/MDPI/AppData/Local/Temp/The_Future_of_Work_for_Smallholder+Farmers+in+Ethiopia.pdf (accessed on 11 December 2021).

12. Holmgren, P. The Role of Forestry and Agriculture in Mitigating Climate Change. In *Climate Action*; United Nations Environment Programme (UNEP), 2016; Available online: https://www.climateaction.org/climate-leader-papers/the_role_of_forestry_and_agriculture_in_mitigating_climate_change (accessed on 11 December 2021).

13. FAO. Adapting to climate change through land and water management in Eastern Africa. *In Results of Pilot Projects in Ethiopia, Kenya and Tanzania; Food and Agriculture Organization of the United Nations: Rome, Italy, 2014.*

14. Bekele, M. Forestry Outlook Studies in Africa (FOSA). Country Report: Ethiopia. 2001. Available online: https://www.fao.org/3/ab580e/ab580e.pdf (accessed on 11 December 2021).

15. Meshesha, T.W.; Tripathi, S.; Khare, D. Analyses of land use and land cover change dynamics using GIS and remote sensing during 1984 and 2015 in the Beressa Watershed Northern Central Highland of Ethiopia. *Modeling Earth Syst. Environ.* **2016**, *2*, 1–12. [CrossRef]

16. Bhat, P.A.; ul Shafiq, M.; Mir, A.A.; Ahmed, P. Urban sprawl and its impact on landuse/land cover dynamics of Dehradun City, India. *Int. J. Sustain. Built Environ.* **2017**, *6*, 513–521. [CrossRef]

17. Mahmood, R.; Pielke Sr, R.A.; Hubbard, K.G.; Niyogi, D.; Bonan, G.; Lawrence, P.; McNider, R.; McAlpine, C.; Etter, A.; Gameda, S. Impacts of land use/land cover change on climate and future research priorities. *Bull. Am. Meteorol. Soc.* **2010**, *91*, 37–46. [CrossRef]

18. Wang, R.; Kalin, L.; Kuang, W.; Tian, H. Individual and combined effects of land use/cover and climate change on Wolf Bay watershed streamflow in southern Alabama. *Hydrol. Processes* **2014**, *28*, 5530–5546. [CrossRef]

19. Woldesenbet, T.A.; Elagib, N.A.; Ribbe, L.; Heinrich, J. Hydrological responses to land use/cover changes in the source region of the Upper Blue Nile Basin, Ethiopia. *Sci. Total Environ.* **2017**, *575*, 724–741. [CrossRef]

20. Woldeyohannes, A.; Cotter, M.; Kelboro, G.; Dessalegn, W. Land Use and Land Cover Changes and Their Effects on the Landscape of Abaya-Chamo Basin, Southern Ethiopia. *Land* **2018**, *7*, 2. [CrossRef]

21. Garg, V.; Nikam, B.R.; Thakur, P.K.; Aggarwal, S.P.; Gupta, P.K.; Srivastav, S.K. Human-induced land use land cover change and its impact on hydrology. *HydroReserch* **2019**, *1*, 48–56. [CrossRef]

22. Berihun, M.L.; Tsunekew, A.; Hargegewyn, N.; Meshesha, D.T.; Adgo, E.; Tsobo, M.; Masunaga, T.; Fenta, A.A.; Sultan, D.; Yibeltal, M. Hydrological responses to land use/land cover change and climate variability in contrasting agro-ecological environments of the Upper Blue Nile basin, Ethiopia. *Sci. Total Environ.* **2019**, *689*, 347–365. [CrossRef]

23. Woldesenbet, T.A.; Elagib, N.A.; Ribbe, L.; Heinrich, J. Catchment response to climate and land use changes in the Upper Blue Nile sub-basins, Ethiopia. *Sci. Total Environ.* **2018**, *644*, 193–206. [CrossRef]

24. Erkossa, T.; Wudneh, A.; Dessalegn, B.; Taye, G. Linking soil erosion to on-site financial cost: Lessons from watersheds in the Blue Nile basin. *Solid Earth* **2015**, *6*, 765–774. [CrossRef]

25. Keesstra, S.; Pereira, P.; Novara, A.; Brevik, E.C.; Azorin-Molina, C.; Parias-Alcántara, L.; Jordán, A.; Cerdá, A. Effects of soil management techniques on soil water and erosion in apricot orchards. *Sci. Total Environ.* **2016**, *551*, 357–366. [CrossRef]

26. Niguissie, Z.; Tsunekeaw, A.; Hargegewyn, N.; Adgo, E.; Nohmi, M.; Tsobo, M.; Aklog, D.; Meshesha, D.T.; Abele, S. Farmers’ perception about soil erosion in Ethiopia. *Land Degrad. Dev.* **2017**, *28*, 401–411. [CrossRef]

27. Mersha, A.; Masih, I.; de Fruiture, C.; Wenninger, J.; Alamirew, T. Evaluating the Impacts of IWRM Policy Actions on Demand Satisfaction and Downstream Water Availability in the Upper Awash Basin, Ethiopia. *Water* **2018**, *10*, 892. [CrossRef]

28. Gebru, S.Y. *The Role of Reservoirs in Drought Mitigation in Ethiopia, Awash River Basin*; NTNU, 2016. Available online: https://ntnuopen.ntnu.no/ntnu-xmlui/handle/11250/2433630 (accessed on 11 December 2021).

29. Taddese, G.; Sonder, K.; Peden, D. *The Water of the Awash River Basin a Future Challenge to Ethiopia*; International Livestock Research Institute: Addis Ababa, Ethiopia, 2003.

30. Hailemariam, K. Impact of climate change on the water resources of Awash River Basin, Ethiopia. *Clim. Res.* **1999**, *12*, 91–96. [CrossRef]
31. Edossa, D.C.; Babel, M.S.; Gupta, A.D. Drought analysis in the Awash river basin, Ethiopia. *Water Resour. Manag.* 2010, 24, 1441–1460. [CrossRef]

32. Yibeltal, T; Belte, B.; Semu, A.; Imeru, T; Yohannes, T. Coping with Water Scarcity, the Role of Agriculture, Developing a Water Audit for AWASH RIVER BASIN. Synthesis Report; GCP/INT/072/ITA: FAO: Addis Ababa, Ethiopia, 2013.

33. Bekele, D.; Alamirew, T.; Kebede, A.; Zeleke, G.; Melesse, A.M. Land use and land cover dynamics in the Keleta watershed, Awash River basin, Ethiopia. *Environ. Hazards* 2019, 18, 246–265. [CrossRef]

34. Lennon, G.W.; Mantel, S. The role of GIS and remote sensing in land degradation assessment and conservation mapping: Some user experiences and expectations. *Int. J. Appl. Earth Obs. Geoinf.* 2001, 3, 61–68. [CrossRef]

35. Alqurashi, A.F.; Kumar, L. Investigating the use of remote sensing and GIS techniques to detect land use and land cover change: A review. *Adv. Remote Sens.* 2013, 2, 193–204. [CrossRef]

36. Rwanga, S.S.; Ndambuki, J. Accuracy assessment of land use/land cover classification using remote sensing and GIS. *Int. J. Geosci.* 2017, 8, 611–622. [CrossRef]

37. Erdogan, E.H.; Erpul, G.; Bayramin, İ. Use of USLE/GIS methodology for predicting soil loss in a semiarid agricultural watershed. *Environ. Monit. Assess.* 2007, 131, 153–161. [CrossRef] [PubMed]

38. Scull, P.; Franklin, J.; Chadwick, O.; McArthur, D. Predictive soil mapping: A review. *Prog. Phys. Geogr.* 2003, 27, 171–197. [CrossRef]

39. Masser, I. Managing our urban future: The role of remote sensing and geographic information systems. *Habitat Int.* 2001, 25, 503–512. [CrossRef]

40. Chuvieco, E.; Aguado, I.; Yebra, M.; Nieto, H.; Salas, J.; Martin, M.P.; Vilar, L.; Martinez, J.; Martin, S.; Ibarra, P. Development of a framework for fire risk assessment using remote sensing and geographic information system technologies. *Ecol. Model.* 2010, 221, 46–58. [CrossRef]

41. Lyon, J.G. GIS for water resources and watershed management. In *GIS for Water Resource and Watershed Management*; CRC Press: Boca Raton, FL, USA, 2002; pp. 17–22.

42. Jha, M.K.; Peiffer, S. Applications of Remote Sensing and GIS Technologies in Groundwater Hydrology: Past, Present and Future; BayCEER Bayreuth, 2006; Available online: http://www.bayceer.uni-bayreuth.de/bayceer/html/bfoe/bfoe112_order.pdf (accessed on 11 December 2021).

43. Singh, V.P.; Fiorentino, M. *Geographical Information Systems in Hydrology*; Springer Science & Business Media: Berlin/Heidelberg, Germany, 2013; Volume 26.

44. Singh, P.; Gupta, A.; Singh, M. Hydrological inferences from watershed analysis for water resource management using remote sensing and GIS techniques. *Eur. J. Remote Sens. Space Sci.* 2014, 17, 111–121. [CrossRef]

45. Ruben, G.B.; Zhang, K.; Dong, Z.; Xia, J. Analysis and Projection of Land-Use/Land-Cover Dynamics through Scenario-Based Simulations Using the CA-Markov Model: A Case Study in Guanting Reservoir Basin, China. *Sustainability* 2020, 12, 3747. [CrossRef]

46. Garedew, E.; Sandewall, M.; Söderberg, U.; Campbell, B.M. Land-use and land-cover dynamics in the central rift valley of Ethiopia. *Environ. Monag.* 2009, 44, 683–694. [CrossRef] [PubMed]

47. Gashu, K.; Gebre-Egziabher, T. Spatiotemporal trends of urban land use/land cover and green infrastructure change in two Ethiopian cities: Bahir Dar and Hawassa. *Environ. Syst. Res.* 2018, 7, 8. [CrossRef]

48. Zhao, A.; Zhu, X.; Liu, X.; Pan, Y.; Zuo, D. Impacts of land use change and climate variability on green and blue water resources in the Weihe River Basin of northwest China. *Catena* 2016, 137, 318–327. [CrossRef]

49. Yira, Y.; Diekkrüger, B.; Steup, G.; Bossa, A.Y. Modeling land use change impacts on water resources in a tropical West African catchment (Dano, Burkina Faso). *J. Hydrol.* 2016, 537, 187–199. [CrossRef]

50. Valle, R., Jr, Siqueira, H.; Guidolini, J.; Abdala, V.; Machado, M. Diagnóstico de mudanças e persistência de ocupação do solo entre 1978 e 2011 no IFTM-CAMPUS UBERABA, utilizando o “Land Change Modeler (LCM)”. *Envol. Biosf.* 2012, 8, 672–681.

51. Khoi, D.D.; Murayama, Y. Modeling deforestation using a neural network-Markov model. In *Geographical Information Systems in Hydrology*; Springer Science & Business Media: Berlin/Heidelberg, Germany, 2011; pp. 169–190.

52. Uddin, K.; Chaudhary, S.; Chettri, N.; Kotru, R.; Murthy, M.; Chaudhary, R.P.; Ning, W.; Shrestha, S.M.; Gautam, S.K. The changing land cover and fragmenting forest on the Roof of the World: A case study in Nepal’s Kailash Sacred Landscape. *Landsc. Urban Plan.* 2015, 141, 1–10. [CrossRef]
57. Eastman, J.; Toledano, J. A short presentation of the Land Change Modeler (LCM). In Geomatic Approaches for Modeling Land Change Scenarios; Springer: Berlin/Heidelberg, Germany, 2018; pp. 499–505.
58. Sangermano, F.; Toledano, J.; Eastman, J.R. Land cover change in the Bolivian Amazon and its implications for REDD+ and endemic biodiversity. Landsc. Ecol. 2012, 27, 571–584. [CrossRef]
59. Kim, O.S.; Newell, J.P. The ‘Geographic Emission Benchmark’ model: A baseline approach to measuring emissions associated with deforestation and degradation. J. Land Use Sci. 2015, 10, 466–489. [CrossRef] [PubMed]
60. Shawul, A.A.; Chakma, S.; Melesse, A.M. The response of water balance components to land cover change based on hydrologic modeling and partial least squares regression (PLSR) analysis in the Upper Awash Basin. J. Hydrol. Reg. Stud. 2019, 26, 19. [CrossRef]
61. Roy, S.; Farzana, K.; Papia, M.; Hasan, M. Monitoring and prediction of land use/land cover change using the integration of Markov chain model and cellular automation in the Southeastern Tertiary Hilly Area of Bangladesh. Int. J. Sci. Basic Appl. Res. 2015, 24, 125–148.
62. Mathioudi, B.; Kenabatho, P.K.; Parida, B.P.; Maphanyane, J.G. Analysis of the Future Land Use Land Cover Changes in the Gaborone Dam Catchment Using CA-Markov Model: Implications on Water Resources. Remote Sens. 2021, 13, 2427. [CrossRef]
63. Daba, M.H.; Songcai, Y. Assessment of Climate Change Impacts on River Flow Regimes in the Upstream of Awash Basin, Ethiopia: Based on IPCC Fifth Assessment Report (AR5) Climate Change Scenarios. Hydrology 2020, 7, 98. [CrossRef]
64. Daba, M.H. Sensitivity of SWAT Simulated Runoff to Temperature and Rainfall in the Upper Awash Sab-Basin, Ethiopia. Hydrol. Curr. Res. 2018, 9, 1–7. [CrossRef]
65. Getahun, Y.S.; Van Lanen, H. Assessing the impacts of land use-cover change on hydrology of Melka Kuntrie subbasin in Ethiopia, using a conceptual hydrological model. Hydrol. Curr. Res. 2015, 6, 1. [CrossRef]
66. Hansen, M.C.; DeFries, R.S.; Townshend, J.R.; Sohldberg, R. Global land cover classification at 1 km spatial resolution using a classification tree approach. Int. J. Remote Sens. 2000, 21, 1331–1364. [CrossRef]
67. Liping, C.; Yujun, S.; Saeed, S. Monitoring and predicting land use and land cover changes using remote sensing and GIS techniques—A case study of a hilly area, Jiangle, China. PLoS ONE 2018, 13, e020493. [CrossRef] [PubMed]
68. Qian, J.; Zhou, Q.; Hou, Q. Comparison of pixel-based and object-oriented classification methods for extracting built-up areas in arid zone. In Proceedings of the ISPRS Workshop on Updating Geo-Spatial Databases with Imagery & the 5th ISPRS Workshop on DMISS; pp. 163–171. Available online: https://www.isprs.org/proceedings/xvi/4-w54/papers/163-171.pdf (accessed on 11 December 2021).
69. Lin, C.; Wu, C.-C.; Tsogt, K.; Ouyang, Y.-C.; Chang, C.-I. Effects of atmospheric correction and pansharpening on LULC classification accuracy using WorldView-2 imagery. Inf. Processing Agric. 2015, 2, 25–36. [CrossRef]
70. Ibharam, N.; Mustapha, M.A.; Lihan, T.; Mazlan, A. Mapping mangrove changes in the Matang Mangrove Forest using multi temporal satellite imageries. Ocean Coast. Manag. 2015, 114, 64–76. [CrossRef]
71. Tilahun, A.; Teferie, B. Accuracy assessment of land use land cover classification using Google Earth. Am. J. Environ. Prot. 2015, 4, 193–198. [CrossRef]
72. Zhang, Z.; Liu, S.; Wei, J.; Xu, J.; Guo, W.; Bao, W.; Jiang, Z. Mass change of glaciers in Muztag Ata–Kongur Tagh, Eastern Pamir, China from 1971/76 to 2013/14 as derived from remote sensing data. PLoS ONE 2016, 11, e0147327. [CrossRef]
73. Story, M.; Congalton, R.G. Accuracy assessment: A user’s perspective. Photogramm. Eng. Remote Sens. 1986, 52, 397–399.
74. Congalton, R.G. A review of assessing the accuracy of classifications of remotely sensed data. Remote Sens. Environ. 1991, 37, 35–46. [CrossRef]
75. Banko, G. A Review of Assessing the Accuracy of Classifications of Remotely Sensed Data and of Methods Including Remote Sensing Data in Forest Inventory; 1998. Available online: http://pure.iiasa.ac.at/id/eprint/5570/ (accessed on 11 December 2021).
76. Congalton, R.G.; Oderwald, R.G.; Mead, R.A. Assessing Landsat classification accuracy using discrete multivariate analysis statistical techniques. Photogramm. Eng. Remote Sens. 1983, 49, 1671–1678.
77. Bishop, Y.M.; Fienberg, S.E.; Holland, P.W. Discrete Multivariate Analysis: Theory and Practice; Springer Science & Business Media: Berlin/Heidelberg, Germany, 2007.
78. Bishop, Y.M.; Fienberg, S.E.; Holland, P.W.; Light, R.J.; Mosteller, F. Book Review: Discrete multivariate analysis: Theory and practice. Appl. Psychol. Meas. 1977, 1, 297–306. [CrossRef]
79. Takada, T.; Miyamoto, A.; Hasegawa, S.F. Derivation of a yearly transition probability matrix for land-use dynamics and its applications. Landsc. Ecol. 2010, 25, 561–572. [CrossRef]
80. Wang, L.; Ye, X.; Lee, J.; Lu, X.; Zheng, L.; Wu, K. Effects of urbanization on ecosystem service values in a mineral resource-based city. Habitat Int. 2015, 46, 54–63. [CrossRef]
81. Eastman, J. TerrSet: Geospatial Monitoring and Modeling Software; Clark Labs, Clark University: Worcester, MA, USA, 2015.
82. John, J.; Chithra, N.R.; Thampi, S.G. Prediction of land use/cover change in the Bharathapuzha river basin, India using geospatial techniques. Environ. Monit Assess 2019, 191, 354. [CrossRef] [PubMed]
83. Pontius, R. Quantification error versus location error in comparison of categorical maps (vol 66, pg 1011, 2000). Photogramm. Eng. Remote Sens. 2001, 67, 540.
84. Eastman, J. IDRISI 15: The Andes Edition; Clark University: Worcester, MA, USA, 2006.
85. Biswas, M.; Banerji, S.; Mitra, D. Land-use–landcover change detection and application of Markov model: A case study of Eastern part of Kolkata. Environ. Dev. Sustain. 2019, 22, 4341–4360. [CrossRef]
95. Memarian, H.; Balasundram, S.K.; Talib, J.B.; Sung, C.T.B.; Sood, A.M.; Abbaspour, K. Validation of CA-Markov for Simulation of Land Use and Cover Change in the Langat Basin, Malaysia. J. Geogr. Inf. Syst. 2012, 4, 2622–2632. [CrossRef]

96. Marhaento, H.; Ahamad, M.S.S.; Hussin, W.M.A.W.; Samat, N.; Ahmad, S.Z.B. Markov CA, multi regression, and multiple decision making for modeling historical changes in Kirkuk City, Iraq. J. Indian Soc. Remote Sens. 2014, 42, 165–178. [CrossRef]

97. Pontius, R.G., Jr.; Schneider, L.C. Land-cover change model validation by an ROC method for the Ipswich watershed, Massachusetts, USA. Agric. Ecosyst. Environ. 2001, 85, 239–248. [CrossRef]

98. Singh, S.K.; Mustak, S.; Srivastava, P.K.; Szabó, S.; Islam, T. Predicting Spatial and Decadal LULC Changes Through Cellular Automata Markov Chain Models Using Earth Observation Datasets and Geo-information. Environ. Processes 2015, 2, 61–78. [CrossRef]

99. Kumar, S.; Radhakrishnan, N.; Mathew, S. Land use change modelling using a Markov model and remote sensing. Geomat. Nat. Hazards Risk 2014, 5, 145–156. [CrossRef]

100. Omar, N.Q.; Ahamad, M.S.S.; Hussin, W.M.A.W.; Samat, N.; Ahmad, S.Z.B. Markov CA, multi regression, and multiple decision making for modeling historical changes in Kirkuk City, Iraq. J. Indian Soc. Remote Sens. 2014, 42, 165–178. [CrossRef]

101. Pontius, R.G., Jr.; Schneider, L.C. Land-cover change model validation by an ROC method for the Ipswich watershed, Massachusetts, USA. Agric. Ecosyst. Environ. 2001, 85, 239–248. [CrossRef]

102. Atile, A.; Asfaw, S.; Tekalign, S. Dynamics of land use/land cover change and its implications for land degradation in Mida Woremo watershed, North Central Ethiopia. Ethiop. J. Soc. Sci. 2021, 7, 49–71.

103. FAO. Africover Land covers Classification. In Environment and Natural Resources Service; Food and Agriculture Organization of the United Nations, Ed.; Food and Agriculture Organization: Rome, Italy, 1997.

104. Lea, C.; Curtis, A. Thematic accuracy assessment procedures: National Park Service vegetation inventory, version 2.0. In National Resource Report NPS/2010/NRR-2010/204; National Park Service, US Department of the Interior: Fort Collins, CO, USA, 2010.

105. Mejia, J.F.; Hochschild, V. Land Use and Land Cover (LULC) Change in the Boconó River Basin, North Venezuelan Andes, and Its Implications for the Natural Resources Management. Environ. Land Use Plan. 2012, 35, 35–68.

106. Almeyda, K.M.; Gessler, P.E.; Hicke, J.A.; Salem, B.B. Land use/land cover change detection and prediction in the north-western coastal desert of Egypt using Markov models–CA. Appl. Geogr. 2015, 63, 101–112. [CrossRef]

107. FAO. National Gender Profile of Agriculture and Rural Livelihoods–Ethiopia; Country Gender Assessment Series; FAO: Addis Ababa, Ethiopia, 2019; p. 84.

108. Haregeweyn, N.; Fikadu, G.; Tsuneakawa, A.; Tsuibo, M.; Meshesha, D.T. The dynamics of urban expansion and its impacts on land use/land cover change and small-scale farmers living near the urban fringe: A case study of Bahir Dar, Ethiopia. Landsc. Urban Plan. 2012, 106, 149–157. [CrossRef]

109. Tsegaye, D.; Moe, S.R.; Vedeld, P.; Aynekulu, E. Land-use/cover dynamics in Northern Afar rangelands, Ethiopia. Agric. Ecosyst. Environ. 2010, 139, 174–180. [CrossRef]

110. Biazin, B.; Sterk, G. Drought vulnerability drives land-use and land cover changes in the Rift Valley dry lands of Ethiopia. Agric. Ecosyst. Environ. 2013, 164, 100–113. [CrossRef]

111. Mundhe, N.N.; Jaybhaye, R.G. Impact of urbanization on land use/land covers change using Geo-spatial techniques. Int. J. Geomat. Geosci. 2014, 5, 50–60.
140. Ngondo, J.; Mango, J.; Liu, R.; Nobert, J.; Dubi, A.; Cheng, H. Land-Use and Land-Cover (LULC) Change Detection and the Implications for Coastal Water Resource Management in the Wami–Ruvu Basin, Tanzania. *Sustainability* **2021**, *13*, 4092. [CrossRef]

141. Kalacska, M.; Arroyo-Mora, J.; Lucanus, O.; Kishe-Machumu, M. Land Cover, Land Use, and Climate Change Impacts on Endemic Cichlid Habitats in Northern Tanzania. *Remote Sens.* **2017**, *9*, 623. [CrossRef]

142. Tahiru, A.A.; Doke, D.A.; Baatuwie, B.N. Effect of land use and land cover changes on water quality in the Nawuni Catchment of the White Volta Basin, Northern Region, Ghana. *Appl. Water Sci.* **2020**, *10*, 198. [CrossRef]

143. Hua, A.K. Land Use Land Cover Changes in Detection of Water Quality: A Study Based on Remote Sensing and Multivariate Statistics. *J. Environ. Public Health* **2017**, *2017*, 7515130. [CrossRef]