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GIS-BASED MODELING OF LAND USE DYNAMICS IN RIVER NZOIA BASIN, KENYA

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ABSTRACT

River Nzoia basin in Kenya is predisposed to degradation associated with land use change. The change is attributable to natural and socio-economic factors and their spatio-temporal utilization due to anthropogenic activities. Therefore, it is important to establish land use change within a specific period of time and spatially project patterns of future changes. Hence, the main objective of this study was to characterize, simulate, and predict spatio-temporal land use change in river Nzoia basin. Examining land use dynamics is valuable for environmental management purposes. It supports the process of decision making in planning for future changes as well as policy formulation to mitigate extreme events associated with the changes. Spatial datasets including: 90m resolution Digital Elevation Model (DEM) and Landsat satellite images (ranging from 1990 to 2010) that depict land use patterns were used to provide spatio-temporal details. Image analysis was carried out by the use of ENVI 4.7 software. Land use change projection integrated Cellular Automata-Markov methods in Remote Sensing (RS) and Geographic Information System (GIS). During for the period 1990, 2000 and 2010, shrubland, annual cropland, and grassland increased by 13.28%, 5.59% and 0.06% while forestland, waterbody and wetlands experienced decrease in percentage coverage by 10.97, 3.78 and 4.18, respectively. The Chi-square test revealed a highly insignificant difference between predicted and reference land use (calculated $\chi^2_{4,0.05} = 2.5356$ where p>0.01). Pearson correlation analysis revealed a highly significant (p<0.01) positive correlation r = 0.999(0.000) between the predicted and the reference land use categories for the year 2010. Cellular Automata (CA)-Markov model projected land use scenario for 2020. Nash Sutcliffe (R^2_{NS} = 99.92%) indicated very satisfactory model performance for land use projection. The study revealed that agricultural expansion is the main driving force for loss of forest in river Nzoia basin and has the potential to continue in future. The projected land use scenario for the year 2020 would provide useful inputs to the land use planners for effective management of river Nzoia basin. Cellular Automata-Markov model predicted a decline in forestland and an increase in annual cropland by 2020. Annual cropland and forestland are the key drivers of land use change in river Nzoia basin. The existing forest cover in river Nzoia basin should be protected and not be released for agriculture or subjected to untenable extraction of forest resources. There is need to embrace afforestation programs to enhance forest cover in the basin.

INTRODUCTION

Land use refers to arrangements, activities and inputs that mankind undertakes in a given land cover type to produce change or maintain it (Campbell, *et al*., 2003). It embraces a mix of socio-economic, cultural and policy factors. According to Soepboer (2001), land use change is the modification in the purpose of the land, which is not necessarily only the change in land cover but also changes in intensity and management. DeBie, *et al*. (1996) define land use as a series of operations on land, carried out by humans, with the intention to obtain products and/or benefit through using land resources including soil resources and vegetation resources. Changes in land use are inherently dynamic and spatial (Aspinall and Hill, 2008).

Globally, transformations of land use within river basins for settlement, agriculture, industrialization and urbanization concomitant to the increasing population affect their functioning. Were (2008) posits that, land use change impacts on the bio-geochemical cycling leading to modifications in surface runoff, carbon and water cycling, soil quality, biodiversity and sediment loading. Mango *et al.* (2011) contend that, land use and management is an important factor affecting different processes in river basins, such as surface runoff, erosion, recharge and evapotranspiration.

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According to Mango *et al.* (2011), the main causes of degradation in river Mara basin are due to poor management of forests and soils, overgrazing, extension of settlements into river basin areas, and improper felling of trees for fuel wood. Studies conducted in Ethiopia (Gete, 1997 *and* Belay, 2002) have shown that deforestation and encroachment of cultivation into marginal areas are the major causes of land degradation. Land degradation mainly results from expansion of agricultural land at the expense of forestlands and increased open grazing areas developing at the expense of shrublands and forests. In Ethiopia, population pressure is inducing, the clearing of forests for agriculture and other purposes.

River Nzoia basin is in western Kenya and originates from South-Eastern part of Mt Elgon and the Western slopes of the Cheranganyi Hills. The Basin covers Marakwet, Keiyo, West Pokot, Trans Nzoia, Uasin Gishu, Nandi North, Lugari, Mt. Elgon, Bungoma, Kakamega, Butere-Mumias, Busia, and Siaya in Western part of Kenya. According to Ssegan (2007), the economy of the basin is largely rural-based and more than 90% of the population earns its living from agriculture and livestock. The farms are privately owned and on average 1- 3 hectares in size. The main food crops include maize, sorghum, millet, bananas, groundnuts, beans, potatoes, and cassava while the cash crops consist of coffee, sugar cane, tea, wheat, rice, sunflower and horticultural crops (WARMA, 2007). The river Basin is of great economic importance at local as well as national levels especially in such sectors as agriculture, tourism, fishing, forestry, mining and transport. It is also the main source of water for domestic, agricultural, and commercial sectors. The industrial establishments in Western Kenya include: Nzoia, Mumias, Butali and West Kenya Sugar companies.

WARMA (2007) identifies some of the main issues in river Nzoia basin as; deforestation, soil erosion, wetland degradation, sedimentation, weak law enforcement, river bank cultivation, and flooding. These issues are attributed to several causes, including; poor farming practices and forest encroachment, population pressure, basin destruction, pressure on arable land, weak legal framework and enforcement, and demand for construction materials. Simiyu, *et al.* (2009) assert that, River Nzoia is experiencing decline in water quality due to degradation attributable to land use change. A study on the impact of environmental change on the hydrology of Nzoia basin by Githui (2008) revealed that agricultural area had increased from about 39.6 to 64.3% between 1973 and 2001, while forest area had decreased from 12.3 to 7.0%. Results also showed that, runoff was highest from agricultural lands followed by shrub grassland and forest. Kiluva, *et al.* (2009) contend that, there is wide spread encroachment into river Nzoia banks which exposes the inhabitants to flood risk during rain seasons.

STATEMENT OF THE PROBLEM

River Nzoia basin is predisposed to land degradation associated with deforestation, overgrazing, poor agricultural practices, soil erosion and deteriorating riparian vegetation. Soil erosion resulting from surface run-off is prevalent in most deforested parts of the basin with hillslopes and annual cropland areas particularly vulnerable. Improper practices of land use including deforestation, expansion of cropland and urbanization are deteriorating river basin conditions. This study therefore sought to characterize and predict spatio-temporal land use change in river Nzoia basin.

METHODS AND MATERIALS

This section introduces and describes methodology used to carry out the study. It presents a description of the river Nzoia basin area based on location, geographical features, climatic conditions and land use

Study area

Figure 1.1 shows river Nzoia basin that lies between latitudes 1º 30'N and 0º 05'S and longitudes 34º and 35º 45'E. River Nzoia originates from Cheranganyi Hills and Mt Elgon at a mean elevation of 2300 m above sea level (asl) and drains into the trans-boundary Lake Victoria at an altitude of 1000 m asl. River Nzoia is 334 km long with a basin area of about 12,900 km^2. It is the largest river basin in Kenya's Victoria basin with heavy forest cover in the upper parts and low trees and bushes in the lower basin (Odira, *et al*., 2010).

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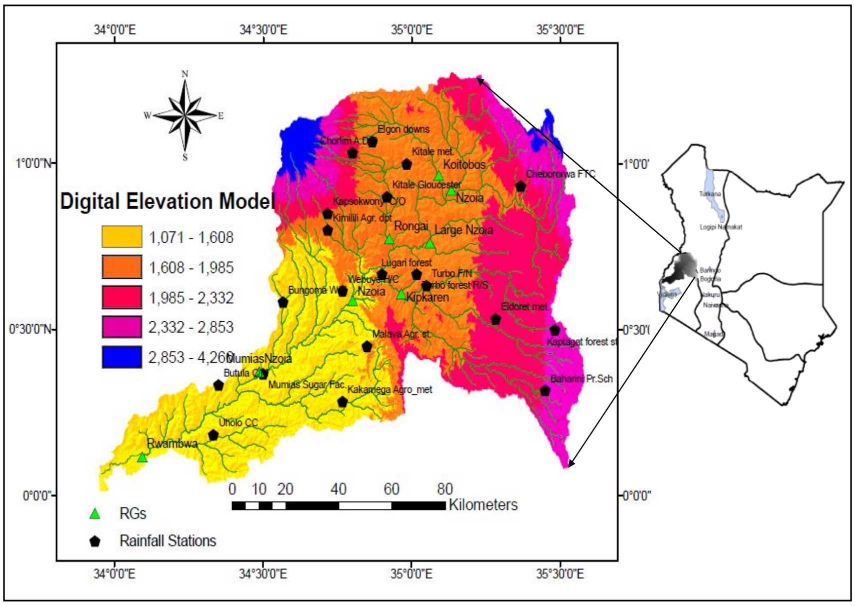

Figure 1.1: Map of the study area

The climate of the basin is mainly tropical humid characterized by day temperatures varying between 16ºC in the highland areas of Cheranganyi and Mt. Elgon to 28º C in the lower semi-arid areas on annual basis. The basin comprises of four distinct zones: mountain zone that is forested but suffers severe land degradation; plateau zone which is majorly under farming, transition zone and lowland zone (Odira, *et al*., 2010). Small scale farming continues in the transition and flood prone lowland areas that are generally flat and swampy.

Methods

River Nzoia basin is mapped fully by four Landsat satellite images, that is: p169r59, p169r60, p170r59 and p170r60, where p-path and r-row. Database for land use was prepared for multispectral, multi-temporal data of years 1990, 2000 and 2010 of Landsat using ENVI 4.7 and ArcGIS10.1 softwares.

Spatial data sets were all converted to appropriate data formats for application in the modelling process and geo-referenced (projected) in the Universal Transverse Mercator (UTM) coordinate system (UTM zone 36N, WGS-84 ellipsoid) for compatibility with the DEM used in this study.

Methodology used in this study involved analysis of satellite Landsat images that enabled characterization of spatio-temporal land use change. Cellular Automata (CA) and Markov model in the Idrisi's Kilimanjaro software was used to simulate and predict land use scenario for the year 2020.

Land use data was obtained by unsupervised classification of Landsat satellite imagery. The imagery was prepared by sub-setting, mosaicking and atmospheric correction for haze and cloud removal. This was finally converted from radiance to scaled surface reflectance values required for use in the land use classification. Land use map was generated by image classification and considered as the baseline scenario for land use change characterization. As contended by Belward, *et al.* (1999), post-classification analysis (predicted and reference land use images) for precision tests was done through computation of coefficient of determination to resolve between different land use categories.

Characterization of spatio-temporal land use change

Calculation of the area in square kilometers of the resulting land use categories were performed to quantify change in the land use categories for three study years 1990, 2000 and 2010 and the results subsequently compared. The comparison of the land use statistics generated from attribute tables assisted in computing the percentage change, trend and rate of change between 1990 and 2010. Six land use categories: forest land, shrubland, annual cropland,

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grassland, waterbody and wetland were used to identify the most dominant type of land use activity as well as land use change driving forces.

Markovian simulation and prediction of land use change

Change prediction was achieved through Cellular Automata and Markov Chain Analysis. According to Opeyemi (2006), Markov Chain Analysis is a convenient tool for modelling land use change. A Markovian process is one in which the future state of a system can be modeled purely on the basis of the immediately preceding state. Future land use changes were achieved by developing a transition probability matrix of land use change from time one to time two. Cellular Automata (CA) was used to add spatial character to the model.

Future land use scenarios were simulated using Cellular Automata (CA)-Markov-model. The model selection criterion was motivated by its capacity to simulate and model land use change and simplicity to implement on a GIS platform (Mhangara, 2011). The 1990 land use map was used as the base (t_1) while 2000 the later (t_2) in Markov model to obtain the transition probability matrix between 1990 and 2000 years for prediction of land use 2010. The CA-Markov's model with the 2010 land use map as the base was used to simulate the scenario for the year 2020.

RESULTS AND DISCUSSIONS

Spatio-temporal land use change

Land use dynamics of river Nzoia basin was studied based on land use maps for 1990, 2000 and 2010. Attribute tables for the three land use maps were summarized as shown in Table 3.1.

Table 3. 1: Land use distribution between 1990 and 2010

Land Use Category	**YEAR**					
	1990		**2000**		**2010**	
	Area (Km^2	**(%)**	**Area (Km^2)**	**(%)**	**Area (Km^2)**	**(%)**
Forest Land	2237.47	17.05	989.87	7.51	766.46	6.18
Shrubland	2030.30	15.47	3202.87	24.29	3625.53	29.25
Annual Cropland	7273.49	55.43	8213.16	62.30	7692.92	62.08
Waterbody	779.87	5.94	556.86	4.22	272.80	2.20
Grassland	27.76	0.21	37.83	0.29	34.10	0.28
Wetland	774.12	5.90	183.46	1.39	1.13	0.01

Results presented in Table 3.1 are a representation of the static area of each land use category for every year of study.

The findings were further jointly illustrated in Figure 3.2. The figure shows that annual cropland was the predominant land use category for the study period while grassland accounted for the least coverage.

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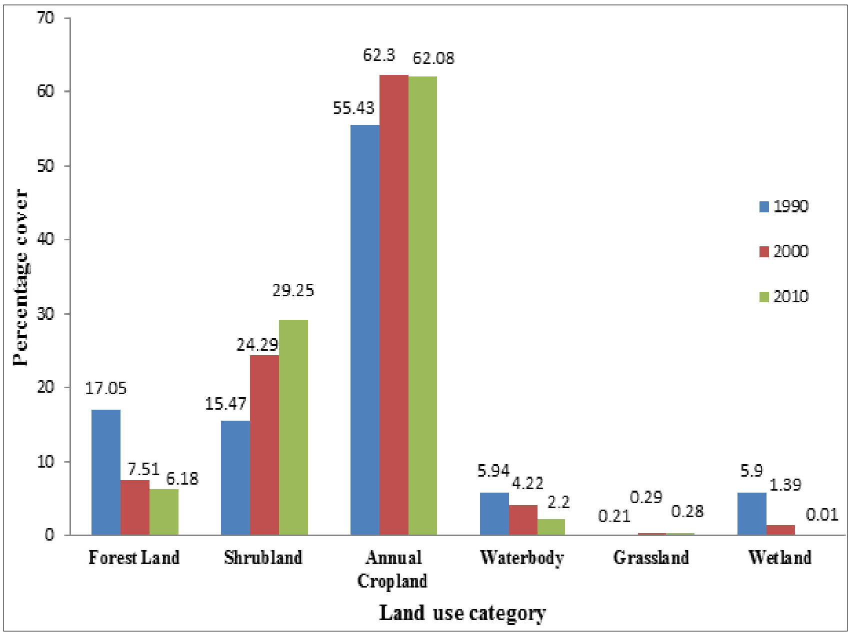

Figure 3.2: Percentage coverage of land use categories for 1990, 2000 and 2010

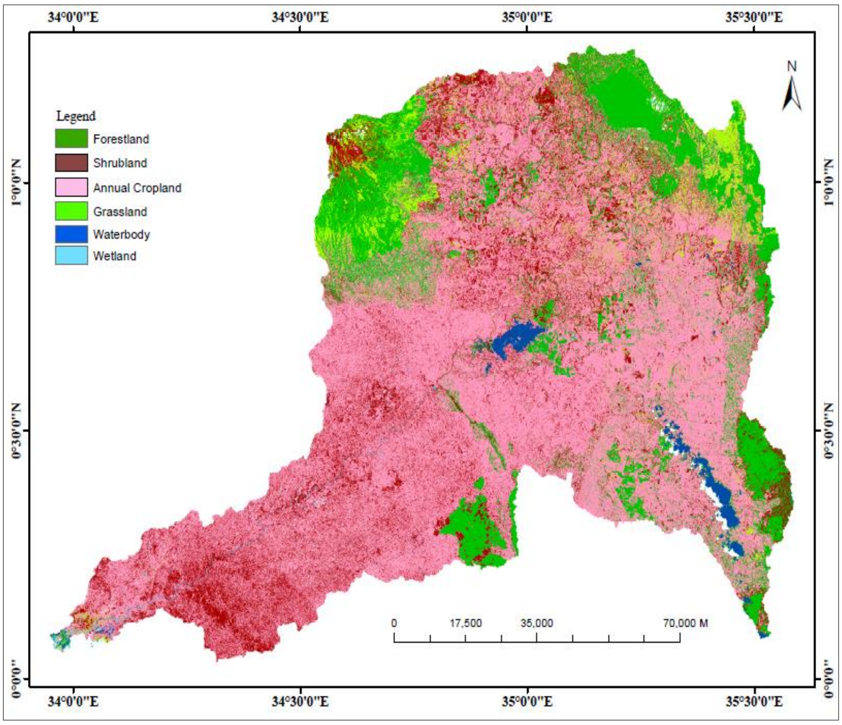

Figure 3.3: River Nzoia basin land use map for the year 1990

Therefore, in 1990 grassland accounted for the minimum area (0.21%) whereas annual cropland percentage (55.43) was the maximum. A Chi-square test was performed to test for variation in the various land use categories. The test yielded $\chi^2_{5,0.05} = 120.41$. Given that it is greater than the expected (Table) value is $\chi^2_{5,0.05} = 11.07$, then it is valid to argue that the calculated chi-square value is significant. Thus, there is a significant difference in the distribution of land use categories for the year 1990.

Respective attributes as shown in Table 3.1 indicated that in 2000, land use pattern had drastic changes with respect to 1990 results. Area under annual cropland witnessed a percentage increase by 6.87, accounting for a total coverage of 62.30% of the study area. Area occupied by forestland decreased by 9.54% leaving a total coverage of only 7.51%. Shrub land and grassland increased by 8.82% and 0.08%, respectively. This was accompanied by a decrease in wetland from 5.90% to 1.39% of the study area. Figure 3.4 is the land use map for theyear2000.

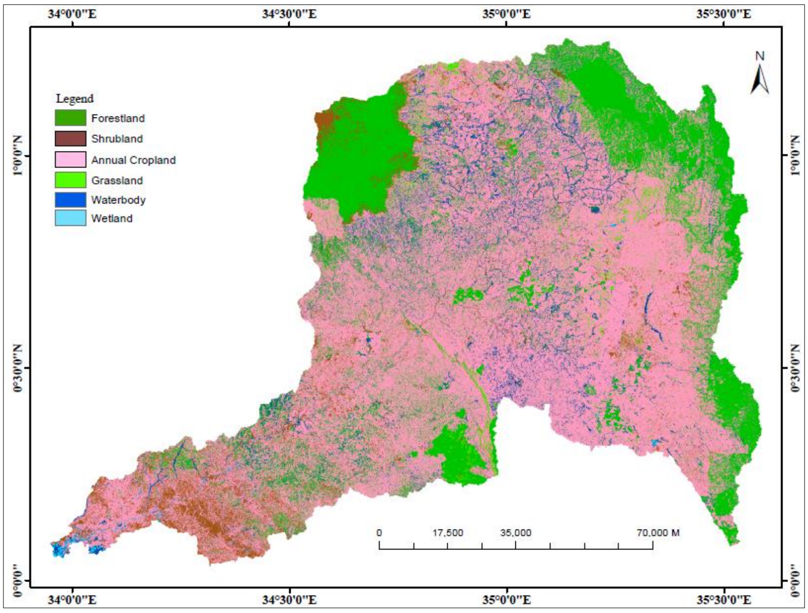

Figure 3.4: River Nzoia basin land use map for the year 2000

In the year 2000, annual cropland and shrub land occupied the largest percentage of 86.59% of the total area. Grassland took up the least percentage of 0.29, see Figure 3.4.Chi-square test with $\chi^2_{5,0.05} = 172.92$ in comparison with the table value of $\chi^2_{5,0.05} = 11.07$ indicated significant variation in land use categories for the year 2000. Land use map for the year 2010 is shown in Figure 3.5.

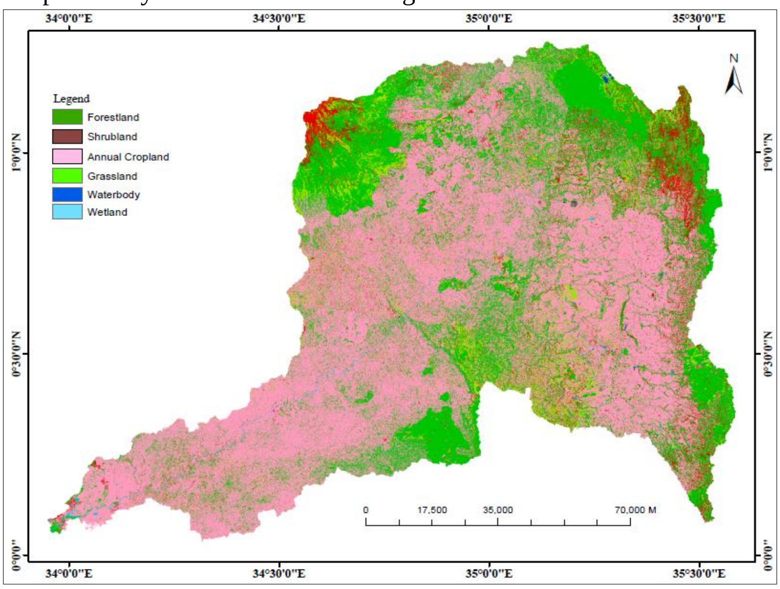

Figure 3.5: River Nzoia basin land use map the year 2010

Then, it can be noted that, the area under shrubland increased by 4.96% while wetland, forestland and annual cropland experienced a decrease by 1.38, 1.33 and 0.22% respectively. Figure 3.1 shows that during the year 2010, annual cropland and shrubland accounted for the maximum basin coverage of 91% while grassland, wetland, waterbody and forestland, cumulatively occupied only 9% of the study area. The Chi-square test gave a $\chi^2_{5,0.05} = 184.79$, portraying a highly significant value. Given that the expected (Table value) value is $\chi^2_{5,0.05} = 11.07$ it depicts a wide variation in the distribution of land use categories.

Figure 3.6 shows the net land use percentage change experienced in the study area between 1990 and 2010.

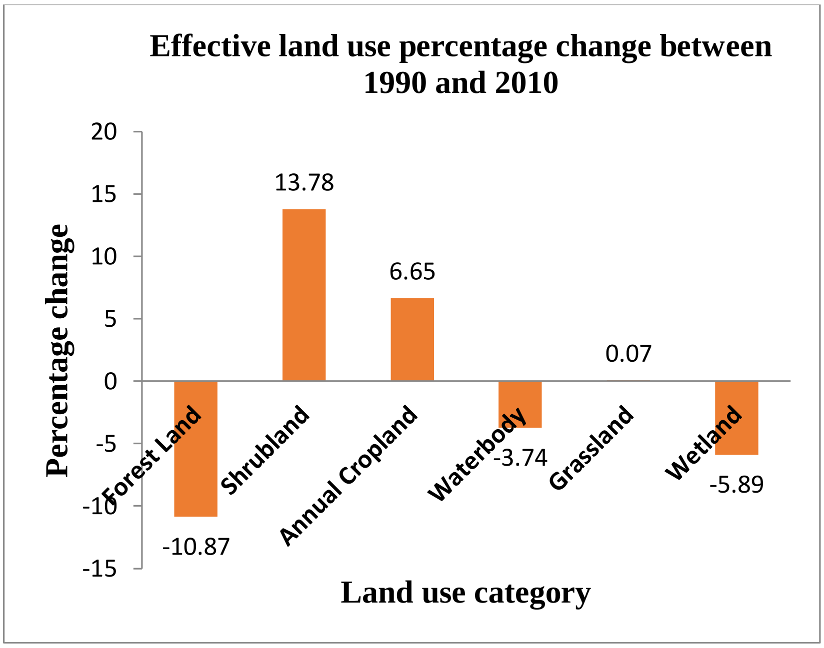

Figure 3.6: Land use percentage change between 1990 and 2010 in river Nzoia basin

Figure 3.6 reveals that for the period ranging from 1990 up to 2010, shrubland, annual cropland, and grassland increased by 13.78%, 6.65% and 0.07% while forestland, waterbody and wetlands experienced decrease in percentage coverage of 10.87, 3.74 and 5.89, respectively. The study findings are in agreement with results of a related study undertaken by Githui, *et.al*. (2010), to estimate the impact of land-cover change on runoff in river Nzoia basin using SWAT model. It revealed that the forest cover had noticeably decreased from 12.3 to 7% while agricultural area had increased to 64.3% in the year 2000/2001.

In a related study by Odira, *et al*. (2010), to determine the impact of land use dynamics on stream flow in river Nzoia basin, it was observed that the basin had experienced various land use dynamics between 1990 and 2010. The key drivers of change were forest and cropland.

A study done by Kigira, *et al*. (2010) sought to model the influence of land use changes on sediment yield and hydrology in Thika river basin using SWAT model. Results revealed that the basin had undergone tremendous changes between the years 1987 and 2000. During this period, forest cover and shrubland had decreased by 36 and 7.5 % respectively. This is in tandem with findings derived from related studies elsewhere. A study conducted in the Keiskamma catchment of South Africa by Mhangara, (2011) revealed that there was land use change experienced. Maitima, *et al.* (2009) noted that land use changes in East Africa have transformed land cover to farmlands, grazing lands, human settlements and urban centres at the expense of natural vegetation. These changes are associated with deforestation, biodiversity loss and land degradation (Kilonzo, 2014). Therefore, there was an increase in non-forest area and decline in the forest cover. This could be attributed to increased demographic pressure which has led to encroachment into forest land in search of space for human settlements, urbanization, farming as well over-exploitation of forest resources as a source of livelihood.

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Land use predictive modelling (CA-Markov modelling)

Land use maps of 1990 and 2000 were used in the Cellular Automata (CA)-Markov model as the 1st ealier and the 2nd land use image. The model then predicted the land use scenario for 2010 at an acceptable error of 0.001. The 2000 and 2010 land use maps of river Nzoia basin were used as the base (t_1) and the later (t_2) map respectively in CA- Markov model to obtain the transition probability matrix, see Table 3.2.

Table 3.2: Transition probability matrix used to simulate land use for 2010

	Land use category	**Initial state**					
		Forest Land	**Shrubland**	**Annual Cropland**	**Waterbody**	**Grassland**	**Wetland**
Final state	Forest Land	0.9999	0.0000	0.0000	0.0000	0.0000	0.0000
	Shrubland	0.0001	0.4935	0.0399	0.0001	0.0001	0.0546
	Annual Cropland	0.4901	0.4279	0.9918	0.0041	0.4524	0.0196
	Waterbody	0.0000	0.0000	0.0000	0.7469	0.0000	0.0001
	Grassland	0.0001	0.4129	0.0068	0.0676	0.0023	0.5933
	Wetland	0.0001	0.0012	0.0000	0.7361	0.0001	0.0173

The probability values in Table 3.2 show the probable land use categories that might convert from one class to another in 2010. For instance, 0.0399 is the probability that annual cropland will transform to shrubland and 0.4279 is the probability that shrubland will change to annual cropland.

In addition, the chance that forest land transforms into annual cropland is 0.4901 while the probability that the reverse would be the case is negligible. This is a precursor to the fact that due to the economic activities taking place in river Nzoia basin, forest cover has been declining, more profoundly in favour of annual cropland. Figure 3.7 shows the relationship between predicted and reference land use percentage coverage values for 2010 with 0.998 as the coefficient of determination (R^2).

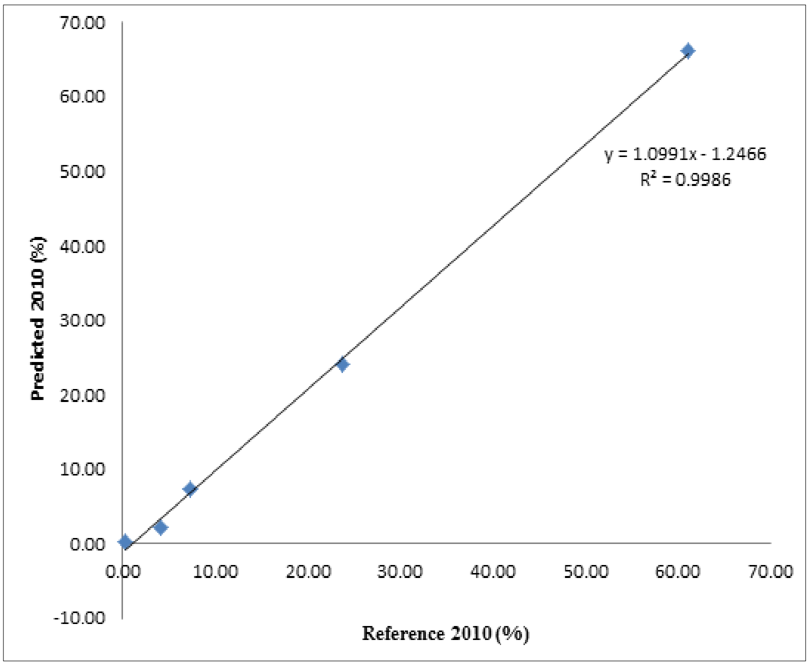

Figure 3.7: Relationship between predicted and reference LU for 2010

Figure 3.7 depicts a linear relationship and implies that Cellular Automata (CA)-Markovian model was able to predict future land use scenario at an acceptable error level of 0. 14%. Therefore, 99.86 % of the variability due to CA-Markovian modelling can be explained. Table 3.3 shows a summary of attribute information between the reference and predicted land use scenario for 2010.

Table 3. 3: Change detection between prediction and reference land use map for 2010

Land use category	Predicted 2010 (%)	Reference 2010 (%)	Change
Forestland	7.36	7.41	0.05
Shrubland	23.81	24.03	0.22
Annual Cropland	61.06	66.22	5.16
Grassland	4.14	2.05	-2.09
Waterbody	0.28	0.28	0.00

The Chi-square test reveals a highly insignificant difference (calculated $\chi^2_{4,0.05} = 2.5356$ while expected $\chi^2_{4,0.05} = 9.4873$) between predicted and reference land use percentage coverage. Thus, there is no significant variation between predicted and reference land use categories for the year 2010.
To determine the existence of a relationship between the predicted and the reference land use maps for 2010, Pearson correlation analysis was performed on the data captured in Table 3.3. The results were summarized in Table 3.4 which shows that r = 0.999(0.000).

Table 3. 4: Correlation between predicted and reference land use maps for 2010

	Land use correlations	Reference 2010
Predicted 2010	Pearson Correlation	.999**
	Sig.(2-tailed)	.000

There is a high significant ($p < 0.05$) degree of positive correlation between the predicted and the reference land use maps for the year 2010. This implies that CA-Markov model predicted land use for 2020 with 99.9% accuracy levels. The predicted scenario infers escalation in land use change. This was complimented by Nash Sutcliffe (R^2_{NS}) value of 0.9992 (99.92%) that equally indicated very satisfactory model performance. Using 2000 and 2010 land use maps and the transition probability matrix, Table 3.2, Idrisis's Kilimanjaro CA-Markov model was used to simulate land use scenario for 2020, see Figure 3.8.

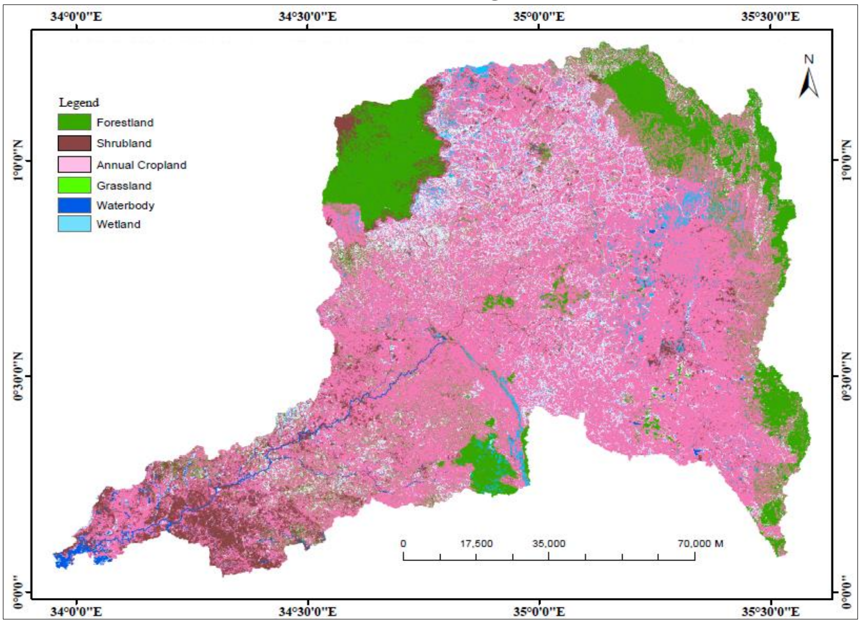

Figure 3.8: River Nzoia basin predicted land use map for the year 2020

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Figure 3.9 illustrates that annual cropland and shrubland would respectively account for up to 64.2% and 30.01% coverage come the year 2020. Forest land will only account for at least 3.25% while water body, grassland and wetland would, respectively cover 1.51, 0.32 and 0.71% of the entire river Nzoia basin.

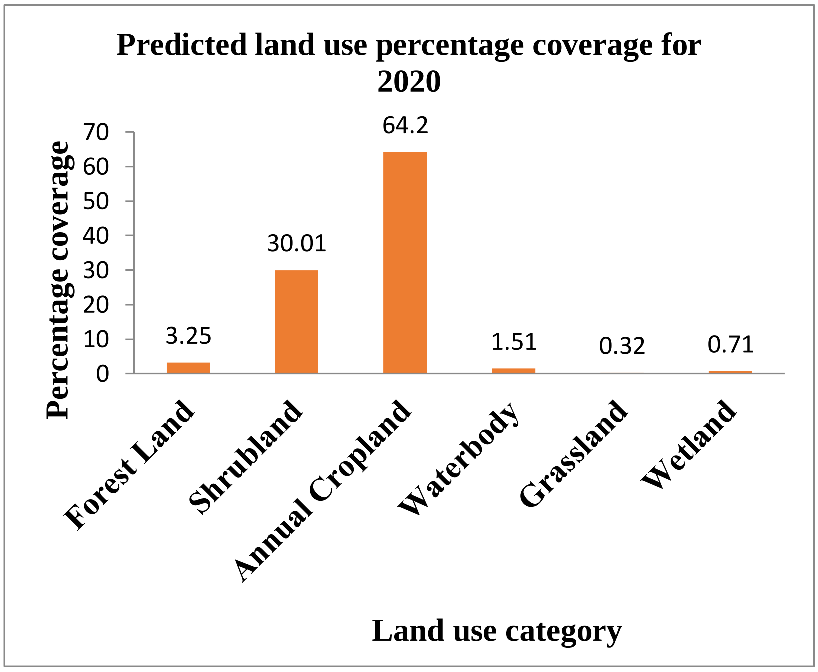

Figure 3.9: Cellular Automata (CA)-Markov predicted land use scenario for 2020

Therefore, CA-Markovian modelling predicted that in the year 2020 annual cropland and shrubland would occupy the largest percentage of 94% of the total area. Lambin, *et al*. (2001) and Mendoza, *et al*. (2006) argue that, significant and consistent land use change can be achieved over 10-15 year interval. In a related study by Mhangara (2011) to model land use change in the Keiskamma catchment using GIS, a projection interval period of 13 years was used. Therefore, the CA-Markovian simulation period of 10 years prediction used in this study was within the requisite range. Results of land use change detection between 2010 and 2020 are shown in Figure 3.10.

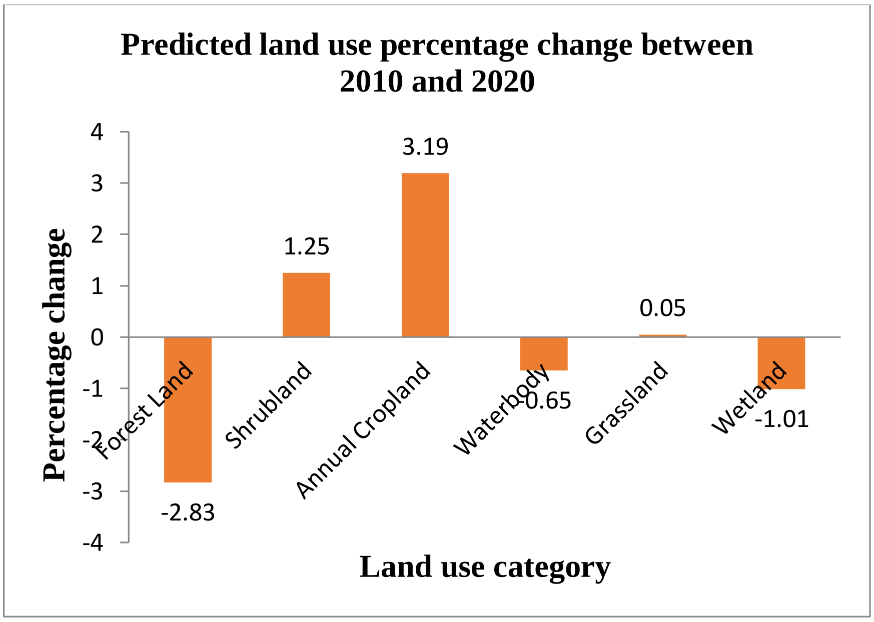

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Figure 3.10: Predicted percentage change between 2010 and 2020

With reference to Figure 3.10, it is evident that, forestland, waterbody and wetland will experience decrease by 2.83, 0.65 and 1.01% while shrubland and grassland will increase in coverage by 1.25 and 3.19% respectively. Thus, expansion of annual cropland, shrubland and grassland account for reduction in coverage by forestland, water body and wetland. However, forest land and annual cropland will remain the principal driving force to explain land use dynamics in future. Effective land use change for the entire study period (1990-2020) was illustrated as shown in Figure 3.11.

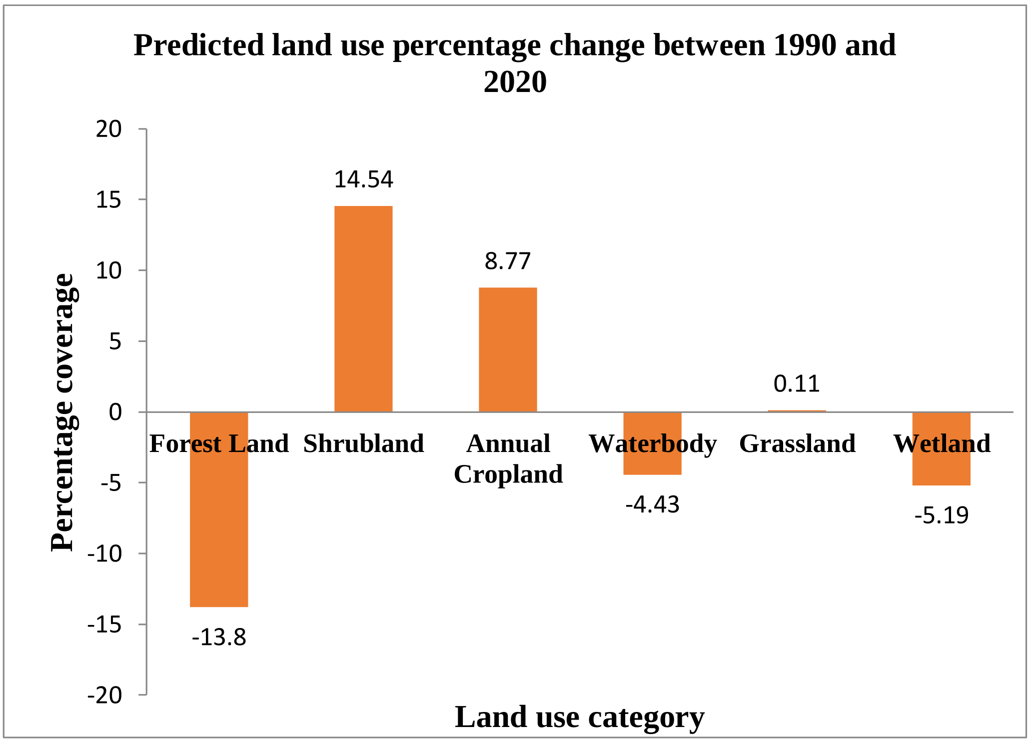

Figure 3.11: Net land use change between 1990 and 2020

Figure 3.11 shows spatio-temporal land use change based on percentage coverage for the entire study period. It can be seen that by 2020, forestland, waterbody and wetland would have decreased by 13.8, 4.43 and 5.19% while shrubland, annual cropland and grassland would have increased by 14.54, 8.77 and 0.11%, respectively.

The Figure depicts that forest land would experience coverage reduction by a large margin, this could be attributed to the increasing population pressure. This may lead to clearing of forest cover in search of land for settlement, pasture and agriculture. This is evidenced from the increased crop land and grasslands coverage. Therefore, owing to economic instability and lack of alternative sources of livelihoods coupled with ever increasing demographic pressure, deforestation is likely to go on in future.

Table 3.4 is a summary of correlation analysis results for land use categories under study over time. The analysis revealed that, there is a significant ($p < 0.05$) negative Pearson correlation ($r = -0.998$) between waterbody land use category and time in years. This can be associated with the encroachment into riparian land for settlement and farming hat has negatively impacted water towers in the basin. The results also indicate that there exists a high, though insignificant ($p > 0.05$), negative correlation between forestland and shrubland ($r = -0.993$), forestland and annual cropland ($r = -0.747$), forestland and grassland ($r = -0.870$), as well as grassland and wetland ($r = -0.823$). This implies that these land use categories are transposable. For instance, some land covered by forestland is most likely that at some point in time will be converted to annual cropland.

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Table 3.4: Land use category correlation analysis

		Forest land	Shrub land	Annual Cropland	Water body	Grass land	Wet land
Year	Pearson Correlation	-.928	.965	.546	-.998*	.623	-.957
	Sig. (2-tailed)	.043	.169	.036	.144	.572	.018
Forestland	Pearson Correlation		-.993	-.747	.900	-.870	.996
	Sig. (2-tailed)		.075	.043	.288	.029	.055
Shrubland	Pearson Correlation			.664	-.945	.806	-1.000*
	Sig. (2-tailed)			.537	.213	.403	.019
Annual Cropland	Pearson Correlation				-.382	.978	-.687
	Sig. (2-tailed)				.750	.134	.018
Waterbody	Pearson Correlation					-.567	.934
	Sig. (2-tailed)					.616	.232
Grassland	Pearson Correlation						-.823
	Sig. (2-tailed)						.384
	N						3

*. Correlation is significant at the 0.05 level (2-tailed).

It is evident that high positive correlation ($r = 0.965$) exists between shrubland land use category and time in years, forestland and waterbody ($r = 0.900$), forestland and wetland ($r = 0.996$), shrubland and grassland ($r = 0.806$), annual cropland and grassland ($r = 0.978$), and waterbody and wetland ($r = 0.934$), see Table 3.4. This can be interpreted to mean that, for instance, increase in forest cover would be accompanied by rise in the amount of water in the basin and that, increasing annual cropland would lead to increased coverage by grassland. This could be a pointer to the skewed healthy status of the basin hydrology characterized with a lot of water losses with minimal percolation into the deep aquifers. Therefore, forest degradation and economic activities have put river Nzoia basin under immense pressure. They have compromised conservation of the fragile ecosystem hence exposing it to soil erosion.

During the actual visits to different parts of the basin, snapshots were taken showing how human activities have contributed to degradation of the basin. Intensive agricultural activities are among the main factors predisposing the basin to soil erosion, see Plate 3.1.

Plate 3.1: Soil erosion on a farm (Chebei)

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Heavy soil losses may lead to reduction in crop yield on the affected cropland. Accelerated erosion affects productivity in crop yields through loss of rooting depth, reduction in plant-available water reserves, nutrient imbalance and degradation of soil structure and decrease in organic matter. Plate 3.2 shows evidence of encroachment into forest in search of fuel inform of charcoal burning. Felling of trees to produce charcoal in turn reduces forest cover thus exposing the affected areas to soil erosive forces.

Plate 3.2: Charcoal burning in Marsek

In addition, charcoal burning affects global warming through production and emission of greenhouse gases, such as carbon monoxide (CO), carbon dioxide (CO_2) and methane (CH_4). Due to reduction in vegetation cover during charcoal burning, the basin hydrology may also be altered. It could lead to increased peak flows and surface runoff as well as shortened flow durations after rainfall events and less evapotranspiration. Forest degradation attributable to charcoal burning negatively affects both quality and quantity of the forest ecosystem services. They include; wild fruits, bush meat, honey, medicinal plants, among others.

Cane farming, brick making and sand harvesting as sources of livelihoods for populations living along the banks of river, see Plates 3.3 and 3.4

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Plate 3.3: Cane farming, brick making and sand harvesting along river Nzoia (Mulima Mukuyuni)

Cane farming, being mono-cultural land use, is linked with loss of natural vegetation cover as well as annual cropland. Therefore, cane farming in river Nzoia basin has directly contributed to forest cover reduction. Furthermore, the heavy use of inorganic fertilizers typically nitrogen and phosphorus is a source of non-point pollution into river Nzoia during surface runoff. This could also be considered a contributory factor to reduced water quality and thus increasing the cost of water treatment for both domestic and industrial utilization. Sugarcane farms are also sources of sediment into river Nzoia, since the cultivated soils on the steep sloping terrains are easily carried into the river during surface runoff.

Rise in population pressure has led to increased need for building materials. As a result, brick making is practiced in the basin to meet this need and also as a source of livelihood to poor households. The process of brick making is universally known to generate greenhouse gas (GHG) emissions due to the low combustion efficiency of the fuels used during baking. This enhances global warming. Extraction of the soil used leaves the land derelicted and thus an environmental hazard. Wood fuel used for baking is associated with deforestation leading to reduced vegetation cover enhancing soil erosion.

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Plate 3.4: Sand harvesting at Rwambwa bridge

Excessive in-stream sand harvesting causes degradation of rivers. It lowers the stream bottom, which leads to bank erosion. In-stream sand harvesting may also result in the destruction of riparian and aquatic habitat attributable to changes in the channel morphology. The potential impact includes river bed coarsening and degradation, channel instability and lowered water tables near the river bed. In-stream sand harvesting also impacts upon the river's water quality inform of increased short-term turbidity due to re-suspension of sediment at the harvesting site and sedimentation.

Thus, in-stream sand harvesting in river Nzoia has resulted in channel instability through the direct disruption of pre-existing channel geometry and through the effects of incision and accelerated river bank erosion. It exacerbates prevalent instability because the incoherence in the sediment supply-transport balance which tends to migrate upstream as the river bed is eroded to make up for the supply paucity. As a result, sand harvesting from relatively restricted sites prompts erosion of the bed and banks, which in turn, increases sediment delivery from the sediment generating sites.

Plate 3.5 shows degraded forest on the slopes of Chetambe hills and Nabuyole falls (Webuye) due to quarrying for building and construction materials.

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Plate 3.5: Deforestation and quarrying (Nabuyole falls)

Intensive quarrying in search of building and road construction materials is going on along the slopes of Chetambe hills in Webuye. This has led to widespread deforestation of the hills which are a source of a tourist attraction site. It thus, has shifted land use from forest cover to shrubland and some parts left bare. Severe degradation of the forest cover could be a precursor to the reduced river Nzoia discharge at this point (as per a community member in Plate 3.5). Quarrying could contaminate surface water inform of sediment loading or suspended solids. It may also affect surface runoff and groundwater quality through contamination with dissolved and suspended materials.

CONCLUSIONS

Land use change in river Nzoia basin is significant with annual cropland and forestland as the key drivers. They are significantly changing and influencing other land use categories in the basin. During the study period, land use has significantly shifted from being largely forested to mostly annual cropland. Thus, annual cropland is the primary driving force for loss of forest cover in river Nzoia basin and has the potential to continue in future. Land use change modelling and scenario analysis provide useful insights to land use planners and decision makers for effective planning, conservation and management of river Nzoia basin.

RECOMMENDATIONS

The existing forest cover in river Nzoia basin should be protected and not be released for agriculture, settlement, urbanization, or subjected to untenable extraction of forest resources. Further development and environmental planning in the basin should take into account the future direction and magnitude of land use change patterns. Cellular Automata (CA)-Markov modelling should be integrated into river Nzoia basin future planning and management processes.

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