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THE DRIVING FORCES THAT INFLUENCE LAND USE LAND COVER CHANGES IN KHWISERO SUB COUNTY, KAKAMEGA COUNTY, KENYA

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Abstract

Land use land cover changes have to a great extent changed the world's landscapes, rebuilding environments and what they provide to humans during the time spent supporting the rising population across the globe. The drivers of these changes vary from location to location causing varying effects that challenge the essential design and the functioning capacity of the land quality with flowing consequences to land quality. A cross sectional descriptive design together with a longitudinal design were used. A random sampling was used to obtain a sample size of 384 from a study population of 113,476. Based on agriculture, forest land, bare land and built up land categories, the study classified Landsat images through supervised classification algorithm then applied post - classification comparison change detection to measure land use land cover percentage area change over time. Primary data was collected through interviews and discussions with key informants, field observations, and questionnaires administered to individual households in Khwisero Sub County. Secondary data involved downloading Landsat images (Landsat 7, 8 and 9; 30-meter multispectral), summaries and citation of other works carried in journals articles, original documents, annual reports, development plans and internet. Quantitative data analysis involved measures of central tendency and measures of dispersion (SPSS) and analysis of variance (ANOVA). Qualitative data was analysed by organizing and grouping the arising issues into various categories relevant to the study. Land use land cover classification of the study area realized four land use land cover classes of agriculture 81.34 km2, forest 52.75 km2, built up 8.86 km2 and bare land 2.65 km2 for the study area as at 2023. Change detection noted that agricultural land use has been reducing from 2002 to 2023, built up has been increasing from 2002 to 2023, bare land increased between 2002 to 2012 but decreased between 2012 and 2023 while forests reduced between 2002 to 2012 but increased between 2012 to 2023 Accuracy assessment for the land use land cover classes for 2002 was 85.45% with a Kappa coefficient of 0.756, 2012 was 83.64% with a Kappa coefficient of 0.5454 while 2023 was 81.82% with a Kappa coefficient of 0.6034 for the land use land cover classes revealing that the classification is accurate. The study revealed that LULCCs are driven by settlement, poverty and climate change mostly thus affecting cropland vegetation and soil fertility majorly. The study concluded that LULCC drivers varied from location to location even within the sub county. The study recommends creation of awareness of understanding the various drivers of LULCCs and impact of each on land quality.

Keywords Land use Land cover change, Drivers, Land use Land cover and change detection.

INTRODUCTION

Changes in land use land cover can happen in response to human and climate drivers, (Abramowitz et al., 2008). Brown and Pervez (2014) also figured out that land use land cover changes (LULCC) can happen in response to both human, climate drivers and are many times in light of economic variables. The drivers change over space due to variations in topography, climate and human activities thus varying effects as pointed out by Munn (2006). Drivers of LULCC in Asian countries include; agricultural development/escalation, deforestation, more waterway damming, expanded urbanization, developing human populace, extension of modern woodland estate and cataclysmic events like flooding and dry season (Spruce et al., 2020). Urbanization driver leads to modification of hydrological cycle and land degradation in form of loss of natural matter through expansion of soil erosion in China (Zhihui et al., 2015). Nepal has a complicated and different geology; ill-advised land use management activities and has water prompted soil disintegration moved to Ganges delta, a downstream stream basin framing islands in the Bay of Bengal (Ives and Messerli, 1989). These drivers in Nepal leads to soil erosion affecting crops (Sharma et al., 2011). In addition, they lead to loss of natural matter, supplements and decrease of landscape efficiency (Nouri et al., 2018). In India, Chauhan and Nayak (2005) reported that industrialization and populace strain in Hazira, Gujarat prompted an increment of urban areas, a reduction in timberland areas and farming regions between 1970-2002.

In Africa, land use land cover changes have been on the ascent because of pressure driven by urbanization and populace development for the need of more land to extend agrarian production and developed regions which leads to deforestation together with infringement in safeguarded regions (FAO, 2014). Mather and Needle (2000) found out that population growth and poverty lead to deforestation in many developing countries. This study further noted that demographic changes are more than other causative factors whereas other studies suggests that economic factors are major drivers to LULCC (Lambin and Geist, 2001). Allen and Barnes (1985) argue that most deforestation happened by the tension from populace development and interest for more food leading to reduction of deforested areas thus affecting soil formation thus affecting food production.

Anne (2022) highlighted various drivers of LULCC in Narok as follows; high population pressure, beliefs, lifestyle of the pastoralists, increase in built-up areas, poverty, politics, weak laws and regulations leading to deforestation and loss of other vegetation covers. This leads to exposure of the soil affecting soil quality through soil erosion. This is supported by Rotich and Ojwang (2021) found out that Cherenganyi Hills areas of West Pokot, Trans Nzoia and Elgeyo Marakwet experienced LULCC that are driven by agriculture, population pressure, excisions, illegal logging, forest fires, climate change, firewood, charcoal burning, policy and institutional failures which has led to massive deforestation and exposure of soil thus leading to erosion which affects soil quality. A study conducted by Abere and Waithaka (2014) found out that population growth driver has reduced the farming land size thus reducing yields in production of maize and beans in Keumbu Region, Kisii County. Drivers to LULCC in Kakamega and particularly Kakamega forest are rapid population growth coupled with land scarcity which has led to increase in agricultural activities exposing the forest to deforestation (C.G.K, 2018-2022). Various studies were very clear on the drivers of LULCC in different areas research was done. The drivers included settlement, agricultural expansion, wood extraction, population pressure, policy and institutional failures, forest fires, climate change, politics, urbanization, beliefs and poverty and cited the effects like deforestation, exposure of top soil leading to erosion, loss of natural matter, decrease in landscape efficiency thus affecting soil quality that varied from place to place. Some studies pointed out demographic factors whereas others pointed out economic and social factors. The drivers change over space due to variations in topography, climate and human activities. It was clear from these studies that the drivers varied from place to place. This is why this study was done to find out the specific drivers to LULCC in Khwisero Sub County one of the sub counties in Kakamega County which can be relied on as a food basket because Kakamega town is extending at a high rate due to increased urbanization and population growth (CGK, 2018 – 2022) then provide suitable interventions within the study area. In addition, the studies were not clear to what extend does the drivers contributed to LULCCs. It's for this reason this study was done to fill the knowledge gap which further established the actual contribution of each driver in this study by use of sensitivity analysis whose output quantified drivers that are more sensitive and less sensitive within Khwisero Sub County. The researcher later ranked the drivers in terms of the most sensitive drivers to less sensitive driver giving the quantified contribution of each driver to achieve targeted interventions fully.

Land cover can be characterized as the actual qualities of the world's surface which includes vegetation, water, soil and other actual elements made through human exercises like settlement while land use alludes to the land used by people for environments concerning financial exercises (Rawat and Kumar, 2015). The causes of changes in uses and covers of land vary from place to place thus the impacts vary too (Zhihui et al., 2014). Poverty and population growth leads to deforestation (Mather and Needle, 2000) in many developing countries. This is supported by Cline - Cole et al. (1990) who found out that the demand for wood fuels especially from the small consuming units cause more deforestation. According to Allen and Barnes (1985) most deforestation happened by strain from populace development and interest for more food. All around the world anthropogenic exercises like agriculture, industry and transport underlined with different financial, political and institutional elements have brought about LULCC (Rowcroft, 2005).

In Europe LULCC are caused by political and financial changes which happened in first 50% of nineteenth Century (Bicik et al, 2015). Berke et al (2006); US Environment Protection Agency (2005) found out that U.S.A has experienced changes in the amount of forest cover due to logging, urban expansion, agriculture and construction of parking lots. Spruce et al. (2020) found out that drivers to LULCC in Asia include agricultural development/strengthening, deforestation, more waterway damming, expanded urbanization developing human populace, extension of industrialization, woodland ranches and cataclysmic events like flooding and dry season. According to a study conducted in China, the impacts can be positive or negative (Zhihui et al., 2014). China experiences LULCC that have both negative and positive effects (Zhihui et al., 2014). According to Zhihui et al. (2014); Long et al. (2007) found out that forests have been converted to agricultural and built-up areas causing negative effects; cultivated areas have been converted to grass lands and forests which improved land quality. The distinction among locales will influence the uses and covers of land, prompting contrast in the way and stretch out of monetary use of land assets (Long et al., 2006). The changes are ascribed to just a single principal figure in terms of size and sample, to be specific populace development (Bai and Dent, 2009).

Wright and Wimberly (2013) figured out that rising populace development straightforwardly and by implication adds to the LULCC in this manner affecting climate. Migration is an important demographic factor causing LULCC (Mathews, 2001). It is a huge driver of LULCC with others that are non-demographic like government strategies, changes in utilization design, financial coordination and globalization (Indian China and USA National Science Academy, 2002). As per Lambin et al. (2002) land use policies and projections representing LULCC future role should not just catch the complex financial and biophysical drivers of LULCC but also represent explicit human climate conditions under which the drivers of change work. Several studies carried out in India identified the following land use land cover changes; forests being turned into urban areas and agricultural land, designated agricultural land being turned into urban areas, grasslands and shrubland being converted to croplands (Chauhan and Nayak, 2005; Jayakumar and Arockiasamy, 2003; Jha et al., 2000; Sharma et al., 2007).Kumar and Jayarama (2013) found out the LULCC in India is due to rapid population, renaming of rural regions as metropolitan regions, absence of valuation of biological services, destitution, obliviousness of biophysical impediments and use of naturally contrary innovations.

Gary and Carmen (2007) identified various LULCC in Pennsylvania. Watershed and forests being converted into urban areas. From the studies and surveys carried out of tropical deforestation support the view that populace development was never the sole and not even significant cause of woods cover change (Geist et al., 2001). Other causes include weak national policies and expanded shifting cultivation (Rudel and Roper, 1996). Iran experiences various land use land cover changes. According to Nouri et al. (2018), Iran's dense forests and low forests are being converted to agricultural areas, mixture of orchards, forests and pastures being converted to human settlement. The rangelands are being converted to croplands (Rafi et al., 2014). Forests are the most dominant land cover in Nepal (Shambhu, 2019). The forests in Nepal are being converted to agricultural areas and urban areas (Ives and Messerli, 1989). Watersheds have been converted to agricultural and built-up areas as forest experience massive deforestation for expansion of agricultural and urban areas in Malaysia (Hua, 2015). This situation really affects the land quality.

Extension of agriculture impacted by populace development is an essential driver of LULCC in Africa (Wood et al., 2004). This is supported by FAO (1999) that LULCC is related with agricultural extension/strengthening, urbanization, deforestation and change of wetlands to pasture and agrarian lands. Sub-Saharan Africa is supposed to represent 20% of the total populace by 2050 (Alexandratos and Bruinsma, 2012) making land to stay under expanding pressure driven by urbanization and populace development (FAO, 2014). Asare et al. (2018) found out that South Africa experiences land use land cover changes like fresh water, woody plants and grassland areas being converted to urban areas and irrigation from the fresh water areas. FAO (2010) noted increased deforestation between 1990 – 2010 in Ghana removing a total of 32 million ha of forest. Climatic changes impact land use changes (Warburton et al., 2012). Leblanc et al. (2008) emphasized that the climatic changes resulted in an enormous scope dry season in West Africa between 1970-1980s.

Zimbabwe's land use land cover changes include; forests converted into agricultural lands and dams being converted to irrigation areas (Gumindoga et al., 2014). The forests found in Zimbabwe reduced between 1984-2013 by 36% and the cultivated areas increased by 13% (Gumindoga et al., 2014). Ethiopia has an extremely different arrangement of biological systems going from damp timberlands and broad wetlands to the desert (Tefara, 2011) and inside these mosaic conditions LULCC are inescapable and normal peculiarities where farming exercises and settlements rule rustic landscapes influencing environment administrations. Eyasu et al. (2018) highlighted that those forests have been undergoing changes into agricultural land, urbanization and general deforestation for the need of timber. In addition, small scale subsistence and large-scale commercial farming is being practiced in forested areas in Ethiopia due to population pressure, multi obtained and proceeds with inflow of migrants, absence of incorporated institutional framework and unsustainable overuse of products from forests (Betru et al., 2019). This calls for constant monitoring so as to protect the resource of land.

Services of land resource are significant for supporting life on the planet and keeping up with trustworthiness of the biological system. Notwithstanding, resources of land are falling under danger and stress in time. LULCC is one of among the really main thrusts (Lambin et al., 2003) on worldwide natural changes however the effects fluctuate across existence (Bryan, 2013; Constanza et al., 2014). The rising interest for food deficiency in arable land and flighty climatic circumstances in East Africa have made a shift from upland developments to Kilombero valley in Tanzania (Kirimi et al., 2018). A study conducted in Kilombero Valley Floodplain found out that the drivers of LULCC in this part of Tanzania included heightening of human exercises like agriculture which was the general driver, others included populace development, developing business sector request cost impetuses for agrarian and timberland items, further developed infrastructure systems and biophysical factors like soil properties, climate inconstancy and landscape qualities (Nagware et al., 2019). On the slopes of Mt Kilimajaro, there is increasing demand for food which results in LULCC (Mateso et al, 2021). The study further found out that increase in farm lands plays a minor role in increasing crop production. From the studies carried out demographic changes are more than other causative factors (Mather and Needle, 2000) Other studies suggest economic factors to be major drivers of LULCC (Lambin and Geist, 2001). It is clear driving forces vary from one locality to another.

Forested regions and grasslands have been switched over completely to developed regions for a time of over 30 years (Ntongani et al., 2014; Leemhuis et al., 2017; Seki et al., 2017). Matano et al. (2015) figured out that the change from normal forest cover to agricultural and pastoral exercises is widespread along the Mara River. Other catchment areas like Lake Victoria (Matano et al., 2017; Ocholla, 2006), Lake Baringo (Kiage et al., 2007), Nzoia, Nakivubo and Simiyu Drainage Basin (Twesigye et al., 2011), Nyando (Olang'et al., 2010) and River Isiukhu (Saidi, 2017) experiences changes like agricultural activities and or human settlement affecting the watersheds negatively. According Adhiambo (2018) the forest habitats and other natural vegetation covers are changing due to pressure for need of more land for agriculture and urbanization activities. These studies showed that drivers and effects of LULCC vary from one locality to the other. The drivers range from poverty and population growth leads to deforestation particularly in developing countries while other parts of the world experiences increased agriculture, industrial and transportation activities, political and financial changes, urban expansion, construction of parking lots, natural hazards from climatic changes, government strategies among others. It is important to understand various geographical localities with their specific drivers.

Theoretical Framework

The world's landscapes have been generally changed (Ellis, 2011), rebuilding biological systems and their administrations during the time spent supporting a populace moving toward eight billion at the time when materials consumed by man are at the highest level. The collection of these changes makes ecological effects that challenge the basic construction and capacity of the world's framework (Arbault et al., 2014; Steffen et al., 2011), with flowing effects on biodiversity, biogeochemical cycling, and climate change (De Chazal et al., 2009). A theory of land frameworks would make sense of the components and cycles creating land uses and land covers concerning social and natural subsystems (Rounsevell et al., 2012). Theories of land frameworks stay tricky (Zhou et al., 2019) as those for human natural connections overally (Roy Chowdhury and Turner, 2019). Briassoulis (2020) figured out that not very many hypotheses make sense of about land use change which she credited to the accompanying reasons; the speculations manage changes of determinants, most speculations are interconnected in nature which implies they don't permit various historical, institutional, political human organization and other more profound variables to go into illustrative schemata used, the description of the focal point of most speculations, joined with a presumption about framework balance produces static speculations for the most part which can't oblige elements of progress which is the pith of clarification, lastly level of investigation assumes a basic part as the genuine informative components of progress may not work at the degree of reference of a given theory. This present circumstance exists regardless of the calculated acknowledgment of natural administrations as a bio directional connect between the two subsystems i.e. human ecological (Angelstam et al., 2019; Bannet et al., 2015; Mace et al., 2012) and hence the call for integrating ecological criticisms in land use theory and models (Lambin and Meyfroidt, 2010; Pogratz et al., 2018). After the improvement of different numerous incorporated evaluation and specialist-based models on components of human climate relationship and the different structures of the subsystem has not yielded the advancement of land framework theory (Turner et al., 2020).

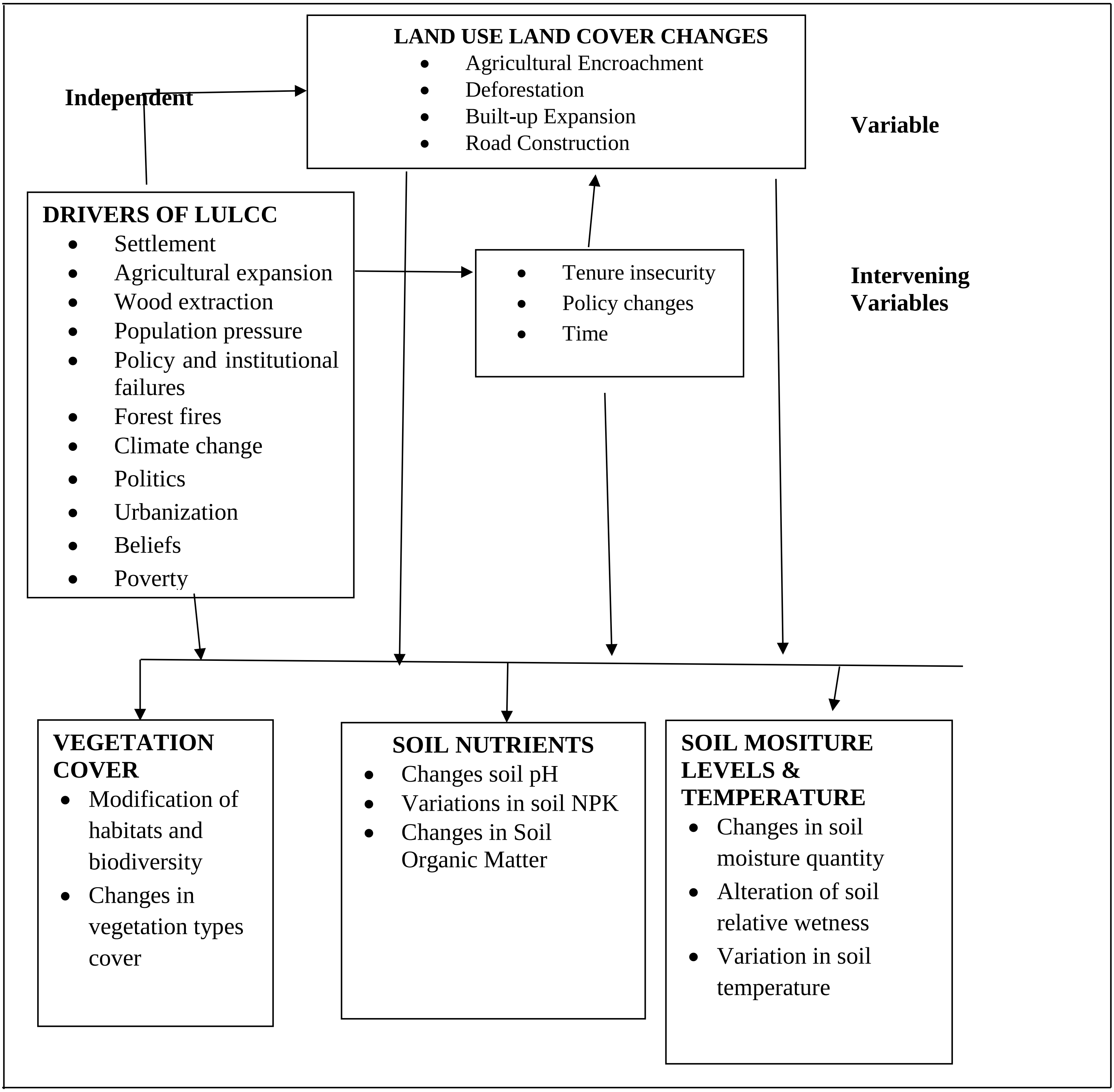
The current theories, speculation and clarifications on land elements don't completely integrate both social and natural aspects, rather they center around the construction, cycle and results in a single subsystem than the other, however completely address the cooperation (Chowdhury and Turner, 2019). As elaborated in their audit; ecological subsystem will in general treat human exercises i.e. land use as aggravations to the biological system working or administrations with negligible thought of the communications inside the social subsystem (Wu and Hobbs, 2002). The social science way to deal with land use will generally focus on components of social subsystem (Rounsevell et al., 2012). Only a rare example of ecological variables will generally impact land use, like soil quality or are impacted by those land uses i.e fossil fuel byproducts, biodiversity misfortune or soil erosion however underemphasizing the interconnection (Roy Chowdhury and Turner, 2019). Briassoulis (2020) noticed that theories that record for the spatial-temporal intricacies don't appear to exist yet.

It is consequently that the land system science community contends that coupling theories gotten from every subsystem stays the most productive integrative right now (Filatova et al., 2013; Vadjunec et al., 2018). This is supported by Briassoulis (2020) who proposed the use of combination of theories as opposed to depending on a solitary theoretical schema by inspecting basically which theories are reasonable for which spatial-temporal level. Subsequently, with the different land use and land cover designs, this study depended on two theories; Alonso's Bid lease theory and Von Thunen's agricultural land use theory. Bid lease theory in light of crafted by Alonso (1964) and Muth (1969) which focuses on how land use patterns are set on the land values (Shieh, 2003).

Land users battle for the most open land inside CBD, accordingly the sum they will pay is called offered lease (Shieh, 2003). This prompted the improvement of concentric land use structure by Alonso and was propelled by Von Thunen (Shieh, 2003). The concentric land use structure portrays city designs from the human natural theories which were created through the cycles of attack and progression; new interests attack specific pieces of the city succeeding the previous tenants who thus move to attack different parts, e.t.c bringing about specific land use designs i.e., concentric rings (Briassoulis, 2020).The concentric zones include: the focal business area, zone of progress, low-pay housing zone, middle pay housing zone and roving zone (Shieh, 2003). Bid lease theory can be related with LULCC of urban extension and road construction. Von Thunen theory of agricultural area makes sense of that the land use types considered are different kinds of agricultural land basically and optionally woods land. It explains that land which is formed into developing kinds of harvests from crops and ranger service of forests. Land is thought to be uniform with motion to all points and it is just leasing that changes with distance from the middle (Braissoulis, 2020). Von Thunen theory of agricultural area can be related with LULCC of farming encroachment, deforestation and wetland alteration. Bid lease theory has been operationalized in computational model displaying, where it has been used to mimic the change of agricultural land into metropolitan improvement in a concentric city model (Filatova et al., 2009). Von Thunnen theory and bid lease theory have been used by Walker (2004) in theorising land cover and land use change in tropical deforestation in the Amazon basin.

Conceptual Framework

The conceptual framework (Figure 1.1) defines four key wide and commonly interlinked variables in particular: drivers of LULCC across the world including; settlement, agricultural development, wood extraction, populace tension, policy and institutional disappointments, timberland fires, urbanization, beliefs, poverty political issues. The changes in covers and uses of land activities in the different parts of the world's surface including; agricultural encroachment, built-up extension, deforestation and road construction. The intervening variables of LULCC; policy changes, tenure insecurity together with time. The final variables are from land quality that are affected by the LULCC. The interlinkages between the independent and dependent variables are given at two levels. First, LULCC as an independent variable and dependent variable when it linked to the cause of the changes. This means that the LULCC will be dependent on the existence of any of the named causes for it to occur, without which no changes may be experienced in the uses and covers of land on the earth's surface. The study concentrates more on LULCC being an independent variable while land quality is the dependent variable. Land quality depend on the uses and covers of land to experience changes that have been shown in the conceptual framework (Figure 1). This includes the following; increased LULCC causes loss of vegetation cover which leads to destruction of habitats and loss of biodiversity. Increased LULCC leads to reduced levels of soil nutrients thus leading to reduced soil pH, NPK, SOM and tampering with the soil temperatures which will cause effects on crop yields during harvesting. Finally, increased LULCC activities affect the soil water levels thus reducing the soil water quantity and soil relative wetness. This has an effect on crop production too because soil moisture is one of the variables in determining where and how well different crops grow.



Dependent variables
Figure 1 Conceptual Framework
Source: Researcher, (2024)

METHODOLOGY

2.1 Research Design

The study used a cross sectional descriptive and longitudinal research designs. Cross sectional descriptive research design targeted drivers of LULCCs which involved visiting individual households. Longitudinal design involved Landsat images (Landsat 7, Landsat 8 and Landsat 9) for the years 2002 – 2023 observed the LULCCs experienced in Khwisero Sub County to establish change detection.

2.2 Study Area

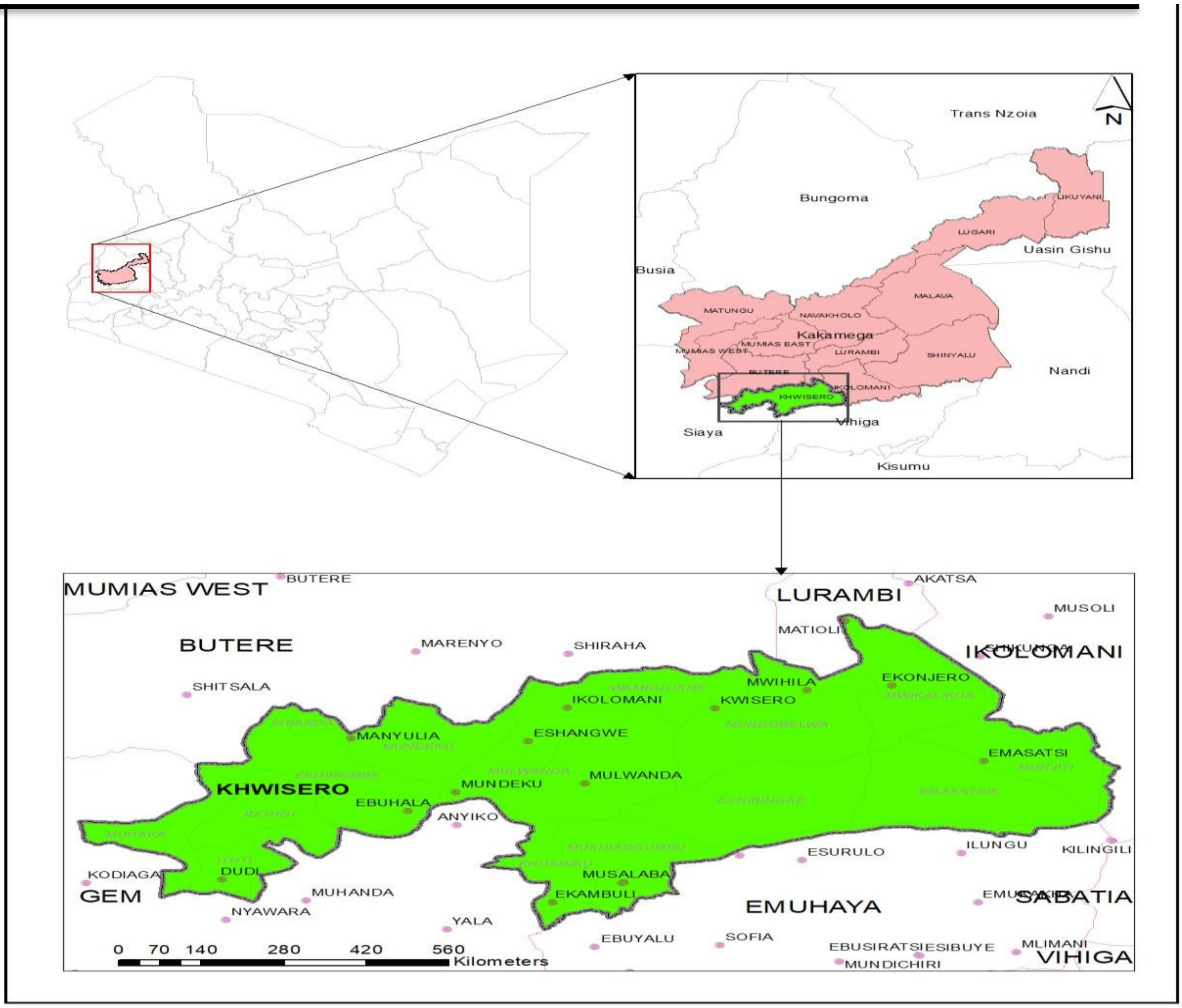
2.2.1 Location

Khwisero Sub County is one of the twelve sub counties of Kakamega County. It borders Butere and Lurambi Sub Counties in the West Ikolomani Sub-County in the East and Vihiga County in the South. Khwisero Sub County lies between longitudes 34.55442° and 34.634420 East and latitude 0.13121° and 0.211210 North. Its average elevation is 1387 meters and covers a total area of 145.6km2. It is the smallest sub county in Kakamega County. The Sub County is divided into four administrative units. Kisa Central leading with the highest numbers of village units and community areas since it covers a large area of 53.5km2. Kisa East is the smallest ward in area (28.7km2) but come second in terms of number of village units and community areas. Kisa North and Kisa West are approximately the same in area and have equal number of village units and community areas. The information can be summarized in the following Table 1.

Table 1: Administrative Units and Area by Wards

Ward	Area (Km^2)	No of village units	No of community areas
Kisa Central	53.5	4	9
Kisa West	28.7	3	6
Kisa East	31.9	2	5
Kisa North	31.5	2	5
Total	**145.6**	**11**	**25**

Source: Kakamega County Development Plan, (2018-2022)



	Legend	
(pink)		Kakamega County
(green)		Khwisero Sub County

Figure 2: Khwisero Sub County Administrative Boundaries by Ward
Source: Kakamega County Development Plan, (2018-2022)

The sub county is divided into two divisions. This are Khwisero East and Khwisero West. Khwisero East has three sub-locations namely; Kisa East, Kisa North and Kisa South. Khwisero West has four locations namely; Eshirombe, Kisa central, Kisa West and Mulwanda. This is shown in Table 2 below.

Table 2: Administrative Units and Area by Location

Location	Area (km^2)	Sub-locations
Kisa East	16.9	3
Kisa North	26.2	2
Kisa South	20.1	3

Eshirombe	10.5	2
Kisa central	25.1	3
Kisa West	17.7	3
Mulwanda	29.2	4
Total	**145.6**	**20**

Source: Kenya National Bureau of Statistics, (2019)

2.2.2 Topography and Hydrology

Khwisero Sub County is situated on the Eastern edges of the Rift Valley in the Southern part of Kakamega County. Its altitude ranges between 1240 metres and 2000 meters above mean sea level. Being in the southern piece of Kakamega County, it is bumpy and is comprised of granite rocks. The sub area has undulating slopes and valleys with streams moving from Northeast to Southwest and flowing into Lake Victoria. River Yala is the major river in Khwisero Sub County which experiences high riverine erosion.

2.2.3 Climate

Khwisero Sub County encounters tropical monsoon climate with reasonably circulated precipitation all through the year with a typical yearly precipitation that ranges from1400 mm to 2000 mm. Temperatures range between 18°C to 29°C. This climate upholds a wide assortment of harvests like tea, maize, sugarcane, horticultural yields and raising of domesticated animals.

2.2.4 Geology

The geological formation of the sub county is made out of significantly the Kavirondian system with few parts with the Nyanzian System rocks notable ones include; granite extension from Mumias and Maragoli granite, mudrock, greywacke, rhyolite/agglomerate, conglomerate, basalt/andesite, grits among others. These rocks have high potential for utilization as building materials and minerals.

2.2.5 Soils and Land Use

The sub county has two principal ecological zones to be specific; upper medium and lower medium. The most predominant ecological zone is the lower medium. The lower medium zone has primarily the red loamy sand soils gotten from sediments and absent rocks. The vitally economic activity is sugarcane production with certain farmers planting maize, yams, tea, groundnuts, cassava and sorghum on a small scale.

2.3 Study Population

Khwisero Sub County has a populace of 113,476 as at 2019 census, with Khwisero West Division leading with a population of 70,765 while Khwisero East Division has 42,711 persons. Mulwanda Location occupies the largest area of 29.2 km2 and thus the leading location in population of 25,186. The highest concentration of population density of 1032 persons per km2 is found in Eshriombe Location which occupies the smallest population of 105km2 with the least population of 10,874 amongst all the locations.

2.4 Sampling Procedure and Sample Size

The sampling area was Khwisero Sub County. The study employed purposive for the study area and key informant and random sampling procedures for households and soil samples. The study area was selected purposively because it is part of Kakamega County which encounters a wide range of environmental issues like land resource exhaustion, deforestation, pollution, water catchment areas destruction and loss of biodiversity (C.G.K, 2018-2022). In addition, KIPPRA (2021) and KNBS (2020) reports shows that Kakamega County is leading in poverty index across the members of the population with 65% of its household lack food stock followed by Homabay at 55%, then Turkana at 52% while counties like Kisii are at 11%, Bungoma 8% and Vihiga is at 4%. This could be mitigated by Khwisero Sub County which is approximately 33 kilometers from Kakamega Town where a lot of subsistence farming take place thus assist in the problem of food security within the county as it is well documented that Kakamega County is not food sufficient (C.G.K, 2018-2022). In addition, SOFDI (2021) cited that Misango Hills in Khwisero Sub County is a geographical feature that has been deforested over long time thus affecting food production potential because of depleted soils caused by erosion and thus making the study necessary.

According to Kenya Population and Housing Census (2019), Khwisero Sub County has a population of 113476 persons. According to Fisher et al (Mugenda and Mugenda 1999), a sample population greater than 10,000 sample size is 384. Therefore, Mugenda and Mugenda recommend the formula;

NF=n/1+(n/N)

to be used to calculate the sample size.

According to the above formula,

NF = the desired sample size when the population is less than 10,000

n = the desired sample when the population is more than 10,000

N = the estimate of the population size

Using the above formula, the sample size will be

Thus, NF = 384/1+(384/113476) = 384

Therefore, sample size of 384 was divided proportionately amongst the locations depending on their percentage of area population as shown in the table 3 below.

Table 3: Sample Size Calculation per Location

LOCATION	TOTAL POPULATION	SAMPLE FORMULA	SAMPLE SIZE
Mulwanda	2.5,186	$\frac{25186}{113476} \times n$	85
Kisa Central	22,291	$\frac{22291}{113476} \times n$	75
Kisa North	18608	$\frac{18608}{113476} \times n$	63
Kisa East	12,665	$\frac{12665}{113476} \times n$	43
Kisa West	12,414	$\frac{12414}{113476} \times n$	42
Kisa South	11,438	$\frac{11438}{113476} \times n$	39
Eshirombe	10,874	$\frac{10874}{113476} \times n$	37
Total	**113,476**	$\frac{(1.96)^2 \times 0.5 \times (1-05)}{(0.05)^2}$	**384**

Source: Researcher, (2024)

Simple random sampling on the other hand was used to select the households, where each household was given an equal chance. But because of the different population sizes in the locations, the sample population was distributed according to the percentage they contribute to the study area population. The area with the most noteworthy populace created the biggest number of samples. The respondents were distributed as shown in Table 3 per location. The research keyed in the names provided by village elders; the names of households were entered into excel then used RANDBETWEEN formula to generate random numbers from the excel.

Purposive sampling was used to select the Key Informants for vegetation types cover data and drivers for LULCC data. The study used 7 agricultural officers; one from each location, the Forestry Officer within the sub county and the Chief Sub County Environmental Officer.

2.5 Data Collection

The study used both primary and secondary data collection so as to achieve the objectives of the study. The study used Landsat images, qustionnaires, interviews and field observation.

2.5.1 Supervised Image Classification

Supervised classification was used in image classification which consists of three stages; training, testing and class allocation (Mathur and Foody, 2008). In the training stage, after classification, ground verification was done in order to check the precision of the classified LUCCs map, NPK, SOM and temperature values. Using ancillary data as a reference, Khwisero Sub County was digitized in an ArcMap creating 55randomly geo referenced points were generated for overall accuracy evaluation. It was done in order to assign different spectral signatures from the Landsat datasets. Furthermore, classification was done on the basis of reflection characteristics of the different LULC types. Different color composites were utilized to improve visualization of different objects on the imagery. Infrared color composite – near – infrared (NIR) (14), short – wave infrared SWIR (5) and Red (3) showed various vegetation of agriculture and forests – green shades; short – wave infrared (7), Near – infrared (4) and Red (2) showed variation in moisture content (because they are sensitive to moisture variation: built-up and bare soils – pink or dark blue.

2.5.2 Training Site Selection

For training site selection reconnaissance survey to the study area was done to determine the major LULC classes and to gather information that would guide the selection of training sites. Different areas of study area were visited to identify the existing LULC category and their GPS coordinates collected. These coordinates were used to identify the same locations on the unclassified maps since they were points of known LULC category. The identified points were then used as training sites to guide the overall accuracy procedures. The training sites were used to develop a signature file which the software used to classify the whole image based on the characteristics of the training sites.

2.5.3 Ground Truthing

After classification, ground verification was made in order to check the precision of the classified LULC map using ancillary data as a reference. Khwisero Sub County was digitized in Arc map. Stratified Random sampling method was applied in selecting reference points 55 then random reference points were generated with 55 being within the study area to obtain representation of land classes. 55 sample reference points per class were transferred to GPS and were physically visited for ground trothing to determine the current LULC classes. Based on ground verification data necessary correction and adjustment were made on the classification maps. The map from 2002 was compared with the map produced at 2023 and a complex matrix of categorical change obtained.

Table 4: Land Class and Definition for Supervised Classification

Class	Definition
Forest	This describes the areas with evergreen trees mainly growing naturally the reserved land
Agriculture	This class of land is used for growing food crops. Crops in this area are grown by rain-fed.
Built-up	This land covered with building in rural and urban i.e. commercial residential, industrial, transportation and infrastructure
Bare land	This is land left without vegetation cover, abandoned crop land eroded land due to land degradation and weathered road surface

Source: Researcher, (2024)

Table 4 above contains the description of the four dominant land use land cover classes that the researcher used in this study namely; forest, agriculture, built up and bare land.

2.5.4 Accuracy Assessment in Remote Sensing

A confusion matrix (or error matrix) is usually used as the quantitative method for characterizing image categorization trueness (Pavel, 2016). As indicated by Pavel (2016) it is a table showing correspondence between the grouping result and a reference image i.e., to make the confusion matrix, we want the ground truth data, for example, cartographic data, results of physically digitizing an image, field work/ground overview results recorded with a GPS-recipient. To ascertain and interpret the confusion matrix in ENVI programming, Confusion Matrix device empowered the study to do that. It makes the confusion matrix and error images for each class. What's more, it works out the category's trueness indices (overall trueness, kappa coefficient, oversight and commission errors for each class). After image classification, accuracy assessment was carried out. This was done in order to assess how well the classification procedure worked. Stratified random sampling was used to determine the number of reference points for every identified LULC category. Reference data was collected through ground trothing with GPS and from aerial photographs from Google earth for the purposes of determining the current class types at specific locations. The reference data was then compared to classified maps. The overall accuracy was determined by use of the formula;

$$\textbf{Total Accuracy} = \frac{\textbf{Number of correct plots}}{\textbf{Total number of plots}} \text{(Eqn … 10)}$$

However, the value obtained by this formula is average. It does not reveal if error was evenly distributed between the classes or if some classes were bad and other good. Therefore, users and producers' accuracy were also determined users' accuracy corresponds to the error of inclusion. It uses the classified maps data thus uses the perspective of the user of the map. This type of accuracy provides information on the number of pixels in the map that are actually under the specific category. Users' accuracy was determined by;

User's Accuracy = Number of correctly identified points on a given map/ (Eqn ... 11)

Number of claimed to be in the map

Procedure's accuracy corresponds to the error of exclusion. It uses the reference data thus; it is viewed from the perspective of the producer of the map. Procedure's accuracy answers eh question how many pixels in the map are labeled correctly for a given class in the reference points. Producer's accuracy was determined by;

Procedure's Accuracy = Number of correctly identified in reference points of a given class/ Number actually in the reference class (Eqn … 12)

Kappa Coeffient formula;

$$K= \frac{N \sum_{i=1}^{r} xii - \sum_{i=1}^{r}(x1+ * x+i)}{N^2 - \sum_{i=1}^{r}(xi+ * x+i)} \text{(Eqn … 13)}$$

K – Kappa Coeffient

R – Number of rows in the matrix

xii – Number of observations in row i and column i

xi + - marginal totals of row i

N – total number of observations

RESULTS AND DISCUSSION

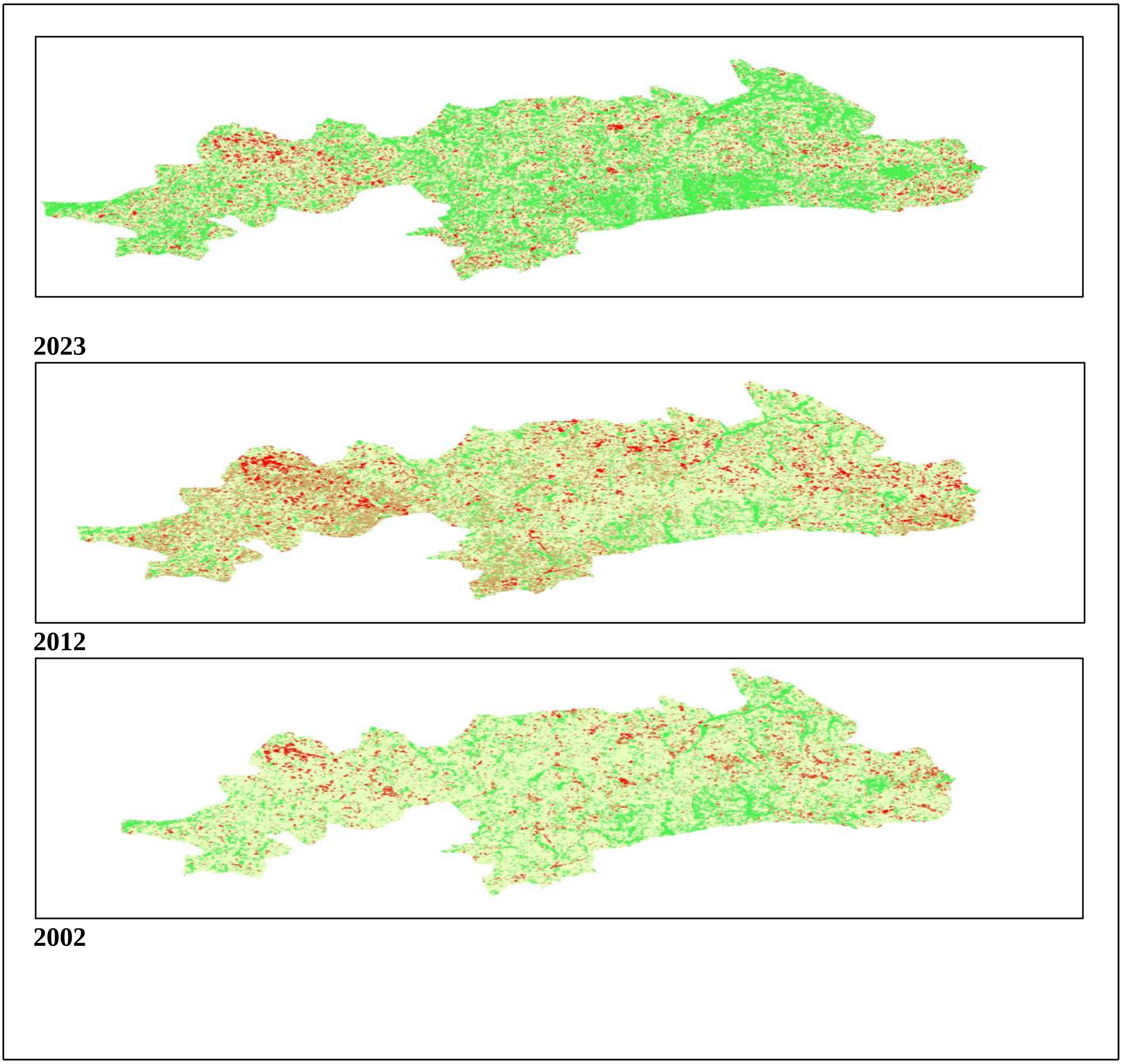
The data collected on drivers of LULCCs focused on land use land cover activities/classification, land use land cover change detection, levels of practice of LULCCs and the general effects of LULCCs on land quality in Khwisero Sub County.

3.1 Land Use Land Cover Classification

The study found out from the respondents in the field that the people of Khwisero Sub County engaged in crop farming, livestock keeping, charcoal burning, brick making, poultry keeping, housing projects, logging, road construction, building of water, reservoirs, excavation of rocks and land fragmentation for sale. These activities are done on land classified as public land, community land, private land, agricultural / arable land, non-arable land and forest land (CGK, 2018-2022). The findings from field data indicate that 72% of the respondents confirmed that the above listed land use land cover activities have been changing leading to land use land cover changes whereas 28% of the respondents noted that the above listed activities do not change.

3.2.1 Land use Land cover Change Detection

The change detection is performed to understand the land transitions and trends in the LULCCs. It is for this purpose that this study categorized the study area into decadal time period of 2002 – 2012 – 2023. The post classification comparison technique was used to calculate class transition and rate of change as shown in Figure 3 and Table 5, 6 and 7 below.



Legend **Name** **Class**
Forest
Agriculture
Built up
Bare land

Figure 3: Land use Land cover map 2002, 2012 and 2023 of Khwisero Sub County
Source: Researcher, (2024)

Figure 3 above shows the land use land cover of Khwisero Sub County for the period 2002 to 2023 where green indicate forested and other vegetation, light green indicates agricultural areas, red indicates built up while light brown shows bare land of the study area. Figure 3 2002 shows less green colour and it is lesser 2012 but it becomes more greener in 2023. Bare land is more dominant in 2012 while red colour for built up is becoming redder in 2023. Light green colour for agriculture is becoming less dominant towards 2023.

Table 5: Area and Percentage of LULCC

LULCC Type	2002 Area (Km²)	%	2012 Area (km²)	%	2023 Area (Km²)	%	LULCC % 2002-2012	LULCC % 2012-2023
Agriculture	110.79	70.1	88.75	61	81.34	55.9	-22.04 19.9%	-7.41 8.3%
Forest	21.81	15	18	12.4	52.75	35.7	-3.81 17.5%	34.75 193.1%
Built up	4.96	3.4	8.75	6	8.86	6.1	3.79 76.4%	0.11 1.3%
Bare land	8.04	5.5	30.10	20.7	2.65	1.8	22.06 274.4%	-27.45 91.2%
Total	**145.6**		**145.6**		**145.6**			

Source: Researcher, (2024)

Table 5 above shows the land use land cover classes, the area covered by each class and the percentage change of each class between 2002 and 2023. The percentage change was calculated as follows;

2002-2012 = percentage change (X%) = $\left(\frac{X2-X1}{X1}\right)$ x 100 (Eqn…15)

Where X2 = 2012

X1 = 2002

2012-2023 = percentage change (X%) = $\left(\frac{X2-X1}{X1}\right)$ x 100 (Eqn…16)

Where X2 = 2023

X1 = 2012

Table 6: Change Distribution Table 2002 to 2012

PIVOT TABLE	
Row Labels	**Sum of Area [km²]**
Bare - Bare	1.357200
Bare – Built up	0.189000
Bare - Forest	0.018900
Bare - Agriculture	3.812400

Buil tup - Bare	0.021600
Built up – Built up	0.032400
Built up - Forest	0.000900
Built up - Agriculture	0.027900
Forest - Bare	0.086400
Forest – Built up	0.022500
Forest - Forest	2.395800
Forest - Agriculture	9.682200
Agriculture - Bare	9.164700
Agriculture – Built up	0.557100
Agriculture - Forest	3.210300
Agriculture - Agriculture	114.000300
Grand Total	**144.579600**

Source: Researcher, (2024)

Table 6 above derived from the GIS software analysed from Landsat 7, 8 and 9 images to account for the losses and the gains of change detection, shows the distribution of the changes that took place in various land classes for the period of 2002 to 2012. The changes are both for the land classes that gained and lost. Table 4.12 indicates which land class gained and lost and at the same time it indicates the land class gained and lost from which land class for the period of 2002 to 2012.

Table 7: Change Distribution Table 2012 to 2023

PIVOT TABLE

Row Labels	**Sum of Area [km^2]**
Bare - Bare	5.982300
Bare – Built up	1.203300
Bare - Forest	0.057600
Bare - Agriculture	3.386700
Built up - Bare	0.468000
Built up – Built up	0.182700
Built up - Forest	0.017100
Built up - Agriculture	0.133200
Forest - Bare	0.341100
Forest – Built up	0.201600
Forest - Forest	1.060200
Forest - Agriculture	4.023000
Agriculture - Bare	31.816800
Agriculture– Built up	7.371000
Agriculture - Forest	2.604600
Agriculture - Agriculture	85.730400
Grand Total	**144.579600**

Source: Researcher, (2024)

Table 7 above derived from GIS software analysed from Landsat 7, 8 and 9 images to account for the losses and the gains of change detected, shows the distribution of the changes that took place in various land classes for the period of 2012 to 2023. The changes are both for the land classes that gained and lost. Table 6 indicates which land class gained and lost and at the same time it indicates the land class gained and lost from which land class for the period of 2012 to 2023.The findings of this study from satellite images as shown in Tables 5, 6 and 7 together with Figure 8 indicate that there has been decline in agriculture land use from 2002 – 2023 which could be attributed to creation of land for built up, bare land and forest as shown in Tables 6 and 7. The study noted that agriculture land use occupies the largest area across the years with 70% in 2002, 61% in 2012 and 55.9% in 2023. The area under forest land use occupies the second largest area which decreased in 2012 from 21.81 km2 to 18 km2 at the rate of 17.5%. This decrease could be attributed to creation of more land for built up area increasing by 76.4% and bare land 274.4% as shown in Table 6 above. However, in 2023 the forested area increased from 18 km2 to 52.75 km2 at the rate of 193.1%. This increase in 2023 could explain the drastic decrease in agricultural land and bare land as seen in Tables 6 and 7. Built up area increased by 50% from 2002 to 2012 (4.96 km2 to 8.75 km2) with a slight increase in 2023of 1.3% from 8.75 km2 to 8.86 km2. Bare land was more than built up in 2002 by 8.04 km2 which tripled in 2012 from 8.04 km2 to 30.10 km2 but in 2023 it reduced in area drastically from 30.10 km2 to 2.65 km2. This drastic decrease of bare land could be attributed to increase in forested areas by four times from 18 km2 to 52.75 km2and increase in built up area by 1.3% based on Tables 6 and 7. Agricultural area has been decreasing and donating space for other land uses and covers as shown in Tables 4.11 and 4.12 but it has remained the land use land cover that covers the largest area of Khwisero Sub County as shown in Figure 3 and Tables 5, 6 and 7. Change detection in other areas across the globe gave varied results.

Change detection that was performed by Mekonnen et al. (2022) revealed increase in agricultural land use and cover in Awash River, decrease in forest land and increase in urban land between 1984 and 2019. This research supports Khwisero Sub County study in built-up only. Another study in Ethiopia by Mehari, Li and Melesse (2022) found out that settlement and forested areas increased while agricultural and bare land decreased. The decrease in agricultural and bare land created room / space for settlement and forested areas (Gelana, 2022). In China, Xiangmei et al. (2016) found out that built-up increased from arable land, forest remained unchanged due to topography and geomorphology whereas agricultural land reduced to built up areas. This study supports Khwisero sub-county study where built up area increased while agricultural land decreased.

A study by Duraisamy et al. (2018) also found out that agriculture in Mula Pravara increased, bare land decreased while built up increased between 199-2016. The built up and bare land uses support the findings of Khwisero land use land cover change detection where; built up areas increased throughout the study period whereas bare land areas decreased. Another study in India particularly urban set up found out that agriculture and forest land uses have been reducing while built up land use has been increasing (Suresh and Anuj, 2013). This study supports the findings of Khwisero land use land cover change detection where agriculture has been reducing with increasing urbanization. Duraisamy et al. (2018) observation on change detection of forest land is similar to Khwisero Sub County where the forest land reduced from 21.81 km2 to 18km2 then increased to 52.75km2as the case of Mula Pravara area where the forests increased, decreased and then increased in area between 1991 and 2016. Forest decrease was attributed to creation of land for agriculture; agricultural land was also converted to built-up while bare land / fallow land was converted to agricultural land (Vijayasekaran et al., 2018). Kafi et al. (2014) study noted a similar scenario in Bauchi city in Nigeria the same as Khwisero Sub County where built-up increased while agriculture decreased between 2003 and 2013. The change detection of Khwisero Sub County can be summarized in the Figure 4 below;

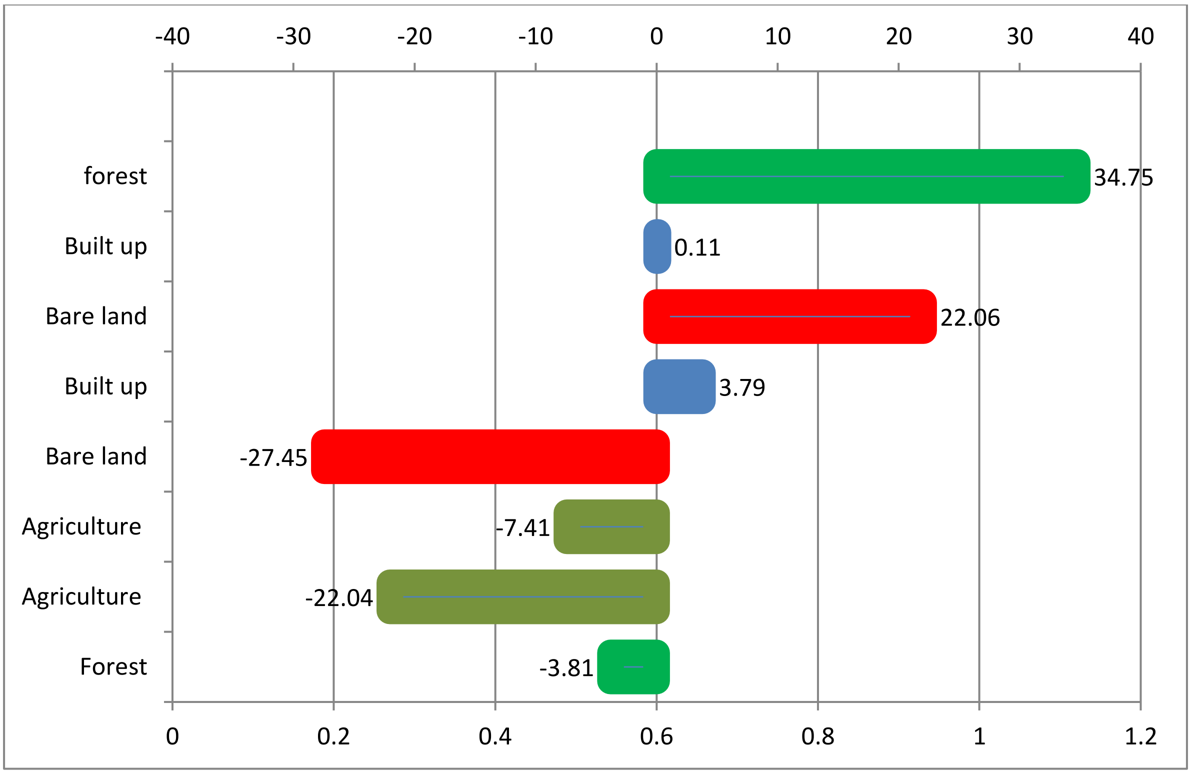


Figure 4: Gains and Loss of Land Use Land Cover Classes
Source: Researcher, (2024)

Figure 4 shows the gains and the losses of the land uses land covers changes of Khwisero Sub County between 2002 and 2023 combined. Bright green shows forest which lost 3.81 km2 between 2002 to 2012 but gained 34.75km2 between 2012 and 2023. Dark green shows agriculture that has lost throughout the study period to a total of 29.45km2. Purple indicates built up that has gained throughout the study period by 3.90km2. Red shows bare land that gained between 2002 and 2012 by 22.06km2 but lost 27.45km2 between 2012 and 2023.

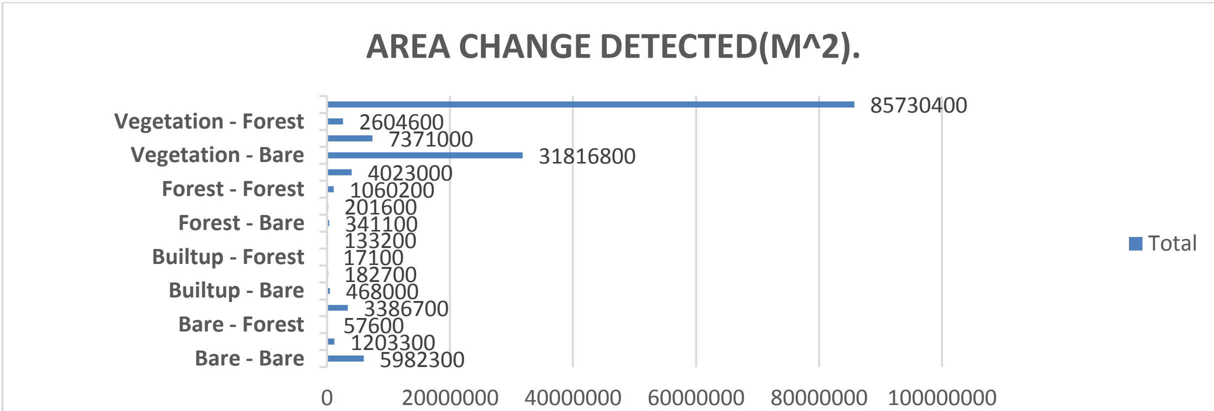


Figure 5: Gains and Loses Distribution 2012 to 2023
Source: Researcher, (2024)

Figures 4 and 5 were derived from GIS software analysed from Landsat 7, 8 and 9 images to account for the change detected for the four land classes for Khwisero study area for the period between 2002 and 2023.

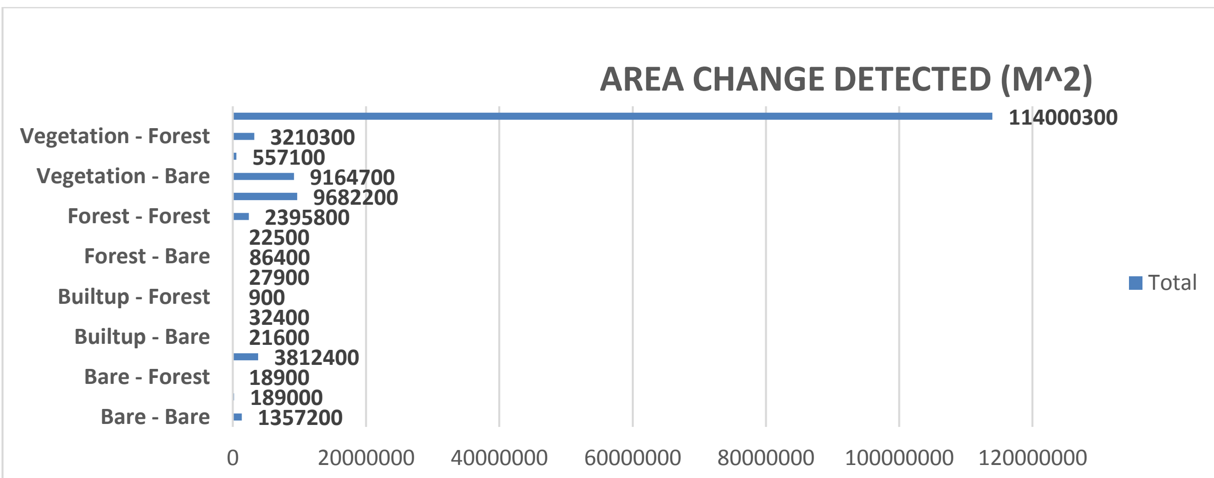


Figure 6: Gains and Loses Distribution 2002 to 2012
Source: Researcher, (2024)

The gains and loses graphs in Figures 4, 5 and 6 indicate that agriculture lost the most of the area i.e., 29.55km2 followed by bare land 27.45km2 then forests 3.81km2. The loses could be attributed to increased built up and forest at 3.90km2 and 34.75km2 respectively. From the data observed in the field and KIIs interviews the respondents attributed these losses to increased settlement, poverty and climate change. Furthermore, the respondents noted that reduced agricultural land and forested land was due to increased settlement together with poverty that led to destruction of forests for timber and other uses in 2002 – 2012.Bare land increased between 2002 and 2012 which could be attributed to climate change which was experienced particularly in 2012.This is supported by Landsat 7, 8 and 9 images whose LST indices increased, SMI decreased and NDVI indices decreased in 2012 as shown and discussed in objective 2, 3 and 4 of this study. Other drivers that could have led to the loss agricultural area and bare land could be the increased population as indicated by The Kenya Population and Housing Census of Kenya (2009) and (2019) that population of Khwisero Sub County was 102, 635 in 2009 but increased to 113, 476 in 2019; 705 person per square kilometers in 2009 to 779 persons per square kilometers in 2019 meaning there was additional of 74 km2persons for the population in Khwisero Sub County in 2019.

Figures 5 and 6 from the Landsat 7, 8 and 9 images indicate clearly which land use land cover lost or gained from a particular land use land cover. Forested land gained the most between 2012 – 2023 (34.75km2) from bare land and agriculture and lost to built up and bare land between 2002 to 2012. Bare land gained from agriculture and forest in 2002 to 2012 but lost to built up and forest between 2012 to 2023. Built up gained throughout 2002 to 2023 from forest, agriculture and forest. Built up gained up to 3.90km2 due to urbanization as pointed out by the field data from the KIIs respondents. Agriculture on the other hand lost throughout to forest, bare land and built up from 2002 to 2023 although it has been expanding as pointed out by the field data from household respondent. Field data of household and KII respondents attributed the losses and the gains to the land cover land uses classes to politics, policies, policy and institution failure.

This study combined both remote sensing and field data both from the household and KIIs to find out the drivers to LULCCS. Similarly various studies used mixed methods to ascertain the drivers to LULCCs. Xiaoming et al. (2020) used geographic object-based image analysis and standardized coefficient of driver's proxies where the study found out that biographical and socio-economic were the major drivers of LULCC in Bangladesh. Abd. El-Hamed (2020) study confirms change in land uses and established population growth to be the leading driver followed by agricultural extension. Janina et al. (2017) used mixed methods that is remote sensing and experts / interviews where the study found out that population growth was the major driver.

In Ethiopia, a study by Mehari (2022) combined approaches (field observation, LULCC household interviews, KIIs remote sensing and FGD's) which linked LULCCS to population growth, settlement and expansion of farmlands. On the other hand, a logistic regression model was created from an independent variable from remote sensing and driving forces for LULCC which produced a statistically significant model (Bekere et al., 2023). In town set up settlement land use land cover class was so high as indicated in a study by Ochola (2019) in Rongo town found out that settlement increased by 48.52% between 2010 and 2018 while plantation/farmland and open land decreased by 48.86% and 12.87% respectively as seen in Landsat images of between 2010 and 2018. In contrast, settlement areas in other rural areas like Malava decreased from 42.21% to 12.99% to create more land for forests same to bare land that declined 8.11% to 6.72% between the years 2013 to 2021 (Masayi, 2021).

3.2.2.1 Classification Accuracy Assessment

Classification accuracy assessment was done to establish the information value of the results from Landsat 7, 8 and 9 images data of 2002, 2012 and 2023 as indicated in Appendix 13 and summarized in Tables 8, 9 and 10.

Table 8: 2002 Classification Accuracy Assessment

Land use Land Cover Classes	Forest Km^2	Vegetation Km^2	Bare land Km^2	Built up Km^2	Total Km^2	Omission %	Commission %	Users Accuracy %
Forest	10	1	0	0	11	0	9.09	90.91
Vegetation	0	29	2	0	31	9.38	6.45	93.55
Bare land	0	2	7	0	9	41.67	22.22	77.77
Built up	0	0	3	1	4	0	75	25
Total	10	32	12	1	55	-	-	-
Procedures Accuracy%	100	990.630	58.33	100	-	-	-	-

Overall Accuracy = 85.45% Kappa = 0.756

Source: Researcher, (2024)

Table 9: 2012 Classification Accuracy Assessment

Land use Land Cover Classes	Forest Km^2	Vegetation Km^2	Bare land Km^2	Built up Km^2	Total Km^2	Omission %	Commission %	Users Accuracy %
Forest	0	2	0	0	2	100	1	99
Vegetation	0	40	5	0	45	4.76	11.11	88.89
Bare land	1	0	2	0	3	75	33.33	66.67
Built up	0	0	1	4	5	0	20	100
Total	1	42	8	4	55	-	-	-
Procedures Accuracy%	0	100	25	100	-	-	-	-

Overall Accuracy = 83.64 % Kappa = 0.5454

Source: Researcher, (2024)

Table 10: 2023 Classification Accuracy Assessment

Land use Land Cover Classes	Forest Km^2	Vegetation Km^2	Bare land Km^2	Built up Km^2	Total Km^2	Omission %	Commission %	Users Accuracy %
Forest	5	0	0	0	5	16.67	0	100
Vegetation	1	27	1	2	31	15.63	12.9	87.1
Bare land	0	5	10	0	15	16.67	33.33	66.67
Built up	0	0	1	3	4	40	25	75
Total	6	32	12	5	55	-	-	-
Procedures Accuracy%	83.33	84.38	83.33	60	-	-	-	-

Overall Accuracy = 81.8181% Kappa = 0.6034

Source: Researcher, (2024)

3.2.2.2 Kappa Coefficient Interpretation

Kappa coefficient is a measure of agreement between two dependent categorical samples. Moreover, it is the overall agreement of a matrix and accounts for all the elements in a matrix and ranges from -1 to +1 and it is interpreted as follows; Less than 0 means no agreement, 0.01– 0.20 means none to slight agreement, 0.21 – 0.40 indicates fair agreement, 0.41 – 0.60 stands for moderate agreement, 0.61 – 0.81 indicates substantial agreement while 0.81 – 1.00 means almost perfect agreement. The results of classification accuracy assessment indicate that overall accuracy for Khwisero Sub County was 85.45% for 2002, 83.64% for 2012, 81.82% for 2023 giving a mean of 83.64% for the three decades. Therefore, the accuracy assessment of land use land cover change detection of Khwisero Sub County can be interpreted as follows;2002 kappa coefficient was 0.756 which is substantial agreement, 2012 was 0.5454 which is moderate agreement and 2023 was 0.6034 which is also moderate agreement.

The kappa results of this study are similar to other studies. A study conducted in Limpopo Province by Rwanga and Ndambuki (2017) realized overall accuracy of 81.7% and Kappa of 0.722 which is substantial agreement hence the classified image found to be fit for further study. This study utilized supervised classification for six LULC classes of agriculture, water, built up, mixed forest, shrubs and bare land. Labisa (2021) conducted accuracy assessment to compare sentinel-2 and ASTER. Sentinel -2 realised overall accuracy of 78.33% and Kappa of 0.71 then 81.25% and Kappa of 0.74 while ASTER realized overall accuracy of 67.17% and Kappa of 0.55 then 72.68% and Kappa of 0.61. This study utilized unsupervised classification for 52 spectral clusters with four LULC classes of urban, agriculture, forest and bare land. These results showed that sentinel -2 is better than ASTER in Indonesia (Labisa, 2021).

Furthermore, Arumugam et al. (2021) study in India realized an overall accuracy of 76.84% and Kappa of 0.722 with six classes of agriculture, forest, fallow, settlement, water and rivers and. An overall accuracy of 84.0% and Kappa 0.79 in 2020, 85.3% and Kappa of 0.8 for 2015 and 80.2% and Kappa of 0.74 for 2010 was realized in 85 random points in Indonesia too with five LULC classes of agriculture, non-agriculture, bare land, settlement and water (Islami et al., 2021). This Kappa coefficient was good and acceptable. Kitada and Fukuyama (2012) realized an overall accuracy of 68% and Kappa of 0.64 together with an overall accuracy of 65% and Kappa of 0.60 both suitable.

Furthermore, Sentinel-2 was used for accuracy test at different levels. Single layered for training and testing resulted in overall accuracy of 91.37% with a Kappa of 0.865 and 93.77% with a Kappa of 0.902 respectively; temporal-layered resulted in overall accuracy both for training and testing of 98.07% with a Kappa of 0.965 respectively; random forest algorithm realized an overall accuracy for both training and testing of 99.79% with a Kappa of 0.996 and 96.98% with a Kappa of 0.954 (Aziz et al., 2024).

Further analysis was done so as to establish the levels of practice of LULCCs ranging from most practiced to less practiced. The results are summarized in Table 11. The result from the household and KIIs portrayed similar finding as the results from Landsat images of land use land cover change detection. The table below shows the levels of practice of LULCCs ranging from most practiced to least practiced.

Table 11: The Level of LULCC Practiced in Khwisero Sub County

LULCCs	Levels of practice of LULCCs (Frequencies/percentages)					Statistics (n = 384)	
	Most	More	Averagely	Less	Least	Mean	St. Dev.
Agricultural Encroachment	224(58%)	62(16%)	83(22%)	11(3%)	4(1%)	4.61	0.944
Deforestation	54(14%)	181(47%)	72(19%)	42(11%)	34(7%)	2.43	1.079
Built up Expansion	74(19%)	150(39%)	104(27%)	33(9%)	23(6%)	2.53	1.133
Road Construction	84(22%)	116(30%)	121(32%)	47(12%)	16(4%)	2.47	1.088
Others	0 (0%)	34(9%)	23(6%)	3(8%)	324(84%)	1.72	0.966

Source: Researcher, (2024)

Table 11 above shows the level of LULCC practiced in Khwisero Sub County. The findings in above clearly shows that agricultural encroachment is the most practiced LULCCs as shown in Table 11 indicate that agriculture occupies the largest area compared to other land use land cover activities as shown from the Landsat images. Deforestation and built up are more practiced. This can explain why in 2012 forest land reduced from 21.81 km2 to 18 km2 as shown in Table 5. From the land use land cover change detection analysis in Table 5, built up has been increasing. This can explain the steady increase in built up between 2002 and 2023. Road construction is averagely practiced while other activities are least practiced. This could explain the steady decrease of agricultural land between 2002 and 2023 to create land for road construction and other activities as explained by the respondents.

3.3 The Drivers of Land use Land cover Changes

Respondents in the study area provided responses on driving factors and the levels at which the drivers affect LULCCs. The results are summarized in the table below. Table 12 shows LULCCs driving factors and the levels at which the drivers affect LULCCs.

Table 12: Driving factors and the Levels they affect LULCCs

Driving Forces of the LULCCs	Levels at which the driving forces affect LULCCs (Frequency/percentages)					Statistics (n = 384)	
	Affect most	Affect more	Affect averagely	Affect less	Affect least	Mean	St. Dev.
Settlement	142(37%)	94(25%)	100(26%)	36(9%)	12(3%)	3.92	0.953
Agricultural extension	38(10%)	96(25%)	110(29%)	90(23%)	50(18%)	3.89	0.987
Urbanization	13(3%)	76(20%)	96(25%)	119(31%)	80(21%)	3.64	0.978
Population pressure	22(6%)	80(21%)	146(38%)	95(25%)	41(11%)	3.77	1.167
Policy and institution failure	11(3%)	62(16%)	90(23%)	134(35%)	87(23%)	3.49	1.067
Forest fires	18(5%)	41(11%)	83(22%)	110(29%)	132(34%)	3.14	1.047
Climate change	295(77%)	57(15%)	10(3%)	22(6%)	0(0%)	4.70	0.750
Politics	7(2%)	68(18%)	121(32%)	107(28%)	81(21%)	3.58	1.093
Beliefs	13(3%)	34(9%)	97(25%)	174(45%)	66(17%)	3.46	1.126
Poverty	270(70%)	72(19%)	32(8%)	10(3%)	0(0%)	4.09	0.861
Wood extraction	8(2%)	29(8%)	75(20%)	157(41%)	115(30%)	3.05	1.184

Tenure insecurity	11(3%)	28(7%)	40(10%)	206(54%)	99(26%)	2.17	1.123
Policy changes	4(1%)	14(4%)	60(16%)	71(45%)	135(35%)	1.43	0.755
Others	0(0%)	16(4%)	19(5%)	31(8%)	318(83%)	1.37	0.794

Source: Researcher, (2024)

From the findings in Table 12, the drivers that affect LULCCs the most are settlement, climate change and poverty. Agricultural extension, population pressure and politics affect LULCCs averagely whereas quite a good number of drivers like urbanization, policy & institution failure, beliefs, wood extraction, tenure insecurity and policy changes affect LULCCs less. Forest fires and other drivers affects LULCCs the least. The drivers affecting LULCCs vary from place to place due to variation in topography, climate and human activities (Munns, 2006). In Ethiopia's rural area of Nashe Watershed Mehari et al. (2022) found out that dam project contributed up to 57% while agricultural extension contributed up to 33.9% of the land use land cover changes. Duraisamy et al. (2018) grouped LULCC drivers as institutional (government policies), economic (agricultural and built-up), technological (agricultural mechanization) and natural factors (long periods of dry spell) as drivers of LULCCs in India. Xiangmei et al. (2016) grouped LULCC drivers in China as follows; physical (topography and geomorphology) and socio-economic factors (population and industrialization). From the literature review Mather and Needle (2004) indicated that demographic factors and poverty seem to be a leading cause of LULCC while Lambin and Geist (2001) suggested that economic factors could be leading cause of LULCC.

In Europe LULCC are caused by political and financial changes (Bicik et al., 2015). Wright and Wimberly (2013) and Mathews (2001) noted that rising population leads to LULCC across the globe. Wood et al (2004) and FAO (1997) noted that agriculture impacted by population growth is the major driver of LULCC in Africa. Studies carried out in Kenya (Matano et al., 2015; Ocholla, 2006; Kiage et al., 2007; Twesigye et al., 2011; Olang' et al., 2010; Saidi, 2017 and Adhiambo, 2018) found out that agricultural extension, population pressure and poverty were lead causes / drivers of LULCC in Kenya. From the other studies Khwisero Sub County drivers to LULCC are not any different with the drivers of other study areas. Most of the above studies support the results of this study whose drivers include settlement, climate change, poverty, agricultural extension population pressure and politics being lead drivers as the case of India, China, Ethiopia, Nigeria and other parts of Kenya. From the gains and loses analysis together with data from the field from household and KII respondents this study categorized drivers to land use land cover changes into four categories ranked from the most observed driver to the least observed driver as shown in Table 13 below.

Table 13: Rank, Drivers and LULCC Affected

RANK	DRIVERS	LULC CLASS
Most	Settlement, Poverty, and Climate change	Forest, Agriculture, Bare land, Built up
Average	Agricultural Extension, Population and Politics	Forest and Agriculture
Less	Urbanization, Policy and Institution failure, Beliefs, Wood extraction, Tenure insecurity and Policy changes	Built up and Forests
Least	Forest fires	Forests

Source: Researcher, (2024)

Table 13 has summarized the drivers, the land use land cover classes they affect and the rank. The drivers that mostly affect land use land cover classes are settlement, poverty and climate change while those that affect land use land cover averagely are agricultural extension, population and politics. On the other hand, urbanization, policy and institution failure, beliefs, wood extraction, tenure insecurity and policy changes affect LULCC classes less while forest fires were least experienced.

Summary of the Findings

The study aimed at examining the driving forces that influence land use land cover changes in Khwisero Sub County. The results from the field indicated that the drivers that influenced LULCC the most were settlement, climate change and poverty with a mean of 4.24. The drivers that averagely influence LULCC at a mean of 3.75 were agricultural extension population pressure and politics. The study also found out that most of the highlighted drivers in the study influenced LULCC less at a mean of 2.89 which included; urbanization, policy & institution failure, beliefs, wood extraction, tenure insecurity and policy changes. The results from the remotely sensed data indicated that build up has been increasing, since 2002 agricultural expansion occupied the highest area since 2002 to 2023, forest reduced between 2002 to 2012 but increased between 2012 to 2023 whereas bare land increased between 2002 to 2012 but reduced between 2012 to 2023. Forest fires affected LULCC the least as indicated by the results from the field. The study conducted an accuracy assessment for the land use land cover class between 2002 and 2023. The results indicated that the accuracy assessment for 2002 was 85.45% with a Kappa coefficient of 0.756, 2012 accuracy assessment was 83.64% with a Kappa coefficient of 0.5454 while 2023 accuracy assessment was 81.82% with a Kappa coefficient of 0.6034.

CONCLUSIONS

Khwisero Sub County experience various drivers that influence LULCCs. Major drivers that influence LULCC include settlement, climate change and poverty while agricultural extension, population pressure and politics influence LULCCs averagely. Other drivers found in the study area included urbanization, policy & institution failure, beliefs, wood extraction, tenure insecurity, policy changes and wild fires were regarded as fewer effective drivers. However, the residents of Khwisero Sub County had little knowledge on the LULCCs drivers' effect on land quality because they lack alternatives.

RECOMMENDATIONS

There is need to create awareness on the need to understand the importance of land quality and how to manage land resources in general to improve the standards of the residents of Khwiser Sub County. In order to ensure sustainable utilization of the land resources in the study area there is need for the residents to understand all the LULCC on their land and the drivers that lead them to change the land uses and land covers thus understand and create alternative sources that are environmentally friendly.

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