

Changes in Cropland between 1986 and 2019 in Kitui Central Sub-County, Kitui County, Kenya

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ABSTRACT

Remote sensing and geospatial technologies are instrumental in identifying, mapping and quantifying changes in valuable resources like croplands. Cropland maps are important in crop monitoring, food security, land planning and management. However, Kitui Central Sub-County has limited cropland maps. This study, therefore, aimed at detecting and quantifying the changes in cropland in Kitui Central Sub-County from 1986 to 2019 using multispectral data obtained from Landsat archives. Cropland, built-up areas, bushland, grassland and water bodies were identified as the main land cover classes in the study area through a reconnaissance study done before the land use and land cover classification. Supervised classification was performed using the Maximum Likelihood Classifier algorithm to map land use and land cover classes of 1986, 2001, 2011 and 2019. Change detection analysis was then performed using post-classification comparison method in order to identify the changes in cropland over the period of study. The results showed that there was an increase in cropland area from 185.23 km² in 1986 to 327.28 km² in 2001. This was followed by a decrease to 231.15 km² in 2011 and a rise to 357.37 km² in 2019. Knowledge of such trends in cropland can be used by agricultural resource managers in sustainable agriculture to manage croplands and boost food production and security in Kitui Central.

Keywords: Land use; land cover; change detection; cropland; remote sensing and GIS

INTRODUCTION

Land acts as an important resource in the provision and supply of food through agriculture. The modification and utilization of land for agriculture, settlement, mining and transport is termed as land use. On the other hand, land cover depicts the physical and biological cover over the land's surface which includes cropland, vegetation, artificial structures, water and bare soil [1]. Changes in land use and land cover are believed to be the primary drivers of global change through emission of greenhouse gases, climate change, loss of biodiversity, land degradation and loss of soil resources [2, 3]. Therefore, the accuracy, consistency and timely detection and quantification of such changes are vital in the sustainable management of land resources [4].

Over the past years, land has become a scarce resource as a result of pressure from agriculture and population [5, 6]. Therefore, information on land use, land cover and their best potential use can be used in sustainable land development to meet the demands created by such pressure [5]. Remote sensing and geospatial techniques have become important in providing and generating such information at various temporal and spatial scales. As such, various studies have employed these techniques to study and map land use and land cover globally. To date, significant attention has been given towards the development of procedures that can accurately map and quantify land surface alterations [4]. These attempts have been boosted immensely by the availability of satellite imagery at various levels of spatial and temporal resolution. These datasets have been used by several studies to map, quantify and model the changes in land use and land cover.

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Received date: July 17, 2021; Accepted date: October 07, 2021; Published date: October 19, 2021

Citation: Oduke WO, Musembi DK, Kariuki PC (2021) Changes in Cropland Between 1986 and 2019 in Kitui Central Sub-County, Kitui County, Kenya. J Remote Sens GIS 10: p132.

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Agriculture is considered a key economic sector in many developing nations [7]. In Kenya, agriculture is the main economic activity that employs about 75% of the population and contributes about 26% of the country’s gross domestic product (GDP) [8]. Due to rapid population growth, urbanization and industrialization, agricultural land is decreasing with time [2]. As such, the determination of suitable land for agricultural production, their expansion and protection of the available arable land has become an issue of great concern among policymakers as well as decision-makers [9].

Studies done [1, 4, 10-14] demonstrate how various areas in Kenya have experienced land use and land cover changes. Researchers have also made attempts to map and quantify agricultural land in various areas of the country [10] concluded that 61.5% of agricultural land was converted to built-up land in Kiambu County between 1986 and 2014 while Ref. Established that agricultural land reduced from 39.7% to 15.8% between 1984 and 2013 in the same county. In Kitui Central Sub-County, there is limited knowledge on the various land use and land cover classes. Moreover, limited research has been done to map and quantify cropland using remote sensing and geospatial techniques. This study, therefore, aimed at exploring this gap in knowledge by mapping and quantifying changes in cropland in Kitui Central Sub-County from 1986 to 2019 using remote sensing and geospatial techniques [14].

MATERIALS AND METHODS

Study Area

The research took place in Kitui Central Sub-County which is located in Kitui County. Kitui Central covers an area of approximately 662.7 km² and has five administrative wards namely Miambani, Kitui Township, Kyangwithya West, Mulango and Kyangwithya East [16, 17]. It forms part of the highland areas of Kitui County which exhibit a sub-humid climate and is, therefore, an important area for agricultural activities. Kitui Central is also the most densely populated constituency in Kitui County [16]. As such, there is a growing demand for food and shelter that strains the available land resources.

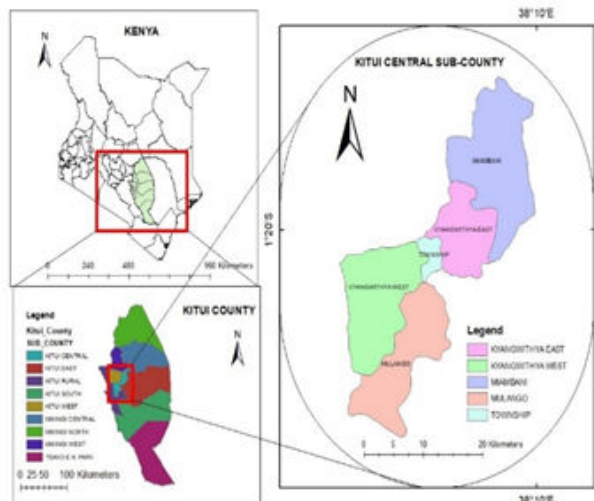


Figure1: Map showing the location of Kitui Central in Kitui County, Kenya.

Data Collection

The study purposed to use Landsat images with a ten-year sequence between 1986 and 2019. However, it was not possible to acquire images sequentially due to poor data quality when images have high cloud cover (10%) or missing information caused by Landsat 7 sensor failure as of July 2003. Similar limitations were reported [18]. while studying land cover and land use dynamics in Rumuruti, Kenya, and Malinda, Tanzania. Landsat images for the years 1986, 2001, 2011 and 2019 were, therefore, downloaded from Landsat archives and used for this study. The satellite images downloaded were already projected to UTM WGS84 zone 37N. Ground truth points were collected using GPS Essentials as well as Google Earth. These points were used in the accuracy assessment and validation of the classified images.

Image Pre-Processing

Landsat images downloaded were stacked to generate a scene image ready for multi-band operations. Layer stacking was done bearing in mind that there have been evolutions in Landsat 8 that are not in Landsat 5.

Table1: Satellite Data Used.

Satellite Data	Date Acquired	No. of Bands	Resolution
Landsat 5 TM	14/01/1986	7	30 M
Landsat 5 TM	04/03/2001	7	30 M
Landsat 5 TM	19/01/2011	7	30 M
Landsat 8 OLI-TIRS	08/10/2019	11	30 M 15 M Panchromatic

Table2: Bands used in stacking

Sensor	Bands Stacked
Landsat 5 TM	1,2,3,4,5 and 7
Landsat 8 OLI-TIRS	2,3,4,5,6 and 7

Band 1 in Landsat 8 was not used because it is a coastal band which was deemed unnecessary for this study. Similarly, thermal bands from both sensors were not used because they have a less distinct appearance compared to the other bands as a result of their low resolution. Moreover, the thermal bands are used in a range of thermal mapping that includes the study of wildfires. As such, the thermal bands were unsuitable for this study. A similar approach was used [19] by omitting the thermal band in band combination while performing land use and land cover classification and mapping of Al-Ahsaa Oasis, Saudi Arabia. Similarly, [20] conducted supervised classification

on six reflective bands (bands 1-5 and band 7) for the years 1989 and 2000 and omitted band 6 while mapping agricultural land in Tov aimag, Mongolia.

Images of 1986, 2011 and 2019 had a cloud cover of less than 10%. The clouds were removed and their shadows masked to reduce error during classification of the imagery. Sub-setting of the imagery was then done using a shapefile of the study area as the area of interest (AOI).

Enhancement

To visualize various features on the clipped images and improve their interpretation, image enhancement was done using colour composites. Colour composites have been widely used [1,12]. to improve the visualization of objects on satellite imageries and, thus, boost the interpretation of the imagery. Similarly, different colour composites were used in this study. For Landsat 8 2019 image, band combinations of 432 (natural colour), 543 (false colour infrared), 764 (urban), 652 (agriculture), 562 (healthy vegetation), 564 (land/water) and 654 (vegetation analysis). For Landsat 5 1986, 2001 and 2011 images, band combinations of 123 (natural colour), 432 (false colour infrared) and 742 were used.

Land Use and Land Cover Classification

To determine the main land use and land cover types, a classification system was prepared (Table 3). According to Ref. [21], the preparation of a classification scheme is a prerequisite in the classification process. In order to generate an appropriate classification scheme, a reconnaissance study was first conducted to identify the various land use and land cover types in the study area. The various land use classes identified were as follows:

Table 3: Land use land cover classification scheme

Land Cover	Description
Cropland	Refers to land mainly used for growing food crops like mangos, pigeon peas, cassava, sorghum beans, millet and maize.
Built-up areas	Refers to land occupied with buildings. It includes residential, industrial, commercial and transportation infrastructure.
Bushland	Refers to areas with trees, bushes and shrubs.
Grassland	Refers to land covered with grass and other short vegetation but grass is the main vegetation cover.
Bare ground	Refers to land without vegetation cover such as abandoned farms, eroded river banks, river beds of seasonal rivers, abandoned mines, rocky surfaces, weathered roads and dry reservoirs.

Water bodies	Refers to land occupied with water like rivers, dams and ponds
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A similar classification system was utilized [12] while conducting land use and land cover analysis in Makueni County. The purpose of image classification was to assign different spectral signatures from Landsat imagery to different classes of land use and land cover based on reflectance characteristics of the classes [12]. According to [22]. A satisfactory spectral signature ensures that there is minimal confusion among the land cover classes being mapped. Knowledge of the existing land use types in the study area combined with spectral reflectance of features on images was used in the selection of training sites (samples). These training samples were used to perform supervised classification of the Landsat images In ERDAS IMAGINE software. Maximum Likelihood Classification scheme was used to conduct supervised classification because it is the most widely used per-pixel method that takes into account the spectral information of the land use classes [3, 23,24].

Accuracy Assessment

[25]. Suggested that accuracy assessment is essential if the data obtained from classification is to be useful in change detection analysis. In this study, accuracy assessment was done for the Landsat 8 OLI-TIRS 2019 image because it is the one which the ground truth data likely equates. Ground verification was done using simple random sampling ensuring that samples from all classes were collected and well distributed within the study area. According to Ref. [1], verification is done using an error/confusion matrix containing information about actual and predicted classes performed by a classification process. A similar approach was used by [12, 19, 24, 26-29]. This study used a similar approach to calculate the overall accuracy by dividing the sum of the correctly classified sample units by the total number of sample units.

Change Detection

[30]. Defines change detection as the process of identifying the differences in the state of an object or phenomenon by observing it at different times. In this study, post-classification comparison method was used in ArcGIS software to detect changes in the various land use land cover classes in Kitui Central with a focus on cropland. The Post-classification comparison method is the most commonly used technique in change detection as it involves the comparison of two independently classified images at different times [28, 30]. [30]. Further stipulates that post-classification comparison method generates ‘from-to’ maps which can be used to evaluate the extent, location and nature of the changes in land use and land cover. Generation of ‘from-to’ maps was deemed necessary in this study and used to understand the changes in cropland in the study area.

RESULTS AND DISCUSSION

Land Use Land Cover Analysis

[3]. Suggested that changes in the global environment are affected by changes in land use and land cover. Population growth, land scarcity, urbanization and expansion of agricultural fields are among the major contributors to changes in land use and land cover [31]. As such, the utilization of remotely sensed data and the application of geospatial techniques in their analysis provide accurate and timely information for detecting, quantifying and monitoring the changes in land cover and land use.

In this study, the overall classification accuracy was 81%. The study area was classified into six land use and land cover classes, namely; cropland, built up, bushland, grassland, bare ground and water bodies as defined in Table 3 of the

Figure3: Land Use Land Cover Map of 2001

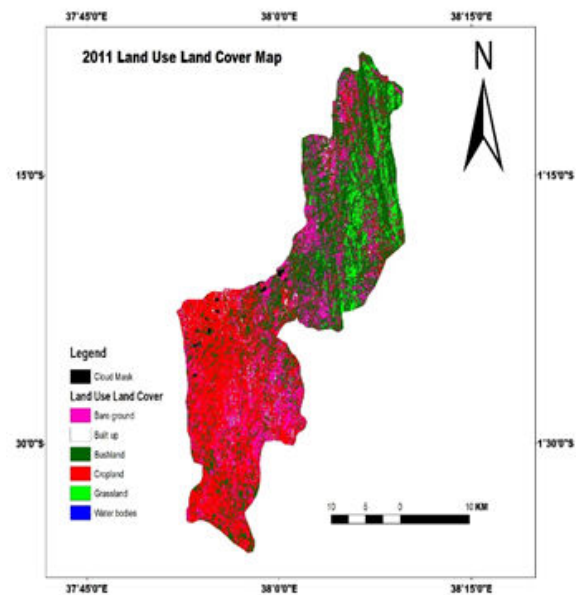


Figure4: Land Use Land Cover Map of 2011

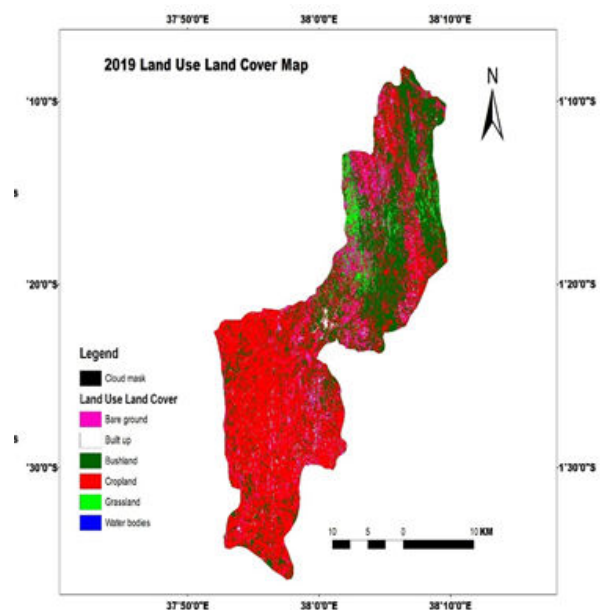


Figure5: Land Use Land Cover Map of 2019

Classification scheme. The results of this study showed that all land cover classes recorded changes (Table 4).

Table4: Area coverage for land covers classes and their respective years

Land Cover	1986		2001		2011		2019	
	Area (Km2)	% Area	Area (Km2)	% Area	Area (Km2)	% Area	Area (Km2)	% Area
Cropland	185.23	27.95	327.28	49.39	231.15	34.88	357.37	53.93

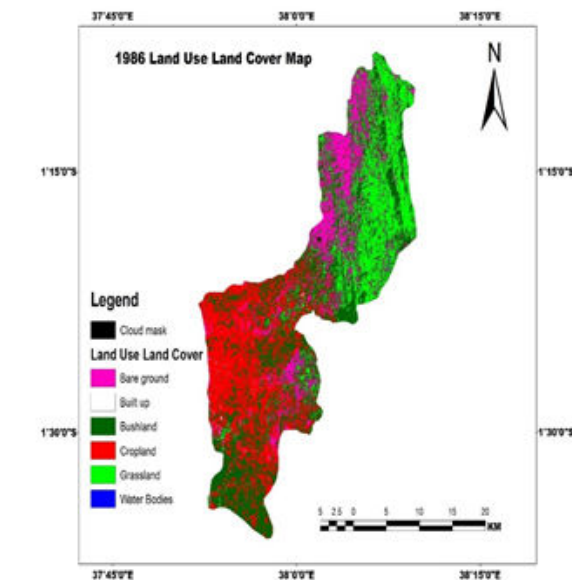
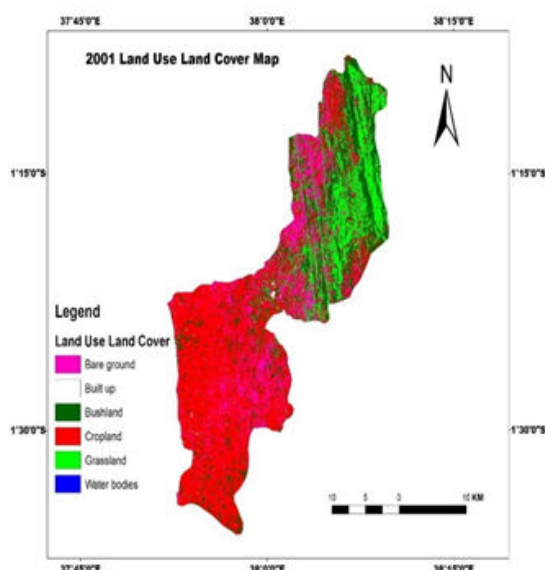


Figure2: Land Use Land Cover Map of 1986



Built-up Areas	1.28	0.19	1.90	0.29	11.50	1.74	13.41	2.02
Bushland	248.32	37.471	127.61	19.269	249.19	37.604	197.44	29.794
Grassland	125.80	18.984	102.74	15.504	39.814	6.014	27.614	4.174
Bare ground	100.75	15.203	103.13	15.564	127.54	19.254	66.714	10.074
Water bodies	0.96	0.14	0.01	0.00	0.68	0.10	0.03	0.00
Cloud mask	0.35	0.05			2.80	0.42	0.12	0.02
Grand Totals	662.7	100	662.7	100	662.7	100	662.7	100

The observed changes in land use and land cover classes took place at the expense of other classes as shown in the change detection matrices (Tables 5-7).

Table 5: Change detection matrix of 1986 and 2001

Land Cover Class	2001		Bare ground		Built-up areas		Bushland		Crown land		Grassland		Water bodies	
	Area (km ²)	% Area	Area (km ²)	% Area	Area (km ²)	% Area	Area (km ²)	% Area	Area (km ²)	% Area	Area (km ²)	% Area	Area (km ²)	% Area
Bare ground	43.85	42.54	0.262	10.10	10.80	35.78	10.94	10.61	10.33					
Built-up areas	0.53	0.52	0.14	7.33	0.00	0.00	0.59	0.18	0.02					
Bushland	21.06	20.96	0.44	23.33	77.60	12.58	37.31	25.75	25.07	0.08	0.03	55.85		
Crown land	26.57	25.78	1.06	55.69	6.32	4.96	14.76	45.17	1.47	1.47	0.07	4.86		

Grassland	10.14	9.84	0.03	1.6	33.42	26.21	17.46	5.34	64.67	62.97	0.00	3.95
Water bodies	0.31	0.33	0.03	1.43	0.08	0.06	0.42	0.12	0.15	0.14	0.05	35.34
Cloud mask	0.08	0.07			0.18	0.14	0.09	0.03	0.09	0.09		
Total	103.1	103.10	1.90	10.00	127.54	107.50	71.07	32.71	102.70	102.70	0.01	10.14

Table 6: Change detection matrix of 2001 and 2011

Land Cover Class	2001		Bare ground		Built-up areas		Crown land		Grassland		Water bodies	
	Area (km ²)	% Area	Area (km ²)	% Area	Area (km ²)	% Area	Area (km ²)	% Area	Area (km ²)	% Area	Area (km ²)	% Area
Bare ground	48.45	38.45	6.71	58.38	22.67	9.16	22.24	9.62	2.47	6.21	0.21	30.24
Built-up areas	0.22	0.15	0.27	2.32	0.01	0.05	1.31	0.57	0.00	0.01	0.01	1.70
Bushland	7.92	6.22	0.22	1.76	99.80	40.07	13.38	5.79	5.54	13.93	0.05	7.26
Crown land	56.71	44.3	4.13	35.9	73.15	29.37	18.9	82.59	1.49	3.75	0.31	45.5
Grassland	14.21	11.15	0.18	1.58	53.41	21.33	4.53	1.96	30.28	76.11	0.17	15.06
Water bodies	0.00	0.00	0.00	0.06	0.00	0.00	0.00	0.00			0.08	0.12

die s	To	12	10	11.	10	24	10	23	10	39	10	0.	10	2.
	tal	7.5	0	5	0	9.1	0	1.1	0	.8	0	7	0	8

Table7: Change detection matrix of 2011 and 2019

Land Cover Class	20 19	2019													
		Bare ground	B uil t- up ar eas	B us hl an d	Cr op la nd	Gr ass la nd	W ate r bo die s	Cl ou d M as k	Ar ea (k m 2)	% Ar ea	Ar ea (k m 2)	% Ar ea	Ar ea (k m 2)	% Ar ea	Ar ea (k m 2)
20 11	Ba re gr ou nd	35 .88	53 88	6.1 5	45 .87	14. 26	7.2 2	65 .97	18. 47	5. 2	18. 85	0. 02	60 .74	0. 00	0. 09
	Bu ilt- up are as	3.1 6	4. 73	1.7 69	12. 24	0. 0.1	0.1 2	6. 33	1.7 7	0. 07	0. 25	0. 00	11. 21		
	Bu shl an d	16. 15	24. 21	0. 89	6. 61	13. 5.	68 .91	79 .9	22 .37	16. 1	58 .00	0. 34	5. 96	0. 04	0. 8
	Cr op la nd	9. 27	13. 91	4. 57	34 .09	19. 82	10. 05	19 6.	54 .03	1.3 88	4. 72	0. 00	15 .11	0. 05	0. 6
	Gr ass la nd	1.7 6	2. 64	0. 06	0. 41	26 .07	13. 21	7.0 5	1.9 7	4. 84	17. 53		0. 01	0. 2	
	W ate r bo die s	0. 31	0. 46	0. 02	0.1 2	0. 07	0. 04	0. 27	0. 08	0. 02	0. 06				
	Cl ou d ma sk	0.1 6	0. 25	0. 03	0. 2	0. 89	0. 45	1.6 4	0. 46	0. 07	0. 24	0. 00	6. 99	0. 00	0. 16
	To tal	66 .7	10 0	13. 4	10 0	19 7.3	10 0	35 7.2	10 0	27. 6	10 0	0. 03	10 0	0.1 0	

The changes in land use and land cover are complex but interrelated in the sense that an increase in one land use class is at the expense of other classes. Furthermore, the changes do not always occur sequentially but may show periods of rapid and

abrupt change followed either by a quick recovery of ecosystems or a non-balanced trajectory.

Change Detection of Cropland

Agriculture plays a key role in Kitui County in terms of food provision, employment creation and as a source of income for domestic needs [34]. However, there is little knowledge about the status of cropland in Kitui Central. This study, therefore, provides information about the changes in cropland between 1986 and 2019 using remote sensing and geospatial techniques.

The results showed that changes in cropland took place at the expense of other land use and land cover classes or gain in cropland as seen in the change detection matrices (Tables 5-7). Expansion of cropland between 1986 and 2001 took place mainly at the expense of bushland (37.63%) and bare ground (10.93%). However, between 2001 and 2011, there was a decline in the area covered by cropland when conversion to bare ground and built-up areas was about 44.48% and 35.9% respectively. The results further showed that between 2011 and 2019, the conversion of bushland and bare ground to cropland was about 22.34% and 18.47% respectively. These results agree with those from other studies [32]. Reports that expansion of cultivated land took place at the expense of forested land between 1957 and 1982 in the Dembecha area, Northwestern Ethiopia. Similarly, [35] Reported that despite there being a prolonged drought in Zimbabwe, there was a general increase in cropland due to human activities and population. Therefore, knowledge of such trends can be applied in Kitui Central and be used to inform policy decisions in the field of sustainable land management, precision agriculture and food security.

CONCLUSION

This study presented the results of land use and land cover classification and analysis with a specific focus on cropland as a type of land cover in Kitui Central. Remote sensing and GIS were valuable tools that facilitated the mapping of land use and land cover as well as detection of changes in cropland for the years 1988, 2001, 2011 and 2019. The results demonstrated evidence of significant land use and land cover changes between 1986 and 2019. These study further shows that the use of multi-temporal satellite data is instrumental in detecting and assessing changes in land use and land cover. Furthermore, the study establishes that local field studies enable the observed changes to be put into a broader perspective and the dynamics of land use and land cover in Kitui Central can be understood.

Kitui Central is among the highland areas of Kitui County that are suitable for crop production and can boost the food security status of its population. As such, the documentation of how past changes in cropland and that of other land use and land cover types have been occurring is vital. The advent of the county system of governance coupled with the growth of Kitui Town has created opportunities in terms of demand for food, office space, accommodation, recreational facilities and other social amenities. This opens up the opportunities to develop and implement policies to ensure the sustainable future development of Kitui Central. Policies should, therefore, enforce

the protection of remaining natural land resources and develop small-holder crop production of drought-tolerant crops like sorghum and green grams towards larger yields. This will raise incomes for farmers as well as aid in preserving natural land resources like grasslands and bushlands.

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