

## Article

# Analysis of Spatiotemporal Dynamics of Land Use/Cover Changes in Jubek State, South Sudan

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**Abstract:** The Republic of South Sudan lacks adequate data to support decision-makers in planning. Therefore, a land use land cover (LULC) study was conducted in Jubek State for 17 years (2000–2017). It was divided into three time intervals, using remote sensing (RS), geographic information system (GIS), Landsat TM, Landsat ETM+, and Landsat 8 OLI approaches. A transition matrix for the total change was developed to generate spatiotemporal and quantitative indicators to analyze LULC spatiotemporal dynamics for better developmental decisions. Overall accuracy assessment results were 97.41% (kappa 0.96), 90.45% (kappa 0.85), and 91.5% (kappa 0.89) for years 2000, 2009, and 2017, respectively. Furthermore, quantitative and spatiotemporal results show that built up areas drastically increase, especially from 2009 to 2017. The most dominant class in the study area was grassland, 9929.9 km<sup>2</sup> (54.22%), followed by forest, 5555 km<sup>2</sup> (30.33%), barren land, 2497.3 km<sup>2</sup> (13.64%), built up areas, 166.7 km<sup>2</sup> (0.9%), farmland, 128.31 km<sup>2</sup> (0.71%), and water bodies, 35.91 km<sup>2</sup> (0.96%). The outcomes of the analysis show that since 1955 Jubek State (Juba) has been the preferable place for the local citizens' settlement in South Sudan. Unfortunately, agricultural production was insufficient due to the limited cultivated area; on the other hand, the study area is rich in natural resources and could meet local people's demand if a proper strategy such as LULC transformation is well implemented.

**Keywords:** land use land cover; Landsat; GIS; remote sensing; Jubek State; South Sudan; land transformation

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## 1. Introduction

Land cover (LC) is any physical material (natural or human-made) that is available on the Earth's surface, and it can affect various processes on the globe, i.e., energy and carbon budget as well as water availability [1]. In different developed models used in the Earth's system, land surface valued LC as an essential parameter [2,3]. Many researchers from different disciplines retrieved physical characteristics of the Earth's surface, and land cover depends on anthropogenic effects and environmental variables that lead to specific land use [4–6]

Due to the importance of land and land resources, it has been used to meet human needs such as spiritual, social, material, and cultural needs. To optimize the utilization of land and the available resources, people across the globe have modified land uses in so many different ways; the transformation of grasslands and natural forests into agricultural land to meet the world's growing population's food demand is one of the practical examples [7].

Across the literature, many researchers have reported on different causes of land use land cover changes; among these, urbanization, tropical deforestation, modification of rangeland, farming, and globalization are the most common causes of land use land cover changes regionally as well as globally [5,6,8–10]. Furthermore, social, biological, physical, and economic features are remarkably associated with landscape changes. The authors recommended that dynamic and in-depth studies on LULC are essential in tackling related implications that influence people's lives and the surrounding environment at various spatiotemporal levels [11–13]. Researchers agreed that studying environmental dynamics and their driving forces on various scales is a practical approach to understanding the effects of social and economic differences on land [14].

Researchers from various disciplines are increasingly interested in relating socio-economic and natural resource studies to LULC, resulting in challenging related research questions [15,16]. It has been claimed in recent decades that human activities and other factors that have altered global LC dramatically [1,5] will influence people's situations in various harmful ways [17]; this scenario will affect the next generation as well [8,18]. The upgrading lifestyle of urban people and village to urban migration are the two critical drivers of urban expansion that are expected to add more than 2.5 million people to urban areas worldwide, whereby Asia and Africa will represent 90% of this growth [19]. Agricultural activities and urbanization are two significant drivers of biodiversity worldwide [20]; land changes caused by climate change, anthropogenic factors, and natural processes are also important [21,22]. Understanding alterations to land surfaces and biotic cover needs attention regarding land use land cover (LULC) change as a coupled human-environment system [23,24]. Rapid urbanization continues to have a powerful impact on changing the planet's face and the lives of its inhabitants as human populations continue to grow and dominate ecosystems around the world [25]. Rural to urban migration has mixed opportunities as well as challenges in both source and destination areas [26–29]. Undoubtedly, the urbanization process, especially in Africa, has resulted in many challenges that need to be urgently addressed [30–32]. It was also wrongly assumed that Africa could not build and develop modern towns and cities; instead, a group of people settled at a specific location [33]. Therefore, it is a challenge for the people in Africa to define the correlation between life and urbanization and social activities in urban life [34]. It is observed that clear policies should mandatorily be formed to tackle issues of LULC as a method to promote urbanization [35]. Strategic planning is a possible way to achieve and maintain a sustained friendly environment [36].

Remote sensing techniques offer an appropriate and timely method to evaluate land change over space and time. In addition, the availability of remotely sensed satellite image data, e.g., Landsat and ASTER, is a drive for studying land change. Multi-spectral bands of the exact location were collected at two or more specific periods. Such a study focused on identifying any difference in a given class that occurred in the same selected area between two or more different selected periods [37,38]. If the aim is to quantify many types of changes from a thematic map, this approach is termed post-classification. Accuracy and success of the classified image result from the map reliability, and the level of success relies on the correct type of maps derived from image classification. An experience from the literature proved that it is easier to map widespread or significant changes in urban areas than degradation of boundaries, erosion, and succession [39–43]. Furthermore, conducting a change detection study of a given geographic area is essential for better understanding and interpretation of remotely sensed data. To monitor a given land change with highly accurate results as well as low cost, it is advisable to use satellite remote sensing methods rather than traditional techniques [44–47].

#### *The Specific Aims of the Study*

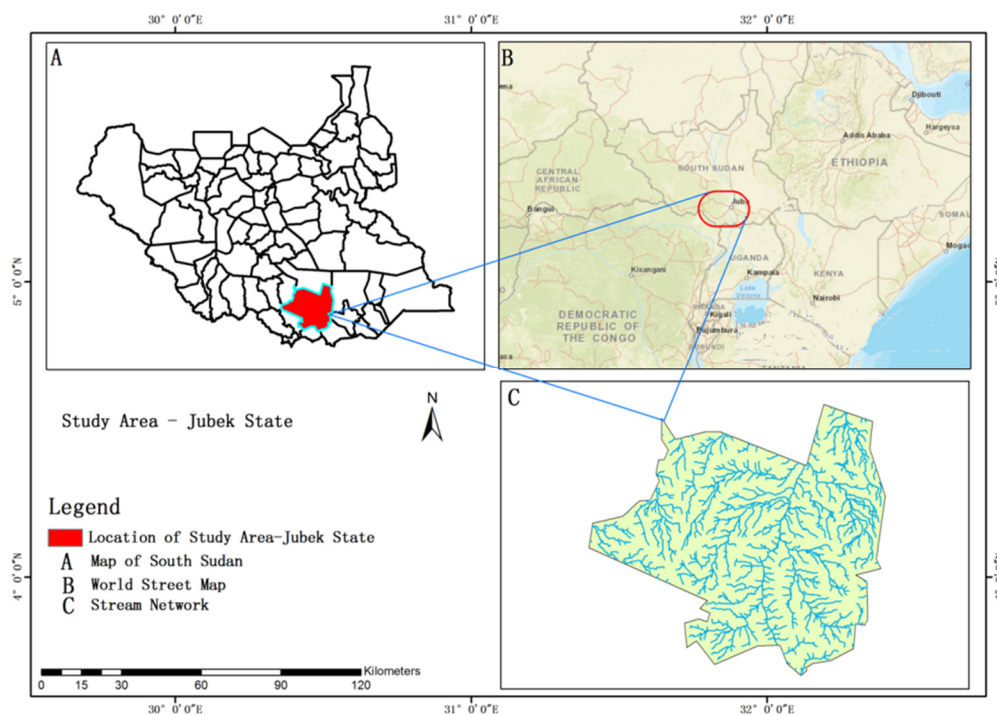
The following specific aims were developed to analyze the spatiotemporal analysis of land use land cover of the study area.

1. To study the land use and land cover of the study area through satellite imagery (Landsat 5, 7 and 8) for three time intervals, i.e., 2000–2005, 2005–2011, and 2011–2017.
2. To establish relationships between civil unrest and spatial land dynamics changes in the study area during the study period.
3. To understand the land's spatial dynamics for better land management.

## 2. Materials and Methods

### 2.1. Study Area

Jubek State is one of the biggest states in the Republic of South Sudan, accommodating the capital city and located in the southern part of the country, covering an area of about 18,313.7 km<sup>2</sup> (Figure 1). It shares a border with four states: Terekeka in the north, Torit in the east, the Yei River in the southwest, and Amadi State in the west. Jubek State consists of fourteen counties, i.e., Lodu, Mangala, Luri, Rejaf Gondokoro, Wonduruba, Lobonok, Ganji Bungu, (Ganzi), Dollo, LyriaRokon, and Oponi. The Nile River divides the entire study area into two parts. In 2014, the population of Jubek State was estimated to be 492,970 in the 1920s; from 1955, the population kept gradually accelerating, especially within Juba town. Evidence in the literature confirmed Jubek State to have been a representative LULC of South Sudan since 1955 [48,49] Figure 1.



**Figure 1.** Location of the study area, Jubek State, South Sudan.

### 2.2. LULC Categories

According to the study objectives, the study duration is 17 years and was divided into three intervals, i.e., during the civil war, immediately after the comprehensive peace agreement (CPA), and during the implementation of the CPA. The land was classified into six classes: built up areas, water bodies, agricultural land, forest land, barren land, and grassland. Based on the ground used attributes, urban, industrial land, IDP camps, paved roads, and rural settlements were attributed as built up areas; rivers, ponds, and reservoirs were attributed as water bodies; crop and empty crop fields were attributed as farmland; deciduous forest, evergreen forest, and orchards were attributed as forest cover; open spaces containing grass were attributed as grassland; and unused lands were

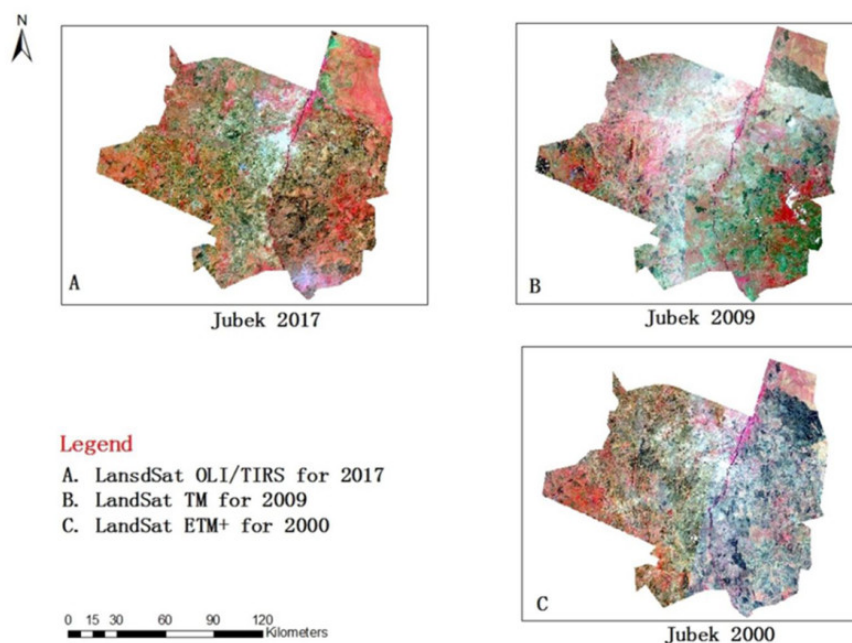
attributed as barren land (Table 1). Table 2 shows satellite images with detailed information on the study area. Landsat images were downloaded during the summer to obtain relatively clear data Figure 2.

**Table 1.** Classes of land use/land cover in Jubek State, South Sudan.

No.	Class Name	Description
1	Built up area	Urban, industrial land, IDPs camps, paved roads, and rural settlements
2	Water bodies	Rivers, ponds, and reservoirs
3	Agricultural land	Crop and bare crop fields
4	Forest cover	Deciduous forest, evergreen forest, and orchards
5	Barren land	Unused land
6	Grassland	Open spaces containing grass

**Table 2.** Satellite images detailed information about Jubek State, South Sudan.

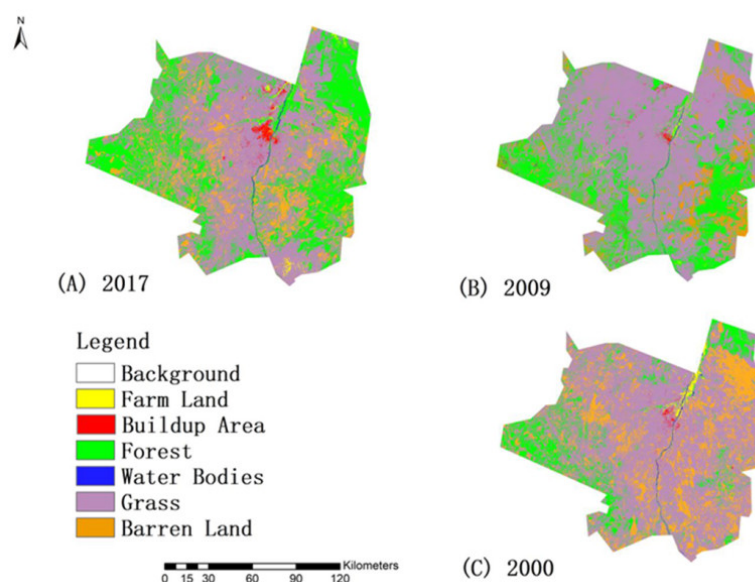
Imagery Date	Spatial Resolution	Sensor Identifier	No. of Bands	Path/Row	Scene Identifier	Format
1 February 2000	30.0 m	ETM+	8	172/56	LT51720562008254MLK00	GEOTIFF
1 February 2000	30.0 m	ETM+	8	172/57	LT51720572008254MLK00	GEOTIFF
1 February 2000	30.0 m	ETM+	8	173/57	LT51730572008245MLK00	GEOTIFF
1 February 2000	30.0 m	ETM+	8	173/56	LT51730562008245MLK00	GEOTIFF
2 May 2009	30.0 m	TM	7	173/56	LE71730562000263SGS00	GEOTIFF
2 May 2009	30.0 m	TM	7	172/56	LE71720562000256SGS00	GEOTIFF
2 May 2009	30.0 m	TM	7	172/57	LE71720572000256SGS00	GEOTIFF
2 May 2009	30.0 m	TM	7	173/57	LE71730572000311EDC00	GEOTIFF
2 August 2017	30.0 m	OLI/TIRS	11	172/56	LC81720562017342LGN00	GEOTIFF
2 August 2017	30.0 m	OLI/TIRS	11	172/56	LC81720562017342LGN00	GEOTIFF
2 August 2017	30.0 m	OLI/TIRS	11	172/57	LC81720572017358LGN00	GEOTIFF
2 August 2017	30.0 m	OLI/TIRS	11	173/57	LC81730572017365LGN00	GEOTIFF



**Figure 2.** Landsat images subsets for Jubek State, South Sudan.

### 2.3. Classification of Land Use/Cover

Due to the complex driving force of LULC in the study area, information exacted from the literature was used for interpretation. Thus, it can utilize comprehensive spectral and spatial features of the downloaded Landsat images and thematic information from multiple references during the classification procedure [50]. Based on the Landsat images' eye observation, training points were marked for each class and crosschecked for verification using a high-resolution image downloaded from Google Earth concerning the selected periods. Each course was created and exported to SVM for each year based on the selected training samples and a signature file. As SVM is most commonly [51,52], it is a post-classification comparison [53]. The resultant thematic maps are compared at pixel bases for the three selected years after each image of one single year was separately classified [54] (Lu et al., 2004). ENVI 5.3, ERDAS 9.2, and ArcGIS 9.3 software were used as a work platform. Interpretation keys were derived from the result of LULC during the study periods, i.e., 2000, 2009, and 2017 Figure 3.



**Figure 3.** The classified thematic maps for land use/land cover (LULC) classes in 2017 (A), 2009 (B), and 2000 (C) of Jubek State, South Sudan.

### 2.4. Classification Accuracy Assessment

In this study, 420 polygons were selected randomly to perform classification and assess classification accuracy, i.e., 67 polygons for Landsat EMT+, 261 polygons for Landsat ET, and 92 polygons for Landsat8 OLI. Table 3 shows the error matrix, overall accuracy, and kappa coefficient. Accuracy assessment was applied for the selected study periods to estimate their accuracy level [55]. To represent each class, a stratified random approach was conducted. Predetermined land use type and training samples for each category were chosen by delimiting polygons around each representative site. The images were interpreted via supervised classification based on the geo-referenced images. Supervised vector machine (SVM) and geometric correction were performed on the images with WGS84 Datum and zone 36 UTM. An average value of 0.5 was chosen as an average root mean square error (RMSE) based on [56]; the producer's and user's accuracy that represents error matrices was determined based on the comparison results of the classified images and reference data [57]. A kappa test was performed as an additional non-parametric evaluation [58]. It was stated that 85% is an acceptable accuracy value while using Landsat for LULC mapping with individual classes not less than 70% [59].

**Table 3.** Accuracy assessment for supervised classification of Landsat ETM+ 2000, TM 2009, and Landsat 8 OLI 2017.

<b>Accuracy Assessment of Landsat ETM+ 2000</b>							
<b>Class</b>	<b>Farmland</b>	<b>Built up Area</b>	<b>Forest</b>	<b>Barren Land</b>	<b>Grassland</b>	<b>Total</b>	<b>PA (%)</b>
Farmland	35.00	0.00	0.00	0.00	0.00	35.00	100.00
Built up Area	0.00	57.00	0.00	0.00	6.00	63.00	86.40
Forest	0.00	0.00	68.00	0.00	1.00	69.00	100.00
Barren Land	0.00	0.00	0.00	173.00	6.00	179.00	100.00
Grassland	0.00	9.00	0.00	0.00	376.00	385.00	96.70
Water Bodies	0.00	0.00	0.00	0.00	0.00	0.00	100.00
Total	35.00	66.00	68.00	173.00	389.00	731.00	
UA (%)	100.00	90.50	98.60	96.70	97.70	100.00	
Overall accuracy = 97.41%, Kappa coefficient = 0.964							
<b>Accuracy assessment of Landsat TM 2009</b>							
<b>Class</b>	<b>Farmland</b>	<b>Built up Area</b>	<b>Forest</b>	<b>Water Bodies</b>	<b>Grassland</b>	<b>Total</b>	<b>PA (%)</b>
Farmland	22.00	0.00	6.00	0.00	0.00	28.00	71.00
Built up Area	0.00	184.00	1.00	0.00	5.00	190.00	69.70
Forest	6.00	37.00	2205.00	12.00	80.00	2340.00	92.60
Barren Land	0.00	0.00	59.00	308.00	43.00	410.00	93.90
Grassland	3.00	43.00	91.00	5.00	1525.00	1667.00	92.20
Water Bodies	0.00	0.00	20.00	3.00	2.00	25.00	81.00
Total	31.00	264.00	2382.00	328.00	1655.00	4660.00	
UA (%)	78.60	96.80	92.40	74.00	91.20		
Overall accuracy = 90.45%, Kappa coefficient= 0.85							
<b>Accuracy assessment of Landsat 8 OLI 2017</b>							
<b>Class</b>	<b>Farmland</b>	<b>Built up Area</b>	<b>Forest</b>	<b>Water Bodies</b>	<b>Grassland</b>	<b>Total</b>	<b>PA (%)</b>
Farmland	91.00	4.00	0.00	0.00	0.00	95.00	71.70
Built up Area	5.00	266.00	0.00	0.00	42.00	313.00	83.10
Forest	7.00	0.00	304.00	0.00	0.00	311.00	99.70
Barren Land	7.00	0.00	0.00	0.00	0.00	7.00	99.70
Grassland	17.00	50.00	1.00	0.00	425.00	493.00	91.00
Water Bodies	0.00	0.00	0.00	45.00	0.00	45.00	100.00
Total	127.00	320.00		45.00	467.00	959.00	
UA (%)	95.80	85.00	97.80	97.80	86.20		
Overall accuracy = 91.51%, Kappa coefficient= 0.89							

### 2.5. Change Detection

Change detection was performed using a cross-tabulation function; each result of two final classified thematic maps (obtained from SVM) was compared to get the quantitative and qualitative details of the changes in Jubek State for the selected time series: 2000–2009, 2009–2017, and 2000–2017 (Tables 3 and 4) [53]. Changes in the six selected LC classes (built up area, agricultural land, barren land, water bodies, forest cover, and grassland) for the SVM classified maps were determined. Change detection outcomes were applied to measure the LULC changes over the 17 years in Jubek State.



**Table 4.** LULC change statistics matrices (km<sup>2</sup>) 2000–2017.

a. 2000–2009								
LULC Classes (2009)	LULC Classes (2000)	FL (km <sup>2</sup> )	BA (km <sup>2</sup> )	F (km <sup>2</sup> )	WB (km <sup>2</sup> )	BL (km <sup>2</sup> )	GL (km <sup>2</sup> )	CT km <sup>2</sup> (2009)
	Farmland	28.45	0.09	29.49	1.18	6.88	44.35	110.44
	Built up Area	0.42	7.7	2.55	0	4.94	58.68	74.29
	Forest	48.94	8.3	978.62	11.55	803.36	2600.63	4451.4
	Water Bodies	0.19	0.03	4.54	27.74	5.03	11.3	48.83
	Grass	75.92	41.23	938.22	1.85	2447.24	8685.57	12,190.03
	Barren Land	0.85	0.62	86.65	3.11	507.97	838.47	1437.67
	2000 Total	154.77	57.97	2040.1	45.43	3775.42	12239	18,312.66
b. 2009–2017								
LULC Classes (2017)	LULC Classes (2009)	FL (km <sup>2</sup> )	BA (km <sup>2</sup> )	F (km <sup>2</sup> )	WB (km <sup>2</sup> )	BL (km <sup>2</sup> )	GL (km <sup>2</sup> )	CT km <sup>2</sup> (2017)
	Farmland	5.02	3.67	37.42	0.14	0.53	81.49	128.27
	Buildup Area	0.61	20.46	14.88	0	0.55	130.2	166.7
	Forest	68.03	4.19	2096.3	9.01	542.59	2831.79	5551.91
	Water Bodies	0.32	0.02	7.2	24.78	2.84	0.73	35.89
	Grass	30.57	42.34	1718	7.03	595.81	7533.47	9927.26
	Barren Land	5.83	3.58	576.14	7.86	294.94	1608.08	2496.43
	2009 Total	110.38	74.26	4450	48.82	1437.26	12,185.76	18,306.46
c. 2000–2017								
LULC Classes (2017)	LULC Classes (2000)	FL (km <sup>2</sup> )	BA (km <sup>2</sup> )	F (km <sup>2</sup> )	WB (km <sup>2</sup> )	BL (km <sup>2</sup> )	GL (km <sup>2</sup> )	CT km <sup>2</sup> (2017)
	Farmland	14.51	1.82	16.97	1.3	18.73	74.94	128.27
	Built up Area	0.65	24.93	1.14	0	9.1	130.88	166.7
	Forest	112.65	1.88	1286.1	4.16	1126.64	3020.35	5551.78
	Water Bodies	0.8	0.04	0.1	33.51	0.93	0.51	35.89
	Grass	23.48	27.04	595.01	0.53	1898.68	7382.43	9927.17
	Barren Land	2.48	2.24	139.09	5.87	720.6	1626	2496.28
	2000 Total	154.57	57.95	2038.4	45.37	3774.68	12,235.11	18,306.09

FL (farmland); BA (built up area); F (forest); WB (water body); BL (barren land); GL (grassland); CT (class total).

### 3. Results

#### 3.1. Evaluation of Classification Accuracies

The classification image's overall accuracy for 2000 was 97.41%, 2009 was 90.45%, and 2017 was 91.5%, with kappa coefficients 0.96, 0.85, and 0.89, respectively. For the selected study time intervals, i.e., 2000, 2009, and 2017, high values of both producer's and user's accuracies for the individual classes were obtained. For the year 2000, producers' and users' accuracy ranges from 100% to 86.4%, with 96.8% to 69.7% in 2009, and 100% to 71.7% in 2017. The study area is characterized by mixed classes, especially in the built up areas; this makes it complicated to perform the classification. Using high-resolution images downloaded from Google Earth for the mentioned study period and the useful techniques in ENVI 5.3 classic achieved the remarkable classification and accuracy results in Figure 4. The classified thematic maps generated for the study period using SVM techniques are shown in Figure 3 and Table 3. They demonstrate the change matrix for the changing areas from one class to another between the selected periods. Therefore, based on the overall accuracy results, it was possible to illustrate the LULC spatiotemporal patterns.

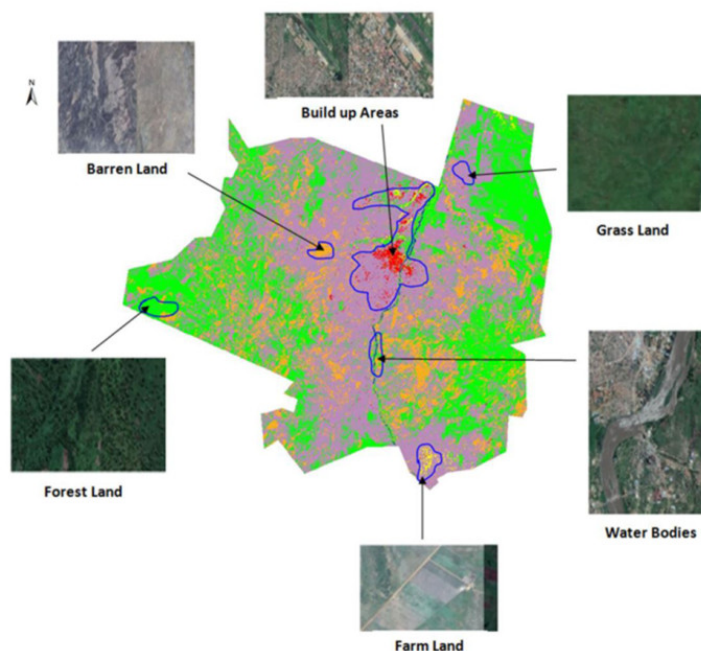


Figure 4. The classes spatial distribution based on Google Earth imagery in 2017.

### 3.2. Overall Pattern of LULC in Jubek State

Figure 3 and Table 3 are derived from Landsat data from 2000, 2009, and 2017. Built up areas show an increase of (57.96 km<sup>2</sup>), 128.2% (74.3 km<sup>2</sup>) and 287.6% (166.7 km<sup>2</sup>) in 2000, 2009 and 2017, respectively Figure 5 The farmland representing the cultivated areas scattered within the urban areas and along the river Nile covered areas of about (154.8 km<sup>2</sup>), 71.4% (110.4 km<sup>2</sup>), and 82.9% (128 km<sup>2</sup>) for 2000, 2009, and 2017, respectively. Forest represents all types of trees within and outside the built up areas; it covered areas of about (2040.6 km<sup>2</sup>), 218.2% (4452 km<sup>2</sup>), and 272.2% (5554.96 km<sup>2</sup>) in for 2000, 2009, and 2017, respectively. Generally, the fundamental LULC pattern illustrated a drastic increase in built up areas and a steady increase in forest areas, whereas other classes relatively fluctuated throughout the study period.

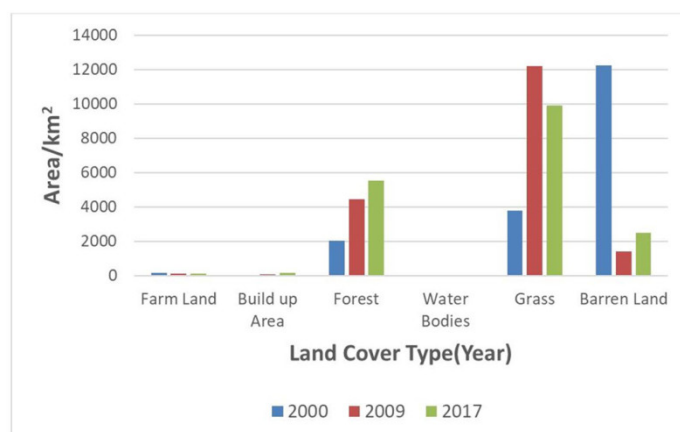


Figure 5. Classified land use land cover of the study area, Jubek State, South Sudan.

### 3.3. Classification and Change Maps Statistics

Figure 2 and Table 3 illustrate the generated classification maps of the three study periods, i.e., 2000, 2009, and 2017. Summarized details of class size area and change statistics of the mentioned periods are shown in Table 5.



From 2000 to 2009, farmland areas decreased by approximately 128.31 km<sup>2</sup> (17.09%) and occupied about 0.70% of the study area, while built up areas increased by 166.7 km<sup>2</sup> (187.6%) and covered 0.91% of the site. Forest increased by 5555 km<sup>2</sup> (172.21%) and covered 30.33% of the area; water decreased by 35.91 km<sup>2</sup> (20.97%) and passed through 0.19% of the site. Grassland decreased by 9929.9 km<sup>2</sup> (18.87%) and accounted for 54.22% of the area, whereas barren land dropped by 2497.3 km<sup>2</sup> (33.85%) and covered 13.64% of the study area.

For the 17-year period (2000–2017), built up areas constantly increased, almost three times more. Farmland, forest cover, and barren land decreased between 2000 and 2009 and slightly increased during 2009–2017. Grassland had shown stability during 2000–2009, whereas it slightly decreased from 2009 to 2017. Water bodies grew during the study's first phase from 2000 to 2009 and reduced between 2009 and 2017.

To further examine and demonstrate the outcome results of the land cover conversion and transformation, land change matrices were developed for periods in the ranges of 2000–2009, 2009–2017, and 2000–2017, as shown in Table 3. In this table, the matrices' major diagonal contains the unchanged pixels, and covered areas were the bases for calculating conversion values. Table 3 illustrates detailed dynamic change data of land cover from 2000 to 2017 in Jubek State. Out of the 166.7 km<sup>2</sup> growth in built up areas from 2000 to 2017, 0.65 km<sup>2</sup> was converted from farmland, 1.14 km<sup>2</sup> from forest land, 9.1 km<sup>2</sup> from barren ground, and 130.88 km<sup>2</sup> from grassland, and water bodies was not affected by the built up growth through the study period. Comparing the selected classified images of Jubek State in Figure 3, the profile of Jubek State remained almost the same from 2000 to 2009, while slight changes can be visually observed whereby there is a difference in terms of expansion in built up areas for the image of 2017 due to transformation of mostly grassland into built up areas. This occurs in the western, southeastern, and northern parts of the capital city (Juba), located almost at the center of the study area.

**Table 5.** LULC area change statistics summary in 2000, 2009, and 2017.

Land Cover Class	2000		2009		2017		Relative Change 2000–2017 (%)
	Area (km <sup>2</sup> )	(%)	Area (km <sup>2</sup> )	(%)	Area (km <sup>2</sup> )	(%)	
Farmland	154.77	0.85	110.43	0.60	128.31	0.70	−17.10
Built up Area	57.96	0.32	74.30	0.41	166.70	0.91	187.61
Forest	2040.60	11.10	4452.00	24.31	5555.00	30.33	172.22
Water Bodies	45.44	0.25	48.82	0.27	35.91	0.20	−20.97
Grass	12,240.00	66.80	12,190.00	66.56	9929.90	54.22	−18.87
Barren Land	3775.50	20.60	1437.70	7.85	2497.30	13.64	−33.85

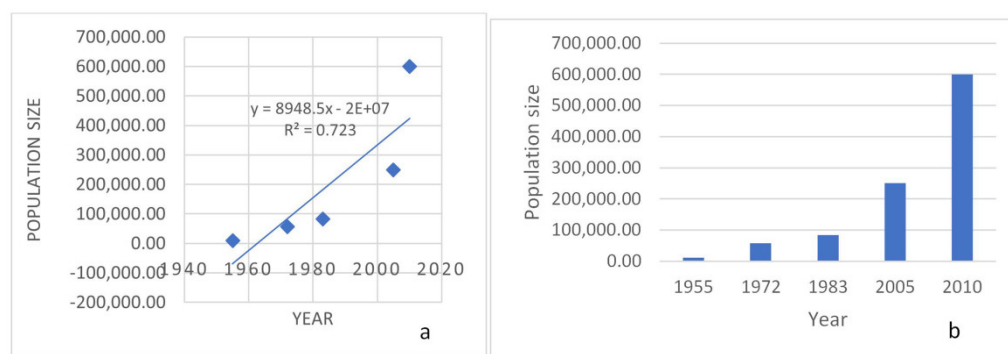
### 3.4. Spatiotemporal Analysis of LULC Jubek State

The facts may indicate that among the six selected classes (built up, farmland, forest land, water bodies, grassland, and barren land), built up areas appeared to be the class with greatest impact on the study area profile. Because most of the types were transformed into built up areas, this may continue to happen, especially due to the mentioned driving factors. From the summary of land use land cover area statistics in Table 5, the forest proportion is the second largest across Jubek State, representing 11.1 % in 2000, 24.31% in 2009, and 30.33% in 2017. This shows constant growth throughout the study period, i.e., no loss was found in forest profile during the 17 years; rather, it gained from other classes through a natural conversion. Out of the entire forest land size (172.22 km<sup>2</sup>), 112.65 km<sup>2</sup> (2.02%) was gained from farmland, 1.88 km<sup>2</sup> (0.034%) from built up areas, 4.16 km<sup>2</sup> (0.75%) from water bodies, 1126.64 km<sup>2</sup> (54.41%) from barren land, and 3020.35 km<sup>2</sup> (20.29%) was converted from grassland. The major contributors to forest land were barren land and grassland; this revealed that forest land was a “no-go zone,” a well-known phenomenon occurring mostly due to insecurity or reserved areas at these locations.

Some areas around Jubek State were not accessible due to civil unrest; this increased the forest sector at a constant rate.

Figure 6a illustrates that the increase in built up areas is connected with the population in a linear fashion as  $R^2$  is 0.72; this implies that community contributes to the growth of built up areas, but some other factors such as security, availability of natural resources, and economic development also play key factors in expanding the site. These can be seen in Figure 6b as the tremendous increase in population over the past 55 years and following the CPA agreement, i.e., after 2005.

After the LULC classification process is achieved, it can be utilized as primary data for generating additional findings, e.g., landscape matrices can be obtained from classification results to study alteration in some known varieties and division of landscape in Jubek State. In addition, classifications could be used as input data for environmental impact analysis and land cover transformation models to predict LULC change. Finally, it can be stated that remote sensing serves as a supporting tool to harvest and filter information that could help to understand the status of land cover on the Earth's surface and atmosphere and locate the areas of their occurrence. Therefore, it could be a significant path to a better understanding of the digital world.



**Figure 6.** (a,b) Relationships between built up areas and the driving factor population over the years.

#### 4. Discussion

##### 4.1. Importance of Monitoring LULC in Jubek State, South Sudan

Researchers agreed that studying environmental dynamics and their driving forces at various scales is a practical approach to understanding the effects of social and economic differences on land (Lal and Margret Anouncia, 2015). Researchers from multiple disciplines are becoming more interested in relating socioeconomic and natural resource studies to LULC, resulting in challenging research questions [15]. In Jubek State, where the capital city of the newest country globally is located, went through a long period of civil war [48]. After the signing of the CPA, the area experienced significant changes, significantly increasing the built up areas and expanding natural resources such as forest land. Several reports were produced by some local and international agencies about the developmental progress and mishandling of natural resources which were frequently reported to impact society and existing resources negatively. Unfortunately, most previous studies analyzed the relationships between LULC and population growth, security, natural resource availability, and economic development. The findings of such studies reflect a few scenarios where land use changes are taking place. However, when generating remotely sensed data in terms of thematic maps for LULC of a particular study area and generating tables for matrices of land cover and change statistics, the advantage of remote sensing should be considered and recommended for various applications. Therefore, combining the driven data through remote sensing approaches and harvesting traditional information from the literature made it easy to understand LULC change forces in Jubek State; thus, better LULC management can be derived from such findings.

#### 4.2. Implications of Spatiotemporal Patterns of LULC

Firstly, for built up areas, in Jubek State, as well as the entire South Sudan, Juba was considered to be the most secure place to stay during the second civil war; this resulted in it becoming home to IDP camps for people migrating from other parts of South Sudan while others fled to neighboring countries [60]. Secondly, post CPA, Juba town has continued to accommodate large numbers of people, i.e., returning residents, IDPs from other locations, and other newcomers such as foreigners and South Sudanese from other states in search of a secure site and improved livelihood and business opportunities [61]. As shown in our change detection result, among the other classified classes, built up areas accounted for the most significant category; this is in line with previous studies conducted based on traditional methods apart from remote sensing data. The study also indicates that the significant expansion phase occurred after the CPA due to stability and developmental progress, as reported earlier. In contrast with previous studies, almost all related classification change statistics were gained from the census tract, and the findings reflect few scenarios regarding the locations of land use changes. Therefore, when generating remotely sensed data in terms of thematic maps for LULC of a particular study area and generating tables for LULC change statistics matrices, the advantage of remote sensing should be considered and recommended for various applications. Figures 2 and 4 show the primary land use results of land cover transformation from one class to another.

Figure 3 illustrates that built up areas were the most changed class, shown in red, primarily located in Juba town at the center of Jubek State, covering 0.9% of the total area (Table 5). The expansion of Jubek State results in splitting the area into 17 counties, with the majority observed at the site's north, west, and southeast.

The expansion of built up areas is commonly related to socioeconomic activities, such as population growth, security, natural resource availability, and economic activities. Although it is complicated to address the impacts of such factors on LULC changes, their influence was investigated by analyzing the links between the built up expansion of Jubek State and population growth, security, natural resources availability, and economic development. Data related to the above influencing factors for Jubek State were harvested from the literature. Therefore, combining the driven data through remote sensing approaches and gathered information from the literature made it easy to understand the force behind LULC change in Jubek State. Figure 6 shows the links between built up areas and the affecting factors over the study period. Though the figures mentioned are more significant than the study period, it explains how the elements affect LULC change in Jubek State. Figure 6a illustrates that the increase in built up areas is connected with the population in a linear fashion as  $R^2$  is 0.72; this implies that community contributes to the growth of built up areas, but some other factors such as security, availability of natural resources, and economic development are also key factors in expanding the site. This can be seen in Figure 6b as the most significant increase in population during the past 55 years occurred after the CPA agreement, i.e., after 2005.

Secondly, farmland in South Sudan covered an area of 285,331 km<sup>2</sup> [62]. This study found that Jubek State alone accounted for 128 km<sup>2</sup>, representing 0.04% of farmland in the country. The percentage of farmland was found to be relatively low across the entire study area, having 0.85% in 2000, 0.60% in 2009, and 0.70% in 2017, showing an aerial decrease (Table 4). Farmland size was not stable during the study period but kept fluctuating with time. Figure 5 shows the total loss and gain statistics of farmland between 2000 to 2017. Among the total size of farmland (128.31 km<sup>2</sup>) from 2000 to 2017, 1.82 km<sup>2</sup> (1.4%) was lost for built up areas, 16.97 km<sup>2</sup> (13.23%) converted to forest, 1.3 km<sup>2</sup> (1.01%) turned into water bodies, 74.74 km<sup>2</sup> (58.42%) converted to grass, and 18.73 km<sup>2</sup> (14.60%) became barren land. We also found that the size kept increasing during the study period and is expected to continue expanding due to the high demand for food items. This result revealed that agriculture was initially well-practiced in Jubek State. Due to the civil war, which caused serious security threats, especially in small villages around Juba, most farmers decided to move to the city, leading to abundant farming activity, especially

from 2000 to 2009. After regaining peace (CPA) and independence in 2011, some people returned to their village and started farming, resulting in a slight increase in farmland area (Table 5).

The study area's population will probably increase. The literature reported an increase in the community of more than 450% in the study area; the current 128 km<sup>2</sup> area of farmland is not enough to feed the population in the study area. Based on a report released by the government of South Sudan and the Integrated Food Security Phase Classification (IPC) report, 4.9 million people, i.e., more than 40% of South Sudan's population is under suspicion of food insecurity and malnutrition. Based on previous records, they stated that the total number of food-insecure people is expected to increase to 5.5 million. Ref. [63] estimated that more than one million children are malnourished across the country. Based on our findings, the land cover transformation approach will help boost agricultural productivity to meet food demand in Jubek State. We agree with the FAO recommendation for poverty management [7].

Thirdly, the study shows an increase in forest-covered areas, covering 30.33% of the study area. During the civil war in South Sudan, most of the forest areas were migrated from and left vacant due to insecurity; this is in line with several findings in the literature stating that war could be an advantage for natural resources and, on the other hand, a disadvantage for the safety of neighboring regions, due to the creation of "no-go zones" or buffers, i.e., such sites are free of human activity, thus leading to the re-growth of various vegetation [64–66]. Unfortunately, after the CPA in 2005 and independence in 2011, the population in Jubek State increased, especially in Juba, as most of the IDPs and South Sudan refugees from the neighboring countries relocated to Jubek State, mainly in the capital city Juba. The population intensity relied on the forest for building materials and an energy source. In 2015, the UN Environment Programme and the government of South Sudan conducted a study survey in Juba to estimate how many trees were being logged annually. The results show that 88% of households, 74% of businesses, and 40% of institutions depend on charcoal energy. Furthermore, 15% of households, 8% of businesses, and 40% of institutions use wood as fuel to supplement charcoal for cooking. Therefore, they concluded that five million trees were being logged annually to supply Juba with charcoal [67]. Some of the logged trees are located outside of the study area, but the product, in the form of wood fuel and charcoal, is brought to Jubek State for market. This indicates that in the near future, the country will be subject to deforestation if the authorities do not establish or update proper policy that will protect the environment. Renewable energy sources for domestic and commercial use could be one of the appropriate approaches to secure the on-going forest cutting.

Fourthly, barren land sized 2497.3 km<sup>2</sup> (13.64) of the total study area kept reducing (−33.85%). As shown in our findings, 2.48 (0.1%) km<sup>2</sup> of barren land was converted to farmland, 2.24 km<sup>2</sup> (0.09%) to builtup areas, 139.09 km<sup>2</sup> (5.57%) to forest, 5.87 km<sup>2</sup> (0.24%) to water bodies, and 1626 km<sup>2</sup> (65.14%) was converted to grassland. The results illustrate natural resource improvement as the result of the development of more water bodies, forests, and grass areas. The increase of farmland and built up areas is evidence of positive progress along the socioeconomic path due to the peace agreement.

Fifthly, grassland shows a slight reduction during the study period; it lost about 23.48 km<sup>2</sup> (0.24%) to farmland, 27.04 km<sup>2</sup> (0.27%) to builtup areas, 595.01 km<sup>2</sup> (6.0%) to the forest, 0.53 km<sup>2</sup> (0.005%) to water bodies, and 1898.68 km<sup>2</sup> (19.12%) to barren land (Table 5). The grassland was almost undisturbed from 2000 to 2009 due to a lack of developmental activities as the study area was under insecurity threats. Up to about an 18.8% reduction of grassland was noticed during the 17 years. The majority of built up areas and farmland was gained from grassland; this revealed the impact of peace on development when most of the study area, especially Juba town, witnessed drastic building and road constructions. Shortage of food supplies also forced the nationals and some foreign farmers to invest in agriculture, transforming the grass into farmland.

Finally, the river Nile passes through the study area, covering about 45.4 km<sup>2</sup>, 48.8 km<sup>2</sup>, and 35.9 km<sup>2</sup> in 2000, 2009, and 2017. The study revealed that, among the other classes of the study area, water bodies were the smallest of all, accounting for about 35.91 km<sup>2</sup> (0.19%) of Jubek State (Table 5). During 2000–2017, it lost around −21%, of which 0.8 km<sup>2</sup> (2.23%) was converted to farmland, 0.04 km<sup>2</sup> (0.11%) to builtup areas, 0.1 km<sup>2</sup> (3.0%) to forest, 0.93 km<sup>2</sup> to barren land, and 0.5 km<sup>2</sup> (1.42) to grassland (Table 5). The river Nile is the major water body source in the study area, characterized by high nutrient concentrations based on its chemical properties [68]. The majority of the loss of the water body could be from some other water sources' disappearance due to seasonal changes, but the main source from the Nile is relatively constant. The river Nile is another important sustainable natural resource that blesses the study area for agriculture, aquaculture, and energy potential.

## 5. Conclusions

Jubek State was selected among other South Sudan nations for various reasons, such as its global attention as the youngest country globally and the most important location in South Sudan regarding political, economic, and social aspects. For South Sudanese, Jubek is the preferred area to stay in due to better lifestyle access. The three time frames selected represent the period during the war (2000), immediately after the CPA (2009), and after the independence of the country (2017). Further destruction and development phenomena occurred during those periods, and it is believed that they might have involved the study area's landscape. Therefore, this study aimed to use remote sensing and GIS techniques to investigate the study area's spatiotemporal dynamics for a 17-year period (2000 to 2017). The results revealed that the war period (2000–2009) played an essential role in natural resource reservation due to the 'no-go zones'. Remarkable expansion in forest and grass was noticed, whereas some of the barren lands converted to forest and grassland. On the other hand, the drawback of war during these periods was demonstrated by the migration of many citizens to IDPs around Juba or refugee camps in the neighboring countries, causing the people to lose farmlands in their villages and resulting in a food shortage in the study area. The period 2009–2017 experienced a significant increase in built up areas due to the CPA and many people's return to the country. Most returnees preferred to relocate to stay within the study area for a better life.

After the LULC classification process is achieved, it can be utilized as primary data for generating additional findings, e.g., landscape matrices can be obtained from classification results to study alteration in some known varieties and division of landscape in Jubek State. In addition, classifications could be used as input data for environmental impact analysis and land cover transformation models to project LULC change. Finally, it can be stated that remote sensing serves as a supporting tool to harvest and filter information that could help to understand the status of land cover on the Earth's surface and atmosphere and locate the areas of their occurrence. Therefore, it could be a significant path to a better understanding of the digital world.

**Author Contributions:** A.J.A.G., J.D. had the original idea for the study, and coauthors conceived and designed the methodology; A.J.A.G., J.D. analyzed the data; A.J.A.G. wrote the paper, with J.D.; conceptualization, A.J.A.G., and J.D. revised; data curation, A.J.A.G.; formal analysis, A.J.A.G.; funding acquisition, A.S.Q.; methodology, A.J.A.G.; project administration, J.D.; resources, J.D.; supervision, J.D.; validation, A.J.A.G.; visualization, A.S.Q.; writing—original draft, A.J.A.G.; writing—review and editing, A.J.A.G., J.D., and A.S.Q. All authors have read and agreed to the published version of the manuscript.

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