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RESEARCH PAPER

Forest resources management using geospatial tools: a case study of Northern Nigeria

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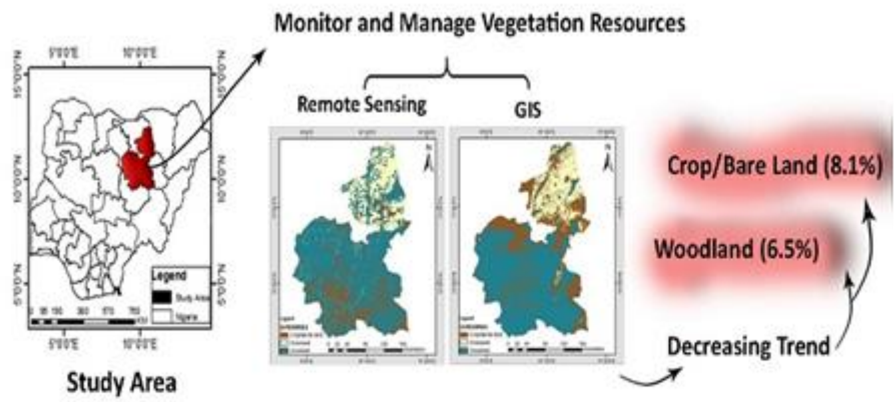
Highlights

- Vegetation cover play crucial role in the provision of food, shelter, wildlife habitat, fuel, daily supplies of medicinal ingredients and paper.
- Vegetation resources especially forests are dynamic in nature, and mostly affected by many coexisting processes such as deforestation, urbanization and wild fire.
- The role of geospatial techniques in forestry and vegetation resource management is highly indispensable for sustainable development.

Graphical Abstract



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Abstract

This research investigates the reliability of Remote Sensing (RS) and Geographical Information System (GIS) in monitor and management of vegetation resources for sustainable development. Vegetation change is a main ecological issue experienced in different land use types particularly in lands under uncoordinated practices. Landsat MSS satellite images, Landsat Operational land imager and field survey were used in this study. Results revealed that woodland (6.5%) and crop/bare land (8.1%) experience a steady decreasing trend. Moreover, annual rate of change for crop/bare land is alarming culminating to about plus 50% during the study, while that of woodland and grassland has been minus 15.59% and 3.9%, respectively. This clearly suggests that vegetation resource in the study area is rapidly decreasing and therefore needs urgent attention. Hence, due to crucial importance of vegetation cover in the provision of food, shelter, wildlife habitat, fuel, daily supplies of medicinal ingredients and paper, forest resources management using geospatial tools is highly indispensable for sustainable development. Remote Sensing, GIS, Forest management, Vegetation change, Northern Nigeria.

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1. Introduction

For effective management of resources, three elements are to be paid attention, including resource information, management policies, and all the stakeholders' participation in the process. Of valuable vegetation resources are forests that provide goods and services, such as food, shelter, fuel, and daily supplies that include medicine and paper. Woodland helps in giving living space to untamed life and improves land quality (Teshome et al., 2016). Likewise, Forests assume a significant job in adjusting the Earth's CO2 flexibly and trade. In view of other research, nearby individuals also accumulate different woodlands for family unit use and money pay (Jain and Sajjad, 2016). Many people rely upon backwoods assets to win their living; they acquire natural products, leaves, and stem for food, medication, and wood for house construction and fire. But these valuable resources are facing severe challenges today, mainly due to population density, agricultural and industrial activities. Verburg and colleagues revealed that, in general, around 6,000,000 hectares of woods lands have changed because of logging, rural, mining, and other human exercises the world over (Verburg et al., 2006).

1.1. Research problem

The major problem lies with the appropriate method to be employed to attain the desire objectives. However, by developing R.S. and GIS, sustainable development of forest resources through monitoring and management of the resources becomes more facile. Since 1972, when Landsat was launched, remote sensing technology has been used to monitor natural resources for proper management of the entire universe. Remote detecting is the science and craft of securing data about a marvel, items, or surface highlights from a far off stage, generally a satellite or airborne sensor without direct contact to an article (Sonti, 2015). Satellite information gets through R.S. are accessible at different ghostly, spatial, and worldly goals and are valuable to map expansive backwoods types, recognize and portray significant woodland changes after some time (Leckie, 1990). On the other hand, GIS is an essential tool for forest management because it answers questions such as location, condition, trends, pattern, and modeling techniques that help in forest management activities (Creutzburg et al., 2017).

As indicated by Guo and associates, utilization of these advancements, either exclusively or in the mix, traverses a wide scope of uses and degrees of intricacy. Historically, Remote Sensing has been an essential tool for vegetation resource data collection in various forms (Guo et al., 2017). In this way, incorporating information from various sorts of remote sensors for the backwoods stock is unequivocally empowered (Sankey et al., 2017). The structure of data obtained from R.S. permits its input into GIS environment for processing, analysis, mapping, and display. On a global scale, such as the vast area of the tropics large volume of data is required to identify and classify vegetation resources. On this premise, coarse goals scanners with fleeting high goals, for example, The Advanced Very High-Resolution Radiometer (AVHRR) of NOAA (National Oceanic and Atmospheric Administration) are needed which has a twice-daily overpass. Fig. 1 shows the map of global vegetation cover classification as derived from AVHRR satellite. The figure shows that North America has been mainly dominated by evergreen and mixed forest, while shrub and brush rangeland is found in Australia and some part of South America; in North Africa, Arab land and some part of middle Asia are dominated with the barren ground while Tundra is found in the extreme end of North America and Northern part of Russia.

The more extensive coverage and resolution of AVHRR enable its data to be used in deriving a map of global biomes, as shown in Fig. 2. The dull blue and green zones speak to thick vegetation, while pink and dim red regions speak to inadequate vegetation. Other high-resolution scanners that are used in the global coverage are Landsat series and Spot, which have repeated cycles of around two weeks. Some studies stated that Landsat TM symbolism had been utilized in a few endeavors to decipher the exactness and even adjust AVHRR symbolism (Stone et al., 1991; Teuber, 1990). Satellite data has also been used to monitor coastal zones' biomes production, as shown in Fig. 3, whereby the pixel size of about 825 m is covered with biomes with six-channel optimization. Remote sensing and GIS technologies have been utilized to monitor vegetation cover changes caused by large-scale deforestation and other incidences such as pests and pollution. The GIS technologies for backwoods management might be seen dependent on two expansive and related viewpoints; the asset stock and observing, just as investigation, displaying, and determining to help dynamic.

The two categories have been used in many parts of the world and Nigeria such as; A study conducted by United States Environmental Protection Agency (EPA) using Landsat Thermatic Mapper (TM) imagery (Ibitoye et al., 2017). Hewitt identified sixteen distinct spectral classes of xeric riparian habitats which further aggregated into three classes namely: water, riparian and non-riparian areas in the eastern Washington State of USA (Hewitt, 1990). Stone and colleagues in Rondania of Brazil used Landsat MSS of 1980 and TM of 1986 imageries to characterize territory and deforestation rates for an examination zone of almost thirty thousand KM² (Stone et al., 1991).

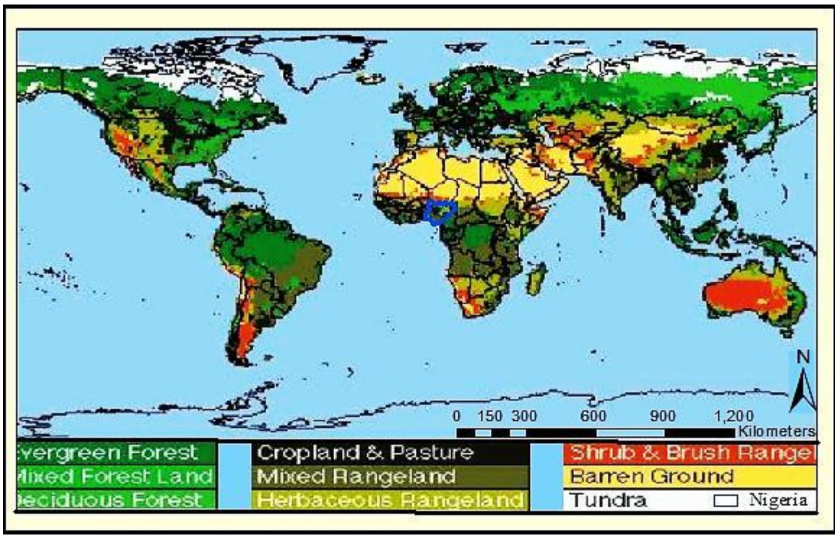

Fig. 1. Global vegetation cover classification (Rogers et al., 1997).

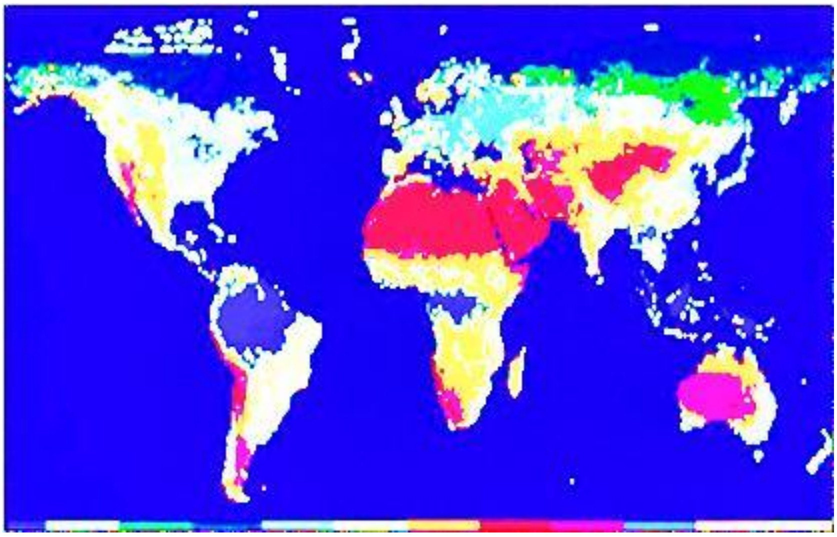

Fig. 2. Global biome map (Rogers et al., 1997).

The analysts found that 3168 KM2 of new clearing happened somewhere in the range of 1980 and 1986. Thus, in the United States of America, Vogelmaun and Rock utilized Landsat TM to survey and screen harm in coniferous timberlands in the province of Vermont. The analysts found that the most helpful ghostly reflectance information was TM4 and TM5. The higher the proportion of the two groups (TM5/TM4), the greater the harm that had happened (Vogelmann and Rock, 1989). One investigation revealed a three-year venture started in Germany in 1986 to set up strategies to distinguish, arrange, and map woodland decrease utilizing a mix of

Landsat MSS and airborne multi-otherworldly symbolism. The outcome uncovered that qualities ghostly marks could be recognized for various tree species (tidy, pine, and beech) contingent upon decay level (Landauer, 1989).

In another work, the created GIS-based displaying device empowered unique liveliness inside the GIS interface. The outcomes indicated that this apparatus could be adjusted to other CA-based spatio-fleeting displaying applications (Yassemi et al., 2008). The researchers present the capability of GIS in two parts. In the first part, only GIS was used, and in the second part, a forest growth model was combined with a GIS. Also, forest cover change and vulnerability analysis in Kenya, supervised by Wachiye and colleagues (Wachiye, 2013).

A gathering of analysts applied satellite remote detecting to groundwater potential displaying. In this investigation, Thematic maps of the topography, the lineament thickness, the lineament-crossing point thickness, the spring thickness, and the spring resistivity of the examination zone were incorporated to group the territory into shifted groundwater potential zones. Results indicated that the groundwater capability of regions around Ejigbo, Osun state is poor to direct level rating (Dasho et al., 2017). In other investigations in the Lower Niger Basin, West Africa, the Spatio-temporal variation in rainfall-runoff erosivity was examined due to climate change. Results indicated the Increasing patterns in yearly erosivity from the gauge atmosphere when all the GCMs were found the middle value of. Likewise, the higher precipitation sums were the significant drivers of the spatial-fleeting changes in erosivity (Amanambu et al., 2019).

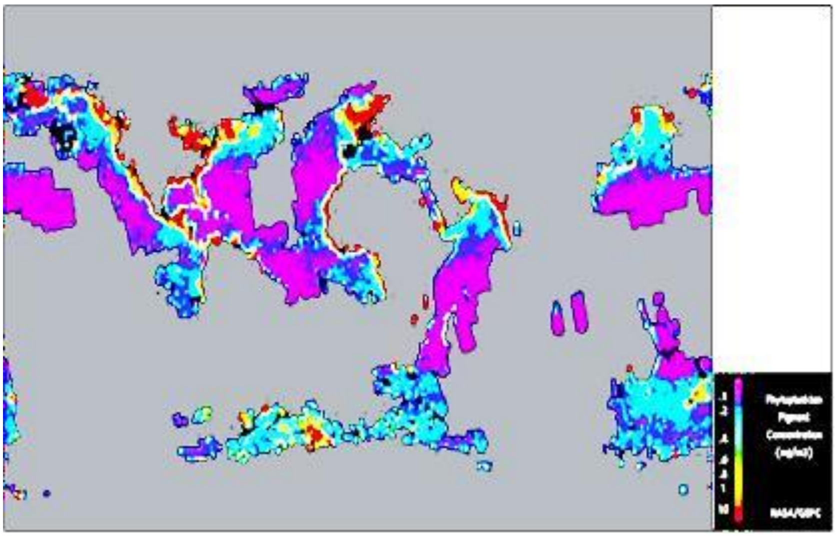

Fig. 3. Coastal zone biomes map (Rogers et al., 1997).

2. Materials and Methods

This research was done using Landsat MSS of 1976 and Landsat Operational Land Imager (OLI) of 2015 with a spatial resolution of 30 m; these data were downloaded from United States Geological Survey (USGS) achieve.

2.1. Study area

The study area lies between 9.49°81′88″–12.52°14′80″N lat. And 8.72°90′70″–11.02°32′73″E long (Fig. 4). The area's population is estimated to be 4,351,007 in 1991, 4,653,066 in 2006, and a projected population of 5,515,303 in 2011. The study area falls within Guinea Savannah Zone of Nigeria; vegetation cover of the area is dominated with woodland in the hills, lowlands and high land area, grass cover, and crop land suitable for various agricultural activities and rearing of animals. The vegetation's idea has been related to the populace thickness and attributes of the region's atmosphere. The temperature is high during the time with a mean limit of around 34 °C and at least around 20 °C. The area has an average annual rainfall of about 1,104.5 mm in 2005 and about

1,621.3 mm in 2009. The annual mean relative humidity at 1500 GMT reach about 35.2% and about 44.3% at 0900 GMT, annual mean radiation of the area is about 21.7mm while evapo-transpiration is about 5.3 mm.

2.2. Data analysis

The information examination strategy for this investigation depended on Remote Sensing and GIS examination utilizing picture grouping procedures in Arcgis 10.2 environ. A picture arrangement method is a way toward allotting pixels to different classes; it is the ID of the example related to every pixel position in symbolism (Rozenstein and Karnieli, 2011). This study employed the use of the two most frequently used techniques namely, the supervised and unsupervised. Maximum Likelihood Classifier (MLC) of supervised Techniques were used on the Landsat MSS imagery of 1976. The Department of Forestry developed a vegetation map of Bauchi State in 1978, the Ministry of Animal and forest resources. The National Industrial Research and Development Agency (NIRDA) was used as a map for generating training sites. Their classification came up with seven land cover classes: Shrubbed woodland hills & mountain complex, Shrubbed woodland lowland complex, Woodland Shrubbed land, Shrubbed grassland & grassland Shrubbed, Woodland grassland, Riparian vegetation, and Settle area/Cultivated land. In this study, however, the classification scheme was modified to present: crop/barren land, grassland, and woodland areas. During the analysis, the researchers examine the frequency of all spectral bands of the imagery using a Histogram, Scattered plot, mean, and covariance.

The benefits of solo grouping are its capacity to execute the order naturally without earlier information on the investigator's territory. Along these lines, the propensity of making a human mistake is limited because the product calculation consequently shows remarkable classes as precise units. The inconveniences of the solo arrangement, then again, incorporate the constrained control of the grouping menu by the expert, which may prompt delivering classes that are not important to the investigator (Tso and Olsen, 2005). Because of this limitation, supervised classification was finally carried out on the already classify imagery using unsupervised classification to come out with the same classes as that of MSS imagery. To analyze trend of the forest and other vegetation cover in the study area, a table showing the area in Kilometer square and the percentage change for the study period measured against each class was developed. Rate change to decide the pattern of progress was then determined by isolating watched change by the entirety of changes duplicated by 100. In acquiring the yearly pace of progress, the rate change is separated by 100 and increased by the quantity of study year (39 years).

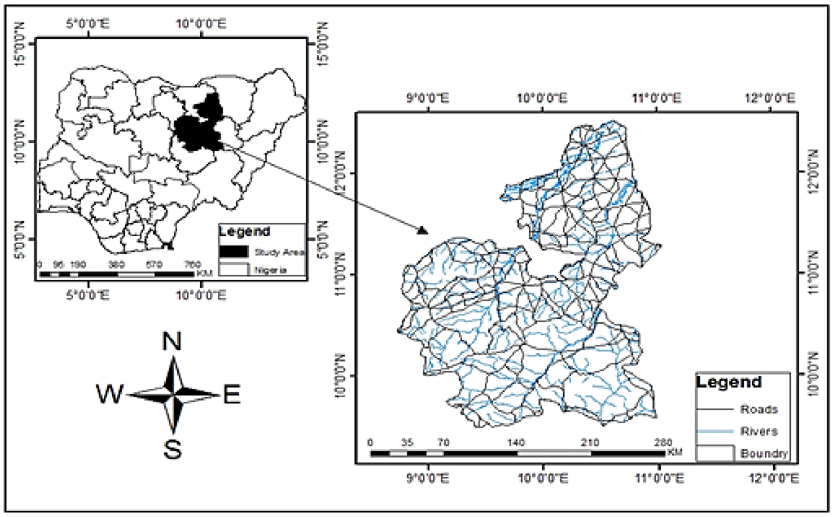

Fig. 4. Map of the study area, Source (GIS lab, ABU, Zaria).

3. Results and Discussion

3.1. Identification of significant vegetation covers classes

Figs. 5 & 6 show the remote sensing and GIS ability to map and monitor the distribution and changes of land cover in the Bauchi state of Nigeria. Based on the above figures and Table 1, the woodland occupied the highest land area of about 65.3% in 1976 but decreased to about 58.8% in 2015. This was followed by crop/barren land with 17.8% in 1976, but it increased to 25.9% in 2015, while grassland occupied the lowest area of only 16.9% in 1976 it decreased to 15.3% in 2015. These results indicated that the Bauchi state's woodland is the highest vegetation cover from 1976 to 2015, even though the area occupied by this type of vegetation is reducing while those occupied by crop/barren land are generally increasing. The findings of this study are in line with that of Hiernaux et al., in Sudano-Sahelian Ecological zones of Nigeria (Hiernaux et al., 2009); Sahebjalal and Dashtekian, in Iran (Sahebjalal and Dashtekian, 2013); Gadiga and Dan, in Yobe (Gadiga and Dan, 2015).

Based on results and study in the Sudano-Sahelian Ecological zones of Nigeria, the Spatio-temporal distribution of vegetation cover in their respective areas studied and should also that vegetation resources, especially forest cover, are continuously decreasing both in height and density. Hence, this study's findings reveal that human activities, mainly farming, are infringing the available forest resource in Bauchi state. The maps produced in this study also shows how geospatial tools could be used to conduct research even in areas that are difficult to reach by human transport system due to the density of vegetation cover or how they are dangerous (Figs. 5 & 6).

Table 1. The aerial extent of vegetation covers classes in the study area (1976 and 2015).

Pattern	1976		2015	
	Area (Km^2)	**Area (%)**	**Area (Km^2)**	**Area (%)**
Woodland	31452.3	65.3	28319.7	58.8
Grassland	8160	16.9	7374.2	15.3
Crop/ barren land	8570.7	17.8	12489.1	25.9
Total	48183	100	48183	100

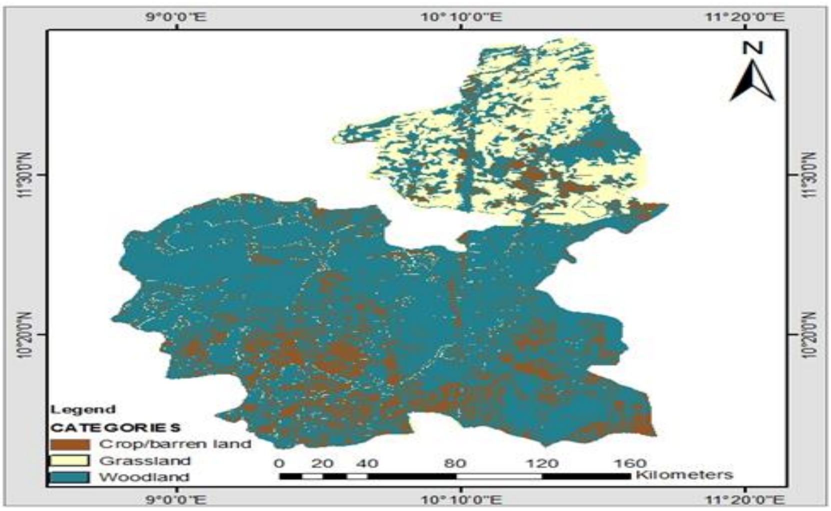

Fig. 5. 1976 vegetation cover of Bauchi State, Source (Author's Data Analysis, 2018).

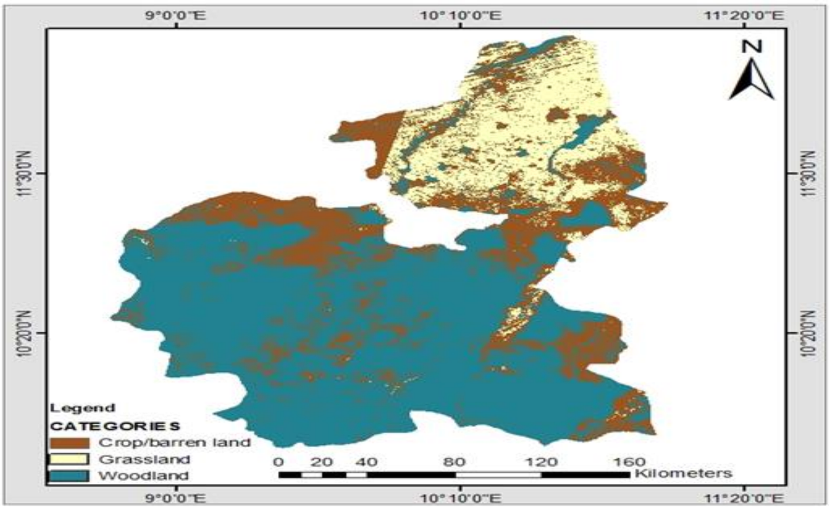

Fig. 6. 2015 vegetation cover of Bauchi State, Source (Author's Data Analysis, 2018).

3.2. Determination of percentage and the annual rate of change

Table 2 showed the share and annual rate of change of vegetation cover in the study area. It revealed that the percentage change of crop/bare land within the study period had been raised by 50% while that of woodland fall by 39.97%. The annual rate of change within 39 years of the study for crop/barren land has been plus 19.5, but that of woodland has been minus 15.59 and minus 3.91 for grassland. The findings of this research are supported by other research in Nigeria's wooded savannah. Based on the results the studied areas occupied by very high vegetation cover and also indicated how crop/barren lands double all other categories of land cover (Fasona et al., 2013).

Table 2. Percentage change and Annual rate of Changes of vegetation cover classes in the study area (1976 and 2015).

Pattern	Change	% Change	Annual Rate of Change
Woodland	-3132.6	39.97	-15.59
Grassland	-785.8	10.03	-3.91
Crop/ barren land	3918.4	50.00	19.5
Total	7836.8	100	0.0

4. Conclusions

In this study, the capabilities of remote sensing and GIS applications in sustainable forest management have been reviewed. Despite the diversity of applications, however, significant conclusions can be drawn about the role of geospatial techniques in forestry and vegetation resource management. It clearly shows that vegetation resource, mainly woodland, is on the decreasing trend in the study area at the rate of 15.59$ while crop/barren lands increase by about 50% within the study period. It is also concluded that vegetation resources, especially forests, are dynamic and are mostly affected by many coexisting processes such as deforestation, urbanization, and wildfire, which need to be monitored and manage through modern technologies such as remote sensing and GIS. The findings of this research further revealed that geospatial technologies could be effectively used to address the problem associated with the changes that occur on vegetation resources.

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