African Journal of Environment and Natural Science Research
ISSN: 2689-9434
Volume 7, Issue 4, 2024 (pp. 119-138)
www.abjournals.org

DETERMINATION OF FOREST HEALTH USING REMOTE SENSING TECHNIQUES IN GASHAKA-GUMTI NATIONAL PARK, NORTHEAST, NIGERIA

Dantani A.

Department of Forestry and Wildlife Management, Faculty of Agriculture, Bayero University Kano, Nigeria.

Email: adantani.fwm@buk.edu.ng

Cite this article:

Dantani, A. (2024), Determination of Forest Health using Remote Sensing Techniques in Gashaka-Gumti National Park, Northeast, Nigeria. African Journal of Social Sciences and Humanities Research 7(4), 119-138. DOI: 10.52589/AJENSR-82LKC8VI

Manuscript History

Received: 11 May 2024

Accepted: 29 Jul 2024

Published: 15 Nov 2024

ABSTRACT: *This study was conducted in order to determine the health status of forest vegetation in Gashaka-Gumti National Park. Landsat images were downloaded from the USGS website. The images were pre-processed using radiometric correction since the reflectance values were needed for computing spectral indices, the digital numbers were converted to radiance and reflectance, and analysis was carried out using a raster calculator. The range of NDVI, GNDVI, ARVI and MSI were used for health assessment. Utilizing NDVI, GNDVI, ARVI, and MSI as assessment tools revealed moderate to good health in most forest regions, with higher ARVI, GNDVI, and NDVI indicating healthier vegetation and elevated MSI values suggesting areas under moisture stress. the average values of NDVI, GNDVI, ARVI, and MSI over three decades indicate a potential decline in overall vegetation health, reduced green vegetation, changes in vegetation conditions, and a decrease in moisture stress, suggesting a potential increase in greening and photosynthetic activities in plants. These trends highlight the dynamic nature of the forest ecosystem over the studied period. Positive correlations between ARVI, GNDVI, and NDVI across years indicate a consistent vegetation pattern, while negative correlations with MSI suggest potential inverse relationships, providing valuable insights into forest health dynamics. Higher values of ARVI, GNDVI, and NDVI generally signify healthier vegetation, whereas elevated MSI values may indicate areas experiencing moisture stress, emphasizing the importance of monitoring these indices for sustainable forest management. The study recommends the sustained use of NDVI, GNDVI, ARVI, and MSI for forest health monitoring in the study area, implementing integrated pest management based on identified stress conditions, utilize spatial maps for strategic timber harvest planning, developing climate-resilient management considering moisture stress, and invest in research for enhanced assessment precision and understanding of ecosystem dynamics.*

KEYWORDS: Forest Health, Remote Sensing, Spectral Indices, Chlorophyll, Vegetation and Landsat.

Article DOI: 10.52589/AJENSR-82LKC8VI
DOI URL: https://doi.org/10.52589/AJENSR-82LKC8VI

African Journal of Environment and Natural Science Research
ISSN: 2689-9434
Volume 7, Issue 4, 2024 (pp. 119-138)

INTRODUCTION

Healthy canopies of green vegetation have a very distinctive interaction with energy in the visible and near-infrared regions of the electromagnetic spectrum. In the visible regions, plant pigments (most notable chlorophyll) cause strong absorption of energy, primarily for photosynthesis. This absorption peaks in the red and blue areas of the visible spectrum, thus leading to the characteristic green appearance of most leaves. In the near-infrared, however, a very different interaction occurs. The energy in this region is not used in photosynthesis and it is strongly scattered by the internal structure of most leaves, leading to a very high apparent reflectance in the near infrared. It is this strong contrast particularly between the amount of reflected energy in the red and near-infrared regions of the electromagnetic spectrum which has been the focus of a large variety of attempts to develop quantitative indices of vegetation condition using remotely sensed imagery (Eastman, 2012). The spectral characteristics of vegetation vary with wavelength. Chlorophyll absorbs radiation in the red and blue wavelengths but reflects the green wavelength. The internal structure of healthy leaves acts as a diffuse reflector of near-infrared wavelengths. Spectral bands are often used both individually and in combination with other bands to obtain vegetation indices (Berra *et al.*, 2014 and Goergen *et al*., 2016). The biometrical properties of vegetation in different wavelengths of the electromagnetic spectrum can be analyzed as well used for modeling and simulating biophysical processes (Salami and Balogun, 2006; Jarocinska and Zagajewski, 2006; Samvedan, 2007). The most common vegetation index in forest classification and land cover change studies is NDVI. It reportedly improves vegetation classifications by partially compensating for variation in illumination due to terrain (Tucker, 1979; Lillesand and Kiefer, 1994). The perceived condition of a forest predicated on factors such as age, structure, composition, function, vigour, the presence of unusual levels of insects or diseases, and resilience to disturbance can be termed forest health (Martin and Aber, 2006). A forest is adjudged to be vigorous if the physical and biotic resources support productive forests, guarantee the sustenance of organisms within the ecosystem and the maintenance of a functional equilibrium between supply and demand of essential resources (Haile *et al.,* 2014). Indicators commonly used in forest health monitoring include tree mortality, tree crown condition, the growth of trees (as shown by basal area, height or volume changes through time), plant diversity, the dominance of native species, soil Morphology and chemistry (Morse *et al.*, 2005).

Many researchers studied chlorophyll concentration of canopy relates to forest health measurement and predicts the stress of vegetation in the forest because defoliation and discolorations determine canopy chlorophyll masses. Ahmad *et al.* (2020) used airborne hyperspectral AVIRIS NG data and leaf pigments and water concentration via spectral signature to measure forest health. Meng *et al.* (2016) calculated the Forest Health Index (FHI) using spectral and textural features retrieved from SPOT 5 satellite data. Canopy health and forest damage by insects has been successfully retrieved from remote sensing imagery using hyperspectral bands in Eucalyptus (Evans *et al.*, 2012). Kumaresan (2018) used Hyperion data sets for spectral discrimination for health assessment through the ENVI forest health toolbox. Zarco-Tejada *et al.* (2018) analysed the temporal changes of red edge spectra which are sensitive to chlorophyll for estimating canopy defoliation and pigment degradation. Kayet *et al*. (2019) worked on forest health analysis using Hyperion data to monitor dust accumulation on leaves in the mining area of Jharkhand state, India. Lots of other studies concentrated only NDVI as an indicator of forest health and these studies does not reflects

Article DOI: 10.52589/AJENSR-82LKC8VI
DOI URL: https://doi.org/10.52589/AJENSR-82LKC8VI

many stressors and therefore does not meet the requirement of FH monitoring (Barkey and Nursaputra, 2019; Dash *et al*., 2017; Housman *et al.*, 2018; Reang *et al.*, 2018). Developing suitable indicators to know the quantity, rate and place of forest health decline is the principle behind forest health monitoring (Meng *et al.*, 2016). The approach based on RS techniques used spectral traits and its variation in a spatiotemporal way for retrieving indicators of forest health (Lausch *et al*., 2017). The forest health indicators accuracy using RS depends upon spectral, spatial, angular, radiometric resolution, the utilization of modelling method (biophysical, biochemical and classification retrieval) suitability for the RS methods and norms of spectral traits (Lausch *et al*., 2016). On the other hand, structural traits for forest health monitoring are essential because forests having complex structures (good condition) supplies more ecological services than forests having simple structures (Meng *et al*., 2014; Brockerhoff *et al*., 2017)

Remote sensing refers to “the practice of deriving information about the earth’s land and water surfaces using images acquired from an overhead perspective, using electromagnetic radiation in one or more regions of the electromagnetic spectrum reflected or emitted from the earth’s surface. (Campbell, 2002) Remote sensors can be deployed on satellites, airplanes, balloons, or remote-controlled vehicles. Current and past satellite remote sensing of forest health has focused on the following categories: vegetation and landscape classification, biomass mapping, invasive plant detection, fire fuel mapping, canopy or foliar water stress, fire detection and progression mapping, post-fire burn area and severity mapping, and insect infestation detection. Most of these studies have analyzed spectral signatures or simple indices (calculated from reflectance data) such as the Normalized Difference Vegetation Index (NDVI). Little has been done for remote sensing of absolute forest water stress (e.g., evapotranspiration [ET]) and biomass growth using physically- and physiologically-based algorithms. Previous studies estimated biomass by using NDVI or other simple indices using correlation and regression methods. The vegetation indices are mathematical combinations of the spectral response of different bands of the electromagnetic spectrum and are indicators of photosynthetic activity and vegetation vigour used as surrogates for vegetation for time-series analysis, vegetation status monitoring and change detection (Brantley, *et al.*, 2011; Hill 2013). The main indices cited recently in the literature use reflectance values in three wavelength bands: the red, red edge and the near-infrared. These indices reduce the volume of data to be analysed and make easier estimates of biophysical structural and physiological variables of the vegetation (Fonseca 2004; Prabhakara, *et al.*, 2015; Pan *et al.*, 2015). However, some indices such as Normalized difference vegetation index – NDVI and Simple Ratio – SR may present saturation problems when measured for areas of vigorous vegetation (Hill 2013; Li *et al*., 2014; Schuster *et al*., 2015).

Forests provide human with many goods, services, and resources, such as recreation, atmospheric purification, and water conservation. In recent years, there have been increasing threats to the health of forests such as global warming due to climate change, environmental pollution, and the growing interest in forests, efforts are being made in various countries for forest management. The sustainable forest management proposed in the Montreal which is an international forest treaty, means sustainable management of the forests in terms of ecological, economic, social and cultural functions in consideration of intergenerational equity. Seven criteria for evaluating the performance of management were presented. In this reason, countries around the world are actively working on the establishment of a forest health survey index using criteria for conservation of

Article DOI: 10.52589/AJENSR-82LKC8VI
DOI URL: https://doi.org/10.52589/AJENSR-82LKC8VI

biodiversity and the third standard for maintaining health and vitality of forest ecosystems. Forest usage include provision of timber, fuelwood, wildlife habitat, natural water supply, recreation, landscape and community protection while others are employment generation (Amarsaikhan, *et al.,* 2012) aesthetically appealing landscapes, biodiversity management, watershed management, erosion control (Khalile, *et al.,* 2018). Forest ecosystems are the most important feature of the earth according to (Ramos, 2010) and it has emerged as a science embraced by the majority of industrialized countries. Generally speaking, intensive and effective forest management requires reliable field data, maps, and plans indicating the current state of the forest (Ayansina, 2017).

LITERATURE REVIEW

Forest health monitoring has a long practice often associated with monitoring programs at national, international, and regional levels in which graded ecological indicators of forest health have been used and created. In Germany, FHM initiative consists of three level of analysis: the first level consists of systematic sample grid of permanent plots, the second level consist of continual sampling in selected forest ecosystems and the third level comprises National Forest Inventory (NFI) at every 10 years and 45 countries integrated into it (Lorenz, 1995; JHTI, 2018). In the USA, USDA forest service performed FHM to determine the changes, status, and trends in indicators of forest health on an annual basis. In Europe and North America, the tree canopy condition, e.g., defoliation and dieback, is mostly used as a pointer for forest wellbeing assessment. Frequency level of five years since 2004, the wellbeing status and environmental elements of forest biological systems were checked and added to the national forest inventory (Yang *et al.,* 2015). At Global level, Global Forest Observations Initiative (GFOI) was setup to supply a platform for coordinated actions at national level and individual countries (currently 45) report their findings to the Food and Agriculture Organization of the United Nations (FAO). Using ecological indicators, the multiple Forest Health Index (FHI) can be adopted to quantify forest health. Forest health, a more formal and scientific term is normally used in forestry to describe the forest stand condition. While this term first appeared in the forestry literature in the 1980s (Waring, 1980; Smith, 1990), there was no widely accepted definition for almost 10 years. The lack of a universal definition hindered the assessment of forest health as well as the monitoring of its dynamics. In this context. (O'Laughlin and Cook, 2003; Tuominen *et al.,* 2009) integrated the definitions of forest, ecosystem and health and finally defined forest health as a condition of forest ecosystems that sustained their complexity while providing for human needs. This definition made a great effort to combine the social, ecological and economical perspectives (Tuominen, *et al*., 2009) and was adopted by the US forest service and is frequently used in the forestry literature (Tuominen, *et al.*, 2009; Lim, 2012; Lim, 2015)

Article DOI: 10.52589/AJENSR-82LKC8VI
DOI URL: https://doi.org/10.52589/AJENSR-82LKC8VI

African Journal of Environment and Natural Science Research
ISSN: 2689-9434
Volume 7, Issue 4, 2024 (pp. 119-138)

METHODOLOGY

Study Area

Gashaka-Gumti National Park is located in the North-Eastern part of Nigeria. It is indeed known for its significant size, making it the largest national park in Nigeria covering approximately 6731km^2. Situated between latitude 6°55' to 8°05' N and longitude 11°01' to 12°13' E, as reported by (Dunn, 1999). The name of the park emerged from the amalgamation of two villages, Gashaka in Taraba State and Gumti in Adamawa State during the military regime by the Federal Government of Nigeria through Decree No. 36 of 1991. The merging of Gashaka and Gumti Game Reserves into one national park reflects the government's commitment to conservation efforts and the protection of natural resources (Marguba, 2002). The establishment of Gashaka-Gumti National Park with its diverse ecosystems aligns with various objectives, viz: preserving the rich biodiversity and ecosystems within the park, providing opportunities for outdoor activities and recreational experiences for visitors, promoting sustainable tourism that focuses on natural and cultural heritage, providing economic benefits while minimizing environmental impact, serving as a hub for scientific research, contributing to the understanding of local ecosystems and potentially leading to advancements in medical and biological fields, supporting and preserving the art, crafts, and cultural values of the indigenous people living around the park. The multi-faceted role that Gashaka-Gumti National Park plays in contributing to environmental conservation, scientific knowledge, and the well-being of both wildlife and local communities around.

The climate of the reserve is classified as savanna woodland. However, it differs from most central habitats due to a long and marked dry season, the rainy season typically begins from March to April and lasts until mid-November, the park exhibits a variation in rainfall across its expanse. The northern part receives approximately 1200mm of rainfall, while the southern part receives a higher amount, around 3000mm (Dunn 1999) and this indicates a north-to-south gradient in terms of precipitation. The high rainfall is attributed to the influence of high mountains. The humidity from the Atlantic is forced to higher elevations, where it cools down and forms rain-bearing clouds, his phenomenon contributes to the growth of moist forests in the park. Understanding the climate is crucial for comprehending the diversity of flora and fauna within the park, as different species may be adapted to specific climatic conditions. The presence of a marked dry season and distinct wet season also plays a role in shaping the ecosystems and wildlife behaviors.

Article DOI: 10.52589/AJENSR-82LKC8VI
DOI URL: https://doi.org/10.52589/AJENSR-82LKC8VI

African Journal of Environment and Natural Science Research
ISSN: 2689-9434
Volume 7, Issue 4, 2024 (pp. 119-138)

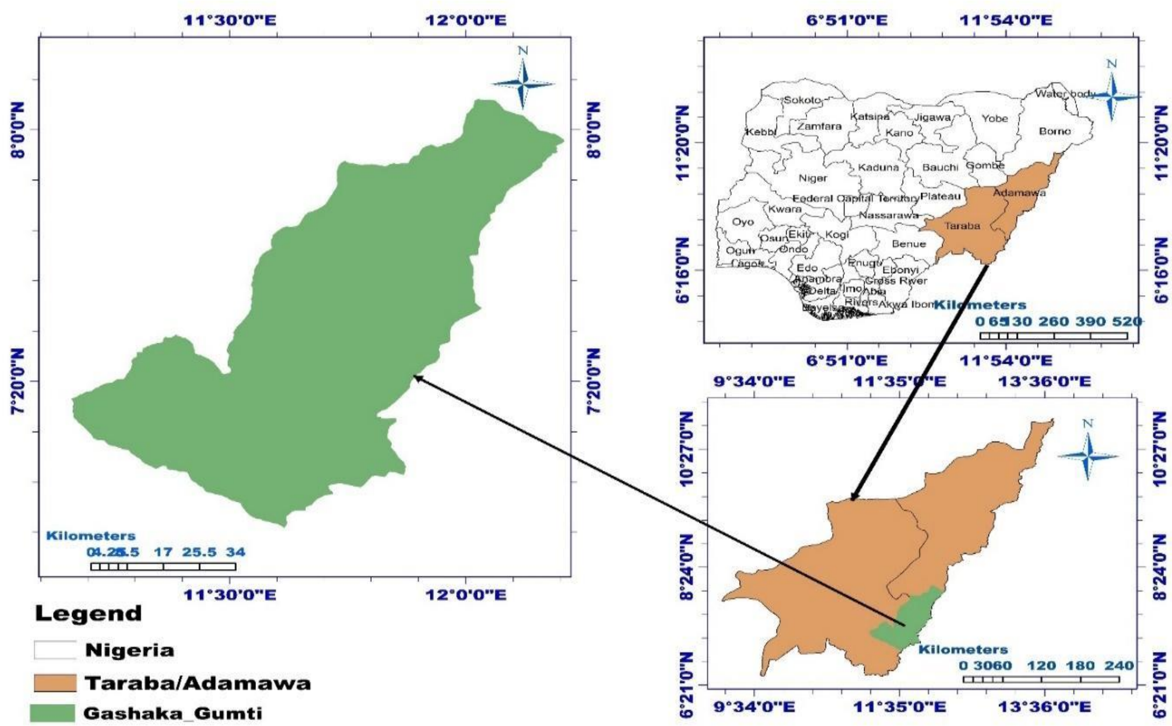

Figure 1: Map of the Study Area

Spatial Data Acquisition

Satellite (Landsat) images of 2003, 2013 and 2023 were acquired on the 1st February 2024 through path and row 1985/055 and 1986/055, downloaded from United States Geological Survey (USGS) website. These sensors include operational land imager (OLI) /Thermal Infrared Sensor (TIRS), Enhanced Thematic Mapper (ETM+).

Image processing

Geometric rectification is critical for producing spatially corrected map of land use/cover changes through time. The Landsat OLI images were in UTM projection (Zone 31N) on WGS84. Therefore, the images of the study area were geometrically corrected. Since the reflectance values will be necessary for the calculation of vegetation indices, the digital numbers (DN) must be converted to radiance and then to reflectance (Chukwuka and Funmilayo, 2018)

Table 1: Adopted data and their attributes

	Data type	Date	Resolution	Source
1	Landsat Image	2003	30m	Earth Explorer USGS
2	Landsat Image	2013	30m	Earth Explorer USGS
3	Landsat Image	2023	30m	Earth Explorer USGS
4	Administration map			Office of the Surveyor General Taraba State

Article DOI: 10.52589/AJENSR-82LKC8VI
DOI URL: https://doi.org/10.52589/AJENSR-82LKC8VI

Overview of Approach

Figure 2. below shows the summary of methods adopted in the study. Data from different sources were acquired and used for the study which includes multi-temporal data (Landsat satellite images). Landsat satellite images of 2003, 2013 and 2023 were acquired from United States Geological Survey (USGS) archive (http://glovis.usgs.gov) the study area was extracted from the data and ArcMap and Idrisi software was used

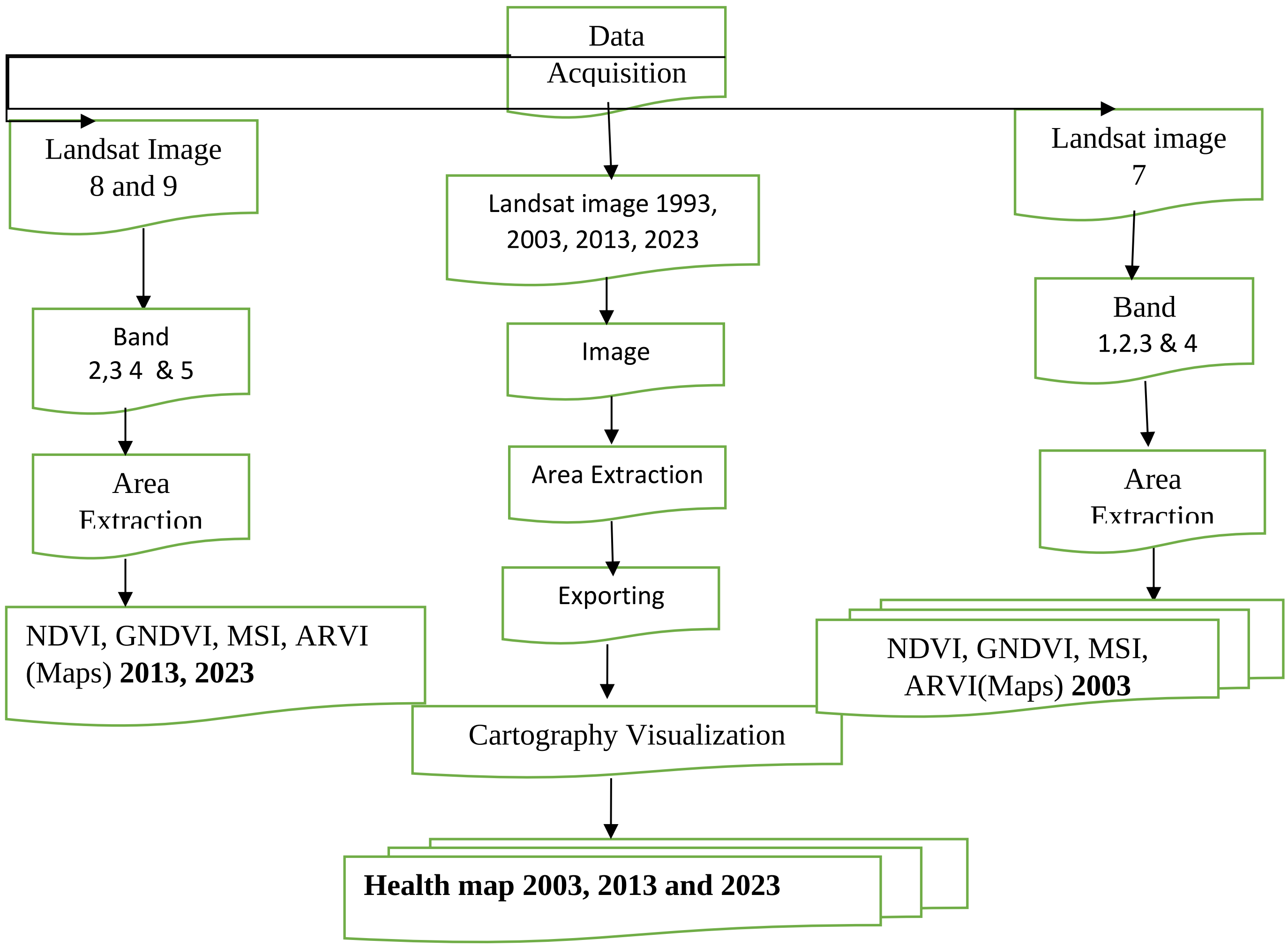

Figure 2: Summary of the methods adopted

Data processing and Analysis

The multi-temporal data (Landsat images) were processed using ArcMap software package. The Landsat imagery was imported, imagery was enhanced using radiometric correction. spectral indices were computed using raster calculator.

Article DOI: 10.52589/AJENSR-82LKC8VI
DOI URL: https://doi.org/10.52589/AJENSR-82LKC8VI

Spectral Indices

i. Normalized Difference Vegetation Index (NDVI)

The Normalized Difference Vegetation Index (NDVI) is a numerical indicator that uses the red and near-infrared spectral bands. Healthy vegetation (chlorophyll) reflects more near-infrared (NIR) and green light compared to other wavelengths. But it absorbs more red and blue light. Overall, NDVI is a standardized way to measure healthy vegetation. When you have high NDVI

values, you have healthier vegetation. When you have low NDVI, you have less or no vegetation (Jaksibaev 2020). To determine the density of live green vegetation on a patch of land the NDVI is calculated from reflectance bands by these individual measurements (Rouse *et al,* 1973; Souza *et al*., 2010) as adopted by Kumaresan (2018).

The formula for

NDVI= (NIR - Red) / (NIR + Red)……………………………………………………….(1)

where NIR is the near-infrared band

Red is the red band of the Landsat imagery.

ii. Green Normalized Difference Vegetation Index (GNDVI)

This index has a lot in common with NDVI. The major difference is that it measures the green spectrum from 540 to 570nm instead of the RED spectrum. This index is also unique because it is very sensitive to chlorophyll concentration. is an index of plant “greenness” or photosynthetic activity? It is a chlorophyll index used at later stages of development, as it saturates later than NDVI. It is one of the most widely used vegetation indices to determine water and nitrogen uptake in the crop canopy. GNDVI is more sensitive to chlorophyll variation in the crop than NDVI, the values given by this index also range from -1 to 1. Values between -1 and 0: are associated with the presence of water or bare soil. It is used mainly in the crop cycle’s intermediate and final stages and values greater than 0: the more intense the green, the more vigorous the vegetation and vegetation cover. (Gitelson and Merzlyak. 1995)

GNDVI = (NIR - Green) /(NIR + Green)……………………………………..…...(2)

iii. Atmospherically Resistant Vegetation Index (ARVI) Calculation

ARVI – (Atmospherically Resistant Vegetation Index) is an enhancement to the NDVI that is relatively resistant to atmospheric factors (for example, aerosol). It uses blue reflectance to correct red reflectance for atmospheric scattering. It is most useful in regions of high atmospheric aerosol content, including tropical regions contaminated by soot from slash-and-burn agriculture. The formula is ARVI is an index of atmospherically resistant vegetation, which is most useful in regions with high concentrations of atmospheric aerosols. It uses blue light reflectance measurements to correct for atmospheric scattering effects that also affect red light reflectance. It is calculated by the following formula: (Kaufman and Tanre, 1992). ARVI values range from -1 to 1, with green vegetation typically corresponding to values in the range of 0.20 to 0.80

Article DOI: 10.52589/AJENSR-82LKC8VI
DOI URL: https://doi.org/10.52589/AJENSR-82LKC8VI

ARVI = (NIR - (2 * Red) + Blue) / (NIR + (2 * Red) + Blue)…………..………………(3)

iv. Moisture Stress Index (MSI)

Moisture Stress Index is used for canopy stress analysis, productivity prediction and biophysical modeling. Interpretation of the MSI is inverted relative to other water vegetation indices; thus, higher values of the index indicate greater plant water stress and in inference, less soil moisture content. The values of this index range from 0 to more than 3 with the common range for green vegetation being 0.2 to 2 (Welikhe *et al.*, 2017).

MSI = (MidIR / NIR)……………………………………………………………….(4)

RESULTS AND DISCUSSIONS

Vegetation Indices and Forest Health Assessment

The health status of the vegetation was analysed using Normalized Difference Vegetation Index (NDVI), Green Normalized Difference Vegetation Index (GNDVI), Atmospherically Resistance Vegetation Index (ARVI) and Moisture Stress index (MSI) are based on the characteristic reflection of plant leaves in the visible and near-infrared portion of light. Th healthy vegetation has a low reflection of visible light since it is strongly absorbed by the leaf pigment known as chlorophyll (Aigbokan 2018). For this research three different Landsat scenes were obtained and analyzed viz: 2003, 2013 and 2023. The techniques for forest health assessment exhibit a spatial map of the overall health and vigour of a forest. It is very good for the detection of pest and blight conditions as well as assessing good area for timber harvests. A forest that is experiencing high stress condition will show signs of dry/drying vegetation condition, very dense or sparse canopy and inefficient light utilization. The results of the findings (Figure 3,4,5 and 6) indicate most of the regions to be moderately healthy and this corresponds with findings of (Kumaran 2018) in his research titled Spectral Based Vegetation discrimination and Forest Health Assessment Using Hyperion where he used nine (9) categories for health classes as a scale.

Article DOI: 10.52589/AJENSR-82LKC8VI
DOI URL: https://doi.org/10.52589/AJENSR-82LKC8VI

African Journal of Environment and Natural Science Research
ISSN: 2689-9434
Volume 7, Issue 4, 2024 (pp. 119-138)

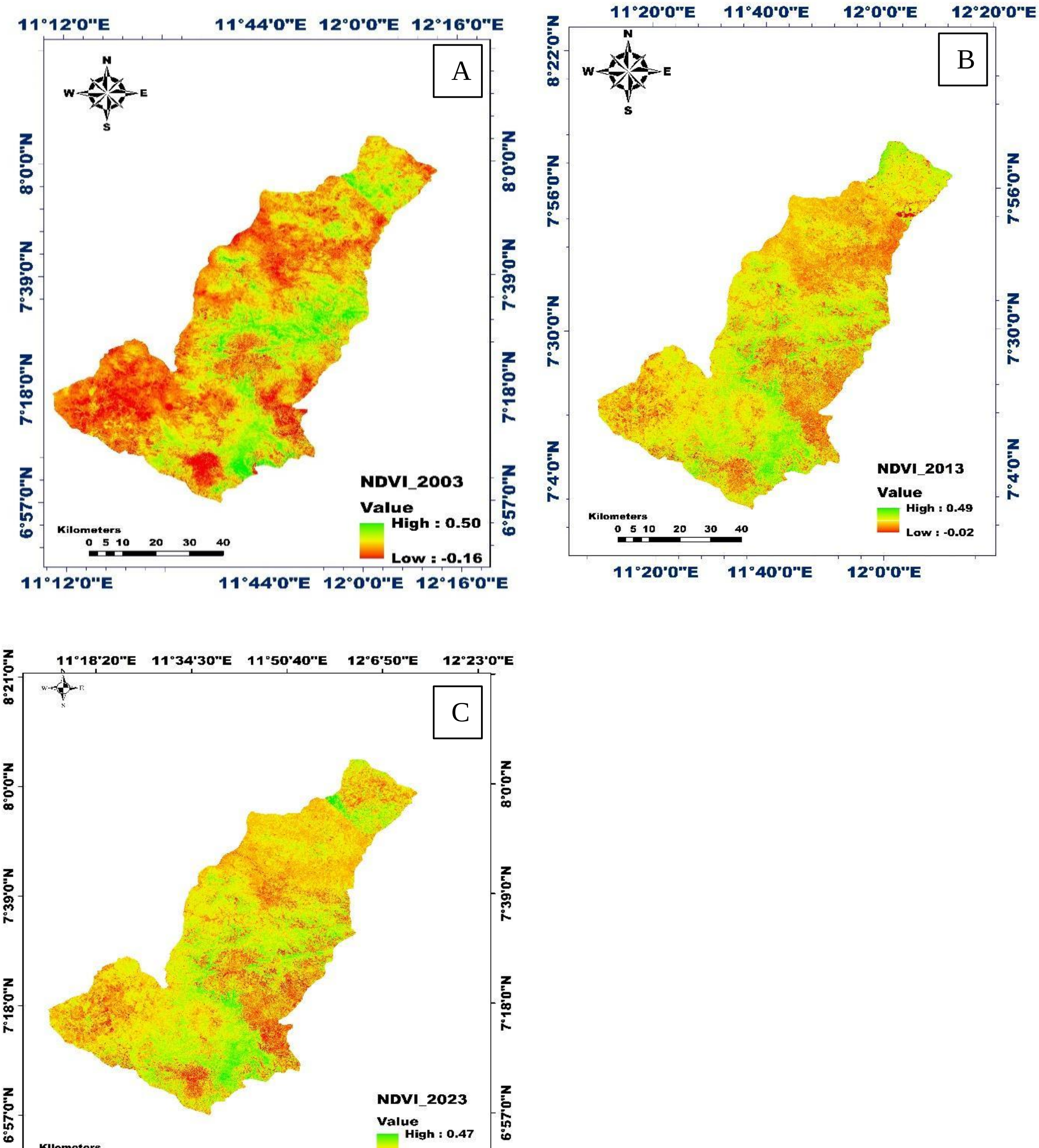

Figure 3: NDVI Maps

From figure 3 (A) maximum and minimum NDVI were 0.50 and -0.16, the red patches are more concentrated in the north towards the western part while northeast and southern part shows increase in the NDVI values signifying better canopy vigour and chlorophyll concentration. Image

Article DOI: 10.52589/AJENSR-82LKC8VI
DOI URL: https://doi.org/10.52589/AJENSR-82LKC8VI

African Journal of Environment and Natural Science Research
ISSN: 2689-9434
Volume 7, Issue 4, 2024 (pp. 119-138)

in 2(B) shows little improvement where maximum and minimum NDVI (0.49 to -0.02) this shows general improvement in the in the chlorophyll content compare to the image in (A). Image in (C) shows positive NDVI values ranging from 0.47-0.01 which represent increase in the chlorophyll content in the leave

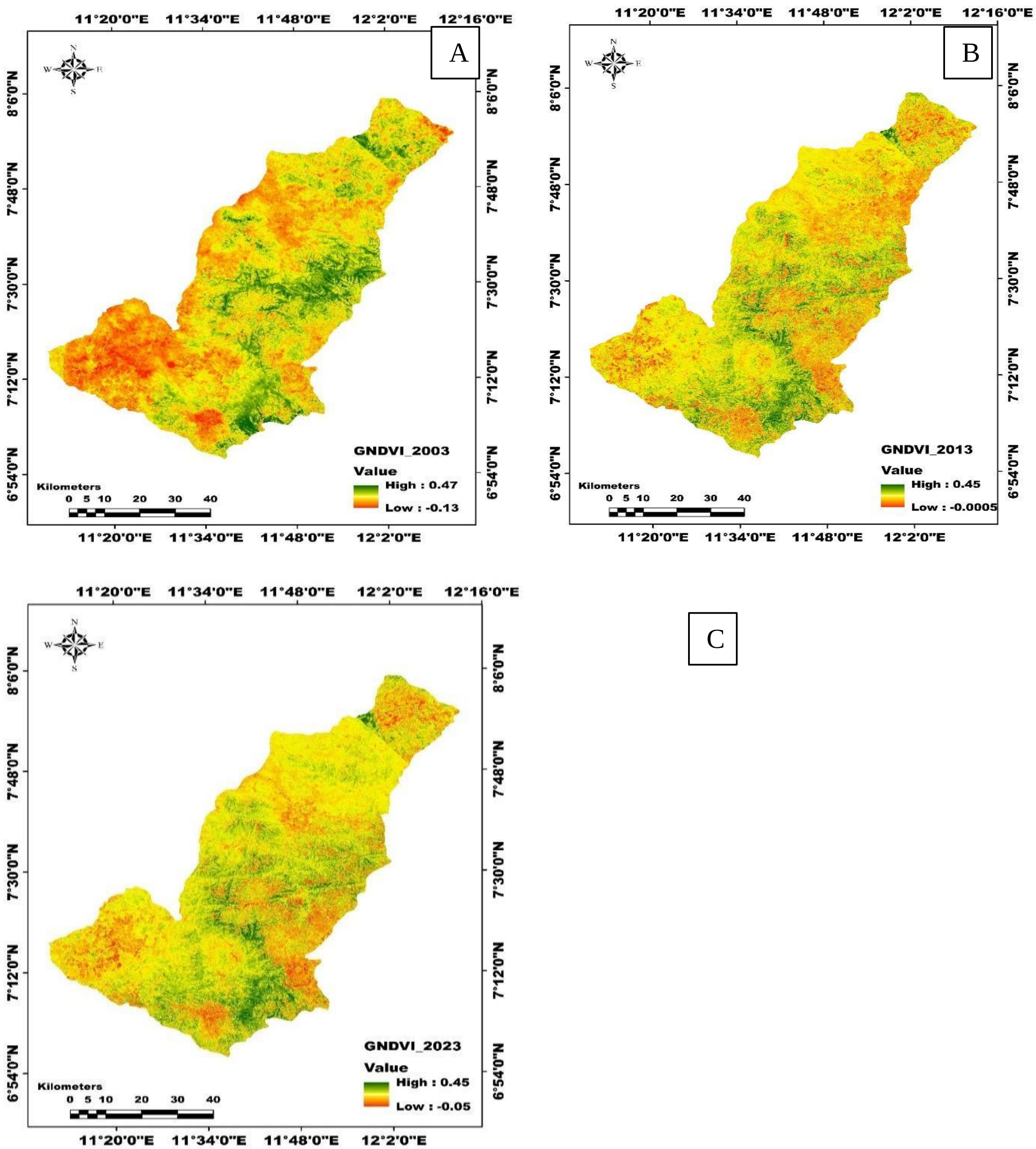

Figure 4: GNDVI Maps

Article DOI: 10.52589/AJENSR-82LKC8VI
DOI URL: https://doi.org/10.52589/AJENSR-82LKC8VI

From figure 4 (A) maximum and minimum GNDVI were 0.47 and -0.13, the red patches are more concentrated in the north towards the western part while northeast and southern part shows increase in GNDVI values signifying increase in chlorophyll concentration. Image in 2(B) shows decrease in GNDVI values where maximum and minimum (0.45 to -0.0005) in the in the chlorophyll content compare to the image in (A). Image in (C) shows positive NDVI values ranging from 0.45-0.05 which represent decrease in the chlorophyll content in the leaves.

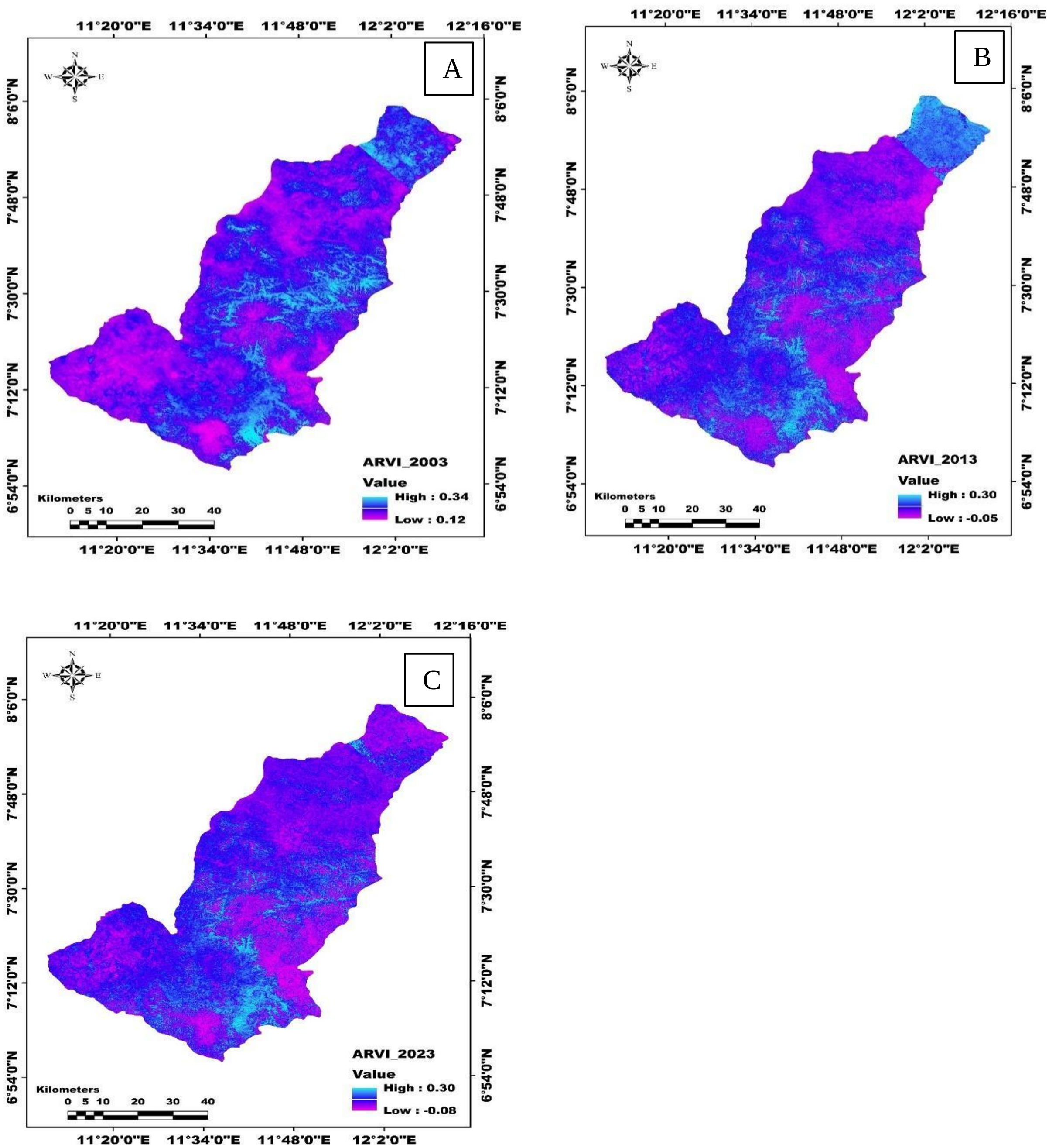

Figure 5: ARVI Maps

Article DOI: 10.52589/AJENSR-82LKC8VI
DOI URL: https://doi.org/10.52589/AJENSR-82LKC8VI

From figure 5 (A) maximum and minimum ARVI were 0.34 and 0.12, the red patches are more concentrated in the north towards the western part while northeast and southern part shows decrease in ARVI values signifying reduction in green vegetation. Image in 2(B) shows decrease in ARVI values where maximum and minimum (0.30 to -0.05) reduced compare to the image in (A). Image in (C) shows reduction values ranging from 0.30 to -0.05 which represent decrease in green vegetation.

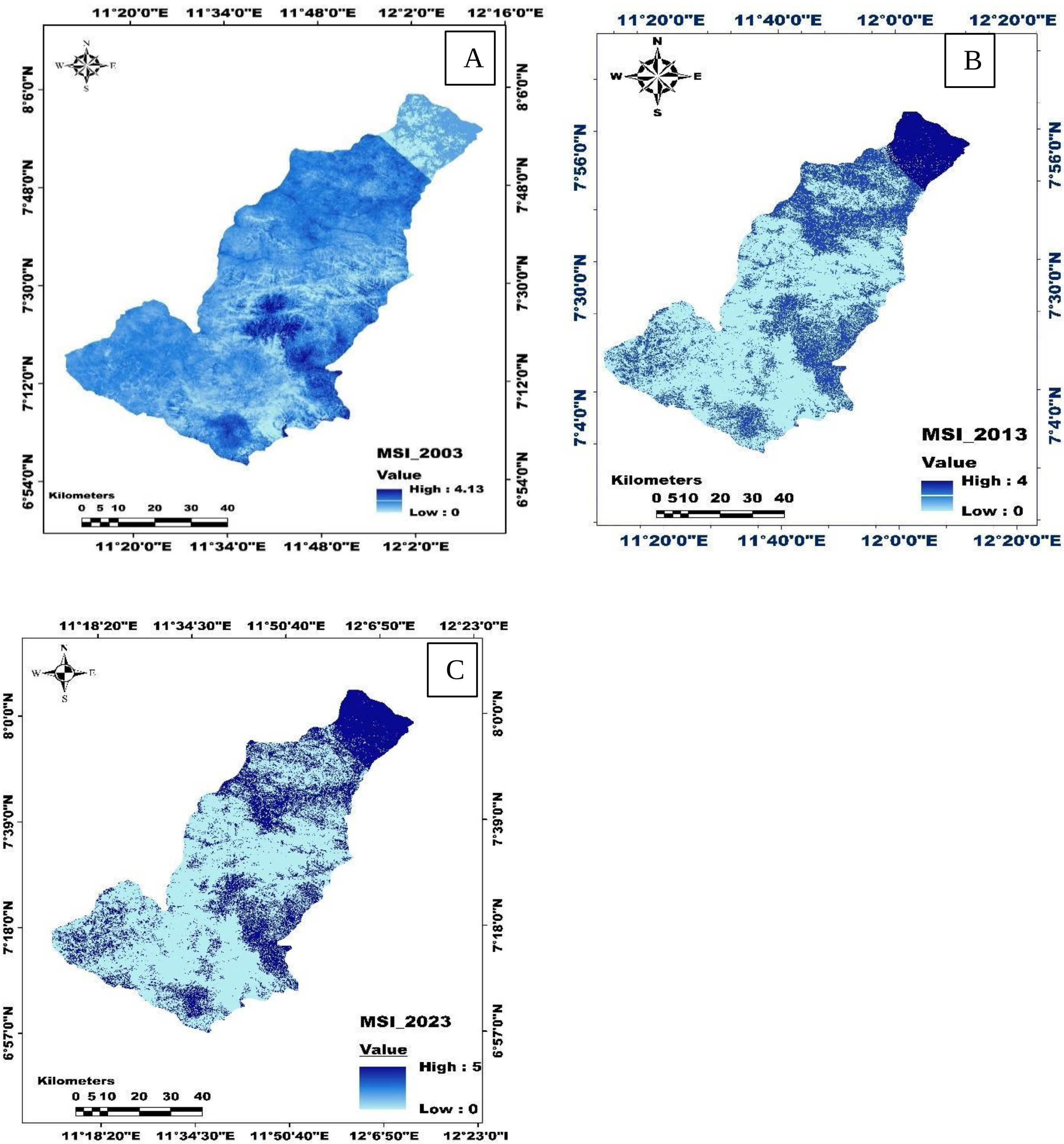

Figure 6: MSI Maps

Article DOI: 10.52589/AJENSR-82LKC8VI
DOI URL: https://doi.org/10.52589/AJENSR-82LKC8VI

African Journal of Environment and Natural Science Research
ISSN: 2689-9434
Volume 7, Issue 4, 2024 (pp. 119-138)

From figure 6 (A) maximum and minimum MSI were 4.13-0, the deep blue color signifies water stress, and almost all the part of the study area. Image in 2 (B) shows decrease in MSI values where maximum and minimum (4 to 0) reduced compare to the image in (A). Image in (C) shows reduction values ranging from 5 to 0 which represent increase in water stress especially towards the more than part of the area.

Mean Values of the Spectral Indices

The figure 7 below shows average values of the spectral indices obtained in three decades. NDVI is a measure of vegetation health, and higher values typically indicate healthier vegetation. The reduction in NDVI from 0.3 in 2003 to 0.2 in 2013 and 2023 suggests a potential decline in overall vegetation health over the decades. GNDVI, like NDVI, assesses vegetation health with an emphasis on greenness, similar to NDVI, the decrease from 0.3 in 2003 to 0.2 in 2013 and 2023 indicates a possible reduction in green vegetation. ARVI is less common and resistant to atmospheric effects, the decline from 0.2 in 2003 to 0.1 in 2013 and 2023 suggests changes in vegetation conditions. MSI is often associated with moisture stress in vegetation, the highest mean value of 0.8 in 2003, reducing to 0.4 in 2013 and 0.29 in 2023, implies a potential decrease in moisture stress over the decades which implies greening and high photosynthetic activities in plant.

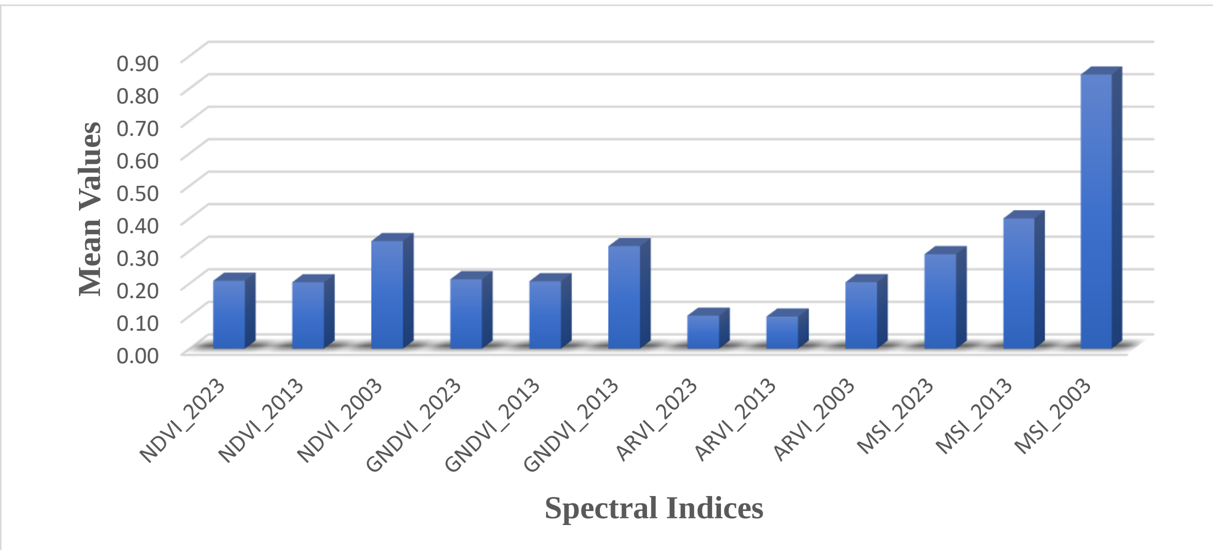

Figure 7: Mean Values of the Spectral Indices

Relationships Between Spectral Indices

ARVI exhibits positive correlations with GNDVI and NDVI in all years, suggesting a coherent relationship with these indices while negative correlation was observed with MSI. GNDVI depict positive correlations with other indices (ARVI, MSI, and NDVI) for all years. MSI shows negative correlations with ARVI, GNDVI, and NDVI across all indices, suggesting an inverse relationship. NDVI exhibits strong positive correlations indicating consistency over time with the exception of MSI which shows negative. Generally, the strong positive correlations among spectral indices viz: ARVI, GNDVI, and NDVI across different years suggest a consistent vegetation pattern. The

Article DOI: 10.52589/AJENSR-82LKC8VI
DOI URL: https://doi.org/10.52589/AJENSR-82LKC8VI

African Journal of Environment and Natural Science Research
ISSN: 2689-9434
Volume 7, Issue 4, 2024 (pp. 119-138)

negative correlations of MSI with other indices indicate potential inverse relationships, implying that as one index increases, the other may decrease. The detailed relationships revealed by these correlations provide valuable insights into the dynamics of the forest health assessment based on spectral indices.

The higher the values of ARVI, GNDVI and NDVI, the lower the values of MSI and the better the vegetation (greenness, moisture level as well as chlorophyll content in the leaves). Higher values of MSI indicate moisture stress which affect the rate of photosynthesis and chlorophyll production in plants leading to the declining health status. Higher values of ARVI, GNDVI, and NDVI generally signify healthier vegetation, while higher MSI values may indicate areas with moisture stress. Monitoring these indices over time can help identify changes in vegetation health, guiding sustainable forest management practices

Article DOI: 10.52589/AJENSR-82LKC8VI
DOI URL: https://doi.org/10.52589/AJENSR-82LKC8VI

Table 2: Correlation Matrix for Spectral Indices

	ARVI 2023	*ARVI 2013*	*ARVI 2003*	*GNDVI 2023*	*GNDVI 2013*	*GNDVI 2003*	*MSI 2023*	*MSI 2013*	*MSI 2003*	*NDVI 2023*	*NDVI 2013*	*NDVI 2003*
ARVI-2023												
ARVI-2013	0.915***											
ARVI-2003	0.663***	0.680***										
GNDVI-2023	**0.916*****	0.796***	0.581***									
GNDVI-2013	0.837***	**0.942*****	0.642***	0.804***								
GNDVI-2003	0.533***	0.521***	**0.919*****	0.540***	0.555***							
MSI-2023	**-0.689*****	-0.597***	-0.456***	**-0.594*****	-0.493***	-0.338***						
MSI-2013	-0.700***	**-0.761*****	-0.553***	-0.591***	**-0.673*****	-0.397***	0.738***					
MSI-2003	-0.720***	-0.746***	**-0.850*****	-0.542***	-0.622***	**-0.632*****	0.595***	0.636***				
NDVI-2023	**0.987*****	0.883***	0.640***	**0.966*****	0.836***	0.541***	**-0.684*****	-0.686***	-0.664***			
NDVI-2013	0.896***	**0.991*****	0.673***	0.807***	**0.977*****	0.538***	-0.578***	**-0.754*****	-0.710***	0.877***		
NDVI-2003	0.635***	0.646***	**0.993*****	0.578***	0.628***	**0.958*****	-0.430***	-0.519***	**-0.801*****	0.621***	0.646***	

Computed correlation used Pearson-method with listwise-deletion.

Article DOI: 10.52589/AJENSR-82LKC8VI
DOI URL: https://doi.org/10.52589/AJENSR-82LKC8VI

Table 3: Summary performance of the spectral indices

	Green	Chlorophyll	Moisture/Stress	Blight	Defoliation	Aerosol	Ranking
NDVI	–	-		–	–		**1**
GNDVI	–	–					**2**
ARVI	–					–	**3**
MSI			–				**4**

CONCLUSION

Healthy vegetation exhibits low reflection of visible light due to strong absorption by chlorophyll, a key leaf pigment. The study spanned a three decades allowing for a temporal analysis of vegetation health over the years (2003, 2013, and 2023). NDVI, GNDVI, ARVI, and MSI were employed as effective tools for assessing forest health. These indices provide insights into factors such as pest and blight conditions and identify suitable areas for timber harvests. Forest health assessment techniques resulted in spatial maps that offer a visual representation of the distribution of health and vigor across the forest landscape. High-stress conditions in the forest were identified through signs such as dry/drying vegetation, variations in canopy density, and inefficient light utilization. The findings indicated that the majority of the forest regions fall within the categories of moderate and good health. Higher values of ARVI, GNDVI, and NDVI generally signify healthier vegetation with optimal greenness, moisture levels, and chlorophyll content in the leaves. Conversely, higher values of MSI indicate areas experiencing moisture stress, potentially leading to a decline in the health status of vegetation

REFERENCES

Ahmad, S., Pandey, A.C., Kumar, A., Lele, N.V., Bhattacharya, B.K., 2020. Forest health estimation in Sholayar Reserve Forest, Kerala using AVIRIS-NG hyperspectral data. *Spatial Information Rese. 28* (1), 25–38.

Aigbokhan (2018). Forest Health Analysis, Using Remote Sensing and GIS Techniques: A Case Study of Omo Forest Reserve, Ogun State. Nigeria. *Continental J. Sustainable Development*, 9 (2): 35 – 45. DOI: 10.5281/zenodo.2528982

Amarsaikhan, D., Saandar, M., Battsengel, V. and Amarjargal, S.H. 2012. Forest resources study in Mongolia using advanced spatial technologies, Full paper published in *International Archives of the Photogrammetry, RS and Spatial Information Sciences*, Vol.XXXIX-B7, XXII ISPRS Congress, Melbourne, Australia.

Ayansina, A. 2017. Remote Sensing Vegetation Dynamics Analytical Methods: A Review of Vegetation Indices Techniques. *GeoinformaticaPolonica*. 16. DOI 10.4467/21995923GP.17.001.7188.

Barkey, R.A. and Nursaputra, M. 2019. The Detection of Forest Health Level as an Effort to Protecting Main Ecosystem in the term of Watershed Management in Maros Watershed, South Sulawesi, in: IOP Conference Series: *Earth and Environmental Science*. 12006

Berra, E.F. 2013. Avaliação e comparação de imagens LISS-III/ ResourceSAT-1 e TM/LANDSAT 5 para estimar volume de madeira de um plantio de Pinus elliottii. 127.

Article DOI: 10.52589/AJENSR-82LKC8VI
DOI URL: https://doi.org/10.52589/AJENSR-82LKC8VI

ISSN: 2689-9434
Volume 7, Issue 4, 2024 (pp. 119-138)

Brantley, S. T., Zinnert, J. C. and Young, D. R. 2011. "Application of Hyperspectral Vegetation Indices to Detect Variations in High Leaf Area Index Temperate Shrub Thicket Canopies." *Remote Sensing of Environment, 115 (2),* 514–523. doi: 10.1016/j.rse.2010.09.020.

Brockerhoff, E.G., Barbaro, L., Castagneyrol, B., Forrester, D.I., Gardiner, B., González-Olabarria, J.R., Lyver, P. O'B., Meurisse, N., Oxbrough, A., Taki, H., Thompson, I.D., van der Plas, F. and Jactel, H. 2017. Forest biodiversity, ecosystem functioning and the provision of ecosystem services. *Biodivers. Conserv. 26* (13), 3005–3035.

Campbell, J.B. 2002. Introduction to remote sensing. The Guilford Press: New York.

Chukwuka, F. A. and Oluwafunmilayo, M. E (2018). Land Surface Temperature Mapping Using Geoinformation Techniques. *Geoinformatics FCE CTU* 17(1), 2018, doi:10.14311/gi.17.1.

Dash, J.P., Watt, M.S., Pearse, G.D., Heaphy, M. and Dungey, H.S. 2017. Assessing very high-resolution UAV imagery for monitoring forest health during a simulated disease outbreak. *ISPRS J. Photogramm. Remote Sens. 131*, 1–14

Dunn, A. 1999. Gashaka Gumti National Park: A Guide Book. National Park Service, Abuja, 1-7.

Eastman, J. R. 2012. IDRISI Selva Tutorial, Manual Version 17.0, Clark University.

Evans, B., Lyons, T., Barber, P., Stone, C., Hardy, G., 2012. Enhancing a eucalypt crown condition indicator driven by high spatial and spectral resolution remote sensing imagery. *J. Appl. Remote Sens. 6* (1), 063605. https://doi.org/10.1117/1. JRS.6.063605.

Fonseca, E.L.D. 2004. Desenvolvimento De Modelo Da Disponibilidade De Fitomassa Aérea Para Formações Campestres Naturais a Partir De Dados Espectrais Orbitais E Agrometeorológicos. São José dos Campos: Instituto Nacional de Pesquisas Espaciais – INPE

Gitelson, A. and Merzlyakb, M. N. 1994. "Quantitative Experiments Estimation of Chlorophyll-u Using Reflectance with Autumn Chestnut and Maple Leaves and Spectra:" *Journal of Photochemistry and Photobiology B: Biology, 22,* 247–252. doi:10.1016/1011-1344(93)06963-4.

Goergen, L.C. De G., Kilca, R. De V., Narvaes, I. Da S., Silva, M.N., Silva, E.A., Pereira, R.S., Adami, M. 2016. *Distinção de espécies de eucalipto de diferentesidades pormeio de imagens TM/Landsat 5. Pesquisa Agropecuária Brasileira,* v.51, p.53-60.

Haile K. 2014. Tadesse and Allan Falconer, 'Land Cover Classification and Analysis Using Radar and Landsat Data In North Central Ethiopia'. ASPRS 2014 Annual Conference Louisville, Kentucky, 23-28.

Hill, M.J. 2013. "Vegetation Index Suites as Indicators of Vegetation State in Grassland and Savanna: An Analysis with Simulated SENTINEL 2 Data for a North American Transect." *Remote Sensing of Environment, 137,* 94–111. doi: 10.1016/j.rse.2013.06.004.

Housman, I.W., Chastain, R.A. and Finco, M.v. 2018. An evaluation of forest health insect and disease survey data and satellite-based remote sensing forest change detection methods: Case studies in the United States. *Remote Sensing, 10,* 1184.

Jaksibaev, R.N., & Aleuov, A.S. (2020). Use of statistical methods in the analysis of land cover. Electronic journal of Actual problems of modern science, education and training, Volume 4, 291-298. ISSN 2181-9750.

Jarocinska, A. and Zagajewski, B. 2006. Remote sensing tools for analysis of vegetation condition in extensively used agricultural areas. University of Warsaw, *K KrakowskiePrzedmiescie 30,* 00-927 Warszawa, Poland.

Article DOI: 10.52589/AJENSR-82LKC8VI
DOI URL: https://doi.org/10.52589/AJENSR-82LKC8VI

Johann Heinrich von Thünen-Institute(JHTI), 2018. Forest Condition Monitoring (FCM) Level-I Monitoring. https://www.thuenen.de/de/wo/ arbeitsbereiche/waldmonitoring/.

Kaufman, Y.J. and Tanre, D., 1992. Atmospherically resistant vegetation index (ARVI) for EOS-MODIS. *IEEE transactions on Geoscience and Remote Sensing*, *30*(2), pp.261-270.

Kayet, N., Pathak, K., Chakrabarty, A., Singh, C.P., Chowdary, V.M., Kumar, S., Sahoo, S. 2019. Forest health assessment for geo-environmental planning and management in hilltop mining areas using Hyperion and Landsat data. *Ecol. Ind. 106,* 105471. https://doi.org/10.1016/j.ecolind.2019.105471.

Khalile, L., Rhinane, H, Kaoukaya, A., and Lahlaoi, H. (2018). Forest Cover Monitoring and Change Detection in Nfifikh Forest (Morocco). *Journal of Geographic Information System*, 10, 219-233. doi.org/10.4236/jgis.2018.102011.

Kumaresan, P.R., 2018. Spectral based vegetation discrimination and forest health assessment using hyperion (EO-1) in Yelagiri Hills, Tamil Nadu. *Int. J. Appl. Eng. Res. 13*, 13826–13832. http://www.ripublication.com

Lausch, A., Erasmi, S., King, D.J., Magdon, P., Heurich, M. 2017. Understanding forest health with remote sensing-part II—a review of approaches and data models. *Remote Sensing 9 (2)*, 129. https://doi.org/10.3390/rs9020129.

Lausch, A., Erasmi, S., King, D.J., Magdon, P., Heurich, M., 2016. Understanding forest health with remote sensing-part I—a review of spectral traits, processes and remote-sensing characteristics. *Remote Sensing, 8* (12), 1029. https://doi.org/ 10.3390/rs8121029.

Li, F., Chen, W., Zeng, Y., Zhao, Q. and Bingfang. W. 2014. "Improving Estimates of Grassland Fractional Vegetation Cover Based on A Pixel Dichotomy Model: A Case Study in Inner Mongolia, China." *Remote Sensing, 6* (6): 4705–4722. doi:10.3390/rs6064705.

Lillesand, T. M. and Kiefer, R. W. 1994. Remote sensing and image interpretation (3rd Ed.). New York: Wiley.

Lim, S.S. 2012. Development of Forest Aesthetic Indicators in Sustainable Forest Management Standards; University of British Columbia: Vancouver, BC, Canada.

Lorenz, M. 1995. International co-operative programme on assessment and monitoring of air pollution effects on forests-ICP forests. *Water Air Soil Pollution 85* (3), 1221–1226.

Marguba, B. 2002. Nigeria National Parks Their Significance and Potentials to the Nation. The Magazine of the Nigeria National Parks, 1, 7-10.

Meng, J., Li, S., Wang, W., Liu, Q., Xie, S., Ma, W. 2016. Mapping forest health using spectral and textural information extracted from spot-5 satellite images. *Remote Sensing, 8* (9), 719. https://doi.org/10.3390/rs8090719.

Meng, J., Lu, Y. and Zeng, J. 2014. Transformation of a degraded pinus massoniana plantation into a mixed-species irregular forest: Impacts on stand structure and growth in southern China. *Forests, 5* (12), 3199–3221.

Morse A., Tasumi M., Allen R. G. and Kramber W. J. 2005 'Forest ecosystem processes at the watershed scale: sensitivity to remotely-sensed leaf area index estimates'. *Int. J. Remote Sensing*, *14*, 2519–2534.

O'Laughlin, J. and Cook, P.S. 2003. Inventory-based forest health indicators: Implications for national forest management. *J. For*. *101*, 11–17.

Pan, Z., Huang, J., Zhou, Q., Wang, L. Cheng, Y., Zhang, H., Blackburn, G. A., Yan, J. and Liu, J. 2015. "Mapping Crop Phenology Using NDVI Time-Series Derived from HJ-1 A/B Data."

International Journal of Applied Earth Observation and Geoinformation, 34 (1), 188–197. doi:10.1016/j. jag.2014.08.011. Elsevier B.V.

Prabhakara, K. W., Hively, D. and McCarty, G. W. 2015. "Evaluating the Relationship between Biomass, Percent Groundcover and Remote Sensing Indices across Six Winter Cover Crop Fields in Maryland, United States." *International Journal of Applied Earth Observation and Geoinformation,39*: 88–102. doi: 10.1016/j.jag.2015.03.002. Elsevier B.V.

Ramos, J. 2010. *The notable trees of Villanova University*. Available at www.47.homepage.villanova.edu/guilla... visited on 21/01/2017

Reang, D., De, A., Das, A.K. and Dhanda, P. 2018. Forest health degradation in Barak valley: a NDVI-based study. *Indian J. Forestry*, *41 4*, 319–328.

Rouse, J.W., Haas, R.H., Deering, D.W. and Sehell, J.A. 1974. Monitoring the vernal advancement and retrogradation (green wave effect) of natural vegetation, Final Report RSC 1978-4. *Remote Sensing Center*, Texas A&M Univ: College Station 1974.

Salami, A. T. and Balogun, E. E. 2006. Utilization of NigeriaSat-1 and other satellites for forest and biodiversity monitoring in Nigeria. a monograph published by National Space Research and Development Agency (NASRDA), Federal Ministry of Science and Technology, Abuja, Nigeria, 31-32.

Samvedan, S. 2007. Remote Sensing and Gis: Knowledge Resources for Remote Sensing and GIS. Reflectance.Html.

Schuster, C., Schmidt, T., Conrad, C., Kleinschmit, B. and Michael, F. 2015. "Grassland Habitat Mapping by Intra-Annual Time Series Analysis -comparison of Rapid Eye and Terra SAR-X Satellite Data." *International Journal of Applied Earth Observation and Geoinformation 34,* (1): 25–34. doi: 10.1016/j.jag.2014.06.004.

Smith, W.H. 1990. Health of north american forests: Stress and risk assessment. J. For. USA, 88.

Souza, A. A., Galvao, L. S., & Santos, J. R. (2010). Relationships between Hyperion-derived vegetation indices, biophysical parameters, and elevation data in a Brazilian savannah environment. Remote Sensing Letters, 1(1), 55-64.

Tucker, C.J. 1979. Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sensing Environ*, *8:* 127-50. [doi:101016/0034-4257(79)90013-0].

Tuominen, J., Haapanen, R., Lipping, T., Kuosmanen, V. 2009. Remote Sensing of Forest Health; INTECH Open Access Publisher: Rijeka, Croatia, 2009.

Waring, R.H. 1980. Forest, fresh perspectives from ecosystem analysis. In Vital Signs of Forest Ecosystems; Oregon State University Press: Corvallis, OR, USA, pp. 131–136.

Welikhe, P., Quansah, J.E., Fall, S. and McElhenney, W., 2017. Estimation of soil moisture percentage using LANDSAT-based moisture stress index. *J. Remote Sens. GIS*, *6*(2).

Yang, J., Dai, G. and Wang, S. 2015. China's national monitoring program on ecological functions of forests: an analysis of the protocol and initial results. *Forests*, *6* (12), 809–826.

Zarco-Tejada, P.J., Hornero, A., Hernández-Clemente, R., Beck, P.S.A. 2018. Understanding the temporal dimension of the red-edge spectral region for forest decline detection using high-resolution hyperspectral and Sentinel-2a imagery. *ISPRS J. Photogramm. Remote Sens.* 137, 134–148.

Article DOI: 10.52589/AJENSR-82LKC8VI
DOI URL: https://doi.org/10.52589/AJENSR-82LKC8VI