Lamenkova, P. (2024). Mapping woodlands in Angola, tropical Africa: calculation of vegetation indices from remote sensing data. Agriculture and Forestry, 70 (3): 185-202. https://doi.org/10.17707/AgricultForest.70.3.13

DOI: 10.17707/AgricultForest.70.3.13

***Polina LEMENKOVA*[1]**

MAPPING WOODLANDS IN ANGOLA, TROPICAL AFRICA: CALCULATION OF VEGETATION INDICES FROM REMOTE SENSING DATA

SUMMARY

This paper presents the application of the scripting algorithm GRASS GIS for calculation and visualization of vegetation indices using satellite data. The data include satellite images Landsat-8 OLI/TIRS covering tropical rainforests of central Angola. The images were acquired in July 2013 and July 2023. The methodology is based on using module 'i.vi' of GRASS GIS which automatically calculated 10 vegetation indices: DVI, NDVI, ARVI, EVI, GEMI, MSAVI2, NDWI, PVI, GARI and IPVI. The algorithms of data processing and calculation of vegetation indices are presented in the scripts. The results include the extracted information on distribution of bright green vegetation compared with other land cover types: tropical forests and coastal areas distinguished from artificial surfaces and urban areas, soils and coastal shores. The results indicated landscape dynamics in Angola with decline in tropical forests since 2013 until 2023. The machine-based workflow increases computational efficiency through fast processing of satellite data. The use of scripts demonstrated that programming method of automated information extraction from satellite images is effective for environmental monitoring of tropical African landscapes in rainforests.

Keywords cartography, programming, environment, ecology

INTRODUCTION

This paper studied the vegetation health in the tropical landscape of southern Africa, Angola, using calculation of vegetation indices. Knowledge of the size, distribution, and evolution of vegetation patches is an essential element of environmental studies on land cover change. Areas affected by deforestation or converted into settlements indicate environmental degradation in tropical regions. Environmental monitoring can be effectively implemented to detect such

[1] Polina Lemenkova (corresponding author: polina.lemenkova2@unibo.it), Alma Mater Studiorum – University of Bologna, Department of Biological, Geological and Environmental Sciences, Bologna, ITALY

Notes: The authors declare that they have no conflicts of interest. Authorship Form signed online.

Received:02/09/2024 *Accepted:28/09/2024*

problems using satellite images (Sunny et al., 2022; Lemenkova, 2022a; Koon et al., 2023).

However, processing remote sensing (RS) data using Geographic Information System (GIS) involves manual work. In contrast, computer vision provides automated approach through algorithms (Dumay and Mainguet, 2009).

RS data has long been used for these purposes in various regions of Africa (Bardinet, 1981; Jacques et al., 1993; Lemenkova, 2023 a, b; Dawelbait et al., 2017). However, the application of RS data in Angola has mainly been used to map general land cover types using traditional GIS (Schneibel et al., 2016; Lourenco et al., 2022; Lehmann et al., 2023; Awadallah et al., 2015). In coastal areas, tropical forests are scattered in wetland ecosystems and are difficult to map using traditional approaches. In contrast, the machine approach can automatically detect areas covered by healthy vegetation discriminating landscape patches on satellite images by the difference in spectral reflectance of bright green leaves. This paper presents the use of such technological approach presented through programming.

STUDY AREA

We used the modules and libraries of the GRASS GIS software (Neteler et al., 2012) to map vegetation indices in central Angola, Figure 1.

Over the last 10 years, land cover types and vegetation in Angola have changed rapidly due to environmental and climate impacts and anthropogenic activities. This trend is visible by comparing satellite images on different data covering the same area. While the definitions of landscape patches and vegetation types are mainly determined using field surveys based on their size and level of complexity, showing the heterogeneity of the area, in the mountainous regions of Angola, the identification of landscape patches is difficult due to the inaccessible region for topographic studies. Therefore, it is worth investigating the dynamics of vegetation growth and plant status with freely available satellite images such as Landsat scenes (Ruppen et al., 2023). Landsat data are widely used for vegetation mapping, calculating vegetation indices, and ecological monitoring.

The landscapes of Angola are characterized by a mosaic of vegetation including coastal plains, tropical rainforests in the central regions, swamps and wetlands dominant in the mountainous regions and to grassy and semi-deciduous forests in the central regions of the country. The details of their distribution are shown in land cover map based on spatial data from the Food and Agriculture Organization (FAO), Figure 2.

The difference between these contrasting vegetation types can be detected using RS data. Specifically, the effective tool for land cover monitoring is the calculation of vegetation indices. Its effectiveness is explained by the difference in spectral reflectance in the Red/NIR channels of satellite images that well indicates the distribution of vegetation contrasting with other land cover types.

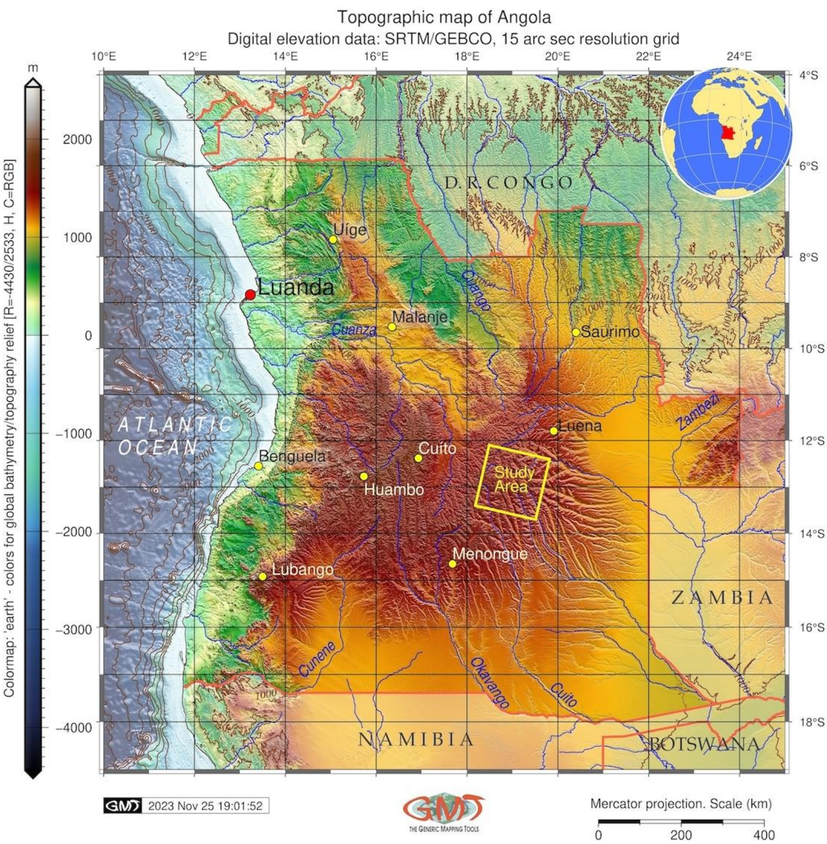

Figure 1. Topographic map of Angola, Africa

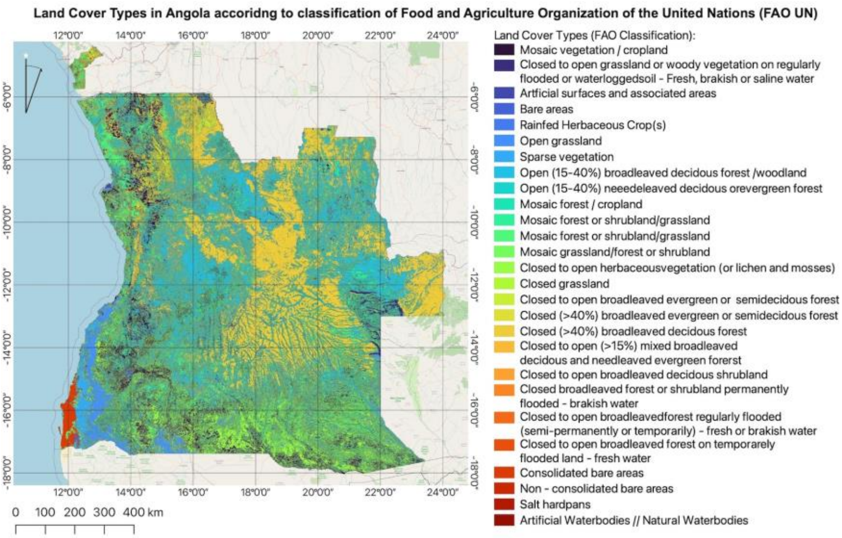

Figure 2. Land use map of Angola.

OBJECTIVES AND GOALS

The objective of this paper is twofold. First, we present an improved GRASS GIS scripting method for computing and visualizing 10 vegetation indices calculated using the 'i.vi' algorithm over study area in a mountainous region of central Angola. Second, we compare the performance of Landsat-8 OLI/TIRS imagery in vegetation mapping on 2013 and 2023. GRASS GIS programming algorithms have are novel method for computing vegetation indices which are usually calculated using traditional GIS approaches. This technique is chosen to improve the implementation vegetation monitoring. Unlike existing methods, this algorithm works automatically in data extraction for different vegetation indices that have been calculated for comparative analysis.

After providing an overview of the GRASS GIS algorithms and offering commentary on the code snippets and modules, we demonstrate how to use this application to map ten distinct vegetation indices using two satellite photos taken between 2013 and 2023. The results of the experiment are then presented, together with a consideration of their implications. In the end, we offer suggestions for potential future research in related fields and draw conclusions.

MATERIAL AND METHOD

Multispectral satellite images Landsat with 30 m resolution were enhanced by adding topographic layers (cities, roads, hydrographic network and country boundaries). The topographic map was produced using Generic Mapping Tools (GMT), a scripting toolset for processing and mapping spatial information using programming codes (Lemenkova, 2022 a; b). The condition for an accurate calculation of vegetation indices is that the images are cloud-free and acquired during the season of high vegetation cover and low humidity, which is October to May for tropical Africa. For these reasons, we used the selected images with cloudiness less than 10% and taken in July 2013 and 2023 during a dry period with low precipitation and humidity, Figure 3.

Launched in 1982, Landsat provides a valuable open source information to monitor vegetation and land cover types. For Angola, satellite images are used for environmental monitoring, such as landscape dynamics, urbanization (Temudo et al., 2019), urban restructuring, deforestation, degradation (Palacios et al., 2015, Lemenkova, 2024a), and increased agricultural activities (Mendelsohn, 2019, Lemenkova, 2024b). We used the latest sensor of Landsat products: OLI/TIRS. Compared to Landsat ETM+ where the usable swath range is limited to the central part of the image, Landsat OLI/TIRS is updated and improved in technical quality and characteristics (Lemenkova, 2023c). The 185 km swath in multispectral cameras enables frequent global coverage. Such a wide swath of is useful where clouds are a major obstacle to image acquisition in clear weather, as in tropical Africa.

Three software were used: 1) GRASS GIS for image processing (GRASS Development Team, 2022); 2) Generic Mapping Tools (GMT) for topographic mapping (Wessel et al., 2019); 3) QuantumGIS (QGIS.org, 2023) for GIS mapping. The codes were based on the existing works (Lemenkova, 2024c). Technically, this allowed to evaluate scripting approach in processing RS data. For environmental analysis, GRASS GIS supported monitoring vegetation cover and distribution of tropical forests.

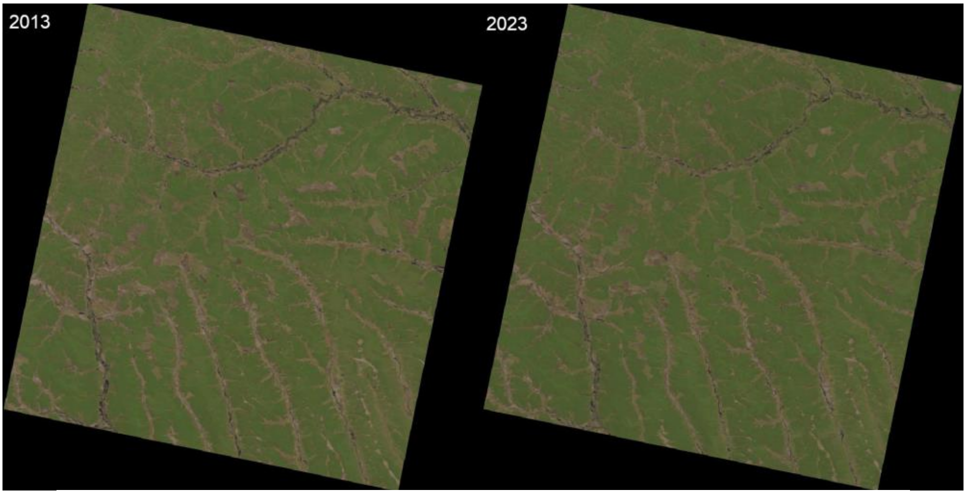

Figure 3: RS data: Landsat 8 OLI/TIRS scenes covering central Angola.

As a computer tool to help ecology and landscape studies, the calculation of vegetation indices is frequently employed in environmental monitoring. The principal methodology relies on the properties of plants whose chlorophyll content causes notable variations in the red and near-infrared regions of multispectral pictures. The presence of vivid green vegetation can thus be highlighted on satellite photos by utilizing the Red and NIR bands in a variety of combinations and formulas. As a result, it is possible to differentiate lush, vibrant vegetation from the surrounding, disparate land cover types, which include urban areas, bare ground, rivers, streams, and meadows adjacent to river valleys.

Numerous vegetation indices have been established in the past to extract data from grayscale photos. Because of its widespread use, the NDVI is the most well-known and well-liked of them. To make the contrast between the built-up regions and the vegetation better, we first employed NDVI and then computed other indices for comparison. Several indices with modified characteristics, such as enhanced atmospheric resistance (ARVI) or ground brightness correction (MSAVI), have been produced as NDVI modifications.

In this study, we tested 10 different vegetation indices: 1. Difference Vegetation Index (DVI); 2. Normalized Difference Vegetation Index (NDVI); 3. Atmospherically Resistant Vegetation Index (ARVI); 4. Enhanced Vegetation Index (EVI); 5. Nonlinear Vegetation Index for Global Environmental Monitoring (GEMI); 6. Modified Soil Adjusted Vegetation Index (MSAVI2) minimizes the effect of bare soil on the Modified Soil Adjusted Vegetation Index

(MSAVI2); 7. Normalized Difference Water Index (NDWI); 8. Perpendicular Vegetation Index (PVI) which is similar to difference vegetation index; 9. Green Atmospherically Resistant Vegetation Index (GARI); 10. Infrared Percentage Vegetation Index (IPVI).

Computing vegetation indices is an important part of ecological monitoring using RS data. The methods applied to the calculation of vegetation indices are based on multispectral transformations of pixels that form the raster structure. This approach converts the radiances recorded by the satellite sensor into quantities. The multispectral satellite images allow to numerically evaluate the state of chlorophyll content in leaves. In this way, the vegetation index reflects the growth stage of plants using these indicators. To calculate vegetation indices, the ‘i.vi’ algorithm was used by GRASS GIS. This module enables to separate vegetation cover from other land cover types, since it is based on automatic machine-based discrimination of spectral reflectance values of vegetation and rainforests on the satellite images.

Algorithm implementation of the GRASS GIS programming for image processing is as follows. First, the images were imported into the GRASS GIS project using the Geospatial Data Abstraction Library (GDAL): "r.in.gdal /Users/polinalemenkova/grassdata/Angola_2023/LC08_<...>_T1_SR_B1.TIF out=L8_2023_01" This is repeated for the 11 necessary bands of Landsat OLI/TIRS Then, the contents of the files were checked using the listing command: g.list rast. After that, the files were preprocessed by copying the Landsat bands to match the input structure of the "i.landsat.toar" module that will be used later to calibrate the digital number (DN) of the Landsat imagery. This is done using the following command: g.copy raster=L8_2023_01,lsat8_2023.1

Afterwards, the DN pixel values were converted to spectral reflectance values using DOS1 from digital number (DN) to reflectance. This is done using module i.landsat.toar which calculates reflectance and temperature of the “top of the atmosphere” for Landsat images. This step is necessary as it converts the DN to reflectance values before creating an RGB composite. Otherwise, the colours of the natural RGB composite do not look convincing but rather blurred. This conversion was done using metadata file with i.landsat.toar by the following command: “i.landsat.toar input=lsat8_2023. output=lsat8_2023_toar. sensor=oli8 method=dos1 date=2023-07-12 sun_elevation=44.08803962 product_date=2023-07-18 gain=HHHLHLHHL”.

After the preprocessing, the next step involves the calculation of 10 vegetation indices. All indices were calculated using the GRASS GIS module "i.vi" and then visualized on the maps using a combination of map processing modules. First, the NDVI calculation was performed using the code: “g.region raster=lsat8_2023_toar.4 -p i.vi red=lsat8_2023_toar.4 nir=lsat8_2023_toar.5 viname=ndvi output=lsat8_2023.ndvi --overwrite r.colors lsat8_2023.ndvi color=ndvi” (here, the example of NDVI).

The next step included cartographic visualization and data representation using several GRASS GIS modules. First, the screen was launched using the 'd.mon' module: d.mon wx0. Then, the region was created to include the extent of the study area by 'g.region' as follows: “g.region raster=lsat8_2023_toar.4 -p. Afterwards, the maps were visualized using the 'd.rast' module (here, the example is given for NDVI): d.rast lsat8_2023.ndvi”.Then the map legend was added using the GRASS GIS module "d.legend" with the map elements and adjustments as follows: d.legend raster=lsat8_2023.ndvi range=-1,1 title="NDVI-2023" title_fontsize=14 font=Helvetica fontsize=12 -t -s -b border_color=white thin=12 label_step=0.1 -d d.out.file output=Angola_NDVI_2023 format=jpg –overwrite.

Using the methodology with technical details described above the 10 maps were generated showing vegetation indices. The difference between indices lies in the approach of the formulas used for calculation.

RESULTS

Vegetation indices are based on characteristics of leaf spectral reflectance and their values in the red/near infrared (NIR) bands in multispectral data. Besides, they are widely used to identify and monitor landscape dynamics as a reliable source of information. Such maps are used for biophysical characteristics: biomass, leaf area index, photosynthetic radiation fraction in canopy. Figure 4 shows the NDVI and DVI computed for the 2013 and 2023 Landsat OLI/TIRS images which illustrate land cover and vegetation changes over the territory.

In order to get the best results, we tested with several vegetation indices utilizing GRASS GIS's i.vi algorithms. The NDVI and DVI hues in this figure correspond to the light vegetation, respectively. The NDVI presents a general approach with fixed variation range: from -1 to +1. The formula for NDVI=(NIR-Red)/(NIR+Red) uses the red and near infrared bands of Landsat, Figure 4. The raw data were pre-processed to convert pixel values to radiance in order to compare the NDVI changes between 2013 and 2023. Every NDVI image and computation receives the application of the mapping. Greater values signify lush, green vegetation. In central Angola, the comparison between 2013 and 2023 shows a loss in vegetation. DVI is calculated using the difference between the maximum absorption in the red, which is dependent on chlorophyll pigments, and the maximum reflection in the infrared (IR), which is due to the leaf's cellular structure. Though not normalized, this indicator is comparable to the NDVI but has more stable results. Red and infrared (NIR) bands are available in most RS data, including Landsat, and are used in NDVI. The drawback of NDVI is its sensitivity to noise and climatic factors like humidity and cloudiness.

The ARVI and EVI indices have been computed and are displayed visually in Figure 5. ARVI was first created for the MODIS EOS sensor, but as it uses the blue, red, and NIR bands for computation, it may also be applied to Landsat data. The ability to adjust for atmospheric effects on vegetation detection is its principal benefit. The deciduous forests of central Angola or mixed deciduous and evergreen forests with needle-leaving trees, such as cone or scale forests, are represented by the highest ARVI values in this region, which range from -0.60 to 0.70. Figure 5 of the ARVI and Figure 6 of GEMI exhibit comparable changes.

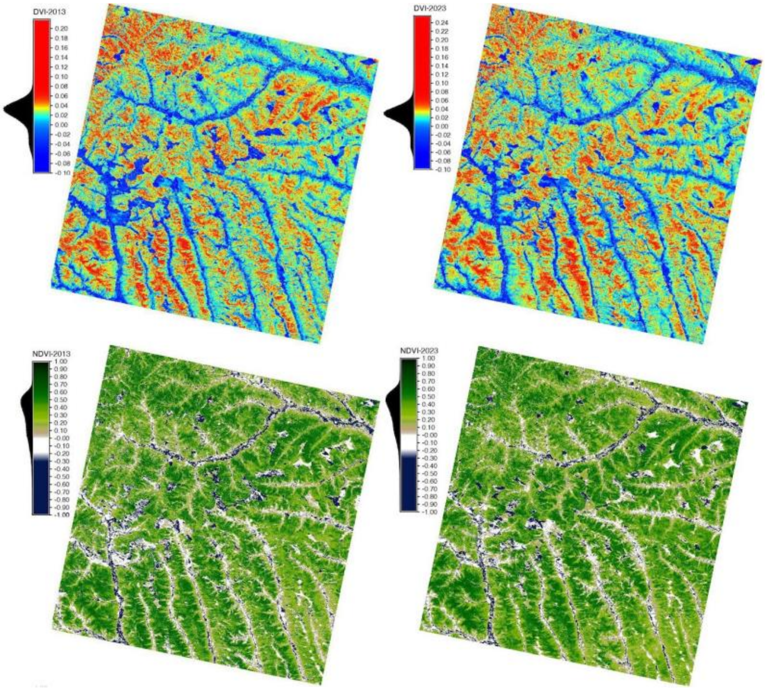

Figure 4: DVI and NDVI for 2013 and 2023.

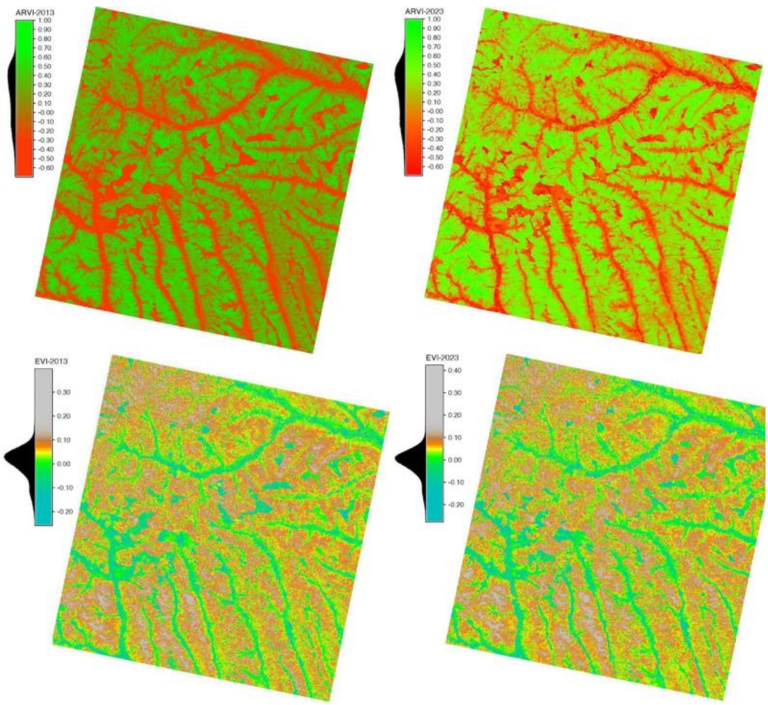

Figure 5: ARVI and EVI indices for 2013 and 2023.

For vegetation mapping in Angola's tropical mountainous regions, ARVI is more accurate than GEMI as it is less susceptible to atmospheric impacts. Bright green shows vegetation in ARVI, whereas bright red indicates river valleys. This index can be used for hydrological and geomorphological mapping since it makes a distinction between densely covered forests and heavily vegetated river valleys that have scant or nonexistent vegetation. The major range of values for the EVI index is between -0.10 and +0.10, as shown on data distribution in the histogram, whereas local minima with a constant of values below -0.20 are filled.

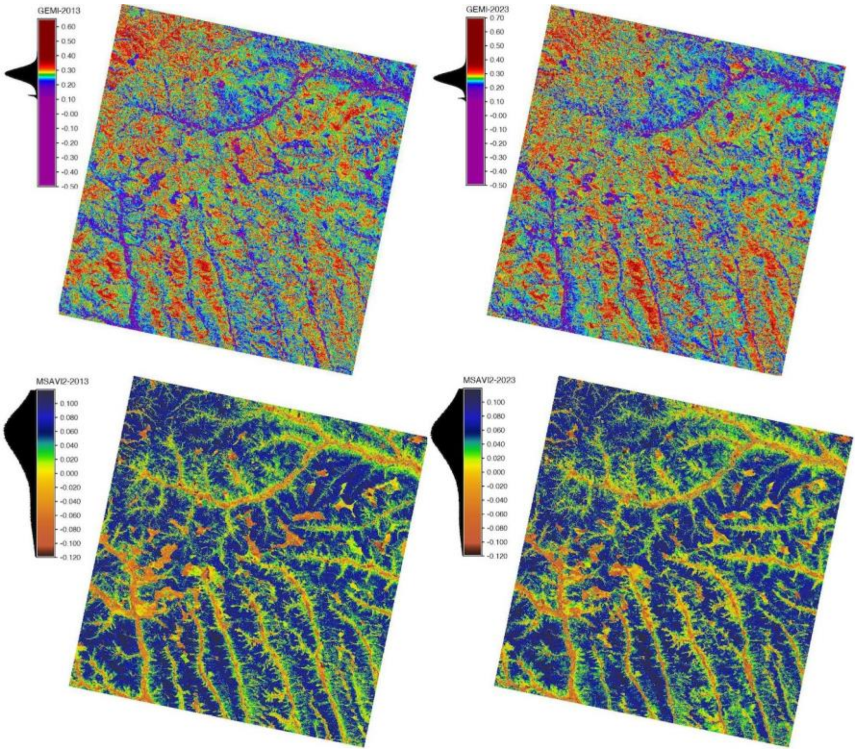

Figure 6: GEMI and MSAVI2 for 2013 and 2023.

Figure 6 displays the computed indices for MSAVI and GEMI. MSAVI accounts for soil reflectance, so its range of values is limited to -0.12 to 0.1. This makes it possible to separate soil from vegetation. The drawback of this method is that it needs a lot of vegetation cover. Due to the soil effects, the reflectance values may be incorrect if vegetation cover is sparse, and due to similar spectral reflectance, plants with comparable photosynthetic properties may be mixed. Conversely, GEMI values are between -0.5 and 0.6, with 0.15 to 0.40 being the most notable numbers. The graphic displays the brilliant plant cover as a black side histogram on the map legends, which indicates data distribution. To reduce the impact of the atmosphere on the measurement of the vegetation index, GEMI takes into account a non-linear connection.

Figure 7 displays the computed values for the PVI and NDWI indices. The amount of biomass, the green area, the health of the crop, and vegetation with active photosynthetic activities are all closely correlated with the plant water content, as the NDWI shows. Accordingly, this index's lowest values in the research region are -0.7-, and its highest values are reached up to 0.20, at which point the values settle. Higher results, over 0.2 and above, correlate to areas of shrubs or natural deciduous and broadleaf forests in high mountains. Very low values, of negative order, depict rocky, sandy, or bare places.

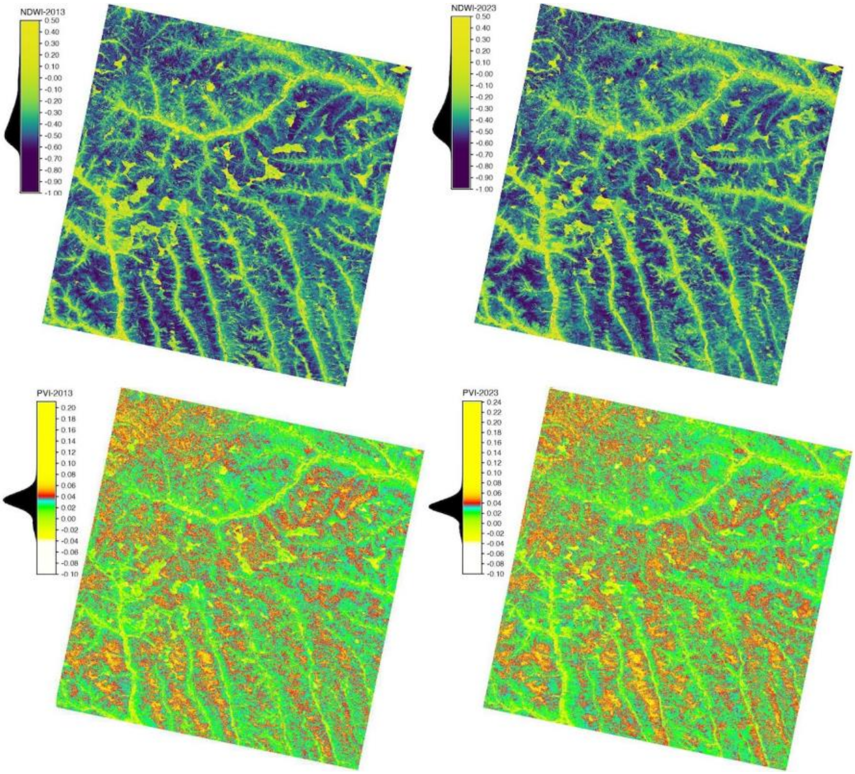

Figure 7: NDWI and PVI for 2013 and 2023.

In central Angola, the PVI ranges from -0.04 to 0.08 (Figure 7). The perpendicular distance between each pixel and the ground line that gives this index its name is used in the calculation. Each pixel's distance from the ground line determines whether it is land cover or vegetation cover. Identification of vegetation is made possible by this index's adjustment to soil reflectivity. Its data distribution range is different from the NDVI's since its values are determined using perpendicular distances to the ground line, represented in reflectivity units. Thus, when compared to the NDVI, this index illustrates better results for differentiating vegetation.

Normalization by the sum of the 2 bands calculated in the IPVI shown in Figure 8 reduces the effects of light and results in values between -0.1 and 0.90. The IPVI maintains values regardless of the illumination. This differentiates it from simple vegetation indices which are sensitive to changes in illumination. The GARI values are between -1 and +1, however, negative values corresponding to non-vegetated surfaces are reduced to -0.50, as land use types corresponding to negative values, such as snow or dense clouds, are absent. The reflectance in the red is higher than that of the NIR, which explains the values. The increase of values to 0.40 means the increase of shrubs and mixed vegetation.

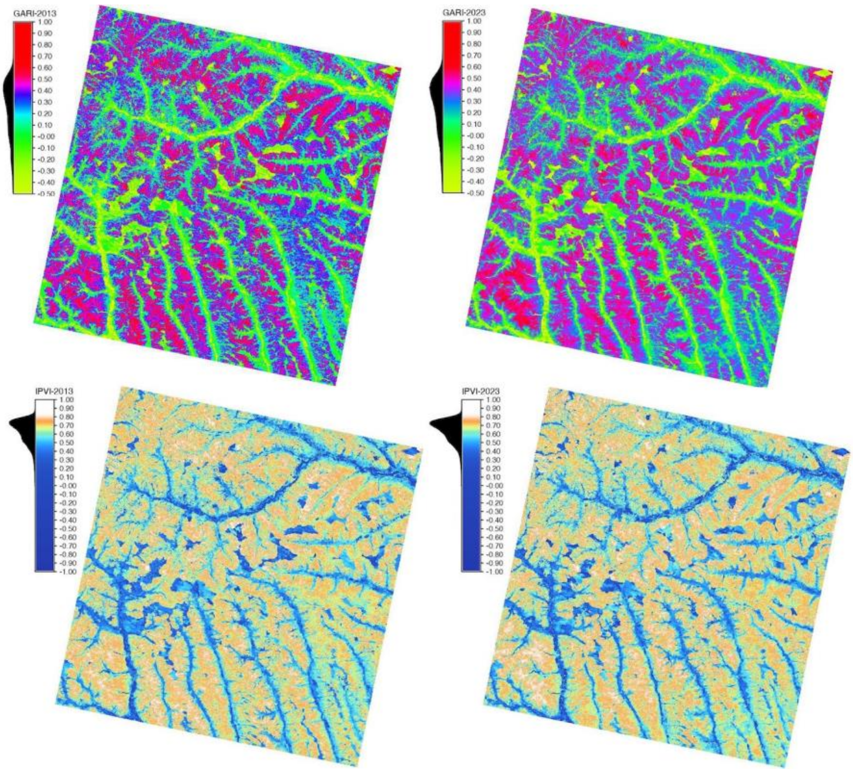

Figure 8: GARI and IPVI for 2013 and 2023.

The results are encouraging for mapping rainforest ecosystems and tropical vegetation in Africa. Therefore, Landsat-8 OLI/TIRS data can be used in similar studies using the presented programming codes as a continuous data source for vegetation monitoring. The presented findings indicate the value of RS data as a source of information for environmental monitoring. Using multi-temporal images, this data can be used to map vegetation cover at all time and spatial scales, hence facilitating the mapping of landscape dynamics. Changes in the terrain and vegetation cover are becoming more obvious in Central and Southern Africa due to the effects of climate change and human activities associated with deforestation. This leads to a complicated alteration in the patterns of land cover, including the fragmentation of landscapes, which lowers biodiversity. As this study demonstrates, research on tropical forest vegetation can advance thanks to the wealth of spectral, resolution, and temporal data offered by satellite imaging and advancements in programming.

Vegetation index computation is essential for environmental monitoring. More suitable features that adapt to various transboundary zones with varied vegetation types (savannah, tropical forests, deciduous forests, mosaic grasslands, or shrubs) should be the focus of future research. Finding places with complex and shifting landscape structures would be made easier by adapting regional characteristics of land cover classes. The GRASS GIS method uses scripts to automate image processing in order to define the cartographic workflow. This makes it possible to identify vegetation traits and distinguish between areas that are diverse or those are homogeneous sections of the landscape.

The tropical forests of Angola are surrounded by agricultural fields, cultivated plantations and urban settlements. They are clearly distinguished from built-up areas and cultivated areas during the growing season. For this reason, we tested several vegetation indices that differ from each other by several technical parameters (use of different Landsat channels and their combination in equations) and adjustments for environmental parameters and atmospheric characteristics.

DISCUSSION

Revealing the geographical distribution and structural properties of vegetation has become increasingly dependent on satellite pictures due to their effectiveness, affordability, and wide coverage (Goodchild, 1994, Altobelli et al., 2007, Lemenkova, 2024d, Burstein et al., 2023). Nevertheless, there are still a lot of difficulties in integrating programming techniques with data from remote sensing to enable vegetation research and modeling (Kopecký and Čížková, 2010; Deepthi Murthy et al., 2023). For various vegetation mapping applications, many image types that differ in their spectral, spatial, radiometric, and temporal features are appropriate. Furthermore, a variety of image interpretation processes and techniques can be used when mapping vegetation using remotely sensed images. Therefore, employing remote sensing data to categorize and map plant cover continues to be a difficult endeavor (Whig et al., 2024).

Satellite images have been successfully utilized by numerous researchers to continuously monitor vegetation at different scales using dynamic processes. For instance, Zhang et al. (1999) evaluated crop condition and variability at different growth phases by monitoring and evaluating vegetation crop management using remotely sensed imagery. Kawamura et al. (2005) monitored seasonal vegetation changes and short-term vegetation phenology with respect to forage quantity and quality using data from sensors that measure the Advanced Very High Resolution Radiometer (AVHRR) and Moderate Resolution Imaging Spectroradiometer (MODIS). Papeş et al. (2012) quantified the impact of vegetation canopy on seasonal migration and behaviour of birds using remotely sensed data.

Moreover, specific soil-vegetation indices are developed for agricultural characteristics. For instance, Herbei et al. (2022) showed that agrochemical indices of pH, humus (H), saturation in bases (V), nitrogen index (NI), phosphorus (P) and potassium (K) content, can be applied for analysis of soil. Finally, vegetation indices, such as NDVI, are used for conservation of biodiversity and ecosystem services using analysis of temporal analysis of vegetation cover (Rios et al., 2024).

Both GIS and remote sensing are limited to approximations of the truth and the geographical continuum can be discretized in a variety of ways, they exhibit inaccuracy and uncertainty (Atkinson and Foody, 2002). The accuracy of differentiating vegetation from other land cover types can be diminished due to mixed pixel difficulties resulting from the spatial resolution limitations of satellite photography (Fairbanks and McGwire, 2004). Spatial uncertainty requires attention in order to facilitate spatiotemporal dynamics through data analysis (Bouaziz et al., 2020). Furthermore, the application capabilities of satellite RS are limited by elements like weather (Khillare and Patil, 2023; Niraj et al., 2023), revisit intervals, and fixed orbits (Tůma et al., 2022).

Compared to other studies that also used vegetation indices (Coles-Ritchie et al., 2007; Mutiibwa and Irmak, 2013; Patra et al., 2024; Zeydan et al., 2023), the obtained results reveal the following advantages. The approach demonstrated in this paper was developed by integrating GIS techniques, RS data, and programming algorithms for satellite image processing. It presented an example of mapping spatial ecology for computing vegetation indices, and demonstrated the usefulness and efficiency of integration of RS data, GIS methodology, and programming techniques. Specifically, we demonstrate the variety and difference of vegetation indices calculated using the GRASS GIS programming approach for the central region of Angola. The computation and visualisation of vegetation indices in tropical rainforests of Angola is important to monitor health vegetation and detect deforestation.

A GRASS GIS script-based method was used for extracting information on distribution of healthy or sparse vegetation and distinguished them from the bare land. The advantage of this method is that it considers band-to-band relationships between pixel spectral reflectance and vegetation cover identification. This is useful for environmental monitoring using Landsat multispectral image processing. Several vegetation indices were computed using formulas based on Landsat bands: NDVI, ARVI, GARI, and GVI. GRASS GIS operations operated excellent with satellite images.

CONCLUSIONS

Landscape dynamics can be examined in greater detail from a spatiotemporal perspective by using image sequences. This data's content can be obtained by analyzing appropriate and adequate features for landscape monitoring using satellite photography. In order to distinguish between land plots with drastically different textural and structural characteristics for the purpose of identifying deforestation, vegetation shrinkage, or other examples of land cover change, it is therefore possible to take into consideration the exact classification of land cover types based on vegetation indices.

This paper illustrated the importance of programming in RS data processing using spectral and texture feature analysis of satellite images for analysis of vegetation indices. Vegetation indices can be applied as characteristics for analysis of landscape heterogeneity. Landscape diversity can manifest itself in different ways depending on the data categories and quantification methods. It is a key feature of the environment and is particularly evident at the landscape scale in regions as complex as in Angola, southern Africa. Therefore, vegetation indices can reveal information on spatial distribution of landscapes which can be studied to analyse spatial heterogeneity of the territory. In turn, landscape diversity at the spatio-temporal scale shows a gradient that illustrates the dynamics of ecosystems in space and time.

Using this information, landscape structure can be analysed through mapping constituting elements which have distinct and complex boundaries and reflected as different patches in the mosaic of vegetation indices on the maps. Automated interpretation of the vegetation distribution through index calculation yields better results than traditional classification. Adaptive vegetation type determination by computed indices is a novel aspect of this study. Landscape monitoring using RS data is an important research topic for climate-environment monitoring in Africa, as automatic processing of satellite images using computer vision algorithms is a challenging task. Detecting vegetation on satellite data using computed indices has shown excellent results on Landsat-8 OLI/TIRS images with simple color texture covering tropical Angola.

The presented maps demonstrated landscape dynamics in Angola. The tropical forests of the country are known for their rich biodiversity and exceptional value to the planet. Nevertheless, the decrease of natural vegetation endangers ecosystems. Cultivated plantations are gradually replacing natural tropical forests for commercial reasons. Landscape mapping and vegetation analysis of landscape units were conducted for the mountainous region of Angola for 2013 and 2023. The consequences of human activities (agricultural practices and commercial deforestation) and climate change (increasing temperatures, periods of drought, erratic rainfall) have strongly contributed to the loss of tropical forests and increased fragmentation of landscapes. The difference in areas occupied by woodlands in 2013 and 2023 is visible on the presented maps.

The dynamics of spatial and temporal landscape diversity allows to measure their heterogeneity. Nevertheless, the contribution of this work and its scope is not only a technical mapping and processing of satellite images but also the assessment of deforestation in Angola for the environmental monitoring of its landscapes. Therefore, this study integrates technical methods and satellite data for environmental monitoring objectives in West Africa based on the vegetation indices computed for selected region of Angola, southern Africa. In future work, we suggest modeling changes of land use types. It might, for instance, investigate segmentation techniques that are applicable to multi-scale satellite picture analysis. Based on the determined vegetation indices, this method's advancement could incorporate automatic segmentation, object classification, and feature extraction from images. The emphasis would be on employing computer vision techniques to automatically recognize different forms of land cover with comparable spectral reflectance.

REFERENCES

Altobelli, A., Bressan, E., Feoli, E., Ganis, P., Martini, F. (2007): Improving knowledge of urban vegetation by applying GIS technology to existing databases. Applied Vegetation Science, 10: 203-210. https://doi.org/10.1111/j.1654-109X.2007.tb00518.x

Atkinson, P.M., Foody, G.M. (2002): Uncertainty in Remote Sensing and GIS: Fundamentals. In: Uncertainty in Remote Sensing and GIS (eds G.M. Foody and P.M. Atkinson). https://doi.org/10.1002/0470035269.ch1

Awadallah A.G., Tabet D. (2015): Estimating flooding extent at high return period for ungauged braided systems using remote sensing: a case study of Cuvelai Basin, Angola. Natural Hazards 77, 255–272. https://doi.org/10.1007/s11069-015-1600-6

Bardinet C. (1981): Télédétection des paysages africains par Landsat et Météosat, Annales de Géographie, 90, n°499, p354-380. https://doi.org/10.3406/geo.1981.20022

Dawelbait M., Dal Ferro N., Morari F. (2017): Using Landsat Images and Spectral Mixture Analysis to Assess Drivers of 21-Year LULC Changes in Sudan. Land Degradation & Development, 28, 116–127. https://doi.org/10.1002/ldr.2556

Deepthi Murthy, T. S., Aryalekshmi, B. N. Nayana, D. K. (2023): District-Level Vegetation and Wetland Analysis with GEE Python API: A Flask Web Application Approach. In: 7th International Conference on Computation System and Information Technology for Sustainable Solutions (CSITSS), pp. 1-6. https://doi.org/10.1109/CSITSS60515.2023.10334172.

Dumay F., Mainguet M. (2009): Lecture de la désertification dans les écosystèmes secs au Sahara d'après les images satellites et les photographies aériennes. In: Genres et usages de la photographie. Actes du 132e Congrès national des sociétés historiques et scientifiques, « Images et imagerie », Arles, 2007. Paris: Editions du CTHS, p25-36.

Fairbanks, D.H.K. and McGwire, K.C. (2004): Patterns of floristic richness in vegetation communities of California: regional scale analysis with multi-temporal NDVI. Global Ecology and Biogeography, 13: 221-235. https://doi.org/10.1111/j.1466-822X.2004.00092.x

Goodchild, M.F. (1994): Integrating GIS and remote sensing for vegetation analysis and modeling: methodological issues. Journal of Vegetation Science, 5: 615-626. https://doi.org/10.2307/3235878

GRASS Development Team (2022): Geographic Resources Analysis Support System (GRASS) Software, Version 8.2. Open Source Geospatial Foundation. Electronic document:. https://grass.osgeo.org

Herbei, M.V., Bertici R., Sala F. (2022): The use of remote sensing images in order to characterize the soil agrochemical indexes in relation to the agricultural crops. Agriculture and Forestry, 68 (2): 23-33. https://doi.org/10.17707/AgricultForest.68.2.02

Jacques P., Massart M., Wilmet J. (1993): Intérêt de l'analyse spatiale dans le traitement des données satellitaires pour un suivi agricole en Afrique Centrale. Innovations et développement rural dans les pays tropicaux. Bordeaux: Presses Universitaires de Bordeaux, p205-212. (Espaces tropicaux, 8)

Kawamura, K., Akiyama, T., Yokota, H.-o., Tsutsumi, M., Yasuda, T., Watanabe, O., Wang, S. (2005): Comparing MODIS vegetation indices with AVHRR NDVI for monitoring the forage quantity and quality in Inner Mongolia grassland, China. Grassland Science, 51: 33-40. https://doi.org/10.1111/j.1744-697X.2005.00006.x

Khillare, A., Patil, K.A. (2023): NDVI: Vegetation Performance Evaluation Using RS and GIS. In: Ranadive, M.S., Das, B.B., Mehta, Y.A., Gupta, R. (eds) Recent Trends in Construction Technology and Management. Lecture Notes in Civil Engineering, 260. Springer, Singapore. https://doi.org/10.1007/978-981-19-2145-2_33

Kopecký, M., Čížková, Š. (2010): Using topographic wetness index in vegetation ecology: does the algorithm matter?. Applied Vegetation Science, 13: 450-459. https://doi.org/10.1111/j.1654-109X.2010.01083.x

Lehmann J., Brower A. M., Owen-Smith T. M., Bybee G. M., Hayes B. (2023): Landsat 8 and Alos DEM geological mapping reveals the architecture of the giant Mesoproterozoic Kunene Complex anorthosite suite (Angola/Namibia). Geoscience Frontiers, 14 5, 101620. https://doi.org/10.1016/j.gsf.2023.101620

Lemenkova P. (2022a): Console-Based Mapping of Mongolia Using GMT Cartographic Scripting Toolset for Processing TerraClimate Data, Geosciences, 12, nº 3, 140. https://doi.org/10.3390/geosciences12030140

Lemenkova P. (2022b): Mapping Climate Parameters over the Territory of Botswana Using GMT and Gridded Surface Data from TerraClimate. ISPRS International Journal of Geo-Information, 11, nº 9, ref. 473. https://doi.org/10.3390/ijgi11090473

Lemenkova P. (2022c): Handling Dataset with Geophysical and Geological Variables on the Bolivian Andes by the GMT Scripts. Data, 7 nº 6, ref. 74. https://doi.org/10.3390/data7060074

Lemenkova P. (2023a): Using open-source software GRASS GIS for analysis of the environmental patterns in Lake Chad, Central Africa, Die Bodenkultur: Journal of Land Management, Food and Environment, 74, nº 1, p49-64. https://doi.org/10.2478/boku-2023-0005

Lemenkova P. (2023b): A GRASS GIS Scripting Framework for Monitoring Changes in the Ephemeral Salt Lakes of Chotts Melrhir and Merouane, Algeria. Applied System Innovation, 6, nº 4, ref. 61. https://doi.org/10.3390/asi6040061

Lemenkova P. (2023c): Monitoring Seasonal Fluctuations in Saline Lakes of Tunisia Using Earth Observation Data Processed by GRASS GIS. Land, 12, 11: 1995. https://doi.org/10.3390/land12111995

Lemenkova P. (2024a): Support Vector Machine Algorithm for Mapping Land Cover Dynamics in Senegal, West Africa, Using Earth Observation Data. Earth, 5(3):420-462. https://doi.org/10.3390/earth5030024

Lemenkova P. (2024b): Artificial Intelligence for Computational Remote Sensing: Quantifying Patterns of Land Cover Types around Cheetham Wetlands, Port Phillip Bay, Australia. Journal of Marine Science and Engineering, 12, (8): 1279. https://doi.org/10.3390/jmse12081279

Lemenkova P. (2024c): Deep Learning Methods of Satellite Image Processing for Monitoring of Flood Dynamics in the Ganges Delta, Bangladesh. Water, 16(8): 1141. https://doi.org/10.3390/w16081141

Lemenkova, P. (2024d): Exploitation d'images satellitaires Landsat de la région du Cap (Afrique du Sud) pour le calcul et la cartographie d'indices de végétation à l'aide du logiciel GRASS GIS. Physio-Géo, 20 (1): 113-129. https://doi.org/10.4000/11pyj

Lourenco M., Fitchett J. M., Woodborne S. (2022): Angolan highlands peatlands: Extent, age and growth dynamics, Science of The Total Environment, 810, 152315. https://doi.org/10.1016/j.scitotenv.2021.152315

Mendelsohn J.M. (2019): Landscape Changes in Angola. In: Huntley, B., Russo, V., Lages, F., Ferrand, N. (eds) Biodiversity of Angola. Springer, Cham. https://doi.org/10.1007/978-3-030-03083-4 8

Mutiibwa, D., S. Irmak (2013), AVHRR-NDVI-based crop coefficients for analyzing long-term trends in evapotranspiration in relation to changing climate in the U.S. High Plains, Water Resources Research, 49. https://doi.org/10.1029/2012WR012591

Neteler M., Bowman M.H., Landa M., Metz M. (2012): GRASS GIS: A multi-purpose open source GIS, Environmental Modelling & Software, 31, 124–130. https://doi.org/10.1016/j.envsoft.2011.11.014

Niraj, K.C., Singh, A., Shukla, D.P. (2023): Effect of the Normalized Difference Vegetation Index (NDVI) on GIS-Enabled Bivariate and Multivariate Statistical Models for Landslide Susceptibility Mapping. Journal of the Indian Society of Remote Sensing, 51, 1739–1756. https://doi.org/10.1007/s12524-023-01738-5

Palacios G., Lara-Gomez M., Márquez A., et al (2015): Spatial dynamic and quantification of deforestation and degradation in Miombo Forest of Huambo Province (Angola) during the period 2002–2015. SASSCAL Proceedings, Huambo, 182 pp

QGIS.org (2023): QGIS Geographic Information System. QGIS Association. http://www.qgis.org

Papeş, M., Peterson, A.T., Powell, G.V.N. (2012): Vegetation dynamics and avian seasonal migration: clues from remotely sensed vegetation indices and ecological niche modelling. Journal of Biogeography, 39: 652-664. https://doi.org/10.1111/j.1365-2699.2011.02632.x

Patra, P., Das, U., Agrawal, S. (2024): Satellite imagery-based tropical cyclone impact assessment on LULC and vegetation: a case study of cyclone Biparjoy. Environ Monit Assess 196, 748. https://doi.org/10.1007/s10661-024-12902-w

Rios, G. S., Santana, D. B., Lense, G. H. E., Silva, B. A., Ayer, J. E. B., Kader, S., Spalevic, V., Rubira, F. G., & Mincato, R. L. (2024): Estimates of soil losses due to water erosion in the Amazon biome. Agriculture and Forestry, 70(1), 361-378. https://doi.org/10.17707/AgricultForest.70.1.23

Ruppen D., Runnalls J., Tshimanga R. M., Wehrli B., Odermatt D. (2023): Optical remote sensing of large-scale water pollution in Angola and DR Congo caused by the Catoca mine tailings spill, International Journal of Applied Earth Observation and Geoinformation, 118, 103237. https://doi.org/10.1016/j.jag.2023.103237

Schneibel A., Stellmes M., Röder A., Finckh M., Revermann R., Frantz D., Hill J. (2016): Evaluating the trade-off between food and timber resulting from the conversion of Miombo forests to agricultural land in Angola using multi-temporal Landsat data, Science of The Total Environment, 548-549, 390-401. https://doi.org/10.1016/j.scitotenv.2015.12.137

Sunny D. S., Ashrafu Islam, K. M., Mullick Md. R. A., Ellis J. T. (2022): Performance study of imageries from MODIS, Landsat 8 and Sentinel-2 on measuring shoreline change at a regional scale, Remote Sensing Applications: Society and Environment, 28, nº 100816. https://doi.org/10.1016/j.rsase.2022.100816

Temudo, M.P., Cabral, A.I.R., Talhinhas, P., (2019): Petro-Landscapes: Urban Expansion and Energy Consumption in Mbanza Kongo City, Northern Angola. Human Ecology, 47, 565–575. https://doi.org/10.1007/s10745-019-00088-6

Tůma, L., Kumhálová, J., Kumhála, F., Krepl, V. (2022): The noise-reduction potential of Radar Vegetation Index for crop management in the Czech Republic. Precision Agriculture, 23, 450–469. https://doi.org/10.1007/s11119-021-09844-5

Wessel P., Luis J. F., Uieda L., Scharroo R., Wobbe F., Smith W. H. F., Tian D., (2019): The Generic Mapping Tools version 6. Geochemistry, Geophysics, Geosystems, 20, 5556–5564. https://doi.org/10.1029/2019GC008515

Whig, P., Bhatia, A.B., Nadikatu, R.R., Alkali, Y., Sharma, P. (2024): GIS and Remote Sensing Application for Vegetation Mapping. In: Choudhury, T., Koley, B., Nath, A., Um, JS., Patidar, A.K. (eds) Geo-Environmental Hazards using AI-enabled Geospatial Techniques and Earth Observation Systems. Advances in Geographic Information Science. Springer, Cham. https://doi.org/10.1007/978-3-031-53763-9_2

Zhang, M., Hendley, P., Drost, D., O'Neill, M., Ustin, S. (1999): Corn and Soybean Yield Indicators Using Remotely Sensed Vegetation Index. In Proceedings of the Fourth International Conference on Precision Agriculture (eds P.C. Robert, R.H. Rust and W.E. Larson). https://doi.org/10.2134/1999.precisionagproc4.c49b

Zeydan, Ö., Tariq, S., Qayyum, F., Mehmood, U., Ul-Haq, Z. (2023): Investigating the long-term trends in aerosol optical depth and its association with meteorological parameters and enhanced vegetation index over Turkey. Environmental Science and Pollution Research, 30, 20337–20356. https://doi.org/10.1007/s11356-022-23553-0