

MAPPING COASTAL REGIONS OF GUINEA-BISSAU FOR ANALYSIS OF MANGROVE DYNAMICS USING REMOTE SENSING DATA

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ABSTRACT

The study presents mapping of land cover changes in Guinea-Bissau using remote sensing data. Study area includes tidal floodplains of the rivers Geba, Caceu, and Rio Grande de Buba. Satellite images Landsat 8-9 OLI/TIRS were classified and analysed to evaluate landscape dynamics from 2017 to 2023. The methodology is based on GRASS GIS modules “i. cluster” and “i. maxlik” for image analysis. The results indicated variations in landscape patterns: decrease in natural forests, decline in mangroves, and expansion of urban and agricultural areas. The coastal region of Guinea-Bissau is one of the least known tropical ecosystems in West Africa, and it is among the most vulnerable African countries to climate effects. The paper contributes to the environmental monitoring of West African coasts.

RÉSUMÉ: Cartographie des régions côtières de la Guinée-Bissau pour l’analyse de la dynamique des mangroves à l’aide de données de télédétection.

L’étude présente une cartographie des changements de couverture terrestre en Guinée-Bissau à l’aide de données de télédétection. La zone d’étude comprend les plaines inondables des rivières Geba, Caceu et Rio Grande de Buba. Les images satellites Landsat 8-9 OLI/TIRS ont été classées et analysées pour évaluer la dynamique du paysage de 2017 à 2023. La méthodologie est basée sur les modules GRASS GIS “i. cluster” et “i. maxlik” pour l’analyse des images. Les résultats ont indiqué des variations dans les modèles de paysage: diminution des forêts naturelles, déclin des mangroves et expansion des zones urbaines et agricoles. La région côtière de la Guinée-Bissau est l’un des écosystèmes tropicaux les moins connus d’Afrique de l’Ouest et l’un des pays africains les plus vulnérables aux effets du climat. L’article contribue à la surveillance environnementale des côtes ouest-africaines.

REZUMAT: Cartografierea regiunilor de coastă din Guineea-Bissau pentru analiza dinamicii mangrovelor utilizând date de teledetecție.

Studiul prezintă cartografierea modificărilor acoperirii terenurilor din Guineea-Bissau folosind date de teledetecție. Zona de studiu include luncile afectate de maree ale râurilor Geba, Caceu și Rio Grande de Buba. Imaginile din satelit Landsat au fost clasificate și analizate pentru a evalua dinamica peisajului din 2017 până în 2023. Metodologia se bazează pe modulele GRASS GIS pentru analiza imaginii. Rezultatele au indicat variații ale modelelor de peisaj: scăderea pădurilor naturale, scăderea mangrovelor și extinderea zonelor urbane și agricole. Regiunea de coastă a Guineei-Bissau este unul dintre cele mai puțin cunoscute ecosisteme tropicale din Africa de Vest și se numără printre cele mai vulnerabile țări africane la efectele climatice. Lucrarea contribuie la monitorizarea mediului pe coastele Africii de Vest.

INTRODUCTION

Background

In recent decades, large-scale environmental problems, including deforestation, soil erosion, and overgrazing, have attracted international attention to Guinea-Bissau. Extensive conversion of salt marshes, forests, and mangroves to agricultural and urban lands is impacting land cover types in the country's coastal regions (Cabral and Costa, 2017) and affecting landscape configuration (Vasconcelos et al., 2002). Mapping land cover changes provides crucial information that supports solving such issues through visualization and spatial analysis. Maps create necessary basis for the development of practical measures aimed at reducing the effects of climate change or human activities. Additionally, maps assist in evaluation of the effectiveness of current agricultural policies and identifying land management changes. Therefore, land cover mapping has become a subject for environmental monitoring as an effective approach to detect vulnerable areas.

Remote sensing (RS) offers crucial data that facilitates decision-making and aids in striking a balance between forest conversion and land use development. Comparison of multi-temporal satellite images enables to highlight trends in landscape dynamics. Such approach helps determine what changes are needed for nature protection and tracks the advancement of current regulations on maps created using spaceborn data. Environmental monitoring supported by RS data is especially crucial in vulnerable landscapes of African regions for planning mitigation and adaptation measures, as well as nature conservation and protection. Moreover, lack of datasets and non-accessible regions in West Africa make the use of satellite images crucial for exposing patterns of land cover types.

With this regard, using RS data for landscape mapping has grown in importance over the past few years as a source of data for environmental and climate research in West Africa. When satellite imagery, and sophisticated processing tools are combined, this kind of information becomes even more pertinent. This necessitates precise reporting of environmental variables (Cabral et al., 2010). At the local, regional, and global levels, changes in land cover have been identified and tracked using a variety of RS data (Dao, 2021). Change detection seeks to detect variations in satellite images between two or more dates, classify the changes, and measure their magnitude. For effective land cover change identification, a variety of computer vision approaches have been developed (Mainguet, 1990). Certain techniques, including image comparison, rationing, or principal component analysis methods (Sharma et al., 2023; Joly et al., 1983), are used to detect changes in the landscape. Nevertheless, the automated comparison of several satellite images is required for comprehensive information on land cover changes.

Traditionally, methods of landscape monitoring compare maps created using supervised human classification to identify specific changes in land cover between satellite images taken at two different dates (Géroyannis, 1984). However, putting such a system in use necessitates separate training grounds and frequently a priori familiarity with the surrounding environment. Since the beginning of satellite missions in the 1970s, satellite images and RS data have been used intensively in environmental and ecological research (Alam and Hossain, 2024; Jombo and Adelabu, 2023; Lavanya et al., 2023; Lemenkova, 2020; Heymann, 1978). In brief, Regrain (1982) summarized the cases using satellite image processing in geographical research throughout this time. The fact that RS data has been continuously used for environmental monitoring over the past 50 years attests to its worth and use as a source of data for geographical research.

Nowadays, satellite imagery presents the most effective source of geospatial data which is actively used for environmental analysis and landscape mapping (Lemenkova, 2024a, b, 2023a, b; Tang et al., 2023). For instance, landscape changes in tropical forests in Africa can be detected using satellite images (Lemenkova, 2024c; Cabral, et al., 2010; Bruneau and Kilian, 1984). Example of multispectral satellite images is presented with Landsat which enable the identification of objects by the light reflected by the Earth's surface. More specifically, satellite images contain information on spectral reflectance of the objects which shows how a surface responds when exposed to the sun's beams through the distinction between the objects that absorb solar radiation and reflect it back to space. The reflected part is the one that is recorded by satellite sensors and used to obtain information for mapping. This fundamental property of RS data enables to use them as a source of information for environmental monitoring and mapping.

Objective and goals

The primary goal of this work is to use the GRASS GIS software's programming method for satellite image processing to address the aforementioned issue of environmental monitoring in Guinea-Bissau region of West Africa (Fig. 1).

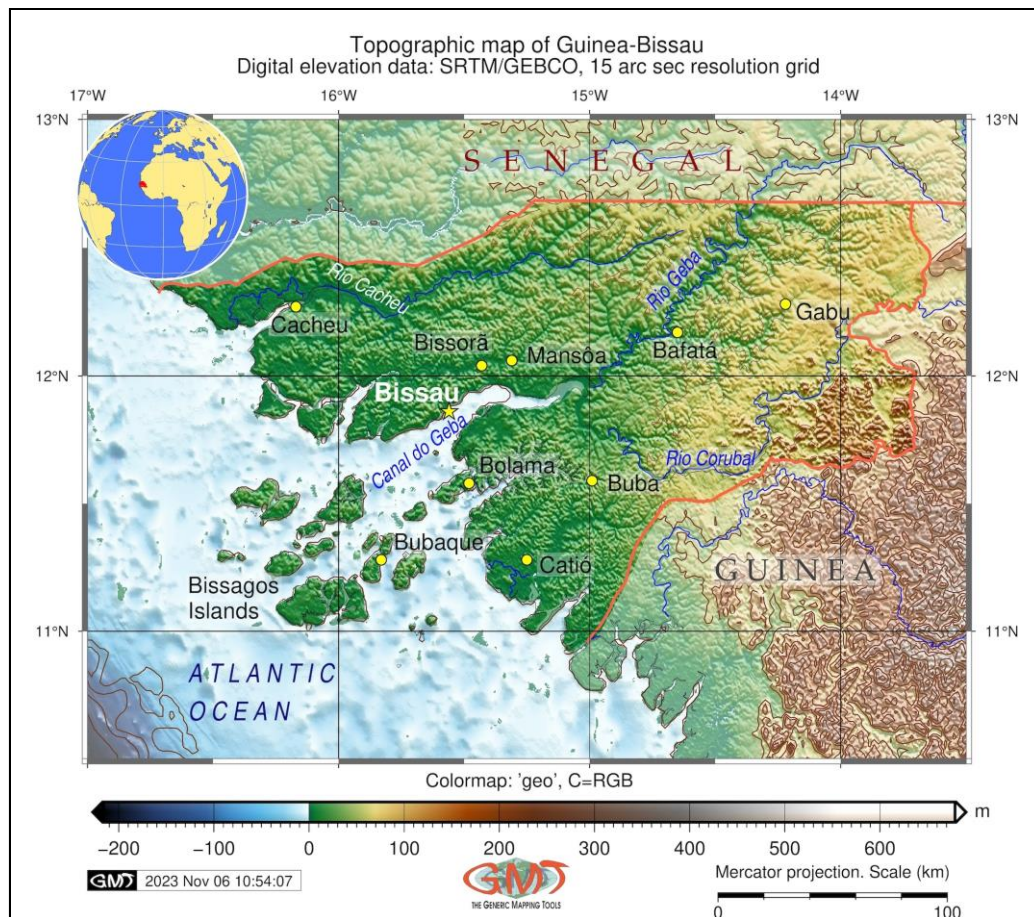


Figure 1: Topographic map of Guinea-Bissau, West Africa.

Using GRASS GIS modules and a scripting approach, a set of Landsat OLI/TIRS images is processed. By employing computer vision techniques to determine the spectral reflectance of the pixels on the images and cluster them into distinct categories, this method automatically performs identification of land cover types. The coastal region of Guinea-Bissau is one of the least known tropical ecosystems in West Africa due to the lack of existing studies. Besides, with regard to the effects of climate change, it is among the most vulnerable and threatened African countries. Such characteristics of the country require additional efforts on environmental monitoring. With this regard, this study contributes to cover the existing lacks in studies on Guinea-Bissau through presented cartographic data processing.

This work provides a machine classification based on the algorithms of computer vision that automatically recognize spectral reflectance at the pixel level, representing landscape dynamics objectively and independently from existing methods. In this study, scripts – a programming technique to geographic data processing – are used as an alternative to current GIS approaches for processing and classifying RS data. Three processed satellite images were used to create map time series in order to accomplish these goals. The primary cover class transitions identified in this study were the development of secondary vegetation and increased agricultural area in place of the loss of intact mangrove forests. According to relevant studies (Carreiras et al., 2012), these transformations align with the primary resource exploitation patterns in the coastal regions (Fig. 1).

There is a fundamental difference in the way that information is extracted between what is classified as satellite images and cartographic data. In traditional cartography, where raw data is used without software processing, visualization is more straightforward, whereas processing data from RS requires more sophisticated technical algorithms. The data retrieved by RS, on the other hand, accurately depicts the terrain. However, RS has certain limitations that can be introduced during the pre-processing, digital and visual classification, rectification to real-world coordinates, post-processing, and registration to other images (Girou et al., 1998; Desjardins and Cavayas, 1991). For these reasons, it is necessary to use advanced image processing methods such as GRASS GIS software that allows for accurate processing and analysis of RS data through the use of special modules and scripts.

This study uses Landsat satellite images from 2013 to 2023 to identify changes in tidal floodplains and mangroves on the coastal regions of the Geba, Caceu, and Rio Grande de Buba rivers. In particular, the research set out to: (1) Create land cover maps by interpreting and classifying Landsat OLI/TIRS satellite images spanning six years, from 2017 to 2023; (2) Use these maps to quantify and visualize dynamic changes in vegetation cover; and (3) Assess the accuracy of digital classification for mapping vegetation in the floodplains and coastal zone. In order to classify and visually interpret the data, the images were digitally processed using scripting algorithms. To assess future changes in land cover types, cartographic data regarding the land cover distribution is necessary. In this study, several land cover maps are made using GRASS GIS, a freely available software for mapping. The maps were created using RS data in order to obtain accurate visualization of land cover types. In this way, this paper contributes to the advancements in Earth system science on a regional scale of Guinea-Bissau.

Study area

The study area is located in the western coastal region of Guinea-Bissau, on the Atlantic coast (Figs. 1 and 2). Geographically, Guinea-Bissau is situated on the west coast of Africa approximately between latitudes 10.5°-13.0°N and longitudes 13.5°-17°W. It spans over 36,125 km² of total area and consists of the continental mainland and a group of islands comprising the Bijagós Archipelago. The environmental vulnerability is caused by its flat

topography and vast meandering coastal zone which is composed of several rivers flowing into the Atlantic Ocean. Besides, ocean tides contribute to local flooding (Temudo et al., 2022). Recent studies (Lopes et al., 2022) reported regarding the ecological vulnerability of Guinea-Bissau's coastal regions.

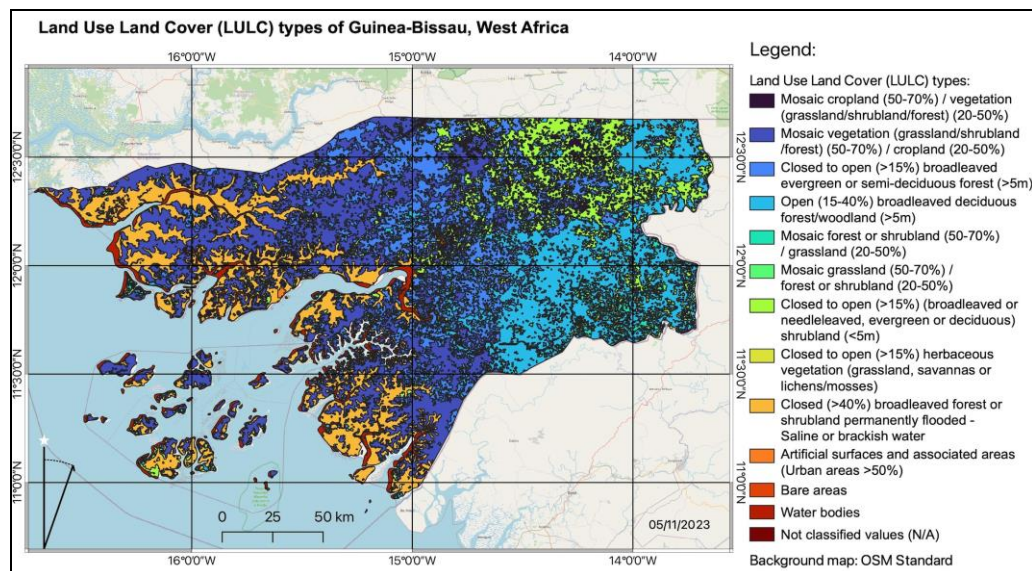


Figure 2: Map of land use types in Guinea-Bissau, West Africa. Data: Food and Agriculture Organisation (FAO). Map source: author. Software: QGIS.

Guinea-Bissau is characterized by contrasting geographical areas and biogeographic regions (Catarino, 2004). From the one part, there are coastal lowland areas, consisting largely of mangroves and swamps stretching from north to south and mainly by a flat land surface with altitudes below 100 m. From the other side, there are areas with forests dominating in the southwest and inner regions of the country. Savanna woodland is present in the northern and eastern regions. Comparison of such varied and contrasting areas enables to support studies of landscape patterns and better analyse landscape dynamics in similar regions of West Africa.

According to Andreetta et al. (2016), Guinea-Bissau is notable for landscape diversity. It comprises a variety of land cover types, including such contrasting classes as mangrove forests, broadleaved forests, flooded forests, grasslands, and urban areas. Agricultural activities in the country are regulated by variations in temperature and the occurrence of wet seasons that alternate with periods of hot, dry winds coming from the Sahara. Changes in land cover types are linked to the intensive agricultural activities (Temudo and Abrantes, 2014) and climate impacts (Dieng et al., 2018). Rising temperatures in the interior regions and periods of drought lead to desertification (Ickowitz, 2006).

In coastal areas, additional impacts on landscape dynamics include the growth of the submerged vegetation, i.e., mangroves. Mangrove habitats are located on the floodplains of the river deltas along the Atlantic coasts and experience the influence of tidal fluctuations related to moon phases, which cause local floods and inundations. The coastal region situated near the Geba River's mouth is characterized by the impacts from its hydrology and effects of coastal circulation and tides. Here, the important role plays the tidal regime. Tides are typically along

the Atlantic coast and the location of river estuary has an impact on the distribution of vegetation in the lagoons along with impacts of salt water from the ocean (Catarino et al., 2002). For example, wet monsoon season, which lasts from June to October and brings heavy rains and hot, humid weather, is different from the dry season, which runs from November to May in tropical environment. Such variations in rainfall regimes between the north and south and east and west affect soil qualities, which influence landscape patterns in Guinea-Bissau.

MATERIAL AND METHODS

Characterizing and assessing spatial phenomena by any of the conventional GIS methods, such as cartographic map analysis, requires many efforts. There are benefits and drawbacks in using different GIS to evaluate landscape diversity and its spatial organization. The primary benefits of GRASS GIS, in contrast to more conventional tools, are its strong programming functionality, advanced tools for RS data processing, and diverse embedded algorithms for geospatial calculation that may be applied to determine the topology, structure, and relationships among landscape elements. Therefore, the programming tools of GRASS GIS software have been used to analyze the landscapes of Guinea-Bissau. Furthermore, this paper outlines a method for integrating geospatial data from several sources for landscape analysis and evaluate environmental dynamics. A novel workflow technique for processing data from RS and mapping is provided by the scripting approach which includes image processing, visualization, and classification.

Data

The data used in this study include Landsat images from May 7, 2023, May 6, 2020, and April 28, 2017, as shown in natural colors (Fig. 3). The data were obtained from the USGS Open Repository where RS data are publicly available from the EarthExplorer archive. To lessen the noise from clouds and atmospheric effects, the data were filtered. For every image, the cloudiness percentage is less than 10%. The images were taken at the end of the dry season. Cloud cover is usually minimal during this time, but the vegetation is distinct from all other land cover types due to vivid green color.

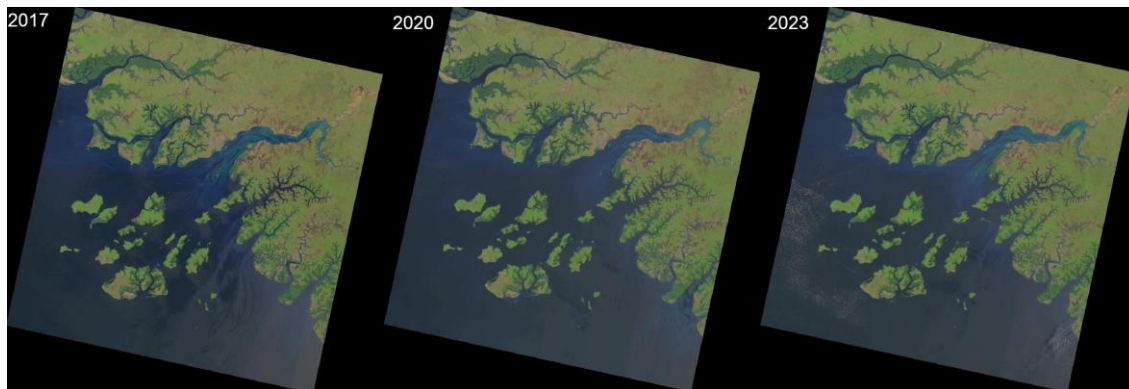


Figure 3: The color composite images over Guinea-Bissau, West Africa. Data source: USGS.

Images were taken on May 7, 2023, May 6, 2020, and April 28, 2017.

Geospatial data enable effective environmental monitoring of Guinea-Bissau and provide the basis for sustainable development, ecological planning, and natural resource management. Landscape change analysis based on satellite images is a technique that performs a comparison between land cover types using multi-temporal images. Comparative analysis of maps created using classified images allows for the detection of landscape changes (Pennober, 2003). The Landsat images were used due to their effectiveness. Literature has provided a

description of the significance of multispectral Landsat data among the other RS data for environmental studies. Studies using Landsat for mapping coastal West Africa are reported (e.g., Lemenkova, 2024a; 2022; Lahuec et al., 1992). Besides, they are employed to record the processes of land cover change and deforestation in Guinea-Bissau (Cuq et al., 1996).

Methods and techniques

The digital image processing used to create a land cover map from Landsat OLI/TIRS imagery was performed in six steps using the techniques of GRASS GIS: 1) image import, 2) data mining and analysis, 3) image classification, 4) image post-processing, 5) mapping, and 6) accuracy assessment. Landsat images were geometrically rectified to EPSG coordinates: 2095, Universal Transverse Mercator (UTM) zone 28N in Guinea Bissau. Satellite images of different dates were classified independently and then the classified images were compared for the years 2017, 2020 and 2023 (Fig. 3). The comparative analysis is based on the values of the individual pixel spectral reflectance on the multi-temporal images. Analysis of changes on the classified images of different dates shows the dynamics of the landscape.

Optimal Landsat band combinations were selected and used for creating false and true color composites (bands 4-3-2, 2-3-4, and 7-6-4 as Red-Green-Blue) and Shortwave Infrared (SWIR2, SWIR1, Red), to ease the processing of the data. Bands 4 (red), 3 (green), and 2 Near Infrared (NIR) produced the best separation for mangroves, tropical forests, agricultural lands, urban regions, and coastal areas. The appropriate modules were applied for color composites and contrast stretching techniques to process multispectral bands (Fig. 4).

Afterwards, unsupervised automatic classification with a variable number of clusters was carried out using module "i.cluster". To statistically assess the accuracy of the land cover maps, the classification algorithms for each image were assessed by creating error matrices and carrying out a Kappa analysis. It is difficult to identify the vegetation types due to similarities in spectral reflectance of different plants that cause spectrum confusion. Therefore, the automatic approach of GRASS GIS was used for vegetation mapping. Since the data do not follow a normal distribution, Landsat images were processed using a computer vision approach based on automated clustering to increase the classification accuracy. This enabled to categorize various land cover types. The maps were created to show landscape dynamics in Guinea-Bissau. Color composites were used from the multispectral bands. Spectral discrimination and spatial analysis were used to examine the images and identify contrasting land cover types: mangrove forests in the coastal areas, inner regions, water, urban areas, etc.

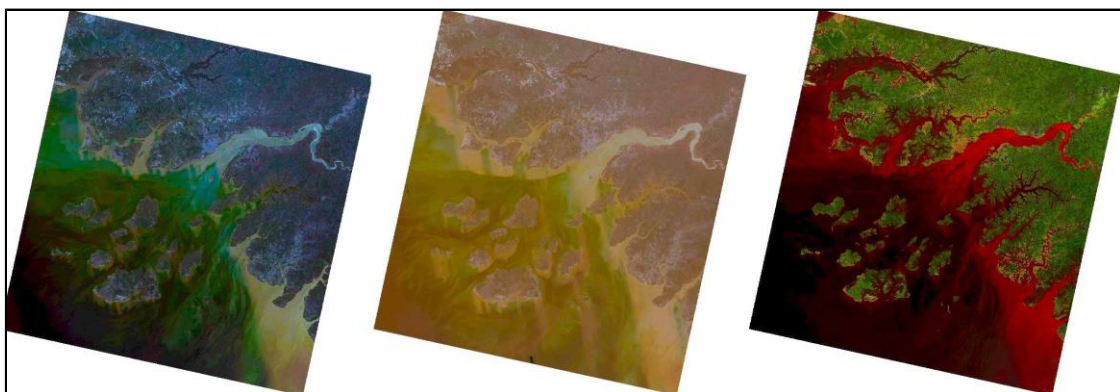


Figure 4: True and false colour composites of Landsat 8-9 OLI/TIRS images (bands 4-3-2, 2-3-4 and 7-6-4), Guinea-Bissau for the years 2017, 2020 and 2023.

RESULTS

The results include three maps of the major categories of land cover which were identified prior to digital classification. These include mangroves, estuaries, cities, and tropical forests, as major categories, as well as minor categories. In total, 12 classes were identified and verified using the unsupervised classification of the satellite images: 1) deep water (ocean); 2) shallow water (shelf); 3) wetlands permanently flooded by saline or brackish water; 4) grasslands; 5) mosaic croplands and agricultural fields; 6) bare soil; 7) coastal mangrove forests; 8) broadleaved evergreen semi-deciduous forests; 9) savannah and shrubland; 10) artificial surfaces (urban and industrial areas); 11) herbaceous vegetation (lichens, mosses, and grassland); 12) woodland and broadleaved deciduous forest (Fig. 5).

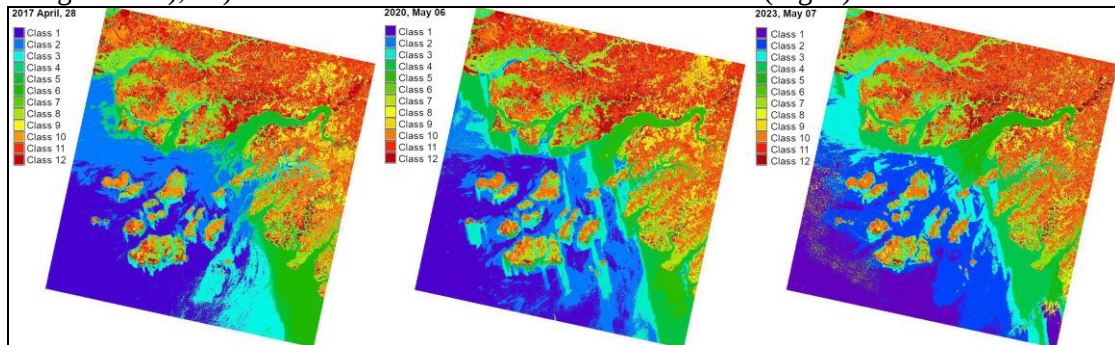


Figure 5: Results of land cover type maps derived from the Landsat 8-9 OLI/TIRS image classification for Guinea-Bissau in the years 2017, 2020, and 2023.

In order to identify 12 common classes for the comparisons, the map legends were combined into a similar nomenclature and color palette. The findings indicate significant variations in the patterns that have been seen in agricultural regions and coastal areas.

There are distinctions between various land use or land cover types. For instance, coastal areas and water surfaces were dark colored. The colors of the salt flats combined with fresh water from the estuaries of the Geba, Corubal, and Rio Grande de Buba rivers are paler than those of the sea. Figure 5 shows how diverse types of vegetation, like mangroves, deciduous forests or woodlands, scrub, and evergreen deciduous forests, exhibit stronger spectral signals and appear in different colors of green. Due to such differences and similarities in their signatures, selected classes have distinct colors, for instance: mosaic vegetation, flooded shrublands and deciduous forests around the Atlantic coasts or estuaries appear dark green. This enables to distinguish these classes from the others which also have a greenish hue. Mangrove plants belong to the same class as flooded estuarine vegetation and show no clear differences from one to another while partially submerged in water (areas colored by cyan).

The results of the classification and validation of the acquired map and images are presented as short-time series (Fig. 5). Color composites made of few multispectral bands are produced. The studied region was analysed for landscape dynamics. The results were: (1) mapping changes in land cover types, with a focus on deforested areas and (2) numerical analyses of changes in land cover types by computed pixels that are associated to each of the 12 classes of Landsat bands for each period (2017, 2020, and 2023); (3) analysis of dynamics in mangrove-covered coastal areas; (4) evaluated the technical feasibility of using GRASS GIS to create land cover maps using moderate resolution (30 m) satellite images Landsat-8 OLI-TIRS. For validation of results, data from the Food and Agriculture Organization (FAO) were used to identify the distribution of land cover types over the studied area. Table 1 shows the calculations of the averages for estimated bands and values for 2017, 2020 and 2023.

Table 1: Calculated values of land cover classes and class means for spectral band Landsat-8 OLI/TIRS. Designations for each band in different wavelengths in the electromagnetic spectrum: Band 1 – Coastal aerosol; Band 2 – Blue; Band 3 – Green; Band 4 – Red; Band 5 – Near Infrared (NIR); Band 6 – Shortwave Infrared (SWIR) 1.

Class	1	2	3	4	5	6	7	8	9	10	11	12
2017	1409	782	537	388	262	327	273	415	369	882	838	438
2020	1105	1120	590	420	438	401	278	100	103	310	468	1589
2023	1203	1065	505	410	440	316	342	138	111	300	603	1509
2017: Class means for each spectral band Landsat-8 OLI/TIRS												
Class	1	2	3	4	5	6	7	8	9	10	11	12
Band 1	7168.48	7617.39	7807.68	8743.92	9897.9	10707.3	8339.52	8198.18	8712.04	8163.95	8543.99	9436.27
Band 2	7700.22	8565.77	8498.15	9545.6	10586.7	11318.8	8770.28	8567.47	9021.95	8461.13	8907.31	9909.03
Band 3	8487.14	10037	9556.42	10868.4	11761	12211.4	9765.21	9583.75	9879.16	9599.46	10028.8	11163.6
Band 4	7658.64	8784.82	8747.36	10311.1	11478.2	11683.4	9770.55	9434.03	10341.6	9371.5	10481.5	12323.2
Band 5	7469.59	7344.08	8560.73	8658.68	9842.98	10868.6	12326.6	14233.5	14109.1	17600.9	16919	16633.3
Band 6	7862.61	7745.24	8818.03	8289.35	8726	10100.1	10468.6	11113.4	15319.1	14055.6	16923	19889.4
2020: Class means for each spectral band Landsat-8 OLI/TIRS												
Class	1	2	3	4	5	6	7	8	9	10	11	12
Band 1	7104.73	7455.29	8500.93	10002.1	10510	8422.6	8203.68	8708.72	9007.16	8187.9	8468.11	9550.18
Band 2	7819.79	8394.61	9358.91	10665.2	11240.1	8954.71	8642.96	9093.69	9409.26	8570.29	8915.8	10059.7
Band 3	8870.45	9823.02	10604.2	11629.1	12514.1	10051.5	9716.14	10014.2	10394.1	9807.74	10181.2	11384.3
Band 4	7844.29	8583.5	9624.92	10875.9	12439.7	10008.8	9554.35	10362.6	11048.1	9600.86	10597.9	12471.5
Band 5	7669.29	8053.91	8770.81	9531.95	10873.6	11718.6	13927.6	13601.6	15040.9	17586.4	17243.2	16944.1
Band 6	8190.72	8555.73	8761.31	9067.82	9575.67	10104.1	10965.4	14153.5	17029.4	14172.6	16750.6	19700.6
2023: Class means for each spectral band Landsat-8 OLI/TIRS												
Class	1	2	3	4	5	6	7	8	9	10	11	12
Band 1	6962.37	8161.88	9118.64	10772.7	11365.2	8740.46	8624.57	9106.88	9354.15	8460.79	8779.7	10154.2
Band 2	8305.26	9469.5	10555	11764.7	12808.7	9889.92	9687.4	10159.3	10388.5	9703.08	10011.1	11470.2
Band 3	7724.79	8350.57	9477.81	11017.6	12971.9	9787.43	9479.7	10411.1	11004.3	9362.82	10207.4	12572.7
Band 4	7936.78	8095.7	8506.35	9718.46	11490.8	11764.6	14237.6	13364.9	15509.6	17907.5	17319.6	16945.2
Band 5	8520.91	8575.67	8658.14	9219.97	9530.32	10149	10976.4	13620	17188.5	13912.2	16008.8	19972
Band 6	8384.81	8440.37	8450.52	8843.81	9072.77	9085.19	9248.41	11874.6	14043.3	10562.5	12365.5	16577.5

Changes in the land cover types in Guinea-Bissau's coastal region were identified and visualized in the target landscapes from 2017 to 2023. In particular, by identifying distinct land cover patches, the satellite images Landsat OLI/TIRS taken at various periods were compared to evaluate the dynamics of diverse land cover types. For instance, for forest class 8 (broadleaved evergreen semi-deciduous forests) the highest variation is found in comparison of images followed by class 12 (woodland and broadleaved deciduous forest) as well as class 3 wetlands permanently flooded by saline or brackish water. Degradation of mangrove areas in Guinea-Bissau is mainly caused by the following factors. First, deforestation is mainly caused by extensive and excessive commercial logging. In addition, uncontrolled artisanal mining, unsustainable logging operations, conversion of forest to agricultural plantations and harvesting of wood for construction and firewood are the other drivers of deforestation in Guinea-Bissau. For class 9 (savannah and shrubland), all maps show a slightly negative variation in distribution of pixels and their assignment to this class. Evergreen or deciduous shrubs with needle-like leaves can be recognized in every shot thanks to a unique spectral signature. Due to spectrum reflection effects and this vegetation type's high backscatter coefficients, they look light in color.

Relatively to grassland class, the obtained maps show negative values, which means the increase of this land class, when comparing with the respective reference map (FAO, Fig. 2). Also, the class 5 (mosaic croplands and agricultural fields) and class 6 (bare soil) both show the trend of increase in values. This indicates the expansion of the agricultural activities and replacement of natural vegetation types through artificial types and land occupied by cultivation and agriculture. Furthermore, small-scale saw-milling for local markets and firewood production are additional triggers of deforestation, as are mining, both commercial and artisanal. Finally, social drivers of deforestation in Guinea-Bissau include processes related to post-conflict population migrations, which lead to additional clearing for agriculture. This includes, for example, the cutting down of forests during clearing for the conversion of land to agriculture, particularly dry rice cultivation.

Woods, mangroves, agricultural land, mudflats, and wetlands in drylands and coastal areas were identified as the principal land cover types that were found. Moreover, the calculations were also performed to evaluate landscape dynamics by comparing and estimating the areas covered by various land cover types. The computed number of pixels attributed to each land cover class for three different years is included in table 1 for comparison of changes. Forests and mangroves were evaluated for regression and progression using numerical calculations of landscape fragments, and the results were presented in cluster reports that indicate which land cover categories are increasing and which are decreasing. The total area of the 12 aggregated classes derived from the comparison of each map obtained from processed satellite images is shown in table 1, as well as variations by multispectral bands.

Figure 6 presents the accuracy assessment that evaluates the cartographic results. For each of the three satellite images, it displays the likelihood that each pixel is assigned correctly to the appropriate class. The comparison of maps obtained on different years for accurate analysis and evaluation of land cover changes is ensured by the geographical correspondence of the satellite images that cover the same area. Clustering-based classification demonstrated the overall accuracy of Guinea-Bissau maps of 2017, 2020, and 2023 for a convergence of 98.1%, 98.2%, and 98.1%, respectively. This demonstrated a high mapping accuracy based on the processing of remote sensing data by GRASS GIS. The coverage of natural vegetation, such as woods, mangroves, shrubs, and grasses, has declined while that has built-up areas and other vegetation types has increased, according to a comparison of the classed maps.

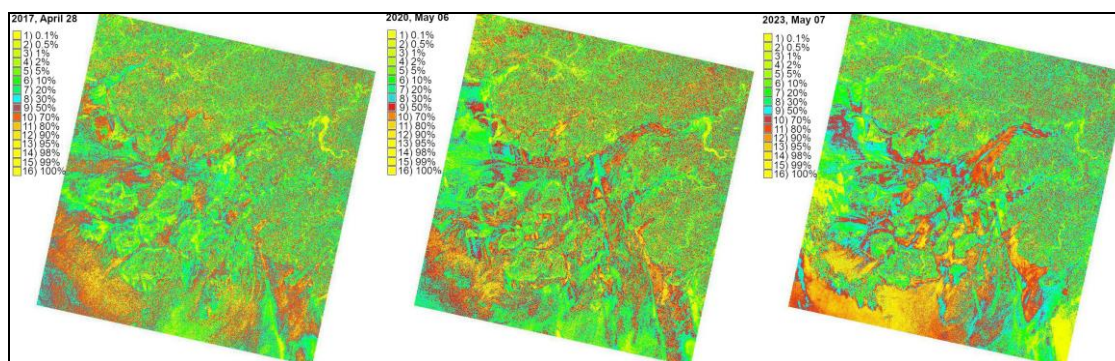


Figure 6: Estimation of pixel confidence levels with rejection probability values for Landsat 8-9 OLI/TIRS images, Guinea-Bissau (2017, 2020, and 2023).

The results of the statistical assessment of the accuracy of the land cover mapping are presented in figure 7 based on the evaluated accuracy of the classification algorithms for each image, including error matrices and Kappa analysis.

##### final results ##### 12 classes (convergence=98.1%)											##### final results ##### 12 classes (convergence=98.2%)											##### final results ##### 12 classes (convergence=98.1%)										
class separability matrix											class separability matrix											class separability matrix										
	1	2	3	4	5	6	7	8	9	10		1	2	3	4	5	6	7	8	9	10		1	2	3	4	5	6	7	8	9	10
1	0										1	0										1	0									
2	1.2	0									2	0.9	0									2	0.8	0								
3	1.5	1.2	0								3	1.9	1.1	0								3	1.5	1.0								
4	2.4	1.3	1.2	0							4	3.4	2.6	1.3	0							4	2.6	2.3	1.2							
5	3.8	2.7	2.3	1.0	0						5	4.3	3.5	2.1	0.9	0						5	3.6	3.4	2.1	1.0						
6	4.6	3.9	2.9	1.9	1.0	0					6	2.4	1.7	1.2	1.6	2.0	0					6	1.9	1.5	1.1	1.5	2.0					
7	2.5	2.3	1.4	1.4	1.7	2.0	0				7	3.2	2.4	2.0	2.6	2.9	0.8	0				7	2.9	2.4	1.9	2.4	2.6	0.7	0			
8	3.5	3.4	2.2	2.2	2.4	2.6	0.5	0			8	3.5	2.9	2.4	2.5	2.7	1.5	1.4	0			8	2.6	2.4	2.0	1.9	1.9	1.1	1.2			
9	4.0	3.8	2.7	2.6	2.5	2.7	1.4	1.5	0		9	5.0	4.2	3.7	3.3	3.3	2.6	2.6	0.9	0		9	4.2	4.0	3.4	3.2	2.7	2.3	2.5	1.0		
10	4.5	4.4	3.2	3.2	3.2	3.3	1.5	1.2	1.1	0	10	4.5	3.7	3.3	3.5	3.5	2.0	1.5	1.0	1.5	0	10	4.1	3.6	3.1	3.7	3.3	1.8	1.4	1.0	1.6	0
11	5.7	5.4	4.0	3.7	3.5	3.6	2.1	2.1	0.6	1.2	11	5.5	4.6	4.0	3.9	4.0	2.7	2.4	1.0	0.7	1.1	11	4.7	4.4	3.6	3.8	3.2	2.3	2.2	1.0	0.8	1.0
12	5.0	4.8	3.8	3.5	3.0	2.9	2.4	2.6	1.3	2.0	12	4.8	4.3	3.8	3.4	3.2	2.9	2.9	1.6	0.9	1.9	12	4.4	4.3	3.7	3.4	2.7	2.8	2.9	1.6	0.9	2.2
	11	12										11	12										11	12								
11	0										11	0										11	0									
12	1.2	0									12	1.2	0									12	1.5	0								

Figure 7: Values for the rejection probability and estimated pixel confidence levels for Landsat 8-9 OLI/TIRS images for the years 2017, 2020, and 2023.

The results show that the areas of mangroves and those of drylands in Guinea-Bissau are increasing. The areas covered by land cover types are reported in details in the available GitHub repository: <https://github.com/paulinelemenkova/Guinea-Bissau-GRASS-GIS>.

DISCUSSION

Environmental development and heritage are reflected in landscape history. Extracting information about the types of land cover changes from the satellite images over time can help explain past events and increase the knowledge on the environmental evolution. Climate-related problems (desertification, erosion, fragmentation of the landscape, degradation of the coasts, and deforestation) raise environmental concerns. Urbanization and intensive agriculture are two examples of anthropogenic activities that trigger these and related processes.

In this work, a programming framework for satellite image processing using GRASS GIS was created using the author's GitHub repository which has made the scripts available for reuse and reference. Besides, the results of image processing are reported in year's tables (2017, 2020, and 2023) and provide a summary of the classification findings for each image. Using the coastal region of Guinea-Bissau, West Africa, as an example, the given scripting technique can be used to achieve real-time change detection for environmental monitoring of African landscapes.

The contribution of this paper can be summarised in: 1) application of advanced technical cartographic methods for satellite image processing and 2) environmental analysis of Guinea-Bissau region using land cover analysis supported by remote sensing. While traditional GIS have limited landscape analysis capabilities and lack essential tools for complex calculations, GRASS GIS algorithms allow performing spatial analysis of landscape structure at an advanced level. In particular, the use of scripts to analyze land use, deforestation and landscape fragmentation from satellite image processing offers the advantage of rapid mapping.

Remote sensing data have been used to analyze these changes in landscape, providing insight into the complexity of tropical forests and coastal areas. Satellite images can be used to obtain the information of landscape development. Although the information is concealed in remote sensing data, but it becomes visible once the images are processed and analyzed with the use of spatial analysis tools. This article proved that GRASS GIS is effective in extracting such information from the satellite image for explaining the landscape dynamics. Using satellite data, one can map past landscapes, forecast potential dynamics, and evaluate the rate at which different types of land cover are changed using various mapping approaches.

For ecological research, environmental mapping, and the prediction of potential changes in coastal areas, accurate mapping and visualization of land cover changes are essential. This study showed how environmental dynamics along Guinea-Bissau's coasts can be analyzed using image processing techniques. The sophisticated method for processing satellite images and reliably mapping changes in the landscape is responsible for the results, which agree with those of earlier research. In a technical sense, we demonstrated that the modules can reliably estimate changes in land cover based on picture analysis and classification. Through the mapping and environmental monitoring of land cover types detected in the satellite images, remote sensing makes it possible to document changes in the environment. To record changes in the types of land cover, many methods are employed for image processing and the mapping that follows. In this study, we used GRASS GIS modules designed for image processing, visualization, and cartographic representation.

CONCLUSIONS

This study demonstrated the effectiveness of the scripting techniques applied for processing time series analysis of satellite images. Such integration of data and methods offer the most reliable means of environmental and ecological research. Specifically, it enables to monitor ecosystems preserving a historical record of the landscape and illustrating changes in land cover over time. A precise and sophisticated tool for environmental mapping and monitoring is also provided by GRASS GIS software, which has numerous map visualization and image processing modules. Employing satellite images as a source of data shows that remote sensing effectively supports environmental monitoring and thematic mapping.

Technically, this study also demonstrates how the suggested GRASS GIS software tools have been successfully used to monitor Guinea-Bissau's land cover and assess the short-term dynamics of the landscape over the last five years (2017-2023). This approach is transferable to different time periods and geographical areas. Using GRASS GIS software, the image processing approach combines a module-based classification methodology to generate unique maps of land cover change with an accuracy assessment following classifications to validate the outcomes. Environmental monitoring of coastal landscapes reveals connections between the spatial structure of coastal landscapes (heterogeneity, connectedness, and fragmentation) and landscape ecology (matrix and corridors). A useful technique for analyzing the dynamics in ecosystems is cartographic integration. The dynamics of African forests and land cover changes are influenced by complex character of landscapes and their interactions with other environmental parameters, such as temperature and hydrology.

REFERENCES

1. Alam S. R. and Hossain M. S., 2024 – Using a water index approach to mapping periodically inundated saltmarsh land-cover vegetation and eco-zonation using multi-temporal Landsat 8 imagery, *Journal of Coastal Conservation*, 28, 19.
2. Andreetta A., Huertas A. D., Lotti M. and Cerise S., 2016 – Land use changes affecting soil organic carbon storage along a mangrove swamp rice chronosequence in the Cacheu and Oio regions (northern Guinea-Bissau), *Agriculture, Ecosystems & Environment*, 216, 314-321.
3. Bruneau M. and Kilian J. 1984 – Inventaires agro-écologiques, paysages et télédétection en milieu tropical, *L'Espace géographique*, 13, 3, 215-224. (in French)
4. Cabral A., Vasconcelos M. and Oom D. 2010 – Comparing information derived from global land cover datasets with landsat imagery for the huambo province and Guinea-Bissau, *Conference Proceedings of the Symposium 100 years of Society for Photogrammetry and Remote Sensing ISPRS – Advancing Remote Sensing Science*, 38, 7B, 107-112.
5. Cabral A. I. R. and Costa F. L. 2017 – Land cover changes and landscape pattern dynamics in Senegal and Guinea Bissau borderland, *Applied Geography*, 82, 115-128.
6. Carreiras J. M. B., Vasconcelos, M. J. and Lucas, R. M., 2012 – Understanding the relationship between aboveground biomass and ALOS PALSAR data in the forests of Guinea-Bissau (West Africa), *Remote Sensing of Environment*, 121, 426-442.
7. Catarino L. M., 2004 – Fitogeografia da Guiné-Bissau (PhD Thesis), Lisboa, Portugal, Universidade Técnica de Lisboa. (in Portuguese)
8. Catarino L., Martins E. S. and Diniz M. A., 2002 – Vegetation structure and ecology of the Cufada Lagoon (Guinea-Bissau), *African Journal of Ecology*, 40, 252-259.
9. Cuq F., Madec V. and Gourmelon F., 1996 – Mise à jour de la carte d'occupation des sols des provinces côtières de Guinée-Bissau, *Mappemonde*, 4, 21-26. (in French)
10. Dao H., 2021 – Télédétection et enjeux environnementaux globaux à l'heure du Big Data, *Le Globe, Revue genevoise de géographie*, 161, 54-71. (in French)
11. Desjardins R. and Cavayas F., 1991 – Possibilités et limites des images satellites TM LANDSAT en matière d'occupation du sol: le cas de Montréal (Québec), *Cahiers de géographie du Québec*, 35, 94, 137-151. (in French)
12. Dieng D., Laux P., Smiatek G., Heinzeller D., Bliefernicht J., Sarr A., Gaye A. T. and Kunstmann H. G., 2018 – Performance analysis and projected changes of agroclimatological indices across West Africa based on high-resolution regional climate model simulations, *Journal of Geophysical Research: Atmospheres*, 123, 7950-7973.
13. Géroyannis H., 1984 – Les traitements numériques en télédétection, *Travaux de l'Institut Géographique de Reims*, 57-58, 35-48. (in French)
14. Girou D., Deschamps N. and Delorme M., 1998 – Apports et limites de la télédétection aérienne et satellitale pour la gestion des milieux naturels en Guyane: exemple du zonage écologique et humain de la région de Saül, *Journal d'agriculture traditionnelle et de botanique appliquée*, 40, 1-2, 423-432. (in French)
15. Heymann Y., 1978 – Les inventaires des ressources naturelles par la télédétection satellite, *Économie rurale*, 127, 2, 31-34. (in French)
16. Ickowitz A., 2006 – Shifting cultivation and deforestation in tropical Africa: critical reflections, *Development and Change*, 37, 599-626.
17. Joly G., Verger F. and Crettez J.-P., 1983 – Classification des données Landsat unitemporelles et multitemporelles par la transformation de Karhunen-Loève, *L'Espace géographique*, 12, 2, 125-141. (in French)
18. Jombo S. and Adelabu S., 2023 – Evaluating Landsat-8, Landsat-9 and Sentinel-2 imageries in land use and land cover (LULC) classification in a heterogeneous urban area, *GeoJournal*, 88, 1, 377-399.

19. Lahuec J.-P., Carn M., Lemoigne O. and Dagorne D., 1992 – La saison des pluies 1991 en Afrique de l'Ouest soudano-sahélienne suivie à partir d'images Météosat, *Norois*, 155, 255-267. (in French)
20. Lavanya K., Gondchar A., Mathew I. M., Sarda S., Ananda Kumar S., Mahendran A. and Perera D. G., 2023 – Land cover classification using Landsat 7 data for land sustainability, *Wireless Personal Communications*, 132, 679-697.
21. Lemenkova P., 2020 – Sentinel-2 for high resolution mapping of slope-based vegetation indices using machine learning by SAGA GIS, *Transylvanian Review of Systematical and Ecological Research*, 22, 3, 17-34.
22. Lemenkova P., 2022a – Mapping Ghana by GMT and R scripting: advanced cartographic approaches to visualize correlations between the topography, climate and environmental setting, *Advances in Geodesy and Geoinformation*, 71, 1, e16.
23. Lemenkova P., 2023a – Monitoring seasonal fluctuations in saline lakes of Tunisia using Earth observation data processed by GRASS GIS, *Land*, 12, 11, 1995.
24. Lemenkova P. 2023b – Mapping wetlands of Kenya using geographic resources analysis support system (GRASS GIS) with remote sensing data, *Transylvanian Review of Systematical and Ecological Research*, 25, 2, 1-18.
25. Lemenkova P., 2024a – Random forest classifier algorithm of geographic resources analysis support system geographic information system for satellite image processing: case study of Bight of Sofala, Mozambique, *Coasts*, 4, 127-149.
26. 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.
27. Lemenkova P. 2024c – Support vector machine algorithm for mapping land cover dynamics in Senegal, West Africa, Using Earth Observation Data, *Earth*, 5, 420-462.
28. Lopes N. D. R., Li T., Matomela N. and Sá R. M., 2022 – Coastal vulnerability assessment based on multi-hazards and bio-geophysical parameters, Case study – northwestern coastline of Guinea-Bissau, *Natural Hazards*, 114, 989-1013.
29. Mainguet M., 1990 – La télédétection et le suivi écologique: outils d'une nouvelle géographie, *Travaux de l'Institut Géographique de Reims*, 79-80, 83-102. (in French)
30. Regrain R., 1982 – Bibliographie analytique des publications de télédétection des équipes Fralit, Lanchad et associées, *Annales de Géographie*, 91, 505, 340-355. (in French)
31. Sharma K. V., Kumar V., Singh K. and Mehta D. J., 2023 – LANDSAT 8 LST Pan sharpening using novel principal component based downscaling model, *Remote Sensing Applications: Society and Environment*, 30, 100963.
32. Tang X., Bratley K. H., Cho K., Bullock E. L., Olofsson P. and Woodcock C. E., 2023 – Near real-time monitoring of tropical forest disturbance by fusion of Landsat, Sentinel-2, and Sentinel-1 data, *Remote Sensing of Environment*, 294, 113626.
33. Temudo M. P. and Abrantes M., 2014 – The cashew frontier in Guinea-Bissau, West Africa: changing landscapes and livelihoods, *Human Ecology*, 42, 217-230.
34. Temudo M. P., Cabral A. I. R. and Reis P., 2022 – The sea swallowed our houses and rice fields: the vulnerability to climate change of coastal people in Guinea-Bissau, West Africa, *Human Ecology*, 50, 835-850.