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MACHINE LEARNING METHODS OF SATELLITE IMAGE ANALYSIS FOR MAPPING GEOLOGIC LANDFORMS IN NIGER: A COMPARISON OF THE AÏR MOUNTAINS, NIGER RIVER BASIN AND DJADO PLATEAU

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Abstract: This study analyses geological landforms and land cover types of Niger using spaceborne data. A landlocked African country rich in geological structures, Niger is notable for contrasting environmental regions which were examined and compared: 1) lowlands (Niger River basin); 2) Aïr Mountains; and 3) Djado Plateau. The methodology is based on machine learning (ML) models and programming applied for Earth observation data. Spatio-temporal analysis was performed using Landsat 8-9 OLI-TIRS multispectral images classified by GRASS GIS. Data were processed by scripts using ML algorithms by modules r.random, r.learn.train, r.learn.predict, i.cluster, and i.maxlik. The algorithms of probabilistic forecasting included support vector machine (SVM), random forest (RF), decision tree classifier and K neighbors classifier. Variations in landscapes caused by water deficit and soil erosion were analyzed, and parallels between geologic and environmental setting were drawn. The intra-landscape variability of patches within Niger is revealed from 2014 to 2024. Landscape patterns are affected by drought periods in central Niger, geological setting of mountains, distribution of crust karst pits and sinkholes in eastern Niger. Western region of the Niger River basin shown land cover patterns linked to hydrological effects of soil erosion. This paper shows the use of ML methods for geological-environmental analysis.

Keywords: machine learning, geology, satellite image, remote sensing, cartography

1 INTRODUCTION

Geological-environmental monitoring is critical for dry arid regions of Sahara-Sahelian Africa. In this region, the variability of landforms, extent of land cover types and the

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complexity of landscape structure are entirely controlled by the rhythm of regional precipitation and climate effects (Gond et al. 2004; Lemenkova 2023a, 2023b). At the same time, in contrast to other African countries, the variability of diverse landscapes of Niger is not well documented. Environmental and geological analysis is also important for modelling groundwater distribution and subsurface resources, which provides socio-economic support of population. Niger, one of the poorest countries in the world, has limited access to safe drinking potable water, especially for rural population (Lasagna et al. 2015). Hence, geological and environmental mapping of its various landscapes using satellite images processed by advanced cartographic tools contributes to monitoring natural resources of Niger. This research presents comparative environmental analysis of Niger. The data were mapped using machine learning (ML) methods of GRASS GIS by cartographic scripts.

2 STUDY AREA

The study area is focused on Niger, a landlocked country in West Africa, Figure 1. Specifically, three contrasting landscape regions of Niger related to diverse watersheds were compared and examined: 1) lowlands (Niger River basin), 2) mountainous area (Aïr Mountains) and 3) plateau (Djado Plateau). The location of Niger is restricted by the coordinates between 11° and 24°N, and 0° and 16°E. In this research, we focus on the three selected study areas of Niger that have contrasting geographic, environmental and geologic setting: lowlands are presented by the Niger River basin, mountainous area is exemplified by the Aïr Mountains and the plateau is studied using Djado Basin. The location of the Landsat images with these three regions on the topographic map of Niger is shown in Figure 1

Geospatial data of reliable source and appropriate resolution is critically important for mapping and environmental research of Niger, because of its complex landscape and data scarcity (Meister et al., 1994). Located between the Sahara and Sahel regions, Niger exhibits significantly variable topography, ranging from its lowest point in the Niger River (200 m heights) until Mont Idoukal-n-Taghès in the Aïr Mountains (or Massif) at 2,022 m (Ingram 1990).

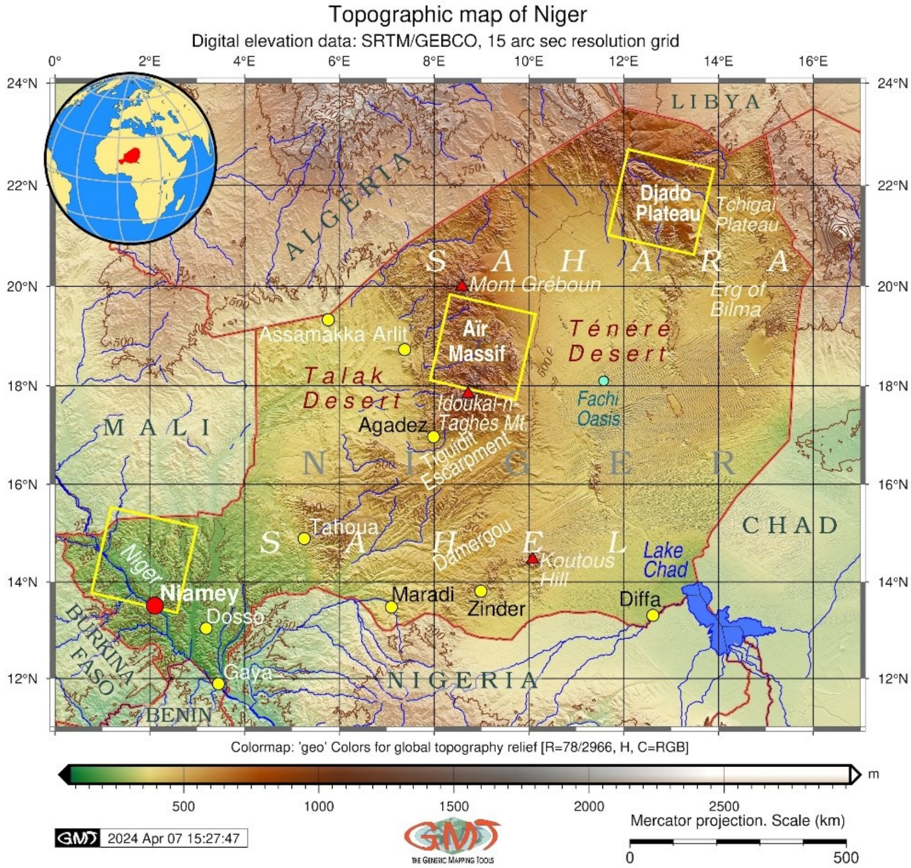

Figure 1 Three study areas on the topographic map of Niger: Niger River flow, Aïr Mountains and Djado Plateau. Data source: GEBCO. Software: GMT version 6.4.0. Map source: author

The geomorphology of Niger includes a variety of Saharo-Sahelian landforms (Keeling 2009) which reflect its complex geologic structure. Thus, Niger's terrain typically exhibits a mosaic of Lower Createaceous (KI), Quaternary (Q) and Tertiary (T) outcrops on the south, and the Precambrian (pCm) groups in the west of the country on the border with Burkina Faso (Chardon, 2023). Steep vegetation slopes of the Tiguidit Escarpment with elevation around 500 m a.s.l. are covered by Cretaceous rocks. Cretaceous assembly and fragmented of Carboniferous rocks are accumulated in the north-eastern region of the country around the Tchigaï Plateau on the border with Chad (Lemenkova, 2023c), which was formed during Paleozoic, Figure 2.

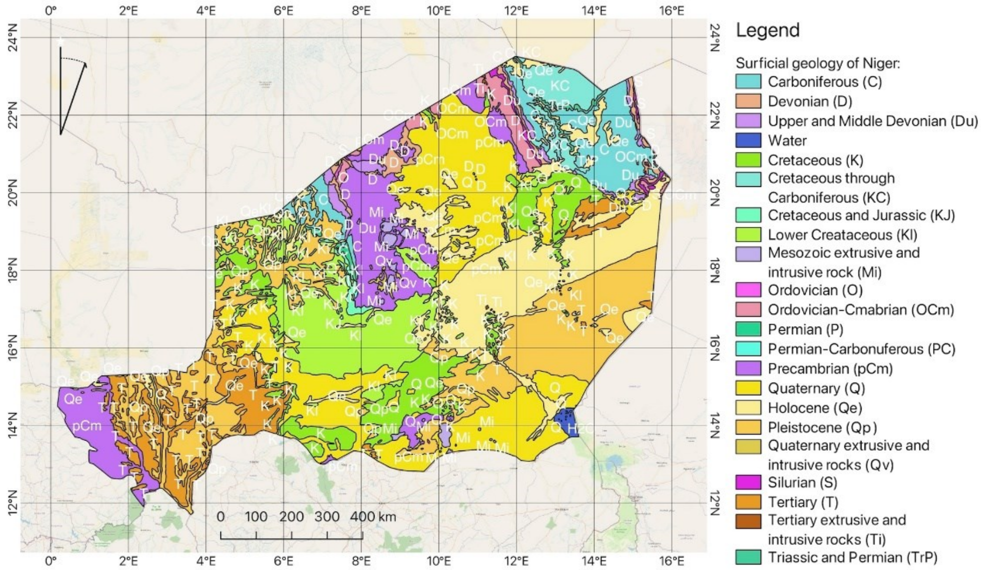

Figure 2 Surficial geology and lithologic units of Niger. Data: USGS, OpenStreetMaps (OSM). Software: QGIS. Map source: author

Western Niger has been largely occupied by the Iullemmeden sub-Saharan inland basin which experienced was subducted and inundated in Permo-Triassic period and then downwarped during the Late Cretaceous to Paleogene which reflected in its sedimentation from Cambrian to Pleistocene periods, Figure 3. Regional distribution of the sedimentary and tectonic provinces Republic of Niger can be classified into two parts (Zanguina et al. 1998): a Palaeozoic platform-type province in the north and west, and a series of Mesozoic grabens in the east that cover the Chad geological province, Figure 3.

As a landlocked country of West Africa, Niger has arid to semi-arid climate varying accordingly to the latitude and regulated by local geomorphic patterns (Favreau et al. 2009). Thus, the hotter and drier climate is notable for desert areas which lead even to fires (Diouf et al. 2012; McShane 1987), while southern region of the Niger River basin has a tropical climate (Lemenkova, Debeir, 2023). Moreover, mountain slopes attenuate temperature fluctuations and support variability of vegetation types. Soil erosion is one of the most important environmental problems in Niger, due to the deficit of water resources and increasing droughts in Sahel.

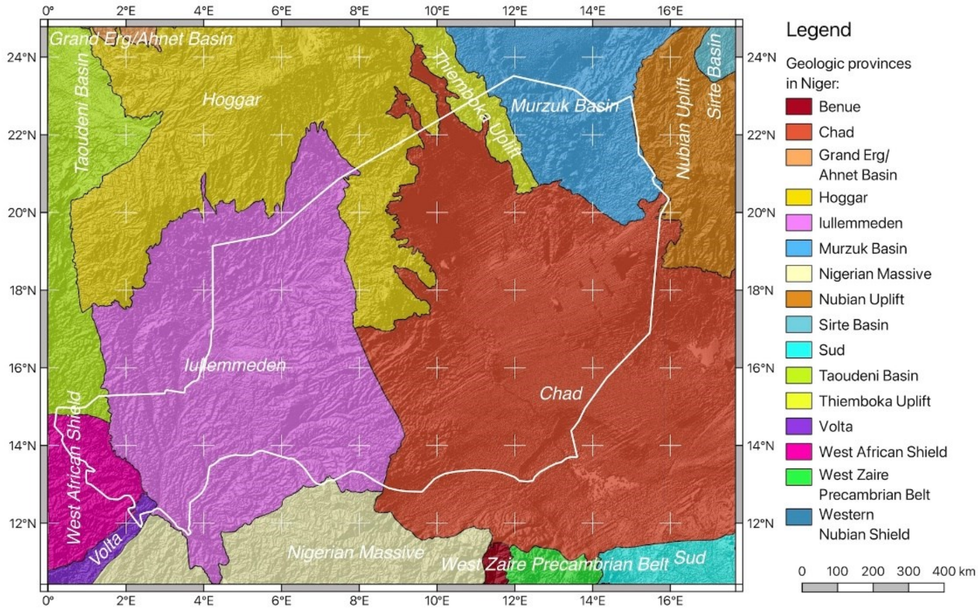

Figure 3 Geologic provinces of Niger. Data: USGS. Background hillshade relief: GEBCO. Software: QGIS. Map source: author.

The effects of the erosion, increased by drying climate, lead to land cover change through the removal of the fertile fraction of the soil which in turn affects vegetation and habitat distribution. Cumulative effects from the irregular rainfall patterns in desert areas, soil erosion and land cover changes have implications for soil and water resources, leads to land degradation and affects agriculture practices in Niger.

Geological processes in Northern Niger favored formation of valuable minerals which is currently reflected in uranium resources around (Sani et al. 2022, Mamane Mamadou et al. 2020). The Devonian and Carboniferous successions are mostly located in the Murzuq Basin and the sub-Basin of the Djado Plateau (Mergl et al 2000). The Djado Basin forms the upper part of the Cambrian – Late Ordovician series, consists of the preglacial Tigillites Sandstone Formation of former ice sheet. Its inner part now consists mostly of glaciomarine deposits that form sandstone ridges of the related series of Felar-Felar Formation (Denis et al. 2007). The petroleum potential in eastern Niger corresponds to the distribution of the complex rift system with sedimentary fill ranging in ages from Late Jurassic to Early Tertiary. Thus, the deposits in eastern Niger include such unique source rocks as organic-rich shales of Oligocene, Eocene, Paleocene, and other ages. These oil-generating samples provide the origin of the hydrocarbons (Harouna, Philp 2012).

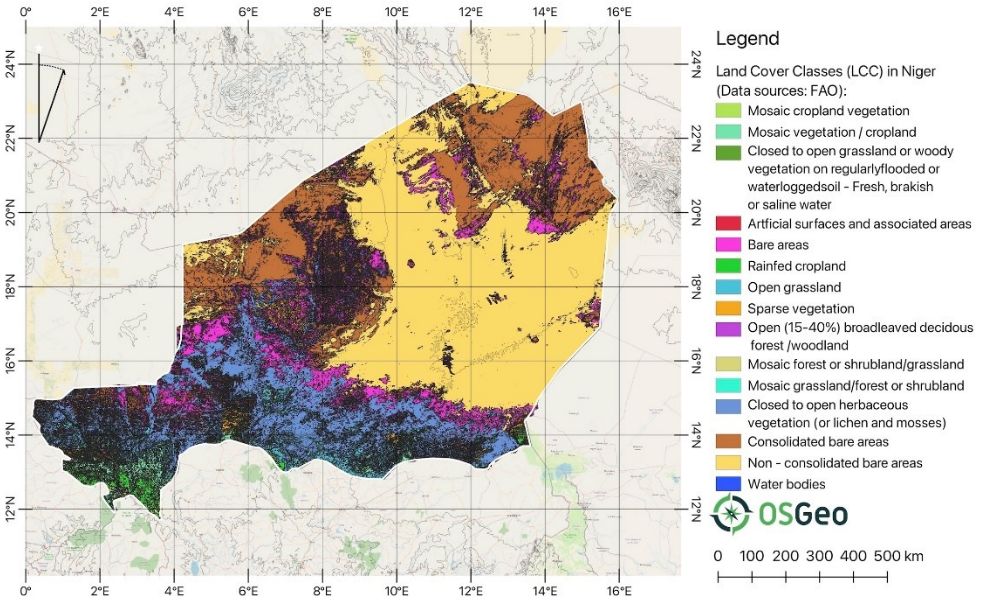

Figure 4 Land cover types in Niger. Data source: Food and Agriculture Organization (FAO). Background map: OSM. Software: QGIS. Map source: author

Geological complexity and variability of the country formed various geomorphic landforms that are reflected in rich landscapes. The predominantly desert plains and sand dunes of Niger alternate with flat to rolling terrain of savanna shapes the landscapes in the south and hills dozens of mountain peaks over 500 m in the north, Figure 1. One of the important peaks is created by the Aïr Massif which presents important environmental feature in northern Niger through regulating climate extremities of Sahara and providing surrounding ecosystems with natural resources and water. The essential hydrological mountains-lowland linkage provides freshwater for the adjacent lowlands (Viviroli et al. 2007).

As a consequence, the Aïr Massif forms an island of green Sahel climate which supports a wide variety of life which well contrasts with the surrounding desert regions of Sahara. For instance, wadis stream originating in the ranges of the Aïr massif provide a habitat for rare species that seek for water from the Saharo-Sahelian deserts (Ostrowski et al. 2001). Moreover, surface runoff from the mountain ranges accumulated in depressions contribute to the groundwater resources which are crucial in arid lands of Niger for supporting life (Molina et al. 2017; Verdin, 1996). Such oases made by ephemeral streams during pluvial periods create sources of rainwater and support life in Sahara-Sahel regions.

The terrestrial ecoregions of Niger are influenced both by climate variations of arid region and regional geologic setting and include diverse types. The essential categories comprise deserts and semi-deserts in the north, steppes, savannah and grasslands in the south (Justice, Hiernaux, 1986), and xeric woodlands in the mountain ranges, Figure 4. Such variety is explained by complex geologic structure which reflects strong relationship between the lithologic setting and land cover types in Niger. This linkage can be explained by soil variables which have a control for vegetation structure and composition. Thus, mineral content of soil is formed under the specific regional lithological setting with rock outcrops that influence local physical characteristics of soil properties (grain size, composition, content, porosity, texture, etc.). Moreover, the hydrogeologic setting and access to groundwater is related to aquifers of soil with diverse properties (Dodo, Zuppi, 1997).

Nevertheless, certain geomorphic processes negatively affect the environmental setting. For example, the Niger River is threatened with silting up due to the development of alluvial fans in south-west Niger around Niamey (Mamane Barkawi et al. 2023).

The examples of the climate effects on current landscapes can be illustrate by the paleogeographic reconstructions in Niger. For example, modern silt-rich lacustrine sediments indicate the distribution of paleolake depressions during earlier periods with high humidity (Felix-Henningsen, 2000). In contrast, during arid climatic period, these paleolakes decresed in size and are currently occupied by dunes and vast areas of sands in deserts. Thus, variations in groundwater in the northern and southern Sahara are related to the climatic oscillations since Holocene which also affected the organic matter content from surface vegetation and level of water infiltration through soil (Dodo, Zuppi, 1999). The remnants of such palaeosoils and aeolian deposits fill karsts and sinkholes in eastern Niger (Sponholz, 1994).

3 DATA

Satellite images provide a precious source of information for environmental mapping which is proved by their use in numerous related studies (Mering et al. 2010, Lemenkova 2023d, Wylie et al. 1992). For instance, remote sensing data can be used to identify the expanding settlements and detecting built-up areas (Tiepolo, Galligari, 2022), for mapping soil in desert regions (Mulders, Girard, 1993) or climate modelling (Dione et al. 2014, Emetere, Akinyemi, 2017). Therefore, in this study, we used the Landsat satellite images which were selected as data source because of their open availability, high quality and reputation in geospatial research.

The original raw data covering three study areas are presented as a series of images in natural colors, Figure 5. The data were downloaded from the open repository EarthExplorer (https://earthexplorer.usgs.gov/) by United States Geological Survey (USGS). The dataset of Landsat 8-9 OLI/TIRS includes six images covering three selected study areas.

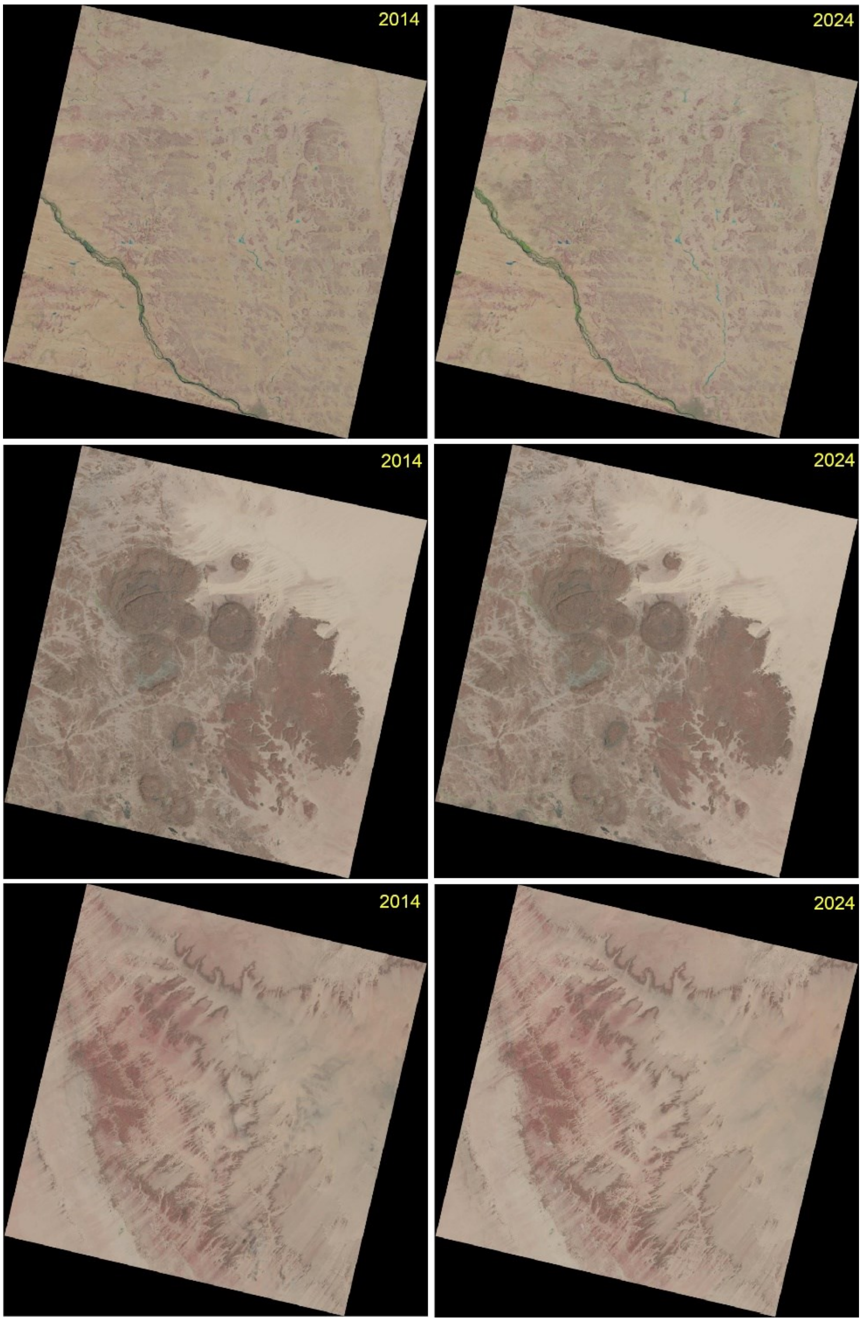

Figure 5 Original data: Landsat 8-9 OLI/TIRS images on three regions of Niger, collected during the spring period (April) on years with ten gap interval on 2014 and 2024. Data source: USGS. Compilation source: author

The selection of these data is explained by well characterization of the diversity of landform types and land cover structure in Niger: 1) lowlands (Niger River basin), 2) mountainous area (Aïr Mountains) and 3) plateau (Djado Plateau). The images were taken on two years: 2014 and 2024 for each scene where the image for 2014 was used as training dataset for supervised machine learning techniques providing seed for classification. The data were selected on March in all cases to cope with climate effects. Thus, the climate area in southern Niger is tropical where wet periods with abundant precipitation and rainfalls lasts normally from June to September, followed by a long dry season October–May (Oguntunde et al. 2014). As a consequence, the quality of satellite images might be affected by haze and higher moisture during this period. Therefore, the images were taken on March for years 2014 and 2024 for all the scenes.

4 METHODS

The methodology is based on the cartographic program GRASS GIS with its modules for machine learning. Specifically, the following four ML algorithms were used for image classification for scenes on 2024: 1) Random Forest Classifier, 2) Decision Tree Classifier, 3) K Neighbors Classifier, and 4) Support Vector Machine Classifier (SVMC). Additionally, clustering using k-means algorithms was performed for images in 2014. These data served as training pixels for ML approach. The high-resolution regional topography of Niger is mapped using GEBCO grid processed using Generic Mapping Tools (GMT) using scripts, as explained in earlier works (Lemenkova, 2022a, 2022b).

Scripting approach to cartographic data processing using several modules of GRASS GIS were performed for six Landsat satellite images by using a combination of the following methodological steps in a single process stepwise.

1. Firstly, the data were imported with the image subset containing 7 Landsat multispectral bands using 'r.import' module: “r.import input=/Users/path/LC08<file_name>B1.TIF output=L_2014_01 extent=region resolution=region”. In the same way, the GEBCO grid was imported for relief background.

2. Secondly, the computational region was defined to match the scene using 'g.region' of GRASS GIS as follows: g.region raster=L_2014_01 -p. This command enabled to clip the necessary part of the region limited to the coordinates of the study areas from the GEBCO map which covers global extent.

3. Thirdly, the assignment of pixels to clusters, fractured surface and diverse land cover types are made by 'i.cluster' module which generates signature file and reports using k-means clustering algorithm. Snippet of the code is as follows: "i.cluster group=L_2014 subgroup=res_30m signaturefile=cluster_L_2014 classes=10 reportfile=rep_clust_L_2014.txt".

4. The unsupervised classification was performed by 'i.maxlik' module using the following code: i.maxlik group=L_2014 subgroup=res_30m signaturefile=cluster_L_2014 output=L_2014_clusters reject=L_2014_cluster_reject. This step includes the unsupervised classification which uses signature obtained in previous step of clustering. The results of the maximum likelihood discriminant analysis classifier are then used as training data for the next step of ML that requires training dataset from previous classification.

5. Generating training polygons was performed using clustering technique by k-means and maximum likelihood discriminant analysis classifier. The data were quantified to detect landform shapes and contours of land cover categories.

6. Examining the obtained product for accuracy was performed using rejection probability function that evaluates the correctness of the assigned pixels using chi-square test. The data are then visualised using a combination of commands as follows: d.rast L_2014_cluster_reject d.legend raster=L_2014_cluster_reject title="2014" title_fontsize=19 font="Helvetica" fontsize=17 bgcolor=white border_color=white.

The next step includes the Machine Learning (ML) method of image classification which included four different algorithms. In general, ML can be defined as a system that models the brain working principle of human beings. ML is comprised of training data that includes the pixels obtained in the previous classifications (in this case, data for 2014).

1. The fist algorithm included the Random Forest Classifier. The process included grouping data by ‘i.group’ which combines the multispectral bands into one group as follows: i.group group=L_2024 subgroup=res_30m input=L_2024_01<...>L_2024_07 –overwrite. Afterwards, the model is trained using ‘r.learn.train’ function as follows: “r.learn.train group=L_2024 training_map=training_pixels model_name=RandomForestClassifier n_estimators=500 save_model=rfc_model.gz.

2. The ML supervised learning algorithm is developed for training machine to classify images which iteratively adapts the pixels into the best suitable class according to its spectral reflectance value. To this end, the prediction of this assignment is performed using the r.learn.predict module as follows: “r.learn.predict group=L_2024 load_model=rfc_model.gz output=rfc_classification_2024”.

3. Afterwards, raster categories are automatically applied to the classification output using ‘r.category’ module as follows: “r.category rfc_classification_2024”. The maps are then displayed using the combination of modules ‘d.rast’ for the images, ‘d.vect’ for isolines derived from GEBCO grid and d.legend for adding the legend on the maps.

The same methodological scheme was applied to the algorithms Decision Tree Classifier, K Neighbors Classifier and Support Vector Machine Classifier (SVM). In those cases, the name of the algorithm is explicitly added in the function of training module “model_name”, e.g. for KNeighborsClassifier it is as follows: "r.learn.train group=L_2024 training_map=training_pixels model_name=KNeighborsClassifier n_estimators=500 save_model=knc_model.gz". The same approach was applied to the algorithms of Decision Tree Classifier and SVM, accordingly.

During the last decades, automation in cartography has been the focus of a great deal of attention in GIS (Noël 1978, Lemenkova, 2021), due to their capabilities in optimisation of mapping workflow by scripting. Scripts have some other unique advantages, such as distributed performance of tasks, increased speed of mapping, minimized handmade routine. Such advantages are achieved in using both GMT and GRASS GIS as advanced software applied simultaneously in this study.

5 RESULTS AND DISCUSSION

The results of this study demonstrate the applicability of a novel ML methods of GRASS GIS to satellite image processing and environmental land cover types of analyses in Niger, and the advantages of four ML algorithms of supervised classification are compared to the unsupervised clustering. Land cover patterns in this classification mostly show more distinct differences in the distribution of herbaceous vegetation in the south-western region of Niger than is the case for north-eastern regions with dominating bare areas occupied by sandy deserts. Overall, comparing the strengths and weaknesses of the approaches used for image processing, the ML methods performed better for automated image classification rather than unsupervised clustering. Below we evaluate the performance of the four supervised learning algorithms adopted from the Scikit-Learn ML library of Python, Figs. 6 – 8.

Land cover patterns in central and northern Niger are more associated with geologic setting while southern region is affected by the Niger River basin. The landscape dynamics in the Niger River basin for the studied 10-year period is associated with regional environmental resistance of riparian zone and surrounding region to the climate and hydrological effects (precipitation patterns and frequency of droughts). Moreover, being the principal river of western Africa providing local with essential natural resources, the coastal plains of the Niger River experience intense human impacts such as practice of agro-pastoralism and crop management which affect surrounding landscapes accordingly, Figure 6.

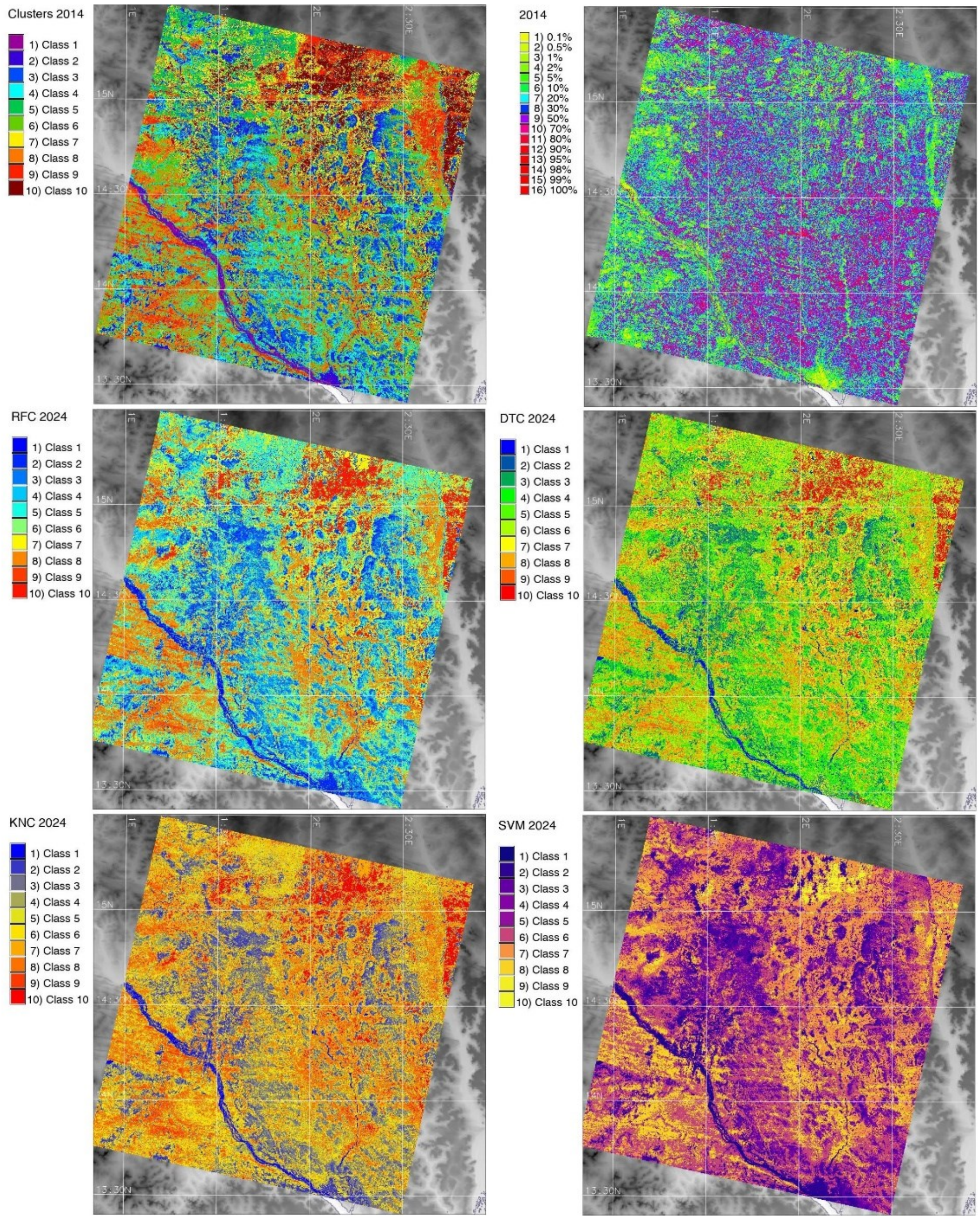

Figure 6 Results of the satellite image processing using classification and ML methods. Region – 1: lowlands in the Niger River basin. Software: GRASS GIS. Map source: author

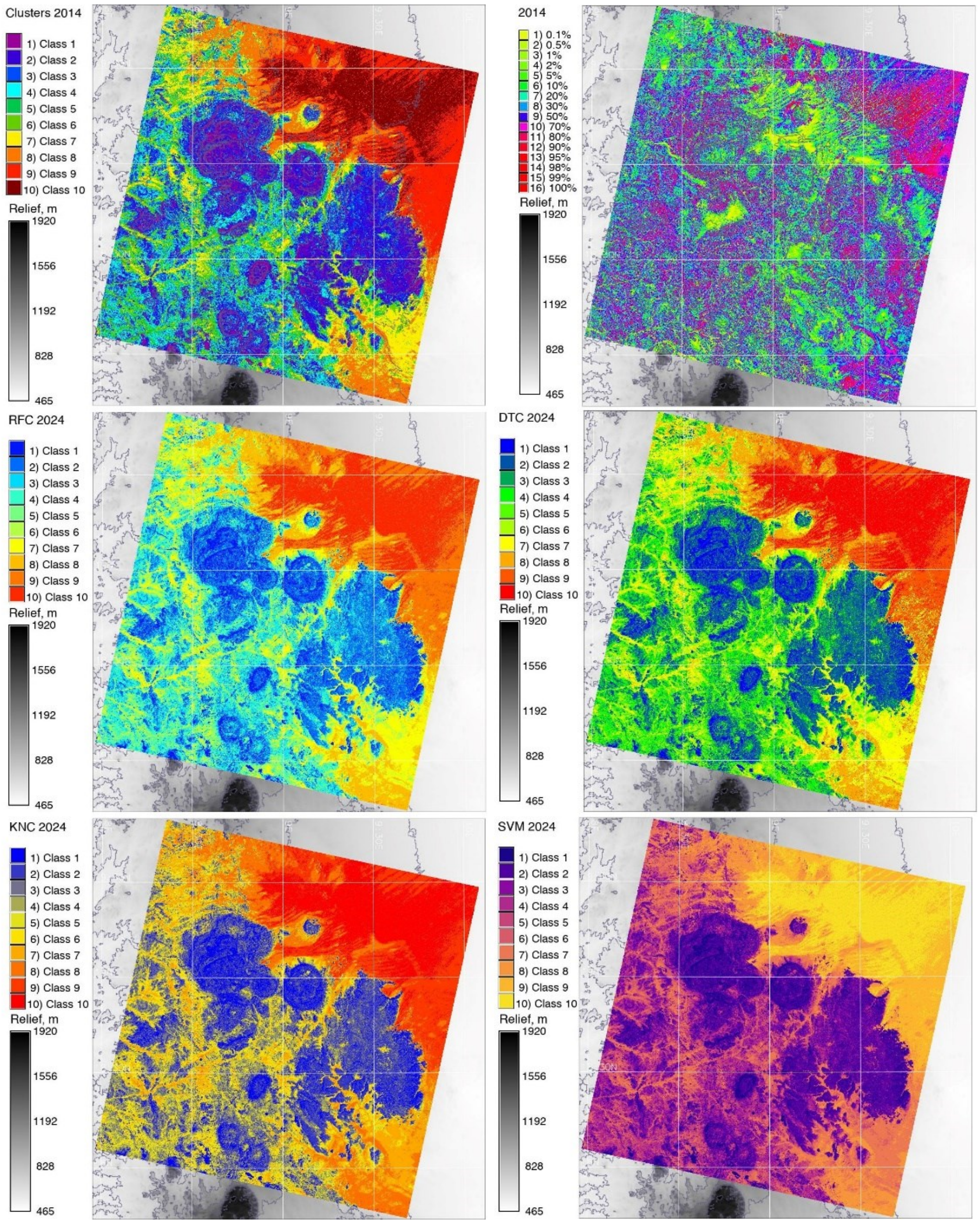

Figure 7 Results of the satellite image processing using classification and ML methods. Region – 2: mountainous area in the Aïr Massif. Software: GRASS GIS. Map source: author

Changes in land cover types in central Niger (Aïr Massif) show which patches experience more fragmentation regarding the distribution of bare rocks, desert sands and vegetated slopes of the mountains during 2014-2024 periods across the region. The difference between the maps performed using different ML algorithms can be summarized as follows. For a classification performed using Random Forest, the algorithms estimate the probability of belonging a selected pixel to specific land cover class. In contrast, the SVM algorithms evaluate the distance to the boundary of these classes with thin Landsat scene, which is then converted to the probability of class using estimation of prediction function by the 'r.learn.predict' module. Hence, for the environmental mapping, SVM generally performs better in terms of precision of pixel's assignment and class separability compared to the Random Forest which is visible for landscapes in Aïr Massif with dominating geologic structures, outcrops and contrasting lithological features, Figure 7.

Nevertheless, Random Forest works well with a mosaic of complex land cover types, such as western Niger which have a mixture of numerical and categorical features. When landscape features are on various scales, such as Djado Plateau, it also performed fine and overall demonstrated the acceptable results. Moreover, Random Forest presents a more straightforward approach to data processing, while SVM maximizes the spatial, that is, geometric, margins of the land cover classes and thus relies on the concept of geospatial distance between pixels that belong to different landscape categories. With this regard, the landscapes with higher class separability and contrasting types (e.g., deserts, vegetated slopes, sands in desert) in northern Niger profit more from the SVM rather them RF classification.

For Djado Plateau in general, the same patterns of land cover types are visible for the ten-year periods for timescales of 2014 to 2024. In Djado Plateau, patterns associated with directions of dunes and eolian conditions are clearly visible and occur in SW-NE direction, which are detected using the computer vision algorithms of GRASS GIS.

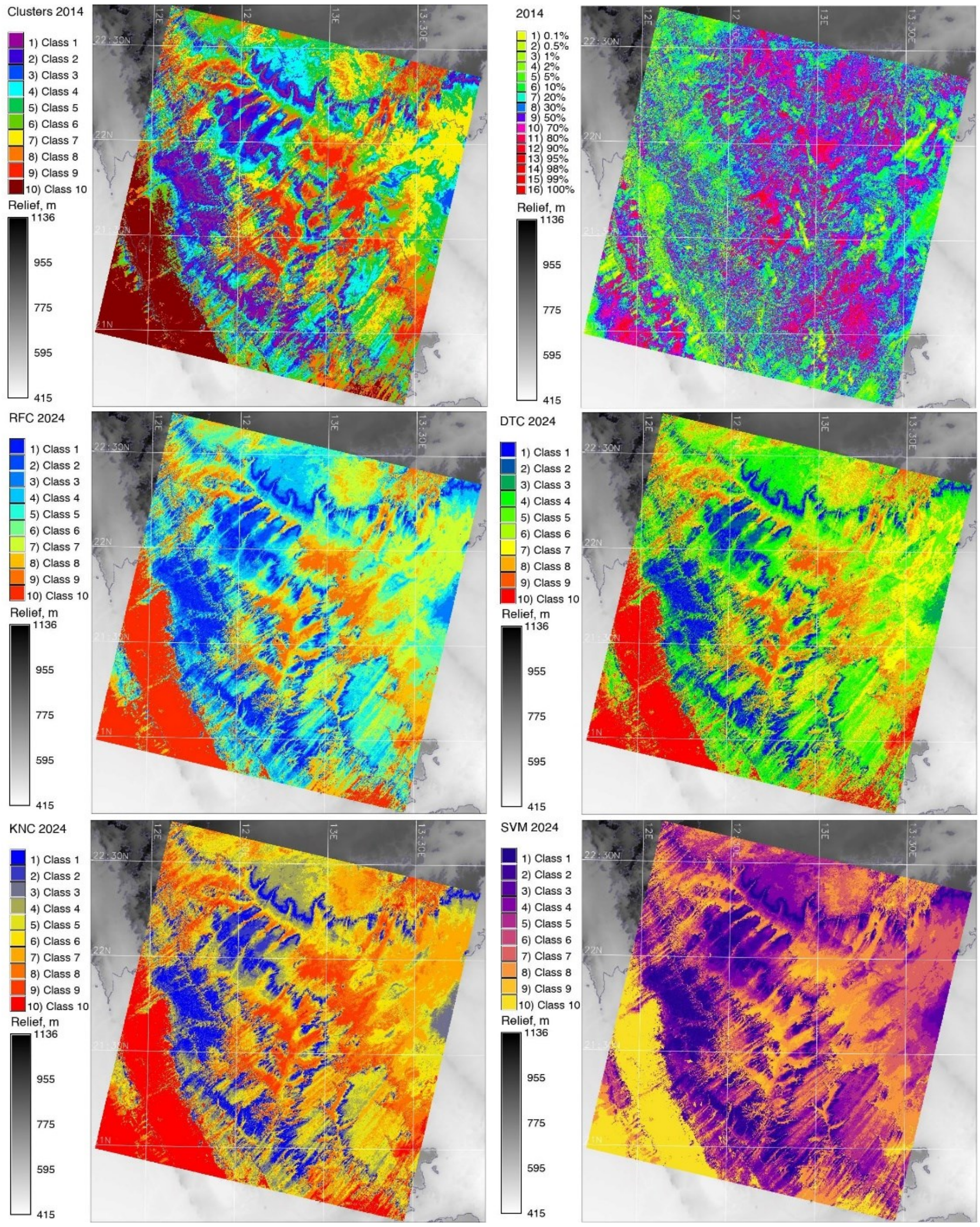

Figure 8 Results of the satellite image processing using classification and ML methods. Region – 3: hills in the Djado Plateau. Software: GRASS GIS. Map source: author

The performance of the Desicion Tree Classifier against the KNeighborsClassifier shown that the Desicion Tree Classifier evaluates the data as hierarchical tree structure where an internal node represents a feature which corresponds to the attributes of landscapes whiel the branch represents a decision rule, and each leaf node represents the outcome with the classified pixels that are assigned to each land cover category, respectively. Hence, the advantages of this algorithm consist in high logical performance and accurate categorization of cells on a raster matrix of Landsat scenes. Regional differences in the land cover patterns associated with geological conditions and detected by the Decision Tree Classifier are shown in Figure 8. As can be noted, the directions of the outcrops here are mostly consist with the stretching of the Ordovician-Cambrian (OCm) formations of central Niger.

The mapping performed using ML algorithms demonstrated superior generalizing capability in terms of image classification, and identification without explicit knowledge supported by training data. Considering the virtues of ML for RS data processing and cartography, with respect to accuracy, speed of data processing and automation, we can conclude that machine learning presents is one of the most perspectives methods for satellite image classification and applications in geoinformatics for environmental mapping. The tuned parameters used for better data processing are constrained by the options of the GRASS GIS which can be compared in terms of time consumption. Thus, there is a significant difference in time which algorithms took for image analysis with SVM being the longest in terms of performance (over 40 minutes) followed by the RF (about 10 minutes). The Decision Tree and K Neighbors Classifiers both performed quickly with completed task within a minute. Besides the technical aspect of data processing, this study also shown the advantages of satellite images for environmental mapping of heterogeneous landscapes of Africa. Namely, a set of six Landsat images is suitable for analysis of landscape patches using GRASS GIS since land cover patterns over Niger show consistency in their distribution for 2014 and 2024 with natural variations driven by climate and environmental forces.

6 CONCLUSION

Landscape dynamics involve environmental regional properties of the land cover types, such as stability and persistence towards external effects (e.g., climate – droughts or flash floods or anthropogenic forces – deforestation, land degradation), and their recovery after such impacts. Therefore, land cover changes are reflected on the space-borne imagery with a wide range of spatio-temporal scales. Such changes are visible, for instance, on time series analysis of the satellite images even for the short-time span (e.g., 10 years as in this study). Hence, shifting mosaic of landscapes towards the steady-state and keeping their resilient properties after the climate effects or human-induced actions can be detectable using a comparison of multi-temporal imagery. In this study, we compared the two scenes (2014 and 2024) for each selected region of Niger (south-west, central and northern regions) to analyze landscapes dynamics on the satellite images Landsat, as well as to evaluate technical performance of various ML algorithms in image processing using GRASS GIS scripting software. The scripting ML method of GRASS GIS is shown to be adequate for RS-based environmental analysis in Niger.

There are several possible directions for future similar research on Niger environment using satellite data. Mapping land cover patterns from higher resolution imagery, such as Sentinel or SPOT data based on time series analysis, in addition to spatial correlation of distribution of land cover types with geologic features, might be useful for geospatial analysis where correlation patterns are notable. Moreover, the methodology reported in this paper could be applied to other regions in Africa in Sahara-Sahel region, and upscaled to worldwide regions with similar arid and semi-arid environment. This is possible using another RS data and satellite imagery with a different data extent. Finally, the predictability of pixels assigned to diverse land cover classes as categories automatically discriminated by computer vision and ML approaches can be investigated further using other algorithms, e.g., Extra Trees Regressor, Gradient Boosting Classifier MLPClassifier and the like. The focus of such research extension would be on the evaluating the effects from drought patterns on the dynamics of land cover types in diverse regions of Africa.

The cartographic interpretations of the land cover type in Niger obtained from the satellite image analysis presented in this study present the qualitative evaluation of landscape dynamics in central Africa. This study contributes to the environmental monitoring of Sahara-Sahel region and presents a useful ML-based approach to RS data processing aimed at reflecting the variability of spatial patterns in Niger caused by climate effects and human activities in the three representative study areas: lowlands of the Niger River basin, mountainous area with the Aïr Mountains and the highlands of the Djado Plateau. The presented series of maps as a result of the outcome of satellite image processing might be of interest to environmental planners and policy makers in suggesting land management in Niger. Besides, actual geo-information on land surface dynamics in the diverse areas of Niger processed by advanced tools of geo spatial analysis is an essential input for sustainable development of Niger and the use of its rich geologic resources. Further, a study on time series analysis of Earth observations data such as Landsat imagery assists in understanding of the environmental and landscape dynamics of the Sahara-Sahelian region of West Africa.

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