

MACHINE LEARNING METHODS OF REMOTE SENSING DATA PROCESSING FOR MAPPING SALT PAN CRUST DYNAMICS IN SEBKHA DE NDRHAMCHA, MAURITANIA

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ABSTRACT. The advances in Machine Learning (ML) and computer technologies enabled to process satellite images using programming. Environmental applications that handle Remote Sensing (RS) data for spatial analysis use such an approach, for example, Python's library scikit-learn using algorithms on pattern identification, predictions or image classification. This paper presents an ML method of satellite image processing using Geographic Resources Analysis Support System (GRASS) Geographic Information System (GIS). The aim is to classify multispectral Landsat images using ML for identification of changes in salt pans of West Mauritania, Africa over the period 2014–2023. We define 10 classes of land cover categories and perform analysis of geological, lithological and landscape setting, and then introduce the principles, algorithms and processing of the ML methods of GRASS GIS. The following classification models were employed to implement image classification with training: Random Forest (RF), Decision Tree, Gradient Boosting and Support Vector Machine (SVM). The results were compared with clustering performed by k-means and maximum likelihood discriminant analysis. The cartographic visualisation and validation was implemented through accuracy analysis. Results for the best performing SVM model with seven-band input produced an overall accuracy of 76%, for the RF model – 73%, compared to 69% for Decision Tree Classifier – 69% and for Gradient Boosting Classifier – 67%. The SVM model embedded in GRASS GIS generates robust land cover maps with good accuracy from multispectral satellite images. The paper demonstrated an ML-based automated approach to satellite image processing, which links Artificial Intelligence (AI) with cartographic tasks.

Keywords: machine learning, Random Forest, Support Vector Machine, GRASS GIS, satellite image, remote sensing, saline lake

1. INTRODUCTION

1.1. Background

During recent decades, the landscapes of the Earth have been changing at an unprecedented rate due to the cumulative effects from climate change and human activities. Mauritania is one of the



African countries most affected by the cumulative effects of natural and anthropogenic effects on land patterns (Choplin and Dessie, 2017). Given the challenges from the environmental and climate change as well as water scarcity in arid areas of Africa, it is becoming more and more crucial to comprehend, map and monitor the sub-Saharan landscapes better for effective land management. Predictive ecosystem modelling and appropriate land management policies in arid regions of West Africa strongly depend on computational data, which support environmental modelling in the context of land cover change (Bojer et al., 2024; Lemenkova, 2024d; Pillay et al., 2021). In environmental mapping of Africa, digital mapping to analyse landscape dynamics remains an open problem despite selected existing research (Ali et al., 2024; Lemenkova, 2024b; Twumasi-Ankrah et al., 2024; Walther and Huettmann, 2021).

Mosaics of vegetation, cropland and shrubland interspersed with sandy areas have historically played significant role in the landscape mosaic of West Africa. However, from the middle of the 20th century, land cover structure in Mauritania has undergone substantial alterations, which were brought about by several triggers. The main drivers of ecosystem dynamics in Africa remain natural factors, climate change and human activities. Natural factors that cause land cover changes in Africa include a variety of processes. Some of them are geological hazards, geomorphological instability in sandy and rocky regions that cause soil degradation, climate-related issues along the coasts of Atlantic (floods, droughts, fluctuations in precipitation and temperature that affect coastal vegetation) and diversity of soil types. To understand the complexity of these factors, advanced computational modelling methods are required.

Within the scope of ecosystem research, there has been some progress towards computational modelling that mostly uses traditional methods of Geographic Information System (GIS) (Dunga et al., 2024; Ebrahim et al., 2024; Fisher-Holloway and Mokhele, 2023; Lemenkova, 2024e; Shoko and Dube, 2024). This paper presents a Machine Learning (ML) framework to direct the analysis of satellite images for detecting and mapping changes in land cover in western Mauritania with a case of saline lake. Comparing several ML methods incorporated into the workflow of Remote Sensing (RS) data processing and cartographic scripts, the changes in fluctuating saline lake were detected using classified satellite scenes.

By utilising Earth observation (EO) data, land cover change detection aims to visualise and monitor the dynamics of various patterns of the landscape as a linked human–environment system. For advanced monitoring, one of the important approaches for identification landscape dynamics in land cover types is the analysis of changes and the rate of exposure of landscapes to climate and environmental effects using multitemporal geospatial RS data. ML is widely recognised as advanced computer application for processing RS data. Besides, it has a powerful functionality as a branch of Artificial Intelligence (AI) (Cedric et al., 2022; Lemenkova, 2025a; Rathore et al., 2016; Yang et al., 2024), including application of RS data processing. The advantages of the RS data for environmental and geological mapping have been discussed in many previous works (e.g. (Ashpole and Washington, 2013; Niang, 2022; Parajuli et al., 2014)). Among the benefits of the RS data, such as satellite images (Grandjean et al., 2006), is mentioned their cost-effectiveness for geological exploration, since the RS data enable precise coverage of vast regions, such as Africa regions, with essential data for resource exploration. The need for satellite images for natural resources management gives rise to the question of their effective processing.

With the recent advances of computing and programming technologies, more and more RS data, namely satellite images, can be processed using ML (Belmahdi et al., 2023; Gómez et al., 2019; Lemenkova, 2020b). Correspondingly, new types of methods of satellite image processing

based on ML emerged recently. Land cover mapping from RS data has progressed from visual and simple statistical approaches to advanced image recognition techniques. These include algorithms developed in Python scikit-learn library and include, for instance, Artificial Neural Networks (ANNs), Random Forest (RF), Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs) and many more. Existing reports on the use of these methods prove their effectiveness in computational RS (Gawusu et al., 2024; Lemenkova, 2024c,f; Nenkam et al., 2024). The key feature and advantage of ML consists in its capability to imitate intelligent human behaviour in the algorithms of image processing and pattern recognition (Ebrahimi and Zhang, 2023; Lemenkova, 2022d; Pande et al., 2024). The ML-based approaches are typically distinguished from conventional GIS methods of image classification and processing by their advanced data handling consisting of application of neural networks for geospatial analysis.

ML methods can be applied for pattern detection and categorisation of land cover types, which could be regarded as a new technical tool of satellite image processing in cartography and geoinformatics. ML-based image processing, as in the case of environmental mapping, can be integrated into various applications of land management. For example, climate-related events such as droughts or floods may change existing landscape patterns and make the current maps of land cover types outdated. In particular, at the current stage, satellite images can be processed by ML methods for supervised classification using training data and machine logic, as pixel based (Ayoade et al., 2023; Rahman et al., 2020) or object based (Karila et al., 2023; Lemenkova, 2015, 2020a). The advantages of both approaches were discussed in details in earlier review works (Abujayyab et al., 2023; Nasiri et al., 2023).

An overview of the field demonstrates existing case studies which use independent specialised packages for image processing and classification, as well as integrated approaches supporting GIS through programming. For instance, many programming libraries and packages of well-known languages (e.g. Python or R; (Lemenkova and Debeir, 2023b) attempt to evaluate patterns on satellite images using geospatial libraries (Lemenkova, 2024a, 2025b), and some of the advanced software consider ML approaches and scripting techniques. Among these, the open-source software Geographic Resources Analysis Support System (GRASS) GIS presents effective approach (Mitasova and Neteler, 2004; Neteler et al., 2012). The available GRASS GIS tools in the ML area ('r.learn.train', 'r.learn.predict') are not implemented natively, but rather depend on such methods which implement the algorithms used in this study. Straightforwardness and robustness of algorithms embedded in GRASS GIS are two fundamental advanced features that support the progress of script-based cartographic methods and allow its development towards automation, reliability and flexibility of mapping (Lemenkova and Debeir, 2023a; Rocchini et al., 2013, 2017). Besides, recent version of this software (GRASS GIS 8.4) has been updated for functionality of satellite image processing. Extended functions now enable to reuse spectral signature files of classifiers, improved output of accuracy assessment and selected methods of ML classifiers (Nartišs and Melniks, 2023). Finally, this software supports diverse approaches of ML through different algorithms combining supervised learning.

1.2. Objectives and Motivation

In the dry areas of Mauritania, salt pan habitats have been identified as important suppliers of mineral elements. Nevertheless, salt pans are also sources of dust emissions, which have effects on the climate processes, lead to the degradation of groundwater, contribute to soil and ocean fertilisation, as well as have impacts on human and ecosystem health in coastal Mauritania. Dust type and emissivity, specifically for Sebkha de Ndrhamcha, are related to the mineralogical

and physical crust composition of soil and local geological features. Understanding seasonal fluctuations of the salt pan and their effects on regional environmental conditions is, therefore, crucial for land management in the arid climate of Mauritania. The advances in modelling salt dynamics can be used, for instance, for predicting dust emissions, which depends on the specifics of the salt pan surface and its changes over time. Knowing how exactly salt pan changes over time may be used for prediction of water scarcity and protection of plants in agricultural activities of farmers.

Hence, there is a growing demand from the environmental decision makers for modelling salt pans in the arid regions of West Africa. Nevertheless, the vast area and challenging access in many regions of Mauritania limit the potential of typical field approaches to investigate salt pan surfaces. At the same time, accurate mapping in the areas that are hard to reach presents difficulties and requires machine-based methods and RS data. These issues have been addressed by processing of RS data because of their capacity to give multitemporal observations and to cover wide areas. To process the RS data effectively, the cartographic use of ML tools presents a novel approach for automated mapping of salt pans. This is principally a new step in mapping arid regions of West Africa, which presents the main goal of this study: application of the advanced ML tools for mapping seasonal fluctuations of the salt pans in Mauritania.

Nevertheless, due to the specific spatiotemporal setting of satellite images, GIS methods are different from scripting libraries related to general programming, and there is a lack of efficient reports on applications of ML to satellite image processing. Thus, there is still a lack of efficient reports on mapping salt pans in the western region of Mauritania which evaluate changes using satellite images according to the review on related works on West Africa and coastal Mauritania. In view of this, we apply and propose a novel method of satellite image classification using GRASS GIS, using the combination of ‘`r.learn.train`’, ‘`r.learn.predict`’ and ‘`r.category`’ modules applied for RS data processing with a case of Landsat images. Instead of a single method, we tested a group of algorithms and evaluated their performance for cartographic data processing and image classification. Various algorithms of ML can be used for environmental monitoring by combining time series analysis of several satellite scenes within the GRASS GIS tools. Furthermore, it is easy to implement and maintain the scripts using the presented codes commented in the ‘Materials and methods’ section. In this way, this manuscript contributes to the future reuse and applications of the proposed methods in similar studies on satellite image processing for environmental monitoring.

This study aims at using ML techniques to study sebkha of Mauritania to test the usefulness of several ML algorithms for processing multispectral Landsat satellite data. To this end, data in the short time period (2014–2023) were applied for analysing pan surface properties of Sebkha de Ndrhamcha and its changes over time. Since no similar studies that use ML tools and RS data for mapping Sebkha de Ndrhamcha exist in modern literature, this study presents an interdisciplinary approach that uses advanced technical tools for environmental purposes

More specifically, in this paper, we present the use of the advanced ML modules for image classification using GRASS GIS (GRASS Development Team, 2022) with the case of Mauritania, West Africa. Specifically, we employ, compare and relate several functions of ML to image processing, namely RF Classifier, Decision Tree Classifier (DTC), Gradient Boosting Classifier (GBC), SVM Classifier, evaluate their performance and compare the results with the approaches of the conventional methods of image classification, such as Minimal–Maximal Discriminant Analysis and k-means clustering. The potential of the ML modules of GRASS GIS (Neteler and Mitasova, 2002) for mapping ecological patterns and processes in arid climate of Sahel is

exemplified with the case of fluctuating sebkhas of coastal Mauritania and associated landscape dynamics in the areas of salt dunes of sub-Saharan Africa.

1.3. Structure

The remainder of the paper is organised as follows. The section ‘Study Area’ gives a formal description of the study area and related geological, topographic and environmental setting illustrated by thematic maps. The section ‘Materials and Methods’ describes the data used for image processing with mentioned metadata, proposes the approaches of GRASS GIS including the comments on its ML module, their principles of RS data processing, functionalities, structure of methodology, and comments the scripts in Appendix. ‘Results and Discussion’ discusses several outcomes of image processing by examples of ML-based maps. The section ‘Conclusion’ shows the implementation of the ML methods of GRASS GIS applied for the salt lakes of Mauritania and concludes the manuscript.

2. STUDY AREA

The study area is located in the coastal region of West Mauritania, which includes the salt pan of the Sebkha de Ndrhamcha 1. Physical processes affecting the formation of sebkhas include the sedimentation in coastal, fluvial and lacustrine environments, as well as aeolian-dominated conditions (the strength and direction of winds). For instance, the Atlantic continental margin to the west of Sahara presents one of the largest dust sources on Earth and is strongly influenced by mass wasting processes (Henrich et al., 2010). Huge aeolian dune fields affect the sedimentary regime on the continental slope and surrounding sebkhas.

The prevalence of one or more of these settings favours formation of the salt pans and results in different level of their salinity (Tari et al., 2017). Thus, marine coastal sabkhas are more associated with the processes of evaporation and accumulation of marine deposits, while continental playas or inter-dune sabkhas are related to barchan formation and dune mobility (Handford, 1981; Ould Ahmedou et al., 2007). Different salinity of salt lake sediments enables to distinguish the north-west Africa hypersaline chotts with saline levels surpassing that of ocean water due to high concentrations of brines (Lemenkova, 2023a) and non-vegetated sebkhas with moderate salinity (Lemenkova, 2023b) from vegetated sebkhas with a relatively low salinity that ranges from 2 to 42 g NaCl per litre (Soulié-Märsche, 2008).

The geological setting of western Mauritania is presented by a series of Quaternary marine deposits formed in the gulfs of Senegalo–Mauritanian Tertiary–Cretaceous basin (Figure 2). During the uplift of the basin in Miocene, this area had undergone four successive transgressions and three regressions, which resulted in the accumulated continental formations covering marine deposits with sandy-glaucinitic facies and diatomite layers (Barry, 2003). Several periods of eustatic movements of the world’s oceans formed the current Quaternary shape of the coastal zone in West Mauritania, with lakes and lagoons becoming sebkhas and bays becoming lagoons during the alternating periods (Einsele et al., 1974b; Elouard and Faure, 1972).

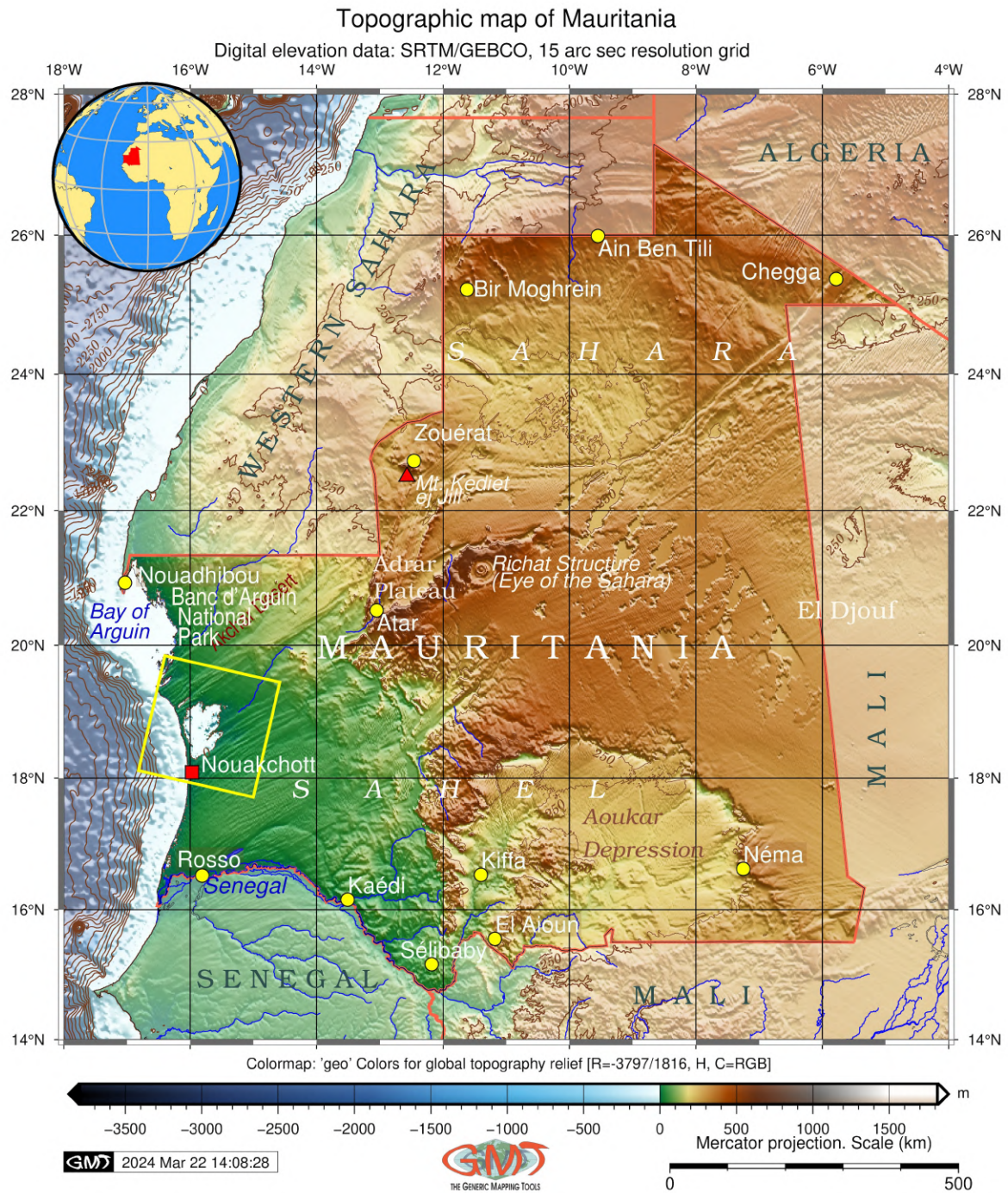


Figure 1. Topographic map of Mauritania showing the extent of the study area of the Sebkhia de Ndrhamcha salt pan (rotated yellow square). Data: General Bathymetric Chart of the Oceans (GEBCO)/Shuttle Radar Topography Mission (SRTM). Software: Generic Mapping Tools (GMT). Map source: author.

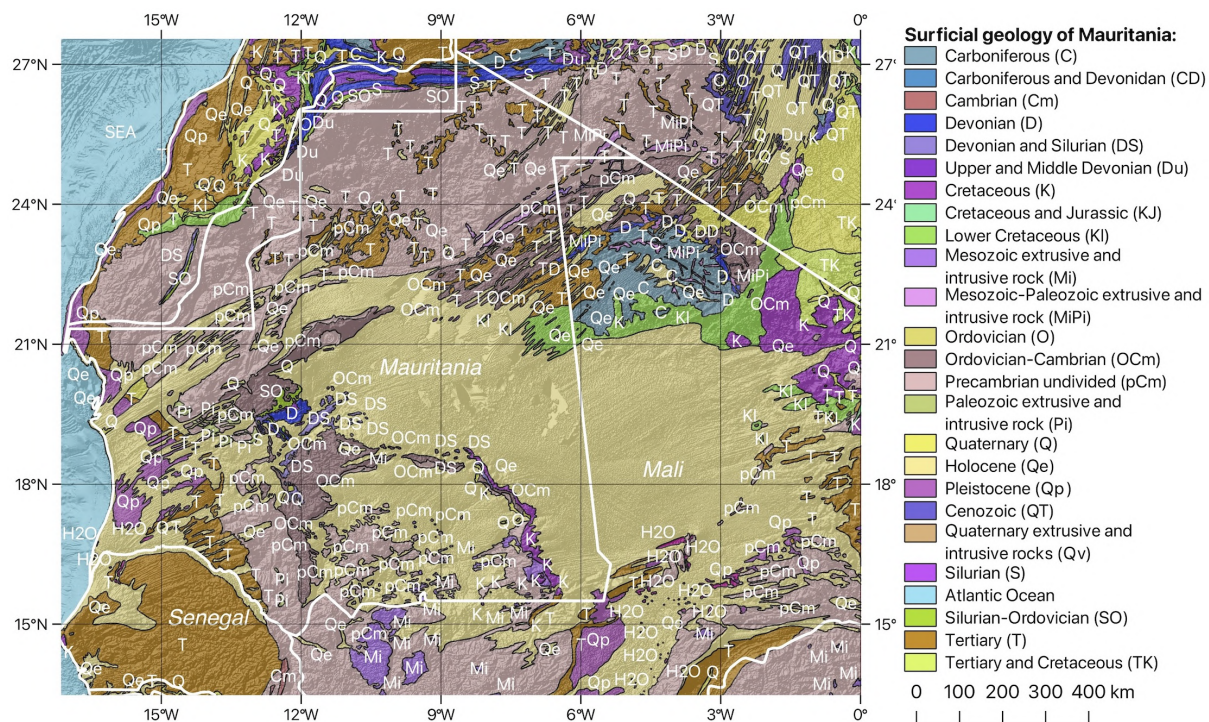


Figure 2. Surfacial geology and lithologic units of Mauritania. Data: USGS, GEBCO.
Software: QGIS. Map source: author.

Successive positive epeirogenic episodes resulted in reduced size of the marine gulfs off Nouakchott since the early Pleistocene to Holocene. The Tafariian sandstones of the Aaiun-Tarfaya Basin belong to the continental environments, such as the lacustrine and sebkha deposits formed under shallow or aerial conditions of Saharan–Sahel environments. Subsequently, the former large marine Tafariian embayment with uplifted sediments was replaced by the sparse lakes and sebkhas (Giresse et al., 2000, 1988). Currently, the mineral content of coastal sabkhas consists of a combination of terrigenous clastics, carbonate–sulphate (or gypsum) minerals, soluble salts (e.g. halites) and similar types of sediments (Kocurek et al., 1991). Such specific mineral content enables discrimination of these sediments on the satellite images using spectral reflectance of the saline minerals which differ by colours and brightness from the surrounding areas and sands. The lacustrine deposits discovered in other regions of Sahara gave rise to the notion of ‘Saharian Seas’ and current lakes as remnants of the endoreic depressions reflecting past geological processes (Lemenkova, 2023c; Plaziat, 1991).

The origin of the Mauritanian sabkhas is strongly related to the effects of climatic and geological factors. The diversity of geological setting of Mauritania geological history is characterised by the great variety of rocks and geological structures. Among them, the Reguibat Shield (500 by 2,000 km, stretching SW to NE) forms the northern part of the West African Craton and belt of Proterozoic rocks (Archean, Paleoproterozoic to Neoproterozoic ages) (Figure 3). The plate tectonic movements formed the West African Shield, which borders the Taoudeni basin (Hamoud et al., 2021). During the Holocene, in the area located on West African Shield and Ougarta Uplift (Figure 3) prevailed wet climate with repetitive marine transgressions and climatic oscillations (succession of humid/arid phases in the region of modern Nouakchott) (Einsele et al., 1974a). Such processes are now reflected in the Holocene stratigraphy and geomorphological landforms (Wissmann, 1982). This is also revealed in the palynological sequences according to stratigraphical and pollen analysis (Medus, 1987). Besides, the fluctuations in sea water

inundation resulted in continuous calcification of the evaporite deposits and marine sulphates that increased the salinity of the area (Manning-Berg et al., 2024).

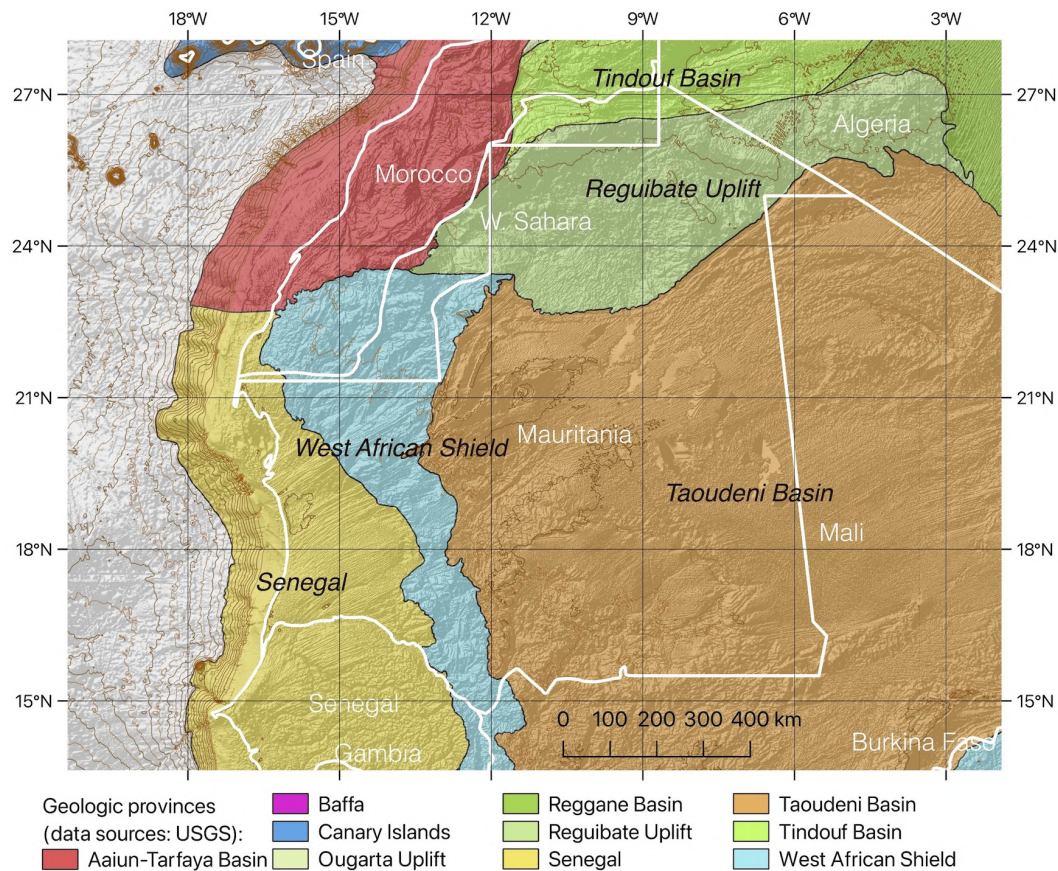


Figure 3. Geological provinces around Mauritania. Data: USGS, GEBCO.
Software: QGIS. Map source: author.

The climate factors are expressed in the temperature, evaporation and drought in the region, while physical processes determine the morphology of sebkhas and the sedimentary response to those processes. Moreover, the effects of climate-oceanological processes on the coastal habitats can be illustrated through the seasonal upwelling, which affects the coastal productivity and distribution of nutrients for aquatic habitats (Vázquez et al., 2023). Such cyclic circulation of water layers has a great ecological and socio-economic importance for the coastal region of Mauritania.

The distribution of minerals, geomorphic landforms and types of soil strongly affect the overall mosaic of habitats and land cover types; they also strongly affect the agriculture resources and crop management (Quebedeaux and Parks, 1984). For instance, in coastal areas, tidal flats and shallow waters favour the distribution of aquatic and regularly flooded vegetation (Wijnsma et al., 1999), while sandy desert regions are mostly covered by sparse herbaceous vegetation. The general map of land cover types and their distribution over Mauritania is presented in Figure 4.

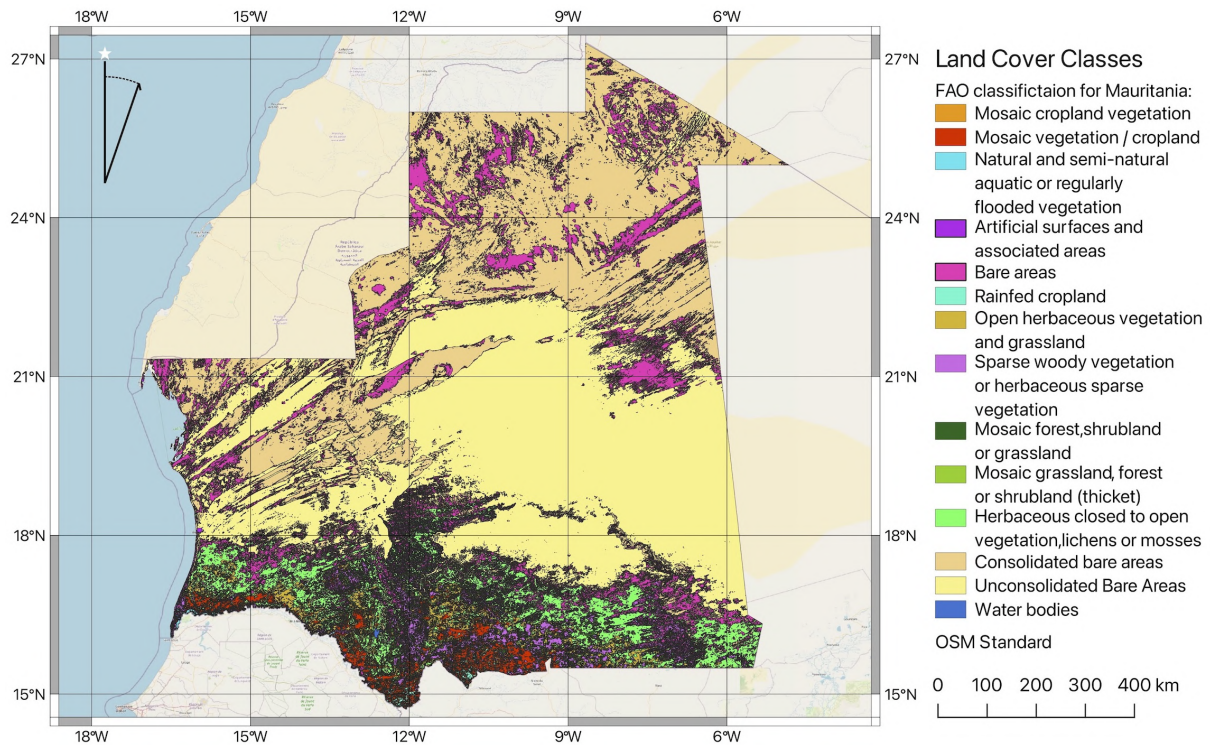


Figure 4. Land cover types in Mauritania. Data: FAO, OpenStreetMaps.
Software: QGIS. Map source: author.

Similar to other regions of Sahara with salt lakes (e.g. (Ali and Abd Ellah, 2023)), the formation of salt pans in Mauritania is related to salt tectonics and accumulation of evaporite deposits. Besides strong climatic factors, the impact of geological setting on the formation of salt pans is explained by rift geometries that are defined by horsts and tilted fault blocks and generate base-salt flat topography, which affects salt accumulation, flow direction, diapirism and deformation of overburden layers (M. Pichel et al., 2019). The distribution of salt minerals is concentrated in desert areas with highly arid climate where evaporation exceeds precipitation. Therefore, the formation of salt lakes, salt pans, chotts and sebkhas in Africa is mostly located in northern regions close to Sahara (van Asten et al., 2003; Álvaro, 2012). The crust of salt deposits and salty compacted sands creates natural resources for the country where salt is being produced for market and industrial purposes.

Current environmental problems in the region include risks of flooding in Nouakchott, which are due to a combination of both natural factors (wave actions and wind strength) (Semega, 2008) and human activities (infrastructure built along the coasts and fragility of the barrier beach) (Ould Sidi Cheikh et al., 2007; Senhoury et al., 2016). For instance, the semi-arid climate of Mauritania creates additional constraints for agricultural activities, which results in construction of large-scale irrigation schemes aimed at increasing yield and irrigation intensity (Borgia et al., 2012). Nevertheless, unsustainable crop management is a threat to ecological sustainability of coastal areas and contributes to the salinisation of soils. Lack of effective drainage system for rain and marine waters and a sewage sanitation system increases the problem of salt accumulation along the coasts of Mauritania and creates additional factors for soil salinisation around Nouakchott.

Flat topographic landforms of the Mauritanian coasts along the Atlantic Ocean, such as the extent of the Aftout Es Sahli (a geomorphological depression running parallel to the coastline) and Sebkha N'Dramcha (a salt pan continuing the Senegalese–Mauritanian sedimentary basin

to the north off Nouakchott), create additional risks for the occasional inundations and floods (Vermeer, 2010). Sea water intrusion contributes to the increase of salinity in the coastal areas and supports formation of sebkhas and accumulation of salt in the submerged landscape patches. Another notable characteristic of the Mauritanian coasts is the upwelling tidal system, which is formed by the effects of the coastal slope topography, ocean currents and winds. As a result, the coastal region of Mauritania is characterised by almost permanent upwelling with maximal intensity in boreal winter and spring (Versteegh et al., 2022).

The cumulative effects of human activities and climate processes, briefly discussed above, lead to the decline of groundwater resources in Mauritania, which is especially notable for its semi-arid areas (Mohamed et al., 2017). All these factors lead to the crucial problems of water deficits and their associated shortages in Mauritania, such as the need for water desalination and the problem of water supply (Bayod Rújula and Dia, 2010), and contribute to the formation of the salt pan Sebkhia de Ndrhamcha.

3. MATERIALS AND METHODS

The data used in this study include six satellite multispectral Landsat images by National Aeronautics and Space Administration (NASA), whose main properties are summarised in Table 1.

Table 1. Metadata of the multispectral satellite images Landsat 8-9 OLI/TIRS, used in this study, obtained from USGS ¹

Date	Spacecraft / ID	Path/ row	Entity product ID	Scene ID	Cloud/ Coverage
27/04/2014	Landsat 8	205/47	LC08.L2SP_205047_20140427_20200911_02.T1	LC82050472014117LGN01	0.00
03/04/2017	Landsat 8	205/47	LC08.L2SP_205047_20170403_20200904_02.T1	LC82050472017093LGN00	0.04
22/04/2018	Landsat 8	205/47	LC08.L2SP_205047_20180422_20201015_02.T1	LC82050472018112LGN00	0.04
11/04/2020	Landsat 8	205/47	LC08.L2SP_205047_20200411_20200822_02.T1	LC82050472020102LGN00	0.17
09/04/2022	Landsat 8	205/47	LC09.L1TP_205047_20220409_20230422_02.T1	LC92050472022099LGN01	0.00
28/04/2023	Landsat 9	205/47	LC09.L2SP_205047_20230428_20230430_02.T1	LC92050472023118LGN00	0.01

¹ The Sensor ID is common for all the scenes: Landsat Operational Land Imager and Thermal Infrared Sensor (OLI/TIRS), Collection 2 Level-2. Image courtesy of the US Geological Survey (USGS). Product DOI: [10.5066/P9OGBGM6](https://doi.org/10.5066/P9OGBGM6).

The input raster scenes were based on the six Landsat images. The imagery data of the Landsat 8-9 Operational Land Imager and Thermal Infrared Sensor (OLI/TIRS) satellites were used in this study because they offer systematic coverage of the study with minimal cloudiness. Besides, technical characteristics of the radiometric and geometric features of the scenes are suitable for environmental monitoring in short-term period (2014–2023) using pixel-based methods of image processing. Such tools are applicable in GRASS GIS which includes a wide range of automated algorithms of image classification in its libraries.

Image analysis and classification of the Landsat 8-9 OLI/TIRS satellite images using pixel-based clustering method was done by k-means and an unsupervised method, which is included in the maximum likelihood discriminant analysis classifier by GRASS GIS. Pixel-based image classification techniques, such as k-means, are becoming more and more acknowledged as a useful cartography method for RS data processing to take advantage of the vast amounts of spaceborne data. Such methods enable creating representative maps for annual or seasonal time periods to use either as input for model building or as visualisation of the environmental situation in the given period. The raw images are presented in Figure 5, which shows the scenes for April month of years 2014, 2017, 2018, 2020, 2022 and 2023.

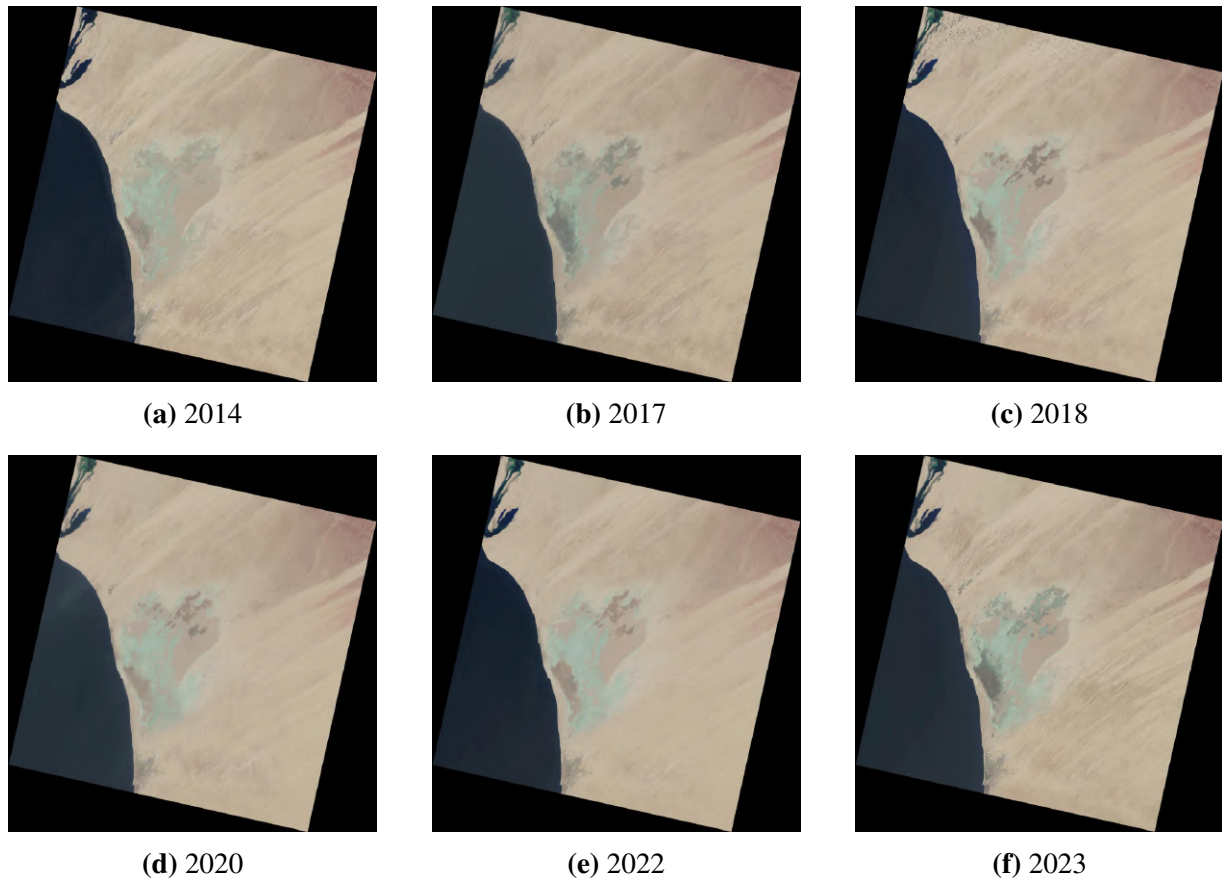


Figure 5. Landsat 8-9 satellite images covering salt pan Sebkha de Ndrhamcha in western Mauritania in natural colours showing floodplain for 6 years (always April): (a) 2014, (b) 2017, (c) 2018, (d) 2020, (e) 2022, (f) 2023. Brief explanations of the colours: black colour indicates water areas of the Atlantic ocean, light beige colour represents sandy areas, brown colour indicates desert and bare lands, dark brown colour shows wet areas, grey colour indicates artificial surfaces (roads and urban areas) and cyan colour indicates salt pans on the original images. The colours are in Red Green Blue (RGB). Data source: US Geological Survey (USGS), downloaded from the EarthExplorer repository.

The map in Figure 1 shows the topographic setting and the location of the study area. The map is made using the Generic Mapping Tools Version 6.4.0 scripting toolset (Wessel et al., 2019). The programming scripts used for cartographic techniques are described in earlier works (e.g. Lemenkova (2022a,b,c)).

The images were processed using the scripts provided in Appendix. First, the data were imported into the GRASS GIS environment and preprocessed using the script provided in Listing 1. Then, the images were classified using unsupervised clustering methods with k-means algorithms. The GRASS GIS script used for unsupervised classification is provided in Listing 2. The results of this classification were used as training polygons for ML methods, providing the ‘seed’ information for supervised learning. The next step included the application of RF Classifier for image classification. The programming code for this is provided in Listing 3. The following step included the use of the DTC for image classification, with the script demonstrated in Listing 4. The algorithms of GBC for image classification were performed using the programming code shown in Listing 5.

Finally, the algorithm of SVM Classifier was applied for supervised image classification using the script in Listing 6. The performance of the algorithms demonstrated different time consumption

and machine resources. Therefore, to note the difference in speed and the time required for execution, we summarise the performance of the methods in Table 2. The quickest algorithm was the DTC, while the longest period of data processing was demonstrated by the SVM Classifier. The data were processed using the MacOS 14.2.1 (23C71), Apple M1 Chip Processor.

Table 2. Processing time of the satellite images Landsat-8 OLI/TIRS showing the effectiveness of ML methods executed by GRASS GIS

Method	Processing time
Clustering	< 1 min
Min-max discriminant analysis	ca. 25 sec
Random Forest Classifier	9 min
Decision Tree Classifier	ca. 34 sec
Gradient Boosting Classifier	23 min
Support Vector Machine Classifier	47 min

4. RESULTS AND DISCUSSION

Environmental and hydrological planning in arid regions of Africa is essential and is largely based on using geoinformation such as satellite images. Due to their severe climate and vast spatial regions, salt pans are extremely dynamic natural features of Mauritania that are challenging to investigate using in situ approaches. This study employs spaceborne multitemporal (2014–2023) multispectral Landsat data combined with thematic on topography and geology of Mauritania to document the spatial distribution of surface crust types over time in the western part of the country: region of Sebkha de Ndrhamcha. For this purpose, six satellite images were collected from the US Geological Survey (USGS) and analysed for spectral differences covering the period 2014–2023, which reflects different seasons and surface conditions of the salt pan. The data regarding the mineralogical and geological setting were analysed using the thematic maps (Figures 2 and 3) as well as distribution of land cover types according to Food and Agriculture Organization (FAO) (Figure 4).

An approach based on the GRASS GIS tools was developed to perform the spatiotemporal analysis of the salt pan crust dynamics in a dense time series consisting of six Landsat 8-9 OLI/TIRS cloud-free scenes between 2014 and 2023, covering major wet–dry cycles in Mauritania. With regard to this, the current paper contributed to mapping of the hydrologically vulnerable areas of Mauritanian coasts through detecting the fluctuating area of sebkhas and crust salt pan. Changes in the land cover types detected and visualised by GRASS GIS are generated from the Landsat 8-9 dataset and shown in the corresponding figures (Figures 6–11 according to the applied methods of unsupervised and supervised classification. RS data were used since they provide reliable source of information to clarify environmental dynamics of salt pans. In addition, they support further investigations on crucial limits on the sedimentological, mineralogical and hydrological history of the salt pans.

The land categories for years 2014–2013 and their statistics are presented in Table 3. Here, land cover classes are designated as the following categories: 1) Water bodies, 2) Shelf and coastal plains, 3) Sebkha, 4) Urban areas, 5) Sahelian grassland, 6) Salty sands, 7) Compact soil, 8) Stony desert and yellow dunes, 9) Sandy desert and white dunes and 10) Bare soil and rocks.

Table 3. Estimated classes of land cover types in western Mauritania, Sebkhha de Ndrhamcha, for April. Map units in measurements: 30 m resolution for each pixel on the multispectral scene of Landsat 8-9 OLI/TIRS.

Year	Classes of land cover types in western Mauritania, Sebkhha de Ndrhamcha									
	1	2	3	4	5	6	7	8	9	10
2014	1410	4	30	79	202	708	1239	1581	1493	178
2017	1386	43	70	141	215	668	1056	1742	1548	144
2018	1384	21	78	110	182	598	1195	1975	1353	117
2020	1395	2	28	145	228	582	881	2502	1231	20
2022	1443	2	20	116	197	532	970	2567	1146	40
2023	1468	31	53	136	253	538	1153	1622	1577	206

The results of the satellite image processing are presented in the maps shown in Figures 6–11 in the following subsections. The results of the ML-based classification for Sebkhha de Ndrhamcha region are shown in the corresponding figures for each method applied (Clustering, RF Classifier, DTC, GBC and SVM), and numerical computation of the area occupied by each land category is summarised in Table 3. The accuracy assessment of the classification model is evaluated using statistical algorithms for computation of the overall accuracy, User’s and Producer’s accuracy and Kappa coefficient. The results are reported in Table 4.

Here, the accuracy is evaluated as the total number of correctly classified pixels on the Landsat scenes divided by the total number of pixels on this image using User’s accuracy and Producer’s accuracy followed by Cohen’s Kappa computation. Hence, the User’s accuracy is defined as the proportion of pixels classified to a specific land cover type among all the evaluated pixels that really belong to that land cover type. The evaluation was performed against the ground truth data referred to the FAO classification and includes the computed false negatives. Table 4 summarises and compares computed parameters of accuracy and Cohen’s Kappa coefficient.

The interpretation of the Cohen’s Kappa statistics is as follows. The highest possible value of 1.0 indicates the perfect precision and accurate classification of variables, while the lowest theoretically possible value of near zero indicates the lowest precision. For both User’s accuracy and Producer’s accuracy, higher values normally mean better results of the classification of the satellite images. Based on the computed values of Cohen’s Kappa coefficient and the accuracy method for the evaluation of classified data, the results suggest that the SVM and RF algorithms are rated as the most reliable approaches due to the high values.

Table 4. Accuracy assessment for ML models in GRASS GIS: 1) Random Forest (RF); 2) Support Vector Machine (SVM); 3) Decision Tree Classifier (DTC); 4) Gradient Boosting Classifier (GBC). Estimated classes of land cover types for 2014–2023 in West Mauritania.

Year	Producer’s accuracy, %				User’s accuracy, %				Kappa statistics			
	RF	SVM	DTC	GBC	RF	SVM	DTC	GBC	RF	SVM	DTC	GBC
Land Cover Class 1: Water bodies												
2014	77	83	74	71	78	88	62	62	0.80	0.74	0.65	0.65
2017	78	84	72	70	77	85	65	67	0.81	0.93	0.53	0.59
2018	76	79	75	69	71	79	66	68	1.00	0.90	0.69	0.61
2020	81	81	73	72	89	89	68	72	0.93	0.95	0.58	0.61

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Table 4 – continued from previous page

Year	Producer's accuracy, %				User's accuracy, %				Kappa statistics			
	RF	SVM	DTC	GBC	RF	SVM	DTC	GBC	RF	SVM	DTC	GBC
2022	82	80	65	73	82	73	75	74	0.95	0.70	0.84	1.00
2023	79	82	66	68	77	74	74	70	0.74	0.79	0.83	0.67
Land Cover Class 2: Shelf and coastal plains												
2014	89	78	72	67	100	98	56	76	0.82	0.91	0.67	0.69
2017	95	91	68	72	92	65	64	65	0.73	1.00	0.56	0.74
2018	100	92	87	91	87	77	63	68	0.78	0.94	0.88	0.68
2020	88	100	86	65	89	87	69	62	0.89	0.84	0.83	0.85
2022	100	95	96	59	78	77	58	59	0.91	0.78	0.72	0.73
2023	84	83	75	71	73	75	74	72	0.92	0.75	0.75	0.56
Land Cover Class 3: Sebkha												
2014	95	78	67	74	92	90	66	67	0.88	0.74	0.68	0.72
2017	85	93	88	72	78	87	69	81	0.78	0.81	0.55	0.56
2018	88	89	63	64	77	94	71	69	0.91	0.88	0.71	0.54
2020	94	75	64	69	93	85	72	65	1.00	0.64	0.75	0.78
2022	73	92	64	81	73	95	59	71	0.84	1.00	0.73	0.78
2023	69	68	76	83	67	89	73	72	0.91	0.90	0.74	0.84
Land Cover Class 4: Urban areas												
2014	87	78	64	68	88	86	67	66	1.00	0.85	0.76	0.81
2017	94	79	69	64	92	75	61	72	0.95	1.00	0.82	0.73
2018	74	91	74	72	91	79	72	74	0.85	0.87	0.75	0.80
2020	69	80	65	76	84	64	68	68	1.00	0.79	0.81	0.69
2022	71	66	83	81	74	62	54	65	0.92	1.00	0.65	0.75
2023	83	65	72	83	79	75	59	71	0.87	0.72	0.69	0.73
Land Cover Class 5: Sahelian grassland												
2014	87	81	65	67	82	90	83	81	0.93	0.74	0.95	0.91
2017	64	65	71	68	76	79	74	78	0.78	0.68	0.76	0.58
2018	78	72	73	57	79	91	68	63	1.00	0.83	0.73	0.79
2020	74	79	72	71	67	77	64	68	0.91	0.65	0.88	0.63
2022	88	82	71	82	81	80	72	69	0.53	1.00	0.54	0.77
2023	91	75	65	64	91	82	71	90	1.00	0.91	0.67	0.82
Land Cover Class 6: Salty sands												
2014	88	72	67	63	91	79	68	67	0.98	0.73	0.73	0.78
2017	72	79	72	76	82	74	65	78	1.00	0.75	0.81	0.75
2018	91	90	64	78	90	78	71	81	1.00	0.81	0.76	0.69
2020	89	85	69	74	85	81	78	82	0.81	0.86	0.88	0.65
2022	90	84	56	71	78	90	64	89	0.84	0.91	0.72	0.67
2023	77	71	68	80	74	72	73	75	0.78	1.00	0.63	0.68
Land Cover Class 7: Compact soil												
2014	89	78	67	63	89	81	69	63	0.88	0.73	0.65	0.61
2017	73	77	63	69	73	72	73	71	1.00	0.61	0.69	0.83
2018	78	69	72	65	85	85	74	70	0.85	0.68	0.81	0.95
2020	88	81	79	71	69	74	65	65	0.97	0.74	0.85	0.74
2022	91	90	80	75	70	78	69	69	0.83	1.00	0.72	0.61
2023	74	75	71	61	66	64	81	74	0.74	0.92	0.78	0.89

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Table 4 – continued from previous page

Year	Producer's accuracy, %				User's accuracy, %				Kappa statistics			
	RF	SVM	DTC	GBC	RF	SVM	DTC	GBC	RF	SVM	DTC	GBC
Land Cover Class 8: Stony desert and yellow dunes												
2014	85	83	75	67	89	73	68	74	0.84	0.81	0.71	0.86
2017	78	88	78	69	93	84	69	82	0.75	1.00	0.82	0.92
2018	89	81	74	78	78	86	89	76	1.00	0.63	0.70	0.84
2020	92	79	91	71	95	72	81	81	0.72	0.79	0.62	0.70
2022	91	84	73	74	81	89	90	89	0.68	0.71	0.59	0.69
2023	84	75	75	73	73	90	83	73	0.66	0.65	0.60	0.76
Land Cover Class 9: Sandy desert and white dunes												
2014	92	81	67	65	81	82	65	71	0.77	0.82	0.77	0.71
2017	83	89	72	81	84	78	78	78	0.81	0.73	0.81	0.55
2018	93	70	68	72	95	73	71	73	0.64	0.67	0.80	1.00
2020	78	93	80	68	88	89	83	67	1.00	0.54	0.68	0.75
2022	77	94	71	73	89	71	69	81	0.98	0.91	0.72	0.67
2023	74	85	81	79	73	69	62	66	0.90	1.00	0.74	0.79
Land Cover Class 10: Bare soil and rocks												
2014	91	83	68	78	84	83	78	74	0.87	1.00	0.73	0.69
2017	89	82	63	72	83	78	73	75	0.81	0.74	0.77	0.57
2018	88	75	65	77	79	69	69	81	1.00	0.73	0.81	0.61
2020	79	69	73	64	74	71	74	67	0.74	0.69	0.80	0.74
2022	82	91	79	69	75	73	81	83	0.63	0.81	1.00	0.83
2023	77	80	75	71	82	95	83	74	0.84	0.68	0.65	0.80

The Producer's accuracy indicates the proportion of pixels that are correctly classified and belong to a target land cover type. The Cohen's Kappa coefficient measures the difference between the actual reference between the data based on the overall accuracy and the actual results of the land cover classification. In other words, it shows the actual changes between the referenced data and a randomly selected pixel classified using a given method. As other correlation statistics, the Kappa values can range from -1 to $+1$. The interpretation of values is as follows. Values of the levels above 60%–80% have a moderate accuracy of pixel's classification, while those above 80% are acceptable and generally demonstrate accurate identification of target class.

Consequently, the values approaching above 90% and nearly 100% indicate almost perfect classification results. Thus, the SVM and RF techniques can be evaluated as robust approaches of GRASS GIS for RS data classification based on accuracy, followed by the DTC and GBC methods. The overall classification accuracy is above 80% with a corresponding overall Kappa coefficient above 0.85 (Table 4). Such results demonstrate robust conceptual agreement of the processed data with ground truth. This indicates that GRASS GIS has a reliable algorithm of RS data processing that can be used in similar works.

4.1. Clustering

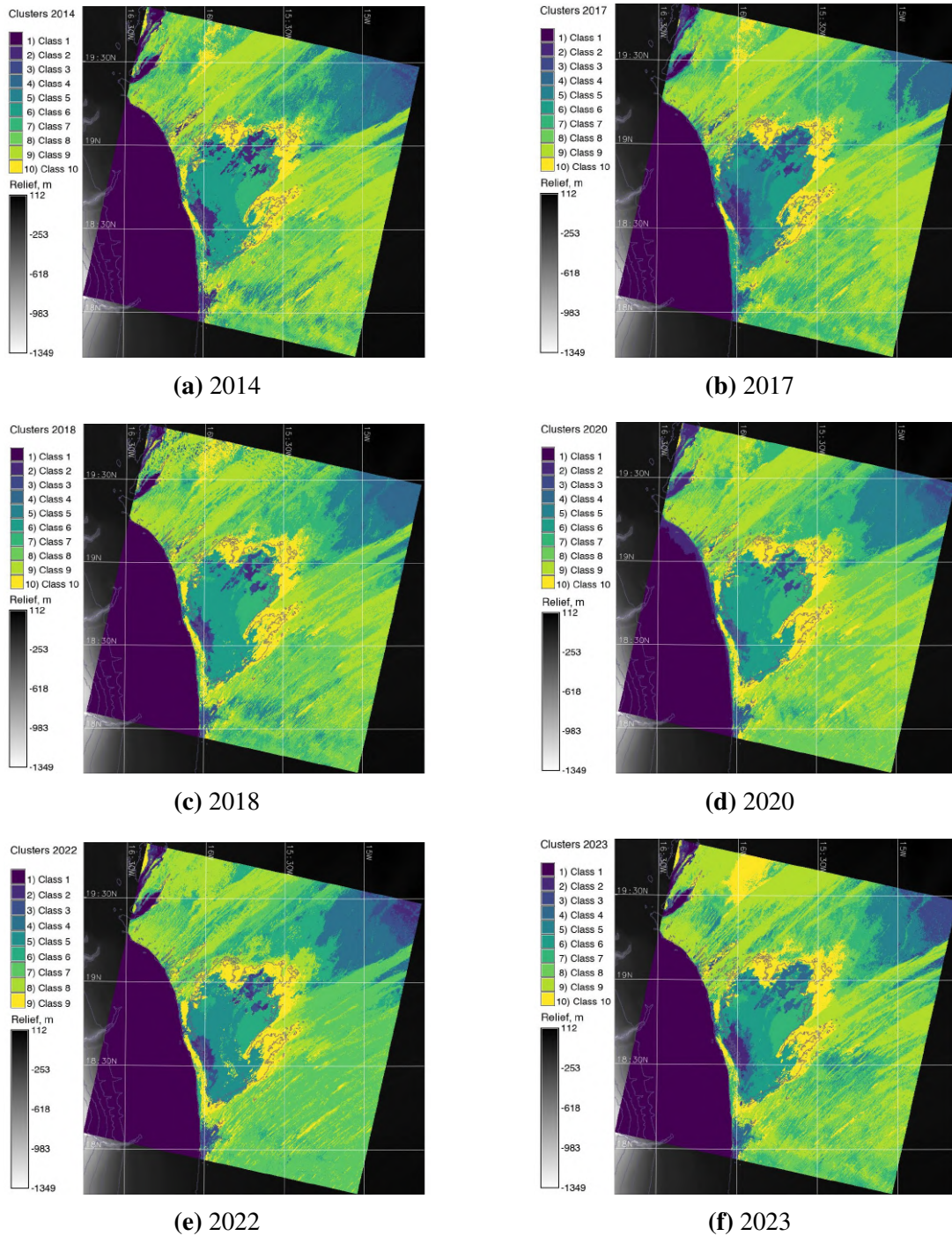


Figure 6. Classified Landsat 8-9 OLI/TIRS images using clustering: (a) 2014, (b) 2017, (c) 2018, (d) 2020, (e) 2022, (f) 2023. Software: GRASS GIS. Source of maps: author.

The accuracy assessment performed using the estimated rejection probability is shown in Figure 7. It shows the correctness of the pixels associated with each land cover class according to the clustering method of k-means used in GRASS GIS. The map of land cover types for 2014 had an overall kappa statistic of 0.97 and an overall accuracy of 98.34%, which indicated the correctly classified pixels with stable points. The classification for 2017 had an overall accuracy of 98.08%, 98.29% for the year 2018, 98.36% for 2020, 98.64% for 2022 and 98.56% of the computed overall accuracy for the year 2023.

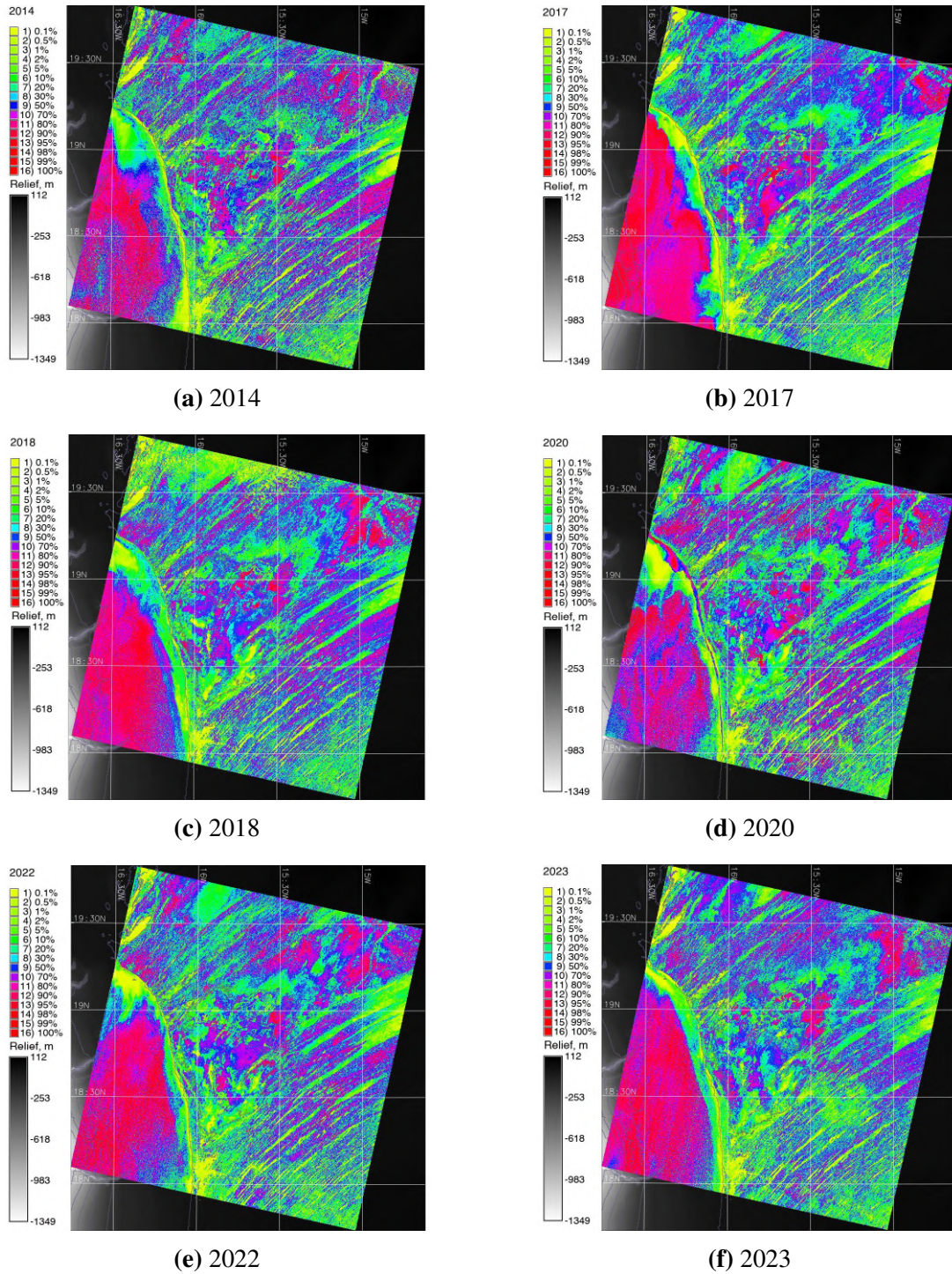


Figure 7. Maps of rejection threshold probability for accuracy analysis of image classification by chi-squared test: (a) 2014, (b) 2017, (c) 2018, (d) 2020, (e) 2022, (f) 2023.

Software: GRASS GIS. Source of maps: author.

4.2. RF Classifier

The results of RF classification applied for mapping sebkhas are shown in Figure 8. The following 10 land cover classes were identified and visualised (Figure 6): 1) Water bodies; 2) Shelf and coastal plains; 3) Sebkhia; 4) Urban areas; 5) Sahelian grassland; 6) Salty sands; 7) Compact soil; 8) Stony desert and yellow dunes; 9) Sandy desert and white dunes and 10) Bare soil and rocks.

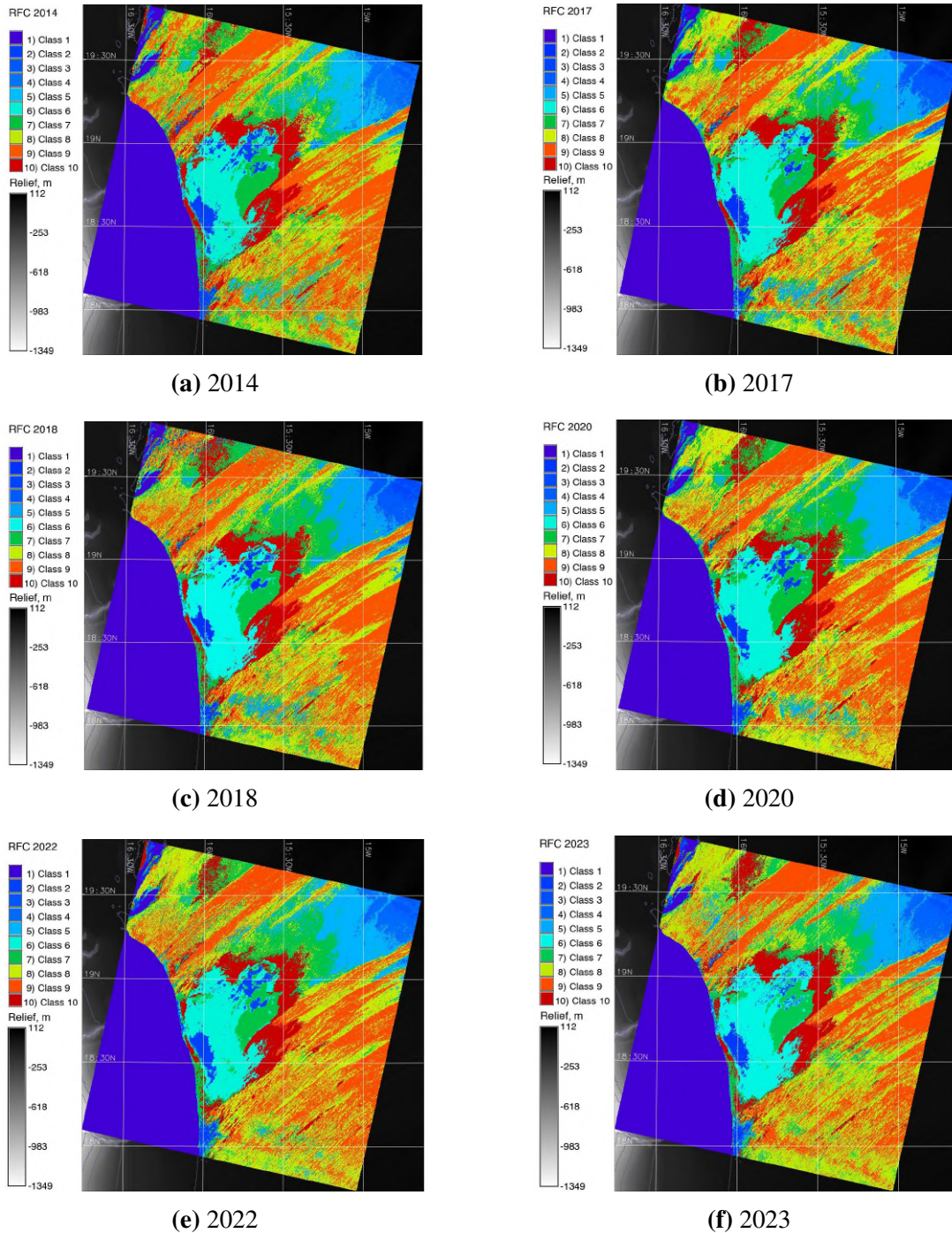


Figure 8. Random Forest Classifier of Machine Learning (ML) classification methods applied for processing of satellite images: (a) 2014, (b) 2017, (c) 2018, (d) 2020, (e) 2022, (f) 2023. Software: GRASS GIS. Source of maps: author.

4.3. Decision Tree Classifier

Based on the presented results, the largest category was barren land subdivided into different classes (Salty sands, Compact soil, Stony desert and yellow dunes, Sandy desert and white dunes), followed by vegetation class (Sahelian grassland) and salt pan (Class 2 of sebkha). The other land use categories included water surfaces, built-up urban areas and agricultural lands. Using the maps demonstrated on the series of images processed by Decision Tree classification, the distinct land cover classes are visualised for the study area, including the location of sebkhas and its changing extent over the years (Figure 9).

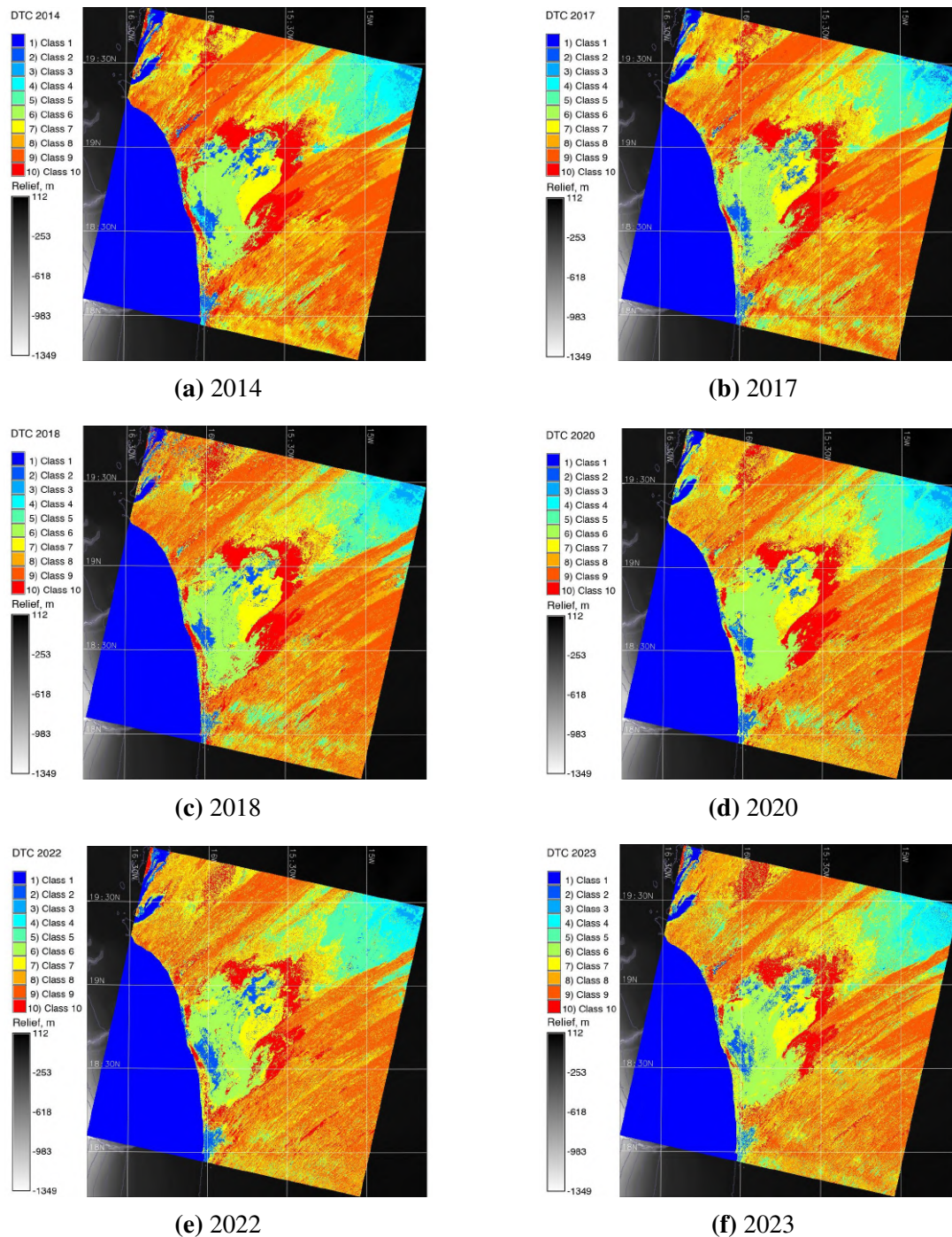


Figure 9. Decision Tree Classifier of Machine Learning (ML) classification methods applied for processing of satellite images: (a) 2014, (b) 2017, (c) 2018, (d) 2020, (e) 2022, (f) 2023. Software: GRASS GIS. Source of maps: author.

4.4. Gradient Boosting Classifier

The areas of diverse land cover types detected using Gradient Boosting (GB) classification method and their changes over the evaluated periods are presented in Figure 10. According to the analysis on satellite images processed by GB, the largest extent of wetlands was reached in 2017 and it reduced in consecutive years (2018–2022), after which the extent recovered in 2023 (Figure 10).

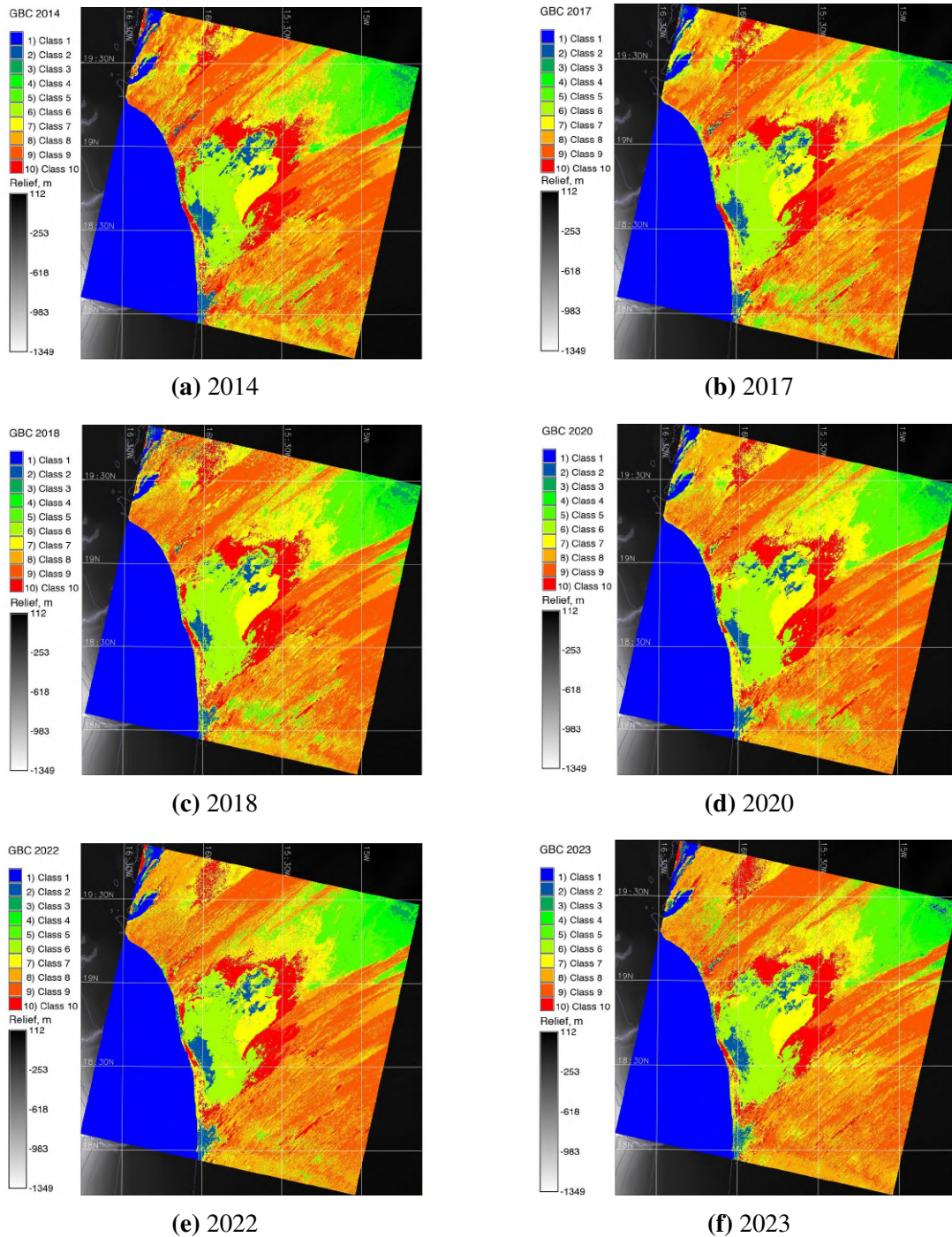


Figure 10. Gradient Boosting Classifier of Machine Learning (ML) classification methods applied for processing of satellite images: (a) 2014, (b) 2017, (c) 2018, (d) 2020, (e) 2022, (f) 2023. Software: GRASS GIS. Source of maps: author.

4.5. SVM Classifier

The SVM method of ML approach of GRASS GIS enabled to reveal hidden information on land cover types and changes in landscape patterns in West Mauritania through processed satellite Landsat images (Figure 11).

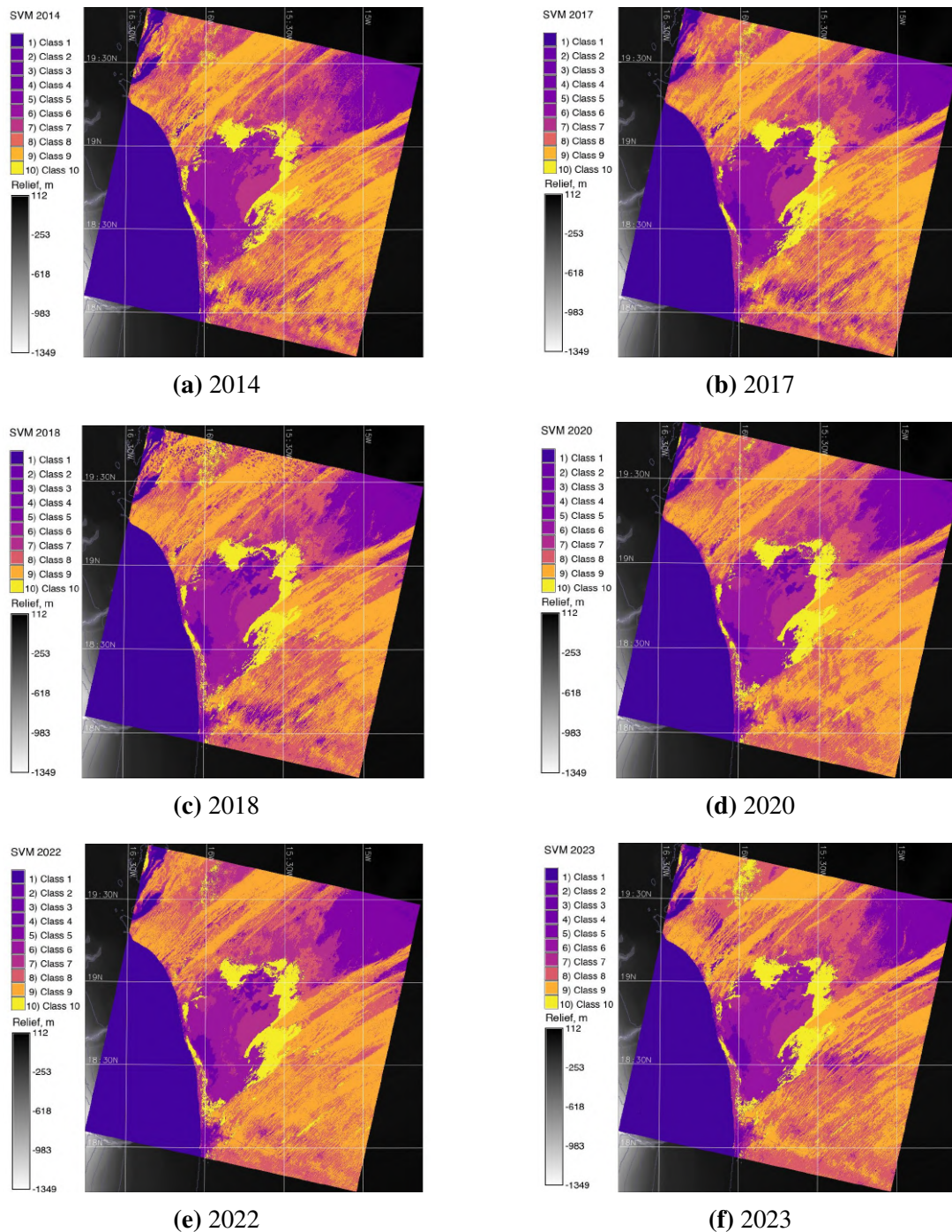


Figure 11. Support Vector Machine (SVM) Classifier of Machine Learning (ML) classification methods applied for processing of satellite images: (a) 2014, (b) 2017, (c) 2018, (d) 2020, (e) 2022, (f) 2023. Software: GRASS GIS. Source of maps: author.

The results revealed that the largest land cover class was Class 8 (Stony desert and yellow dunes) according to the extent of the satellite images, followed by Class 7 (Compact soil and barren land) in the desert areas, which represent the dunes of the Sahara. It was then followed by water surfaces (Class 1), which occupy shelf areas, Class 7 (Compact soil of the pre-Sahara lands) and Class 6 (Salty sands located in the saline soils). The distribution of other land cover types is summarised in Table 3. The smallest class is occupied by Class 2, which is represented by the narrow shelf strip of the coastal plains with specific aquatic vegetation between the water area and coastal regions.

It is worth comparing the classifier algorithms used in this study—RF Classifier, DTC, GBC and SVM Classifier—with CNNs, which provides the following remarks. In contrast to the ML methods, Deep Learning (DL) approaches have also increasingly been applied to the tasks of spatial data processing, including image classification or segmentation. Among them, the CNN method has distinct methodological framework. Thus, in contrast to RF or SVM, CNN consists of a sequence of three layers: convolution, non-linearity and pooling.

Repeated iteratively several times as gradient descent, this operation is followed by a step to determine the land cover class with the highest probability using the final fully connected layer. In this way, CNN discovers the most discriminative features in a satellite image and evaluates the context of the surrounding landscapes using weights of the Neural Network (NN) learnt through previous iterative stochastic algorithm. Hence, in comparison to SVM, CNN is distinct of being non-parametric and able to handle large volumes of data with low risk of overfitting. Such properties of CNN are useful for big data processing, for example, large series of images. Besides, CNN is generally quick and easy to configure using programming tools.

The ML used for image classification in this study demonstrated robust results for diverse tasks of image processing. Some of them are land cover classification, recognition of buildings and geometric objects on the images and classification of diverse land surface types to evaluate environmental dynamics. For instance, the thematic maps can be used for visualising the landscapes affected by tsunami or floods, which can be detected using times series of images before and after the catastrophic events. Besides, the ML approaches work well in object detection tasks. As demonstrated in this study, the accuracy of the land cover classifications using ML methods demonstrated the highest results for RF and SVMs, which reflects the ability of these methods to exploit, through embedded algorithms, spatial and textural features on the processed images. Moreover, these methods enable extracting spectral information from the spatial patterns on the satellite imagery. The ability of ML methods to process this information suggests their application in similar studies that use moderate to resolution imagery for environmental monitoring and mapping.

5. CONCLUSIONS

This paper showed the application of GRASS GIS modules of ML for satellite image processing. Practical use of the presented maps consists in the support to make use of geoinformation, adjust it for land monitoring and discover the climate factors which cause landscape dynamics in the coastal regions of Africa. Using the algorithms of image processing from statistical and programming libraries, the changed landscape patterns were detected and the cartographic visualisation was adjusted from a computer vision perspective using several ML-based algorithms, which are RF Classifier, DTC, GBC and SVM Classifier. The traditional unsupervised methods of classification were compared with the ML-based methods. While clustering demonstrated difficulties in correct detection of land parcels using spectral reflectance, the ML-based supervised techniques of trained learning, as a complement, detected, identified and recorded such information using computer vision algorithms in an automated manner. The outcomes can also be employed to enhance or control the quality of current land cover maps in Mauritania.

To cope with the problem of soil salinisation in the drought-prone region of arid Africa, such as coastal Mauritania, EO data are needed as effective data source for comparison and visualisation of changes and dynamics of salt crust. However, the use of the traditional methods of RS data processing is time-consuming and might be prone to misclassification. In contrast, ML methods applied to EO data processing ensure automated and effective way to visualise, classify and

numerically estimate changes in land cover types using algorithms of statistical data processing and computer vision. With regard to this, this manuscript contributes to the development of such methods in West Africa.

This study presents the ML-based cartographic analysis of changes in land cover changes in the coastal region of southwestern Mauritania, including the salt pan of Sebkha de Ndrhamcha, to visualise dynamics in salt crust and surrounding landscapes. The data and methods were selected to achieve this goal according to the cartographic techniques of satellite image processing. Hence, the data used for evaluation included satellite Landsat images obtained from USGS as the RS dataset from 2014 to 2023. The methods used for evaluation and cartographic work included unsupervised and supervised classification used for comparison between traditional and ML GIS techniques of GRASS GIS. The results indicated that there was a change in land cover types. The changes between the class occupied by compact soil and bare soil and rocks correlate well with those in sandy desert and dunes. This is especially notable for the years 2020 and 2022, which shows regional climate impacts with the effects of winds and aeolian processes that increase the areas of dunes and sandy areas and decrease bare soils, accordingly. Likewise, the decrease of shelf and coastal plains is visible for the same period, which might be related to the active upwelling processes in this time.

In general, the coastal region of southwestern Mauritania, along Sebkha de Ndrhamcha, has experienced considerable changes in land cover classes over the past decade (2014–2023), throughout the area of categories, including their fragmentation and extent. However, changes have been significant in the central part of the salt pan, which also supports the main fluctuations of saline crust and salinisation of soils in the surroundings. Thus, the results of this study revealed that over the past 10-year period, salinisation of the sandy areas around salt pan increased, whereas the barren lands decreased in the study area and were replaced by the salty sands and dunes of desert. The details of land cover changes are shown in corresponding figures made with various techniques of ML algorithms using GRASS GIS. The overall results of the study highlighted that GRASS GIS techniques of ML are highly effective for satellite image processing as advanced and straightforward methods of supervised image classification.

The satellite-based evaluation of landscape in western Mauritania is focused on the Sahara–Sahel transition zone of arid and semi-arid climate. Scarce water resources and fluctuation of salt lakes and sebkha motivate the need for mapping of water availability and distribution of salt pans. Changes in land cover classes including fluctuations in salinisation were revealed using ML methods of satellite image processing using GRASS GIS. Practical application of this work consists in land management since visualisation of the extents of wetlands and water bodies enables to plan potential drainage networks based on the hydrological connections, as well as evaluate spatial location of aquatic habitats Campos et al. (2012). Hence, new created maps demonstrated changes in distribution of sebkhas and can assist land planners and environmentalists specialised on Mauritania.

The limited scope of this study was focused on the preselected tools with the available libraries of GRASS GIS, which present an interface to the scikit-learn library of Python. Therefore, future similar research can be proposed with the focus on further development of spatiotemporal analysis using GRASS GIS. For example, the use of GRASS GIS with the available ML tools may be extended towards its more sophisticated tools for spatiotemporal analysis (t.* commands). The quality control and enhancement of current land cover products in Mauritania could be achieved through land cover maps produced using such ML techniques. Furthermore, we also recommend the use of other satellite products such as Sentinel-2. The application of RS data with

high resolution would be useful for broad-scale land cover mapping in West Africa over selected time periods. The Sentinel-2 data can be achieved based on Copernicus open-access repository. Finally, future work is suggested to produce and evaluate the effectiveness of a satellite time series of broad scale covering Mauritania for annual land cover mapping. The comparison of such data with existing reference land cover products would be useful for operative monitoring of arid areas of West Africa.

To conclude, the demonstrated case of environmental mapping by satellite data processing by using ML algorithms supports the analysis of salinisation in salty sand areas and sebkha of West Mauritania related to climate change. Using GRASS GIS as a powerful cartographic tool promotes the use of scripts as advanced techniques for processing geoinformation. Such technologies ensure future research efforts, which can continue further the presented study through focus on identifying salinisation of soil for other time periods. GRASS GIS-based methods of processing EO data and formulating optimal ML approaches among the existing algorithms enable to develop effective methods for satellite image processing. In turn, efficient cartographic instruments supported by programming methods for image processing provide technical support for the environmental climate visualisation and analysis of rare areas such as Sebkhah de Ndrhamcha, West Mauritania.

ABBREVIATIONS

AI	Artificial Intelligence
CNN	Convolutional Neural Network
DCW	Digital Chart of the World
DL	Deep Learning
EO	Earth Observation
GEBCO	General Bathymetric Chart of the Oceans
GIS	Geographic Information System
GMT	Generic Mapping Tools
GRASS	Geographic Resources Analysis Support System
Landsat OLI/TIRS	Landsat Operational Land Imager and the Thermal Infrared Sensor
NASA	National Aeronautics and Space Administration
NN	Neural Network
SRTM	Shuttle Radar Topography Mission
USGS	United States Geological Survey

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REFERENCES

- Abujayyab, S. K., Almajalid, R., Wazirali, R., Ahmad, R., Taşoğlu, E., Karas, I. R. and Hijazi, I. (2023). Integrating object-based and pixel-based segmentation for building footprint extraction from satellite images, *Journal of King Saud University - Computer and Information Sciences* **35**(10): 101802.
- Ali, A. O., Morshedy, A. S., El-Zahhar, A. A., Alghamdi, M. M. and El Naggar, A. M. (2024). African continent: Rich land of minerals and energy sources, *Inorganic Chemistry Communications* **169**: 113123.

- Ali, M. M. and Abd Ellah, R. G. (2023). Chapter 1 - history and formation of african lakes, in M. El-Sheekh and H. E. Elsaied (eds), *Lakes of Africa*, Elsevier, pp. 1–31.
- Ashpole, I. and Washington, R. (2013). A new high-resolution central and western saharan summertime dust source map from automated satellite dust plume tracking, *Journal of Geophysical Research: Atmospheres* **118**(13): 6981–6995.
- Ayoade, O., Rivas, P., Orduz, J. and Rafi, N. (2023). Chapter 13 - satellite image classification using quantum machine learning, in Z. Sun, N. Cristea and P. Rivas (eds), *Artificial Intelligence in Earth Science*, Elsevier, pp. 337–355.
- Barry, S. (2003). Contribution à l'étude géomorphologique de la cote mauritanienne: cas de nouakchott et ses environs, *DES en géographie, Université Cheikh Anta Diop de Dakar, Département de géographie*, 116p .
- Bayod Rújula, A. A. and Dia, N. K. (2010). Application of a multi-criteria analysis for the selection of the most suitable energy source and water desalination system in mauritania, *Energy Policy* **38**(1): 99–115.
- Belmahdi, F., Lazri, M., Ouallouche, F., Labadi, K., Absi, R. and Ameer, S. (2023). Application of dempster-shafer theory for optimization of precipitation classification and estimation results from remote sensing data using machine learning, *Remote Sensing Applications: Society and Environment* **29**: 100906.
- Bojer, A. K., Woldetsadik, M. and Biru, B. H. (2024). Machine learning and cordex-africa regional model for assessing the impact of climate change on the gilgel gibe watershed, ethiopia, *Journal of Environmental Management* **363**: 121394.
- Borgia, C., García-Bolaños, M. and Mateos, L. (2012). Patterns of variability in large-scale irrigation schemes in mauritania, *Agricultural Water Management* **112**: 1–12.
- Campos, J. C., Sillero, N. and Brito, J. C. (2012). Normalized difference water indexes have dissimilar performances in detecting seasonal and permanent water in the sahara–sahel transition zone, *Journal of Hydrology* **464-465**: 438–446.
- Cedric, L. S., Adoni, W. Y. H., Aworka, R., Zoueu, J. T., Mutombo, F. K., Krichen, M. and Kimpolo, C. L. M. (2022). Crops yield prediction based on machine learning models: Case of west african countries, *Smart Agricultural Technology* **2**: 100049.
- Choplin, A. and Dessie, E. (2017). Titling the desert: Land formalization and tenure (in)security in nouakchott (mauritania), *Habitat International* **64**: 49–58.
- Dunga, L., Lück-Vogel, M., Blamey, L. K., Bolton, J., Rothman, M., Desmet, P. and Sink, K. (2024). Mapping south africa's canopy-forming kelp forests using low-cost, high-resolution sentinel-2 imagery, *Estuarine, Coastal and Shelf Science* **310**: 108989.
- Ebrahim, G. Y., Stefan, C., Sallwey, J. and Lautze, J. (2024). Mapping the potential of managed aquifer recharge in africa: Gis-based multi-criteria decision analysis approach, *Groundwater for Sustainable Development* **27**: 101374.
- Ebrahimi, H. and Zhang, Z. (2023). Per-pixel accuracy as a weighting criterion for combining ensemble of extreme learning machine classifiers for satellite image classification, *International Journal of Applied Earth Observation and Geoinformation* **122**: 103390.
- Einsele, G., Herm, D. and Schwarz, H. (1974a). Holocene eustatic (?) sea level fluctuation at the coast of mauritania, *Meteor Forschungsergebnisse: Reihe C, Geologie und Geophysik* **18**: 43–62.
URL: <https://oceanrep.geomar.de/id/eprint/56634>

- Einsele, G., Herm, D. and Schwarz, H. (1974b). Sea level fluctuation during the past 6000 yr at the coast of mauritania, *Quaternary Research* **4**(3): 282–289.
- Elouard, P. and Faure, H. (1972). Quaternaire littoral de la région de Nouakchott et de la sebkha de Ndrhamcha, *Actes 6e Congr. panaf. Prréhist. Etude Quat.*, pp. 49–54.
- Fisher-Holloway, B. and Mokhele, M. (2023). Geographical patterns of warehousing facilities in the cape functional region, south africa, *Regional Science Policy & Practice* **15**(6): 1317–1338.
- Gawusu, S., Mvile, B. N., Abu, M. and Kalimenze, J. D. (2024). Machine learning based prospect targeting: A case of gold occurrence in central parts of tanzania, east africa, *Ore and Energy Resource Geology* **17**: 100065.
- Giresse, P., Barusseau, J.-P., Causse, C. and Diouf, B. (2000). Successions of sea-level changes during the pleistocene in mauritania and senegal distinguished by sedimentary facies study and u/th dating, *Marine Geology* **170**(1): 123–139.
- Giresse, P., Diouf, M. and Barusseau, J.-P. (1988). Lithological, mineralogical and geochemical observations of senegalo-mauritanian quaternary shoreline deposits: Possible chronological revisions, *Palaeogeography, Palaeoclimatology, Palaeoecology* **68**(2): 241–257. Quaternary Coastal Changes.
- Grandjean, G., Paillou, P., Baghdadi, N., Heggy, E., August, T. and Lasne, Y. (2006). Surface and subsurface structural mapping using low frequency radar: A synthesis of the mauritanian and egyptian experiments, *Journal of African Earth Sciences* **44**(2): 220–228. Remote Sensing Applications to Geological Problems in Africa.
- GRASS Development Team (2022). *Geographic Resources Analysis Support System (GRASS GIS) Software, Version 8.2*, Open Source Geospatial Foundation.
- URL:** <https://grass.osgeo.org>
- Gómez, D., Salvador, P., Sanz, J., Casanova, C., Taratiel, D. and Casanova, J. (2019). Desert locust detection using earth observation satellite data in mauritania, *Journal of Arid Environments* **164**: 29–37.
- Hamoud, A., El Hadi, H., Tahiri, A., Chakiri, S., Mehdioui, S., Baghdad, B., El Maidani, A., Bejjaji, Z. and Aoufa, M. (2021). Mauritanian geological resources: A lever for sustainable regional development via geotourism, *International Journal of Geoheritage and Parks* **9**(4): 415–429.
- Handford, C. (1981). A process-sedimentary framework for characterizing recent and ancient sabkhas, *Sedimentary Geology* **30**(4): 255–265.
- Henrich, R., Cherubini, Y. and Meggers, H. (2010). Climate and sea level induced turbidite activity in a canyon system offshore the hyperarid western sahara (mauritania): The timiris canyon, *Marine Geology* **275**(1): 178–198.
- Karila, K., Matikainen, L., Karjalainen, M., Puttonen, E., Chen, Y. and Hyypä, J. (2023). Automatic labelling for semantic segmentation of vhr satellite images: Application of airborne laser scanner data and object-based image analysis, *ISPRS Open Journal of Photogrammetry and Remote Sensing* **9**: 100046.
- Kocurek, G., Havholm, K. G., Deynoux, M. and Blakey, R. C. (1991). Amalgamated accumulations resulting from climatic and eustatic changes, akchar erg, mauritania, *Sedimentology* **38**(4): 751–772.
- Lemenkova, P. (2015). Topology, Homogeneity and Scale Factors for Object Detection:

Application of eCognition Software for Urban Mapping using Multispectral Satellite Image, in A. Girgvliani, A. Bardavelidze, D. Zautashvili and M. Kotishadze (eds), *Internet and Society*, ATSU Press, pp. 80–85.

Lemenkova, P. (2020a). Object Based Image Segmentation Algorithm of SAGA GIS for Detecting Urban Spaces in Yaoundé, Cameroon, *Central European Journal of Geography and Sustainable Development* **2**: 38–51.

Lemenkova, P. (2020b). 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**: 17–34.

Lemenkova, P. (2022a). A Script-Driven Approach to Mapping Satellite-Derived Topography and Gravity Data Over the Zagros Fold-and-Thrust Belt, Iran, *Artificial Satellites* **57**: 110–137.

Lemenkova, P. (2022b). Console-Based Mapping of Mongolia Using GMT Cartographic Scripting Toolset for Processing TerraClimate Data, *Geosciences* **12**(140): 1–36.

Lemenkova, P. (2022c). Handling Dataset with Geophysical and Geological Variables on the Bolivian Andes by the GMT Scripts, *Data* **7**: 74.

Lemenkova, P. (2022d). Mapping Climate Parameters over the Territory of Botswana Using GMT and Gridded Surface Data from TerraClimate, *ISPRS International Journal of Geo-Information* **11**: 473.

Lemenkova, P. (2023a). A GRASS GIS Scripting Framework for Monitoring Changes in the Ephemeral Salt Lakes of Chotts Melrhir and Merouane, Algeria, *Applied System Innovation* **6**: 61.

Lemenkova, P. (2023b). Monitoring Seasonal Fluctuations in Saline Lakes of Tunisia Using Earth Observation Data Processed by GRASS GIS, *Land* **12**: 1995.

Lemenkova, P. (2023c). 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**: 49–64.

Lemenkova, P. (2024a). Approche cartographique par le sig grass pour l'analyse de la structure du paysage au libéria, afrique de l'ouest, *Dynamiques environnementales. Journal international de géosciences et de l'environnement* **53**: 1–36.

Lemenkova, P. (2024b). Approche cartographique par le SIG GRASS pour l'analyse de la structure du paysage au Libéria, Afrique de l'Ouest, *Dynamiques environnementales* **53**: 1–36.

Lemenkova, P. (2024c). 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**: 1–27.

Lemenkova, P. (2024d). Mapping Coastal Regions of Guinea-Bissau for Analysis of Mangrove Dynamics Using Remote Sensing Data, *Transylvanian Review of Systematical and Ecological Research* **26**: 17–30.

Lemenkova, P. (2024e). Mapping Woodlands in Angola, Tropical Africa: Calculation of Vegetation Indices From Remote Sensing Data, *Agriculture and Forestry* **70**: 185–202.

Lemenkova, P. (2024f). Support Vector Machine Algorithm for Mapping Land Cover Dynamics in Senegal, West Africa, Using Earth Observation Data, *Earth* **5**: 420–462.

Lemenkova, P. (2025a). Automation of image processing through ml algorithms of grass gis using embedded scikit-learn library of python, *Examples and Counterexamples* **7**: 100180.

Lemenkova, P. (2025b). Improving bimonthly landscape monitoring in morocco, north africa, by integrating machine learning with grass gis, *Geomatics* **5**(1).

Lemenkova, P. and Debeir, O. (2023a). Computing Vegetation Indices from the Satellite Images Using GRASS GIS Scripts for Monitoring Mangrove Forests in the Coastal Landscapes of Niger Delta, Nigeria, *Journal of Marine Science and Engineering* **11**: 871.

Lemenkova, P. and Debeir, O. (2023b). Time Series Analysis of Landsat Images for Monitoring Flooded Areas in the Inner Niger Delta, Mali, *Artificial Satellites* **58**: 278–313.

M. Pichel, L., Finch, E. and Gawthorpe, R. L. (2019). The impact of pre-salt rift topography on salt tectonics: A discrete-element modeling approach, *Tectonics* **38**(4): 1466–1488.

Manning-Berg, A. R., Goodman, E. E. and Kah, L. C. (2024). Calcitized evaporites in the mesoproterozoic atar and el meriti groups, mauritania, africa, *Palaeogeography, Palaeoclimatology, Palaeoecology* **636**: 111974.

Medus, J. (1987). West african holocene stratigraphy, transgressions and climatic changes, *Progress in Oceanography* **18**(1): 167–175.

Mitasova, H. and Neteler, M. (2004). Grass as open source free software gis: Accomplishments and perspectives, *Transactions in GIS* **8**(2): 145–154.

Mohamed, A.-S., Leduc, C., Marlin, C., Wagué, O. and Sidi Cheikh, M.-A. (2017). Impacts of climate change and anthropization on groundwater resources in the nouakchott urban area (coastal mauritania), *Comptes Rendus Geoscience* **349**(6): 280–289. Vulnerability of inter-tropical littoral areas.

Nartišs, M. and Melniks, R. (2023). Improving pixel-based classification of grass gis with support vector machine, *Transactions in GIS* **27**(7): 1865–1880.

Nasiri, V., Hawryło, P., Janiec, P. and Socha, J. (2023). Comparing object-based and pixel-based machine learning models for tree-cutting detection with planetscope satellite images: Exploring model generalization, *International Journal of Applied Earth Observation and Geoinformation* **125**: 103555.

Nenkam, A. M., Wadoux, A. M.-C., Minasny, B., Silatsa, F. B., Yemefack, M., Ugbaje, S. U., Akpa, S., Zijl, G. V., Bouasria, A., Bouslihim, Y., Chabala, L. M., Ali, A. and McBratney, A. B. (2024). Applications and challenges of digital soil mapping in africa, *Geoderma* **449**: 117007.

Neteler, M., Bowman, M. H., Landa, M. and Metz, M. (2012). Grass gis: A multi-purpose open source gis, *Environmental Modelling & Software* **31**: 124–130.

Neteler, M. and Mitasova, H. (2002). *Open Source GIS: A GRASS GIS Approach*, 0893-3405, 2 edn, Kluwer, Boston, MA.

Niang, A. J. (2022). *Remote Sensing and GIS Application for Natural Hazards Assessment of the Mauritanian Coastal Zone*, Springer International Publishing, Cham, pp. 195–223.

Ould Ahmedou, D., Ould Mahfoudh, A., Dupont, P., Ould El Moctar, A., Valance, A. and Rasmussen, K. R. (2007). Barchan dune mobility in mauritania related to dune and interdune sand fluxes, *Journal of Geophysical Research: Earth Surface* **112**(F2).

Ould Sidi Cheikh, M. A., Ozer, P. and Ozer, A. (2007). Risques d'inondation dans la ville de nouakchott (mauritanie), *Geo-Eco-Trop: Revue Internationale de Géologie, de Géographie et d'Écologie Tropicales* **31**.

Pande, C. B., Egbueri, J. C., Costache, R., Sidek, L. M., Wang, Q., Alshehri, F., Din, N. M., Gautam, V. K. and Chandra Pal, S. (2024). Predictive modeling of land surface temperature

- (Ist) based on landsat-8 satellite data and machine learning models for sustainable development, *Journal of Cleaner Production* **444**: 141035.
- Parajuli, S. P., Yang, Z.-L. and Kocurek, G. (2014). Mapping erodibility in dust source regions based on geomorphology, meteorology, and remote sensing, *Journal of Geophysical Research: Earth Surface* **119**(9): 1977–1994.
- Pillay, T., Cawthra, H., Lombard, A. and Sink, K. (2021). Benthic habitat mapping from a machine learning perspective on the cape st francis inner shelf, eastern cape, south africa, *Marine Geology* **440**: 106595.
- Plaziat, J.-C. (1991). Paleogeographic significance of the cardium, potamids and foraminifera living in intra-continental salt lakes of north africa (sahara quaternary, egypt present lakes), *Journal of African Earth Sciences (and the Middle East)* **12**(1): 383–389. Sedimentary and Diagenetic Dynamics of Continental Phanerozoic Sediments in Africa.
- Quebedeaux, B. and Parks, L. L. (1984). Vegetable crop development in mauritania, *Agricultural Administration* **15**(3): 133–156.
- Rahman, A., Abdullah, H. M., Tanzir, M. T., Hossain, M. J., Khan, B. M., Miah, M. G. and Islam, I. (2020). Performance of different machine learning algorithms on satellite image classification in rural and urban setup, *Remote Sensing Applications: Society and Environment* **20**: 100410.
- Rathore, M. M. U., Ahmad, A., Paul, A. and Wu, J. (2016). Real-time continuous feature extraction in large size satellite images, *Journal of Systems Architecture* **64**: 122–132. Real-Time Signal Processing in Embedded Systems.
- Rocchini, D., Delucchi, L., Bacaro, G., Cavallini, P., Feilhauer, H., Foody, G. M., He, K. S., Nagendra, H., Porta, C., Ricotta, C., Schmidtlein, S., Spano, L. D., Wegmann, M. and Neteler, M. (2013). Calculating landscape diversity with information-theory based indices: A grass gis solution, *Ecological Informatics* **17**: 82–93. Special issue of the 7th International Conference on Ecological Informatics, 13-16 December 2010, Ghent, Belgium: 'Unravelling complexity and supporting sustainability'.
- Rocchini, D., Petras, V., Petrasova, A., Chemin, Y., Ricotta, C., Frigeri, A., Landa, M., Marcantonio, M., Bastin, L., Metz, M., Delucchi, L. and Neteler, M. (2017). Spatio-ecological complexity measures in grass gis, *Computers & Geosciences* **104**: 166–176.
- Semega, B. (2008). Energie éolienne et dessalement dans le contexte mauritanien, des modèles de développement pour le sud, *Energie Francophonie* **179**.
- Senhoury, A., Niang, A., Diouf, B. and Thomas, Y.-F. (2016). *Managing Flood Risks Using Nature-Based Solutions in Nouakchott, Mauritania*, Springer International Publishing, Cham, pp. 435–455.
- Shoko, C. and Dube, T. (2024). A review of remote sensing of flood monitoring and assessment in southern africa, *Physics and Chemistry of the Earth, Parts A/B/C* **136**: 103796.
- Soulié-Märsche, I. (2008). Charophytes, indicators for low salinity phases in north african sebkhet, *Journal of African Earth Sciences* **51**(2): 69–76.
- Tari, G., Novotny, B., Jabour, H. and Hafid, M. (2017). Chapter 15 - salt tectonics along the atlantic margin of nw africa (morocco and mauritania), in J. I. Soto, J. F. Flinch and G. Tari (eds), *Permo-Triassic Salt Provinces of Europe, North Africa and the Atlantic Margins*, Elsevier, pp. 331–351.
- Twumasi-Ankrah, M. J., Zhan, J. and Asamoah, E. F. (2024). Mapping ecoregional vulnerability

to climate change for africa, *Science of The Total Environment* **953**: 176219.

van Asten, P., Barbiéro, L., Wopereis, M., Maeght, J. and van der Zee, S. (2003). Actual and potential salt-related soil degradation in an irrigated rice scheme in the sahelian zone of mauritania, *Agricultural Water Management* **60**(1): 13–32.

Vermeer, D. (2010). *Mauritania*, Springer Netherlands, Dordrecht, pp. 917–919.

Versteegh, G. J. M., Zonneveld, K. A. F., Hefter, J., Romero, O. E., Fischer, G. and Mollenhauer, G. (2022). Performance of temperature and productivity proxies based on long-chain alkane-1, mid-chain diols at test: a 5-year sediment trap record from the mauritanian upwelling, *Biogeosciences* **19**(5): 1587–1610.

Vázquez, R., Parras-Berrocal, I., Koseki, S., Cabos, W., Sein, D. and Izquierdo, A. (2023). Seasonality of coastal upwelling trends in the mauritania-senegalese region under rcp8.5 climate change scenario, *Science of The Total Environment* **898**: 166391.

Walther, B. A. and Huettmann, F. (2021). Palearctic passerine migrant declines in african wintering grounds in the anthropocene (1970–1990 and near future): A conservation assessment using publicly available gis predictors and machine learning, *Science of The Total Environment* **777**: 146093.

Wessel, P., Luis, J. F., Uieda, L., Scharroo, R., Wobbe, F., Smith, W. H. F. and Tian, D. (2019). The Generic Mapping Tools Version 6, *Geochemistry, Geophysics, Geosystems* **20**(11): 5556–5564.

Wijnsma, G., Wolff, W. J., Meijboom, A., Duiven, P. and De Vlas, J. (1999). Species richness and distribution of benthic tidal flat fauna of the banc d’arguin, mauritania, *Oceanologica Acta* **22**(2): 233–243.

Wissmann, G. (1982). Stratigraphy and structural features of the continental margin basin of senegal and mauritania, *Geology of the Northwest African Continental Margin*, Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 160–181.

Yang, J., Fricker, P. and Jung, A. (2024). From intangible to tangible: The role of big data and machine learning in walkability studies, *Computers, Environment and Urban Systems* **109**: 102087.

Álvaro, J. J. (2012). Colour banding in a latest neoproterozoic–cambrian microbially variegated sabkha of the taoudeni basin, adrar of mauritania, *Palaeogeography, Palaeoclimatology, Palaeoecology* **367–368**: 209–218. Special Issue: Time-Specific Facies: the color and texture of biotic events.

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APPENDIX

GRASS GIS scripts for RS data processing

```
1 r.import input=/Users/polinalemenkova/grassdata/Mauritania/\
2   LC09_L2SP_205047_20230428_20230430_02_T1_SR_B1.TIF
3   output=L_2023_01 extent=region resolution=region
4 r.import input=/Users/polinalemenkova/grassdata/Mauritania/
5   LC09_L2SP_205047_20230428_20230430_02_T1_SR_B2.TIF
6   output=L_2023_02 extent=region resolution=region
7 r.import input=/Users/polinalemenkova/grassdata/Mauritania/
8   LC09_L2SP_205047_20230428_20230430_02_T1_SR_B3.TIF
9   output=L_2023_03 extent=region resolution=region
10 r.import input=/Users/polinalemenkova/grassdata/Mauritania/
11   LC09_L2SP_205047_20230428_20230430_02_T1_SR_B4.TIF
12   output=L_2023_04 extent=region resolution=region
13 r.import input=/Users/polinalemenkova/grassdata/Mauritania/
14   LC09_L2SP_205047_20230428_20230430_02_T1_SR_B5.TIF
15   output=L_2023_05 extent=region resolution=region
16 r.import input=/Users/polinalemenkova/grassdata/Mauritania/
17   LC09_L2SP_205047_20230428_20230430_02_T1_SR_B6.TIF
18   output=L_2023_06 extent=region resolution=region
19 r.import input=/Users/polinalemenkova/grassdata/Mauritania/
20   LC09_L2SP_205047_20230428_20230430_02_T1_SR_B7.TIF
21   output=L_2023_07 extent=region resolution=region
22 # check up the raster files
23 g.list rast
24 # adding shaded relief
25 r.import input=/Users/polinalemenkova/grassdata/
26   Mauritania/gebco_2023.tif output=shaded_relief extent=region --overwrite
27 r.contour shaded_relief out=isolines step=200 --overwrite
```

Listing 1. GRASS GIS script for data import and preprocessing

```
1 # Setting computational region to match the scene
2 g.region raster=L_2023_01 -p
3 # grouping data by i.group
4 i.group group=L_2023 subgroup=res_30m \
5   input=L_2023_01,L_2023_02,L_2023_03,L_2023_04,\
6   L_2023_05,L_2023_06,L_2023_07 --overwrite
7 # Generating signature file and report using k-means clustering algorithm
8 i.cluster group=L_2023 subgroup=res_30m \
9   signaturefile=cluster_L_2023 \
10  classes=10 reportfile=rep_clust_L_2023.txt --overwrite
11 # Classification by i.maxlik module
12 i.maxlik group=L_2023 subgroup=res_30m \
13   signaturefile=cluster_L_2023 \
14   output=L_2023_clusters reject=L_2023_cluster_reject --overwrite
15 r.colors L_2023_clusters color=viridis
16 r.colors shaded_relief color=grey -n
17 # Mapping
18 g.region raster=L_2023_01 -p
19 d.mon wx0
20 d.rast shaded_relief
21 d.rast L_2023_clusters
22 d.vect isolines color='100:93:134' width=0
23 d.grid -g size=00:30:00 color=white width=0.1 fontsize=16 text_color=white
24 d.legend raster=L_2023_clusters title="Clusters 2023" title_fontsize=19 \
25   font="Helvetica" fontsize=17 bgcolor=white border_color=white
26 d.legend raster=shaded_relief title="Relief, m" title_fontsize=19 \
27   font="Helvetica" fontsize=17 bgcolor=white border_color=white -f
28 d.out.file output=Mauritania_2023 format=jpg --overwrite
29 # Mapping rejection probability
30 d.mon wx2
31 g.region raster=L_2023_clusters -p
32 r.colors L_2023_cluster_reject color=rainbow -e
33 d.rast shaded_relief
34 d.rast L_2023_cluster_reject
35 d.vect isolines color='100:93:134' width=0
36 d.grid -g size=00:30:00 color=white width=0.1 fontsize=16 text_color=white
37 d.legend raster=L_2023_cluster_reject title="2023" title_fontsize=19 \
```

```

38 font="Helvetica" fontsize=17 bgcolor=white border_color=white
39 d.legend raster=shaded_relief title="Relief, m" title_fontsize=19 \
40 font="Helvetica" fontsize=17 bgcolor=white border_color=white -f
41 d.out.file output=Mauritania_2023_reject format=jpg --overwrite

```

Listing 2. GRASS GIS script for image clustering and classification

Machine Learning scripts of GRASS GIS for image processing

```

1 # Generating training pixels from an older land cover classification:
2 r.random input=L_2014_clusters seed=100 npoints=1000 raster=training_pixels
3 # training a model using r.learn.train
4 r.learn.train group=L_2023 training_map=training_pixels \
5     model_name=RandomForestClassifier n_estimators=500
6     save_model=rfc_model.gz --overwrite
7 # perform prediction using r.learn.predict
8 r.learn.predict group=L_2023 load_model=rfc_model.gz
9 output=rfc_classification_2023 --overwrite
10 # check raster categories which are applied to the classification output
11 r.category rfc_classification_2023
12 # display the results
13 r.colors rfc_classification_2023 color=roygbiv -e
14 d.mon wx0
15 d.rast shaded_relief
16 d.vect isolines color='100:93:134' width=0
17 d.rast rfc_classification_2023
18 d.grid -g size=00:30:00 color=white width=0.1 fontsize=16 text_color=white
19 d.legend raster=rfc_classification_2023 title="RFC 2023" title_fontsize=19
20 font="Helvetica" fontsize=17 bgcolor=white border_color=white
21 d.legend raster=shaded_relief title="Relief, m" title_fontsize=19
22 font="Helvetica" fontsize=17 bgcolor=white border_color=white -f
23 d.out.file output=RFC_2023 format=jpg --overwrite

```

Listing 3. Random Forest Classifier script for image classification

```

1 # training a model using r.learn.train
2 r.learn.train group=L_2023 training_map=training_pixels \
3     model_name=DecisionTreeClassifier n_estimators=500
4     save_model=dtc_model.gz --overwrite
5 # perform prediction using r.learn.predict
6 r.learn.predict group=L_2023 load_model=dtc_model.gz
7 output=dtc_classification_2023 --overwrite
8 # check raster categories automatically applied to the classification output
9 r.category dtc_classification_2023
10 # display
11 r.colors dtc_classification_2023 color=bcyr
12 d.mon wx0
13 d.rast shaded_relief
14 d.vect isolines color='100:93:134' width=0
15 d.rast dtc_classification_2023
16 d.grid -g size=00:30:00 color=white width=0.1 fontsize=16 text_color=white
17 d.legend raster=dtc_classification_2023 title="DTC 2023" title_fontsize=19
18 font="Helvetica" fontsize=17 bgcolor=white border_color=white
19 d.legend raster=shaded_relief title="Relief, m" title_fontsize=19
20 font="Helvetica" fontsize=17 bgcolor=white border_color=white -f
21 d.out.file output=DTC_2023 format=jpg --overwrite

```

Listing 4. Decision Tree Classifier script for image classification

```

1 # training a model using r.learn.train
2 r.learn.train group=L_2023 training_map=training_pixels \
3     model_name=GradientBoostingClassifier n_estimators=500
4     save_model=gbc_model.gz --overwrite
5 # perform prediction using r.learn.predict
6 r.learn.predict group=L_2023 load_model=gbc_model.gz
7 output=gbc_classification_2023 --overwrite
8 # check raster categories automatically applied to the classification output
9 r.category gbc_classification_2023
10 # display
11 r.colors gbc_classification_2023 color=bgyr

```

```

12 d.mon wx0
13 d.rast shaded_relief
14 d.vect isolines color='100:93:134' width=0
15 d.rast gbc_classification_2023
16 d.grid -g size=00:30:00 color=white width=0.1 fontsize=16 text_color=white
17 d.legend raster=gbc_classification_2023 title="GBC 2023" title_fontsize=19
18   font="Helvetica" fontsize=17 bgcolor=white border_color=white
19 d.legend raster=shaded_relief title="Relief, m" title_fontsize=19
20   font="Helvetica" fontsize=17 bgcolor=white border_color=white -f
21 d.out.file output=GBC_2023 format=jpg --overwrite

```

Listing 5. Gradient Boosting Classifier script for image classification

```

1 # training a model using r.learn.train
2 r.learn.train group=L_2023 training_map=training_pixels \
3   model_name=SVC n_estimators=500 save_model=svc_model.gz --overwrite
4 # perform prediction using r.learn.predict
5 r.learn.predict group=L_2023 load_model=svc_model.gz
6   output=svc_classification_2014 --overwrite
7 # check raster categories applied to the classification output
8 r.category svc_classification_2023
9 # display the results
10 r.colors svc_classification_2023 color=roygbiv -e
11 d.mon wx2
12 d.rast shaded_relief
13 d.vect isolines color='100:93:134' width=0
14 d.rast svc_classification_2023
15 d.grid -g size=00:30:00 color=white width=0.1 fontsize=16 text_color=white
16 d.legend raster=svc_classification_2023 title="SVM 2023"
17   title_fontsize=19 font="Helvetica" fontsize=17
18   bgcolor=white border_color=white
19 d.legend raster=shaded_relief title="Relief, m" title_fontsize=19
20   font="Helvetica" fontsize=17 bgcolor=white border_color=white -f
21 d.out.file output=svc_2023 format=jpg --overwrite

```

Listing 6. Support Vector Machine (SVM) Classifier script for image classification