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Machine learning algorithms for optimization of image classification in spatially constrained regions: A case of Eritrea, East Africa

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ABSTRACT

This paper presents the application of Machine Learning (ML) algorithms to solve the problem of optimization of classification tasks in Remote Sensing (RS) data processing. RS data is effective in spatial environmental monitoring since it enables detection of areas affected by natural hazards: droughts, desertification, coastal floods and deforestation. Vulnerable regions can be identified using analysis of spaceborne images for strategic land planning and decision making. The effectiveness of several ML models was tested using Geographic Resources Analysis Support System (GRASS) GIS software for satellite image analysis. Employing ML enabled to perform image classification tasks based on similarity of spectral reflectance of pixels. The following algorithms were tested and compared: Gaussian Naive Bayes (GNB), Decision Tree Classifier (DTC), and Linear Discriminant Analysis (LDA). The ML models were adopted to classify a time series of the Landsat 8-9 OLI/TIRS images and evaluate changes in land cover types in coastal and desert areas of Eritrea. This region encompasses the protected Semenawi Bahri National Park, notable for a diverse range of unique wildlife near the Massawa Channel, Red Sea. The results demonstrated changes in land cover types over the period of 2014-2024 which proved the climate-related effects on landscape dynamics. This paper demonstrated the efficiency of the ML methods in Geographic Information Systems (GIS) tailored to solve specific spatially constrained problems of land cover type identifying using scripting in GRASS GIS.

KEYWORDS

Machine learning, Image analysis, Africa, GRASS GIS, Remote sensing

1. INTRODUCTION

Non-linear modelling and large volumes of spatial data are often the issue in complex task of detecting interactions between variables which require a high level of automation [1-4]. Modelling environmental interactions in African region is surrounded by uncertainties due to the landscape diversity and non-differentiable parameters that affect ecosystem formation: geology, topography, soil, climate and vegetation [5-6]. Remote sensing (RS) is a set of techniques used for Earth observation which can solve the problem of complex mapping through the analysis, and interpretation of objects visible on the Earth's surface. More specifically, the energy of electromagnetic radiation, emitted or reflected by objects, is measured remotely without physical contact and then analyzed from the data captured on the satellite images. With this regards, environmental problems related to RS data processing require the use of the advanced methods, as their integrated use ensures high-quality geospatial analysis.

Rapid development of machine learning (ML) methods in Geographic Information Systems (GIS) made a precious contribution to the advancement of spatial analysis and environmental sciences using RS data. In contrast to the traditional tools of image analysis, ML operates with provides a problem-solved solutions of image classification through spatial optimization [7-8]. Projects dedicated to Earth observation using high spatial and medium temporal resolution satellites have also been developed which increased the volume of data available for processing and analysis. In this regards, ML-based GIS analysis of satellite images supports processing of large amounts of data which requires building complex models, and performing complex spatial calculations [9-11]. In such cases, exact methodological solutions are resource-intensive and time-consuming. To optimize spatial analysis, heuristic approaches and automated ML methods allow finding prioritized solutions to satellite image analysis. Albeit not always perfect, the sufficient decisions in image analysis are acceptable for practical needs, speeding up the process and facilitating data analysis [12]. Specifically for environmental mapping, advanced methods of data analysis support decisions in complex cases where multiple factors and parameters (topography, climate, vegetation, geology) affect modelling [13-14].

To assess the potential improvement of several factors (climate-topographic, geologic and land cover types, the RS data provides solutions to monitoring landscape dynamics through image classification. Such automated methods are performed using clustering search of pixels while categorizing land cover types and ensuring more efficient analysis of landscape dynamics. In this way, image analysis is used to detect deforestation and land cover change through integrated multi-factor analysis of geologic, topographic and vegetation variables. Moreover, RS-based mapping is time-efficient and effective in analysis and geospatial solutions process. Integration of ML and RS data methods support optimization of GIS analysis through optimized landscape mapping. In view of the effectiveness, this research presents automated methods of image processing and analysis for environmental monitoring.

2. STUDY AREA

The study area encompasses coastal and desert areas of Eritrea around the Massawa Channel and includes the Semenawi Bahri National Park stretching along the west coasts of the Red Sea, Figure 1.

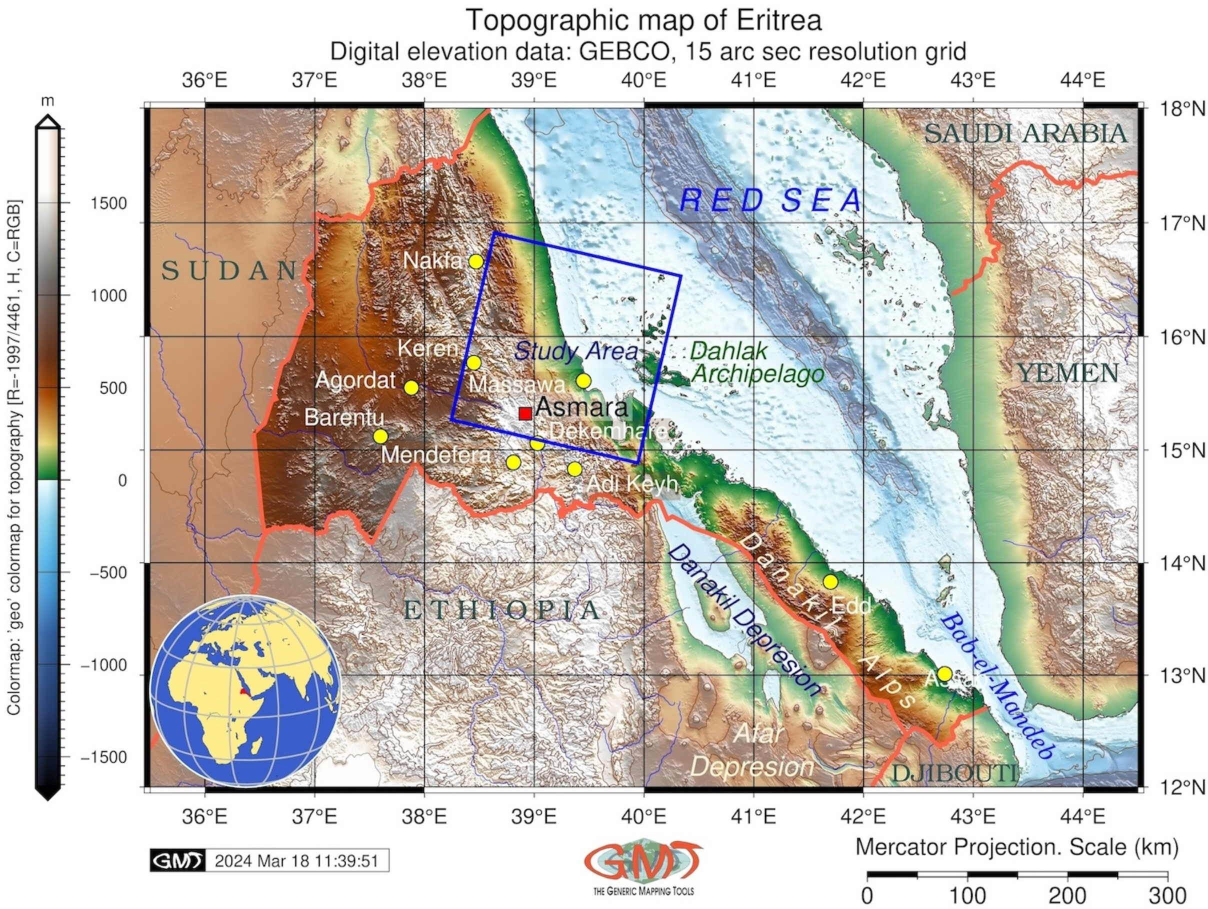

Figure 1: Study are on the topographic map of Eritrea. Software: GMT. Map source: author.

Landscape dynamics in Eritrea has a complex pattern which differ regionally demonstrating a variety of land cover types, Figure 2. Diverse habitats of the country include tropical and subtropical grasslands, grasslands in savannah, shrubland and xeric vegetation in semi-desert and desert regions, moist broadleaf forests along the mountainous slopes. Recently, climate warming and anthropogenic impacts (nomadism and land overuse) caused savannah encroachment in semi-natural grasslands in mountains and plateaus. Such processes lead to habitat fragmentation and land cover changes. Important environmental problems of Eritrea include desertification and changes in land cover patterns. Landscapes of Eritrea are very contrasting, since they are located at the intersection of three African main climate zones: temperate, arid and tropical savannah. Major vegetation types include highland xeric bushes, Acacia woodlands and riverine forests.

Coastal regions of Eritrea are one of the least known ecosystems in East Africa. Their extended location along the Red Sea makes Eritrea vulnerable to climate change. Dominated by mangrove forests and seagrasses, coastal zones are notable for high biodiversity, rare and precious bird species of the Red Sea. The Massawa Channel separating the archipelago of Dahlak Marine National Park from mainland is notable for rich wildlife. Here, high biodiversity includes unique fish species, migratory birds and rare mammals [15]. At the same time, this region is affected by climate warming: repetitive droughts, seasonal rainfalls with irregular patterns and high evaporation during dry periods. Land cover change is triggered by climate-related processes: extreme temperature in inner deserts, irregular and low precipitation, high evapotranspiration. Significant changes in air temperature in Eritrea are recorded with daily min/max values constantly increasing for ca. 0.20°C per decade [16]. Such processes cause water deficit which lead to the desertification and aridification of landscapes, and land cover types [17-18].

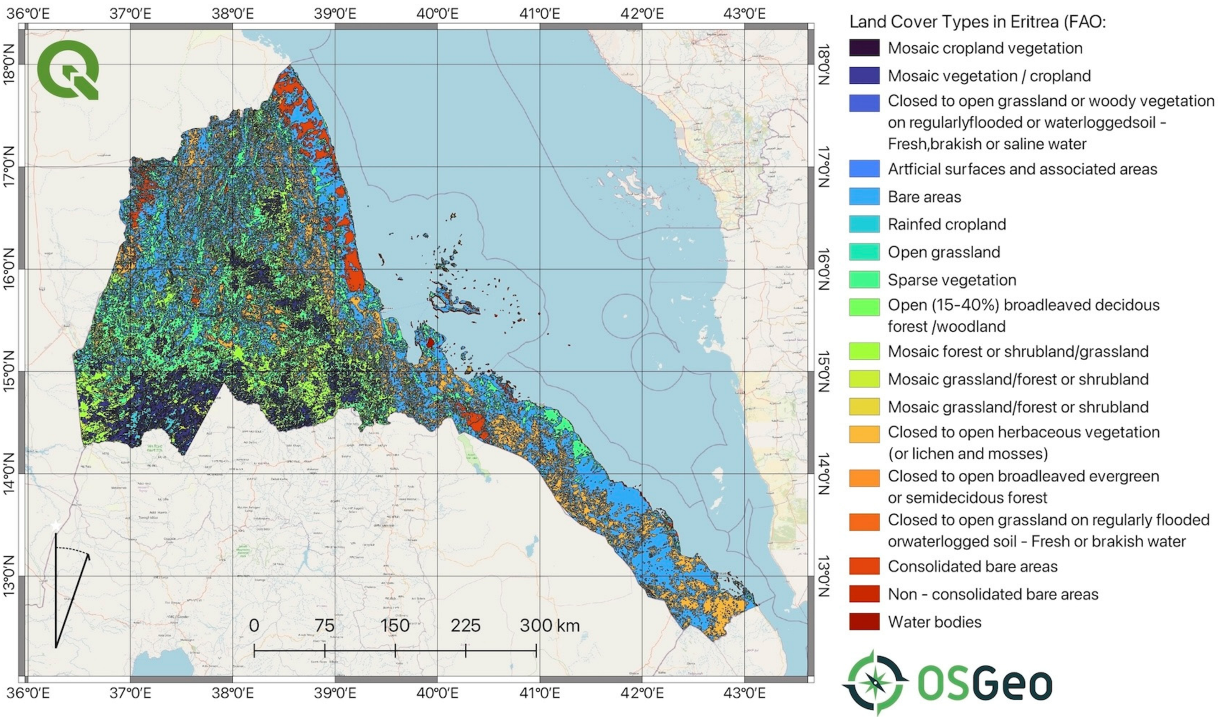

Figure 2: Land cover types in Eritrea. Data source: FAO. Map source: author.

Extreme weather induces water deficit and affects vegetation coverage causing land degradation, overgrazing, deforestation, soil erosion and desertification. The environmental problems of Eritrea are exaggerated by the specific topography: the Danakil Depression is the third lowest located place on the African continent and the hottest place on Earth with regard to the mean temperatures. Typical landscapes are presented by hot and dry deserts with barchan dunes [19]. In such conditions, rare species depend on the availability of water and have to adapt to climate seasonality.

Decadal variations in temperature and salinity of water in southern Red Sea affect regional environmental setting [20]. Rising temperatures contribute to degradation of mangroves and coral reefs where coastal plains provide habitats for migrating birds and endemic species [21]. Besides, riparian vegetation in the coastal regions of Eritrea are washed away over decades due to river widening [22]. Seasonal climate gradient is more pronounced in the south of shelf ecosystems [23] where unique landscapes support local inhabitants through essential services of livelihood. In coastal areas of the Red Sea, riverine resources are being actively used by population for economic reasons as source for timber, wood, fuel, charcoal, food and livestock. Such intense anthropogenic activities triggered land cover changes across various regions of Eritrea.

3. OBJECTIVES AND GOALS

The research objective is to understand the potential influence of climate effects on landscapes and fluctuations of water level in eastern Eritrea using advanced methods of image analysis. A qualitative-quantitative approach of the environmental analysis using RS data allows understanding not only the patterns and trends of biodiversity and land cover change, but also compute the rates of changes to understand the reasons why they are changed. To this end, a series of Landsat imagery on 2014, 2018, 2022 and 2024 was processed and analyzed using heuristic cluster search. To find optimal method of image analysis, we aim at testing and comparing several ML methods of image analysis using advanced cartographic software Geographic Resources Analysis Support System (GRASS) GIS. The core issue is to employ the objectivity and automation of the computer vision algorithms of GRASS GIS and to use the advantages of ML techniques. The ML-based automated approaches of image analysis aim to extract information on land cover types from satellite images, limiting human intervention into the classification process. To achieve this, ML-based classification methods associate each pixel in the image automatically with a land cover class based on the value of spectral reflectance. Algorithms of ML are based on the principle of ML which simulates computer vision approaches of visual data analytics that enable machines to discriminate, interpret, and classify data into clusters. ML outperforms the traditional methods of classification through increased precision and accuracy of mapping. Technically, the ML approach of GRASS GIS for mapping and image classification relies on the algorithms of Pythons' Scikit-Learn library. Detailed statistical results on the classified images are included in the GitHub repository with reports for each year.

4. MATERIALS AND METHODS

4.1. Data

In this study, we used the most well-known RS data sources are satellite images of the Landsat program launched by the National Aeronautics and Space Administration (NASA) in 1972. Initially dedicated to assessing grain harvests, this program now allows the study of the entire continental surface to analyze environmental dynamics of the Earth. A total of eight satellites were launched between 1972 and 2013, three of which are used in this study: Landsat-8 and 9 Operational Land Imager (OLI) Thermal Infrared Sensor (TIRS) provides images at a resolution of 30 meters for eight spectral bands with a revisit time of sixteen days.

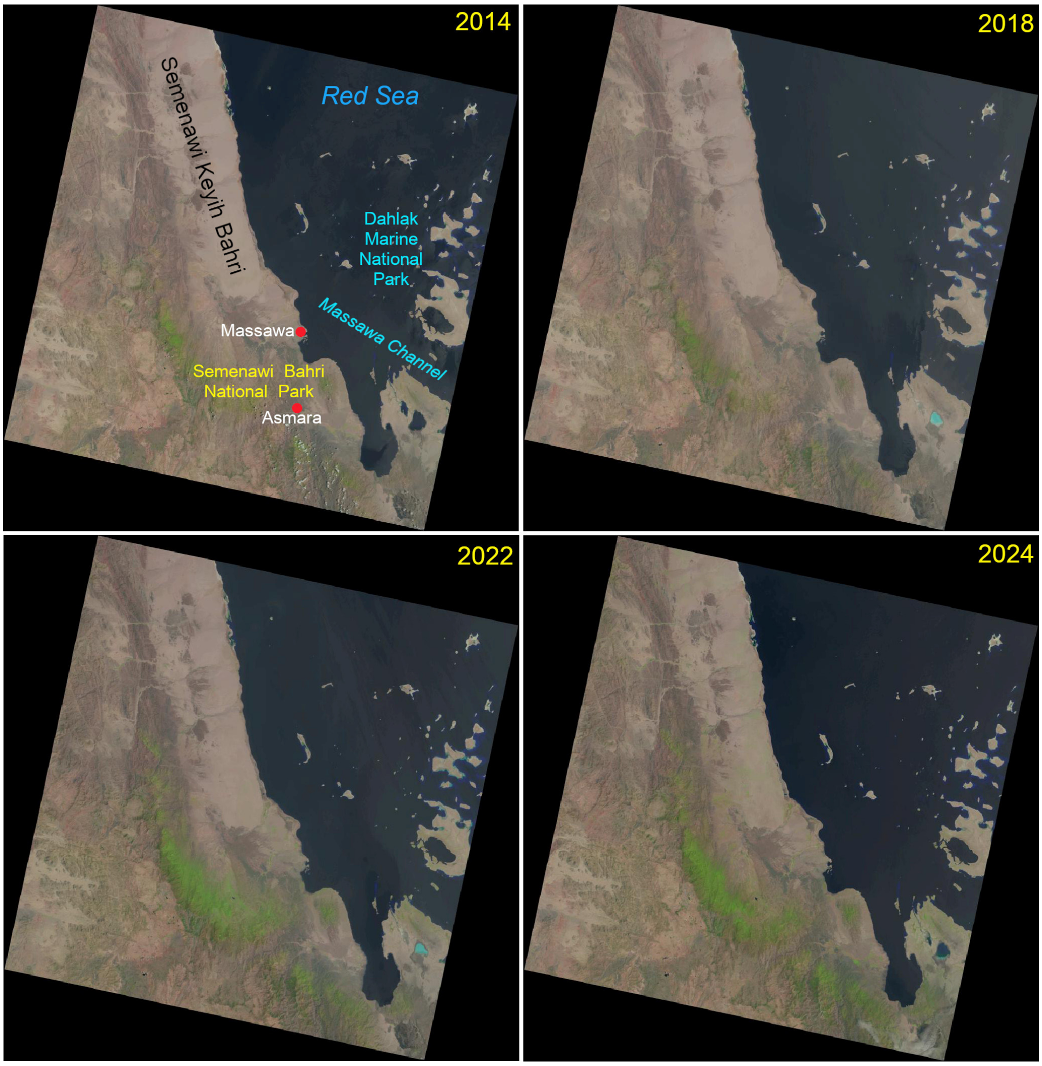

Figure 3: Original images of the Landsat 8 OLI/TIRS in RGB colours. Annotations of major geographical features are added on the first image. Data source: USGS. Compilation source: made by the author.

The data were obtained from the USGS EarthExplorer repository (https://earthexplorer.usgs.gov/) as time series analysis of the satellite images on years 2014, 2018, 2022 and 2024, Figure 3. There are numerous examples of the use of Landsat for the environment monitoring of the African coastal regions. [24-26]. Figure 3 shows the set of a satellite image time series and its associated characteristics. Spatial resolution, coupled with the imaged area, defines the image size, while the number of bands indicates the multispectral character of the images. Temporal resolution allows the same scene to be viewed multiple times which enabled time series analysis: 2014, 2018, 2022 and 2024.

4.2. Workflow

Image processing and classification has been performed using console-based techniques of GRASS GIS software [27]. This software was selected due to its effectiveness and functionality: it processes diverse data format, supports complex functionality of image processing and imports the results into the bitmap data format. The embedded algorithms of GRASS GIS modules for image processing enable to perform accurate training of the models using scripting approaches [28]. The AI-driven GRASS GIS ML framework of image processing described below was employed to map seasonal variations in the Eritrea using satellite multispectral Landsat 8-9 OLI/TIRS data with repetitive time span. The performance of the both AI-driven and MaxLike methods of image classification was visualised, compared and evaluated with 30-m resolution Landsat OLI-TIRS images with as colour composites.

The land cover data were obtained from FAO dataset: https://data.apps.fao.org/catalog/iso/c1f0e345-8ef1-45a2-a0b3-13e183bf13ff using the GlobeCover dataset. As the original dataset depicts the land cover in globe scale, it was downscaled to the study area. The topographic data and a shaded relief background in the classified satellite images were collected from the General Bathymetric Chart of the Oceans (GEBCO): https://www.gebco.net The topographic map was plotted in Generic Mapping Tools Version (GMT) using existing methods of cartographic scripts [29]. The methodology of RS data processing employs Python's libraries of Scikit-Learn [30] with algorithms of supervised classification such as LDA, DTC, GND. These algorithms were compared among each other and with those obtained from the traditional approach of Maximal Likelihood Discriminant Analysis that uses unsupervised classification approach. The best results were demonstrated by the LDA due to detailed classification in mapping. The workflow scheme is presented in Figure 4.

Figure 4: Schematic workflow of image processing and data analysis in GRASS GIS. Source: author.

4.3. Algorithms of image processing

The scripts are available in the GitHub: https://github.com/paulinelemenkova/GRASS-GIS-scripts-ML-SVM-Eritrea

The algorithms of the automatic image classification included the sequence of the technical steps of data processing which included the following cartographic workflow:

First, the multispectral channels of Landsat were grouped to avoid the panchromatic bands using the following code:

- g.region raster=L_2024_01 -p i.group group=L_2024 subgroup=res_30m
- input=L_2024_01,L_2024_02,<...>,L_2024_07

The data were imported into the working folder using model 'r.import':

- r.import input=/Users/<path>/<name>.TIF output=L_2024_04 extent=region resolution=region

In this snippet of code, the functions 'extent' and 'resolution' define spatial borders and spectral resolution of the input data. In the same way, all the Landsat images and topographic shaded relief from GEBCO grid were imported.

The content of the files was checked using 'g.list rast' module. The next step included creating colour composites. Colours composites were generated using module 'r.composite' because band combinations of the multispectral images detail features on the land surface and provide more information compared to the monochrome bands taken separately. Different combinations of colour composites demonstrate that the texture of land cover types is highly diversified due to the natural processes of water evaporation from the basin and drying desert landscapes. Creating colour composites was done as follows:

- r.composite blue=L_2024_07 green=L_2024_05 red=L_2024_04 output=L_2024_754

The isolines were added on the maps using 'r.contour' module with 200 m interval using following code:

- r.contour shaded_relief out=isolines step=200 --overwrite

Spectral signatures for land cover types were generated using module 'i.cluster' of clustering algorithm, which performs the unsupervised automatic classification with a variable number of clusters. Specifically, it detects and recognises spectral reflectance values of pixels of the images. Practically, the code used for this step is as follows:

- i.cluster group=L_2024 subgroup=res_30m
- signaturefile=cluster_L_2024 classes=10 reportfile=rep_clust_L_2024.txt

The results of data handling are saved for each image. The signature file was used as input for 'i.maxlik' to generate an unsupervised image classification using information in signature file. The maximum-likelihood classifier uses the cluster means and covariance matrices obtained from the signature file generated by the 'i.cluster'. Here, the algorithms define to which category based on the definition of spectral class belongs each cell in the satellite image. This partition is done based on the evaluation of the probability of belonging of each cell to the classes (here, the example for the image on 2024, repeated for each year). The classification model of GRASS GIS is defined by the module 'i.maxlik' which performs image partition using a maximum-likelihood discriminant analysis classifier using the following code:

- i.maxlik group=L_2024 subgroup=res_30m signaturefile=cluster_L_2024
- output=L_2024_clusters reject=L_2024_cluster_reject

4.4. Algorithms of machine learning (ML)

The ML algorithms included the Gaussian Naive Bayes (GND), Decision Tree Classifier (DTC), and Linear Discriminant Analysis (LDA). All the ML models were trained and randomly selected points from the test image. The ML approach was realised in GRASS GIS relevant modules and the following scheme. First, the training pixels were generated from an older land cover classification using the following code by 'r.random' module:

- r.random input=L_2014_clusters seed=100 npoints=1000 raster=training_pixels

This module generates randomly placed raster pixels which is useful for creating training data for ML approaches. First, we used the GNB classifier which is based on Bayes' theorem, the Gaussian Naive Bayes algorithm – a ML classification method that assumes that features have a normal distribution. It works especially effectively with datasets that contain continuous characteristics, such as landscapes of the Earth. The next approach of classification used the DTC which uses a decision tree to make predictions using hierarchical data assessment. The DTC is a method of ML that incorporates non-parametric supervised learning and is utilized for classification and regression. Hence, the principle follows a dendrite-like model of decisions taken by the algorithm and possible assignment of pixels to a given class of land cover types. The objective of DTC is to learn basic decision rules derived from the data features in order to build a model that forecasts the value of a target variable. A tree can be thought of as an approximation of a piecewise constant. The DTC functions by iterative splitting the pixels on the image into subclasses based on the most significant values of spectral reflectance of pixels that form classes representing the nodes of the tree. The technical approach employs n_estimators parameter in every ML model, included in the syntax of the code. The number of estimators parameter is derived from Scikit-Learn library of Python and affects only tree-based estimators, such as Random Forest. In this context, it specifies the number of separate decision trees trained on subsets of observations.

A supervised ML technique of LDA is employed for dimensionality reduction and classification. Its specific feature is that it looks for a linear feature combination in a dataset that best divides two or more classes. Therefore, the major approach of the LDA algorithm is that it solves the multi-class classification problem in highly diversified patterns of landscape with repetitive mosaics. It separates multiple classes which have diverse several features by reducing the data dimensionality. The programming code of the LDA algorithm in the GRASS GIS is as follows. First, the data are trained using the function 'training_map' in the 'r.learn.train' module as follows:

- r.learn.train group=L_2024 training_map=training_pixels

The use of supervised ML classification methods to obtain land cover maps requires training samples to train the classification algorithm. These training samples are described by a vector of variables extracted from satellite data and a label provided by the reference data. The label is an indication of the land cover class of the training samples, which is used in decision-making to assign the class of new observations. The quality of the labels is therefore directly related to the accuracy of the decision rule learned by the classification algorithm. In this study, we used the available FAO map for training polygons to train the ML models. Afterwards, the ML model was selected for discriminating categories.

- model_name=LinearDiscriminantAnalysis save_model=lda_model.gz

Afterwards, the fitted Scikit-Learn estimator is applied to rasters using 'r.learn.predict':

- r.learn.predict group=L_2024 load_model=lda_model.gz output=lda_classification_2024

Following that, the raster files were visualised using the combi nation of modules: "d.rast" for visualization of grids as explained above, 'd.vect ' was used for plotting the isolines as follows:

- d.vect isolines color='100:93:134' width=0

Different colour palettes were applied for visualising classification results of various ML models (byr for LDA, roygbiv for GNB and plasma for DTC). This was done for distinguishable visualization of the results and comparison of maps. Using the selected palette for all the maps was supported by the legends where the same set of classes is present and described in classification according to the designated classes. The cartographic grid was added using 'd.grid' module:

- d.grid -g size=00:30:00 color=white width=0.1 fontsize=16 text_color=white

Two legends were added using the 'd.legend' module with defined parameters of the cartographic code:

- d.legend raster=L_2024_clusters title="Clusters 2024"
- title_fontsize=19 font="Helvetica" fontsize=17 bgcolor=white

The same principle of mapping was used for all the visualised maps. The given procedure was completed for all the maps and visualised for GNB algorithm of ML. The key approach of the GNB as a ML classification technique consists in an assumption that supposes that each land cover class follows a normal distribution. It presumes that each parameter of vegetation reflectance has an independent capacity of predicting the output variable. This is advantageous for homogeneous classes. However, for landscapes of Eritrea, the input data are heterogeneous and selected classes (xeric vegetation in semi-desert areas and mangroves along the coasts of the Red Sea, mosaic grasslands and shrubland) do not contain such normal distribution and have regional distribution patterns.

Since RS have limitations and inherent errors that can be introduced during image processing, numerical and visual classification, rectification to real-world coordinates, the accuracy assessment was performed as post-processing and recording of data accuracy on the classified images. Hence, advanced methods of RS data processing were used to evaluate accuracy of mapping through script-based image analysis. The overall performance of the tested ML classifiers was assessed using metrics of accuracy, F1 score and Cohen's kappa coefficient. The Cohen's kappa is a quantitative metric used to analyze the correctness of pixels' assignment to various land cover classes and the dependability of rating coefficients [31]. The Cohen's Kappa method was selected because of its robustness for data evaluation reported earlier in research papers [32-34].

5. RESULTS AND DISCUSSION

The presented series of maps show changes in land cover types and desertification indicating climate effects of drought, raise in temperature and aridification in Eritrea, Figures 5-7. In the context of land use mapping, ML classification algorithms exploit the spectral variability of objects on the surface visible on the satellite data [35]. Indeed, this variability induced by different factors that affect vegetation and soil properties. In turn, these depend on several factors such as climate processes, human activities, and differences in soil properties that complicate the appearance of land use classes on the images. Furthermore, this variability becomes more contrasting for large areas, such as African regions. The classification of the satellite images revealed significant changes in land cover in Eritrea during recent decades. These included including a notable desertification and reduction in forest and vegetation cover. The reasons of such phenomena refer to resource exploitation, population pressure, and climate change. In particular, the comparison of the classified images from 2014 to 2024 indicated the decline in forest cover and the increase of lands occupied by deserts.

Deforestation and land degradation in Eritrea may have negative effects on the ecosystem services, resulting in food and water insecurity. The comparison of the results with available data on earlier periods show the consists of trends of land degradation in Eritrea. Thus, according to Global forest water survey, as of 2000, Eritrea had 5 ha of tree cover, equivalent to less than 0.1% of its land area and < 0.1% of the global total. Besides, less than 0.1% of land cover in Eritrea was classified as tree cover with over 30% of canopy density. Moreover, the top regions representing 93% of all tree cover belongs to the Semenawi Keyih Bahri which had the most tree cover at 40 ha compared to an average of 7 ha, as of 2010 [36]. In addition, changes in land cover types and habitat loss impact wildlife habitats and species distribution which can have implications for biodiversity. Moreover, environmental degradation increases vulnerability of the ecosystems to climate change, and extended and repetitive droughtse. Such environmental problems indicate the persistent issue of land degradation in East Africa and the need for measures on sustainable land management to support the environmental sustainability of this region.

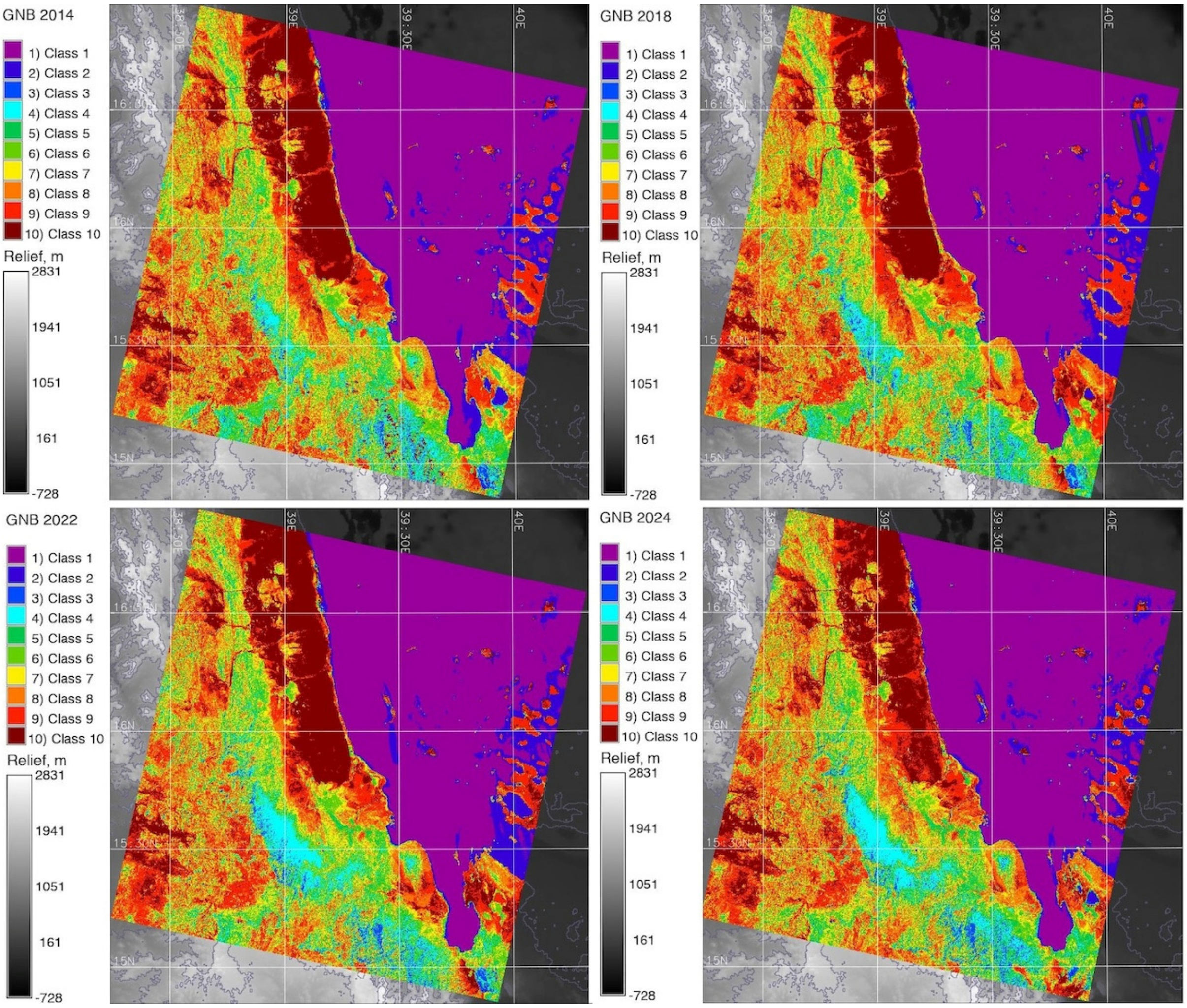

Figure 5: Classified images Landsat 8 OLI/TIRS using GNB algorithm. Source: author.

Spatial analysis was performed at basin and landscape scales by combining different GIS and ML measurement approaches. Specifically, we proposed an AI-driven workflow framework that combines traditional classification of the satellite images based on clustering, maximal likelihood and ML method using Python's Scikit-Learn library embedded in GRASS GIS to assess the reliability of modelling and mapping. The series of several Landsat-8 OLI/TIRS satellite images processed in this study by ML techniques illustrated the process of intense land cover changes that is related to climate processes, such as rise in temperatures, lack of precipitation and increased evaporation of water over coastal Eritrea, which proves the previous results reported earlier [37-38]. Climate fluctuations over Eritrea in period 2014 to 2024 was found to play a dominant role in the precipitation and evapotranspiration partitioning which resulted in changed land cover types, Figure 5. The algorithms included AI application for image analysis of Python's Scikit-Learn library: GND, DTC and LDA. The statistical characteristics on the initial image properties for four scenes are summarised in Table 1.

Table 1: Numerical characteristics of the initial properties of multispectral bands in satellite Landsat scenes

Year	Stat	Band 1	Band 2	Band 3	Band 4	Band 5	Band 6	Band 7
2014	Means	9162.01	9860.14	11384.9	12259.4	13715.7	15723.4	14815
	St. Dev.	1665.86	1904.88	2890.35	4024.82	5046.8	6495.05	5919.18
2018	Means	9154.1	9938.56	11577.5	12482.2	13883	15826.9	14922.7
	St. Dev.	1797.38	1923.61	2703.44	3791.01	4719.46	6077.47	5511.82
2022	Means	8899.43	9658.08	11188.3	11874.6	13591.5	15141.3	14002.1

Year	Stat	Band 1	Band 2	Band 3	Band 4	Band 5	Band 6	Band 7
	St. Dev.	1634.65	1801.18	2557.68	3574.09	4676.77	5836.53	5099.32
2024	Means	8785.91	9433.87	10727.5	11383.4	13271.2	14787	13712.2
	St. Dev.	1453.00	1651.73	2503.25	3468.44	4725.69	5879.95	5185.96

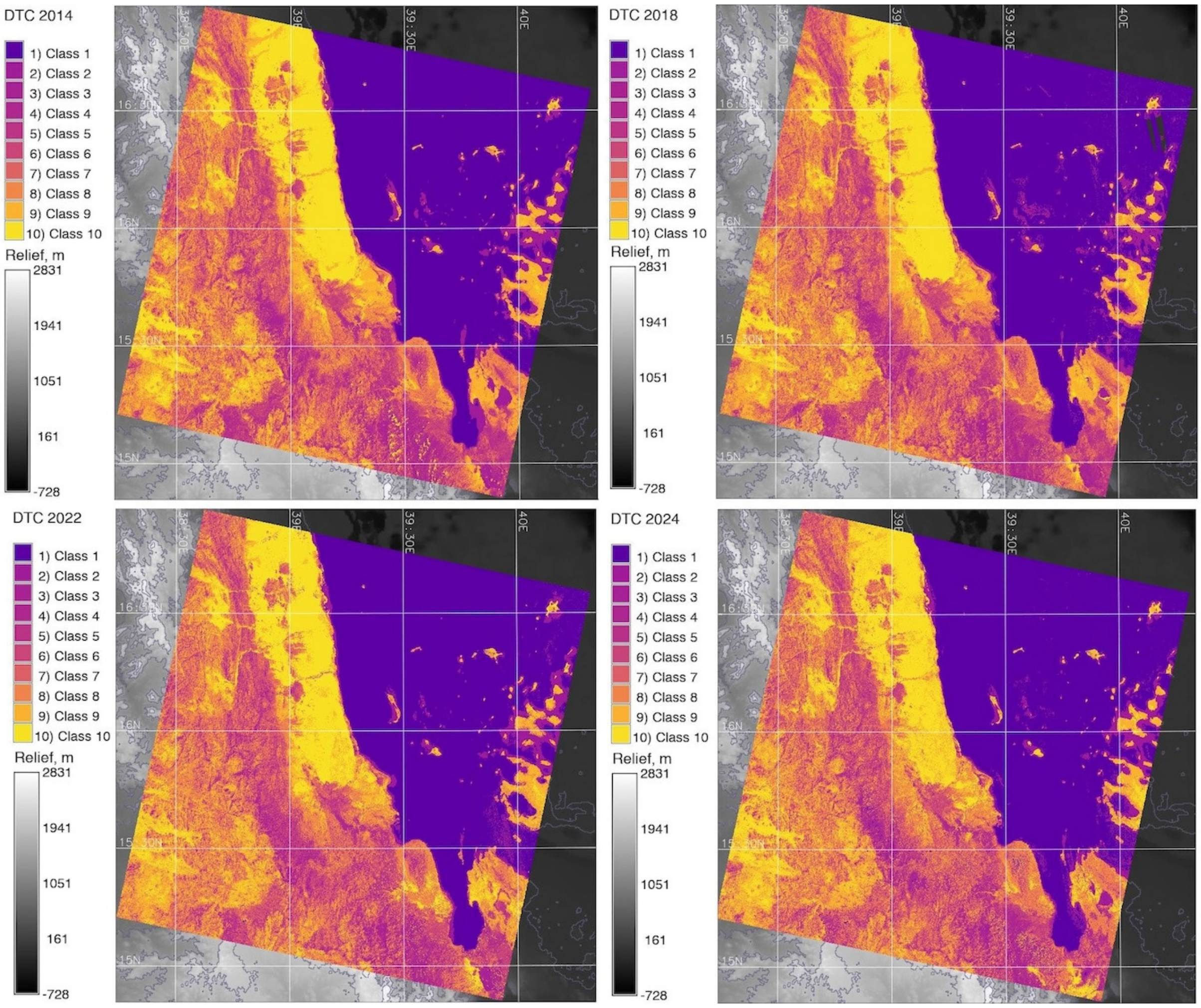

Figure 6: Classified images Landsat 8 OLI/TIRS using DTC algorithm. Source: author.

Processes of environmental changes are notable in the coastal areas due to the distribution of wetland ecosystems, comparing four images on several dates: 2014, 2018, 2022 and 2024. The DTC algorithm (Figure 6) has a high automation in image processing, accuracy in pixel assignments, increased details of classification with more fragmented identified patterns in the landscapes of eastern Eritrea. The detected landscape dynamics enabled to demonstrate the robustness of the AI-based classification method to monitoring seasonal variations using Earth observation data. The drawbacks of the DTC for image processing include the instability to changes and noise in the dataset (even low cloudiness might affect the output). The reported advantages of the DTC include the distinguishability of urban areas from barren and bare land use types, such as beach and coastal cities [39] and crop areas [40].

Besides, the algorithm is based on complex calculations and is computationally expensive with need for computer memory and resources which is demanding for large datasets and limited computer memory. Finally, the classified categories are unbalanced as the algorithm is non-continuous. The results on computed class means for each of the 10 classes and four evaluated years are reported in Table 2.

Table 2: Results on computational analysis: means of pixels for each of the 10 classes in Landsat images.

Year	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9	Class 10
2014	2438	178	71	184	351	568	729	930	789	771
2018	1914	650	66	170	330	578	768	862	908	748
2022	2388	206	125	316	184	544	798	828	808	808
2024	2490	119	198	145	364	497	708	909	844	827

The AI-driven approach was employed to classify a series of multispectral Landsat 8-9 OLI/TIRS images in order to indicate, detect and visualise the dynamics of water evaporation and the increase in desertification in eastern Eritrea basin, and to show changes in the coastal landscapes. Comparative analysis of these images shows gradual changes in land cover types. Here, plant transpiration is lower compared to the savannah stands in the central regions of the country. As a result, the evapotranspiration of soil and understory contribute considerably to water balance. Moreover, raised temperature caused reduced throughfall in a mixed type of land cover and as well as lower rain precipitation events in central Eritrea. Consequently, the reduced discharge reducing volume of water in soil horizon which leads to desertification. As a result, dry soil and lack of humidity play a major role in controlling vegetation cycle, which is especially notable in yearly hydrological balance during summer period. The algorithm of LDA was evaluated for performance with results shown in Figure 7.

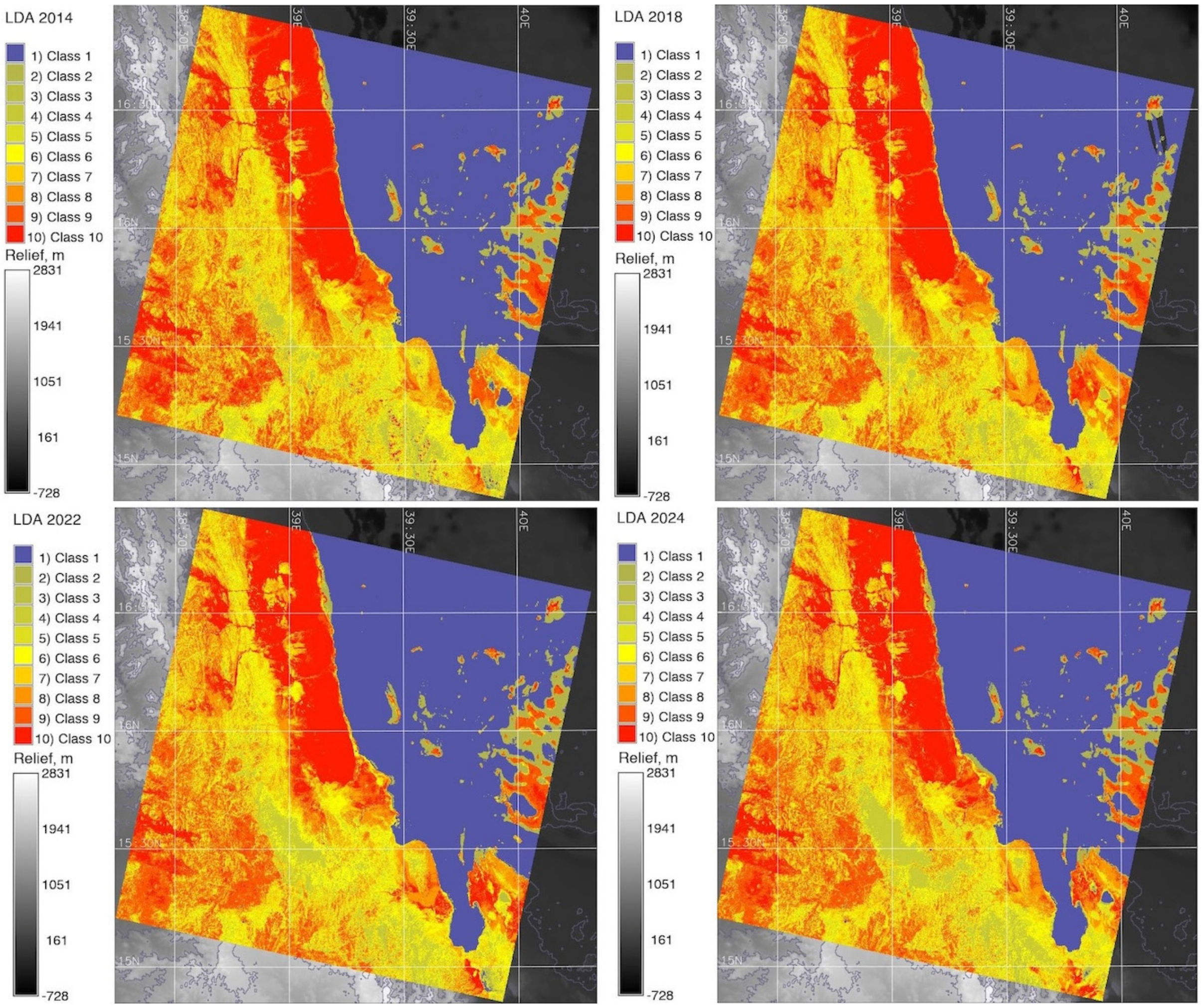

Figure 7: Classified images Landsat 8 OLI/TIRS using LDA algorithm. Source: author.

Environmental processes related to climate change are especially pronounced for arid hot climate of Eritrea. Here, land cover changes indicate the effects of seasonal fluctuations in water balance which are visible as the changes in land cover classes during the recent decade, from 2014 to 2024. The categories were checked using the 'r.category' module, after which the visualization was performed using steps explained earlier. The main feature of the LDA algorithm consists in the optimization of the ML models for image processing through partition of classes that represent land cover types. The disadvantages of LDA which affects its performance in image classification include several issues which should be briefly mentioned. This algorithm is sensitive to outliers which means that selected patches of landscapes can be ignored. Besides, the LDA might miss local geometric information in highly rugged patches with irregular shapes of the polygons which limits its robustness and efficiency in complex mosaics of landscapes. The LDA has the problem of the small sample size while training the data, which affects its performance in practical issues of image analysis.

The results suggest that the application of ML techniques of GRASS GIS combined with multispectral RS data return accurate categorization of land cover types. The accuracy was computed for 3 ML algorithms in GRASS GIS – LDA, DTC and GNB with results reported for land cover classes in 2014, 2018, 2022 and 2024 in the tested region of Eritrea. Cohen's kappa coefficient accuracy and the F1 score metrics were compiled and reported in Table 3. The results indicate that the best outcomes are demonstrated by the LDA techniques with 0.85 Cohen's Kappa coefficient and 0.94

F1 score. Such results are regarded as having an excellent strength of agreement. Hence, according to the calculated values of the F1 method and Cohen's Kappa coefficient for the assessment of categorized data, the LDA algorithms has the best results I the text ML methods.

Table 3: Estimation of accuracy assessment using Kohen's Cappa and F-1 Score of Predictive Performance for three tested ML algorithms in GRASS GIS: (1) GNB (2) DTC (3) LDA.

	Kohen's Cappa			**F-1 Score of Predictive Performance**		
Year	GNB	DTC	LDA	GNB	DTC	LDA
2014	0.76	0.79	0.85	0.81	0.84	0.92
2018	0.74	0.78	0.83	0.85	0.82	0.91
2022	0.75	0.74	0.82	0.83	0.81	0.93
2024	0.81	0.77	0.85	0.77	0.83	0.94

In terms of accuracy, the LDA technique can be considered as a robust method for classifying satellite images, with GNB and DTC coming in 2nd and 3rd places. The F-1 score can be interpreted as follows. While the lowest theoretically possible value of 0 denotes the lowest precision or recall, which in this case is zero, the greatest value of 1.0 shows the perfect precision and recall of variables. Greater values of the F-1 score show better outcomes for image classification.

Apart from technical application of the ML methods in cartography and using algorithms of GRASS GIS for modelling RS data, this study demonstrated the usefulness of the satellite images as a data source for environmental monitoring, Figures 5-7. Time series analysis enable to perform environmental monitoring and detect cycles of flooding and droughts in the ecosystems of eastern Africa. Thus, the comparison of satellite scenes indicated that landscapes of Eritrea undergo intense changes related to climate issues, such as desertification and aridification. In recent ten evaluated years, the landscape has changed significantly due to the gradual development in salinization of the coastal Eritrea. Such processes are related to the hydrological cycle including evaporation of water during dry periods which coincides with the cycle of flooding and evaporation in the coastal Eritrea. Dry period reaches its peak in August while the most water-filled period is in March.

Two factors affect the results of image classification: 1) quality of input data; 2) technical methods of data processing [41-43]. The resolution of the satellite images used as input data for the classification system affect the final quality of maps [44-45]. The second factor is the ML methods used for image classification [46-47]. As shown in this paper, several ML algorithms have different results due to technical parameters. However, overall, ML algorithms prove robustness and agreement in image processing which proves their suitability for the needs of environmental mapping [48-50].

The efficiency of the environmental mapping that operate with the satellite images for monitoring seasonal fluctuations in land cover types can now be improved by using the ML methods of Python integrated with cartographic tools of GRASS GIS. Three ML supervised algorithms are studied to address the challenge of satellite image analysis and classification. We highlighted the good performance of all approaches (GND, DTC and LDA) with slightly better performance of the LDA due to its technical parameters and properties. The effective solutions of ML to problem solving in image processing enable to analyse and interpret complicated cases of the heterogeneous landscapes. This is especially notable for transitional areas located on the land-water border of the coasts. With these advantages in mind, GRASS GIS has been designed to advanced cartographic exploration of the RS data. Recent updates included the ML-modules for RS data processing which is possible using the embedded Python's library of Scikit-Learn. As demonstrated, geospatial problems of RS data processing can be solved using ML and scripting algorithms through a modelling process where parameters are iteratively refined. Changes in habitat structure and fragmentation in coastal Eritrea detected on the satellite images are related to the cumulative effects from climate and anthropogenic factors.

6. CONCLUSION

6.1. Summary

In this study, we demonstrated that AI-driven methods of RS data processing are effective for visualization, processing and classification of Earth observation data for landscape mapping. Image analysis revealed that mountainous areas of Eritrea experienced substantial changes over the last decades. Partly due to the socio-ecological reasons (outmigration of local population replacing traditional agro-forestry activities), partially due to the climate change reasons (desertification and aridisation of the region due to the increased temperatures and decreased precipitation), the landscapes were progressively abandoned and desert areas expanded substantially. Besides, the biodiversity trends in Eritrea observed on the satellite images experienced desertification during recent years. Remote sensing (RS) data, such as satellite images, support understanding of the decadal impacts of the environmental challenges. The application of the ML methods using algorithms of GRASS GIS with heuristic approach utilized the embedded libraries of

Python Scikit-Learn for image processing. Using time series of satellite images, we quantified the changes in land cover types caused by the increased frequency of droughts in coastal Eritrea. This study sought to classify land cover changes over Eritrea, East Africa. A time series of the satellite images Landsat-8 OLI/TIRS was classified using diverse methods of GRASS GIS for unsupervised and supervised classification. The ML techniques of GRASS GIS are based on the embedded algorithms of Python's Scikit-Learn library. The GND, DTC and LDA models were employed to classify satellite images and evaluate changes in land cover types in 2014, 2018, 2022 and 2024. In this way, presented study contributed to the environmental monitoring of the coastal zones around the Massawa Channel in southern Red Sea and Semenawi Bahri National Park, Eritrea, East Africa.

6.2. Recommendations

This study proposed an interdisciplinary data-driven approach of ML methods of image analysis for environmental information extraction. The results presented series of maps that visualize the environmental trends of plant land cover types in the mountainous, coastal and desert areas of Eritrea. Future studies may continue this research on developing evaluating of the rate of ecosystem transition. For instance, using other dataset, the decline of greenness in canopy and desertification can be detected in other regions using quantification of landscape patches that were replaced by bare land. This can be further visualised using land cover type mapping based on image analysis. Alternatively, the differences between several images taken at different time periods can be computed using map algebra in GRASS GIS. Moreover, future studies may extent the time span of image series to other periods. This would enable to visualise and analysis environmental changes under spatial-temporal constraints. Technically, scripts can be reused and applied regionally in future studies and applied in comparable cartographic tasks employing satellite imagery.

Furthermore, in future studies, we recommend to continue using Scikit-Learn library of Python for the benefits of the ML in cartographic approach. This supports effective image processing and modelling and generates maps based on the images analysed through computer vision. For change detection, the satellite time series needs to cover the same area and be free of clouds. In the context of time series classification over large areas, such as East Africa, the choice of classifier is critical. For this problem, the algorithm of ML classification should find a good compromise between the following criteria: accuracy, computational time, parameterization, stability and consistency of algorithm in heterogeneous areas, and robustness to the presence of mislabeled data (e.g., land categories with similar spectral reflectance values). The ML methods are helpful for similar environmental studies and thematic mapping. The snippets of scripts are included and commented. The explained codes used for image processing can be reused and referenced in similar studies. Using ML methods propose algorithms that learn from training RS data for classification tasks.

6.3. Benefits and advantages

This study demonstrated the potential of the ML-based supervised classification of satellite images for land use mapping. We demonstrated the application of RS data as medium-resolution satellite imagery Landsat and compared landscape dynamics through analysis of time series. To this end, time series analysis of the satellite images demonstrated effective method for monitoring landscapes. Change detection was performed using a comparison of several scenes collected during dry and wet periods. Since the existing GIS methods are far from being operational and many challenges remain, we used ML methods GNB, LDA and DTC to compare their functionality and applicability for mapping Earth observation data. An important benefit of automatic ML-based classification of RS data by GRASS GIS consists in independency from the field work and sampling. This allows for production of the high-quality and reliable maps based on the classified images. Such advantage becomes more crucial for regions with restricted and difficult access, as the hot arid regions of East Africa of Eritrea. this article contributes to the existing gap through integrated study which included heuristic cluster search approach of GRASS GIS for environmental mapping of Eritrea. To show the landscape dynamics in the coastal regions of Red Sea, we presented a series of maps based on the classified satellite images Landsat. We developed a ML-based methodology based on GRASS GIS software where the important issue consists in the automatic classification. This advantage becomes more crucial for regions with difficult access, such as the arid regions of Eritrea. Since the most regions of Eritrea do not have reliable land cover type maps based on RS data, this paper fills this gap by presenting a series of classified images showing regional landscape dynamics.

This paper also described briefly the environmental issues and problems of Eritrea. Landscape dynamics is a critical issue for ecosystems of East Africa with contrasting pattern for mountainous and coastal regions. Changes in land cover types are linked to the cumulative effects from climatic and human-related processes. For instance, land degradation caused by urban activities is notable in central highlands which is the most populous part of the country. Vegetation distribution is strongly related to local climate and affected by regional variations in rainfall patterns. Thus, low precipitation and extreme temperatures in central regions trigger weather extremes: droughts and occasional flash floods. Such hazards lead to soil depletion, erosion and the decline in vegetation coverage which ultimately results in land degradation. In view of the importance of this topi, current study contributes to the environmental monitoring of African landscapes using ML methods and satellite image processing with a case study of Eritrea, East Africa.

REFERENCES

[1] D. Karssenberg and K. De Jong, “Dynamic environmental modelling in GIS: 1. Modelling in three spatial dimensions”. International Journal of Geographical Information Science, Vol. 19(5), pp. 559–579, https://doi.org/10.1080/13658810500032362, (2005)

[2] P. Lindh and P. Lemenkova, “Utilising Pareto efficiency and RSM to adjust binder content in clay stabilisation for Yttre Ringvägen, Malmö”. Acta Polytechnica, Vol. 63(2), pp. 140-157. https://doi.org/10.14311/AP.2023.63.0140, (2023)

[3] T. Li, X. Chen, X. Wang, L. Zhao, X. Zhou, A. Zou, and H.O. Ikhumhen, “Grid computing method for atmospheric environmental capacity coupled with ventilation coefficient using CALPUFF simulation and GIS spatial analysis technology”. Environmental Technology, Vol. 45(2), pp. 294–305. https://doi.org/10.1080/09593330.2022.2109993, (2022)

[4] P. Lindh and P. Lemenkova, "Shear bond and compressive strength of clay stabilised with lime/cement jet grouting and deep mixing: A case of Norvik, Nynäshamn". Nonlinear Engineering, Vol. 11(1), pp. 693-710. https://doi.org/10.1515/nleng-2022-0269, (2022)

[5] P. Lemenkova, “Tanzania Craton, Serengeti Plain and Eastern Rift Valley: mapping of geospatial data by scripting techniques”, Estonian Journal of Earth Sciences, Vol. 71, 2, pp. 61–79, https://doi.org/10.3176/earth.2022.05, (2022)

[6] V. Kumar, K. V. Sharma, T. Caloiero, D. J. Mehta, and K. Singh, “Comprehensive overview of flood modeling approaches: A Review of Recent Advances”, Hydrology, Vol. 10(7), p. 141, https://doi.org/10.3390/hydrology10070141, (2023)

[7] M. Xie, W. Wang, W. Yin, and J. Dong, "IFAO-Simo: A spatial-simulation based facility network optimization framework", 2007 Winter Simulation Conference, Washington DC (USA), pp. 2221-2226, https://doi.org/10.1109/WSC.2007.4419857, (2007)

[8] B. Saeidian, M. S. Mesgari, B. Pradhan, and M. Ghodousi, "Optimized location-allocation of earthquake relief centers using PSO and ACO, complemented by GIS, clustering, and TOPSIS", ISPRS International Journal of Geo-Information, Vol. 7(8), p. 292, https://doi.org/10.3390/ijgi7080292, (2018)

[9] B. Y. Chen, H. Yuan, Q. Li, S. L. Shaw, W. H. K. Lam, and X. Chen, “Spatiotemporal data model for network time geographic analysis in the era of big data”, International Journal of Geographical Information Science, Vol. 30(6), pp. 1041–1071, https://doi.org/10.1080/13658816.2015.1104317, (2015)

[10] P. Lemenkova, “Mapping Ghana by GMT and R scripting: advanced cartographic approaches to visualize correlations between the topography, climate and environmental setting”, Advances in Geodesy and Geoinformation, Vol. 71(1), e16, pp. 1-20, https://doi.org/10.24425/gac.2022.141169, (2022)

[11] P. Yue, F. Gao, B. Shangguan, and Z. Yan, “A machine learning approach for predicting computational intensity and domain decomposition in parallel geoprocessing” International Journal of Geographical Information Science, Vol. 34(11), pp. 2243–2274, https://doi.org/10.1080/13658816.2020.1730850, (2020)

[12] A. Lakhouit, G. M. T. Abdalla, E. H. O. Elsadig, W. S. Al-Rashed, I. Abdel-Magid, A. Ben Messaoud, A. H. A. Yassin, O. A. Sayed, M. B. Elsawy, and G. Hayder, "Sustainable airport planning using a multi-criteria decision-making approach with fuzzy logic and GIS integration”, Buildings, Vol. 15(10), p. 1749. https://doi.org/10.3390/buildings15101749, (2025)

[13] N. Tavoularis, “Soil Erosion and Landslide Susceptibility Mapping in Western Attica, Greece: A Rock Engineering System Approach. Geosciences, 13(11), 338. https://doi.org/10.3390/geosciences13110338, (2023).

[14] P. Lemenkova, “Machine Learning algorithms of remote sensing data processing for mapping changes in land cover types over central Apennines, Italy”, Journal of Imaging, Vol. 11(5), p. 153. https://doi.org/10.3390/jimaging11050153, (2025)

[15] D. Zinner, F. Peláez, and F. Torkler, “Distribution and habitat of grivet monkeys (*Cercopithecus aethiops aethiops*) in eastern and central Eritrea”, African Journal of Ecology, Vol. 40, pp. 151-158. https://doi.org/10.1046/j.1365-2028.2002.00360.x, (2002)

[16] M. Fessehaye, Y. Brugnara, M. J. Savage and S. Brönnimann, “A note on air temperature and precipitation variability and extremes over Asmara: 1914–2015”, Internatioanl Journal of Climatology, Vol. 39, pp. 5215–5227, https://doi.org/10.1002/joc.6134, (2019)

[17] M.G. Ghebrezgabher, T. Yang, X. Yang, and C. Wang, "Assessment of desertification in Eritrea: land degradation based on Landsat images", Journal of Arid Land, Vol. 11, pp. 319–331, https://doi.org/10.1007/s40333-019-0096-4, (2019)

[18] P. Lemenkova, "Evapotranspiration, vapour pressure and climatic water deficit in Ethiopia mapped using GMT and TerraClimate dataset", Journal of Water and Land Development, Vol. 54(7-9), pp. 201–209, https://doi.org/10.24425/jwld.2022.141573, (2022)

[19] P. Billi, "Geomorphology of Eritrean river systems", in: Landscapes and Landforms of the Horn of Africa, P. Billi, Ed., World Geomorphological Landscapes. Springer (Switzerland), https://doi.org/10.1007/978-3-031-05487-7_4, (2022)

[20] M. Ionita, T. Felis, G. Lohmann, N. Rimbu, and J. Pätzold, "Distinct modes of East Asian winter monsoon documented by a southern Red Sea coral record", Journal of Geophysical Research: Oceans, Vol. 119, pp. 1517–1533, https://doi.org/10.1002/2013JC009203, (2014)

[21] Z. Girma, Y. Mamo, G. Mengesha, A. Verma, and T. Asfaw, "Seasonal abundance and habitat use of bird species in and around Wondo Genet Forest, south-central Ethiopia", Ecology and Evolution, Vol. 7, pp. 3397–3405. https://doi.org/10.1002/ece3.2926, (2017)

[22] J. Nyssen, M. Haile, J. Naudts, N. Munro, J. Poesen, J. Moeyersons, A. Frankl, J. Deckers, and R. Pankhurst, "Desertification? Northern Ethiopia re-photographed after 140 years", Science of The Total Environment, Vol. 407(8), pp. 2749–2755, https://doi.org/10.1016/j.scitotenv.2008.12.016, (2009)

[23] R. Klaus, "Coral reefs and communities of the Central and Southern Red Sea (Sudan, Eritrea, Djibouti, and Yemen)", in: The Red Sea. Springer Earth System Sciences, N. Rasul, I. Stewart, Eds., Springer, Berlin(Germany), https://doi.org/10.1007/978-3-662-45201-1_25, (2015)

[24] T. D. Bhaga, T. Dube, M. D. Shekede, and C. Shoko, "Investigating the effectiveness of Landsat-8 OLI and Sentinel-2 MSI satellite data in monitoring the effects of drought on surface water resources in the Western Cape Province, South Africa", Remote Sensing Applications: Society and Environment, Vol. 32, p. 101037, https://doi.org/10.1016/j.rsase.2023.101037, (2023)

[25] G. L. Feyisa, H. Meilby, R. Fensholt, and S. R. Proud, "Automated water extraction index: a new technique for surface water mapping using Landsat imagery", Remote Sensing of Environment, Vol. 140, pp. 23–35, https://doi.org/10.1016/j.rse.2013.08.029, (2014)

[26] P. Lemenkova, "Random forest classifier algorithm of geographic resources analysis support system geographic information system for satellite image processing: Case study of Bight of Sofala, Mozambique", Coasts, Vol. 4(1), pp. 127-149. https://doi.org/10.3390/coasts4010008, (2024)

[27] M. Neteler, M. Hamish Bowman, M. Landa and M. Metz, "GRASS GIS: A multi-purpose open source GIS", Environmental Modelling & Software, Vol. 31, pp. 124-130, https://doi.org/10.1016/j.envsoft.2011.11.014, (2012)

[28] P. Lemenkova, "Support vector machine algorithm for mapping land cover dynamics in Senegal, West Africa, using Earth observation data", Earth, Vol. 5(3), pp. 420-462. https://doi.org/10.3390/earth5030024, (2024)

[29] P. Lemenkova, "Console-based mapping of Mongolia using GMT cartographic scripting toolset for processing TerraClimate data", Geosciences, Vol. 12(3), pp. 140. https://doi.org/10.3390/geosciences12030140, (2022)

[30] P. Lemenkova, "Automation of image processing through ML algorithms of GRASS GIS using embedded Scikit-Learn library of Python", Examples and Counterexamples, Vol. 7(100180), https://doi.org/10.1016/j.exco.2025.100180, (2025)

[31] J. Wang, Y. Yang, and B. Xia, "A simplified Cohen's Kappa for use in binary classification data annotation tasks", IEEE Access, Vol. 7, pp. 164386-164397, https://doi.org/10.1109/ACCESS.2019.2953104, (2019)

[32] D. Sudiana, S. H. Putri, D. Kushardono, A. S. Prabuwono, J. T. Sri Sumantyo, and M. Rizkinia, "CNN-random forest hybrid method for phenology-based paddy rice mapping using Sentinel-2 and Landsat-8 satellite images", Computers, Vol. 14(8), p. 336, https://doi.org/10.3390/computers14080336, (2025)

[33] P. Lemenkova, "Artificial neural networks for mapping coastal lagoon of Chilika Lake, India, using Earth observation data", Journal of Marine Science and Engineering, Vol. 12(5), p. 709, https://doi.org/10.3390/jmse12050709, (2024).

[34] V. Sood, R. K. Tiwari, S. Singh, R. Kaur, and B. R. Parida, "Glacier Boundary mapping using deep learning classification over Bara Shigri glacier in western Himalayas", Sustainability, Vol. 14(20), p. 13485, https://doi.org/10.3390/su142013485, (2022)

[35] P. Lemenkova, "Deep learning methods of satellite image processing for monitoring of flood dynamics in the Ganges Delta, Bangladesh", Water, Vol. 16(8), p. 1141, https://doi.org/10.3390/w16081141, (2024)

[36] Global Forest Watch report, https://www.globalforestwatch.org/dashboards/country/ERI/?category=land-cover

[37] E. Symeonakis and N. Drake, "Monitoring desertification and land degradation over sub-Saharan Africa", International Journal of Remote Sensing, Vol. 25(3), pp. 573–592. https://doi.org/10.1080/0143116031000095998, (2004)

[38] J. A. Mabbutt, "Desertification and the future of the arid lands" Australian Geographer, Vol. 14(3), pp. 141–150. https://doi.org/10.1080/00049187908702754, (1979)

[39] L. Hua, W. Man, Q. Wang, and X. Zhao, "A new decision tree classification approach for extracting urban land from Landsat TM in a Coastal City, China," 2012 Fourth International Symposium on Information Science and Engineering, Shanghai (China), pp. 282-286, https://doi.org/10.1109/ISISE.2012.71, (2012)

[40] H. C. Verma, T. Ahmed, and S. Rajan, "An approach to estimate the instability and growth trends of Mango Crop area by using the optical satellite images", IGARSS 2022 – 2022 IEEE International Geoscience and Remote Sensing Symposium, Kuala Lumpur (Malaysia), pp. 4887-4890, https://doi.org/10.1109/IGARSS46834.2022.9884462, (2022)

[41] P. Lemenkova, "Handling dataset with geophysical and geological variables on the Bolivian Andes by the GMT scripts", Data, Vol. 7(6), p. 74, https://doi.org/10.3390/data7060074, (2022)

[42] P. Lemenkova, "Machine learning methods of remote sensing data processing for mapping salt pan crust dynamics in Sebkha de Ndrhamcha, Mauritania", Artificial Satellites, Vol. 60(2), pp. 37-69, https://doi.org/10.2478/arsa-2025-0003, (2025)

[43] Y. Bo and D. Song, "The effect of landscape patterns on the accuracy of land cover map from multi-resolution remote sensing data classification", IGARSS 2008 - 2008 IEEE International Geoscience and Remote Sensing Symposium, Boston (USA), pp. III - 1008-III - 1011, https://doi.org/10.1109/IGARSS.2008.4779523, (2008)

[44] R. Islam, M. Khatun, and S. H. Popy, "TL-GAN: transfer learning with generative adversarial network model for satellite image resolution enhancement", 26th International Conference on Computer and Information Technology (ICCIT), Cox's Bazar (Bangladesh), pp. 1-5, https://doi.org/10.1109/ICCIT60459.2023.10441504, (2023)

[45] A. K. Venkat and K. Kulkarni, "Enhanced super-resolution with EDSR: Optimizing image quality across multiple scaling factors", 2025 International Conference on Intelligent and Innovative Technologies in Computing, Electrical and Electronics (IITCEE), Bangalore (India), pp. 1-6, https://doi.org/10.1109/IITCEE64140.2025.10915430, (2025)

[46] P. Lemenkova, "Improving bimonthly landscape monitoring in Morocco, North Africa, by integrating machine learning with GRASS GIS", Geomatics, Vol. 5(1), p. 5, https://doi.org/10.3390/geomatics5010005, (2025)

[47] G. Thiyagarajan and V. Vijayalakshmi, "Classification of land cover using machine learning models in Landsat satellite data", 15th International Conference on Computing Communication and Networking Technologies (ICCCNT), Kamand (India), pp. 1-6, https://doi.org/10.1109/ICCCNT61001.2024.1072549, (2024)

[48] S. Sourav, N. Kaur, and B. Kaur, "A comprehensive review of machine learning for remote sensing: Current state, challenges, and future directions", First International Conference on Technological Innovations and Advance Computing (TIACOMP), Bali (Indonesia), pp. 283-288, https://doi.org/10.1109/TIACOMP64125.2024.00054, (2024)

[49] P. Gupta and D. P. Shukla, "Combined optical and SAR remote sensing for LULC mapping of Imphal valley using machine learning algorithm", International Conference on Machine Intelligence for GeoAnalytics and Remote Sensing (MIGARS), Hyderabad (India), pp. 1-4, https://doi.org/10.1109/MIGARS57353.2023.10064582, (2023)

[50] M. Mrithika, R. Vanitha, J. Jagan, D. P. Freeda, and M. Jayapranesh, "Land cover classification using satellite imagery and machine learning algorithm", International Conference on Advanced Computing Technologies (ICoACT), Sivalasi (India), pp. 1-6, https://doi.org/10.1109/ICoACT63339.2025.11005205, (2025)