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Impact of Changes in Vegetation Cover on Temperature in the Mahajanga II district, Madagascar

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Abstract

This study analyzes changes in temperature and vegetation cover in the Mahajanga II district (Madagascar) between 1994 and 2024. The spatial distribution of temperatures was determined using an autoencoder, while vegetation cover dynamics were assessed using NDVI indices obtained from Landsat images. The results show a significant increase in temperatures over the study period, more pronounced in inland areas than along the coast, with a cumulative increase of approximately 2°C for central areas and 1°C for coastal areas. At the same time, dense and very dense vegetation cover has declined sharply, replaced by very sparse vegetation and the expansion of bare soil, while water surfaces have also decreased. These changes indicate that vegetation loss contributes directly to local temperature increases by reducing the capacity of ecosystems to moderate the climate and maintain hydrological balance. The use of the autoencoder has made it possible to identify the areas most vulnerable to warming, providing a relevant tool for environmental planning and sustainable land management. The preservation and restoration of vegetation therefore appear to be essential measures for limiting local warming and maintaining the ecological functions of the district.

Keywords

Vegetation cover, Temperature, NDVI, Autoencoder, Artificial Intelligence

1. Introduction

Vegetation cover plays a decisive role in regulating the climate at local, regional, and global scales. Through its biophysical and biogeochemical processes, it controls energy exchanges between the Earth's surface and the atmosphere, notably by modulating albedo, evapotranspiration, and solar radiation absorption [1]. These mechanisms actively contribute to limiting surface warming and stabilizing air and soil temperatures, making vegetation a key component of the climate system.

In tropical regions, which are subject to increasing anthropogenic pressure, changes in land use linked to deforestation, agricultural expansion, and urbanization are leading to a marked decline in vegetation cover. This transformation of landscapes disrupts the surface energy balance and amplifies thermal contrasts, promoting a local rise in temperatures [3]. Conversely, areas with dense vegetation are generally characterized by more moderate and stable thermal conditions, confirming the ability of vegetation to mitigate excessive heat [6].

This study addresses this issue and aims to analyze the influence of changes in vegetation cover on temperature variability in the Mahajanga II district. The aim is to assess the contribution of the dynamics of vegetation cover degradation to the increase in temperatures observed over the last few decades, while highlighting the interaction between vegetation and maritime influence in local thermal regulation.

2. Methodology

2.1. Study Area

The district of Mahajanga II is located in the Boeny Region, in northwestern Madagascar, between 15° and 16° south latitude and 46.4° to 48° east longitude. It covers an area of approximately 468,721 hectares and comprises nine rural communes, including Ambalabe Befanjava, Ambalakida, Andranoboka, Bekobay, Belobaka, Betsako, Boanamary, Mahajamba Usine, and Mariarano.

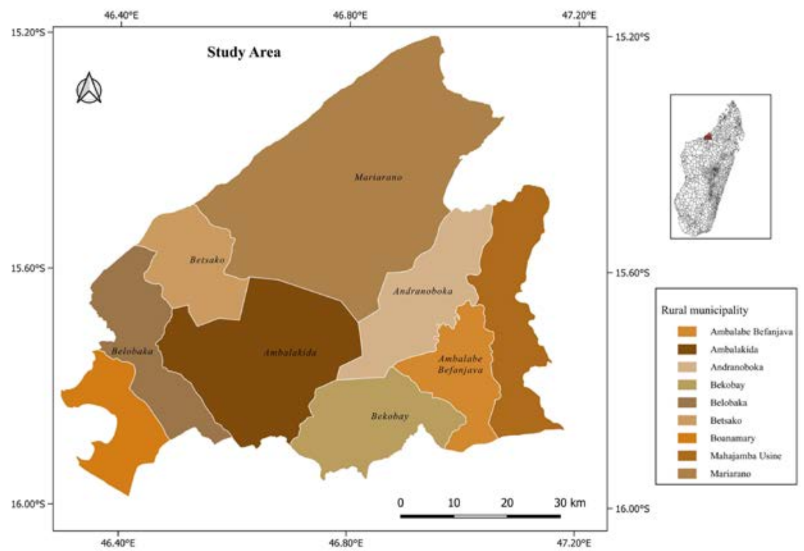

Figure 1. Study Area

2.2. Database

The data used in this study fall into two main categories:

- Landsat satellite data (USGS): Landsat images were used to calculate the normalized difference vegetation index (NDVI), a key indicator of vegetation density and vigor. Two periods were considered, namely August 1994 and August 2004, in order to assess changes in vegetation cover over a decade. The images have a spatial resolution of $\mathbf{30\,m} \times \mathbf{30\,m}$, providing a level of detail appropriate for analyzing changes in land cover at the local scale.
- Climate data: Surface temperature data comes from the European Center for Medium-Range Weather Forecasts (ECMWF), via the Copernicus Climate Data Store (ERA5-Land) platform. This data is provided in the form of a regular grid based on latitude, longitude, and time, with a spatial resolution of $\mathbf{0.1}° \times \mathbf{0.1}°$, or approximately $\mathbf{9\,km}$. It covers the period from 1994 to 2024, allowing for analysis of the spatio-temporal variability of temperature in the study area over a thirty-year scale.

2.3. Calculation of NDVI

The Normalized Difference Vegetation Index (NDVI) is based on the ability of vegetation to absorb light in the visible red range $(\approx \mathbf{0.63 - 0.69}\ \mu\boldsymbol{m})$ and reflect strongly in the near infrared $(\approx \mathbf{0.75 - 0.90}\ \mu\boldsymbol{m})$, due to the cellular structure of leaves [8]. This spectral property makes it possible to assess the density and vigor of vegetation, thus serving as a proxy for biomass and plant health. It is represented by this equation:

$$NDVI = \frac{Nir - \mathrm{Re}\,d}{Nir + \mathrm{Re}\,d} \qquad (1)$$

Where Nir is the reflectance in the near-infrared band and Red is the reflectance in the red band.

NDVI values theoretically range from $\mathbf{-1}$ to $\mathbf{+1}$. Values close to $\mathbf{+1}$ indicate dense, healthy vegetation, while values close to $\mathbf{0}$ or negative correspond to non-vegetated areas, water, or areas with sparse vegetation [5].

In order to interpret the vegetation index (NDVI) values, a thematic classification was applied to distinguish between different types of vegetation cover and their ecological conditions. The thresholds used are based on previous studies and adapted to the ecological characteristics of tropical areas [9].

Table 1. NDVI index classification

NDVI Value	Class	Ecological Interpretation
< 0.0	Water, clouds, snow	Absence of vegetation
0.0 – 0.1	Bare soil	Urban areas, exposed soils
0.1 – 0.2	Very low vegetation	Dry savanna, steppe
0.2 – 0.3	Low vegetation	Sparse grasses
0.3 – 0.5	Moderate vegetation	Croplands, pastures
0.5 – 0.7	Dense vegetation	Secondary tropical forests
> 0.7	Very dense vegetation	Humid tropical forests, lush vegetation

2.4. Autoencoder method

An autoencoder is an unsupervised neural network used to reduce the dimensionality of a dataset while preserving its essential characteristics. It consists of two parts:

- Encoder: compresses the input data $\boldsymbol{x}$ into a latent representation $\boldsymbol{z}$ of lower dimension.
- Decoder: reconstructs the original data $\hat{\boldsymbol{x}}$ from $\boldsymbol{z}$.

The model is trained to minimize the difference between x and $\hat{\boldsymbol{x}}$, usually via the mean squared error (MSE):

$$L(x,\hat{x}) = \left\| x - \hat{x} \right\|^2 \qquad (2)$$

This approach allows relevant latent features to be extracted, which are useful for tasks such as classification, clustering, or pattern detection in environmental data, such as soil or air temperature [2].

2.5. Silhouette Index

The Silhouette index measures the cohesion and separation of clusters for each point. For a point $\boldsymbol{i}$:

$$s(i) = \frac{b(i) - a(i)}{\max(a(i), b(i))} \qquad (3)$$

Where

- $\boldsymbol{a}(\boldsymbol{i})$ is the average distance between point i and all other points in the same cluster,
- $\boldsymbol{b}(\boldsymbol{i})$ is the average distance between point i and all points in the closest different cluster.

The average index $(\bar{\boldsymbol{x}})$ across all points varies between $\mathbf{-1}$ and $\mathbf{1}$: values close to $\mathbf{1}$ indicate good clustering, while values close to $\mathbf{0}$ or negative indicate poorly defined clusters [7].

3. Results

3.1. Indice de NDVI

Figures 2 and 3 illustrate the spatial distribution of vegetation cover and its proportion of the total area in the Mahajanga II district in August 1994, based on Landsat 5 images. Analysis of these maps highlights the existence of particularly green areas, reflecting the presence of water bodies and dense vegetation in certain parts of the district. At that time, very dense vegetation and dense vegetation accounted for 6% and 16.5% of the total area, respectively, indicating that vegetation cover was still well developed.

Most of the territory is dominated by medium-density vegetation, which occupies 39.3% of the study area. Formations with low and very low vegetation cover 21.9% and 3.7% of the district, respectively. Bare ground areas remain marginal, accounting for only 0.5%. Finally, water bodies represent 12.1% of the total area, playing a significant role in the landscape organization and local distribution of vegetation.

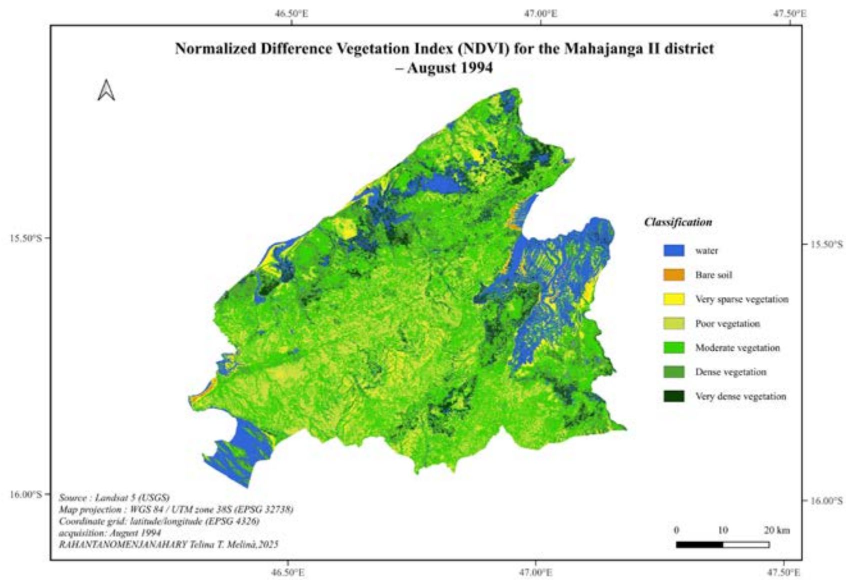

Figure 2. Vegetation cover index in 1994

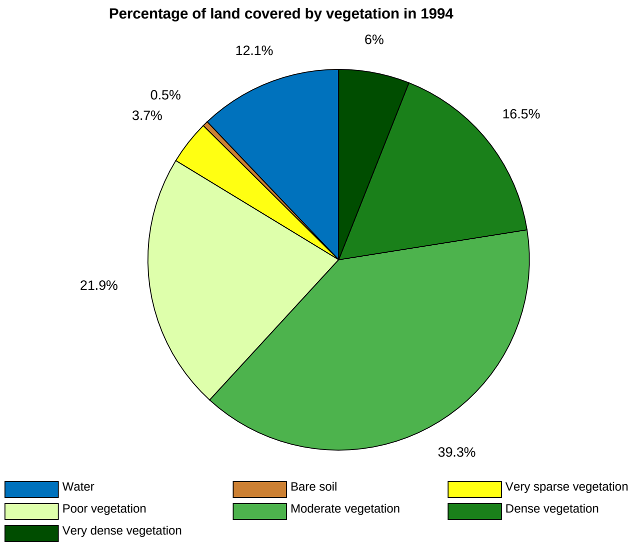

Figure 3. Area of vegetation cover classification as a percentage

Figures 4 and 5 show the spatial distribution of vegetation cover and its proportion of the total area in the Mahajanga II district in 2024. The results highlight a marked degradation of vegetation cover over the last few decades. Dense vegetation now covers only 14.58 ha, while very dense vegetation covers only 0.18 ha, representing a negligible proportion of the total area. This decline reflects a significant loss of plant biomass and a decrease in the natural regeneration capacity of ecosystems.

Most of the territory is now dominated by very sparse vegetation, which occupies 58.3% of the area studied, reflecting an advanced state of deforestation. Bare soil accounts for 5.1% of the district, while water surfaces now cover only 2.9%, reflecting the gradual drying up of wetlands.

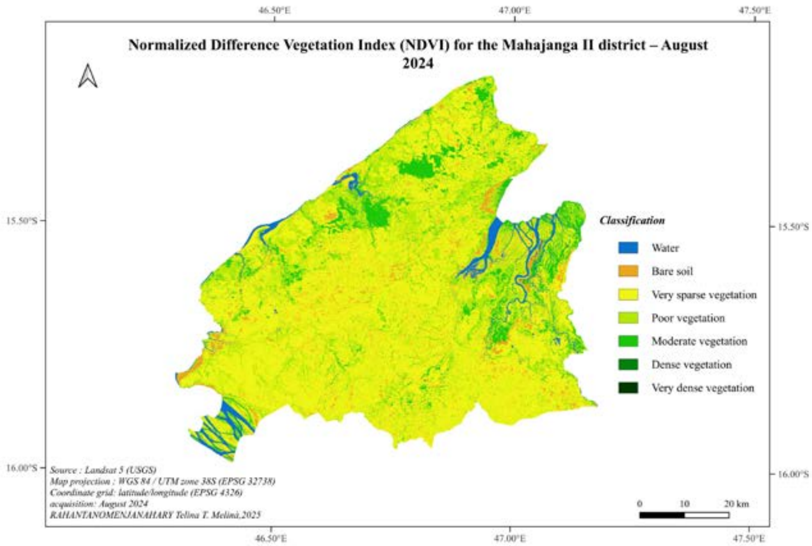

Figure 4. Vegetation cover index in 1994

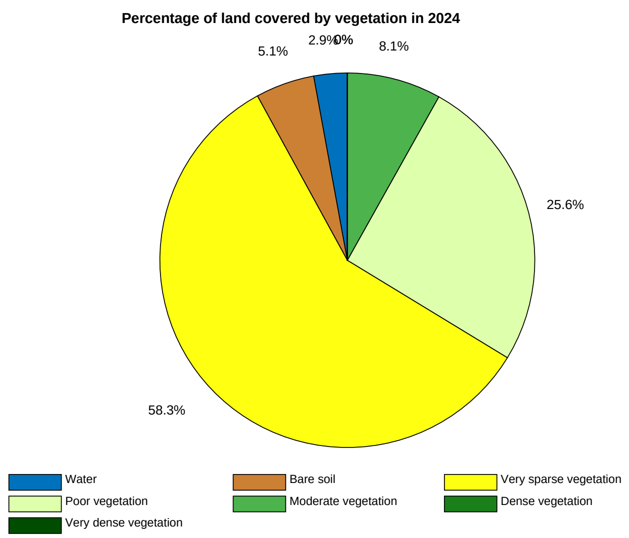

Figure 5. Area of vegetation cover classification as a percentage

3.2. Temperature classification using the autoencoder method

3.2.1. Features of the autoencoder

As shown in Figure 6, the autoencoder consists of an input layer of 12 neurons, an encoder that reduces the data dimension from 12 to 4 neurons through a linear transformation followed by an activation function, and a decoder that reconstructs 4 to 12 neurons. The output layer, which is the same size as the input layer, allows the model's performance to be evaluated based on the reconstruction error.

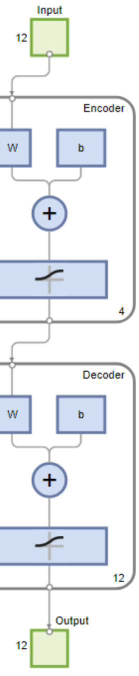

Figure 6. Autoencoder Structure

3.2.2. Regionalization of the study area

The study area was subdivided into two groups based on the air temperature at 2 m.

- Group 1 has an average temperature of around 30°C over the last 31 years, with a maximum in April and a minimum in January. This group mainly corresponds to the coastal municipality of Mariarano, whose temperature regime is strongly influenced by its proximity to the sea.
- Group 2, which includes several municipalities in the Mahajanga II district located inland, has a higher average temperature of around 31.5°C. In this area, the temperature gradually increases with distance from the coast. The minimum is also observed in January, while the maximum is reached in October, unlike in group 1, where it occurs in April. These contrasts reflect the combined effect of continentality and seasonal dynamics on the spatial distribution of temperatures.

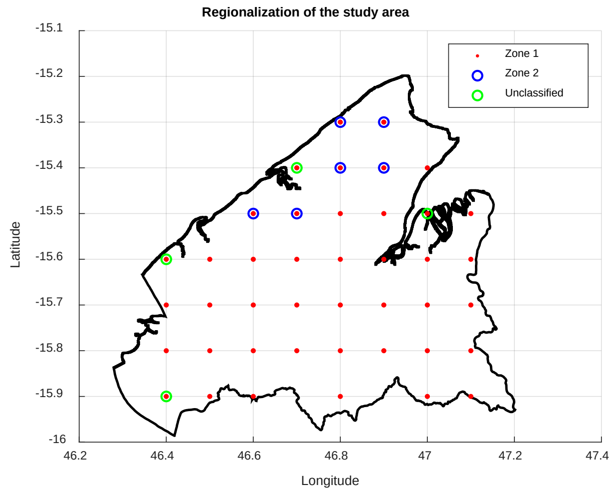

Figure 7. Regionalization of the study area

3.2.3. Validation

The average Silhouette index obtained is 0.814, indicating that the clustering performed is of very good quality. The points in each cluster are well grouped together and clearly separated from other clusters. This suggests that the classification of areas according to temperature is consistent, and that the groups identified reliably reflect spatial differences within the study area.

3.3. Annual temperature change

The temperature trend in the Mahajanga II district (Figure 8) shows a highly significant upward trend in both areas studied, but with different rates of increase: 0.0216 °C/year for area 1 and 0.0185 °C/year for area 2, according to the results of the Student's t-test.

The minimum temperature for both areas was observed in 1996, with a value of approximately 29.5°C, a period corresponding to well-preserved vegetation cover, which is favorable for regulating the local climate. In the following years, the gradual degradation of the vegetation cover was accompanied by a continuous increase in temperatures, leading to a cumulative increase of approximately 2°C in zone 1 and 1°C in zone 2 between 1994 and 2025.

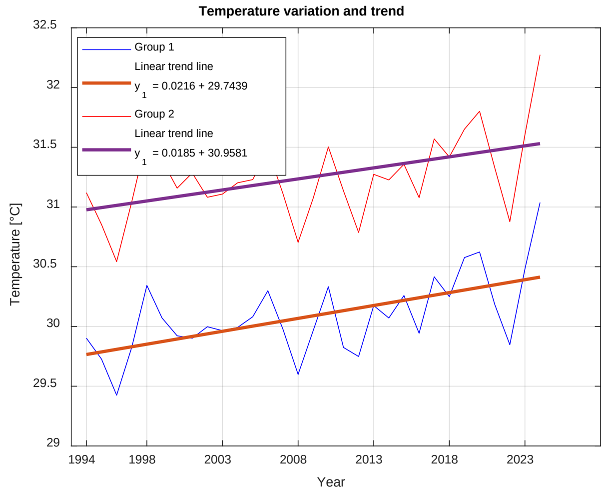

Figure 8. Temperature variation with linear trend line

4. Discussion

The evolution of temperatures in the Mahajanga II district between 1994 and 2025 reveals a significant increase, which is more pronounced in inland areas than on the coast. This spatial differentiation can be explained by the proximity of the ocean, which moderates coastal temperatures thanks to the maritime thermal effect, while more continental areas experience greater variations.

Analysis of vegetation cover using NDVI shows a marked deterioration in dense and very dense cover, replaced by very sparse vegetation and an increase in bare soil. Although this study does not include a direct statistical correlation analysis between temperature and vegetation, the literature indicates that vegetation loss contributes to higher local temperatures by reducing evapotranspiration and increasing soil exposure to solar radiation ([3], [6]). The decrease in water bodies observed over the same period also accentuates the warming trend by limiting the natural thermal regulation of ecosystems.

5. Conclusion

In conclusion, the study of the Mahajanga II district highlights a significant increase in temperatures between 1994 and 2025, which is more pronounced in inland areas than along the coast. This change coincides with a marked deterioration in vegetation cover, where dense and very dense vegetation has almost disappeared, giving way to a predominance of very sparse vegetation and the spread of bare soil.

These results indicate that vegetation loss contributes directly to local temperature increases by reducing the capacity of ecosystems to moderate the climate and maintain hydrological balance. The preservation and restoration of vegetation, as well as the protection of wetlands, appear to be essential measures for limiting local warming and maintaining the ecological functions of the district.

Finally, the use of autoencoders for temperature regionalization has made it possible to identify the most vulnerable areas, providing an operational tool for environmental planning and sustainable natural resource management.

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