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Modeling the evolution of temperature in the Boeny region using the convolutional neural network method

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Abstract

This article focuses on the modeling and analysis of temperature evolution in the Boeny region between 1979 and 2024. To achieve this objective, we first performed an annual temperature analysis, followed by a break test to identify significant changes in the trend. The anomaly was then used to examine deviations from the annual averages. Finally, a prediction model based on a convolutional neural network was developed. The study showed that the temperature in the Boeny region has followed a general upward trend since 1979. Over the past 25 years, positive anomalies have occurred consecutively, with a major shift observed in 2022, corresponding to an increase of 1.3°C. The model thus created allowed for the prediction of a continuous temperature rise over the next five years.

Keywords

Artificial Intelligence, Temperature, Anomaly, Modeling, MAPE

1. Introduction

Global climate warming continues to intensify, as evidenced by recent temperature records. The year 2024 was officially declared the hottest on record, with a global average temperature exceeding pre-industrial levels by 1.55°C, according to the World Meteorological Organization [1]. This critical threshold set by the Paris Agreement marks an alarming turning point in the global climate trajectory [2]. In January 2025, a new monthly record was set, with an anomaly of +1.75°C, despite the presence of the La Niña phenomenon, known for its moderating effect on global climate [3].

The consequences of this global warming are already observable: accelerated glacier melt, increased tropical nights, continued sea-level rise, and intensification of extreme weather events [4].

In this concerning global context, it is essential to study the local evolution of temperatures, especially in vulnerable regions like Boeny, in northwestern Madagascar. This region is facing growing pressure from climate change, which is affecting not only environmental conditions but also social dynamics. Indeed, the Boeny region is increasingly impacted by internal migration, particularly from the southern regions of Madagascar, which are severely affected by drought and food insecurity. This migratory pressure exacerbates the weakness of local ecosystems and increases the adaptation challenges for populations and local authorities.

This article aims to analyze the recent temperature evolution in the Boeny region, using climate data from reanalysis and observations, in order to assess current trends and their implications for environmental sustainability and territorial development.

2. Methodology

2.1. Study Area

The Boeny region is located in the northwestern part of Madagascar, between latitudes 15°S and 17.5°S and longitudes 44.5°E and 47.5°E. It covers a vast coastal area characterized by a diversity of landscapes, including alluvial plains, wetlands, mangroves, and savannas. Administratively, the region is composed of six districts: Ambato-Boeny, Mahajanga I, Mahajanga II, Marovoay, Mitsinjo, and Soalala.

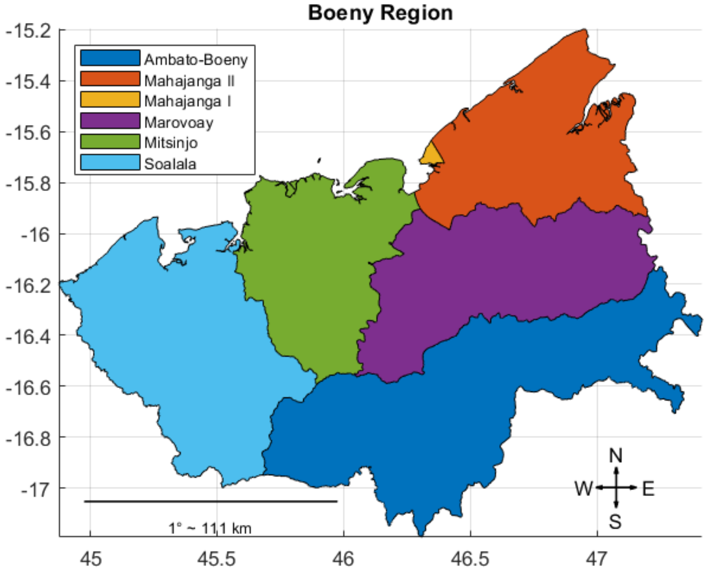


Figure 1. Study Area

2.2. Database

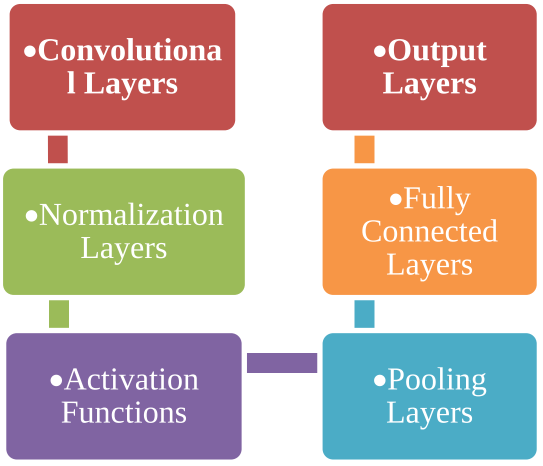
The data used in this study concern air temperature at 2 meters above ground level, obtained from the Copernicus Climate Data Store platform. They cover the period from 1979 to 2024 and are available as georeferenced time series, varying according to latitude, longitude, and time.
These are reanalysis data, meaning they are produced using numerical weather prediction models combined with historical observations from various sources (weather stations, satellites, weather balloons, etc.). Reanalyses allow for the reconstruction of a coherent and continuous image of past climate, especially in regions where direct observations are scarce or incomplete, as is the case for much of Madagascar.

2.3. Break Detection Method

Break detection was performed using MATLAB's findchangepts function, which is specifically designed to identify changes in the linear trend of a time series. This method is commonly used to analyze time series in fields such as climate science, where breakpoints can signal significant events or changes in environmental trends [5].
The findchangepts function detects breakpoints by identifying points where the slope of the time series changes in a statistically significant way. It helps to pinpoint moments when the data follows a new trend, which is essential for understanding climate variations.

2.4. Convolutional Neural Network

A Convolutional Neural Network (CNN) is a type of artificial neural network designed to process data with a grid-like structure, such as an image or a time series [6].
It is generally composed of several layers:



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The general methodology for using a Convolutional Neural Network (CNN) follows five main steps:

- Data preparation: the data are formatted and normalized to facilitate learning [7].
- CNN network construction: the network architecture is defined by selecting convolutional layers, activation functions, and associated parameters [8]
- Model training: the network is trained using an optimizer, such as Adam, to minimize the loss function through backpropagation [9].
- Model validation: the performance is evaluated on an independent dataset to assess generalization ability.
- Prediction: the final model is used to make predictions on new data.

The MAPE (Mean Absolute Percentage Error) methodology is used to evaluate the accuracy of a prediction model by calculating the average absolute error expressed as a percentage relative to the actual values. It is obtained using the following formula:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{\left(y_i - \widehat{y}_i\right)}{y_i} ? \ 100$$

Where $\boldsymbol{y_i}$ is the actual value, $\boldsymbol{\hat{y}_i}$ is the predicted value, and n is the total number of observations.

3. Results

3.1. Annual evolution of temperature in the Boeny region from 1979 to 2024

The analysis of temperature variation in the Boeny region revealed that the district of Ambato-Boeny exhibited the highest temperatures, while Mahajanga II recorded the lowest among the six districts studied. All districts show an upward trend, with varying slopes; Mahajanga I is particularly concerning, with an increase of 0.027 °C over the period, corresponding to a rise of 1.27 °C compared to the temperature observed in 1979.

The year 2024, officially declared the hottest on record by the World Meteorological Organization (WMO), confirms these observations. After the detection of a change point, the trend curves highlighted a gradual shift characterized by a steady rise in temperature across all districts starting in 2022. These findings indicate that a localized climate change has recently occurred in the region. Furthermore, the hottest months are observed in April and November.

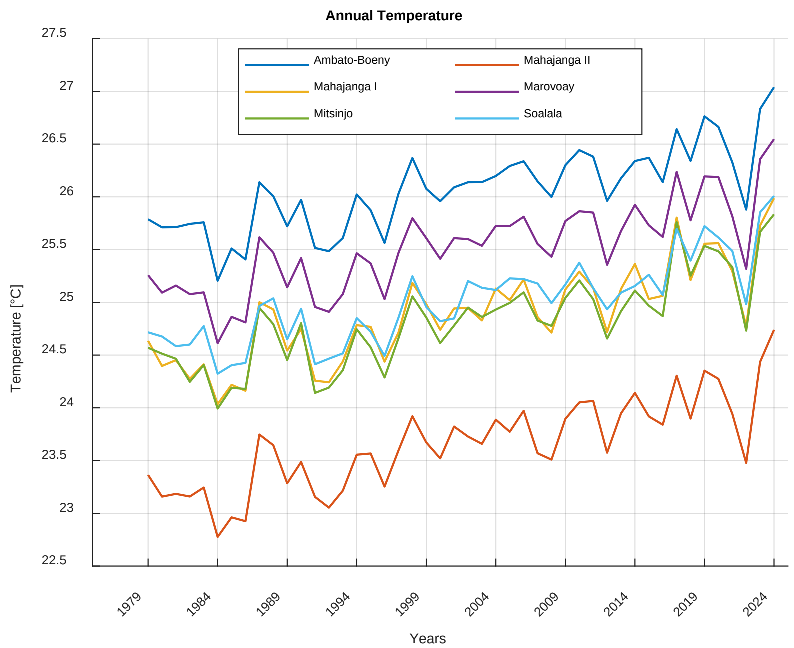

Figure 2. Variation of the annual temperature in the Boeny region between 1979-2024

3.2. Distribution of temperature in the Boeny region in 2024

The temperature distribution in the Boeny region shows a strong variation between coastal areas and inland regions. Along the coast, particularly in the districts of Mahajanga I and Mahajanga II, the temperatures are relatively cool, ranging from 22 to 23°C, due to the moderating effect of the Mozambique Channel, which reduces temperature fluctuations. Moving inland, the temperature gradually increases, reaching higher values, from 26 to 27°C, especially in the districts of Marovoay and Ambato-Boina. This temperature difference, around 5°C, is explained by the increasing distance from the maritime influence and the intensification of continental warming, as shown in Figure 3.

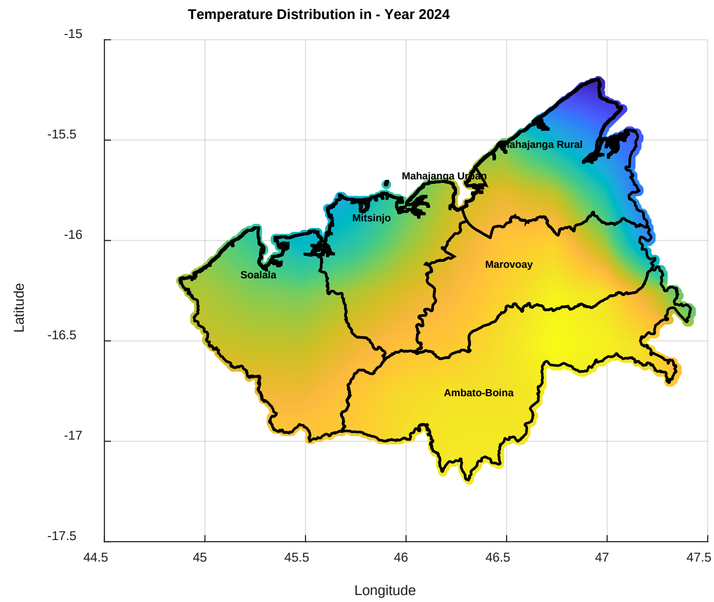

Figure 3. Temperature Distribution in the Boeny Region

3.3. Temperature Anomaly

The temperature anomaly is calculated by comparing each annual measurement to the average of the reference period 1979–2024. A positive anomaly indicates a temperature higher than this average, reflecting a temperature increase, while a negative anomaly indicates a temperature lower than the average, signifying relative coolness.

Over the period 1979–2024, the analysis of anomalies reveals 34 positive years compared to 12 negative years. This shows that the Boeny region is particularly affected by global warming, especially during the last 25 years, a period in which positive anomalies have been nearly continuous. This trend has intensified, reaching a maximum anomaly of +1.3°C in 2024, highlighting a significant and persistent warming in the region.

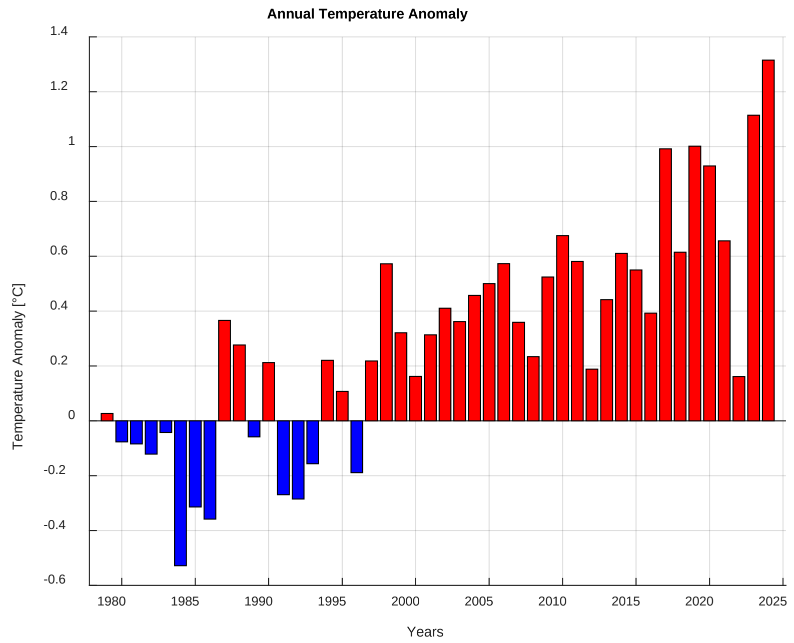

Figure 4. Annual Temperature Anomaly of the Boeny Region between 1979-2024

3.4. Modeling with Convolutional Neural Network

The modeling of annual temperature for the Boeny region was carried out using a method based on a Convolutional Neural Network (CNN). This approach allows for predicting the evolution of temperature over several years by exploiting the temporal features of past data. Figure 6 presents the results obtained from this model.

The network consists of an input layer (imageInputLayer), followed by a 2D convolution with 64 filters of size [4 1], batch normalization, and ReLU activations. It then includes dropoutLayer (with a rate of 0.2), two fully connected layers with 8 and 1 neurons respectively, and a regression layer for the final prediction.

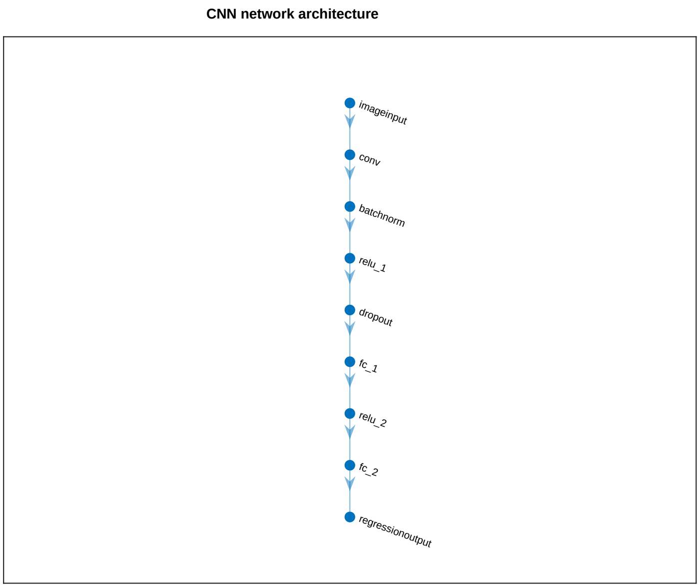

Figure 5. CNN network architecture

The model was trained for 1,000 epochs, corresponding to 2,000 iterations, with two iterations per epoch. The learning graph shows a rapid decrease in error (RMSE) at the beginning of training, followed by a gradual stabilization toward a low value. This trend indicates that the model quickly captured the main patterns in the data before progressively fine-tuning its adjustments in the subsequent iterations. The fact that the error no longer decreases significantly after around 800 to 1,000 iterations suggests that the model has reached a form of convergence. Moreover, the absence of any notable rebound in the RMSE or loss function indicates that the model does not show signs of overfitting, and that the constant learning rate set at 0.005 helped avoid oscillations, ensuring stable optimization. Training was stopped at 2,000 iterations, the maximum planned, indicating that the process was carried out to the end of the initial training schedule in order to achieve the best possible performance.

Figure 6 illustrates the annual evolution of temperature, including actual data, predictions on the training and test sets, as well as future forecasts. The historical data, shown in black, reveal an overall upward trend between 1979 and 2021, with interannual variability. The predictions on the training set, shown as blue dotted lines, closely follow the curve of the actual data, demonstrating the model's ability to learn historical dynamics. Predictions on the test set, shown as red dotted lines, logically extend this trend, with a slight increase in error, which is expected for data not used during training. Finally, the future forecasts, shown in green, indicate a continued upward trend through 2029, with more pronounced fluctuations. This trajectory remains consistent with the context of climate change, confirming that the model is capable of capturing the temporal dynamics of temperature and providing a plausible extrapolation.

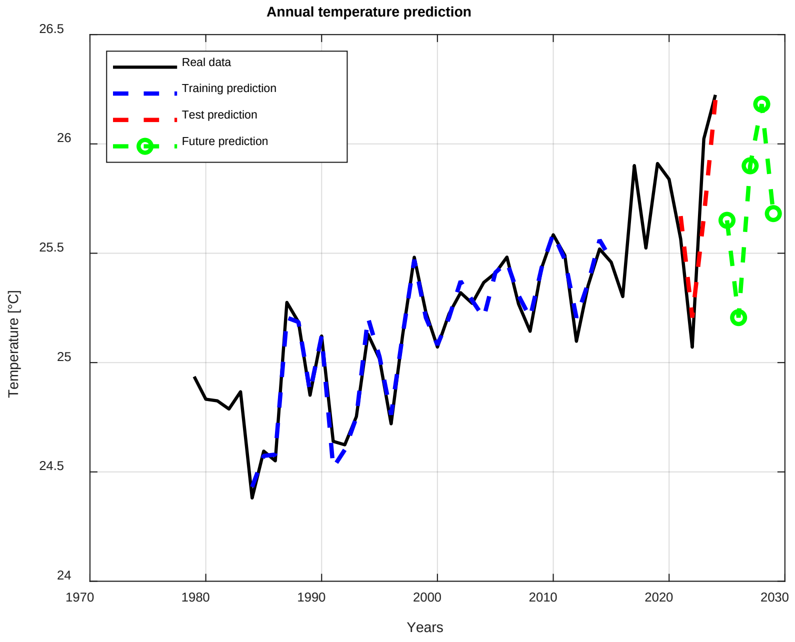

Figure 6. Annual temperature prediction

4. Discussion

The analysis of annual temperatures in the Boeny region shows a marked warming trend, with 2024 being the hottest year recorded between 1979 and 2024. Although global warming remains below 1.5°C, this trend is confirmed by the World Meteorological Organization (WMO), which also designated 2024 as the hottest year globally. This local warming can be partly explained by factors such as the increase in bushfires, rapid urbanization, deforestation, as well as population growth and internal migration.

Bushfires, often used to clear land for agriculture, contribute to the release of greenhouse gases, thus aggravating warming. Urbanization, on the other hand, leads to the formation of urban heat islands, raising local temperatures. At the same time, deforestation reduces the capacity of ecosystems to store carbon and alters the properties of the land surface, favoring temperature increases. Additionally, population growth and internal migration put increased pressure on natural resources, amplifying demand for agricultural land and infrastructure. These combined factors act as catalysts for climate warming, highlighting the need for local adaptation strategies and sustainable management practices.

5. Conclusion

In summary, the study conducted on the evolution of temperature in the Boeny region, using a Convolutional Neural Network (CNN), has yielded significant results in terms of forecasting and understanding climate warming in this area. The analysis of temperature data from 1979 to 2024 reveals a general upward trend, with projections suggesting that this trend may continue in the coming years. The warming observed over the past few decades is particularly pronounced, and the year 2024 recorded a notably high temperature anomaly, making it the hottest year in the study period. This rapid and inevitable climate evolution could have dramatic consequences for local ecosystems, agriculture, and populations, exacerbating the risks of drought, water resource depletion, and biodiversity loss. In the face of this urgent situation, the adoption of ambitious environmental policies and sustainable management of natural resources is crucial to mitigate the impacts of this warming and safeguard the region's future.

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