Vol-1 Issue-1 2023
Scientific Research Journal of Environment, Earth and Physical Science
ISSN: 2584-0614, Peer Reviewed Journal

A LOOK AT HOW RAINFALL CHANGES AND HOW THE RAINY Period CHANGES OVER TIME IN MADAGASCAR'S FAR NORTH

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ABSTRACT

Anomalous Deposition and self-organizing patterns (Kohonen Networks) are two essential methods for analyzing the variability and growth of rainfall over the wet season. The coordinates (latitude/longitude) 13°-17° S / 44°-56° E define the area we study. Regionalization using Kohonen networks identified 20 distinct zones based on the average annual precipitation in our study region between 1980 and 2020. Anomaly accumulation tells us that the northern Madagascar monsoon season usually begins in early December and ends in early April. An average of 125 days, or about 34 months, is how long it lasts. The duration of the wet seasons has been trending downwards. However, with the exception of the eastern maritime areas of our study region, precipitation amounts have increased.

Keywords: *Climates, meteorological, rainfall, precipitation, latitude, meteorology*

INTRODUCTION

Madagascar is not immune to the effects of global warming that are presently being felt all across the planet. A significant sector of the island's economy, agriculture, is suffering the most from the effects of global warming. Agriculture accounts for a significant portion of the economy and daily life for most Malagasy people. But the planting schedule has been flipped due to climatic unpredictability and change. As a result, at the beginning of each rainy season, the Madagascar Climate through the Department of Transport, Tourist industry, and Atmospheric Science in collaboration with the Minister of Farming, Livestock, and the Fishing industry produces a crop schedule following the seasonal projections explicitly intended for farmers to help them make decisions to reduce risks and improve profitability. [1] (Weather in Madagascar 2019) The island's geography, a form of relief, marine impact, and wind regime all produce the island's wide range of climates. Primarily, Madagascar has two distinct climates: a dry and relatively cold period between April 16 and October 16, and a hot and humid period between October 16 and April 16. Madagascar's climate is often divided into two distinct seasons, with April 17 and October 17 as convenient dividing dates. They alternate between seasons with a month-long break in between each.

Our study focuses on the extreme northern region of Africa and Asia, specifically the latitudes of 12° to 15° South and the longitudes of 48° to 50° East, and examines the variation of the monsoon season (beginning and end of the rainy season) and the transformation of the amount of rainfall from 1980 to 2020.

It's helpful to think of this project as having two halves. In this first section, we will examine various tools and resources. Next, we will go into the findings and their significance.

MATERIAL AND METHODS

Used resources and information database

Data :

We used precipitation statistics. These data have been reanalyzed daily from 1980 to 2020 and are available for download in ECMWF at a spatial resolution of 1° x 1°. We utilized MATLAB to create algorithms for statistical and computational analysis and data processing, while Office 2007 Excel was used for more targeted computations.

Presentation of the study area:

A rectangle table depicting precipitation statistics is given. The relationship between each observation or person is like a longitude and a latitude meeting at a particular place. This means there are 69 people in the region under consideration. The following illustration shows how the names of the persons in the table were chosen to make the data more legible. Monthly average rainfall amounts serve as the independent variables. The average monthly rainfall from 1980 to 2020 is used to place a point representing each person in a 12-dimensional space.

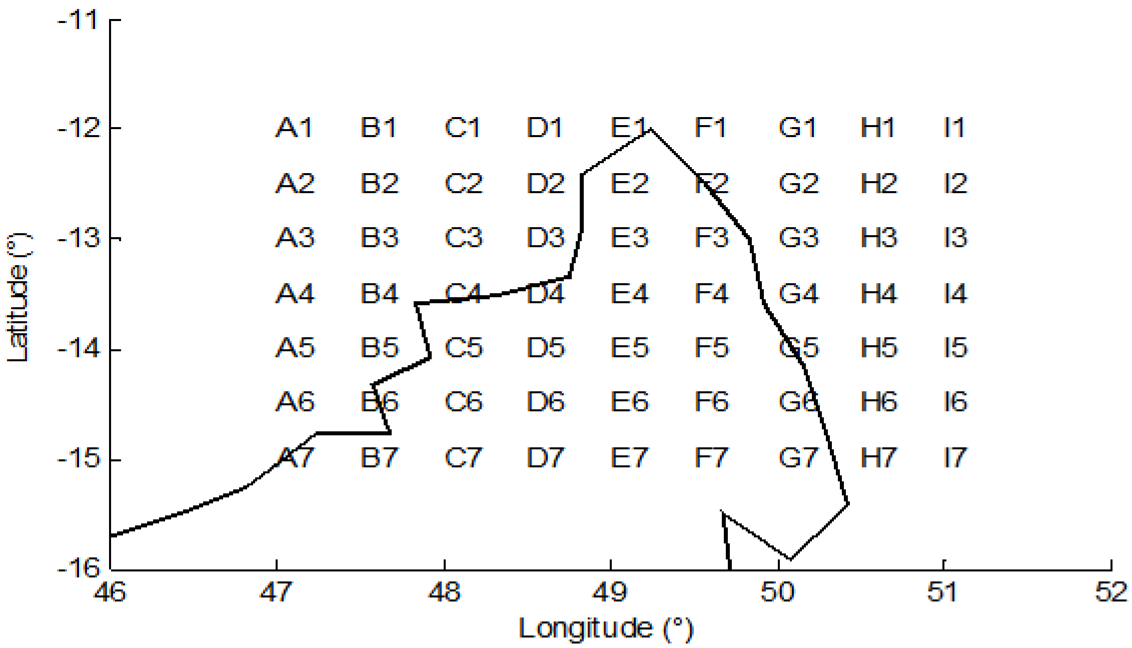


Figure 1: Presentation of individuals in our study area

Approaches

Kohonen network

Deep neural networks, known as self-adaptive maps, self-organizing maps, and topological maps, are a kind of learning algorithm known as unlabelled data. Identity maps, or SOMs for short, were first developed by T. Karasek in 1981. (Dreyfus et al, 2004; Kohonen, 1990; El Golli, 2004; Boinee, 2006; kolehmainen, 2004).

The architecture of Kohonen maps

The SOM consists of M neurons arranged in a low-dimensional grid (or matrix). Neurons often take on a hexagonal or rectangular shape depending on the structure's needs. In most cases, the Kohonen map will have two neuron layers a hidden layer (here, the atmospheric variables) and an output neuron (topological layer). To wit: (Soufiane khedairia, 2014)

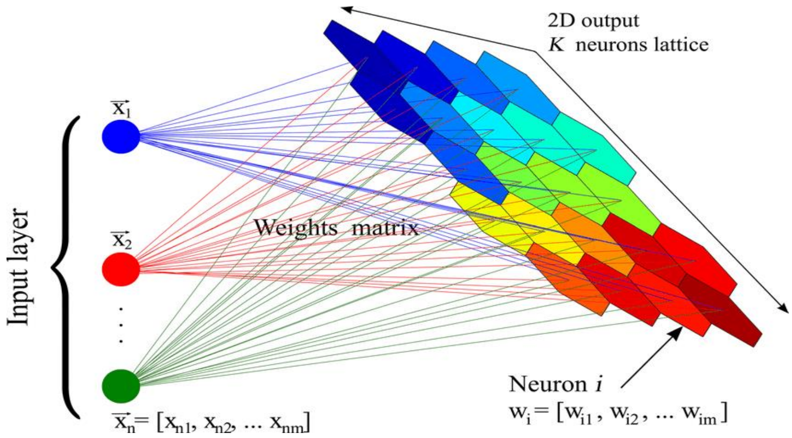


Figure 2: Organizing principles of a self-map.

They are projecting x(t), an input vector, onto the hidden layers. The SOM's inputs are all coupled to the network's neurons through weighted connections (wji). Consequently, a binary image of size M is allocated to each neuron in the SOM.

$$w_j = [w_{j1}, \dots, w_{jM}]^T$$

Initiating Knowledge of the SOM

The learning process starts after the initialization of the referent vectors or prototypes. Although the SOM is very forgiving of a poor startup, it will learn more quickly if its settings are correctly set. For t iterations of training, the SOM algorithm is shown the learning set of people. An epoch is a whole training cycle (when all data have been shown). The number of train cycles, denoted by t, is a whole number combination of the epoch count. In each cycle, the neurons compete to identify which part of the grid has to be tweaked, and then the weights in that part of the grid are adapted to the projected person. (Pölzlbauer, 2004; Dreyfus et al., 2004)

Arena for the Competition

At the heart of the neuronal struggle is a discriminant function. To find the neuron that is nearest to the input sequence and hence the winner of this competition, we must compare all of the candidates. That is, c, the victorious neuron, is the neurotransmitter in the map with the shortest distance between its synapse weight vector and the support vectors.

$$\left|x(t) - w_j(t)\right| = \min_{j \in m} \left\|x(t) - w_j(t)\right\|$$

An input element's winning neurons is also known as the map's excitement center. While the Distance measure is the most common form of relationship utilized between z and y vectors, other distances may also be employed.

Adaptation phase

Remapping is required for the leading neurons and their companions when input vectors with comparable features change. This approach seeks to improve comparable mapping inputs to adjacent neurons inside the mapping by reducing the scores of surrounding neurons to draw near to the input sequence. As errors are corrected, the synaptically biased vector wj of layers of neurons and their connections to the personality map is revised.

$$w_j(t+1) = w_j(t) + \Delta w_j(t)$$
$$= w_j(t) + a(t) h_{cj}(r(t))[x(t) - w_j(t)]$$

The weights may be tuned more precisely as the learning coefficient, a(t), decreases. The winning neuron's location in space is established by computing its center and diameter (t). The weight of each neuron is adjusted based on its closeness to the winning neuron in the array. The BMU's neighborhood sets the active zone, and it shrinks as the BMU gains knowledge. This is done by fine-tuning the learning parameters from an initial rough phase with a vast area of effect, and rapid development of the hypotheses matrices to a final acceptable improvement was made with a limited community diameter and prototype vectors that progressively adapt to data. Most neighbor functions are of the Continuous formula kind. The neighborhood function uses the distance between neurons to determine how much to change the delta connection weights of neuron I at period t. Let c represent the winning neuron, and I represent an adjacent neuron. But this separation is specified in the map's metric space, not the input structure:

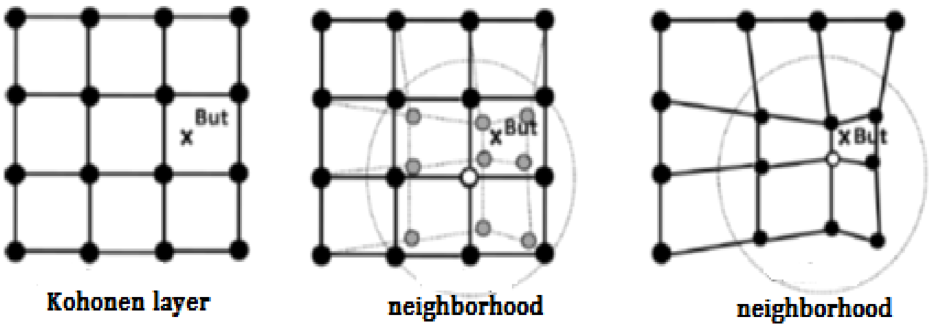
$$\delta_{ci}^2 = \|c - i\|^2$$

$$h_{ci}(t) = \exp\left(-\frac{\delta_{ci}^2}{2r(t)^2}\right)$$

Here r(t) is the diameter of the neighborhood. The equation may be used to calculate this radius:

$$\delta_k = \delta_i \left(\frac{\delta_f}{\delta_i}\right)^{\frac{k}{k_{\max}}}$$

Learning stops when one or more of the two constraints is satisfied: the required number of epochs has been completed, the efficiency has dropped below a threshold, or the maximum length of class activity has been achieved.



(a) **(b)** **(c)**

Figure 3: Example of adopting the SOM technique: (a) lag phase, (b) phase k situation, and (c) phase k+1 state.

Classifying multivariate datasets using Kohonen maps has proven helpful in dealing with nonlinear problems. The SOM method was chosen for this exploration because it can identify the statistical aspects of the meteorological parameters contained in the input data. Train the network using a sample size that is statistically significant to the total data set for best results. In this case, the whole database is necessary for precise modeling because of the obscurity of the meteorology data's statistical features. Learning in a sequential fashion, as in basic SOM, is the term used to describe this kind of study. One other fundamental principle of learning is group training, which is based on corrected repetition and hence much faster in terms of processing time. The BMUs are calculated for all input sequences simultaneously at each stage, and the model vectors are updated in the ways described below.

$$m_i(t+1) = \frac{\sum_{j=1}^{n} h_{ic(j)}(t)x_j}{\sum_{j=1}^{n} h_{ic(j)}(t)}$$

DISCUSSION AND RESULTS

Kohonen networks for rain categorization.

Identifying People Through a Map

On the map, each neuron's classifications are represented by a hexagon. When two or more similar facts, we project them into the same plane. The hexagon's shape represents the neuron's ability to categorize people (see Figure 5)

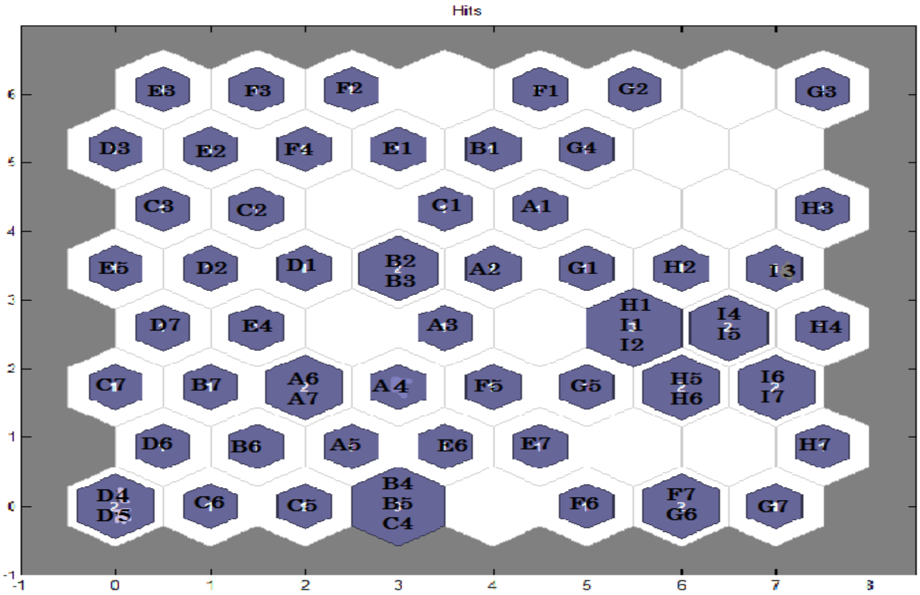


Figure 4: Identifying People Through a Map

Locator map

Ranges between adjacent neurons in the map are shown in Figure 6 using Euclidean measures. Color gradients in the illustration represent the growing separation between these neurons. In this picture, red denotes an edge, while blue represents a region where the distances among synapses are modest, and the topography is uniform (a set of neurons with little difference). The data shows that 63 people may be divided into 20 unique clusters, each with a boundary indicating a statistically significant resemblance between its (area).

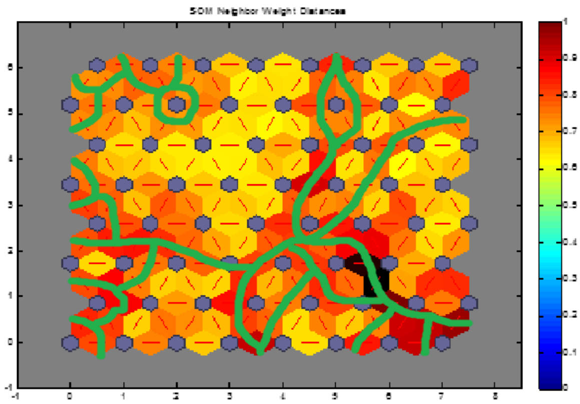


Figure 5: Distances between neurons as measured in Euclidean space

Input-dimensionality-weighted heat maps

Figure 7 displays the input-dimensional weight map. You may examine the response of the map's various regions to each independent variable. This will be pretty helpful for deciphering the categories established following classification:

- Despite the summer months, zone 5 received ample rainfall every single month (very light colour of the variable in the South-East corner of the map)
- Except for G3, all regions have very significant precipitation in January and February (dark colour of these variables in the northeast corner of the map)
- Madagascar's seaside region and northeast coast get heavy precipitation during the wet season (November to April) (light colour in the east of the map).

The weight training map also allows for an examination of inter-variable relationships (in the sense of a "map of people"). The projections of related variables are the same in this situation. There is a lot of connection between the season June to September among variables. January and December have a modest degree of correlation. Both May and the preceding month of April have many similarities.

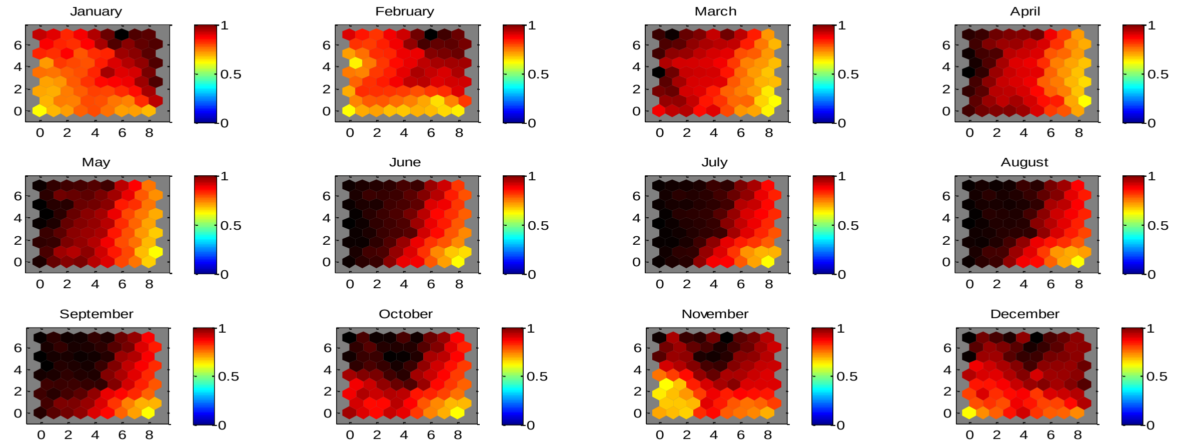


Figure 6: coefficient distribution according to the input variable

Considering the connection between persons and the factors influencing the amount of precipitation. There are twenty distinct subareas within our research region. Figure 8 depicts the position of these 20 different zones.

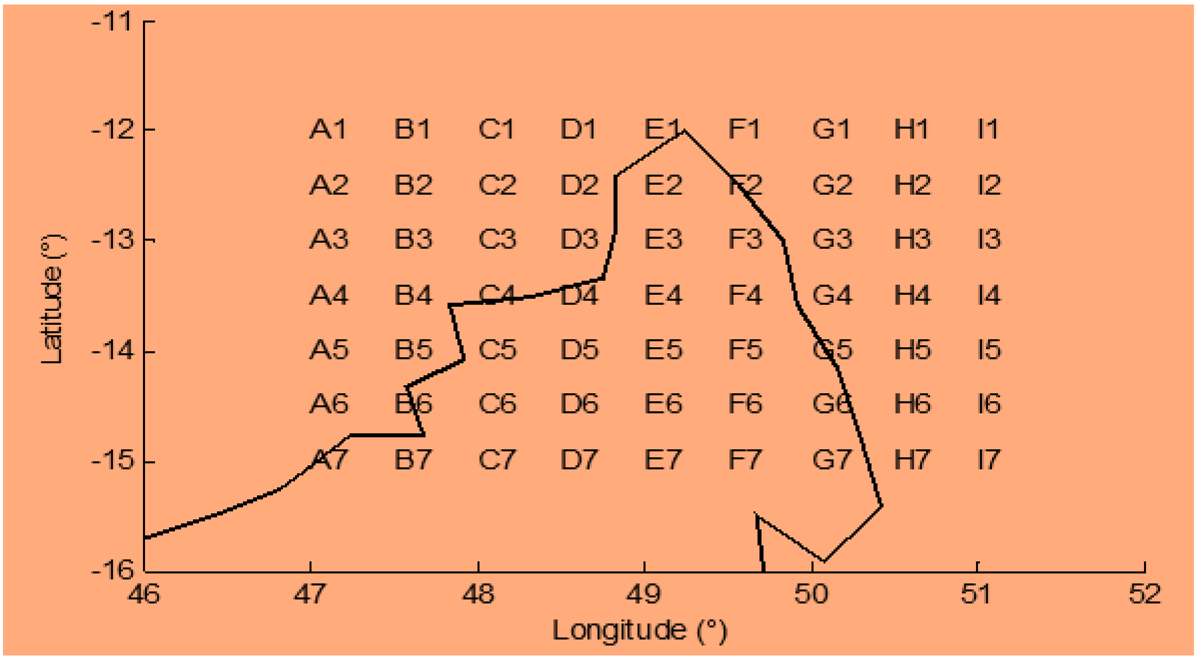
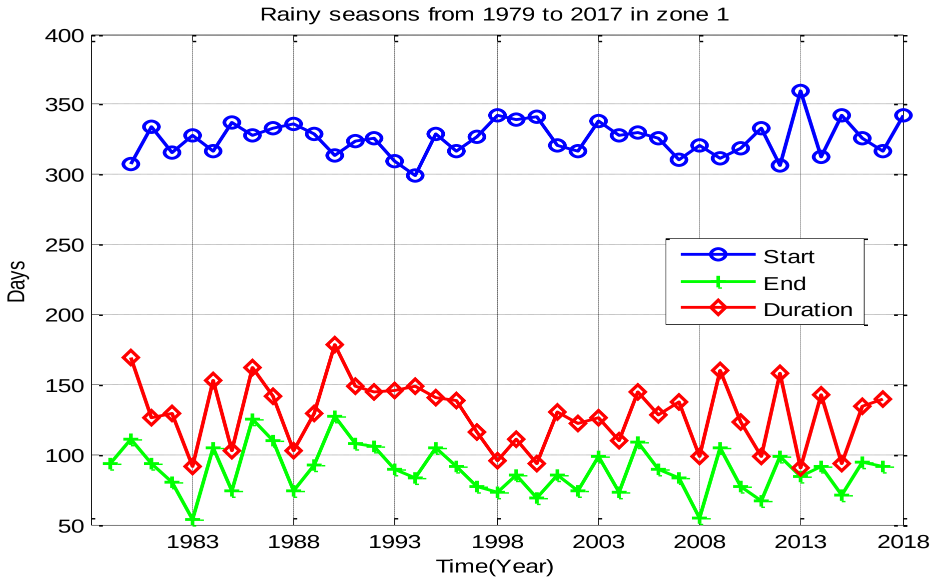


Figure 7: How the Kohonen system disperses the rain-free zone



(a)

Chart- 1: Changes in precipitation patterns from 1980 to 2020

Chart 1 shows that the average rainfall in zone 1 is 3,100 mm (green). The length of the wet seasons has been decreasing. This shortening is significant, with a loss of 16 days over 39 years. This behaviour, however, runs counter to seasonal rainfall totals. Between 1980 and 2020, we found a linear trendline with an average rainfall during the rainy season and a positive slope tendency of 22.256, which translates to an increase of 858 mm in annual rainy season precipitation. The seasonal trend in duration and total precipitation are presented for each region, with their respective interpretations provided.

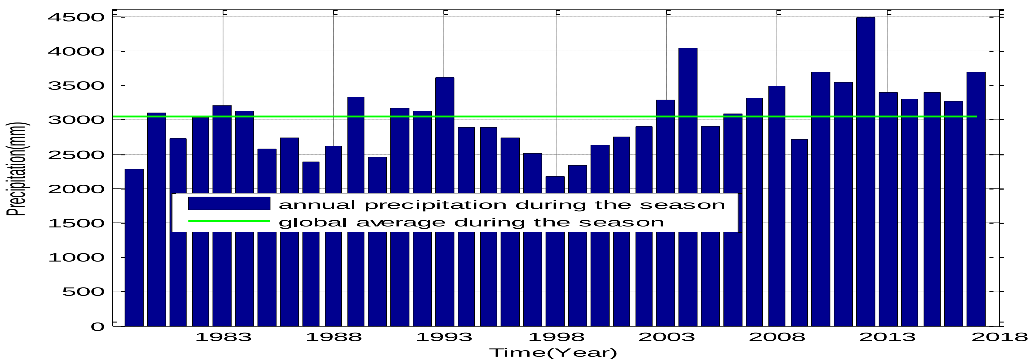


Chart- 2: Changes in average rainfall from 1980 to 2020, broken down into wet and dry seasons

CONCLUSION

This work may be broken down into three major phases: dividing the research area into distinct regions as established by the Kohonen network, identifying the beginning and ending of the rainy season in each of these regions using the A technique, and analyzing the results. The precipitation patterns in our research area from 1980 to 2020 were used to divide the area into 20 distinct zones, as determined using Kohonen network analysis. Precipitation during the monsoon season has risen across the board climatologically, except in regions 4 and 10. You've reached the coastal regions to the east of our main research area. The agricultural cycles in this region of Madagascar may be understood by learning about the rainy seasons and their unique features. In order to modernize the agricultural calendar, we propose forecasting the beginning and end of the rainy season using a nonlinear technique, such as a synthetic neural network.

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