Carolina Aparecida Pereira Alves

Analysing the correlation between climatic variables and Dengue cases in the Municipality of Alagoinhas/BA

Alagoinhas

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Orientador: Dr. Marcos Batista Figuereido

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Wasn't it me who ordered you? Be strong and courageous! Do not be dismayed or discouraged, for the Lord your God will be with you wherever you go (Joshua 1:9). I dedicate this master's degree to God, who is worthy of all honour and glory. To my parents, Fátima Aparecida Fonseca and José Raimundo Alves, for being the pillars that have sustained me in all circumstances, no words will ever be enough to express the immense love and gratitude I feel for you, I love you! To my beloved nephews and nieces, who fill my life with light with their joys and tenderness, I dedicate unconditional love, I love you

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Abstract

The Aedes aegypti mosquito is the main vector of dengue, being an extremely Synanthropic and due to its anthropophilic nature it has the reproductive needs moreover, they need tropical regions that provide climatic conditions prone and that favor the development of the vector. Favorable weather conditions, such as high temperatures, high humidity and abundant rainfall, created an environment favorable for the high temperatures of the mosquito and, consequently, for the increase of dengue transmission. As well as the relative humidity of the air, it plays a role extremely important for the survival and reproduction of Aedes aegypti, high humidity favors young transmitting mosquitoes and is harmful to transmitting mosquitoes old. The influence of climate on dengue cases may vary depending on the region geographic and local characteristics, as is the case of the municipality of Alagoinhas-BA with humid and subhumid climate. In this context, the present work aims to present the analysis of the correlation between the climatic variables air temperature, relative humidity of air, weekly average precipitation and cases of dengue in the municipality of Alagoinhas, Bahia. The data collected regarding the climate and cases of dengue in the region of Alagoinhas were in the periods from 2017 to the beginning of 2021 obtained through INMET (National Institute of Meteorology) and InfoDengue. For this purpose, the cross-correlation coefficient was applied without trend, $\rho_{DCCA}(n)$, being a generalization of the trendless fluctuation analysis, where we calculated the cross-correlation between the time series to establish the influence of these variables in the occurrence of dengue disease and an analysis of trends and seasonality in the two time series. The results obtained here were a moderate correlation between the relative humidity of the air and the (between 0.333 to 0.666) incidence of cases of dengue, we associate the color to an interval of $\rho_{DCCA}(n)$ (yellow), having a low correlation for relative air temperature and precipitation (between 0.000 to 0.333). For the analysis of time series, the climatic element that achieved the most growth favorable in the trend was the relative humidity of the air during a certain period of time, while in seasonality the climatic elements maintained the behavior with repetitions and oscillations over time. However, the predominant factor in the incidence of cases of dengue in the city of Alagoinhas is the relative humidity of the air and not the temperature of air and precipitation.

Keywords: Climatic variables. Dengue. Cross Correlation Coefficient.

List of Figures

List of Tables

List of symbols

ρDCCA	Cross Correlation Coefficient
$DCCA$	Detrended Cross-Correlation Analysis
DFA	Detrended Fluctuation Analysis
ST	Série Temporal
UR	Relative humidity
T	Trend
S	Seasonality
$INMET$	National Institute of Meteorology

Contents

1 Introduction

The Aedes aegypti mosquito is the main vector of dengue fever. It belongs to the genus Aedes, subgenus Stegomyia, a species of synanthropic insect with an anthropophilic nature that has specific reproductive needs, i.e. it lives close to humans, and the presence of this vector is common in urban areas.

Above all, dengue is a public health problem that affects several municipalities in Brazil (SOUZA et al., 2022), and the main transmitting agent is the female and its transmission occurs through its bite passing the virus to the host, since the female needs human blood to mature its eggs, however, the individual can develop the disease or not (COUTINHO et al., 2022).

Dengue affects people of all ages, but adults and young people have been most affected by the disease since the virus was introduced in Alagoinhas. However, from 2006 onwards, some states showed recirculation of the DENV2 serotype and after a few years the DENV3 serotype predominated. This scenario has led to an increase in the number of cases of severe forms and hospitalisations in children, especially in the north- east of the country . (MINISTéRIO; SAúDE; EPIDEMIOLóGICA, 2009)

These epidemics were characterised by a pattern of reduced severity for children, who accounted for more than 50% of the patients admitted to hospital in the municipalities with the largest populations. Even in municipalities with smaller populations, more than 25% of the patients admitted to hospital due to dengue were children, which highlights the fact that the whole country has been similarly affected by these changes in the disease's profile (MINISTéRIO; SAúDE; EPIDEMIOLóGICA, 2009). Despite the reduction in the severity of the disease, dengue continues to be a public health problem, especially in municipalities with low populations, such as Alagoinhas/BA, where this research was carried out.

The presence of Aedes Aegypti in urban centres is directly related to climatic conditions and public sanitation, with climatic variables playing a significant role in mosquito distribution (PIOVEZAN-BORGES et al., 2022). Currently, various phenomena have caused global variations in climatic conditions, an example of which are the projections that indicate an increase of between 1.8°C and 4°C. (RAMSFIELD et al., 2016) na in temperature, in Brazil temperatures are expected to rise between 1.8°C and 4°C (MARENGO; BERNASCONI, 2015).

Rising temperatures have favourable or unfavourable effects on the dynamics of the mosquito population, larval growth and the acceleration of the vector's development process, which leads to an increase in the number of bites in the adult stage. The incubation of the virus occurs during its life cycle (JÁCOME; VILELA; YOO, 2019).

For the mosquito to proliferate, it needs a temperature of between 20°C and 46°C, since the mosquito has developed over the years an adaptation in its behaviour in tropical areas with a hot and humid climate, however, climatic conditions have been favourable for the dengue vector (FREITAS et al., 2019).

However, other authors state that based on the current understanding of the close relationship between climate and the life cycle of the mosquito vector, a projected temperature rise of 2°C aby the end of the 21st century is likely to increase the distribution of dengue fever worldwide (BORGES, 2021). On the other hand, a temperature rise of 35°C, or more, with high rainfall, will decrease the survival rate of Aedes aegypti, which could reduce the transmission of dengue, Zika and chikungunya (XU et al., 2010).

There is a mutual interest among researchers in the influence of climate variability parameters, and great efforts have been made to understand the correlations between climate variability and the dynamics of the Aedes aegypti mosquito population through computer models, such as the trendless cross-correlation coefficient model- ρDCCA, which has been used to analyse non-stationary time series to assess the linearity between two time series or independent variables.

Several researchers, such as: (KRISTOUFEK, 2014), (FERREIRA et al., 2019), (GUEDES; FILHO; ZEBENDE, 2021),(QIAN et al., 2015) e (SILVA, 2021)applied in his research uses the $\rho_{DCCA}(n)$ model to estimate whether there is a relationship between two variables, to try to predict the variation of one variable given the other variable and thus assess the strength of this relationship, which allows rational and objective decisions to be made.

PTo carry out this work, combined data were used, the first being from the meteorological station in the city of Alagoinhas and epidemiological data between 2017 and 2020 for both, and using the cross-correlation coefficient without trend to identify the correlation between the time series. However, the municipality has two climatic types: humid and sub-humid, with tropical climate conditions and characteristics of high rainfall in summer and an annual average of 808mm, with relative humidity ranging from 68.58% (December) a 82.57% (June), cwith an average temperature of 24,6°C and temperatures varying by de 4.4°C throughout the year.

This work is divided as follows: chapter1 presents the question addressed in this research, with the motivation, the research problem and its objectives, chapter2 builds the state of the art regarding the influences of climatic variables, chapter4 analyses the two time series climatic variables and dengue cases, in chapter5, sthe research method will be presented in detail, in chapter6 related to the results, the results obtained throughout the research will be presented and finally in chapter7 the final considerations, the conclusions and future work will be presented, addressing the main results and their implications, as well as suggestions for future research.

1.1 Motivation

By understanding how climatic variables influence the incidence, prevalence and severity of dengue fever, we can develop better strategies to prevent and control the disease. When we correlate levels of rainfall, temperature and relative humidity, we can understand which environmental factors or climatic variables are most conducive to the growth and reproduction of the dengue mosquito and which prevention and control strategies are most effective.

We consider that each region has its own peculiarities when it comes to climatic factors, related to geographical densities, vegetation, altitude and latitude, all of which can alter the climatic elements that are temperatures, relative humidity, rainfall and others. As is the case with global warming, which is one of the factors contributing to the expansion of the most affected geographical areas and an expansion of the period of highest mosquito incidence, which occurs seasonally (OLIVEIRA et al., 2017).

Dengue fever is associated with the climate of tropical regions, as it allows the female mosquito to reproduce due to the favourable climate. During the hottest months of the year, the reproductive climax of Aedes aegypti occurs, where the metabolism of the transmitting vector increases in this time interval, reducing its evolutionary cycle by up to 8 days or extending it by up to 22 days in the colder months (FREITAS et al., 2019).

1.2 The problem

B y identifying the factors that contribute to the incidence of the disease through data analysis, the research can detect patterns in the behaviour of climatic variables that are associated with an increase in the incidence of dengue cases, which would be important for the development of disease control strategies based on forecasting and prevention, as well as being able to predict possible outbreaks of the disease according to the climatic context

As far as statistical analysis is concerned, the seasonality of dengue cases in Alagoinhas, their behaviour over the years and regional differences should also be taken into account. It is hoped that the research will result in valuable information for to understand how climatic conditions affect the spread of the disease. Using correlation analysis techniques, is it possible that climatic variables influence the occurrence of dengue cases? based on these conjectures we can establish the objectives of this work.

1.3 Objective

The tool applied to the model we proposed classifies it as time series data, in which all the information is relevant to understanding the behaviour of Aedes aegypti in relation to the influence of climate variables. According to (ZEBENDE, 2011) " o ρDCCA aims to quantify the level of cross-correlation between non-stationary time series, based on the DFA and DCCA methods".

1.3.1 General Objective

To analyse the correlation between the climatic variables air temperature, relative humidity and average weekly rainfall and dengue cases in the municipality of Alagoinhas, Bahia.

1.3.2 Specific objectives

- Collect and correlate historical climate data series for Alagoinhas;
- To analyse whether variations in temperature levels influence the incidence of dengue cases;
- To analyse the effects of relative humidity levels on the occurrence of dengue fever in the population of Alagoinhas;
- To study future climate trends and the possible consequences for dengue cases in Alagoinhas;
- Simulating epidemiological scenarios for the vector in the Alagoinhas region;
- Present a modelling of the trend-free cross-correlation coefficient model - ρDCCA (ZEBENDE, 2011).

1.4 Main contributions of the work

The overall vision consolidated in the effective contribution of this work is to determine which climate variable in the Municipality of Alagoinhas has influenced the incidence of dengue cases between 2017 and 2021; to analyse the results of the studies to identify climatic variables most relevant to the spread of dengue, this will make it possible to establish risk thresholds for each variable, as well as inform the authorities and the population in the event of high dengue incidence rates; identification of risk factors from the study of the dynamics between climatic variables and dengue cases, can help to identify the risk factors associated with an increase in the incidence of the disease, as well as high levels of temperature and relative humidity, which can create suitable conditions for the reproduction of the mosquito vector and an increase in the population of infected mosquitoes; seasonal patterns in the incidence of dengue related to climatic variations, helps to understand at what time of year there is a greater spread of the disease and which climatic factors influence it.

2 State of the Art

The expansion of studies into the interdependence of the influence of climatic variations on the incidence of Aedes aegypti, in order to introduce this relationship into a single context to propose instruments for mediating public health, with the aim of understanding the behaviour and correlation of the mosquito vector with climatic variations. Today, the world is undergoing long-term changes in climate due to the sharp rise in temperature, leaving insects (Ae. aegypti) more vulnerable, since they are ectothermic, i.e. they cannot maintain body temperatures, need external temperatures and depend on water to complete their life cycles, thus influencing the insect's development. In this chapter, we will discuss how the dengue-transmitting mosquito adapts to the conditions of climatic variables that interfere with the dynamics of the vector's population.

2.1 Influence of climate variables

One of the most talked about issues in the world today is the instability of climate change and the collateral effects that can be seen in every part of our planet. Some of these effects are perceptible directly and indirectly in the economy, in health, in the proliferation of insects (vectors) and in the spread of diseases. These instabilities in climatic factors (latitude, altitude, sea level, sea currents, vegetation and relief) accelerate the process of climatic elements (maximum and minimum temperatures, relative humidity, rainfall, etc.).

(ZHANG; ZHANG; KHELIFI, 2018) astates that "global climate change is one of the greatest threats to human survival and social stability that has occurred in human history". (NOBRE; MARENGO, 2017) emphasises that the current scenario is worrying in the context of studies into the influence of climate and the environment on the transmission of diseases and other human health problems.

Climate variables have a major impact on the environment, as they directly affect temperature, humidity, the amount of sunlight and other factors. These factors, in turn, influence the lives of all living beings, from plants to animals and humans, as is the case with global warming being one of the main factors affecting the climate worldwide.

Andrade and (ANDRADE; BASCH, 2012) state that "climatic factors are elements capable of influencing and altering the characteristics or dynamics of a region's climate, whether natural or not". However, they are responsible for determining whether the temperature that region is high or low, or if it's wet and dry.

Many of these changes in the characteristics of each region's climate are caused by the increase in global carbon emissions, caused by human action that generates something unusual in its natural course, such as deforestation and the burning of fossil fuels, which leads to an excessive rise in temperatures or low temperatures.

With the imbalance in climatic patterns, diseases emerge that spread more quickly according to the climatic situation that best favours them. According to (ARAÚJO; UCHÔA; ALVES, 2019) climate change can accelerate disease transmission cycles, thus increasing the number of infectious agents when they reach a susceptible host in a hurried manner, extending their geographical distribution areas to both higher latitudes and altitudes. This is the case with the vector transmitter Aedes aegypti, an infectious agent that is gaining resistance in the climatic conditions that best favour its growth.

Temperatures, for example, are a predominant factor in relation to the development of the aedes aegypti insect, since these insects are petilothermic, better known as "cold-blooded", the body temperature of the vector varies according to the ambient temperature, this occurs due to the procedure of biochemical and physiological functions, having a profound effect on the metabolic rate and growth of the aedes aegypti (COURET; BENEDICT, 2014).

The relative humidity of the air is also a predominant factor in interfering with the performance of these vectors that transmit the dengue virus, mainly favouring the young mosquito when the relative humidity is high and disfavouring the adult mosquito (ARAÚJO; UCHÔA; ALVES, 2019). Some studies have shown that relative humidities between 70 and e 80% are ideal for mosquito development, while humidities below 50% are unfavourable, however Aedes aegypti is more active in areas with high humidity, as this condition helps keep its skin moist and when humidity is too low, the mosquito cannot survive (KAKARLA et al., 2019).

In the research by (RAMALHO, 2008), he states that "in experimental conditions, higher temperatures (28°C) and lower humidity (50-55%), were more favourable for mosquitoes, however, they bred more in search of food, compared to lower temperatures (25°C) and higher humidity (85-90%)".

In addition, the ambient temperature has a strong effect on the mosquito's biology: the warmer it is, the faster the mosquito's life cycle is completed and the larger the population can become, thus invading new areas and potentially transmitting more pathogens. In the opinion of (REINHOLD; LAZZARI; LAHONDÈRE, 2018) "better understanding how environmental temperature affects mosquito biology seems essential to deciphering the factors that drive the ability of these species to invade new areas, where they could potentially transmit pathogens."

The ambient temperature affects the development of the mosquito, its activities being the search for hosts and ingestion of blood, as well as the development and transmission of pathogens. Consequently, it affects the geographical distribution of species, spatial distribution and population dynamics (REINHOLD; LAZZARI; LAHONDÈRE, 2018).

(AZEVEDO, 2015) emphasises that "environmental conditions interfere significantly with immatures and adults, affecting larval growth rate, development time, body size, longevity, fecundity and blood feeding". However, the quality and quantity of water, temperature, humidity, quality of lighting and other factors also directly affect the mosquito's behaviour, including its movement, feeding, reproduction, oviposition, survival and predisposition to carrying diseases.

In part, the population levels of Aedes aegypti are dynamic and vary greatly between regions according to the different geographical locations and are attributed to climate change, thus occurring a local adaptation of temperature and other environmental variables, altering the average development time of this mosquito, among other aspects (AZEVEDO, 2015).

Thus, considering the aspects described above, the Intergovernmental Panel on Climate Change (IPCC) estimates that approximately 1.5 to 3.5 billion people worldwide will be at risk of dengue infection by 2080 due to climate change and its influences on the vectors that transmit dengue (KAKARLA et al., 2019).

3 Statistical Analysis

With regard to analysing the correlation between two time series in the field of statistics, through the process of extracting knowledge from data, a descriptive statistical analysis was carried out on the raw series, 1, pto identify and quantify the level of the relationship between two time series, in this case climate variables and dengue cases. Since climatic elements play an important role in the ecology of the Aedes aegypti mosquito and the transmission of its disease.

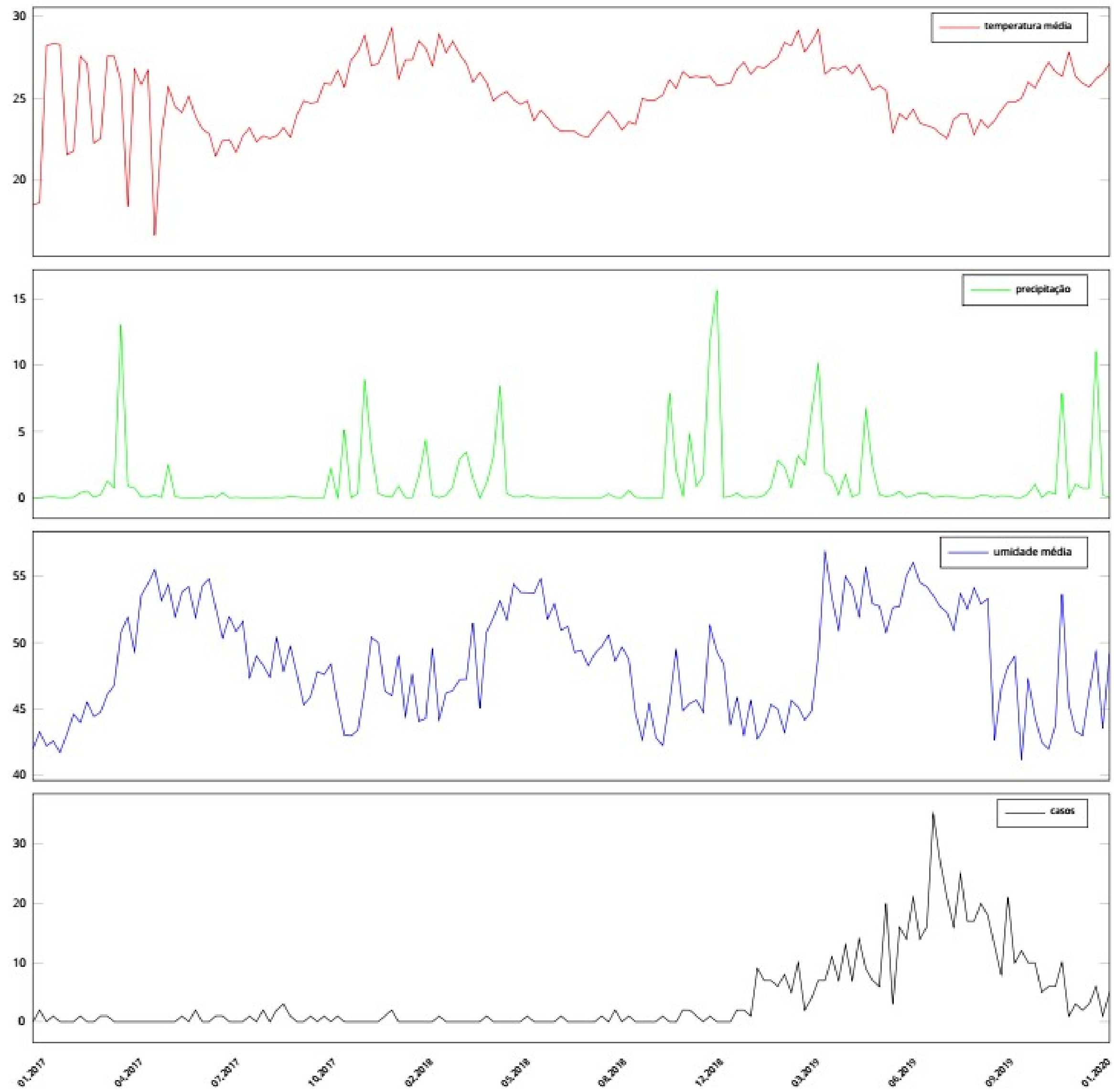


Figure 1 – Raw data referring to climate variables and dengue cases in the municipality of Alagoinhas-BA, analysed over time from 2017 to 2021. Source: Author.

The analysis of time series plays an extremely important role lies in its ability to provide insights into the dynamic behaviour of a phenomenon over time and is especially useful when dealing with sequential data, where the order of the values is fundamental to understanding the dynamics of the phenomenon under study. Through this analysis, it is possible to understand fluctuations, identify seasonal patterns and capture long- term trends that may be present in the data.

In this context, the two time series in question were subjected to a comprehensive analysis in order to understand the behaviour, trends and seasonalities that occurred over the periods from 2017 to 2021 in the Municipality of Alagoinhas. The size of the series in this case is represented by N=5.

In addition to analysing the time series, the main method used in this research is the trendless cross-correlation coefficient ρDCCA de (ZEBENDE, 2011), by calculating the DFA and DCCA ratio. This method is important for quantifying the correlation between time series whose characteristics change over time, i.e. non-stationary time series.

With the development of the Zebende method applied to verify the magnitude of the correlation between climate variables and dengue cases, the graphs presented in the descriptive analysis of the data were then created. The graphs were constructed and organised using the Maiastatistics software and the Python programming language. The data acquired from the InfoDengue platform (dengue data for the city of Alagoinhas) and INMET (meteorological data for Alagoinhas) was organised and analysed.

For more detailed information, transparency and the method applied, the time series analysis is presented in the next section, followed by materials and methods.

4 Time Series Analysis

A time series is a set of observations collected and ordered sequentially over time (MORETTIN; TOLOI, 2006),They can be recorded at regular intervals, such as hours, days, months or years, and are used to study the behaviour of a phenomenon over a period of time. For (TIBULO et al., 2014) when referring to a study of the series, it investigates the entire mechanism that generates the time series, which involves predicting future behaviour based on historical data, evaluating the factors that influence its behaviour, looking for cause and effect relationships.

Time series studies have a wide application in various fields of knowledge, some examples of fields in which time series analysis is applied include: in medicine and health (used to analyse health data over time, such as monitoring warning signs, analysing electronic medical records, predicting epidemics and analysing epidemiological data), in meteorology and climatology (used to study climate and weather, analyse historical data on temperature, precipitation, relative air humidity, wind and other meteorological parameters, identify seasonal patterns and climate trends), in economics and finance (widely used to forecast market trends, analyse financial data, model stock price series, forecast exchange rates, monthly unemployment rate) and social sciences (analyse demographic data, population trends, social indicator series, crime rate, and study human behaviour over time).

As a group of observations obtained sequentially over time, time series can be defined by a set of values Z_{t_1}, Z_{t_2}, ..., Z_{t_N}, onde Z_{t_1} refers to the series observed at time t, N being the size of the series, with i= 1, 2, 3,...,N (BRITO, 2021).

(PARMEZAN, 2016),conceptualises that the relationship of data between time series - TS observed in the time domain is of paramount importance, because the relationship between chronologically adjacent TS encompasses the dependence that one has on the other. However, TS are characterised in different ways, depending on the characteristics and properties of the data, such as:

- Discrete, where observations are recorded at discrete and defined intervals in time, where T is a set of specific points over time at fixed or irregular intervals, equally spaced $T = \{t_1, t_2, ...t_n\}$ .For example, meteorological observations and dengue cases, which are recorded daily, by days, month and year;
- Continuous, in which data observations are recorded continuously over a specific time interval T, $T = \{t : t_1 < t < t_2\}$. For example, the temperature in a given

location over a continuous period of time, with measurements taken every second, millisecond or even at shorter intervals;

- Multivariate, in which there is more than one variable being observed simultaneously over time, $Y_1(t), ...Y_k(t), t \in T$,for example, the performance of several shares on the stock exchange over time, in which case we would have daily data for several shares in certain companies;

- Deterministic, where the behaviour or pattern of the data can be completely determined by a mathematical function or a set of predefined rules;

- Stochastic, in which random components are involved in generating data with one or more input and output variables over time. For example, daily variation in the price of a share traded on a stock exchange, share prices can be influenced by a variety of random factors, such as economic news, political events, company performance, among others.

(MORETTIN; TOLOI, 2018), points out that time series have two objectives: to understand the generating mechanism of the series, foreshadowing the future behaviour of the series analysed, and to build models for the series, for specific purposes. Thus, in view of of a time series represented by $Z_{(t_1)}, ..., Z_{(t_n)}$, being observed at time $t_1, ..., t_n$, we may be interested in:

- Investigating the mechanism that generates the time series is a process of analysing and discovering the underlying elements, factors and patterns that explain the variations and behaviours observed in the data over time, for example, when analysing a climate time series and dengue cases, we might want to know if there is any recurring trend or pattern in the two series;

- Forecasting the future values of the series means estimating or projecting the values that the series will take on at subsequent times, based on historical data and the patterns identified. It is also an important stage in time series analysis, as it makes it possible to anticipate the future behaviour of the variable under study, for example for long-term series such as climate variables, population variables, etc;

- Describing only the behaviour of the series is intended to gain an initial understanding of the nature of the data and to support subsequent analyses, without necessarily involving the prediction of future values, by constructing graphs to identify the existence of upward or downward trends, cycles, seasonal variations or regular oscillations, whether there are peaks or dips at specific points in time.

Therefore, the study of time series makes it possible to understand the patterns, trends and regularities present in the data, as well as to make predictions, using mathematical models, spectral analysis, smoothing, shape and other approaches to understand and describe the behaviour of data over time.

4.0.1 Trends

According to (PARMEZAN, 2016) "the trend can be defined as a regular and slowly developing movement over the series. In other words, this component encompasses long-term behaviour". Thus, it can be increasing, indicating an increase in values over time in the series, or decreasing, indicating a decrease in values over time.

A time series with an upward trend can be caused by a variety of specific factors, stemming from phenomena linked to demographic development, economic factors, climate change that influences the gradual increase in climatic elements. On the other hand, a time series with a downward trend can be related to mortality rates, technological advances, for example, the development of renewable energy technologies can reduce the demand for fossil fuels over time, leading to a downward trend in the fossil fuel industry, resource depletion, for example, if overfishing leads to a decrease in the amount of fish in a given location, a time series that records the catch of fish will show a downward trend over time, among others (PARMEZAN; BATISTA, 2016).

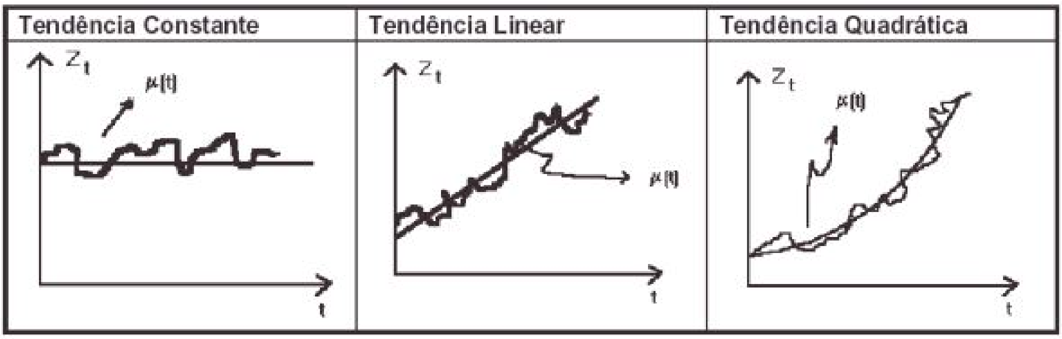


Figure 2 – Fonte: (GUTIÉRREZ, 2003)

The trends that occur most often in a TS are constant: where the values of the series are stable over time, in which case there is no pattern of continuous growth or decline; linear: where the data of a time series follows a straight line over time, this straight line can have a positive slope, indicating a constant increase in the values of the series, or a negative slope, indicating a constant decrease; quadratic: can be characterised by an acceleration or deceleration in the rate of change of the values of the series over time, initially, the series can increase or decrease rapidly, being represented on the graph by a smooth "U" or "V" shaped curve, as shown in figure 2 .

According to (MORETTIN; TOLOI, 2022) there are several methods for estimating a T_t", which depend on the specific characteristics of the time series, the assumptions made about the data and the objectives of the analysis. The most commonly used are:

i adjust a function of time, such as a polynomial, exponential or other smooth function of t;

ii smooth (or filter) the values of the series around a point, to estimate the trend of that point;

iii smoothing the values of the series by successively adjusting the weighted least squares lines.

Thus, the trend is estimated using $\hat{T}_t$, obtaining the trend-adjusted or trend-free series, $Y_t = Z_t - \hat{T}_t$ (MORETTIN; TOLOI, 2006).

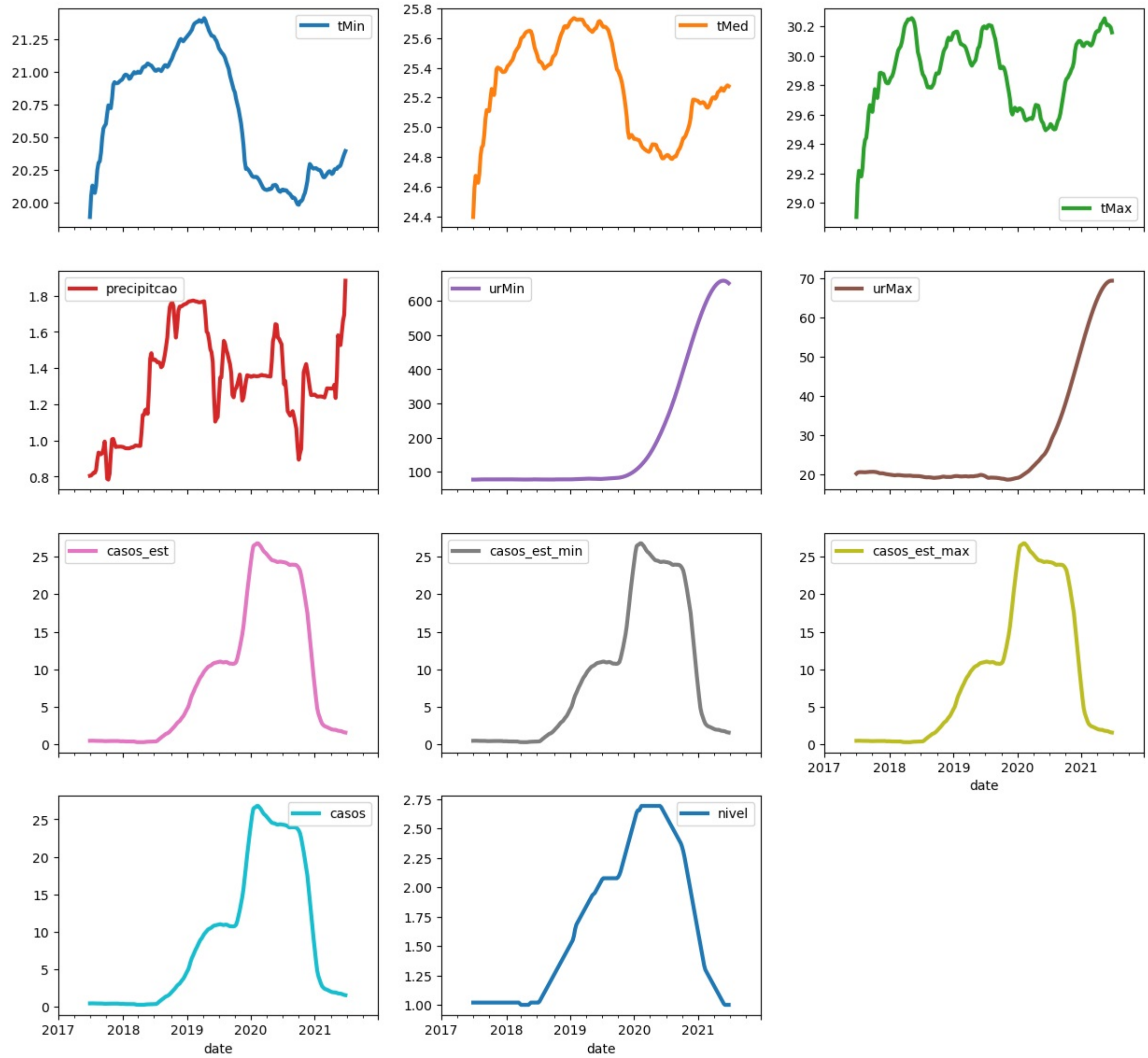
In addition, we have plotted the trend in this work, referring to the time series studied, climatic variables and dengue cases in the municipality of Alagoinhas, these graphs offer a clear visual representation of the changes and patterns observed. For example, the graph in Figure3, shows a clear upward and downward trend in the climatic elements (maximum, minimum and average temperatures, maximum and minimum humidity and rainfall) and dengue cases over a given period, with the climatic elements increasing between 2017 and 2019, except for relative humidity, which decreased between 2017 and 2019 and only saw a relative upward trend from the beginning of 2020 to 2021.

Trends generally occur in climatic elements due to mild changes in the climate, leading to an increase or decrease in average values over the period (RIBEIRO et al., 2014).These increases in the trend that has been occurring over the years have the consequences of the anthropogenic greenhouse effect, resulting from the intensification of human action on the environment.

On the other hand, relative humidity levels tend to increase in the same proportion as the temperature decreases. There are various factors that can contribute to the humidity levels tending to increase as the temperature decreases. According to (FALCãO et al., 2010) "humidity is strongly concentrated in the lower layers of the atmosphere (in the first 2,000 metres of altitude), and there is generally a decrease in humidity as altitude increases".

(ZANATTA et al., 2016), states that the decrease in humidity is related to When the temperature rises, the water vapour in the air is diluted, but the total amount of water vapour does not remain constant, so the relative humidity of the air decreases. This is because the holding capacity of the air increases with temperature and the amount

Figure 3 – Temperature trends.



Source: Autho.

of water vapour remains the same. However, the relative humidity, which is the ratio between the amount of water vapour present and the maximum holding capacity at a given temperature, decreases.

In short, the relationship between relative air temperature and relative humidity is complex and varies according to the atmospheric conditions of each region, persistent and seasonal changes.

4.1 Seasonality

According to (FILHO, 2019) "Seasonality is any event or behaviour that always happens at the same time within a specific time interval, i.e. a behaviour or pattern that is repeated from time to time". These variations in behaviour can be observed on different time scales, such as daily, monthly, quarterly, annually or even seasonality due to special events.

For (MORETTIN; TOLOI, 2006) fphenomena that occur regularly from year to year (or some other temporal cycle) are considered seasonal, such as an increase in airline tickets in the summer, an increase in milk production in Brazil in the months of November, December and January, an increase in commercial sales at Christmas time, etc.

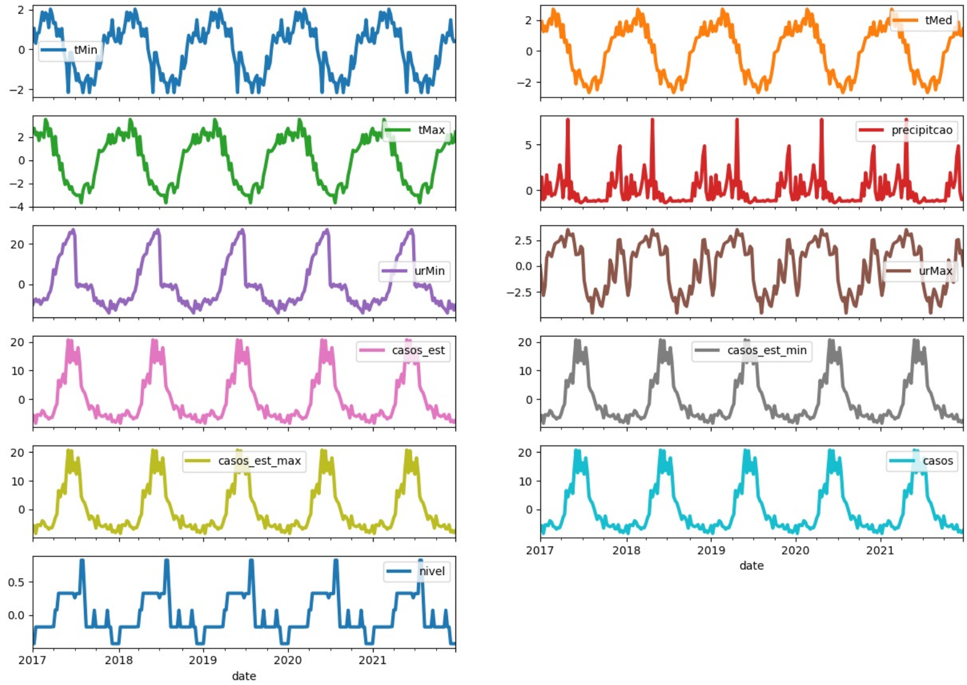
There are other characteristics related to the seasonal component in which it can be categorised, according to its variation, into two types, such as additive seasonality, where the series presents stable seasonal fluctuation, without taking into account the overall level of the series and multiplicative seasonality, which occurs when the size of the seasonal fluctuation varies according to the overall level of the series (PARMEZAN; BATISTA, 2016).

The seasonality of a time series of climatic variables, on the other hand, can be influenced by the characteristics of each region, where the geographical location, latitude and topography of a region can play an important role in climatic seasonality. For example: tropical regions, some regions close to the equator, where variations in sunlight throughout the year are less pronounced; climatic seasonality can be more influenced by factors such as the rainy season and the presence of specific climatic phenomena; mountain regions, climatic seasonality can be influenced by the jump and local topography, variations in temperature, precipitation and snow can be more pronounced at different altitudes, represented in specific seasonal patterns.

AJust as seasonality occurs in the time series of climate variables and dengue cases in Alagoinhas, we can see in Graph 4 the annual pattern that repeats itself each time period, totalling five periods, with a fixed time interval and a random conduct that precisely differentiates between the shape of one wave and another. As Alagoinhas is close to the equator, precipitation becomes a little higher, thus undergoing some kind of oscillation in seasonality, but it is worth noting that human actions also cause these kinds of changes in precipitation.

In short, analysing seasonality in time series is crucial for understanding seasonal patterns and identifying unusual events. However, in order to obtain a more comprehensive analysis of a series that involves all three components at the same time, it is necessary to use decomposition of the series, i.e. trend, seasonality and randomness or noise.

Figure 4 – Traçando a Sazonalidade.



Fonte: De autoria própria.

4.1.1 Decomposition

Analysing a set of temporally varying data to identify trends, seasonalities and randomness in different components of a series, which can have causes and consequences in different areas, are known as time series decomposition techniques (COSTA et al., 2019).

(PARMEZAN, 2016) defines decomposition in a time series as useful for understanding and modelling the different elements that create patterns observed in TS and is used in the concept of a finite set of independent elements. This form of decomposition is convenient for understanding the underlying structure of the data and can help in forecasting and identifying patterns, allowing the different components to be isolated for a more detailed analysis and making it possible to model each component individually.

There are two common approaches to the form of additive and multiplicative time series, which correspond to Z_t, T_t, S_t, and E_t, being trend, seasonality and noise at an instant of t (SOARES, 2019):

- Z_t: Time series being observed at an instant in time;
- T_t: Trend in an instant of time;
- S_t: Seasonality in an instant of time;
- E_t: irregularity (noise) in an instant of time.

Additive is a type of time series representation model in which the values of the components are added together to cover the same unit of observation Z_t, éand is expressed by:

$$Z_t = T_t + S_t + E_t \tag{4.1}$$

The multiplicative model is a representation of a time series, where the trend has the same unit as the variable under investigation and the other components show values that alter the trend, and is expressed by:

$$Z_t = T_t \times S_t \times E_t. \tag{4.2}$$

Figure 5a eand Figure 6b show the decomposition of two additive time series related to relative humidity and dengue cases in the municipality of Alagoinhas, where the decomposition is divided into three components (Trend, Seasonality and Noise). Observa-se na figura 5 ashows that the trend component remains constant until a certain period between 2017 and 2019, after which there is a very visible increase in the trend from 2020 onwards. The seasonality component contains oscillations with rises and falls that are repeated every time period, and the oscillations may be caused by some kind of climatic anomaly.

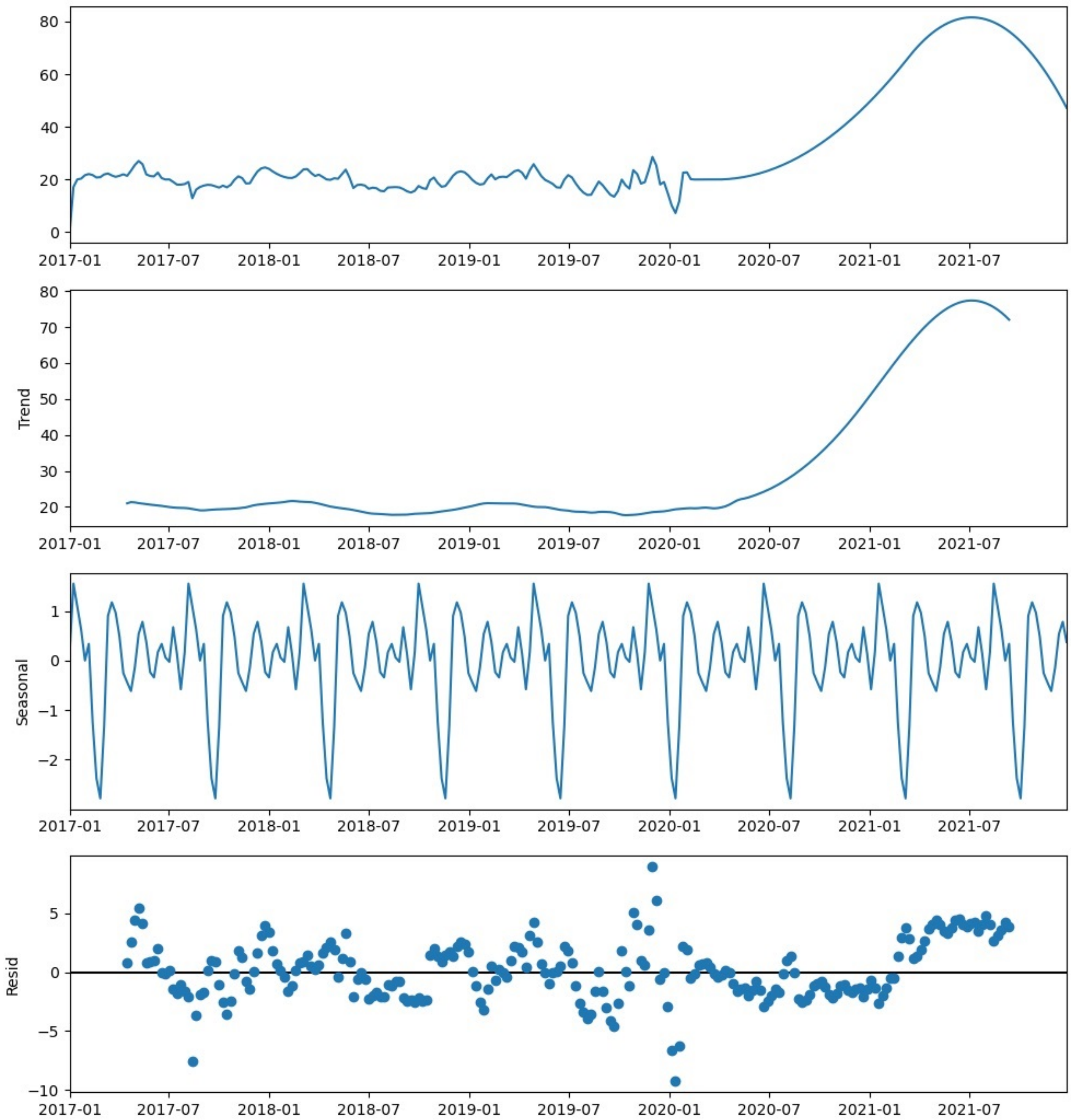


Figure 5 – (a) Relative humidity, additive. Source: Author's own work.

Figure 6b shows the decomposition of the incidence of dengue cases, considering an additive decomposition, obtaining a constant trend between the periods from 2017 to the beginning of 2018, from 2019 to 2020 there was a significant rise in the series, while seasonality maintains the repetition of frequency over the fixed period of time.

As for the noise in this decomposition, in figures 5a and 6b, fit was limited to visualising random fluctuations and irregularities or forecast errors that cannot be explained by the trend or seasonality in this time series.

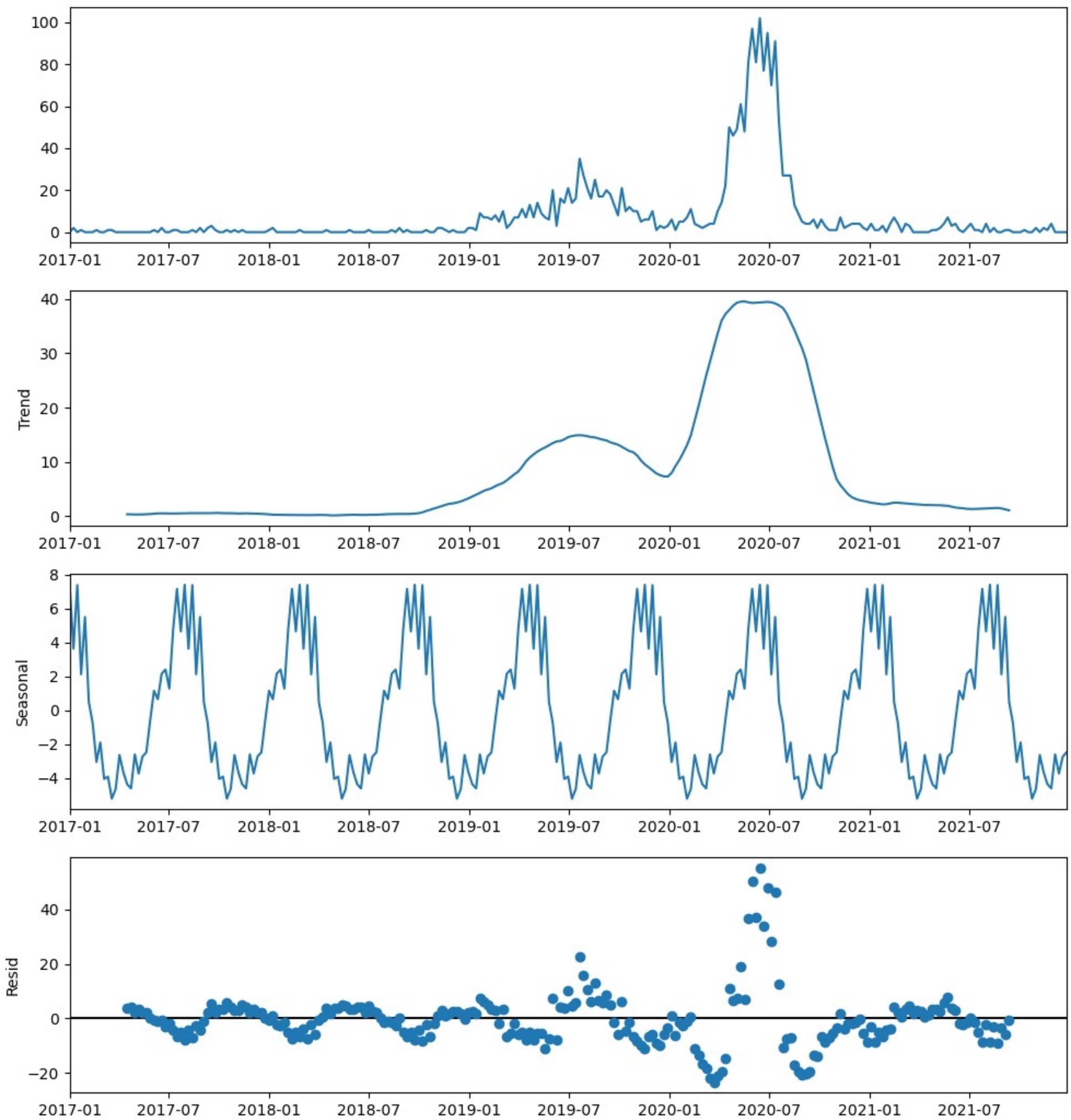


Figure 6 – (b) Dengue cases, additive. Source: Author's own work.

5 Materials and Methods

5.1 Introduction

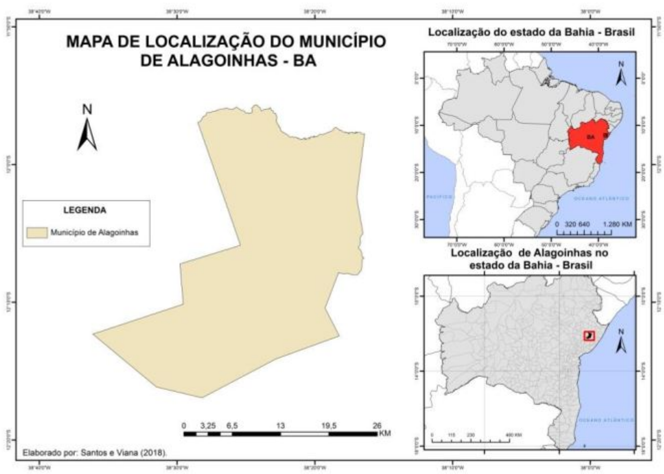
This chapter presents the procedures that were used to conduct the research and understand the theoretical conceptualisation of the study. These procedures include the development of the data collection tools, which were separated by year, month and day, both for the meteorological data of Alagoinhas and for the notifications of dengue causes in the city.

5.2 Type and Place of Study

This study focuses on the city of Alagoinhas, which is a Brazilian municipality in the state of Bahia, located in the North Coast and Agreste Bahia identity territory, with an area o f 718,089 square kilometres and a population of 153,023 in 2020, with characteristics of the humid and sub-humid climate type, according to the IBGE.

With a population density of 210.05 inhabitants per square kilometre, it is bordered to the north by the municipality of Inhambupe, t o t h e south by the municipality of Catu, to the east by the municipality of Araçás, to the west by the municipality of Aramari, to the northeast by the municipality of Entre Rios and to the southwest by the municipality of Teodoro Sampaio. The municipality is cut off by the BR-101 motorway, which runs in the direction of the state of Sergipe figure7.

Figure 7 – Location of the Municipality of Alagoinhas, Bahia



Source: Santos, Juliana (2018).

with the main rivers that surround it: Rio Aramari, Rio Catu, Rio Saupe and Rio Sumbaúma, between the following geographical coordinates: 12° 7' 13" e -12.1203 de latitude sul, 38° 24' 35" and -38.4098 west longitude and an average altitude of 212m (NASCIMENTO et al., 2006).

To summarise, since this is a computational ecological study based on time series, covering the years 2017 to 2021, this municipality was chosen because it has seen a significant increase in dengue cases in the region, influenced by climatic variables.

5.3 Study period

This study was carried out chronologically, with two stages to analyse the cross-correlation between the variables. The first stage involved collecting data from the weather station in the city of Alagoinhas, Bahia, maintained by the National Meteorological Institute (INMET), while the second stage involved epidemiological data from the FioCruz dengue observatory for the municipality of Alagoinhas, available in csv files.

Using the data obtained during the study, we separated the data columns corresponding to dengue cases, air temperature, relative humidity and average weekly rainfall. We used this data to calculate the trend-free cross-correlation coefficients, ρDCCA (ZEBENDE et al., 2018), for air temperature, relative humidity and rainfall in relation to confirmed dengue cases, in order to establish the influence of these variables on the occurrence of the disease.

We then plotted the ρDCCA dof the variables collected in order to study the influence of these variables on dengue cases. The scales were determined automatically by the MaiaStatistics software (MONTEIRO,) which follows the algorithm defined by (PENG et al., 1994) and (ZEBENDE, 2011).

The period of this analysis of dengue cases in the municipality was 4 years, and 1483 confirmed cases were recorded, which indicates an incidence of around 35% in the population during the period described. According to the methodology described in the dengue technical note from the National Council of Health Secretariats on the dengue incidence rate.

However, for this study we obtained a duration of 209 days for each situation regarding the thorough survey in data collection, along with the development of the cross-correlation coefficient.

5.4 Epidemiological data

CAs mentioned above, it was necessary to acquire epidemiological data on the number of confirmed cases, which were collected through InfoDengue (CODECO et al., 2018) a warning system for arboviruses based on hybrid data generated t h r o u g h t h e integrated analysis of data mined from the social web, gaining national scope with the support of the Ministry of Health carrying out analyses at state level.

Data on the municipality's epidemiological situation is published weekly by the system, and in order to obtain this data, it is necessary for the city's health professionals to fill out a notification form, which feeds the municipal database, where it is consolidated at state level and at federal level by the Ministry of Health. Then, based on the notified cases, the incidence indicators that feed the InfoDengue system are calculated (CODECO et al., 2018).

To search for the data in the InfoDengue system, we entered the name of the municipality we wanted, in this case Alagoinhas-BA, the date and year (2017 to 2021) of the dengue incidence to be analysed, and the system automatically processed the requested data in the form of a csv file, separated by year, month and day. However, the file contains information that is not essential to the research, making it necessary to remove some of this information and only leave the most relevant information about dengue cases.

For this study, the variables of daily records (date) including the years 2017 to 2020, estimated minimum cases, estimated maximum cases, cases and level, were indispensable for constructing the analysis of correlations between one variable and another, together with the meteorological data.

5.5 Meteorological data

The meteorological data was obtained from the National Meteorological Institute (INMET) website, which aims to provide reliable meteorological information for the whole of Brazil by monitoring, analysing and forecasting the weather and reporting on climate conditions.

INMET's main tasks include producing and disseminating daily weather forecasts, warnings and special meteorological bulletins at national level, offering extensive data processing on temperature, relative humidity, wind direction and speed, atmospheric pressure, precipitation, among other variables.

The home page of the INMET site has the option of meteorological data and meteorological database, which redirects the user to the page to fill in the climate data and the desired region, as requested by the user the file is sent to the requester's e-mail address.

A figura8 mshows the organised data with the municipality's main climatic variables, separated by year.

Figure 8 – Climate data for Alagoinhas/BA 2017 to 2020.

	Temp. Min (°C)	Temp. Max (°C)	Temp. Med (°C)	Air humidity Max (%)	Air humidity Min (%)	Air humidity mean (%)	precipitation (mm)
Year 2017							
Mean	19.821429	28.785714	24.303571	76.895697	19.913402	48.404549	0.803516
Std	2.397123	3.393907	2.821127	7.577282	3.877057	4.015551	2.298717
Min	13.285714	19.428571	16.642857	61.857143	0.000000	41.740387	0.000000
Max	23.285714	34.714286	28.857143	89.571429	27.009996	55.504998	13.042857
Year 2018							
Mean	21.019231	29.934066	25.476648	77.218930	19.445824	48.332377	1.447473
Std	1.576648	2.271042	1.764026	7.281375	2.632054	3.408632	3.122513
Min	17.571429	26.428571	22.642857	65.000000	15.038893	42.266736	0.000000
Max	24.000000	35.285714	29.285714	91.714286	23.931910	54.809667	15.654286
Year 2019							
Mean	21.184066	30.203297	25.693681	78.599152	19.560227	49.079689	1.132912
Std	1.548298	2.358156	1.799100	9.793907	3.267813	4.752521	2.129416
Min	18.428571	26.000000	22.571429	64.000000	13.439754	41.184116	0.000000
Max	24.571429	34.571429	29.214286	92.428571	28.582917	56.791616	10.028571
Year 2020							
Mean	20.107143	29.508242	24.807692	43.260871	26.979886	35.120379	1.525330
Std	1.646385	2.231036	1.803166	26.108015	9.533392	13.130460	2.850252
Min	13.571429	25.571429	19.571429	10.170849	7.239520	15.094769	0.000000
Max	22.857143	33.285714	27.428571	93.728746	48.572965	56.858965	11.055714

5.6 Data processing

The data collected in its raw form can contain noise, inconsistencies, missing values and even anomalies, which jeopardises the validity and reliability of the transients. In this way, the process of properly processing the data is of paramount importance to ensure the quality of the results in this research and the robustness of the analyses carried out.

In this context, this study adopted a rigorous approach to processing the data collected during the research period. The processing stages were developed in accordance with the best methodological practices, seeking to address crucial aspects such as cleaning, standardisation, normalisation and selection of relevant variables. In the initial phase, data pertinent to the scope of the research was collected and organised, as mentioned in Chapter5.

Subsequently, the relevant variables for data processing were segregated, such as climatic variables (maximum, average and minimum temperature, maximum, average and minimum relative humidity, rainfall) and dengue cases. After this stage, missing data was identified, possibly due to technical failures or operational problems. Once the data had been cleaned, the following techniques were applied simple linear regression, it is important to note that only the data for the period between 2017 and the beginning of 2021 were considered, since in the latter period the COVID-19 pandemic broke out, leading to the interruption of automated measurements, which prevented manual observations from being made at the station.

The aim of this work is that the detailed description of the careful treatment of the data in the dissertation research will provide a clear and comprehensive view of the methodological steps employed. This transparency is essential to guarantee the validity, replicability and reliability of the results obtained, as well as making a significant contribution to the advancement of knowledge in the field of study.

5.7 Trendless Cross Correlation Coefficient (ρDCCA)

The trendless cross-correlation coefficient -ρDCCA, is a method with the ability to quantify and detect the level of cross-correlation between non-stationary time series (ZEBENDE, 2011). This method, developed by Zebende, is based on the definition of trendless fluctuation analysis - DFA (PENG et al., 1994) and trendless cross-correlation analysis - DCCA (PODOBNIK; STANLEY, 2008).

However, the DCCA is based on the DFA method, which is extended to non-stationary time series, i.e. it shows significant changes over time, and the values of the time series do not remain constant, but change over time. According to (VASSOLER, 2012)"the DCCA estimates whether or not there is a long-range cross-correlation between the two time series analysed, by means of the trendless covariance function".

The trend-free cross-correlation coefficient ρDCCA, is defined by the relationship of F^2_{DCCA} which represents the covariance function without trend and F_{DFA} which represents the variance function without trend, where the two functions are mainly caused by the trend or if the two variables actually vary together, regardless of the trend. However, being a series in which the data shows no upward or downward trend over time. The ρDCCA equation is defined by the following expression:

$$\rho_{DCCA}(n) = \frac{F^2_{DCCA^{(n)}}}{F_{DFA-x^{(n)}}\, F_{DFA-y^{(n)}}} \tag{5.1}$$

By creating o ρDCCA through the ratio of DFA and DCCA, represented by equation5.1, where ρDCCA is a dimensionless coefficient whose range of variation is -1 $\leq \rho$DCCA $\leq$ 1. Sendo ρDCCA = 0,there is no cross-correlation between the time series, and if ρDCCA = 1 is positive, there is perfect cross-correlation, that is, as one time series increases or decreases, the other time series also increases or decreases in the same proportion and for ρDCCA = -1, it means that it is a perfect cross-correlation, that is, the first time series is increased and the second time series is decreased in the same proportion.

A tabela1shows the interval correlation level conditions presented by (ZEBENDE, 2011). For the purposes of applying the ρDCCA method, provides the following step-by-step instructions for calculating the trend-free cross-correlation coefficient for two time series of air temperature and relative humidity:

Table 1 – Correlation condition

ρDCCA	Condition
1	Perfect cross-correlation
0	No cross-correlation
-1	Perfect cross-correlation

Source: Zebende, 2011.

1. Calculate the average value of two time series (which can be called x and y);
2. Each value i n the time series is subtracted from the average, for example, air temperature values are subtracted from the average temperature value;
3. For each calculated average value (values from the series subtracted by the average), the difference is obtained in relation to each calculated point;
4. After obtaining the differences, they are squared, resulting in an integrated series;
5. The total number of points that generated the average value is divided;
6. I set the box to 5 with size n=4 (the size of the time scale);
7. Take the average value of each temperature X humidity box (F^2_{DCCA}),the average value of each temperature box (F^2_{DFA}) and the average value of each humidity box (F^2_{DFA}), then the square root is calculated to obtain the F^2_{DCCA}, F^2_{DFA} and F^2_{DFA};
8. And finally, the calculation is made

$$\rho_{DCCA}(n) = \frac{F^2_{DCCA^{(n)}}}{F_{DFA-x^{(n)}} F_{DFA-y^{(n)}}} \tag{5.2}$$

.

Currently, ρDCCA has been used in various fields of research, such as: analysing biometric signals(URSULEAN; LAZAR, 2009), applications in the fields of physics, economics and biology (FILHO, 2018), climate phenomena (VASSOLER, 2012), (SANTOS et al., 2010), (ZEBENDE et al., 2018), (BALOCCHI; VARANINI; MACERATA, 2013), (YUAN; FU, 2014), the effect of the oil and stock crisis in 2008 (FERREIRA et al., 2019), time series analysis in homicide and attempted homicide (FILHO; SILVA; ZEBENDE, 2014), non-stationary time series analysis (KRISTOUFEK, 2014), (QIAN et al., 2015),

(PODOBNIK; STANLEY, 2008), (PALHINHAS, 2021), (COSTA, 2021), (KRISTOUFEK, 2014), analysing the correlation between climate variables and Dengue cases (FIGUEREDO MARCOS BATISTA E MONTEIRO,).

One of the outstanding advantages of the ρDCCA, method is its mutual ability to measure the level of cross-correlation between non-stationary time series on different time scales n, thus identifying which time series are correlated. In addition, the development of ρDCCA takes into account the order of the pairs of values in the time series, which does not contradict the basic principle of time series analysis, which is time dependence between the values in the series (FILHO; SILVA; ZEBENDE, 2014).

Subsection 5.8 shows how the calculation of the cross-correlation coefficient without trend, applied in the research, was carried out.

5.8 How to Calculate the Coefficient

The trendless cross-correlation coefficient, ρDCCA (Zenbende) is used to determine whether two time series y and $y\prime$ have a negative, zero or positive correlation on a scale of n, with values in the range -1 $\leq$ ρDCCA $\leq$ 1. We calculate $\rho_{DCCA}(n)$, for a scale of n using Equation5.3 .

$$\rho_{DCCA}(n) = \frac{F^2_{DCCA^{(n)}}}{F_{DFA^{(n)}_y} \times F_{DFA\prime^{(n)}_y}} \tag{5.3}$$

Where $F^2_{DCCA^{(n)}}$ is the DCCA (PODOBNIK; STANLEY, 2008), for time series y and y' at scale n, where $F_{DCCA^{(n)}_y}$ is the DFA (PENG et al., 1994),for the time series $y$on the n scale $F_{DCCA\prime^{(n)}_y}$) is the DFAfor the time series y' at scale n.

To calculate the value of $F^2_{DCCA^{(n)}}$ we use equation 5.4 where N corresponds to the number of elements in each time series, n the scale size(box) and $f^2_{DCCA^{(n.i)}}$ ccorresponds to the value of the average of the products of the residuals of each series and each range, given by equation5.5.

$$F^2_{DCCA^{(n)}} \equiv (N-n)^{-1} \times \sum_{i=1}^{N-n} f^2_{DCCA^{(n,i)}} \tag{5.4}$$

$$F^2_{DCCA^{(n,i)}} \equiv \frac{1}{n+1} \times \sum_{k=1}^{1+n} (R_{k-\tilde{R}_{k,i}}) \times (R'_{k-\tilde{R}'_{k,i}}) \tag{5.5}$$

In equation5.5 R_k is the y series integrated in k box given by equation5.6 and $\tilde{R}_{k,i}$ is the value of the linear fit, using the least squares method, for the y series, in the point i

and R'_k and the series y' integrated in box k, given by equation5.7, while $\tilde{R}'_{k,i}$ is the value of the least squares linear fit for the series y', at point i.

$$R_k \equiv \sum_{i=1}^{K} yi \tag{5.6}$$

$$R'_k \equiv \sum_{i=1}^{K} y'_i \tag{5.7}$$

To calculate the $F_{DFA}{}^{(n)}$) of each series on each scale (box 0) n we use equation 5.8, which corresponds to the value of the square root of the squared residuals in each box, where $y^{(k)}$ is the value of the series at point k and $y_n(k)$is the value of the linear fit, using the least squares method, for the y, series at point k.

$$F_{DFA}(n) = \sqrt{\frac{1}{n} \sum_{k=1}^{k} [y^{(k) - y_n(k)}]^2} \tag{5.8}$$

We used equations5.3, 5.4, 5.5, 5.6, 5.7, 5.8 eand the MaiaStatistics software (MONTEIRO,) to calculate the value of ρDCCA.

5.8.1 Chapter Conclusion

In this chapter we show the influence of climatic variables, global warming that intervenes in temperatures, the ambient temperature that provides Aedes aegypti with favourable conditions for its proliferation which consequently spreads pathogens, in this case in the transmission of the dengue virus and being a challenge for public health. We discussed the main climatic elements that most influence the development of the vector, how it exerts a strong effect on its biology and how it behaves in search of its host according to the favourable environment.

We used methods that guarantee the reliability of the results, providing a solid basis for understanding the relationship between climate variables and dengue cases in Alagoinhas, as well as the use of the trendless cross-correlation coefficient method - ρDCCA,providing a more robust approach to analysing the dynamics between two non-stationary time series.

Several research studies have converged on a single specific point in relation to the climate that drives temperatures and relative humidity, where they have direct effects on oviposition, the rate of development, mobility and saturation of Aedes aegypti mosquito larvae, however, the lower temperature limit for the vector to develop is 16 $\circ$ C, while 34 $\circ$ C is the upper limit (REINHOLD; LAZZARI; LAHONDÈRE, 2018). Above all, adult vectors are even more influenced by climatic variations, as their size, feeding and activity are affected by various climatic factors.

In summary, Aedes aegypti population levels are dynamic and vary greatly between regions, depending mainly on climatic conditions and other factors, such as the choice of food availability that the environment favours. However, in some regions with higher humidity, the Aedes aegypti population tends to be larger and longer, as these climatic conditions are favourable for its development.

6 Results

6.1 Introduction

Due to its ubiquity in the region, Alagoinhas has been particularly vulnerable to the side effects of dengue fever, which in turn is associated with the local climate. The results of this study show the relationship between climatic variables and dengue cases in the Alagoinhas region, which through these results will provide strategic paths for understanding the effects of climatic conditions on the development and spread of dengue.

This chapter presents the results of this study through statistical analysis with graphs, to facilitate understanding, comparison and exploration of the information obtained through the data, as established in chapter 3 with materials and methods.

It is important to point out that the correlation found does not in itself imply causality; other socio-environmental and behavioural factors can also contribute to the incidence of dengue in Alagoinhas. Therefore, the results will be interpreted with scientific rigour, considering their limitations and the relevance of further studies to understand this relationship more comprehensively.

6.2 Climatic characteristics of the area

The city of Alagoinhas is located close to the equator (12°8′9"S38°25′8"C), which makes it difficult to characterise the seasons, presenting a climate between 2017 and 2021 with low annual rainfall. The remarkable inter-annual variability of rainfall, associated with low total annual rainfall values, is a reflection of the macroclimate of the Northeast region of Brazil and one of the main factors for the occurrence of "drought" events, characterised by a marked reduction in total seasonal rainfall during the rainy season.

The interannual variability of rainfall in the city is associated with variations in sea surface temperature (SST) patterns over the tropical oceans, which affect the position and intensity of the Intertropical Convergence Zone (ITCZ) over the Atlantic Ocean (BRITO et al., 2007).

However, the city of Alagoinhas has a measured rainfall described in Figure9, which shows that rainfall occurs seasonally abruptly and in short periods of time, being influenced by the tropical climate and seasonal patterns. Most of the rainfall occurs during the rainy season, which generally lasts from April to August, during which time it is common to see an increase in precipitation.

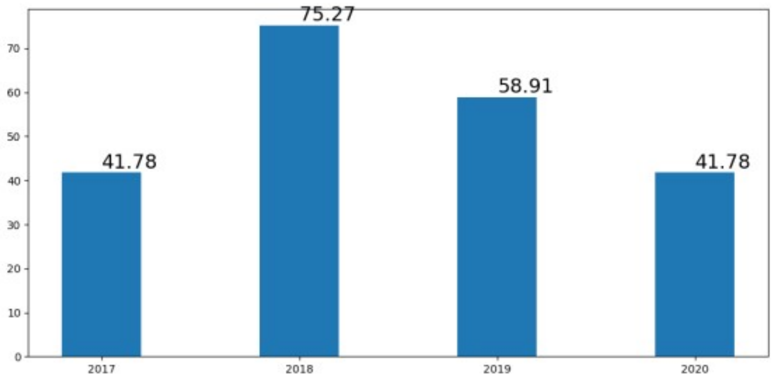


Figure 9 – Accumulated rainfall.

The association of these climatic characteristics with dengue cases is a complex and multifactorial issue, although the climate can directly influence the incidence of dengue, as is the case with relative humidity in the Alagoinhas region, which has a predominant influence on dengue cases and can thus affect mosquito survival and egg hatching.

Using appropriate statistical techniques, we sought a more in-depth understanding of the relationship between these two twe were able to determine the existence of a correlation between climate variables and dengue cases, the average correlation between relative humidity and confirmed dengue cases and a low correlation between the relative air temperature and precipitation variables. Although several authors (ABDULLAH et al., 2022) state that the variables air temperature and precipitation have a direct influence on the incidence of dengue, in the city of Alagoinhas these variables are slightly less relevant than humidity.

The correlation between the two time series, relative humidity and dengue cases, can be clearly seen in figure10, In this graphical representation, it is possible to visualise the size of the scale n=35, as a function of the coefficient which varies between 1 and -1, showing the relationship between the two variables. There is a positive correlation between relative humidity and dengue cases, while the other climatic variables show an anti-correlation.

According to the six levels described in Table2 (three positive and three negative), we can associate a colour with a range of ρDCCA, In our case, the ρDCCA value was positive for humidity and is in the yellow range, while this perception is not observed for the other variables, which are in the range between blue and light green. In addition, we can see that precipitation shows a drop on the scale of 28, and the temperature is in the yellow range.

In the specific context of Alagoinhas and based on the data obtained, as shown in figure10, we identified a localised anti-correlation pattern (represented by the blue colour) with a value of approximately $n \approx 2$, in the windows of approximately $n \approx 32$, it is possible

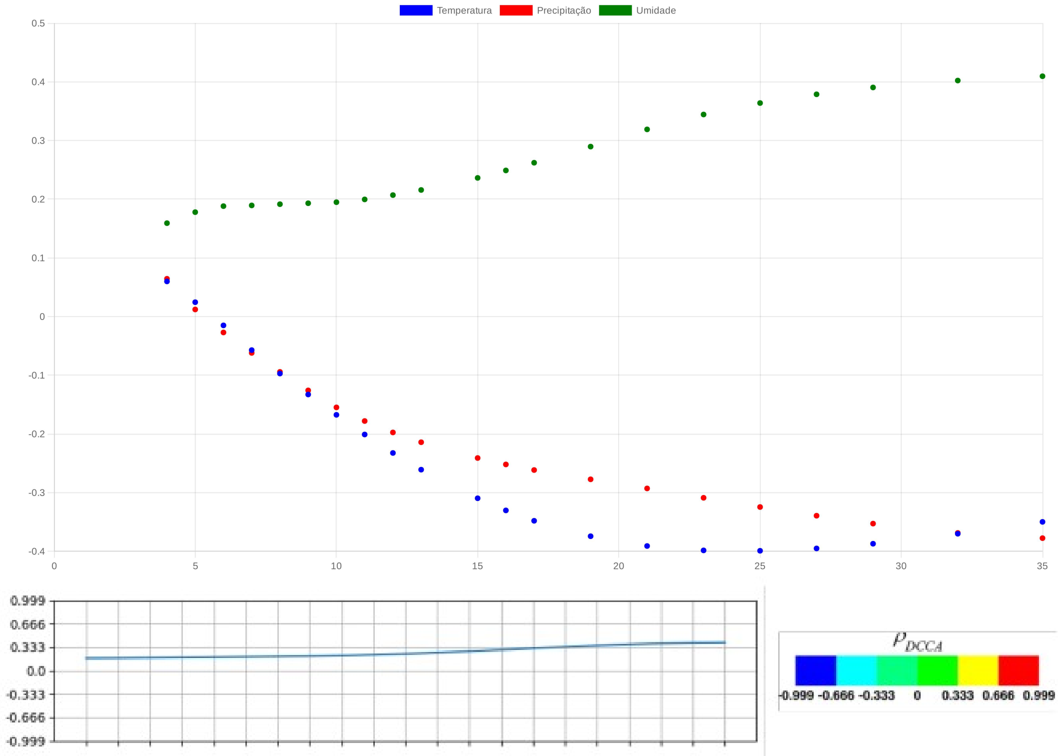


Figure 10 – Correlation between relative humidity and dengue cases.

Table 2 – Cross-correlation intervals without trend.

Condition	ρ_{DCCA}
Weak	$\pm 0{,}000 \mapsto \pm 0{,}333$
Average	$\pm 0{,}333 \mapsto \pm 0{,}666$
Strong	$\pm 0{,}666 \mapsto \pm 0{,}999$

to observe a correlation for humidity, while the dynamics are weaker for the temperature and precipitation variables. These observations show that humidity has a more significant influence on dengue cases in the Alagoinhas region than other climatic variables.

The importance of considering humidity as a key factor in understanding the correlation with dengue cases in the locality in question, through the ρDCCA, method, provides information that can guide the formulation of effective strategies for the prevention and control of the disease, seeking to minimise its impact on the community and promote more effective public health.

6.3 Conclusion

The convergence of various studies towards a common centre on the relationship between climate and dengue incidence is motivated by convincing scientific evidence that points to the influence of certain climatic factors on the spread of the disease. In this context, it is clear that human actions and global warming play crucial roles in habitat changes, directly impacting the behaviour of the mosquito vector, the development of the virus and the feasibility of transmission.

In this chapter we applied the trendless cross-correlation coefficient, ρDCCA,to measure the two-by-two correlation of these non-stationary series. The interesting fact observed during the application of the method is that, contrary to what the literature states, the predominant factor in the incidence of dengue cases in the municipality of Alagoinhas-BA is a direct positive correlation with relative humidity - RH - and the existence of an inverse correlation between air temperature and rainfall, compared using weekly data. In addition, the aim was to demonstrate the relevance of the influence of a specific climatic element on the development of the Aedes aegypti mosquito and its main implications for the transmission of the disease.

However, it is important to emphasise that this is only the first step in an ongoing process of research and investigation; further studies are needed to deepen understanding of the complex interactions between climatic variables and dengue transmission. In addition, consideration of other factors, such as behavioural and socio-economic factors, is also essential for a more complete understanding of the epidemiological scenario.

7 Final considerations

7.1 Introduction

The Aedes aegypti population is highly dynamic, varying from year to year according to climatic conditions and other environmental factors. The population of this vector can increase rapidly in response to climate change, such as an i n c r e a s e i n temperature and especially relative humidity, or in response to an increase in the availability of breeding sites, which is consequently accompanied by an excessive increase in the dengue virus.

What's more, municipalities with more than 50,000 inhabitants have higher rates of dengue case notification, around 70% per cent, because the growing population density can increase the conditions necessary for mosquito development (CESAR; LABINAS, 2006). Today, Alagoinhas has a population density of 153,023 inhabitants, as mentioned in subchapter 5.2 and is more prone to higher rates of dengue spread.

The aim of this research was not just to analyse the correlation between the climatic variables air temperature, relative humidity, average weekly rainfall and dengue cases in the municipality of Alagoinhas, but to be able to demonstrate the importance of a climatic element influencing the development of Aedes aegypti and its main implications, as well as to be able to analyse the two time series.

NNot only did we apply the ρDCCA, cbut we also used time series models to analyse the data to determine recurring patterns and trends over time. Using the python tool, we generated graphs to compare the data from the time series (climate variables and dengue cases), and during the course we observed that the trend evolved over time for both series, and we also generated decompositions to understand the dynamics of changes in the behaviour of a time series.

There was an upward trend in RH, with high values in the 2019 periods from August to December and low values from January to July; in 2020 there was also an upward trend with high values from June to December and low values in relative humidity from January to May. While seasonality continued to repeat its behaviour over the period.

However, when there is an increase in the relative humidity trend, it means that the amount of water in the air is increasing, causing there to be more water vapour in the atmosphere, in which case the air becomes denser and warmer. In addition, high humidity levels can play a role in the spread of dengue fever and can be key to the development of effective prevention measures.

The model applied using ρDCCA and python to develop the graphs for comparing the data from the two time series shows a satisfactory performance in displaying the two series that have evolved over time with the trend and the climatic element that influences the incidence of the arbovirus. However, it is necessary to take a deeper look at understanding the direct impact of climatic conditions and dengue cases in order to validate the direct existence of this correlation, which provides a vision for future work.

7.2 Future work

Other studies can be carried out in the future to continue the research and stimulate growth in the scientific field in a holistic way in the real context. Below are some proposals that could be discussed in future studies:

- To study the dynamics of the behaviour of the Aedes aegypti population in relation to climate change and how it can affect dengue transmission over time;
- To investigate the association between climatic factors and dengue incidence over time, going beyond the most recent data to cover long-term trends;
- Investigating climate data to predict seasonal variations in dengue cases;
- Developing a Machine Learning (ML) algorithm that analyses weather patterns and possible dengue cases, predicting the neighbourhoods most vulnerable to the emergence of cases, which have never been observed before, this tool can be used to prevent dengue outbreaks and treat the disease more effectively;
- Developing autonomous robots to catalogue areas where the dengue vector can reproduce in places at risk, these robots could detect and indicate places outside the monitored areas with a higher risk of cases and thus prevent possible outbreaks;
- Carry out a more in-depth analysis of dengue incidence data in relation to climate data, in order to obtain more specific answers to the correlation between the variables;
- Formalise a statistical regression model that defines parameters for how the dependent variable (number of dengue cases) is influenced by covariates (climate variables);
- To work with the Alagoinhas city council to apply a standardised model to a database that only includes information on dengue cases and the city's climate, in order to obtain strategies for combating and taking preventive measures against the proliferation of dengue.

7.3 Conclusion

Science has increasingly turned its attention to understanding the impact of climatic conditions on the incidence, prevalence and characteristics of the disease caused by Aedes aegypti in various locations. This has long been a public health problem due to the large number of cases that have been occurring in Brazil, especially in cities that have infrastructure problems. Not only do climate and infrastructure factors play a relevant role in the development of Aedes aegypti, but other factors that exceed the spread of this vector are human behaviour and environmental factors.

Considering the results obtained in the correlation between climate variables and dengue cases in the municipality of Alagoinhas, it was possible to establish the relationship between the two time series within the proposed model. The results showed a positive correlation between Relative Humidity (RH) and dengue cases, in the average range between 0.333 and 0.666, represented by the yellow colour on the correlation scale, as discussed in Chapter6. It's important to note that when relative humidity averages between 70% and 100%, it becomes a favourable factor for all stages of the Aedes aegypti mosquito's life cycle, significantly increasing the risk of dengue transmission.

As it happened in the second half of 2021, when the RH was high, but dengue case notifications that year were low due to t h e COVID-19 pandemic, it is believed that there was an excessive increase in people contracting dengue, however, it was impossible to make any kind of analysis between the RH and dengue cases in 2021. According to the data and results presented during the research, climatic variables had a certain influence on the incidence of d e n g u e cases, and in 2019 and 2020 there was a greater concentration in the proliferation of dengue.

Another important point in the approach to the analysis of the time series with regard to seasonality and trend, provided a broad assessment of the behaviour of the two time series, where the trend was present in the temperatures with a slight precipitation did not grow significantly, but there were oscillations over time, while relative humidity grew favourably over a certain period of time. The most interesting thing is that t h e RH trend increased as temperatures fell and the temperature trend increased when the RH was low, while seasonality maintained a behaviour with repetitions and oscillations over time in the climatic variables.

Understanding and analysing all these climatic elements in detail is extremely important for improving effective dengue prevention and control strategies, especially understanding how the Aedes aegypti mosquito behaves in the face of climatic variations, which is essential for mitigating the impacts caused by the vector.

In short, the research has shown that relative humidity is one of the most influential factors in the spread of the dengue virus in the Alagoinhas region, also revealing the behaviour of Ae. aegypti in the face of climatic conditions. However, in order to achieve more robust results and compare the evolution of the disease over time in the municipality, it is necessary to obtain older data on reported dengue cases. Unfortunately, the city of Alagoinhas lacks a complete database on arboviruses, which makes a more comprehensive analysis difficult.

Continued research in this field is extremely important for advancing knowledge and developing more comprehensive, evidence-based policies. This approach is essential for promoting safer and more resilient collective health in the face of vector-borne diseases such as dengue.

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