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Paradox between adequate sanitation and rainfall in dengue fever cases

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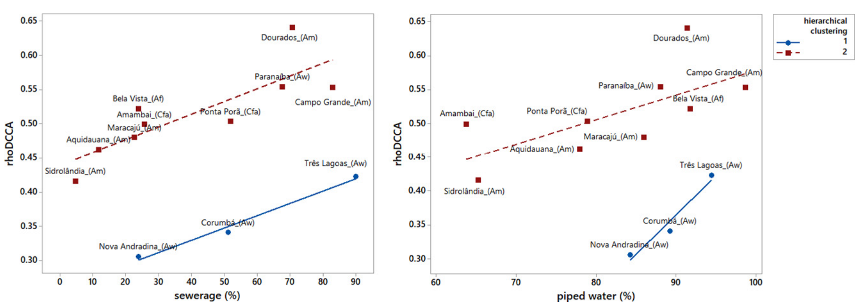
HIGHLIGHTS

- Our results show a paradox regarding the relationship between adequate sanitation and the rainfall-dengue DCCAC.
- If water sanitation improvement actions are implemented in the city, such as piped water and sewerage, the cross-correlation between rainfall and dengue increases.
- If water sanitation improvement actions are implemented in the city, such as piped water and sewerage, the cross-correlation between rainfall and dengue increases.

GRAPHICAL ABSTRACT



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ABSTRACT

Background: Dengue fever is a tropical disease and a major public health concern, and almost half of the world's population lives in areas at risk of contracting this disease. Climate change is identified by WHO and other international health authorities as one of the primary factors that contribute to the rapid spread of dengue fever.
Methods: We evaluated the effect of sanitation on the cross-correlation between rainfall and the first symptoms of dengue in the city of Mato Grosso do Sul, which is in a state in the Midwest region of Brazil, and employed the time-lagged detrended cross-correlation analysis (DCCAC) method.
Results: Co–movements were obtained through the time-phased DCCAC to analyze the effects of climatic variables on arboviruses. The use of a time-lag analysis was more robust than DCCAC without lag to present the behavior of dengue cases in relation to accumulated precipitation. Our results show that the cross-correlation between rain and dengue increased as the city implemented actions to improve basic sanitation in the city.
Conclusion: With climate change and the increase in the global average temperature, mosquitoes are advancing beyond the tropics, and our results show that cities with improved sanitation have a high correlation between dengue and annual precipitation. Public prevention and control policies can be targeted according to the period of time and the degree of correlation calculated to structure vector control and prevention work in places where sanitation conditions are adequate.

1. Introduction

Dengue fever is a neglected tropical disease (NTD) of major public health concern (Gubler and Clark, 1995; WHO, 2021). NTDs also include Chagas disease, chikungunya, schistosomiasis, leishmaniasis, ectoparasitoses and

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other diseases (WHO, 2021). The U.S. Centers for Disease Control and Prevention estimate that almost half of the world's population lives in areas at risk of contracting dengue, with as many as 400 million people infected with dengue virus (DENV) and 20,000 dying from severe dengue fever every year (CDC, 2021).

DENV is transmitted by the *Aedes aegypti* mosquito, which belongs to the *Flaviviridae* family and the *Flavivirus* genus and has four different serotypes (*DENV1–4*) (Bhatt et al., 2013). *Aedes aegypti* is native to Africa, and its larvae are found in several places, mainly in urban environments, facilitating the propagation of the species. The transmission of arboviruses is complex, involving different aspects of the behavior of those infected, and it is strongly influenced by precipitation, temperature and degree of urbanization (Hales et al., 2002; Bhatt et al., 2013; Liu et al., 2018; Salles et al., 2018; Wilder-Smith et al., 2019).

The most widely used strategy to prevent dengue disease is to fight water accumulation, which favors the reproduction of mosquitoes. The use of insecticides and the sterilization of mosquitoes by genetic modification are other initiatives to reduce the vector that have been used by the city government. Although many mosquito control policies have been implemented every year in Brazilian cities, the prospects for dengue control are not promising (Salles et al., 2018). DENV remains a prevention challenge and an important public health problem associated with morbidity, mortality and significant economic costs, particularly in developing countries (Harapan et al., 2020).

Between 2012 and 2020, the WHO, governments, foundations, NGOs and other institutions planned for the eradication of NTDs. NTDs can cause multidisciplinary care needs, increasing costs and making treatment difficult for populations located in hard-to-reach places. However, not all goals were achieved in the planning period (The Lancet, 2022), and the prospects for dengue control are not promising. The number of dengue cases increases proportionally to the factors of deforestation, migration, disorderly occupation of urban areas and poor sanitation and climate change. These factors all help the propagation of the vectors of this disease, significantly increasing the risk to populations that live in these areas (Salles et al., 2018; Mota et al., 2016; Pasteur, 2018).

To reduce NTDs, efforts are needed to reduce poverty and improve living conditions. Specifically, these efforts include budgetary investments in health, water, sanitation and hygiene, and education. Moreover, food security needs to be ensured, especially in endemic countries. In addition, climate change, precipitation and temperature contribute to the transmission of diseases in parts of central Europe and the United States (The Lancet, 2022). Climate change is a concern for arboviral diseases because mosquitos can better proliferate and spread into warm zones and the Earth continues to warm over time (Gainor et al., 2022). Warmer water also accelerates the maturation of mosquito larvae, and warmer climates tend to be associated with an increase in the mosquito feeding rate, providing more opportunities for virus transmission (Githeko et al., 2000). Nosrat et al. (2021) also showed an abundance of mosquito eggs and adults after wet months.

Not only are cases increasing because of climate change, but more outbreaks are occurring as the disease spreads to new regions. Local transmission was first reported in France and Croatia in 2010, and imported cases were detected in 3 other European countries. In 2012, more than 2000 cases of dengue fever broke out in the Madeira Islands, and imported cases were found in Portugal and 10 other European countries. Autochthonous cases are now observed annually in a few European countries (WHO, 2022).

Mone et al. (2019) noted that understanding the trend and evolution of the virus over time is important given seasonal influences and the impact of climate change. Several models have been developed to successfully forecast dengue outbreaks by correlating dengue cases with climate data, such as models employed in Singapore (Hii et al., 2012), China (Guo et al., 2019), Malaysia (Jayaraj et al., 2019) and Brazil (Lowe et al., 2014). (Franklinos et al., 2019) says that the disease investigation should not only focus on climate change but also consider increasing evidence of supplementary factors that modulate disease risk; for instance, socioeconomic factors are increasingly being recognized as important predictors of disease transmission.

Despite all efforts to develop effective vector control measures, the general trend in recent years in Brazil has been an increasing burden of dengue disease. Reported cases in Brazil exceeded 1.6 million in 2016 and reached 2.1 million in 2019 (Brito et al., 2021). Brazil experienced a hyperendemic scenario with the co-transmission of the four DENV serotypes in 2019 and a high occurrence of severe and fatal cases, as well as recent co-transmission with other arboviruses, such as Zika, Yellow Fever and Chikungunya (Nunes et al., 2019).

The mosquito usually chooses artificial reservoirs, preferring to reproduce in clean water to avoid exposing the larvae to the action of predators (Varejão et al., 2005). The viability of *A. aegypti* is about 60 % in rainwater and 10 % in raw sewage (Beserra et al., 2009). As dengue is a water-associated disease, the following question arises: may the availability of clean water and adequate sanitation influence the correlation strength between rainfall and dengue cases?

The objective of our study was to evaluate the effect of sanitation on the cross-correlation between rainfall and the first symptoms of dengue in several cities of Mato Grosso do Sul (MS), a state in the Midwest region of Brazil. This state is in an area with the highest mortality rates, and dengue in this area was responsible for 18 % of all deaths in the country in 2015 (Nunes et al., 2019). We employed the time-lagged detrended cross-correlation analysis (time-lagged DCCA coefficient) method to detect nonlinear and nonstationary correlations, a behavior found in weather-sensitive infectious disease incidences (Ehelepola et al., 2021).

2. Materials and methods

2.1. Dengue incidence, climate classifications and geographic coordinates

In the present retrospective study, notifications of the first symptoms of dengue for confirmed cases in twelve cities in the MS were daily collected from the database of the *Sistema de Informação de Agravos de Notificação* (SINAN) through the *Department of Informatics of the Unified Health System* (DATASUS) of the Ministry of Health. All records from the database with a diagnosis of dengue (*CID A90*) were used in the evaluation. The anonymized data was downloaded on 5/21/2021 and is publicly available at (DATASUS, 2022).

MS is in the Midwest region of Brazil. It has a territorial area of 357.125 km^2 (IBGE, 2021), contains 79 cities and borders five Brazilian states and two countries (Fig. 1). It consists of three biomes, Pantanal, the Atlantic Forest and Cerrado, that cover most of the area. Four climate classifications predominate in the state: a tropical savanna climate (*Aw*), a humid subtropical climate (*Cfa*), a humid or super humid tropical climate (*Af*) and a tropical monsoon climate (*Am*).

The twelve most populous cities in MS that are geographically distributed to cover the four climatic classifications of the state and in which data from meteorological stations by INMET were available were selected for this study.

The climate of *Aw* covers a vast area of Brazil (25.8 % of its territory). It is present mainly in the central region of Brazil. It features high temperatures and has seasonal characteristics, such as dry winters and summer rains. The *Am* climate covers approximately 27.5 % of the Brazilian territory, making it the most representative climate in Brazil. It has a rainy season in the summer (November to April) and a dry season in the winter (May to October), and July is considered the driest month (Alvares et al., 2013; Thornthwaite, 1948).

The *Cfa* climate covers 6.5 % of the Brazilian territory and is found mainly in the states of the southern region of Brazil. In Mato Grosso do Sul, this climate is found in the plateau regions, including the Pantanal biome, in the plateaus of the Paraguay River region, where altitudes are above 900 m. This climate classification is characterized by abundant and distributed precipitation throughout the year. The *Af* climate is found in 22.6 % of the territory, covering 82.3 % of the state of Amazonas. In Mato Grosso do Sul, the *Af* climate is found in the Pantanal, and it always

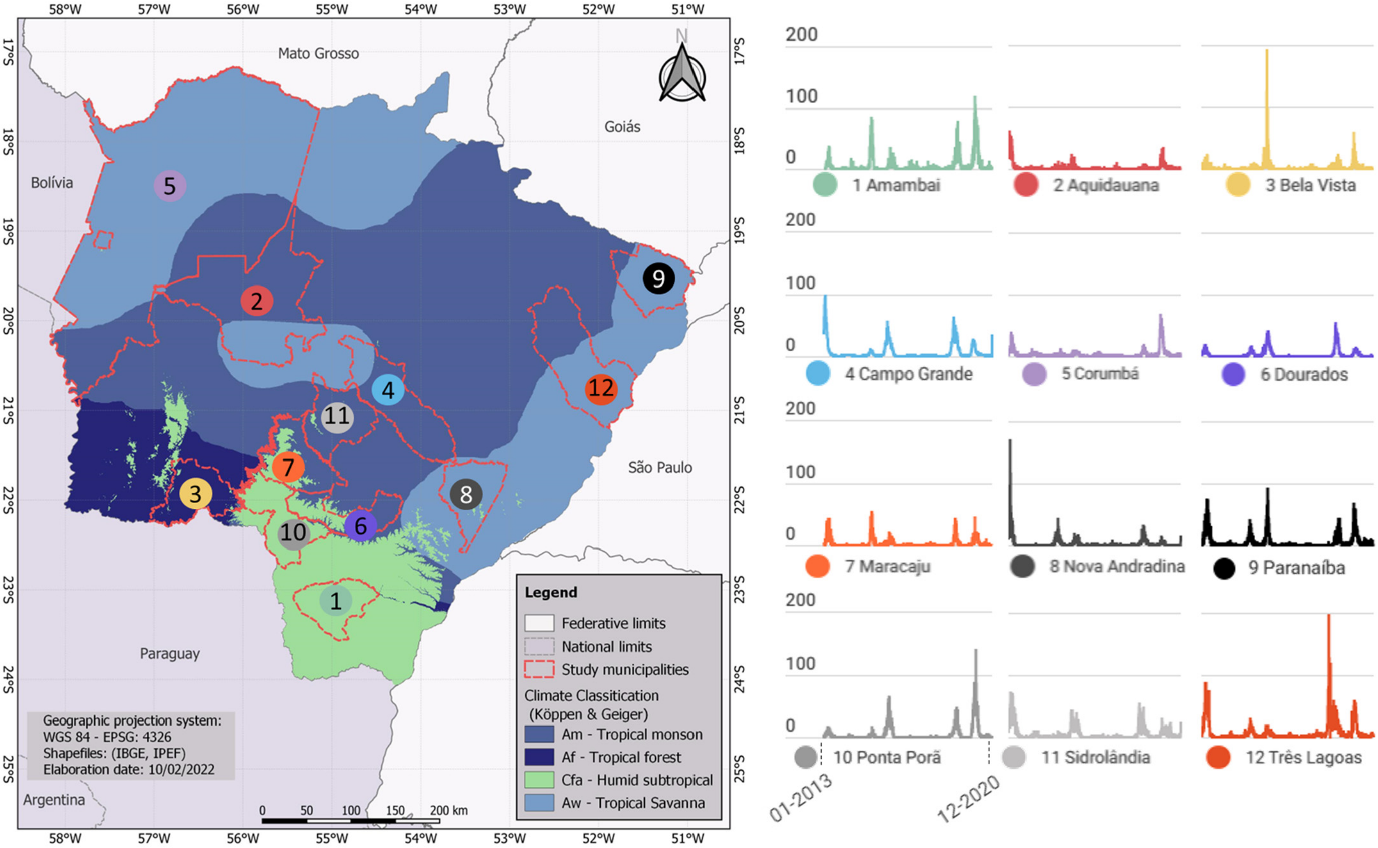

Fig. 1. Map of the state of Mato Grosso do Sul with climate classification, limits and studied cities followed by timeline graphs with the monthly incidences of the first reported symptoms of confirmed dengue cases per 100,000 inhabitants between 2013 and 2020.

occurs at altitudes below 400 m, with annual rainfall between 1.400 and 1.800 mm. The *Af* climate is dry in the summer, with winter and autumn rains and high temperatures (Alvares et al., 2013; Thornthwaite, 1948).

We chose the MS state because it has a mid-high incidence of dengue fever (Brito et al., 2021) and a severe dengue fatality rate that exceeded 61–80 % in 2015 (Nunes et al., 2019). It also has four different climate classifications (Fig. 1) and several economic and social profile differences within its cities (see Supplementary Material).

2.2. Precipitation data

For the accumulated rainfall, the data were collected from the Instituto Nacional de Meteorologia (INMET) database. As a complementary support, we used the records of *NASA The Power Project* for cases in which this information was not available (NASA, 2022). For instance, this method of filling gaps has already been used in other research on the performance of gap-filling methods of meteorological data for the western region of Paraná (Giovanella et al., 2021) and to estimate daily solar radiation data for the continental United States (White et al., 2011). Our model uses the daily accumulated rainfall for each city.

2.3. Sanitation data

Unique data on health indicators of 2020 were collected from the *MUNICÍPIOS E SANEAMENTO* platform with data from the main official sources, downloaded on 2022-19-04 (IAS, 2022).

The piped water indicator consists of the activities, infrastructure and facilities necessary for the supply of water from the capture to the building connections and respective measuring instruments. The sewerage indicator consists of the activities, infrastructures and operational installations of adequate collection, transport, treatment and final disposal of sanitary sewage, from the building connections to the final release into the environment.

Table 1 shows the values, in percentages, of the indicators for 2020 for the analyzed cities.

2.4. Detrended cross-correlation analysis

The dispersal of DENV and other arboviruses is considered a complex system (Salles et al., 2018; Harapan et al., 2020). The analysis of dengue fever as a nonlinear system can contribute to the understanding of the behavior of this disease (Murari et al., 2021). The assumption of stationarity of random variables in the time series is necessary to perform several mechanisms of statistical inference (Al Salameen et al., 2020), and nonstationary data make Pearson's correlation coefficient an inefficient method for identifying true correlations on different time scales (Piao and Fu, 2016; Kristoufek, 2014).

Table 1
Sanitary indicators analyzed.

City/Koppen	Piped water (%)	Sewerage (%)
Amambai (*Cfa*)	63.78	25.76
Aquidauana (*Am*)	77.97	11.77
Bela Vista (*Af*)	91.75	23.93
Campo Grande (*Am*)	98.66	82.88
Corumbá (*Aw*)	89.21	51.08
Dourados (*Am*)	91.41	70.6
Maracajú (*Am*)	85.99	22.64
Nova Andradina (*Aw*)	84.23	23.93
Paranaíba (*Aw*)	88.07	67.67
Ponta Porã (*Cfa*)	78.91	51.91
Sidrolândia (*Am*)	65.28	4.71
Três Lagoas (*Aw*)	94.41	89.97

Unlike Pearson's coefficient, the DCCA coefficient (DCCAC) can estimate the true correlation coefficient between series despite the nonstationarity strength of the data (Kristoufek, 2014). DCCA-related methods are both more robust to contaminated noises and less sensitive to the amplitude ratio between slow and fast components than the Pearson method (Piao and Fu, 2016).

Due to the nonstationarity of the spread of dengue (Nascimento Filho et al., 2018; Saba et al., 2014) and the known time-lag condition between weather conditions and dengue cases (Hii et al., 2012; Ehelepola et al., 2015; Jayaraj et al., 2019; Gagnon et al., 2001), the time-lagged DCCA coefficient was employed in this study. Time-lagged generally refers to the correlation between two-time series relatively displaced in time (Shen, 2015).

Time-lagged DCCAC (Shen, 2015) can be considered a generalization of the nontrend cross-correlation analysis schemes. Based on DCCA, the time-lagged DCCA was developed to measure the strength of time-lagged cross-correlations between two nonstationary time series (X_k and Y_k) at different time lags, recognizing that the largest correlation occurred at lags of X_k, which may support the prediction of Y_k (Ehelepola et al., 2021). This method has been applied in different areas, such as in meteorological time series (Malik et al., 2018; Nogueira, 2019; Shen, 2015) and public health issues (Ehelepola et al., 2021).

2.4.1. Time-lagged DCCAC method

DCCAC was proposed and implemented by Zebende (Zebende, 2011) and can identify the level of cross-correlation based on detrended fluctuation analysis (DFA) (Peng et al., 1994) and detrended cross-correlation analysis (DCCA) (Podobnik et al., 2011). Specifically, it has been applied to astrophysics (Zebende et al., 2005; Moret, 2014), biological process (Figueiredo et al., 2010), climate (Santos et al., 2019) and epidemic data series (Azevedo et al., 2016). The objective of this method is to create a scale to quantify the level of cross-correlation between nonstationary time series. Analyzing the fluctuations allows us to ascertain the characteristics of the evolution of dengue that are not evident compared to traditional statistical methods.

We calculated the cross-correlation by applying the DCCAC statistical method with a lag calculation to evaluate the relationship between the notifications of the first symptoms of dengue in the population and precipitation information between 2013 and 2020 for the twelve most populous cities in the state of Mato Grosso do Sul according to the climatic classifications of the state: tropical savanna climate (*Aw*), tropical monsoon climate (*Am*), humid subtropical climate (*Cfa*) and humid or super humid tropical climate (*Af*). The analysis of the time-phased cross-correlations between nonstationary time series can be useful to better understand the influence of rain on the notifications of dengue in a city.

Research into cross-correlations with lags has been ongoing for several years. Studies with lagged DFA for nonstationary time series have found greater correlations in positive lags (Alvarez-Ramirez et al., 2009). Using the DCCA method, researchers have studied the dynamics of cross-correlations involving the stock market with a time delay (Lin et al., 2012).

First, we calculated the DCCAC, idealized by Zebende (Zebende, 2011). This coefficient can quantify the level of cross-correlation based on the DFA and the DCCA. This coefficient is calculated according to the following equation (Eq. (1)):

$$\rho DCCA(n) = \frac{F^2_{DCCA}}{F_{DFA(y)}(n) * F_{DFA(y')}(n)} \tag{1}$$

ρDCCA is a dimensionless coefficient with a variation interval between -1 and $+1$, which are interpreted as follows:

- ρDCCA $= 0$: indicates no cross-correlation between the analyzed series;
- ρDCCA $= +1$ indicates a perfect cross-correlation;
- ρDCCA $= -1$ indicates perfectly anticorrelated.

To analyze the results, the statistical test in which the correlation was significant was considered. Specifically, the values in the scatter plots that are outside the lines (upper and lower) represent a significance of 95 %, with the hypothesis test H0: ρDCCA $= 0$ and H1: ρDCCA $\neq 0$. The coefficients were classified as weak, medium or strong to describe the results, and the discussion in this research was based on the work of (Zebende et al., 2018) (Table 2):

The DCCAC calculates the covariance of the residuals in each box of size *n*. The time lag calculates the lagged covariance of the residuals in each box of size n between two-time series, and the average lagged covariance over all N - n - $|\tau|$ boxes. We implemented the lagged DCCAC. τ was used to denote the time interval and can be positive or negative. In general, a positive τ indicates that $Y(_k + \tau)$ lags X_k, whereas a negative τ means that $X(_k + \tau)$ lags in Y_k (Shen, 2015).

Studies using the time-lagged DCCAC have been used in several areas, such as in oil and gas production forecasts (de Oliveira Werneck et al., 2022), in engineering operations in the district heating system (Sun et al., 2021), in economic studies of the relationship between the uncertainty of economic policy and the future price of oil (He et al., 2021), and in the stock market (Ren et al., 2020), among others.

In this study, the calculations of DCCAC were applied for different time lags as follows: 0, 15, 30, 45, 60 and 75 days (lag 0, lag 15, lag 30, lag 45, lag 60, and lag 75, respectively). This lag period is related to the mosquito development cycle, such as the development of breeding sites, the evolution of vectors, the transmission process, and the incubation period, as well as the diagnosis and notification of the disease (Duarte et al., 2019; Guzman and Harris, 2015).

3. Results and discussion

We calculated the DCCAC between the accumulated precipitation and time-lagged notifications of the first symptoms of dengue for the cities of Maracajú, Dourados, Sidrolândia, Aquidauana and Campo Grande, which belong to the climate classification *Am*. This parameter was also calculated for Amambai and Ponta Porã, which belong to the *Cfa* climate classification, and Bela Vista, which belongs to the climate classification *Af*. Lastly, this parameter was also calculated for the cities of Nova Andradina, Corumbá, Paranaíba and Três Lagoas, which are under the climate classification *Aw* according to the Map 1 (see Supplementary Material).

Based on the time-lagged DCCAC, we verified that there are significant values, up to a medium correlation range, between the accumulated precipitation and the notifications of the first symptoms of dengue, with particularities in each city. However, the highest DCCAC values occurred for a *n* of 1 year for all cities, indicating that the time series represented a long-range dependence.

In Dourados, the time-lagged DCCAC values became significant after the 100*th* day, and the highest correlation occurred within the *n* of 362 days. The highest coefficient occurred between lags of 45 and 75 days, reaching a maximum value of 0.640 for a lag of 75 days, which is considered moderately (Fig. 2).

The city of Nova Andradina presented the lowest DCCAC values in our research. Only the lags of 45, 60 and 75 days presented significant values. The highest value of the coefficient in Nova Andradina occurred at a lag of 75 days. The DCCAC value was 0.306, which is considered a weak cross-correlation (Fig. 3).

Unlike the other cities analyzed, the highest values in Três Lagoas for the time-lagged DCCAC occurred for a lag of 0, with a value of 0.429 occurring between *n* 200 and 400. This value represents a moderate cross-correlation (Fig. 4).

Table 2
Cross correlation coefficient ranges, based on:(Zebende et al., 2018).

Condition	ρDCCA
Weak	$\pm 0.000 \rightarrow \pm 0.333$
Medium	$\pm 0.333 \rightarrow \pm 0.666$
Strong	$\pm 0.666 \rightarrow \pm 0.999$

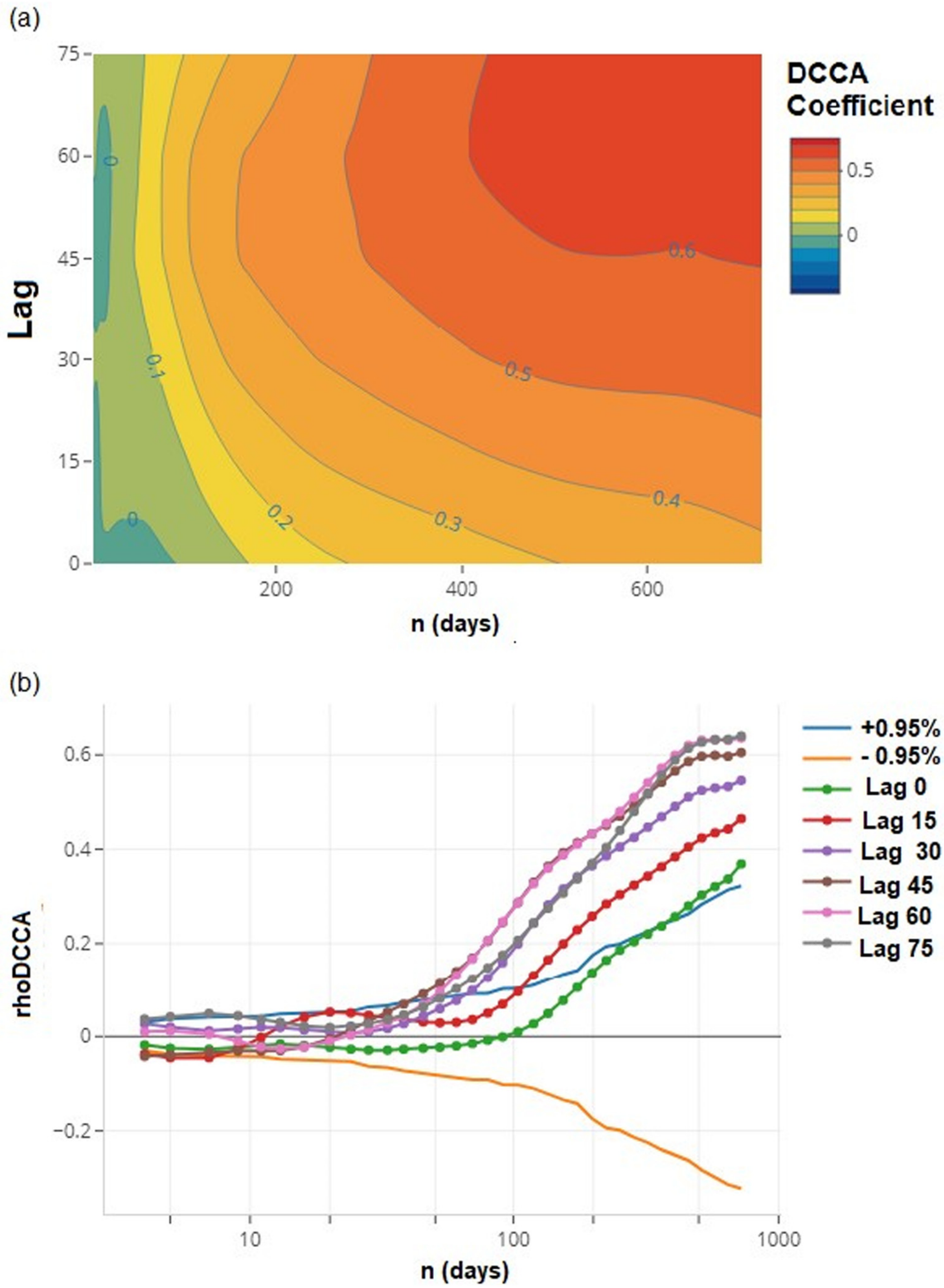

Fig. 2. Dourados - Correlation MID-HIGH: DCCAC visual results. (a) Contour graph, with a gradual color scale, where blue represents the lowest correlation and red represents the highest correlation. (b) Line graph with time-lagged DCCAC results for the city, with a 95 % confidence interval, where the x-axis represents the n (days) calculated according to the size of the time series.

Although the relationship between precipitation and the first symptoms of dengue differed in each city based on correlation values found with the calculated DCCAC and the rainfall cycles, we observed in Fig. 5 that the highest correlation values occurred from one year onward (*n* of 362 days). The beginning of plateau start in the box of 362 days. This box size may be also representative of typical annual precipitation. Based on these results, we selected the highest DCCAC values for any time lag where *n* is equal to 362 for each city. This coefficient was used to evaluate the relationship between dengue, rainfall and the socioeconomic indicators of sanitation.

Regarding precipitation, some studies have reported a time lag and the optimal time cycle for the correlation between rainfall and dengue disease. Hii et al. (2012) revealed a negative relationship between rainfall and dengue from weeks 0 to 22, and their study showed that a model with a weather time cycle of 20–24 weeks at a lag term of 16 weeks performed better than other lag setups. Jayaraj et al. (2019) also found a negative association between rainfall and dengue, with a lag of 5–6 months of dry weather observed prior to the spike of dengue cases. The same behavior was found in Sri Lanka (Ehelepola et al., 2015) and Indonesia (Gagnon et al., 2001).

However, rainfall positively correlated with dengue in Malaysia (Cheong et al., 2013) for lags of 4–8 weeks and South America (Colombia, French Guyana, Indonesia, and Suriname) (Gagnon et al., 2001) for lags of 1 month and 2–4 weeks. This time lag may be explained by the effects of weather conditions on the lifecycle of the *Aedes aegypti* mosquito as it matures from an egg into an adult, including prolonged egg hatching and the tendency of *Aedes aegypti* eggs to survive months without water (Hii et al., 2012; Sota and Mogi, 1992; Fouque et al., 2006).

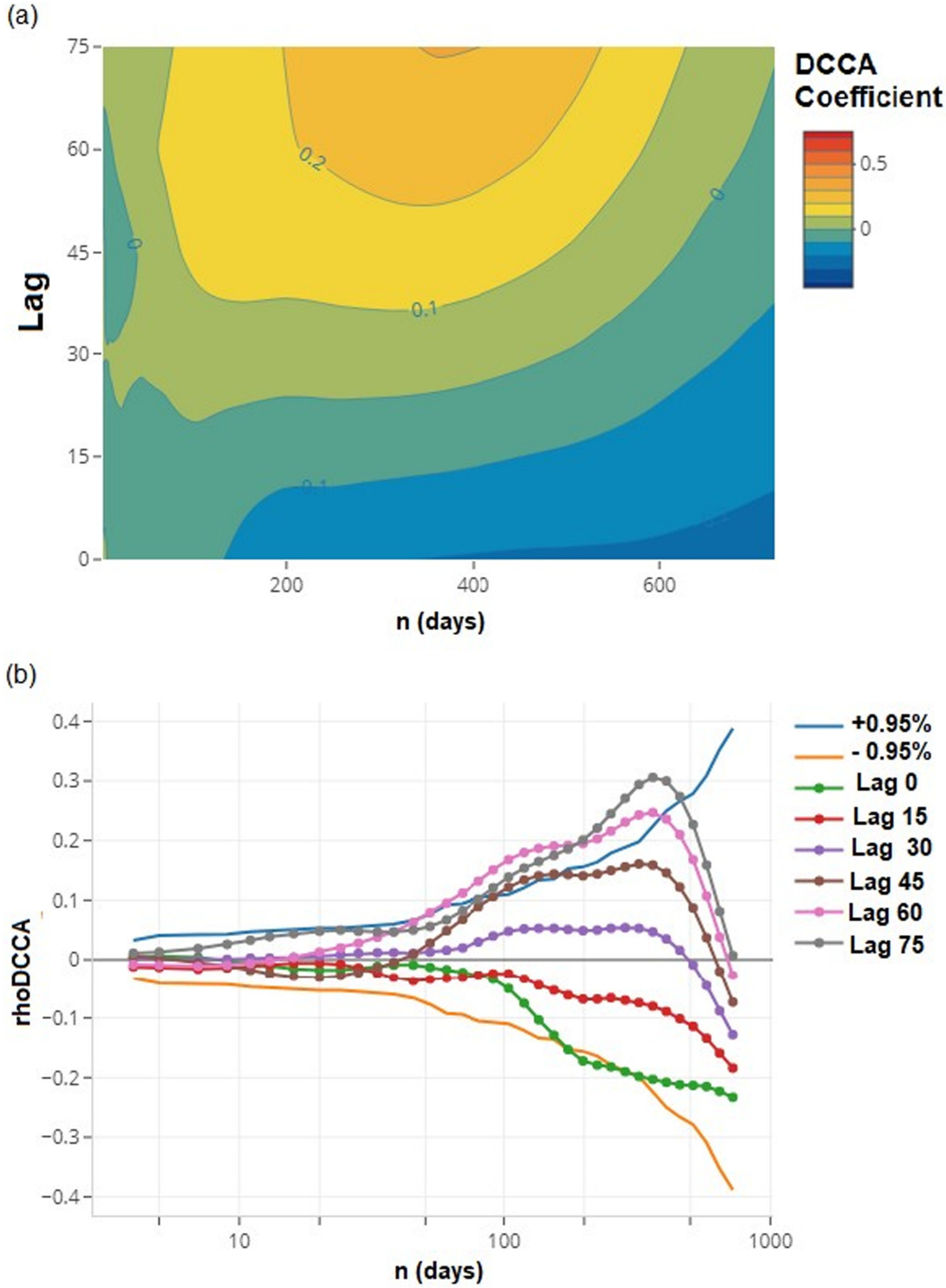

Fig. 3. Nova Andradina - Correlation LOW: DCCAC visual results. (a) Contour graph, with a gradual color scale, where blue represents the lowest correlation and red represents the highest correlation. (b) Line graph with time-lagged DCCAC results for the city, with a 95 % confidence interval, where the x-axis represents the n (days) calculated according to the size of the time series.

Our results show the absence of a unique time-lag range, confirming the analyzed studies. Therefore, models with the goal of forecasting dengue and models that consider rainfall may be adjusted to the climatic conditions of the region or city analyzed. A better understanding of this correlation between rainfall and dengue is relevant to improve future forecasts of dengue fever outbreaks.

We also built a hierarchical cluster diagram that considered the highest DCCAC value for the *n* of 362 days and the sanitary indicators of piped water and sewerage percentile available to the population (Fig. 6). We have conducted the evaluation of the distances between rows using Mahalanobis. Two large groups can be observed for a height ratio of 100 %, where C1 consists of only 3 cities of the climatic classification *Aw*. The C2 group consists of all other cities (climate classifications *Cfa, Am, Af* and the city of Paranaíba (*Aw*)).

Paranaíba differs from other *Aw* cities in terms of monthly rainfall, although it is part of the same climate classification. This difference is also highlighted by (Abreu et al., 2021); this study used adjusted polynomial models to estimate the average monthly precipitation and reported that the influence of meteorological systems that form over the Amazon region may affect the area of the city of Paranaíba.

The effect of the piped water percentile available to the population in each city on the cross-correlation between rainfall and the first symptoms of dengue is shown in Fig. 7. The factors exhibit a positive visual correlation: an increase in the available piped water increased the correlation

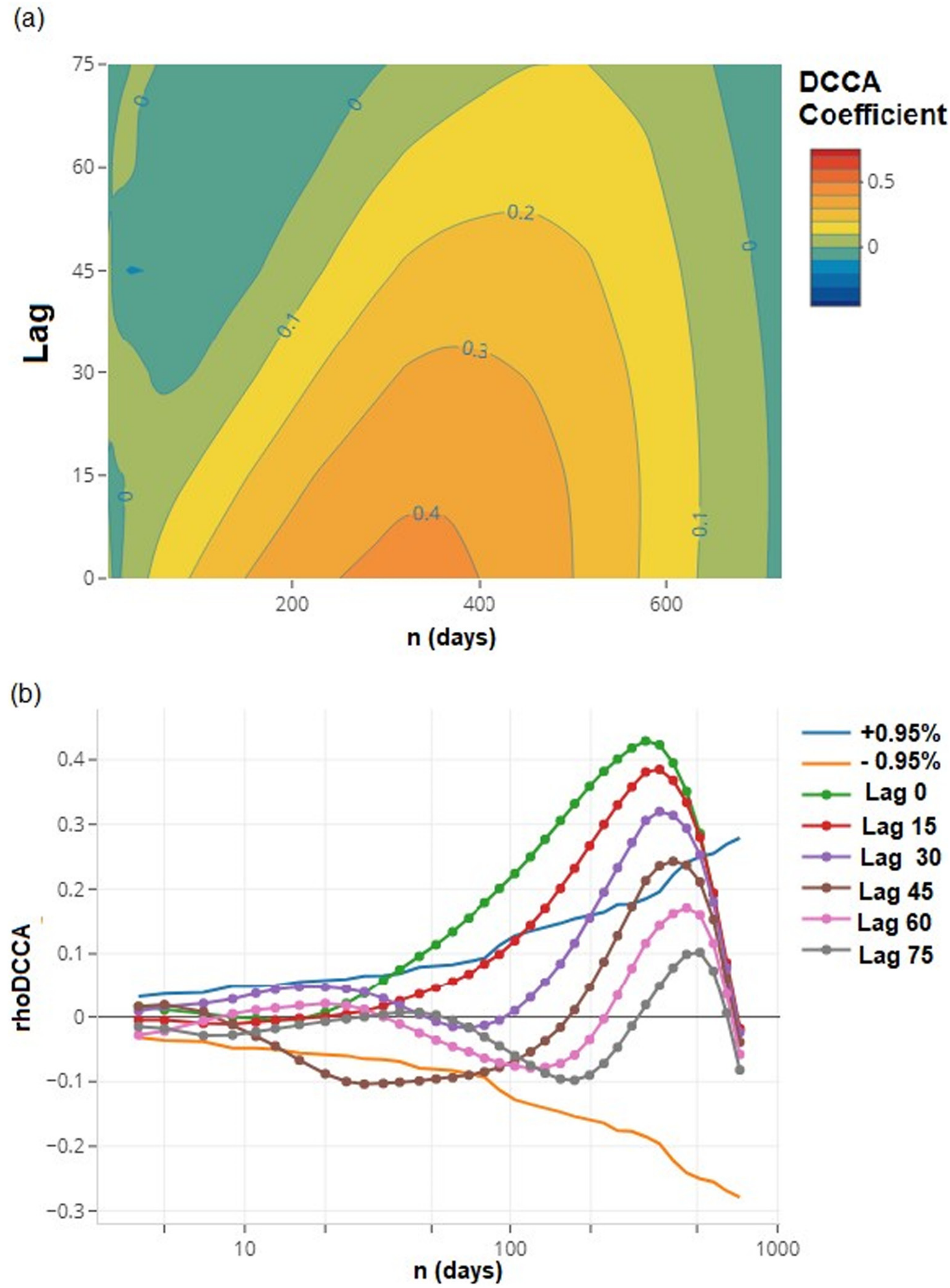

Fig. 4. Três Lagoas - Correlation MID: DCCAC visual results. (a) Contour graph, with a gradual color scale, where blue represents the lowest correlation and red represents the highest correlation. (b) Line graph with time-lagged DCCAC results for the city, with a 95 % confidence interval, where the x-axis represents the n (days) calculated according to the size of the time series.

index between rain and dengue. The Pearson correlation for the C2 cluster was 0.679, indicating statistical significance.

The effect of an adequate sewerage system is similar to that of piped water availability in the city. An increase in the availability of sewage systems for the population of the city also increases the cross-correlation index between rain and dengue (Fig. 8). The Pearson correlation between the sewerage and DCCAC results was 0.829 for the C2 cluster, and this correlation was also statistically significant. Research related to sewerage and dengue cases may explain these results. The quality of water reservoirs can influence the lifecycle of *A. aegypti*. The mosquito has a predilection for artificial reservoirs, preferring to reproduce in clean waters to avoid exposing the larvae to the action of predators (Varejão et al., 2005). For instance, the viability of *A. aegypti* larvae is only 10 % in raw sewage and more than 60 % in rainwater and dechlorinated water (Beserra et al., 2009).

4. Conclusions

The main contribution of this work is to extend the application of the co-movements obtained through the time-lagged DCCAC for the analysis of the effects of climatic variables on arboviruses. The use of a time lag analysis provided more information than DCCAC without lag to represent the behavior of dengue cases in relation to accumulated precipitation for different climatic classifications and geographic locations, for instance, the beginning and duration, in days, in which the highest correlation indices occur.

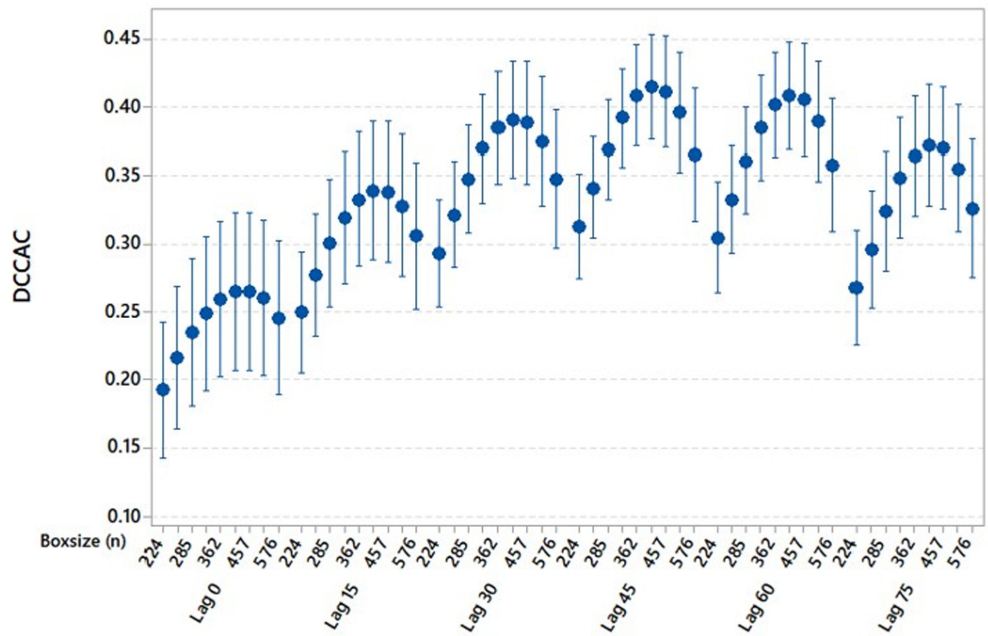

Fig. 5. Average DCCAC values for all *n* from 224 to 576. The DCCAC starts to decay after *n* of 407 days. The vertical line with horizontal lines represents one standard error from the mean.

The analysis primarily shows weak to medium DCCAC results for a time lag of 60 days with long-range memory. Long-range cross-correlations between two-time series suggest that each series independently has a long memory of its own previous points and a long memory of preceding points of the other time series (Podobnik and Stanley, 2008).

The results show significant differences in the cross-correlation between rainfall and dengue for cities in different Köppen-Geiger climate classifications. The cities of Três Lagoas, Corumbá and Nova Andradina, which are all in *Aw*, exhibited different behavior than all other cities in the state. These cities have high temperatures and seasonal characteristics, such as dry winters and summer rains. The other evaluated cities have distributed rainfall throughout the year.

Poverty, high urbanization, poor hygiene and poor sanitation are some of the known factors that contribute to the propagation of dengue (Salles et al., 2018; Pasteur, 2018; Mota et al., 2016). This study presents a new paradox in the relationship between adequate sanitation and rainfall-dengue DCCAC. Our results show a rise in the cross-correlation between rainfall and dengue as water sanitation improvement actions are implemented in the city, such as piped water and sewerage. Therefore, sewage drainage seems to be a favorable habitat for *A. aegypti*, as the continuous availability of water in sewage drains and septic tanks make permanent habitats for vector reproduction (Pasteur, 2018; Mota et al., 2016).

Because dengue is strongly influenced by precipitation, temperature and degree of urbanization, the presented result for water sanitation is limited for the studied region and should be interpreted cautiously. For instance, the average temperature is constant within the studied cities from November to April, the dengue fever season in the region. The average temperature is above 17 °C and below 30 °C, inside the temperature range

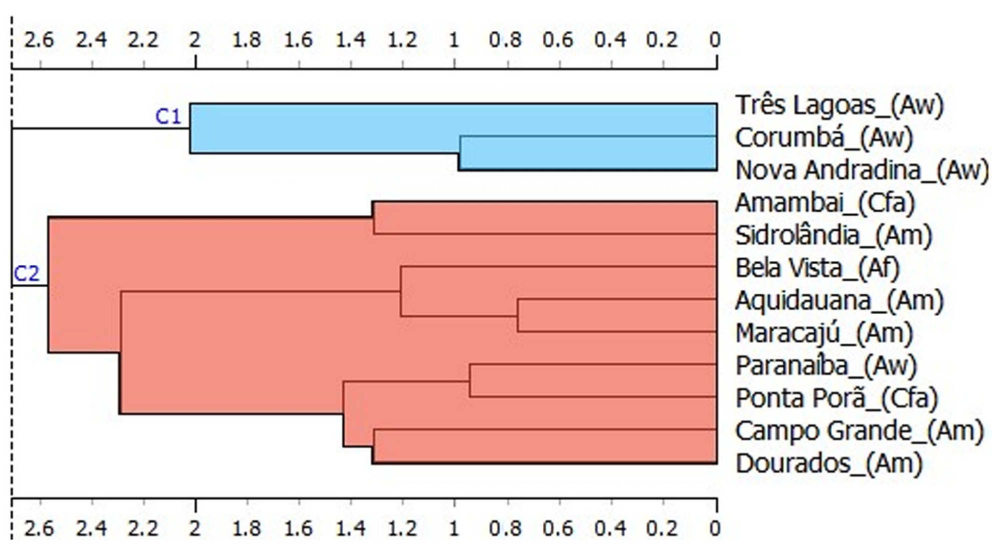

Fig. 6. Hierarchical clustering of all studied cities for DCCAC, piped water and sewerage percentile available to the population. The C1 cluster consists of Três Lagoas, Corumbá and Nova Andradina, whereas all other cities are part of the C2 cluster for a height ratio of 100 %. The X axis is the height that indicates the distance between the objects.

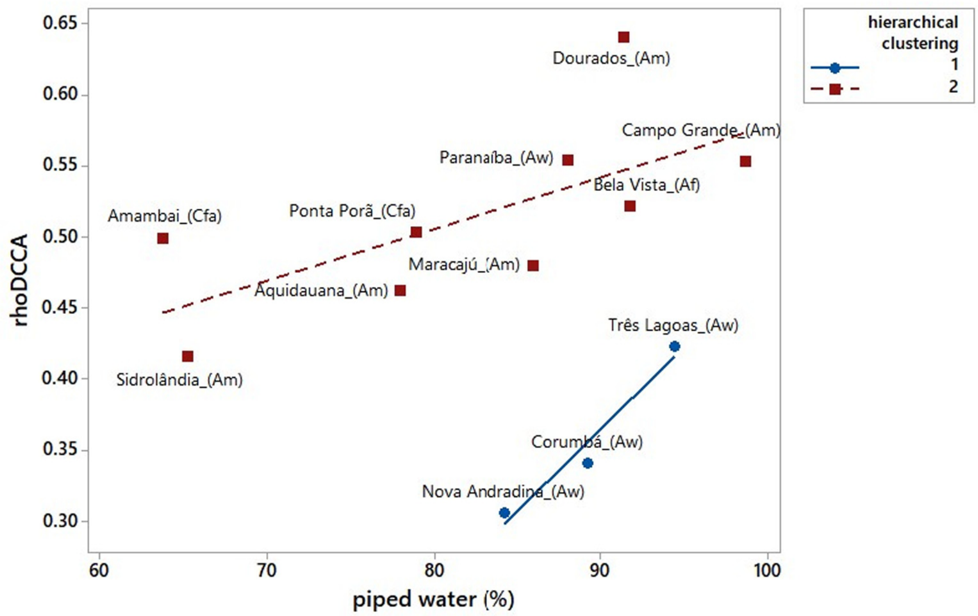

Fig. 7. The effect of piped water percentile on the cross-correlation between rainfall and the first symptoms of dengue.

for the *A. aegypti* viability (Reinhold et al., 2018). On the other hand, the monthly accumulated precipitation variation is significant in the same period. Future studies may evaluate other regions of Brazil in order to determine whether the rise in DCCAC between rainfall and dengue is similar to that found in MS after the implementation of water sanitation actions.

Different public policies for dengue prevention and vector control can be effectively targeted to each city according to the time period and the degree of correlation calculated. In addition to improving sanitation, working on the behavior of the population that will use this benefit and having competent authorities are important to structure vector control and prevention work in places where sanitation conditions are adequate.

With climate change and the increase in the global average temperature, mosquitoes are advancing beyond the tropics (WHO, 2021; Bhatt et al., 2013; Harapan et al., 2020). Thus, urbanized cities in other places, such as Europe and the United States, are presently at risk for dengue cases in the coming years. Specifically, our results show that cities with a high level of sanitation may have a high correlation between dengue and annual precipitation.

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CRediT authorship contribution statement

Jéssica B. Oliveira: Conceptualization, Data curation, Formal analysis, Investigation, Software, Validation, Visualization, Writing – original draft,

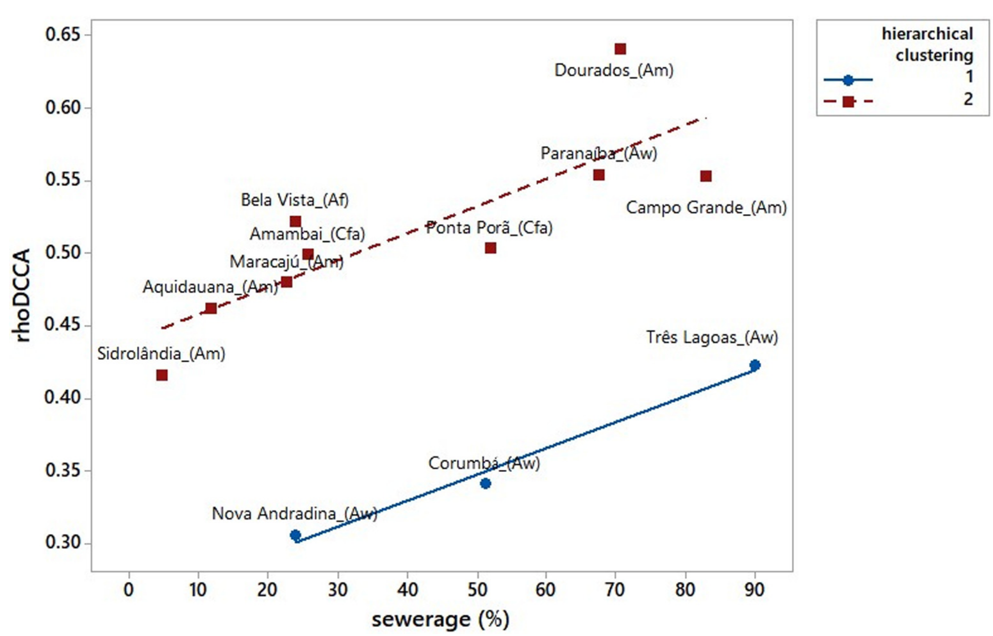

Fig. 8. The effect of sewerage percentile on the cross-correlation between rainfall and the first symptoms of dengue.

Writing – review & editing. **Thiago B. Murari:** Conceptualization, Formal analysis, Investigation, Methodology, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Aloisio S. Nascimento Filho:** Conceptualization, Writing – original draft, Writing – review & editing. **Hugo Saba:** Conceptualization, Writing – original draft, Writing – review & editing. **Marcelo A. Moret:** Conceptualization, Validation, Visualization, Writing – original draft, Writing – review & editing. **Claudia Andrea L. Cardoso:** Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Writing – original draft, Writing – review & editing.

Data availability

Data is available from the corresponding author on request.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2022.160491.

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