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Infectious diseases transmitted by animals: beyond symptoms, how socioeconomic and environmental conditions can influence them

> **Nina Ferreira Brandão** Federal University of Fronteira Sul

**Otavio Ananias Pereira da Silva Ribeiro** Federal University of Fronteira Sul

> **Betina Drehmer da Rosa** Federal University of Fronteira Sul

> **André Firmino Neves** Federal University of Fronteira Sul

**Pedro Lucas dos Santos Cardoso** Federal University of Fronteira Sul

> **Kassia Maria Cruz Souza** São Paulo State University

> **Renata Calciolari Rossi**

University of Oeste Paulista *Corresponding author*

**Débora Tavares de Resende e Silva** Federal University of Fronteira Sul [debora.silva@uffs.edu.br](mailto:debora.silva@uffs.edu.br)

**Abstract.** Vector-borne diseases, such as dengue, chikungunya, zika, and leishmaniasis, represent a global public health challenge. This study aimed to understand the impact of socioeconomic, environmental, and healthcare access variables on the incidence of infectious diseases from 2012 to 2021, investigating patterns and correlations. Variables analyzed included the number of healthcare facilities, average income, population size, Gross Domestic Product (GDP), and accumulated deforestation. Multiple linear regression and correlations were used, with data from the Notifiable Diseases Information System (SINAN) and the National Institute for Space Research (INPE). Dengue showed a strong correlation with GDP, the number of healthcare facilities, and deforestation. Chikungunya was associated with population, GDP, and deforestation. Zika showed correlations with population growth and deforestation. Leptospirosis was negatively influenced by healthcare facilities and GDP, while hantavirus infection was inversely related to population growth and healthcare facilities. Leishmaniasis had positive correlations with GDP, healthcare facilities, and deforestation. This study reveals complex interactions between socioeconomic, environmental, and health variables in the incidence of infectious diseases. Understanding these patterns is crucial for formulating effective public policies, highlighting the need for integrated and holistic strategies in the control and prevention of these diseases. **Keywords:** Environmental, Healthcare access, Public health, Socioeconomic factors, Vector-borne diseases

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#### **Introduction**

Vector-borne diseases and zoonoses pose significant global public health challenge (Skorokhod, Vostokova, & Gilardi, 2023; Eassa & Abd El-Wahab, 2022). The spread of these diseases is intrinsically linked to a complex network of socioeconomic, environmental, and health factors (Jones et al., 2023; Adepoju et al., 2023). To

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effectively address this issue, it is essential to adopt a multidisciplinary and integrated approach that takes all these variables into account.

These diseases are transmitted through different mechanisms involving vectors such as mosquitoes, sandflies, and rodents. For instance, dengue is primarily transmitted by the mosquito Aedes aegypti, which breeds in stagnant water containers in urban and peri-urban areas. Chikungunya is also transmitted by the same vector and has been a growing concern due to frequent outbreaks. The Zika virus, in addition to being transmitted by Aedes aegypti, can also be transmitted sexually and during pregnancy, and is associated with severe neurological complications such as Guillain-Barré syndrome and microcephaly in fetuses (Weeratunga et al., 2017; Natal, 2002). Leptospirosis is a zoonosis transmitted by the urine of infected animals, which contaminates aquatic environments and moist soils, with humans becoming infected through exposed skin or mucous membranes. Hantavirus infection is transmitted by wild rodents that shed the virus in their feces, urine, and saliva, which can be inhaled by humans in dust or airborne particles, especially in rural areas. American tegumentary leishmaniasis is caused by protozoa of the genus Leishmania, transmitted to humans by the bite of infected sandflies, commonly found in areas of dense vegetation.

Socioeconomic conditions play a crucial role in the dynamics of vector-borne diseases and zoonoses (Borges et al., 2022). Low-income populations often live in precarious conditions, with limited access to basic sanitation and adequate healthcare services (Addo et al., 2023). This makes them more vulnerable to these diseases. Moreover, socioeconomic inequality exacerbates these disparities, increasing the risks for the most marginalized communities (Iyengar, Azar, & Gallagher-Thompson, 2023; Manta et al., 2023). Therefore, public policies that ensure equity and help reduce socioeconomic inequalities can play a crucial role in reducing the incidence of these diseases.

Environmental variables also play a significant role in the spread of these diseases. Deforestation, for example, alters the natural habitats of vectors and zoonoses, pushing them into human-inhabited areas (Silva et al., 2022). Climate change, in turn, alters weather conditions and the geographical distribution of these animals, creating conducive areas for disease transmission (Ngcamu, 2023; Silva et al., 2022). Additionally, uncontrolled urbanization provides ideal environments for vector breeding in urban areas (Silva et al., 2022). Thus, sustainable urban planning and proper environmental management are essential to mitigate the transmission risks of these diseases.

Therefore, a comprehensive understanding of the interactions between socioeconomic, environmental, and health variables is fundamental

for developing effective prevention and control strategies. In this context, this study aimed to answer the following questions: a) are there patterns between socioeconomic and environmental variables and the incidence rates of vector-borne diseases during the study period? b) how do socioeconomic, environmental, and healthcare access variables impact the incidence of infectious diseases between 2012 and 2021? c) how can the findings be applied to develop effective intervention and control strategies for these diseases?

# **Material and Methods**

*Study Area, Study Population, Period and Data Sources*

This study was conducted using epidemiological data on infectious diseases and socioeconomic, environmental, and health variables from 2012 to 2021. The area of analysis covered the state of Santa Catarina, Brazil (Figure 1). The information on the incidence of infectious diseases, including dengue, chikungunya, zika, leptospirosis, hantavirus infection, and American tegumentary leishmaniasis, was obtained from the database of<br>the Notifiable Diseases Information System the Notifiable Diseases Information System (SINAN), a national disease notification system in Brazil. Data on confirmed cases per 100,000 inhabitants were extracted from the Ministry of Health's website

(https://datasus.saude.gov.br/acesso-a-

informacao/doencas-e-agravos-de-notificacao-de-

2007-em-diante-sinan/), based on reports provided by state health departments and compiled by the Brazilian Ministry of Health. It is important to note that the disease data were sourced from notifications made by state health departments to federal agencies, which may be subject to underreporting due to the lack of medical consultation by the population and the presence of asymptomatic cases.

Information on native vegetation loss in Santa Catarina was obtained from the National<br>Institute for Space Research (INPE) Institute for Space Research (INPE) (http://terrabrasilis.dpi.inpe.br/app/map/deforestation ). The system used was the Real-Time Deforestation Detection System (DETER), which employs images from the WFI/CBERS-4 and AWiFS/IRS sensors to cover the region and detect deforestation polygons with an area greater than 0.03 km<sup>2</sup>. The high frequency of images provided by DETER made it an effective tool for quickly informing enforcement agencies about new deforestation in the studied region. Socioeconomic data were obtained from the Brazilian Institute of Geography and Statistics (IBGE)

(https://ftp.ibge.gov.br/Indicadores\_Sociais/Sintese\_

de Indicadores Sociais/). All data used in this study were obtained from federal agencies and are supported by federal legislation on open data and access to information (Law Nº. 12,527/2011).

**Brandão et al.** Infectious diseases transmitted by animals: beyond symptoms, how socioeconomic and environmental conditions can influence them



**Figure 1.** Study Area Location: Santa Catarina, Brazil. The map was created using the geobr package in R software.

#### *Variables*

In this study, the analysis was conducted considering various crucial variables to understand the dynamics of infectious diseases in Santa Catarina. First, the average monthly number of basic health units (ABH) was considered, providing insights into the available public health infrastructure in the region. Additionally, the average habitual real income from all jobs for people aged 14 and over (R\$/month) (ARI) was explored as a direct reflection of the economic conditions of the inhabitants, allowing for an in-depth analysis of the correlations between health and financial situation. The population size (POP) variable was included to assess population density and possible relationships with the spread of the studied diseases.

The per capita Gross Domestic Product (GDP), an essential indicator of economic development, was analyzed to understand its role in the incidence rates of infectious diseases. Moreover, the Gini Index (GIN) was used as a critical measure of economic inequality in the region, revealing important socioeconomic patterns that may influence the spread of diseases. Finally, accumulated deforestation (DEF) in square kilometers was considered to understand environmental changes over time, exploring their possible connections with public health. These variables were fundamental for a comprehensive and contextualized analysis of infectious diseases, providing a holistic view of the socioeconomic and environmental factors shaping epidemiology in the Santa Catarina region of Brazil.

## *Data Processing andStatistical analysis*

Statistical analysis was conducted using R software version 4.3.1 (R Core Team, 2023). For each disease (dengue, chikungunya, zika,

leptospirosis, hantavirus infection, American tegumentary leishmaniasis), three statistical analyses were performed: correlation networks, correlation plots, and linear regression. A correlation network analysis was performed to explore the complex interactions between all variables, including diseases. This approach allowed for the identification of intricate patterns of correlations between different variables, providing a deeper understanding of the relationships within the dataset. The qgraph package was used for this analysis (Epskamp et al., 2012).

Additionally, specific Correlation Plots for each disease were created using the chart.correlation function from the PerformanceAnalytics package (Peterson & Carl, 2020). These plots help visualize the relationships between the selected variables and each disease in more detail, highlighting visual patterns that may not be obvious in numerical analyses. By graphically visualizing the correlations, specific associations that warranted further investigation could be highlighted. Statistical analyses were conducted considering a time interval from 2012 to 2021, which was fundamental for understanding the relationships between socioeconomic and environmental factors and the incidence of infectious diseases in Santa Catarina, Brazil. For the linear regression analysis, each disease was regressed against each of the variables selected in this study. This method allowed for the exploration of linear relationships between these socioeconomic and environmental variables and the incidence of diseases, providing insights into how specific factors might be correlated with disease incidence. The lm function from the stats package was used for this analysis (R Core Team, 2023).

### **Results and discussion**

The average incidence of dengue was 61.33 cases with a standard deviation (SD) of 89.33, ranging from 1.44 to 77.47 (Table 1). Chikungunya had an average of 3.72 cases  $(SD = 4.01)$ , while zika had an average of 1.56 cases  $(SD = 1.64)$ . American cutaneous leishmaniasis had an average of 0.31 cases  $(SD = 0.07)$ , and leptospirosis had an average of 4.62 cases  $(SD = 1.87)$ . Hantavirus infection had the lowest average, with 0.19 cases  $(SD = 0.09)$ . The average population density was 72.49 inhabitants per  $km^2$  (SD = 3.19), and the average per capita GDP was  $R$40,373.37$  (SD = 9,198.67). The average number of basic health units was  $14,661.20$  (SD = 2,323.20), while the average habitual real income from all jobs was R\$2,758.24  $(SD = 47.32)$ . The Gini index had an average of 0.43  $(SD = 0.01)$ , indicating income inequality, and the average accumulated deforestation was 76.86% (SD  $= 0.46$ ).

**Table 1.** Descriptive Statistics (N=10).

Variables	Mean	SD <sup>1</sup>	Min <sup>1</sup>	Max <sup>1</sup>
Dengue	61.33	89.33	1.44	77.47
Chikungunya	3.72	4.01	0.00	9.60
Zika	1.56	1.64	0.00	4.85
American cutaneous leishmaniasis	0.31	0.07	0.20	0.40
Leptospirosis	4.62	1.87	2.03	8.11
Hantavirus	0.19	0.09	0.03	0.33
Population density (population/km <sup>2</sup> )	72.49	3.19	66.68	76.66
Gross Domestic Product per capita (R\$)	40,373.37	9,198.67	27.771.85	60,275.48
Average number of basic health units	14.661.20	2,323.20	11.777.50	18,825.58
Average real income usually from all jobs (R\$/month)	2,758.24	47.32	2,677.69	2,828.95
<b>GINI</b> index	0.43	0.01	0.41	0.44
Accumulated deforestation (%)	76.86	0.46	76.17	77.47

<sup>1</sup> SD: standard deviation; Min: minimum; Max: maximum.

Considering only the significant correlations with confirmed disease cases in the state of Santa Catarina, we observed interesting patterns in socioeconomic relationships regarding disease incidence in the studied region (Figure 2). Firstly, there is a strong positive correlation between GDP and disease incidence, indicating that as GDP increases, there tends to be a higher incidence of diseases. Additionally, the correlation with population (POP) is positive and significant, suggesting that population growth tends to present more disease cases.

In the context of health services, the average number of basic health units (ABH) exhibits a strong positive correlation (Figure 2). Conversely, the real mean monthly income (RMT) shows a moderately negative correlation, suggesting that areas with higher average income may have fewer incidences of infectious diseases. Moreover, there is a moderately positive correlation between accumulated deforestation and disease incidence, indicating that greater accumulated deforestation might result in more disease cases. Finally, the Gini index shows a relatively weak positive correlation, indicating a positive, albeit not very strong, relationship between inequality and disease incidence. These correlations provide crucial insights into how socioeconomic factors are related to the spread of diseases in the region, highlighting areas of concern and potential research areas for public health interventions and policies.

The incidence of dengue cases shows a strong positive correlation with GDP (0.832), indicating that areas with higher economic development are more prone to higher disease incidence (Figure 3A). Additionally, there are significant positive correlations with ABH (0.823) and

the variable related to DEF (0.631), suggesting that areas with more public health facilities and regions with higher deforestation are more susceptible to dengue cases. These associations highlight the complexity of socioeconomic and environmental interactions in the spread of dengue.

For chikungunya, significant correlations were observed with several variables (Figure 3B). There was a strong positive association with the variable DDE (0.88), indicating that areas with population growth are more prone to this disease. Additionally, robust positive correlations were found with government investment in public health, represented by the ABH indicator (0.85), and with GDP (0.79), suggesting that regions with better economic conditions and investments in health have higher disease incidence, possibly reflecting urban expansion. The DEF variable, representing accumulated deforested areas over time, showed a strong positive correlation (0.90), indicating that regions with a history of deforestation are more susceptible to chikungunya cases.

Regarding Zika, the correlation analysis indicated significant correlations with only two variables, DDE and DEF (Figure 3C). Population growth showed a significant correlation with increased Zika cases (0.64). The DEF variable also showed significant correlations with the increase in this disease's cases in this study (0.63). For the incidence of American cutaneous leishmaniasis (ACL), a positive relationship with GDP (0.80) was observed (Figure 3D). Furthermore, there are relevant positive correlations with ABH (0.78) and the variable related to accumulated deforestation (0.78). These associations clearly demonstrate that environmental and socioeconomic interactions are complex in the spread of this disease.



**Figure 2.** The correlation network analysis for infectious diseases (DOE) in Santa Catarina includes the following variables: population density (POP), per capita Gross Domestic Product (GDP), average habitual real income from all jobs for people aged 14 and over (R\$/month) (RMT), average number of basic health units (QMA), accumulated deforestation (DES), and the Gini index (GIN). The network illustrates the strength and direction of correlations between these variables and the incidence of infectious diseases.

The Pearson correlation for leptospirosis revealed significant correlations with various variables (Figure 4A). A strong negative association with the average monthly number of basic health units (ABH) (-0.79) was observed, indicating that areas with more health facilities are less prone to leptospirosis cases. Additionally, inversely proportional correlations were found with GDP (- 0.76) and accumulated deforestation over time (DEF) (-0.73), suggesting that regions with better economic conditions and health investments have lower incidences of the disease.

The incidence of hantavirus presented an inversely proportional relationship with population increase (DDE) (-0.61) and the increase in the average monthly number of basic health units (ABH) (-0.57), meaning that with an increase in population size and health facilities, there was a decrease in hantavirus cases. The strongest relationship was found between accumulated deforestation (DEF) and hantavirus, evidenced by a negative correlation (-0.67), similar to other findings for this disease. Therefore, this relationship indicates that with the increase in accumulated deforestation, the number of hantavirus cases decreased.

There is a significant relationship between population density (inhabitants/km²) and dengue cases, with a moderate fit  $(R^2 = 0.56)$  (Figure 5A). The relationship is quadratic, suggesting that both low and high values of population density may be associated with different levels of dengue incidence. There is a significant and strong relationship ( $R^2$  = 0.85) between GDP per capita and dengue cases (Figure 5B). The quadratic relationship indicates that variations in GDP per capita have a considerable impact on the incidence of dengue. There is a significant and very strong relationship ( $R^2 = 0.89$ ) between the average number of Basic Health Units (UBS) and dengue cases (Figure 5C).

There is no significant relationship between average real income and dengue cases, given the high P-value and the low adjusted  $R^2$  (0.19) (Figure 5D). There is also no significant relationship between the GINI index (measure of inequality) and dengue cases, as indicated by the high P-value and the very low adjusted  $R<sup>2</sup>$  (0.04) (Figure 5E). There is a significant and strong relationship  $(R^2 = 0.71)$ between accumulated deforestation and dengue cases (Figure 5F). The quadratic relationship shows that deforestation has a considerable impact on dengue incidence.



**Figure 3.** Pearson Correlation for Dengue cases (A), Chikungunya cases (B), Zika cases (C), and American Cutaneous Leishmaniasis cases (D) with Variables: Population Density (DDE), Gross Domestic Product per Capita (GDP), Average Real Monthly Income from All Jobs for People Aged 14 and Over (R\$/month) (ARI), Average Monthly Number of Basic Health Units (ABH), Accumulated Deforestation (DEF), and Gini Index (GINI) (2012-2021). Significance levels: \*, \*\*, and \*\*\* represent significance at 0.05, 0.01, and 0.001, respectively.



**Figure 4.** Pearson correlation for leptospirosis cases (A) and hantavirus cases (B) with the variables: population density (DDE), Gross Domestic Product per capita (GDP), average real income of all workers aged 14 years or older (R\$/month) (ARI), average monthly number of basic health units (ABH), accumulated deforestation (DEF), and GINI index (GIN), (2012-2021).

\*, \*\*, and \*\*\* represent significance at 0.05, 0.01, and 0.001, respectively.



**Figure 5.** Linear regression for the incidence of dengue cases per 100,000 inhabitants, with the variables: population density (DDE), Gross Domestic Product per capita (GDP), average real habitual income from all jobs for people aged 14 and over (R\$/month) (ARI), average monthly number of Basic Health Units (ABH), accumulated deforestation (DEF), and GINI index (GIN), (2012-2021).

There is a significant and strong relationship between population density (inhabitants/km²) and chikungunya cases, with a high fit  $(R^2 = 0.81)$ (Figure 6A). The quadratic relationship suggests that variations in population density significantly variations in population density significantly influence chikungunya incidence. There is a significant relationship between GDP per capita and chikungunya cases, with a moderate fit  $(R^2 = 0.63)$ (Figure 6B). The quadratic relationship indicates that variations in GDP per capita affect chikungunya incidence. There is a significant and strong relationship  $(R^2 = 0.78)$  between the average number of Basic Health Units (UBS) and chikungunya cases (Figure 6C). The quadratic

relationship suggests that the presence of UBS impacts chikungunya incidence in a complex manner. There is no significant relationship between average real income and chikungunya cases, given the high P-value and the low adjusted  $R<sup>2</sup>$  (0.12) (Figure 6D). There is also no significant relationship between the GINI index (measure of inequality) and chikungunya cases, as indicated by the high P-value and the low adjusted  $R<sup>2</sup>$  (0.12) (Figure 6E). There is a significant and strong relationship  $(R^2 = 0.80)$ between accumulated deforestation and chikungunya cases (Figure 6F). The quadratic relationship shows that deforestation has a considerable impact on chikungunya incidence.



**Figure 6.** Linear regression for the incidence of chikungunya cases per 100,000 inhabitants, with the variables: population density (DDE), Gross Domestic Product per capita (GDP), average real habitual income from all jobs for people aged 14 and over (R\$/month) (ARI), average monthly number of Basic Health Units (ABH), accumulated deforestation (DEF), and GINI index (GIN), (2012-2021).

A significant and strong relationship is observed between population density (inhabitants/km<sup>2</sup>) and zika cases, with a high fit ( $R^2$  = 0.83) (Figure 7A). The quadratic relationship suggests that variations in population density significantly influence the incidence of zika. There is a significant relationship between GDP per capita and zika cases, with a moderate fit  $(R^2 = 0.61)$ 

(Figure 7B). The quadratic relationship indicates that variations in GDP per capita affect the incidence of zika. A significant and strong relationship ( $R^2 = 0.77$ ) is observed between the average number of Basic Health Units (BHU) and zika cases (Figure 7C). No significant relationship is found between average real income and zika cases, as indicated by the high P-value and low adjusted R² (0.06) (Figure 7D).

Similarly, there is no significant relationship between the Gini index (a measure of inequality) and zika cases, as indicated by the high P-value and the adjusted R² (0.00) (Figure 7E). A significant and strong relationship ( $R^2 = 0.82$ ) is found between accumulated deforestation and zika cases (Figure 7F). The linear relationship shows that deforestation has a considerable impact on the incidence of zika.

There is a positive and significant relationship between population density and American cutaneous leishmaniasis cases (Figure 8A). Approximately 47% of the variation in leishmaniasis cases can be explained by population density. Similarly, there is a positive and significant relationship between GDP per capita and American cutaneous leishmaniasis cases, with 47% of the variation explained by GDP per capita. A strong and significant positive relationship is observed between the average number of BHUs and American cutaneous leishmaniasis cases (Figure 8C), with 91% of the variation in cases explained by the number of BHUs. Conversely, there is no significant relationship between average real income and American cutaneous leishmaniasis cases (Figure 8D), nor is there a significant relationship between the Gini index and American cutaneous leishmaniasis cases (Figure 8E). However, there is a positive and significant relationship between accumulated deforestation and American cutaneous leishmaniasis cases (Figure 8F), with 83% of the variation in cases explained by accumulated deforestation.

A significant and strong relationship is observed between population density (inhabitants/km²) and leptospirosis cases, with a high fit  $(R^2 = 0.54)$  (Figure 9A). The linear relationship suggests that variations in population density significantly influence the incidence of leptospirosis. Additionally, a significant relationship is found between GDP per capita and leptospirosis cases, with a moderate fit  $(R^2 = 0.58)$  (Figure 9B). The linear relationship indicates that variations in GDP per capita affect the incidence of leptospirosis. A significant and strong relationship ( $R^2 = 0.66$ ) is also identified between the average number of BHUs and leptospirosis cases (Figure 9C).

Conversely, no significant relationship was observed between average real income and leptospirosis cases, as demonstrated by the high pvalue and low adjusted  $R^2$  (0.02) (Figure 9D). Similarly, no significant relationship was found between the Gini index, which measures inequality, and leptospirosis cases, as indicated by the high pvalue and the adjusted R² (0.00) (Figure 9E). Finally, a significant and strong relationship ( $R^2 = 0.64$ ) was found between accumulated deforestation and leptospirosis cases (Figure 9F). The quadratic relationship suggests that deforestation has a considerable impact on the incidence of leptospirosis.

A significant and strong relationship was observed between population density (inhabitants/km²) and hantavirus cases, with a high

fit ( $R^2$  = 0.44) (Figure 10A). The linear relationship suggests that variations in population density significantly influence the incidence of hantavirus. A significant relationship was identified between GDP per capita and hantavirus cases, with a moderate fit  $(R<sup>2</sup> = 0.33)$  (Figure 10B). The linear relationship indicates that variations in GDP per capita affect the incidence of hantavirus. A significant and strong relationship  $(R^2 = 0.43)$  was found between the average number of basic health units (UBS) and hantavirus cases (Figure 10C).

The analysis of average real income did not show a significant relationship with hantavirus cases, as evidenced by the high P-value and low adjusted R² (0.05) (Figure 10D). Similarly, the GINI index, which measures inequality, did not show a significant relationship with hantavirus cases, as indicated by the high P-value and adjusted  $R<sup>2</sup>$  (0.00) (Figure 10E). Finally, a significant and strong relationship  $(R^2 = 0.46)$  was found between accumulated deforestation and hantavirus cases (Figure 10F). The linear relationship suggests that deforestation has a considerable impact on the incidence of hantavirus.

This study revealed that vector-borne diseases (transmitted by insects) and zoonotic diseases (transmitted by rodents, etc.) exhibited different relationships with the independent variables analyzed. This differentiation is significant compared to other published works to date, as it offers a unique analysis of how these two types of diseases are influenced by environmental and socioeconomic factors. The integrated and comparative approach of this study allows for a more comprehensive understanding of the dynamics involved in the spread of these diseases.

Between 2012 and 2021, it was possible to observe the impacts of socioeconomic, environmental, and health service access variables on the incidence of infectious diseases. For<br>example, population growth and increased example, population growth and increased deforestation were associated with a significant increase in the occurrence of these diseases (Figure 2). These results suggest that population growth and environmental changes, such as deforestation, can create favorable conditions for the spread of these diseases in a general context (Silva et al., 2022; Borges et al., 2022; Hong et al., 2020). Additionally, the increase in the availability of health services, indicated by the number of health facilities, correlated with higher rates of these diseases, possibly due to better detection and reporting of cases (Manica et al., 2023). These specific correlation patterns can provide valuable insights for formulating targeted and effective intervention strategies in combating these diseases, as they alter the relationship of the resident population with health services and social determinants of health (Dimenstein, 2020).



**Figure 7.** Linear regression for the incidence of Zika cases per 100,000 inhabitants, with the variables: population density (DDE), Gross Domestic Product per capita (GDP), average real habitual income from all jobs for people aged 14 and over (R\$/month) (ARI), average monthly number of Basic Health Units (ABH), accumulated deforestation (DEF), and GINI index (GIN), (2012-2021).



**Figure 8.** Linear regression for the incidence of leishmaniasis cases per 100,000 inhabitants, with the variables: population density (DDE), Gross Domestic Product per capita (GDP), average real habitual income from all jobs for people aged 14 and over (R\$/month) (ARI), average monthly number of Basic Health Units (ABH), accumulated deforestation (DEF), and GINI index (GINI), (2012-2021).



**Figure 9.** Linear regression for the incidence of leptospirosis cases per 100,000 inhabitants, with the variables: population density (DDE), Gross Domestic Product per capita (GDP), average real habitual income from all jobs for people aged 14 and over (R\$/month) (ARI), average monthly number of Basic Health Units (ABH), accumulated deforestation (DEF), and GINI index (GIN), (2012-2021).



**Figure 10.** Linear regression for the incidence of hantavirus cases per 100,000 inhabitants, with the variables: population density (DDE), Gross Domestic Product per capita (GDP), average real habitual income from all jobs for people aged 14 and over (R\$/month) (ARI), average monthly number of Basic Health Units (ABH), accumulated deforestation (DEF), and GINI index (GIN), (2012-2021).

This study identified two distinct patterns. The first is that there is a direct proportional relationship between socioeconomic and environmental variables with the increase in diseases, specifically dengue, chikungunya, Zika, and American cutaneous leishmaniasis. The main association of these diseases was with accumulated deforestation, as it has a strong and direct correlation with population growth (0.99), GDP

(0.91), and the average number of public health units (0.94). However, it is worth noting that the average monthly number of basic health units was influenced by population growth (0.94) and GDP per capita increase (0.98) (Figures 3A, 3B, 3C, and 3D). Various studies indicate that natural environment modification and rapid urbanization processes favor the spread of these diseases (Silva et al., 2022;

Guégan et al., 2020; Castro et al., 2019; Burkett-Cadena; Vittor, 2018).

The second pattern found exhibited an inversely proportional relationship between socioeconomic and environmental variables with the increase in leptospirosis and hantavirus cases. Here, accumulated deforestation, population growth, and the number of public health units hold the same relevance (Figures 4A and 4B). As mentioned earlier, deforestation and population are directly related, promoting an increase in public health units. Both diseases have rodents as a common vector, so the presence of more health units can improve the living conditions of people residing in these regions (McMichael, 2000). Therefore, it is evident that not only socioeconomic, environmental, and health service access factors impact the incidence of these diseases but also the type of vector somehow influences the relationship of their occurrence with the analyzed variables.

When estimating the cases of these diseases through multiple linear regression, it is observed that each disease exhibited distinct behavior. For dengue, the model revealed that the average monthly number of basic health units (ABH), the average real income of individuals aged 14 and over (ARI), and accumulated deforestation (DEF) play fundamental roles in determining infection rates (Table 1). Interestingly, population size (POP) was not statistically significant, indicating that other socioeconomic and environmental factors exert a more direct influence on dengue propagation. In the context of chikungunya, the significant impact of the average real income of individuals aged 14 and over (ARI), the GINI index, and accumulated deforestation on the incidence of the disease stands out (Table 1).

The differentiation of models for each disease, considering specific variables, is relevant because it reflects the complexity of interactions between socioeconomic, environmental, and health factors that influence the spread of infectious vectorborne diseases. Each disease may have different vectors, transmission patterns, and epidemiological characteristics, which implies the need for specific models to fully understand the determinants of their incidence. Detailed analysis of specific variables for each disease allows for a more accurate understanding of the factors contributing to their spread, enabling more targeted and effective interventions.

This more specific approach is also relevant because previous studies have shown that different vector-borne diseases respond differently to socioeconomic and environmental variables. By considering these nuances, the models can better capture the dynamics of each disease and provide more precise insights for intervention planning. Furthermore, differentiating models can also help identify specific factors that can be targets for priority interventions for each disease. For example, if the average real income of individuals aged 14 and over (ARI) proved to be a significant determinant for

chikungunya, public policies aimed at improving economic conditions in this demographic group may have a positive impact on reducing the incidence of the disease. By understanding the most relevant variables for each disease, resources can be allocated more effectively, maximizing the impact of public health interventions.

In this study, it was found that population growth is associated with an increase in GDP and accumulated deforestation. This is partly because, for population growth to occur, more areas need to be available for habitation, which can drive increased accumulated deforestation (Dos Santos et al., 2020). Another relevant point is that GDP grows when the economically active population also grows, as there are more workers contributing to economic growth (Kremer; Deina; Siqueira; 2019). It is also related to the increase in public health facilities, as WHO reports indicate that with population growth, the number of health facilities needs to increase (WHO, 2023), leading to a reduction in underreporting of these cases, providing greater visibility to occurrences. More health units provide better control of diseases present in society (Massetti et al., 2022).

These results have significant implications for the population and the formulation of public health policies. Firstly, they highlight the need for an integrated approach in resource management and health service allocation (Fattahi et al., 2023; Eriskin; Karatas; Zheng, 2022), especially in areas with high incidence of vector-borne diseases. The availability of public health facilities and the quality of services offered can play a crucial role in the effective prevention and treatment of diseases (WHO, 2023; Massetti et al., 2022). Additionally, understanding these correlations can guide intervention strategies, directing resources to more vulnerable areas and implementing specific preventive measures, such as vector control programs and awareness campaigns (Chastonay; Chastonay, 2022; Dalpadado et al., 2022).

From a public health policy perspective, these results underscore the importance of considering not only medical aspects but also socioeconomic and environmental factors when formulating disease prevention and control strategies (Gainor; Harris; Labeaud, 2022; Yin et al., 2022). Policies aimed at socioeconomic development, health education, and environmental preservation (Silva et al., 2022; Reich et al., 2020) can play a vital role in reducing the incidence of these diseases, promoting the well-being of the population and contributing to the construction of healthier and more resilient communities.

Analyzing the significant correlations with confirmed disease cases reveals complex and interconnected patterns that provide deep insights into socioeconomic and health dynamics. The notable positive relationship between GDP per capita and disease incidence highlights a concerning trend: regions with higher economic development often face a greater burden of infectious diseases

(Silva et al., 2022). This phenomenon can be attributed to various factors, such as population growth, social mobility, and differential access to healthcare, emphasizing the urgent need for public health strategies sensitive to socioeconomic disparities (Figueiredo, 2020; WHO, 2023).

Conversely, the moderate negative correlation with the average real income of individuals aged 14 and over (ARI) suggests that areas with better socioeconomic conditions may be associated with lower disease incidence, underscoring the direct influence of living conditions on community health (Dimenstein; Neto; 2020). These findings highlight the urgent need for integrated and holistic approaches in public health<br>policy formulation that not only address policy formulation that not only demographic factors but also deeply consider socioeconomic and environmental aspects to<br>
implement effective control and prevention implement effective control

strategies for infectious diseases.<br>Various public polici Various public policies have been implemented to control vector-borne and zoonotic diseases with varying degrees of success. A successful example is Brazil's Aedes aegypti control program, which uses a combination of chemical, biological, and educational measures to reduce the incidence of dengue, Zika, and chikungunya. Studies show that integrating different strategies can significantly increase the effectiveness of disease control (Zara et al., 2016).

It is worth noting that this study shed light on the relationship between the studied variables and tropical diseases. However, its main limitation was the use of data from only one Brazilian region. Thus, it is suggested that future studies extrapolate the

# **Conclusion**

The results of this study highlight the influence of socioeconomic and environmental variables on the incidence of infectious diseases transmitted by vectors and zoonoses, allowing their categorization into two distinct groups. The first group reveals a directly proportional relationship between socioeconomic and environmental variables and the increase in the incidence of diseases such as dengue, chikungunya, Zika, and American cutaneous leishmaniasis. These findings indicate that accumulated deforestation, population growth, and the availability of public health units are crucial factors contributing to the spread of these diseases.

The second group shows an inversely proportional relationship between socioeconomic and environmental variables and the increase in cases of leptospirosis and hantavirus. This finding is particularly relevant as it suggests that the presence of more health units can promote improvements in living conditions and consequently reduce the incidence of these diseases.

Furthermore, the multiple linear regression analysis demonstrated that each disease presents distinct behaviors concerning the studied variables. For dengue, the average monthly number of basic

data to other regions of Brazil or other countries also affected by such diseases. The study relies on data from the Notifiable Diseases Information System (SINAN) and the National Institute for Space Research (INPE). However, these data sources have limitations that should be considered. Underreporting of cases in SINAN can lead to underestimation of the actual incidence of diseases, while inconsistencies in the data can affect the accuracy of the analyses. Additionally, variation in the quality of data reported by different states may introduce biases in the results (Sallas et al., 2022).

Additional research questions could explore the effectiveness of different combinations of control strategies for vector-borne and zoonotic diseases. Methods integrating more robust data and varied sources, such as remote sensing and real-time public health data, can provide a deeper understanding of the relationships identified in this study. Furthermore, investigations including costeffectiveness analyses of different control strategies can offer valuable insights for formulating more effective public policies. This study emphasizes the need for integrated and evidence-based strategies for controlling and preventing vector-borne and zoonotic diseases. It is recommended to implement policies that combine chemical, biological, and educational interventions, aligned with the socioeconomic and cultural realities of affected communities. The adoption of community education programs and active participation in vector surveillance and control can increase the sustainability and effectiveness of implemented measures (Claro; Tomassini; Rosa et al., 2004).

health units, the habitual real average income of people aged 14 years or older, and accumulated deforestation play fundamental roles in determining infection rates. In the case of chikungunya, the significant impact of the habitual real average income of people aged 14 years or older, the GINI index, and accumulated deforestation were determinants for the disease incidence. These differentiations reflect the complexity of the interactions between socioeconomic, environmental, and health factors that influence the spread of infectious diseases transmitted by vectors.

The results of this study have significant implications for the formulation of public health policies. Firstly, they highlight the need for an integrated approach to resource management and health service allocation, especially in areas with high incidences of vector-borne diseases. The availability of public health facilities and the quality of services offered play a crucial role in the prevention and effective treatment of these diseases. Additionally, understanding the correlations between socioeconomic and environmental variables can guide intervention strategies, directing resources to more vulnerable areas and implementing specific preventive measures, such as vector control programs and awareness campaigns.

From a public policy perspective, it is essential to consider not only medical aspects but also socioeconomic and environmental factors when<br>formulating disease prevention and control formulating disease prevention and control strategies. Policies aimed at socioeconomic development, health education, and environmental preservation can play a vital role in reducing the incidence of these diseases, promoting the wellbeing of the population, and contributing to the construction of healthier and more resilient communities.

This study also points to the need for future research to explore the effectiveness of different combinations of control strategies for vector-borne and zoonotic diseases. Methods that integrate more robust data and varied sources, such as remote sensing and real-time public health data, can offer a deeper understanding of the relationships identified in this study. Additionally, investigations that include cost-effectiveness analyses of different control strategies can provide valuable insights for the formulation of more effective public policies.

This study emphasizes the importance of integrated and evidence-based strategies for the control and prevention of vector-borne and zoonotic diseases. It is recommended to implement policies that combine chemical, biological, and educational interventions, aligned with the socioeconomic and cultural realities of the affected communities. The adoption of community education programs and active participation in vector surveillance and control can increase the sustainability and effectiveness of the measures implemented, contributing to the effective combat of these pathologies and the promotion of public health.

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