v. 3, n. 33, 2023

Journal of
Engineering
Research

ANALYSIS OF SOCIO-ENVIRONMENTAL VULNERABILITY IN THE MUNICIPALITIES OF THE STATE OF PARÁ AS A SUBSIDY FOR THE PREVENTION AND CONTROL OF DENGUE

Luiza de Nazaré Almeida Lopes
http://lattes.cnpq.br/3332622265434535

Luiza Carla Girard Mendes Teixeira
http://lattes.cnpq.br/9773700229115395

 DOI 10.22533/at.ed.3173332325094

Abstract: The research proposes the construction of the Dengue Socio-Environmental Vulnerability Index (IVD) in the municipalities of the state of Pará, from 2007 to 2017. The study considered the selection of 34 indicators of the three fundamental components of socio-environmental vulnerability: exposure, sensitivity and capacity adaptive. The methodology for the IVD was composed of the steps:(i) selection of indicators;(ii) definition of indicators;(iii) statistical treatments;(iv) calculation of the index by multivariate analysis;(v) normalization; and (vi) classification of the index using the percentile technique. The results showed that 43 municipalities (30%) were classified as "Low vulnerability", with values ranging from 0.483 to 0.262. Around 57 municipalities (40%) presented values with "Medium vulnerability" in the range of 0.581 to 0.483. With reference to "High vulnerability", 43 municipalities (30%) stood out, distributed in the range of 0.771 to 0.582. The results obtained from the profile that characterized the IVD showed a predominance of "Medium to Low vulnerability". The city of Belém, capital of Pará and located in the Guajará region, presented the lowest value for the IVD (0.262). On the other hand, most municipalities in the Marajó region presented the highest IVD values, namely: Cachoeira do Arari, Chaves, Ponta de Pedras, Melgaço, Santa Cruz do Arari and Anajás. The factor that most influenced the result of the index was the "socioeconomic" of the populations, especially the indicators of poverty, income, urbanization, illiteracy and solid waste management. It can be seen that the index is an important tool to assist in dengue prevention and control strategies in municipalities.
Keywords: Socio-environmental vulnerability, dengue, Multivariate analysis, index

INTRODUCTION

The *Aedes aegypti* mosquito is the main vector responsible for the spread of viral diseases around the world, such as dengue fever (DENV), which has become one of the main public health problems in Brazilian cities. Climate change and the uncontrolled urbanization process constitute an important factor in the permanence of the Aedes aegypti mosquito in cities, with its population being influenced by environmental and human aspects (WHO, 2012; PAHO, 2017; GUO et al., 2017).

The incidence of dengue is commonly observed in tropical and subtropical regions, where the dengue virus has the potential to be transmitted, mainly between the parallels (latitudes) 35° North and 35° South, (MORIN et al. 2013; MURRAY et al., 2013). The relationship between global warming and Neglected Tropical Diseases (NTDs), as well as the increase in temperature in areas affected by tropical diseases, such as malaria and dengue, is expected to expand mainly in urban and semi-urban areas (NAISH, S et al., 2014; EBI; NEALON, 2016; MORAES et al., 2019).

This study analyzes socio-environmental vulnerability, through synthetic indices that present the diversity in the municipalities of the state of Pará, based on the correlation of several variables to compose the fundamental components of vulnerability, considering that exposure and sensitivity can increase the vulnerability of municipalities analyzed, while adaptive capacity can reduce it (SANTOS et al. 2017; QUINTÃO, 2017 and MENEZES; 2018). Thus, the present study aims to develop and apply a Dengue Socio-Environmental Vulnerability Index (IVD), which will help to combat the disease in the 143 municipalities of Pará, based on data available from 2007 to 2017, in order to measure the reality of the population and provide decision makers with indispensable information aimed at developing health surveillance strategies for the prevention and control of dengue.

METHODOLOGY

The state of Pará, belonging to the North region, is considered the second largest state in the country in terms of territorial extension, covering an area equivalent to 15% of the national territory (IPEA, 2015; IBGE, 2017). The state's municipalities are part of the twelve Integration Regions considered planning units recognized by Decree No. 1,066, June 19, 2008, as shown in Figure 01, they represent the main rivers in their territories, physical aspects and socioeconomic dynamics being defined by: Araguaia (15 municipalities), Baixo Amazonas (13 municipalities), Tocantins (11 municipalities), Carajás (12 municipalities), Guamá (18 municipalities), Lago de Tucuruí (7 municipalities), Marajó (15 municipalities), Guajará (5 municipalities in Metropolitana), Rio Caeté (15 municipalities), Rio Capim (16 municipalities), Tapajós (6 municipalities), and Xingu (10 municipalities) (PARÁ, 2008).

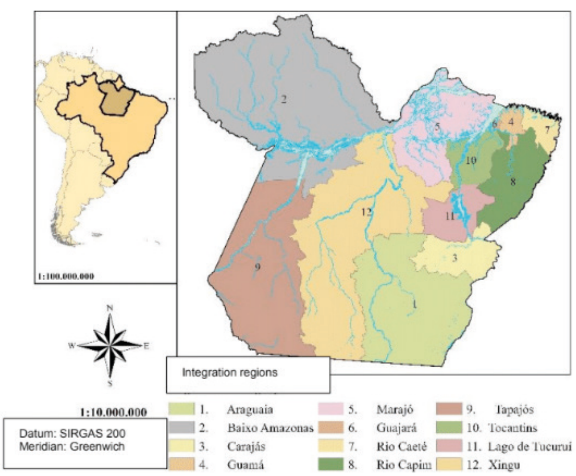

Figure 01 – Study area, municipalities comprising the Integration Regions of the state of Pará.

Source: Research data (2022)

For Cutter (2011), vulnerability science is a study associated with losses or damages that seeks to explain social, natural and artificial interactions, becoming a multidisciplinary field in the approach to risk reduction policies. The IVD is composed of 3 (three) fundamental components: exposure (E), sensitivity (S) and adaptive capacity (CA). The IPCC (2007) defines vulnerability by the intrinsic relationship between these three elements in a generic way by Equation (1):

$$V = f(E, S, CA), \qquad (1)$$

In which, ``E`` means system exposure (who or what is at risk); S, its sensitivity (how much people or systems can suffer from shocks) and CA, its adaptive capacity (the ability to adapt to impacts).

The methodology consisted of the following steps: (i) selection and grouping of indicators; (ii) definition of indicators; (iii) statistical treatments; (iv) calculation of the index by multivariate analysis; (v) index normalization; and (vi) classification of the index using the percentile technique. Once this was done, the data was analyzed based on a systemic perspective, so that its IDV value varies between 0 (zero) and 1 (one), where the value "zero" represents less vulnerability and the value "one", greater vulnerability.

In the study, 34 indicators were selected resulting from an exploratory analysis of various scientific literature, as shown in Figure 02, which were aggregated based on the three components of socio-environmental vulnerability. In studies by Lindoso et al. (2014); Quintão et al. (2017) and Menezes et al. (2018) exposure and sensitivity can increase vulnerability in the analyzed system, while adaptive capacity can reduce it. The database was obtained at the municipal level, from 2007 to 2017, through free access to information to the public from government institutions comprising the municipalities in the state of Pará.

When constructing the index, the

quantities were considered in the same unit, that is, to check the property of commensurability and place them on the same scale. According to Santos et al. (2017) and Menezes et al. (2018) the 0-1 transformation method, for any variable X, the value of the transformed variable 0-1 for the ith observation is given by Equation (2):

$$v_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \quad (2)$$

Where: $v\ i$ is the transformed value of the ith observation of the variable; $x\ min$ is the minimum value of the variable X; $x\ max$ is the maximum value of the variable X.

The IVD was constructed using the multivariate statistical technique of factor analysis (FA) presented in matrix form in Equation (3), according to DILLON & GOLDSTEIN (1984), with p being the random variables, m being the common factors and $m<p$. Using this technique, the aim is to reduce data and create indicators that represent the original variables, as well as identify the degree to which each variable is explained for each dimension or factor, aiming to explain the set of variables with the same ability or capacity. cognitive (HAIR et al., 2009; FIELD, 2009; LÉLIS et al., 2016).

$$X_i = \sum_{j=1}^{m} \lambda_{ij} F_j + \varepsilon_i \quad (3)$$

Where: Xi = original variables, represents the ith score of the standardized variable; λij = factorial loadings of the ith variable on the jth common factor; Fj = unobservable variables or latent variables; εi = error term or specific factors that describe the specific residual variation of the ith variable (residual that affects only Xi).

To adapt the statistical model, some recommendations were analyzed, such as the Kaiser-Meyer-Olkin (KMO) Adequacy Measure, which varies between 0 and 1. Hair et al. (2009) recommends 0.50 as an acceptable level. Bartlett's Test of Sphericity evaluates the general significance of the correlation matrix, that is, it tests the hypothesis that the variables are not correlated in the population. Therefore, the anti-image matrix, which provides the Sample Adequacy Measure (MAA), the closer the value is to 1, the more appropriate the use of the AF technique.

The Principal Components method was adopted to extract the factors to calculate the IVD and, subsequently, orthogonal rotation of the factors using the Varimax method. To choose the number of factors, the Latent Root criteria, percentage of variance, and Scree-plot Test (Eigenvalue versus Factor) were used. According to Hair et al. (2009) commonality indicates the proportion of the total variance of each variable, which is explained by the set of common factors, it is recommended that the number of factors chosen corresponds to at least 60% of the variance. By adopting the suitability criteria, the data set was also reduced, as low commonality was observed in some indicators.

This way, the IVD was defined by the linear combination of the factor scores estimated by the Regression Method and the proportion of variance explained by each factor in relation to common factors (MINGOTI, 2005; HAIR et al., 2009). For each factor fi, the ith extracted factor score is obtained by Fij, as expressed in Equation (4) (CHAVES et al., 2013; GU et al., 2018).

$$Fij = b_1xi1 + b_2xi2 + \ldots + b_px_{ip} \quad (4)$$

Where: Fij is the unobservable dependent variable; bi are the estimated regression coefficients for the n common factor scores; xij are the n observations of the p observed variables, and p is the number of observable variables.

Thus, the IVD estimate was obtained from the conceptual discussion of vulnerability

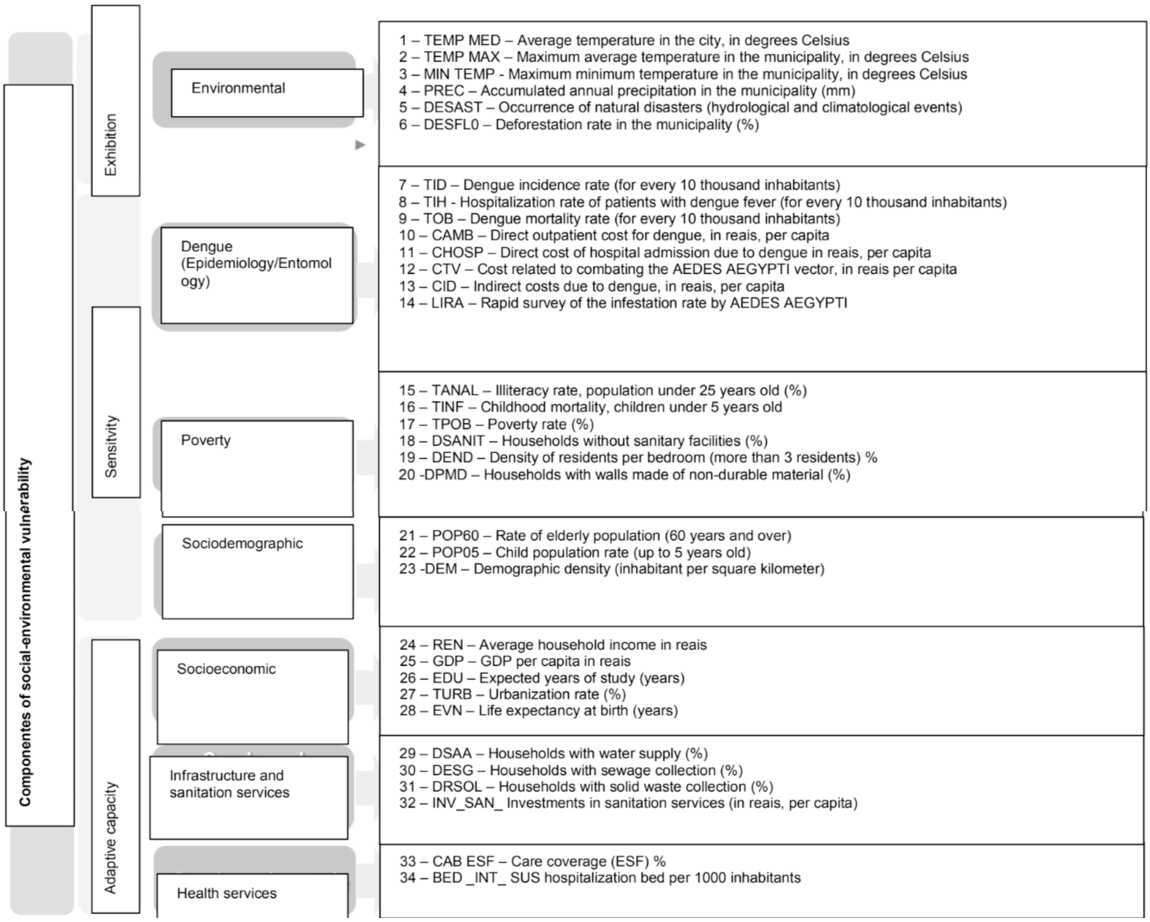

Figure 02 – Methodological scheme for selecting research indicators to compose the IVD.

Source: Own elaboration (2022).

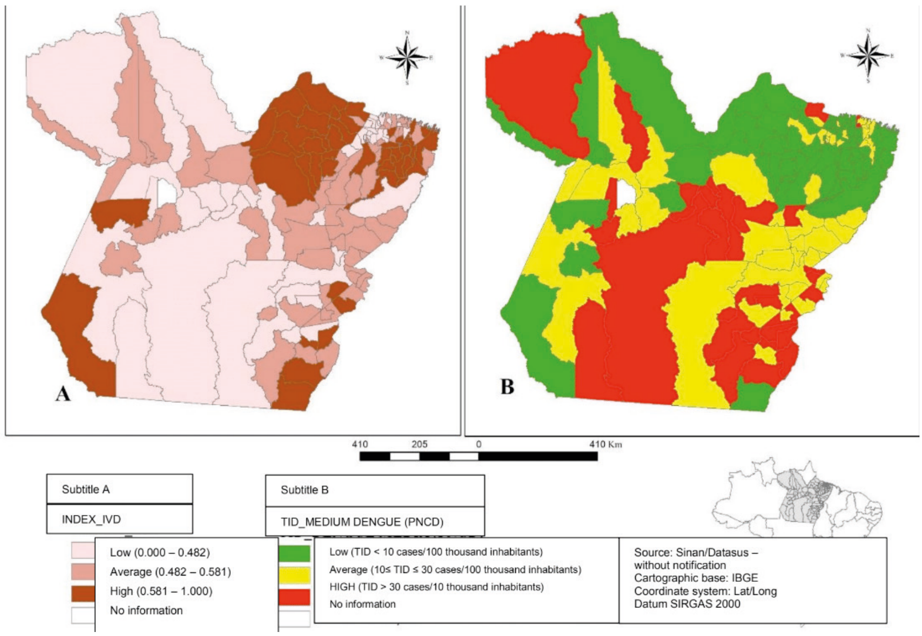

Figure 05 – Mapping of the IVD and average TID (2007-2017) of the municipalities in the study area.

Source: Own elaboration (2022). ≤

to the presentation of the synthesis measure (response), according to Equation (5).

$$IVD = \sum_{j=1}^{q} \left(\frac{\lambda_j}{\sum j\lambda_j} . FP_{ij} \right), 0 \leq IVD \leq 1 \quad (5)$$

Where: λi represents the variance explained by each factor; $\Sigma j\ \lambda i$ is the sum total of the variance explained by the set of common factors and FPij is the standardized score to obtain the positive values of the original active scores to rank the municipalities, since the values of the proposed index are obtained between 0 (zero) and 1 (one), through the Equation (1).

The municipalities were categorized corresponding to the percentiles (P30; P70) of the calculated index: "Low" for IVD values ≤ P(30); "Medium" for values between P(30) ≤ IVD ≥ P(70) and "High" for IVD values ≥ P(70) (PARENTE et al., 2012; CHAVES et al., 2017; MENEZES et al, 2018). Finally, it used the spatial statistical analysis of the Moran Index with the values of the average Dengue Incidence Rate for the period (TID) and the IVD values per municipality, aiming to identify spatial associations and priority areas for combating dengue.

RESULTS AND DISCUSSIONS

In the research, 184 thousand cases of dengue fever were considered in the state, of which 92 thousand were hospitalized by the SUS, in the period from 2001 to 2017. Of these, around 125 thousand occurred in the period from 2007 to 2017, equivalent to 14% of cases of the Legal Amazon and 21% of cases in the North region, accumulating 125 cases of deaths in this period.

The incidence rates of dengue in Brazil, in 2007 and 2017, were 264.4 and 115.3 per 100 thousand inhabitants, respectively. In the Amazon, the highest rate occurred in 2010 with 548.8 per 100 thousand inhabitants, with this growth being noticed in the North Region and Pará in 2011 with 709.6 and 218.6, respectively (SINAN-MS, 2017; PAHO, 2017). Studies by Böhm et al. (2016) on analyzing the trend in dengue incidence in Brazil, from 2002 to 2012, revealed that the annual increase rates were stable in the state of Pará.

In this study period, the five municipalities with the highest reported cases of dengue in descending order are: Belém, Parauapebas, Altamira, Santarém and Marabá. Furthermore, the number of deaths increased by an average of 11 cases (2007-2017), with 25 cases occurring in 2007 (SINAN-MS, 2017), showing the importance of understanding the dynamics of the disease in the state. Since then, dengue has remained present in most municipalities, becoming priority municipalities for the National Dengue Control Program (BRASIL, 2002; BRASIL, 2015).

The epidemiological profile of dengue in Pará indicated seasonality of the disease, occurring mainly in the quarter from January to March. The study by Corrêa et al. (2016) and Moraes et al. (2019); also observed that cases of the disease begin to appear when the rainy season begins in each municipality in Pará, from 2007 to 2011. Studies by Moraes et al. (2015); Souza et al. (2017); Ferreira Filho et al. (2020) that rainfall has greater variability between 1300 and 3500 mm, but it is observed that in December the rainy season begins in most locations in the state of Pará.

Pará is located in the equatorial belt with an average annual temperature varying between 22 °C and 32 °C, relative humidity levels around 85% (SOUZA et al., 2017). Therefore, the state has important climatic variables such as precipitation and temperature for the incidence of vector-borne diseases. In this context, social, economic and environmental constraints act to limit the expansion of the vector, as well as the dynamics of its spatial and temporal distribution (MORIN et al. 2013;

NAISH et al., 2014; EBI; NEALON, 2016).

Initially, 34 indicators were considered for calculating the IVD by applying factor analysis, however, adopting the suitability criteria, the data set was also reduced to 20 indicators, removing 8 indicators directly related to dengue and 6 indicators removed from the statistical model due to their low communality value ($h2<0.60$), were the following: DSANIT, DPMD, DEM, DESG, INV_SAN and LEIT_INT.

In the model, the KMO Test value was obtained equal to 0.79, which indicates the adequacy of the data set to the technique, and the significance level of the Bartlett Test ($p<0.001$), which indicates the rejection of the hypothesis that the variances are equal, which allowed the use of factor analysis to extract factors and estimate factor scores. Both Hair et al. (2009) suggests that factor extraction must continue until the researcher captures at least 60% of the variance. Finally, the model's anti-image matrix was analyzed, as the closer the MMA value is to one, the more appropriate the use of the technique is, as shown in Table 1.

The model resulted in 6 (six) factors that explain 84.5% of the total variance of the data set. In view of the above, the groupings of indicators under study were as follows: Factor 1 (26.5%) with the greatest representation was called the "socioeconomic" dimension, Factor 2 (17.8%) explains the "climatic" dimension, the Factor 3 (12.6%) explains the "demographic" dimension, Factor 4 (11.8%) explains "health", Factor 5 (8.2%) explains the "land use and cover" dimension and Factor 6 (7.7%) explains the "environmental" dimension.

The choice of variables that make up each of the factors was based on the factor loadings, so that Factor 1 with the "socioeconomic" dimension, with greater representation, acquired 8 (eight) significant factor loadings. The results show that some indicators contributed decisively to the formation of Factor 1, emphasizing the living conditions of the populations, especially on issues of poverty, income, urbanization, illiteracy and solid waste management, as shown in Table 01.

According to the results of the IVD, the municipalities were categorized according to the concepts of socio-environmental vulnerability used in the research. It is observed that 43 municipalities (30%) were classified as "Low vulnerability", with values ranging from 0.483 to 0.262. Around 57 municipalities (40%) presented values with "Medium vulnerability" in the range of 0.581 to 0.483. With reference to "High vulnerability", 43 municipalities (30%) stood out, distributed in the range of 0.771 to 0.582, as shown in Figure 03. The results obtained from the profile that characterized the IVD showed a predominance of Medium to Low socio-environmental vulnerability.

Figure 04 illustrates the average TID by integration region, period 2007-2017, in order to compare with the IVD values in the same period. It was found that 66 municipalities (46%) were classified as "Low incidence", 47 municipalities (33%) presented values with "Medium incidence" and in the "High incidence" category, 30 municipalities (21%) were identified.

The results obtained from the average TID were predominantly Medium to Low.

In the IVD results, the municipalities classified as "High socio-environmental vulnerability" by region stood out, in descending order: Marajó (15/16 municipalities or 95%), Rio Capim (8/16 municipalities or 50%), Tocantins (8/ 11 municipalities or 36%), Rio Caeté (5/15 municipalities or 33%), Tapajós (2/6 municipalities or 33%), Araguaia (4/15 municipalities or 27%), Carajás (2/12 municipalities or 17%) and Guamá (3/18 municipalities or 17%).

The municipalities classified as "Medium

Variables	Rotating factor loadings (Varimax)						h2	Rotating factor loadings	MSA
	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6			
TEMPMED	-0,121	**0,972**	-0,138	0,028	-0,019	0,004	0,979	0,972	,642a
TEMPMAX	-0,087	**0,959**	-0,139	0,036	-0,011	-0,053	0,951	0,959	,667a
TEMPMIN	-0,096	**0,936**	-0,098	0,021	0,013	0,117	0,910	0,936	,725a
PRECACUM	0,079	-0,439	0,039	0,206	0,412	**0,610**	0,784	0,610	,750a
DESAST	-0,017	-0,144	0,139	-0,022	-0,004	**-0,906**	0,862	-0,906	,550a
DESFLO	0,033	-0,007	0,034	0,133	**-0,868**	-0,113	0,786	-0,868	,590a
TANAL	**0,683**	0,184	0,209	0,108	-0,373	0,168	0,723	0,683	,827a
TINF	0,267	0,045	-0,011	**0,938**	-0,083	0,050	0,962	0,938	,683a
POB	**0,855**	-0,194	0,139	0,325	0,153	0,045	0,919	0,855	,801a
DEND	0,388	**-0,533**	0,505	0,094	0,347	0,219	0,867	-0,533	,893a
POP60	0,016	0,078	**-0,755**	0,303	0,418	-0,014	0,843	-0,755	,590a
POP05	0,537	-0,214	**0,631**	0,088	0,052	-0,030	0,744	0,631	,879a
TURB	**0,852**	-0,138	-0,072	0,112	-0,087	-0,016	0,770	0,852	,873a
EVN	0,296	0,049	-0,002	**0,933**	-0,077	0,049	0,968	0,933	,694a
REN	**0,830**	-0,139	0,073	0,342	0,143	0,121	0,865	0,830	,836a
PIB	**0,615**	-0,178	-0,024	0,417	0,197	0,345	0,742	0,615	**,941a**
EDU	**0,661**	0,042	0,467	0,039	-0,358	0,189	0,823	0,661	,855a
DSAA	**0,634**	-0,283	0,496	0,037	0,228	-0,020	0,782	0,634	,887a
DRSOL	**0,911**	-0,050	-0,011	0,087	-0,060	-0,173	0,873	0,911	,886a
CAB_ESF	-0,018	-0,173	**0,825**	0,082	0,050	-0,185	0,755	0,825	,744a
Eigenvalues	5,295	3,550	2,513	2,359	1,649	1,541	16,91	-	-
Variance Explained by the Factor (%)	26,477	17,752	12,567	11,794	8,246	7,703	84,54	-	-
Accumulated Variance (%)	26,477	44,229	56,796	68,589	76,836	84,539		-	-
Factor Loadings	0,795	0,759	0,563	-0,433	-0,207	-0,575		-	-
Number of variables	8	4	3	2	1	2	20	-	-
Cronbach's alpha	0,921	0,467	-0,748	0,997	-	-1,255	0,768	-	-

Table 01 – Statistical results obtained for factor selection using the principal components method, orthogonal rotation using the varimax method.

Measures of Sampling Adequacy (MSA); Extraction Method: Principal Component Analysis; Rotation Method: Varimax with Kaiser Normalization; Rotation converged in 6 iterations; Final commonality (h2).

Source: Own elaboration (2022).

vulnerability" by region were: Lago de Tucuruí (5/7 municipalities or 71%), Carajás (7/12 municipalities or 58%), Baixo Amazonas (6/12 municipalities or 50%), Araguaia (7/15 municipalities or 47%), Rio Caeté (7/15 municipalities or 47%), Tocantins (5/11 municipalities or 45%), Rio Capim (7/16 municipalities or 44%), Xingú (4/10 municipalities or 40%), Tapajós (2/6 municipalities or 33%), Guamá (5/18 municipalities or 28%), Guarajá (1/5 municipalities or 20%) and Marajó (1/16 municipalities or 6%).

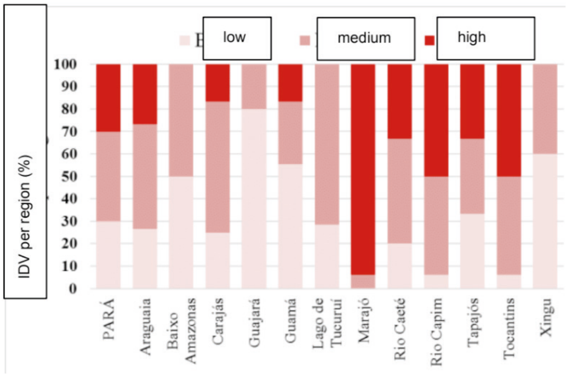

Figure 03 – IVD result by integration region, period 2007-2017

Source: Own elaboration (2022).

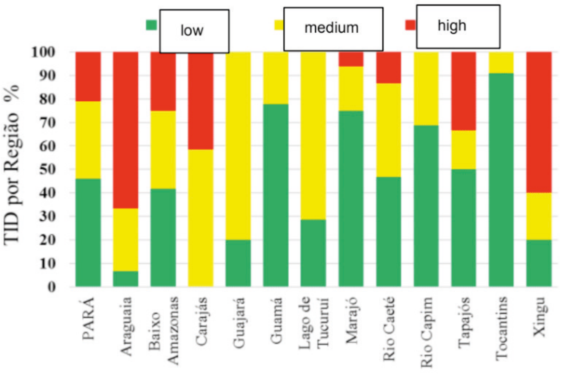

Figure 04 – Average TID result by integration region, period 2007-2017.

Source: Own elaboration (2022).

While the municipalities classified as "Low vulnerability" by region were: Guarajá (4/5 municipalities or 80%), Xingú (6/10 municipalities or 60%), Guamá (10/18 municipalities or 56%), Baixo Amazonas (6 /12 municipalities or 50%), Tapajós (2/6 municipalities or 33%), Lago de Tucuruí (2/7 municipalities or 29%), Araguaia (4/15 municipalities or 27%), Carajás (3/12 municipalities or 25%), Rio Caeté (3/15 municipalities or 20%), Tocantins (2/11 municipalities or 18%) and Rio Capim (1/16 municipalities or 6%).

The results indicate that the majority of municipalities in the Guajará RI (4 of the 5 municipalities) were those that stood out most in the IVD classification as "Low vulnerability", with a decreasing variation from 0.411 to 0.262, were evidence for the municipalities: Belém (state capital), Benevides, Ananindeua and Santa Bárbara do Pará.

The results indicate that the majority of municipalities in the Marajó RI (10 of the 16 municipalities) obtained the "High vulnerability" classification from the IVD, with a decreasing variation from 0.771 to 0.619; The following municipalities were highlighted: Cachoeira do Arari, Chaves, Ponta de Pedras, Melgaço, Santa Cruz do Arari, Anajás, Bagre, Curralinho, Afuá and Muaná.

Figure 05 illustrates the spatial distribution of IVD and average TID in the state in the period from 2007 to 2017, with a predominance of the "High socio-environmental vulnerability" profile in the Marajó and Rio Capim RI, but with a predominance of the classification of municipalities in "Low incidence of dengue". In Marajó, the IVD demonstrated a scenario of high susceptibility to the occurrence of dengue, but it is attributed that its impact is reduced due to the fact that the population has low mobility in the region, socioeconomic difficulties and lack of health services, especially in the notifications of compulsory diseases.

At the other extreme of the analysis is the

"Low socio-environmental vulnerability" in the Xingú RI and the predominance of the classification of municipalities in the region as "High incidence of dengue". This profile indicated a scenario of low susceptibility to the occurrence of dengue, but attributed due to the high impact on the population due to the occurrence of major works and population growth in the period analyzed, however, this result may not configure the actual existing situation.

Figure 6 presents the results of the Moran Map for the IVD and the average TID in the same period. The bivariate analysis showed a negative autocorrelation, with a value equal to - 0.409, indicating that municipalities with a high (or low) frequency of IDV and a high (or low) frequency of TID were spatially associated with other municipalities with the same profile.

The spatial autocorrelation between TID vs. IVD in the state of Pará was significant ($p<0.05$) for 48 municipalities, which indicates the rejection of the null hypothesis of spatial independence. It appears that only one municipality is significant for the high-high spatial pattern in the Portel case (RI Marajó), that is, municipalities that presented "High vulnerability" also presented an increase in TID values. However, two municipalities referred to the low-low standard: Jacareacanga (RI Tapajós) and Limoeiro do Ajuru (RI Tocantins). For the low-high standard, 21 municipalities were classified, the largest portion located in the Marajó and Baixo Tocantins region, and the smallest portion in the Xingu and Tocantins RI. Finally, in the high-low pattern, 24 municipalities were presented, the majority located in the Araguaia and Carajás region, but the smallest portion in the RI of Xingu, Tocantins and Rio Capim. The Moran Map results also showed that 96 municipalities did not present statistically significant values.

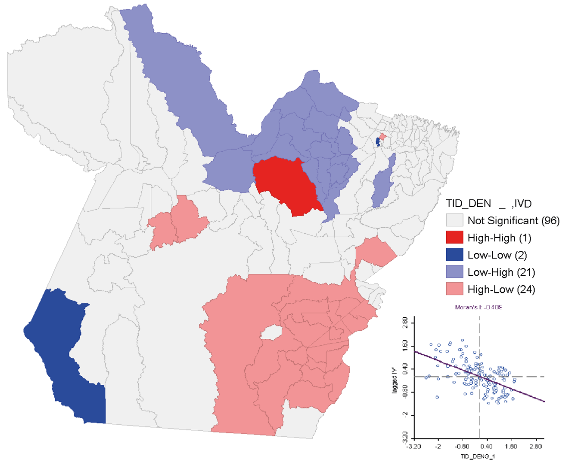

Figure 6 – Moran Map mapping of the IVD and average TID (2007-2017) of the municipalities in Pará.

Source: Own elaboration (2022).

The study presented relevant information about dengue for the development of guidelines for the Contingency Plan to combat Dengue in the integration regions of the state of Pará. Therefore, the research findings can help in the development of prevention and control strategies for the disease, aimed at regions or groups of municipalities with "High socio-environmental vulnerability" or "High incidence of dengue", mainly in areas identified at risk of outbreaks of the disease.

CONCLUSIONS

To this end, the development of tools to measure the degree of socio-environmental vulnerability of the population through synthetic indicators aiming to analyze how the different systems studied, becomes necessary to guide public policies and decision-making in municipalities. Factor analysis proved to be the appropriate index aggregation method to measure the degree of socio-environmental vulnerability to combat dengue.

The IVD results were satisfactory in mapping the most vulnerable areas, as it was observed that 43 municipalities (30%)

were classified as "Low vulnerability", 57 municipalities (40%) presented "Medium vulnerability" and 43 municipalities (30%) with "High vulnerability". The results obtained from the profile that characterized the IVD showed a predominance of Medium to Low. In view of the analyzes obtained from the IVD, it can be seen that it can be used as an important tool for managing dengue health surveillance in the Amazon region, with the potential to be applied in other regions of Brazil where the disease occurs. The findings also indicate that dengue prevention and control actions must be linked in the state, aiming at the effectiveness of entomological control of vectors and epidemiological control of dengue, including health education to engage the population in planning these actions in the municipality.

In view of the analyzes presented, the results explained here can contribute important information for public managers (state and municipal) who share responsibility for dengue control, mainly in the development of guidelines for Contingency Plans to combat Dengue and other diseases. diseases, such as Chikungunya and Zika, at the state and municipal level, aiming to prevent and control epidemic processes, as well as reducing hospitalizations and deaths.

REFERENCES

BOHM, A. W. *et al.* Tendência da incidência de dengue no Brasil, 2002-2012. **Epidemiologia e Serviços de Saúde**, Brasília, DF, v. 25, n. 4, p. 725-733, 2016.

BRASIL. Ministério da Saúde. Fundação Nacional de Saúde. Programa Nacional de Controle da Dengue. Brasília, DF: Ministério da Saúde, 2002.

BRASIL. Ministério da Saúde. Plano de Contingência Nacional para Epidemias de Dengue. Brasília, DF, 2015. Disponível em: https://bit.ly/3vA5pnJ. Acesso em: 13 jun. 2019.

CHAVES, A. F. F. *et al.* Ambiente e saúde: prioridades nos estados da Amazônia Legal. **Enciclopédia Biosfera**, Goiás, v. 9, p. 2241-2258, 2013.

CHAVES, E. C. *et al.* Condições de vida populacional e incidência de dengue no estado do Pará, Brasil. **Pará Research Medical Journal**, Belém, v. 2, n. 1-4, 2018. Disponível em: https://bit.ly/35uTzAG. Acesso em: 10 dez. 2017.

CORRÊA, J. A. J. *et al.* Associação entre a precipitação pluviométrica e a incidência de dengue em sete municípios do estado do Pará. **Revista Brasileira de Geografia Física**, Rio de Janeiro, v. 9, n. 7, p. 2264-2276, 2016.

CUTTER, S. L. A ciência da vulnerabilidade: modelos, métodos e indicadores. **Revista Crítica de Ciências Sociais**, Coimbra, v. 93, n. 1, p. 59-69, 2011.

DILON, W.R.; GOLDSTEIN, M. Multivariate Analysis: methods and applications. New York: John Wiley & Son, 1984.

EBI, K.; NEALON, J. Dengue in a changing climate. **Environmental Research**, San Diego, v. 151, p. 115-123, 2016.

FIELD, A. **Descobrindo a estatística usando o SPSS**. 2. ed. Porto Alegre: Artmed, 2009.

FERREIRA FILHO, D. F. *et al.* 2020. Análise pluviométrica no estado do Pará: comparação entre dados obtidos de estações pluviométricas e do satélite GPCC. **Revista Brasileira de Climatologia**, Curitiba, v. 26, 2020.

GUO, C. *et al.* Global Epidemiology of Dengue Outbreaks in 1990–2015: A Systematic Review and Meta-Analysis. **Frontiers in Cellular and Infection Microbiology**, Switzerland, v. 7, n. 317, 2017.

HAIR, J. F. *et al.* **Análise multivariada de dados**. 6. ed. Porto Alegre: Bookman, 2009.

IBGE. **Censo Demográfico de 2010**: resultados do universo. Brasília, DF, 2010. Disponível em: http://downloads.ibge.gov.br/downloads_estatisticas.htm. Acesso em: 10 nov. 2016.

IBGE. **Cidades@:** Santos. Brasília, DF: IBGE, 2010. Disponível em: https://bit.ly/3sC1bu9. Acesso em: 12 jan. 2017.

IPCC. **Climate Change 2007**: the physical science basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge: Cambridge University Press, 2007.

IPEA**. Atlas do desenvolvimento humano nos municípios brasileiros**. Brasília, DF: IPEA, 2015. Disponível em: http://ivs.ipea.gov.br/index.php/pt/. Acesso em: 23 maio 2017.

MENEZES, J. A. *et al.* Mapping human vulnerability to climate change in the Brazilian Amazon: The construction of a municipal vulnerability index. **PLOS One**, San Francisco, v. 13, n. 2, 2018.

MORIN, C. W. *et al.* Climate and Dengue Transmission: Evidence and Implications. **Environmental Health Perspectives**, Research Triangle Park, v. 121, n. 11-12, p. 1264-1272, 2013.

MORAES, B. C. *et al.* Climatologia da precipitação na Amazônia. **Revista Brasileira de Geografia Física,** Rio de Janeiro, v. 8, n. 5, p. 1359-1373, 2015.

MORAES, B. C. *et al.* Sazonalidade nas notificações de dengue das capitais da Amazônia e os impactos do El Niño/La Niña. **Cadernos de Saúde Pública**, Rio de Janeiro, v. 35, n. 9, 2019.

MURRAY, N. E. A. *et al.* Epidemiology of Dengue: Past, Present and Future Prospects. **Clinical Epidemiology**, New York, v. 5, p. 299-309, 2013.

NAISH, S. *et al.* Climate change and dengue: a critical and systematic review of quantitative modelling approaches. **BMC Infectious Diseases**, London, v. 14, n. 1, 2014.

LÉLIS Félix da Silva; *et al.* Dimensões do Uso e Cobertura da Terra nas Mesorregiões do Estado do Pará. **Espacios.** Vol. 37 (Nº 05) Año 2016. Pág. 5. ISSN 070981015. Disponível em: https://www.revistaespacios.com/a16v37n05/16370505.html

LINDOSO, D. P. Vulnerabilidade e resiliência: potenciais, convergências e limitações na pesquisa interdisciplinar. **Ambiente & Sociedade**, São Paulo, v. 20, n. 4, p. 127-144, 2017. Disponível em: https://bit.ly/3hAJG7a. Acesso em: 18 jan. 2021.

PARÁ. Decreto nº 1.066, de 19 de junho de 2008. Dispõe sobre a regionalização do Estado do Pará e dá outras providências. **Diário Oficial do Estado do Pará**, Belém, 2008. Disponível em: https://bit.ly/35tLZ9v. Acesso em: 15 ago. 2017.

PARÁ. Secretaria do Estado do Pará. Coordenação de Vigilância em Saúde. Departamento de Controle de Doenças Transmissíveis. **Plano Estadual para a Prevenção e Controle de Epidemias de Dengue**. Belém, 2015.

PARENTE, A. T. *et al.* A ocorrência de malária em quatro municípios do estado do Pará, de 1988 a 2005, e sua relação com o desmatamento. **Acta Amazônica**, Manaus, v. 42, n. 1, p. 41-48, 2012. Disponível em: https://bit.ly/3psVYmr. Acesso em: 11 jan. 2021.

PAHO. **Alerta epidemiológico**: dengue nas Américas. [*S. l.*], 2017. Disponível em: https://bit.ly/3IDrV2N. Acesso em: 10 jun. 2016.

SANTOS, M. R. S. *et al.* Vulnerabilidade e mudanças climáticas: análise socioambiental em uma mesorregião da Amazônia. **Revista Ambiental & Água**, Taubaté, v. 12, n. 5, p. 842-854, 2017.

SANTOS, R. B. *et al.* Construção e aplicação de um índice de vulnerabilidade humana à mudança do clima para o contexto brasileiro: a experiência do estado do Espírito Santo. **Saúde e Sociedade**, São Paulo, v. 28, n. 1, p. 299-321, 2019. Disponível em: https://bit.ly/3hCiXal. Acesso em: 17 jan. 2021.

SOUZA, M. L. A. *et al.* Bayesian estimates for the mapping of dengue hotspots and estimation of the risk of disease epidemic in Northeast Brazil. **Urban Climate**, Netherlands, v. 26, p. 198-211, 2018.

SOUZA, E. B. Padrões Climatológicos e Tendências da Precipitação Nos Regimes Chuvoso E Seco Da Amazônia Oriental. Revista Brasileira de Climatologia, Curitiba, v. 21, 2017.

SINAN. Notificações registradas no Sistema de Informação de Agravos de Notificação Pará. Brasília, DF: Ministério da Saúde, 2017. Disponível em: https://bit.ly/3vvkHdD. Acesso em: 10 jan. 2019.

WHO. Global Strategy for Dengue Prevention and Control, 2012-2020. Geneva: WHO, 2012.

WHO. Estimated number of dengue infections each year. Geneva: WHO, 2016. Disponível em: https://bit.ly/3ICQflq. Acesso em: 21 fev. 2018.