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Title: Characterizing risk for Dengue in Brazil: a multi-dimensional approach

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Characterizing risk for Dengue in Brazil: a multi-dimensional approach

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Abstract

Dengue is the most common mosquito-borne infectious disease worldwide, primarily caused by the Aedes Aegypti mosquitoes. There are approximately 100-400 million cases annually, with roughly half of the global population at risk. In recent years, and particularly in 2024, there has been a major increase in Dengue cases in North and South America. One of the most heavily affected countries is Brazil, where there has been a 230% increase in cases in 2024 compared to 2023. In a report in June 2024, the CDC released a report indicating 3 risk groups for dengue: infants aged ≤1 year, pregnant women, and adults over 65 years old. Due to the spike in cases, it's important to understand what factors contribute to Dengue risk and create a model to quantify it in order to inform decisions on how to respond. The main 2 parts of this project were a) exploring the spatial relationships between these 3 Dengue risk group populations and aedes aegypti mosquitoes in Brazil and b) creating an index to quantify risk for Dengue in Brazil. The 10 cities with the highest risk were identified, and it was found that the east coast and southern regions are at highest risk. The findings in this study provide insights into cities and areas of Brazil that should be focused on for targeting Dengue spread.

Background

Dengue is the most common mosquito-borne infectious disease worldwide, primarily caused by the Aedes Aegypti mosquitoes, and has approximately 100-400 million cases annually, putting roughly half of the global population at risk [1]. In recent years, and particularly in 2024, there has been a major increase in the number of Dengue cases in the United States and South America. One of the most heavily affected countries is Brazil, where a record high number of 7,866,769 Dengue cases have been reported in the first 23 weeks of 2024, an increase of 230% compared to 2023 [2]. In a report in June 2024, the CDC released a report indicating 3 risk groups for dengue: infants aged ≤1 year, pregnant women, and adults over 65 years old [2]. Due to the lack of treatments for dengue, it's important to understand what factors contribute to Dengue risk and create a model to quantify it in order to inform decisions on how to respond.

There were 2 main goals of this project. First, to explore the relationship between risk group populations density, populations of aedes aegypti mosquitoes, and access to healthcare resources in Brazil. Second, to create an index to quantify risk for Dengue based on these risk contributors, and use it to predict Dengue risk in each Brazilian municipality in order to identify areas of high risk in Brazil. The hope is that through characterizing Dengue risk in Brazil, I can identify areas that a) should be avoided by travelers in order to prevent Dengue contraction and b) should be focused on for preventative measures. For instance, if it is known which cities are high risk, then preventive measures can be taken such as setting up mosquito traps in high risk hot spots in those cities to prevent Dengue spread.

Methods

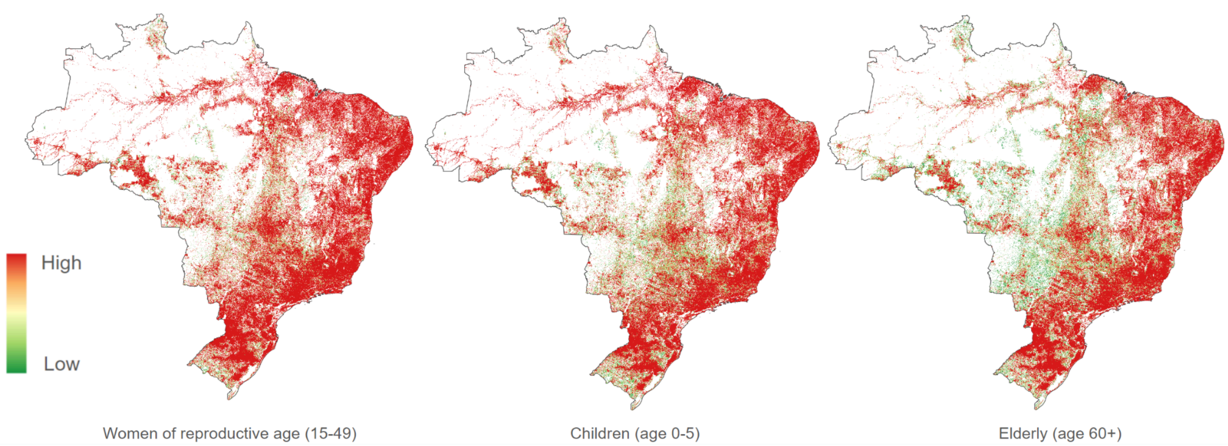
First, I obtained all of the geospatial data to be analyzed for the study. The data were all obtained from public open-source databases. The aedes aegypti mosquito habitat suitability data were downloaded in the geotiff file format [3]. The population density data for the 3 risk groups were downloaded both in the geotiff and csv format [4]. It should be noted that the population density of the risk groups used in this study are not identical to the Dengue risk groups identified by the CDC. The 3 risk groups reported by the CDC were infants under the age of 1, elderly above the age of 65, and pregnant women. However, the closest available geospatial data for Brazil (that I downloaded and used in this project) were children under the age of 5, women of reproductive age, and elderly above the age of 60. The healthcare facilities data, which includes pharmacies, clinics, hospitals, and doctor's offices were downloaded in the shapefile format.

Then, I mapped all of the data and clipped it to the map of Brazil by clipping it to Brazil's borders using the QGIS software. Then, I used rasterio, geopandas, pandas, numpy, and other packages in python to compute correlations between my variables. Then, I created a risk index for dengue by filtering out all of the outliers from the dataset, performing min-max normalization of each variable except for healthcare facilities to normalize it on a 0-1 scale, and finally computed the risk index by averaging out the normalized data for each risk contributor. The reason why the healthcare facilities data was excluded from the risk index calculation was because it was of a different data type than the other contributors; data on population density and mosquito populations were of the raster data type, while the healthcare facility data was in the vector data type. This made working with both data types in one final risk layer very difficult, so healthcare facilities were excluded from the risk index. After computing this risk index for each pixel in Brazil, I plotted the risk values on the map of Brazil. Then, I used the rasterio and geopandas packages in python to identify the list of top 10 municipalities with the highest risk index, using the average values of the risk index for each pixel within each municipality. Next, I used the matplotlib and pandas packages in python to visualize the risk index distribution.

Results

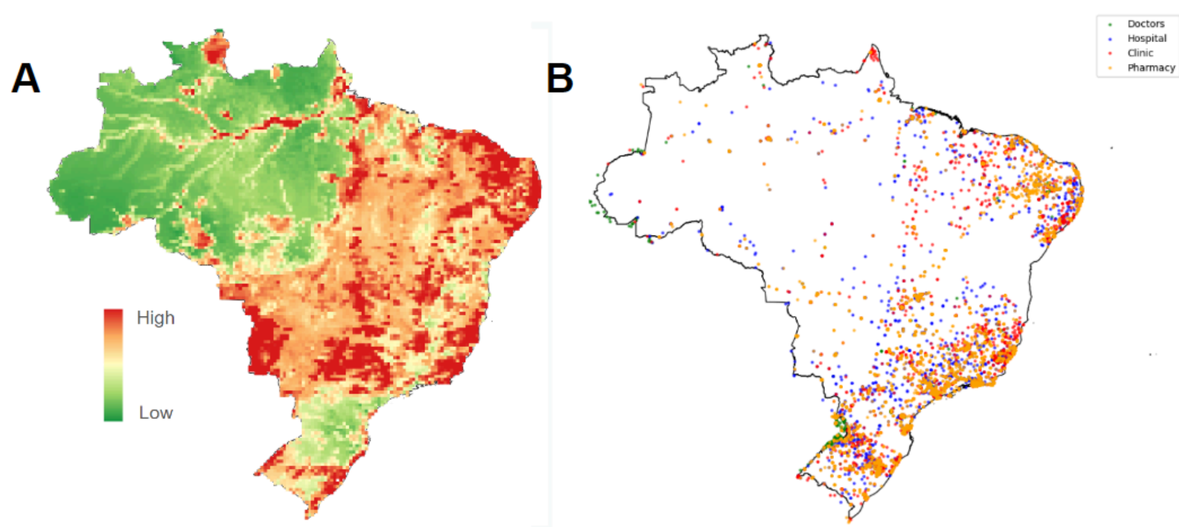
As aforementioned, I first plotted all of my data for my risk contributors on the map of Brazil in order to get a sense of the geospatial distributions of each risk contributor individually (figure 1-2). The maps of population density and mosquito populations are displayed on the green-red color scale, where green color indicates low levels and red indicates high levels.

Figure 1. Maps of population density of 3 risk groups in Brazil.



For the healthcare facilities data, I plotted each facility as points, colored by the type of healthcare facility. 50.5% of the facilities are pharmacies, 27.4% were clinics, 15.5% were hospitals, and 6.5% were doctor's offices.

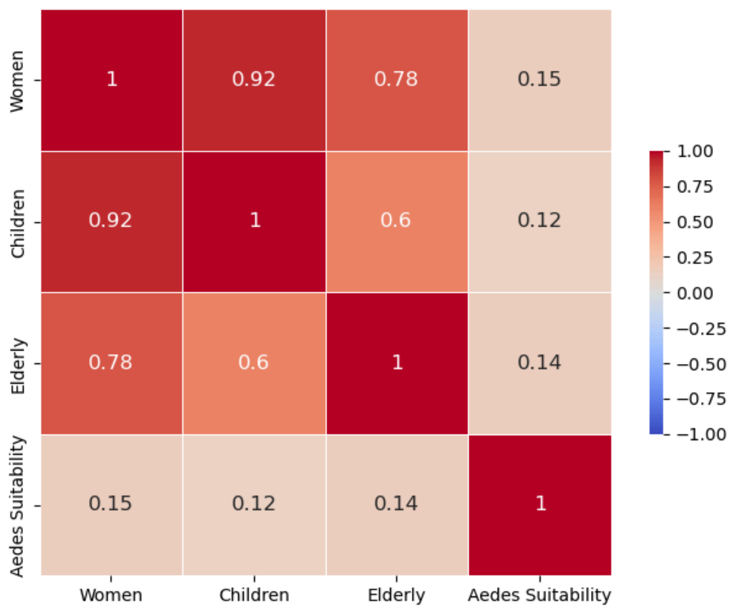
Figure 2. Maps of **A)** aedes aegypti habitat suitability and **B)** healthcare facilities in Brazil.



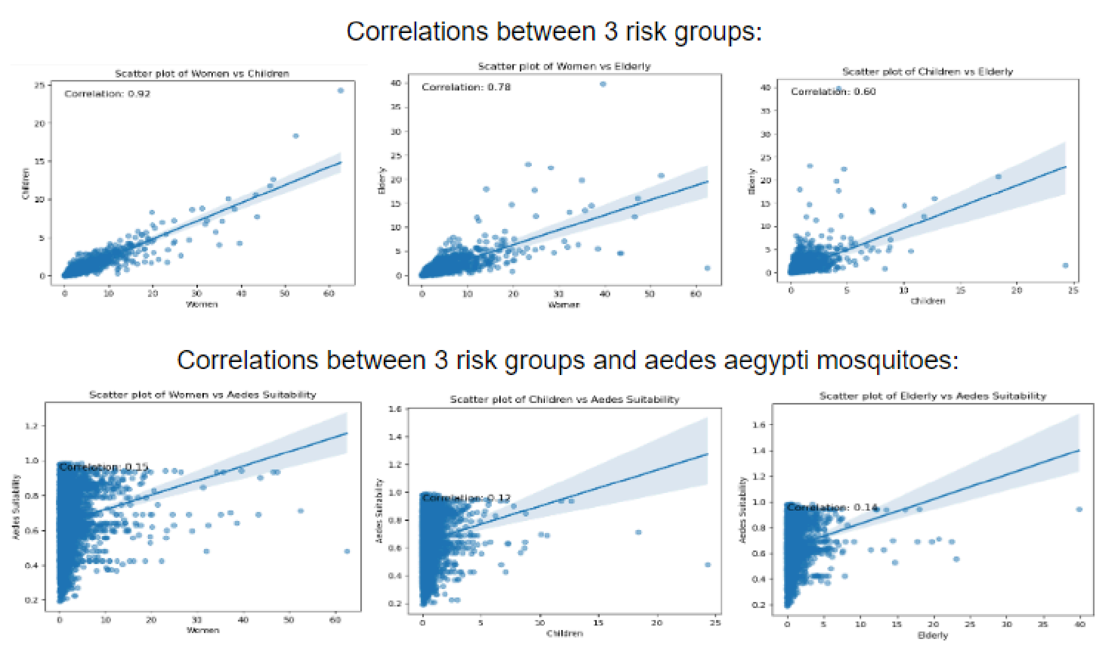
Next, I computed the correlations between my aedes aegypti distribution data and my population density data (figure 3). There were a total of 6 correlation combinations: women and children, women and elderly, children and elderly, women vs aedes aegypti mosquitoes, children vs aedes aegypti mosquitoes, and elderly vs aedes aegypti mosquitoes.

Figure 3. A) Correlation matrix and **B)** scatterplots of 3 risk groups and aedes aegypti habitat suitability.

A)



B)



Next, I computed the Dengue risk index for each pixel in Brazil (figure 4) and identified the 10 municipalities with the highest risk (table 1). Dark green colored pixels indicate areas with no risk data, while lighter green color indicates low risk, and red color indicates high risk. All risk values are on the 0-1 scale as a result of min-max normalization of each risk contributor.

Figure 4. Map of Dengue risk in Brazil.

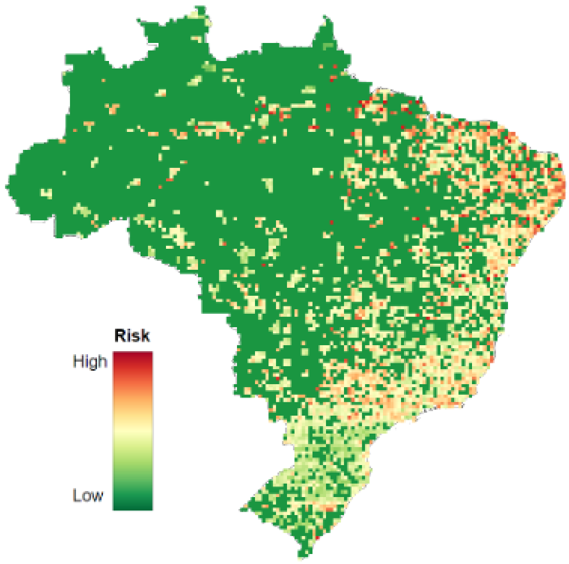


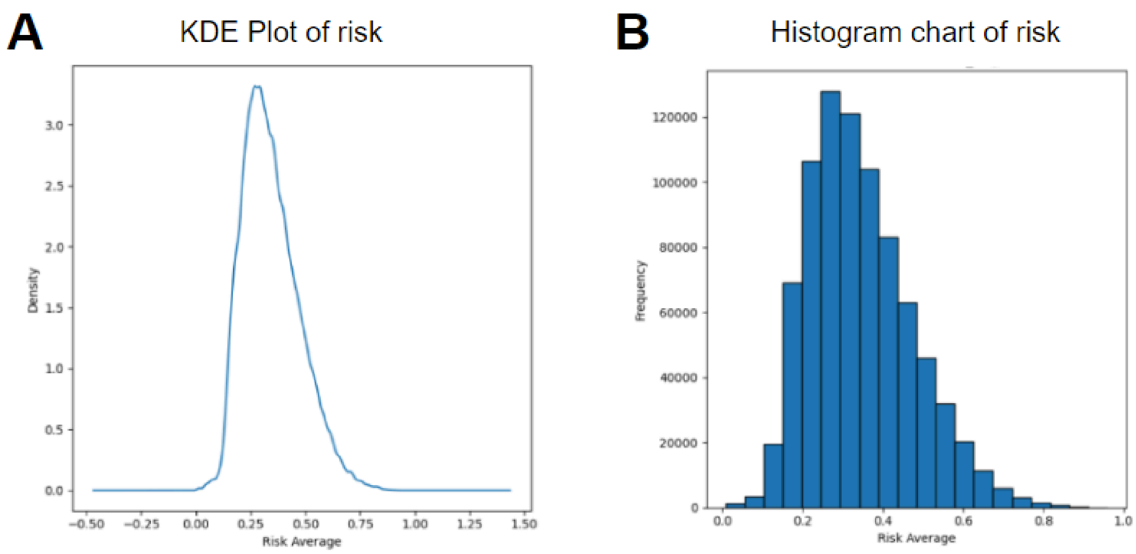
Table 1. Top ten municipalities with highest Dengue risk in Brazil.

City Name	Dengue Risk Index	Women NPD*	Children NPD	Elderly NPD	Aedes Aegypti habitat suitability
São João do Rio do Peixe	0.782	0.966	0.468	0.856	0.842
Jaguaruana	0.725	0.687	0.377	0.909	0.919
Igreja Nova	0.658	0.961	0.468	0.314	0.895
Água Doce do Norte	0.655	0.843	0.522	0.413	0.746
São Francisco do Brejão	0.648	0.758	0.57	0.477	0.86
Campo Maior	0.635	0.906	0.358	0.485	0.778
Canarana	0.607	0.71	0.396	0.705	0.616
Serra Sapã	0.607	0.441	0.433	0.638	0.931
Pau dos Ferros	0.607	0.577	0.207	0.808	0.85
Poço Branco	0.596	0.935	0.387	0.365	0.691

*NPD = normalized population density

Finally, I plotted 2 different representations of the distribution of the Dengue risk index (figure 4). The risk index appears to follow a normal distribution, due to the fact that it's normalized on the 0-1 scale.

Figure 4. Distribution of Dengue risk displayed as **A)** a KDE plot and **B)** a histogram chart.



Discussion

In this project, I explored the relationships between risk groups' population densities, mosquito populations, & healthcare facilities in Brazil using open-source geospatial data. I then correlated each of these variables and found that there were strong positive correlations (average of 76.7%) between risk groups, but weak positive correlations (average of 13.7%) between risk groups and aedes mosquito levels. More specifically, the strongest correlation between 2 risk contributors was population density of women of reproductive age versus population density of children under the age of 5, which had a correlation of 92%. This is expected because children tend to live with their mothers, creating strong spatial correlations in terms of population density of the 2 groups. The lower correlations between women and elderly and children and elderly (78% and 60%, respectively) may be explained by the fact that the elderly tend to live in different communities than women and children.

Using this data, I created a risk index for Dengue in Brazil, and computed the index for each pixel in Brazil, resulting in a map of risk in Brazil. I used this map to determine the top 10 municipalities in Brazil with the highest risk. One of the key findings is that cities in the east coast and southern regions of Brazil have the highest risk. Due to the high population density in these areas, this is concerning, and may explain recent spikes in 2024 in Dengue Cases in these regions.

There are some limitations of my project and methodology that should be addressed. Perhaps the greatest limitation is that I filtered out the outliers from the dataset before I normalized the data and computed the risk index. This is problematic because it likely excludes the highest risk cities from the dataset. As such, the list of 10 highest risk cities that I identified may not be correct, as the highest risk cities may have been excluded from this list. Filtering out the outliers (which accounted for roughly 20% of the dataset) also created pixels in which there was no risk data, creating empty (dark green) spaces on the risk map. The problem of filtering out the outliers could have potentially been avoided by using a log scale instead of min-max normalization. This could normalize the data without removing a significant portion of the dataset and could lead to a more accurate list of high risk municipalities. Another limitation is that the population density data (& thereby risk) was unavailable for significant areas of Brazil, particularly in the Northeast region. Additionally, we only focused on 1 mosquito species (aedes aegypti), which is a limitation because there are other species of mosquitoes that also cause Dengue.

There are a number of ways that this project could be extended further. One avenue is to incorporate more variables into the risk index model, such as socioeconomic status, climate variables, land type, proximity to bodies of water, and ranges of other mosquito species. Adding more variables could increase the accuracy of the risk prediction because risk is based on a complex network of interacting and intersectional factors. As such, accounting for more risk contributors when assessing risk can provide a more accurate representation of risk. Another avenue that I think would be quite interesting is to do a deep dive into highest risk cities to find what characteristics and practices make them high risk for Dengue. As an example, one could look into what agricultural practices are common to that city to see if those practices are attracting mosquitoes. Furthermore, another way to extend the project would be to predict future dengue risk in Brazil by using predicted future data (eg, 2050 and 2090 mosquito projections) in order to predict how risk will change over time. This information would be informative in understanding which areas risk for Dengue will likely increase over time, and could lead to focusing on preventative measures in those areas.

Works Cited:

1) Dengue and severe dengue." World Health Organization, World Health Organization, 23 Apr. 2024, https://www.who.int/news-room/fact-sheets/detail/dengue-and-severe-dengue.

2) "Health Alert Network (HAN) - 00511." Centers for Disease Control and Prevention, Centers for Disease Control and Prevention, 25 June 2024, emergency.cdc.gov/han/2024/han00511.asp.

3) Morgan E. Gorris, Andrew W. Bartlow and Travis Pitts et al. Projections of Aedes and Culex mosquitoes across North and South America in response to climate change. The Journal of Climate Change and Health. 2024. DOI: 10.1016/j.joclim.2024.100317

4) Facebook Connectivity Lab and Center for International Earth Science Information Network - CIESIN - Columbia University. 2016. High Resolution Settlement Layer (HRSL). Source imagery for HRSL © 2016 DigitalGlobe. Accessed 11 July 2024.