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Spatio-temporal analysis of dengue fever in Bolivia: climatic, environmental and sociodemographic factors

Análisis espacio-temporal del dengue en Bolivia: factores climáticos, ambientales y sociodemográficos

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Resumen

Dengue is a prevalent arbovirus globally, with incidence rising sharply in the Americas due to climate change and increased human mobility. Bolivia recorded its highest cumulative incidence in early 2023, signaling a severe public health crisis. **Objective**: To analyze dengue cases in Bolivia (2014-2023) from a spatio-temporal perspective, identifying the climatic, environmental, and sociodemographic factors associated with transmission and the expansion of Aedes aegypti vector. **Methods**: A longitudinal observational study was conducted using departmental data. Annual Standardized Incidence (ASI) was calculated. calculated. Climatic and environmental variables included NDVI, maximum temperature, and precipitation. Generalized Additive Models (GAM) were applied to interpret spatio-temporal structures. **Results**: The highest ASI values were concentrated in the eastern departments: Pando, Beni, Tarija, and Santa Cruz. Major outbreaks (2015, 2016, 2020, and 2023) coincided with the rainy season. NDVI showed the strongest correlation with incidence. The optimal GAM explained 67.8% of the variance. Incidence stabilized after 20 mm of rain and decreased below 20 °C. **Conclusion**: Dengue transmission in Bolivia is driven by climatic and environmental factors, primarily affecting the eastern regions. Foreign mobility and rainwater collection tanks are emerging risks. The study supports integrating eco-epidemiological models under a One Health approach for effective cross-border control.

Keywords: Aedes aegypti, Arbovirus, climate change, Dengue epidemiology.

Abstract

El dengue es un arbovirus global, . En América, su incidencia ha aumentado de manera significativa en los últimos años, impulsada por el cambio climático y la movilidad humana. Bolivia registró su mayor incidencia acumulada a principios de 2023, lo que representa un importante problema de salud pública. **Objetivo**: Analizar la incidencia del dengue en Bolivia (2014-2023) desde una perspectiva espacio-temporal, identificando los factores climáticos, ambientales y sociodemográficos asociados a la transmisión y a la expansión del vector Aedes aegypti. **Métodos**: Se realizó un estudio observacional longitudinal con datos departamentales. Se calculó la Incidencia Estándar Anual (ISA). Las variables climáticas y ambientales incluyeron NDVI, temperatura máxima y precipitación. Se aplicaron Modelos Aditivos Generalizados (GAM) para capturar asociaciones no lineales y para interpretar las estructuras espacio-temporales. **Resultados**: Las ISA más altas se concentraron en los departamentos orientales: Pando, Beni, Tarija y Santa Cruz. Los brotes críticos (2015, 2016, 2020 y 2023) coincidieron con la temporada de lluvias. El NDVI mostró la correlación más fuerte con la incidencia. El modelo GAM óptimo explicó el 67,8% de la varianza. La incidencia se estabilizó a los 20 mm de lluvia y descendió con temperaturas inferiores 20 °C. **Conclusión**: La transmisión del dengue en Bolivia está impulsada principalmente por factores climáticos y ambientales, con riesgos emergentes asociados a la movilidad de población extranjera y al almacenamiento de agua de lluvia. Los hallazgos respaldan la integración de modelos eco-epidemiológicos bajo un enfoque enfoque One Health para un control transfronterizo más efectivo.

Palabras claves: Aedes aegypti, Arbovirus, Cambio climático, Epidemiología del dengue.

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Dengue, one of the world's most prevalent and serious arboviruses, poses a risk to up to 40% of the world's population, with 390 million infections and 20,000 deaths annually in more than 125 countries[1,2]. In the Americas, dengue cases have increased significantly, with 2.8 million cases reported in 2022, more than double the figures recorded in 2021. The surveillance and monitoring undertaken by the World Health Organization (WHO) showed that 2023 began with strong dengue transmission in the South American, and this is expected to increase in the near future due to favorable weather conditions for mosquito proliferation[2].

The effects of climate change, such as increased rainfall and higher average temperatures, have created ideal conditions for the colonization of new areas by the *Aedes aegypti*, spreading dengue to non-tropical South American countries, such as Bolivia[3].

While dengue is a multifactorial disease[4], increased internal and external travel traffic, driven by road and air movement, migratory populations, trade, and tourism, facilitates the transport of arboviruses by infected travelers (imported cases)[3], which can subsequently lead to the establishment of local transmission in new areas, which is exacerbated by vector activity and population susceptibility[5].

During the first quarter of 2023, the highest cumulative incidence observed until now in Bolivia was recorded, reaching 264.4 cases per 100,000 population[2]. Furthermore, several different serotypes have been circulating in Bolivia since 2014. A previous study[4] highlighted the key role of serotype in disease severity, for example, DENV-2 can cause seven times more cases of severe disease compared to other serotypes, due to its higher pathogenicity and faster replication. Furthermore, it has been shown that Aedes aegypti species successfully adapted to altitudes above 2,200 m, colonizing, for example, the Bolivian department of Cochabamba[6].

Consequently, communicable diseases often cross borders, requiring special attention[4,5]. The focus on the dengue health crisis in South America, given the current emergence of dengue in previously unaffected areas could lead to the development of a potential terrestrial border transmission pathway, affecting countries that are geographically connected, such as Chile, Bolivia, and Peru. In this new scenario, the urgent collaboration of national and international agencies will be necessary to address the public health problem.

This study aims to analyze dengue cases in Bolivia from a spatio-temporal statistical perspective. It will consider the climatic, environmental, and sociodemographic factors involved by performing an exploratory statistical analysis and implementing Generalized Additive Models (GAM) alongside etiological analysis. The goal is to identify factors that contribute to understanding the unexpected appearance of Aedes aegypti. To achieve this, the study will use annual dengue incidence data aggregated by province in Bolivia during the period of 2014-2023.

Although recent studies in Latin America have researched the influence of climate on dengue, most of these studies are descriptive and focus on limited regions or specific time periods. For instance, studies conducted in Peru emphasize the role of El Niño, without applying spatiotemporal models capable of capturing nonlinear dynamics[3]. This gap highlights the scarcity of studies that integrate climatic, environmental, and demographic variables into a unified framework to explain the incidence of dengue in heterogeneous ecological contexts. Our study addresses this need by using Generalized Additive Models (GAMs), which allow for the modeling of flexible and nonlinear relationships, offering a more robust understanding of dengue dynamics in Bolivia.

Material and methods

The study design is longitudinal observational and uses statistical modeling with an exploratory focus, aimed at identifying

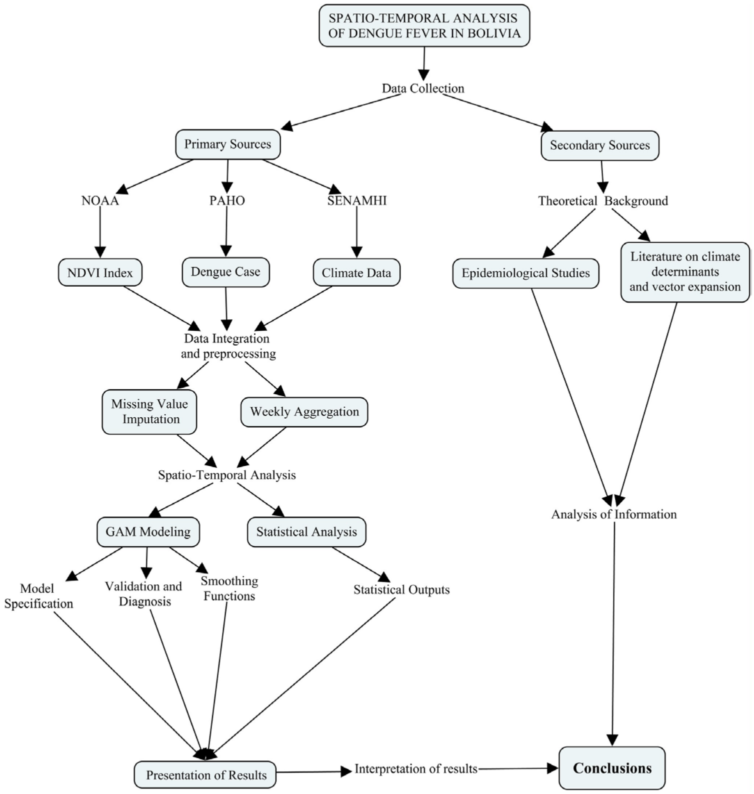

Figure 1. Flowchart created with CmapTools of the methodological process for the spatio-temporal analysis of dengue in Bolivia. It describes the primary and secondary data sources, the integration and preprocessing steps, and the analytical methods applied.

spatiotemporal patterns in the incidence of dengue in Bolivia between 2014 and 2023. This study was exempt from ethical review and approval because it was not conducted on animals or humans, it was based on the integration of publicly available data from official sources. Bolivia[7,8], with an area of 1,098,581 km^2, is in the center of South America. It borders five countries and is administratively divided into nine departments. The methodological process, as illustrated in Figure 1, is structured in five phases that allow for the reproducibility of the study.

First Phase Data Collection:

We compiled data from both primary and secondary sources. Primary sources involved:

- **Epidemiological and demographic data***:* Epidemiological data on dengue cases in Bolivia, were obtained from the Pan American Health Organization (PAHO)[9] weekly reports and aggregated from January 2014 to September 2023. Population data in Bolivia was obtained from the National Institute of Statistics (INE) of Bolivia[10].
- **Meteorological data and Environmental data***:* The climatic data for Bolivia were provided by the National Meteorological and Hydrological Service (SENAMHI)[11]. Maximum temperature and precipitation were selected as key variables, due to its proven relationship with dengue fever[12]. The values of the El Niño 3,4 Sea Surface Temperature (SST) Anomaly Index obtained from the National Oceanic and Atmospheric Administration (NOAA)[13].

The NDVI anomaly value was obtained from Food and Agriculture Organization of the United Nations (FAO)[14] and NOAA[13]. The Normalized Difference Vegetation Index (NDVI) is utilized for the distribution of environmental data, the NDVI index[15]. It is an indicator for evaluating vegetation indicating the density and health of vegetation.

Second Phase Data Integration and Preprocessing*:*

All datasets were synchronized at each department and aggregated weekly. Missing values were imputed using a previous value interpolation strategy, repeating the last available value or adding it to the previous period in the event of interruptions[16]. The Annual Standardized Incidence (ASI) per 100,000 inhabitants was calculated for each department using:

Table 1 presents a summary of the variables to be incorporated into the spatio-temporal analysis of dengue incidence in Bolivia.

Table 1. Summary of the variables used in Spatio-Temporal Analysis in this study.

Variable	Type	Unit of Measurement	Variable type in the model	Observation
Standard Incidence of dengue	Quantitative	#Cases/100,000 inhabitants	Dependent	Dengue cases over time and space
Mean temperature	Quantitative	°C	Independent	Impacts vector reproduction and survival
Total precipitation	Quantitative	mm	Independent	Affects reproduction site availability for the mosquito
NDVI	Quantitative	Index (-1 to +1)	Independent	Vegetation cover, important to the vector's habitat
Population density	Quantitative	Inhabitants/km^2	Independent	Influence exposure and transmission
SST	Quantitative	Index (-4 to +4)	Independent	Correlation with changes in atmospheric circulation and weather patterns
Department	Categorical	Spatial	Geographic	Administrative division departmental
Year/Month	Categorical	Year/Month	Adjustment	Supports modeling of seasonal and temporal effects

The table classifies each variable according to its function within the GAM framework, its nature, and the justification for its inclusion. Climatic variables, such as precipitation and maximum temperature, were selected for their proven influence on mosquito reproduction and viral transmission. NDVI was included as an indicator of vegetation cover and ecological suitability of habitats. The ENSO 3.4 SST index was incorporated to capture large-scale climate variability affecting regional patterns. Finally, demographic indicators, such as total population by department, were integrated to standardize incidence rates and reflect population exposure.

Third Phase Spatio-Temporal Analysis:

We applied A Generalized Additive Model (GAM)[17], this extends generalized linear models by replacing linear predictors with the sum of smoothed functions of the variables, capturing nonlinear relationships between dengue incidence and climatic/environmental predictors. The modeling process incorporated:

- Model specification using cubic smoothing splines.
- Estimation via restricted maximum likelihood (REML) and marginal likelihood.
- Validation and diagnostics, including residual analysis, explained deviance, and penalized criteria using Generalized Cross Validation (GCV) and Akaike Information Criterion (AIC) scores for optimal performance.

Statistical outputs and The models were implemented in R (v4.3.3)[18] using the ***mgcv***[17] and ***MASS***[19] packages. The graphs of the results were also created using the R language and the ***ggplot2***[20] package.

Fourth Phase Interpretation of Results:

An epidemiological interpretation of the results was performed, identifying critical areas, periods of high transmission, and the possible association of interannual variation in incidence with climatic phenomena.

Fifth Phase Conclusions:

This consisted of discussing the findings to generate conclusions and public health recommendations, focusing on epidemiological surveillance and vector control strategies.

Results and analysis

The results of the exploratory spatiotemporal analysis are shown in Figure 2. The results identified higher ASI values in Pando, Beni, Tarija, and Santa Cruz, while Oruro and Potosí registered the lowest incidence rates. The most critical years were 2015, 2016, 2020, and 2023, with a maximum incidence rate of 30,2 per 10,000 inhabitants in 2023 in Tarija, with high dengue incidence values during the first 20 weeks in all departments. An increase in ASI values was observed from week 40 onwards, especially in Beni, Pando, and Cochabamba, indicating a seasonal variation associated with climatic factors[6,21].

The results also detected an interannual oscillation in dengue incidence during 2016, 2020, and 2023. The underlying causes of this phenomenon could be related to the impact of the El Niño Southern Oscillation (ENSO)[6,21].

As can be seen, dengue outbreaks in Bolivia tend to coincide with the rainy season, which generally occurs from week 40 of one year to week 20 of the following year. According to data reported by SENAMHI, maximum temperatures during this period ranged from 20,0°C to 35,0°C in Beni, La Paz, Pando, and Santa Cruz, conditions that favor the proliferation of *Aedes aegypti*[3].

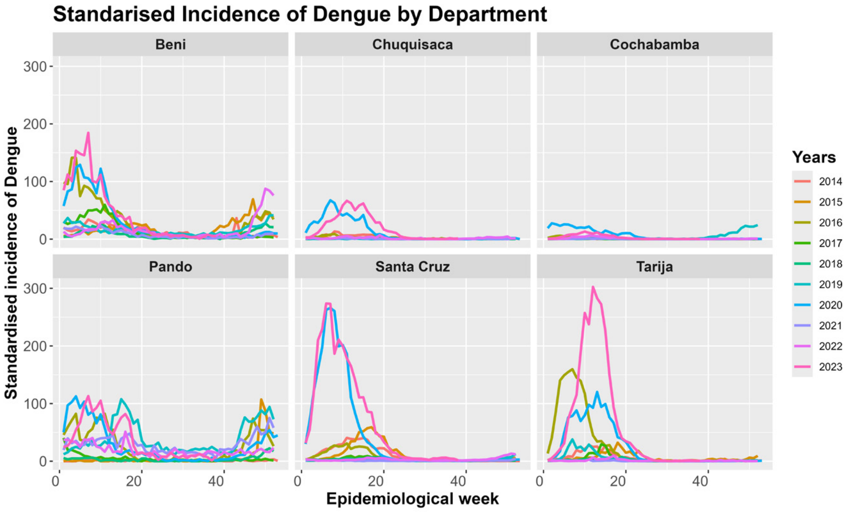

Figure 2. Departmental ASI of dengue in Bolivia, aggregated from 2014 to 2023 showing an increase in dengue cases from week 40 onwards with interannual fluctuations in 2016, 2020 and 2023, indicating seasonal variations related to climate.

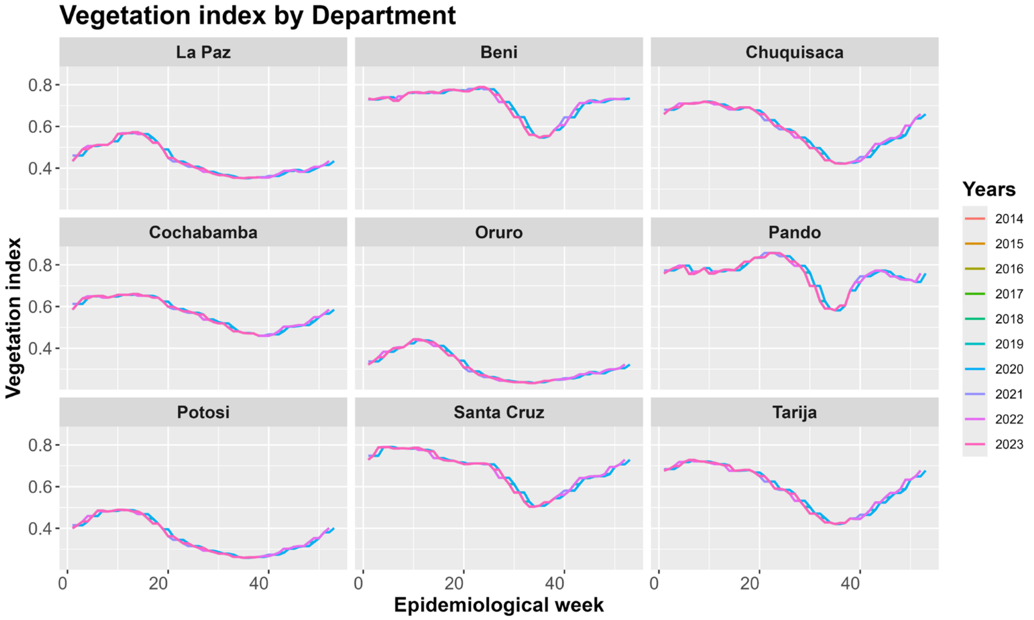

Figure 3. Highlights the weekly patterns of NDVI in the Bolivian departments. All years show a seasonal trend with a decrease around week 20 and an increase around week 40. The departments with the lowest NDVI levels have the lowest dengue incidence rates

Figure 3 shows the departmental patterns of NDVI aggregated weekly during the period under study. A seasonal trend was observed for all years, with a drop in the level around week 20 and an increase around week 40, following a similar pattern during the first weeks of the following year. La Paz, Oruro and Potosi showed the lowest NDVI levels. It is precisely in these departments where dengue incidence rates are lowest.

Table 1. GAM models performed to assess whether climate variables and the NDVI index explain the incidence of dengue in Bolivia during the period January 2014 to September 2023.

		Model 1		Model 2		Model 3		**Model 4**	
	Variable	Coeffic	p-value	Coeffic	p-value	Coeffic	p-value	**Coeffic**	**p-value**
	Intercept	1.147	$< 2e^{-16}$	1.147	$< 2e^{-16}$	0.7079	$2e^{-12}$	0.689	$6.5e^{-6}$
Department	Oruro	-1.742	$4.5e^{-10}$	-1.742	$4.5e^{-10}$	-1.659	$1.3e^{-8}$	-1.585	$9.8e^{-8}$
	Potosí	-3.882	$2.7e^{-13}$	-3.882	$2.7e^{-13}$	-3.806	$1.2e^{-12}$	-3.716	$5.3e^{-12}$
	Pando	-1.274	$<2e^{-16}$	-1.274	$< 2e^{-16}$	-0.695	$1.7e^{-5}$	-0.697	$2e^{-5}$
	Beni	-0.853	$1.5e^{-9}$	-0.853	$1.5e^{-9}$	-0.511	0.001	-0.614	$9.8e^{-5}$
	Chuquisaca	-0.712	$1.3e^{-11}$	-0.712	$1.3e^{-11}$	-0.713	$1.3e^{-8}$	-0.710	$9.8e^{-8}$
	Cochabamba	-0.559	$3e^{-6}$	-0.559	$3e^{-6}$	-0.311	0.025	-0.237	0.101
	Santa Cruz	-0.981	$<2e^{-16}$	-0.981	$< 2e^{-16}$	-0.644	$3.9e^{-7}$	-0.609	$3.3e^{-6}$
	Tarija	0.162	0.108	0.162	0.108	0.132	0.273	0.138	0.284
		Smooth terms	p-value	Smooth terms	p-value	Smooth terms	p-value	**Smooth terms**	**p-value**
	Precipitation	1.930	$<2e^{-16}$	1.930	$<2e^{-16}$	3.918	$<2e^{-16}$	4.170	$<2e^{-16}$
	Max Temperature	1.722	$<2e^{-16}$	1.722	$<2e^{-16}$	3.971	$<2e^{-16}$	5.853	$<2e^{-16}$
	NDVI	1.000	$<2e^{-16}$	1.000	$<2e^{-16}$	3.979	$<2e^{-16}$	5.861	$<2e^{-16}$
	Niño 3.4	1.865	$<2e^{-16}$	1.865	$<2e^{-16}$	3.747	$<2e^{-16}$	5.732	$<2e^{-16}$
	General indicators								
	R-square (adj)	0.149		0.149		0.23		0.251	
	Deviance explained	64.8%		64.8%		66.6%		67.8%	
	UBRE	0.1722		0.1722		0.1167		0.0778	
	AIC	19102.24		19102.24		18849.9		18671.9	

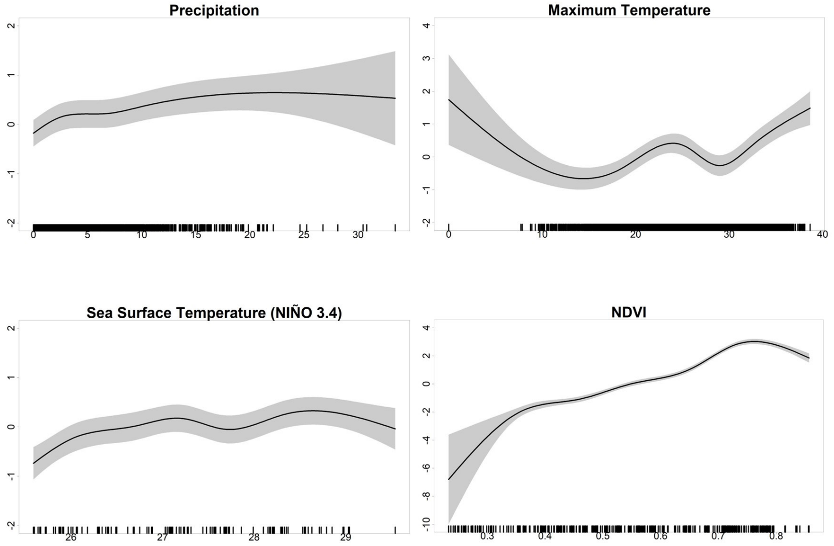

Figure 4. Estimated smooth functions from GAM optimal model (model 4), using epidemiological data for dengue fever in Bolivia from 2014 to 2023, showing that the incidence of dengue cases is correlated with rainfall per epidemiological week

Between 2014 and 2023, dengue incidence showed the strongest correlations with NDVI, maximum temperature, and precipitation, while the Niño 3,4 index displayed only a weak association. Analyses focused on critical years—2016, 2020, and 2023—confirmed these trends, with NDVI consistently yielding the highest correlation coefficients. Precipitation dynamics, potentially influenced by El Niño events, may contribute to increased dengue incidence in the region.

Four representative GAM models were implemented and evaluated for comparative purposes. Table 2 comparatively summarizes the coefficients and goodness-of-fit statistics (R-squared, explained deviance, UBRE, and AIC) across the four models. This comparison allows us to evaluate which specification best captures the spatio-temporal variability of dengue incidence. Model 4 arises as the optimal model, explaining 67,8% of the variance and showing the lowest AIC and UBRE values, representing the best data and, consequently, its optimal predictive performance.

The spatial patterns revealed by Model 4 indicate that Oruro and Potosí exhibit the lowest incidence trends, while departments such as Pando, Beni, Chuquisaca, Cochabamba, Tarija, and Santa Cruz show moderate trends. Likewise, rainfall and maximum temperatures were of interest, supported by NDVI and Niño 3,4 which effectively smooth these values. These results are illustrated in Figure 4, which depicts the smooth functions of Model 4. The figure demonstrates the non-linear relationship between rainfall and dengue incidence, confirming that incidence stabilizes after approximately 20 mm of rainfall—a threshold consistent with the biological resilience of Aedes aegypti eggs and its capacity for vertical transmission[6].

In relation to maximum temperature, dengue incidence is observed to decrease below 20 °C, while this counter-intuitive pattern is consistent with similar temperature effects observed in other parts of the world[6]. Furthermore, higher NDVI values are linearly correlated with dengue incidence, making it an indicator that could be useful, and it should be evaluated for other geographic locations. Finally, in the case of El Niño 3,4, temperatures between 26 and 29 ºC increase the incidence of dengue cases, but temperatures above 29 ºC decrease it. There is a probability that this is due to the influence of El Niño on precipitation.

Discussion

The application of Generalized Additive Models (GAM) coupled with NDVI, and the El Niño 3.4 SST index proved effective in identifying climatic and environmental variables associated with dengue transmission in Bolivia. However, the explanatory power of these models was not absolute, underscoring that dengue incidence cannot be fully explained by climatic, environmental, or sociodemographic variables alone. Other determinants, such as human behavior, population density, migratory flows, deficiencies in public services, and the ecological distribution of mosquito species, remain largely unaccounted for and should be incorporated into future analyses[4,21].

The present study shows that dengue incidence in Bolivia is greatest in eastern areas, which could spread to the west and south of the country. The disease mainly affects vulnerable young people aged 10-39 years, according to studies conducted in other parts of the world[22]. The health situation in Bolivia could also worsen in the future, due to the precariousness of the Bolivian health. Although dengue is not a new disease in the southern part of the continent (particularly Chile and Bolivia), public health information is only disseminated in a very few media outlets largely limited to publications aimed at tourists, and there are also few epidemiological studies on the subject.

The study also demonstrates that the spatial and temporal trend of dengue is related to climatic, environmental and sociodemographic factors at the regional level, confirming the future impact of climate change on the proliferation of dengue and other arboviruses, driven by future sociodemographic and ecological changes. These findings are consistent with previous studies conducted by other authors[3,12,23]. a study in Argentina reported a strong relationship between climate variables and dengue dynamics[12] . In Peru, recent studies have pointed to the importance of population mobility and urban density as risk factors[3].which have similarly identified climate variability, land use patterns, and population dynamics as key drivers in the expansion and intensification of dengue transmission.

Increasing mobility of foreigners and the proliferation of rainwater tanks may facilitate dengue transmission in areas previously free of Aedes aegypti. The abundance of mosquitoes correlates with temporary breeding sites that increase during the rainy season. Aedes aegypti eggs can survive dry for 12 to 15 months and hatch with rainfall. If these eggs are infected by vertical transmission, the new larvae can transmit the virus to humans immediately after hatching, resulting in a higher incidence of dengue after heavy rains, especially in densely populated border areas[23].

Similarly, that the demographic variable of total population by department was incorporated for the calculation of the ASI, this study has limitations due to the lack of open, homogeneous, and disaggregated sociodemographic data in Bolivia (e.g., population density, poverty levels, mobility, etc.). This restricts accurate assessment of the role of social determinants in dengue transmission, despite using the total population for incidence. It is recommended that future studies integrate additional sources (surveys, detailed records) to strengthen eco-epidemiological models and improve prediction.

This study also highlights the need for future studies examining the redistribution of the mosquito population in Bolivia, particularly to areas not yet invaded, mainly located on the border with Chile, and the need for ecological and epidemiological studies covering various stages of the disease and in different settings. In addition, eco-epidemiological models should be incorporated into public health responses, with a One Health perspective in cross-border contexts[4,5].

Although our results offer important insights, it is necessary to approach them carefully because of possible biases and errors in the methodology. First, there is potential selection bias arising from heterogeneous epidemiological surveillance capacity across departments, as surveillance capacity varies geographically. Second, measurement bias is possible due to heterogeneity in the spatial distribution of weather stations, which may not fully capture local climate variability. Third, systematic errors could result from underreporting or misclassification of dengue cases in official records, a widespread problem in endemic regions. Finally, the use of aggregated departmental data may mask intradepartmental heterogeneity, limiting the accuracy of spatial inferences.

Conclusions

This study confirms the importance of climatic and environmental variables on population health in relation to dengue. It is likely to be applicable to other Aedes-borne diseases, such as chikungunya[24], Mayaro[24,25], and yellow fever[26].

As the global incidence of these diseases increases with climate change and increased migration, the urgent incorporation of epidemiological studies of vector-borne diseases in public health contexts becomes increasingly critical[2,5,6,27]. Therefore, a much more reliable monitoring system with comprehensive spatial and temporal scale records would provide the increasingly needed effective responses in the fight against vector-borne infectious diseases.

In line with eco-epidemiological models and the One Health framework, such systems should integrate climatic variables (precipitation, temperature), environmental indicators (NDVI), and large-scale climate oscillations (ENSO 3.4 SST), as these determinants have been theoretically and empirically linked to dengue transmission dynamics in Latin America[5,28]. Comparative studies in Argentina and Brazil have demonstrated that rainfall and temperature thresholds are critical drivers of epidemics[29], while systematic reviews in Peru highlight the role of climate variability and El Niño events in expanding risk areas[3].

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All authors have read and agreed to the published version of the manuscript.

Data availability: The datasets analyzed in this study are public and open access and are available in their respective repositories, which are cited in the text of the manuscript and linked to in their respective references.

Artificial Intelligence: The main idea, research and writing of this manuscript are entirely human-generated, and any use of AI was limited to non-substantive editorial support, such as grammatical correction.

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