Dengue outbreaks on the rise: A statistical and spatial analysis approach to dengue incidence, climate and environmental patterns, drivers and implications in Piura, Peru

A thesis submitted by

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in partial fulfillment of the requirements for the degree of

Master of Science

in

Environmental Policy and Planning

Tufts University

August 2025

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Abstract

Dengue epidemics are an escalating public health and climate policy concern, particularly as the disease expands into areas previously considered climatically unsuitable. In Peru, the dry and arid northwestern coastal region of Piura has experienced unprecedented increases in dengue incidence over the past two decades. This re-emergence challenges the traditional assumption of dengue as a disease of tropical, humid cities and highlights the need for integrated urban and environmental planning approaches. Effective early warning systems must consider local exposure to both climate and urban infrastructure vulnerabilities, especially in the context of intensifying climate change.

This thesis analyzes district-level dengue incidence in Piura from 2003 to 2023 and its relationship with climate and urban features using spatial statistics (EHSA, LOA), econometric modeling (OLS, Fixed Effects) and ArcGIS, Geographically Weighted Regression (GWR). Results show that dengue outbreaks in Piura are temporally and spatially heterogeneous, with the region acting as a sporadic but intense hotspot. Temperature exhibited a non-linear and delayed relationship with dengue incidence, becoming a strong and spatially consistent predictor during ENSO years. Precipitation showed a small but significant effect, with the relationship turning negative during ENSO events. Humidity was not found as a strong predictor of dengue incidence. Overall, the three climate variables demonstrated context-dependent and localized effects. Notably, access to piped water showed paradoxical results -acting as both a mitigating and risk-enhancing factor depending on the district and year. These findings underscore the critical importance of reliable water infrastructure and sound water management practices in dengue mitigation strategies, particularly in the context of a changing climate.

Key Words

Climate change; Climate-health nexus; Dengue fever; Econometrics; El Niño Southern Oscillation (ENSO); Environmental planning; Epidemiology; Early warnings; Geographically Weighted Regression (GWR); Hotspot analysis; Peru; Piura; Piped water access; Public health; Spatial clustering; Spatial statistics; Spatiotemporal analysis; Urban infrastructure; Vector-borne diseases.

Acknowledgements

This thesis marks the culmination of a two-year journey as an international graduate student and the realization of a longstanding dream to study and live abroad. In my pursuit for knowledge and skills to become an expert in climate and environmental policy and planning, I found mentors, friends, and a city I now dearly call home. None of this would have been possible without their support and the unwavering love of my family and friends, both in Mexico and in Boston.

I dedicate this thesis to my parents, Cristina and Arturo, and my aunt and uncle, Adriana and Agustín. To you I am grateful for all the strength, wisdom and warmth that carried me through and helped bring this adventure to a successful end. To Aimé and Daniel: thank you for your ceaseless encouragement that has always inspired me. Watching you thrive from the distance has given me the joy and peace of mind I needed to write this thesis. And to my dear Iván, I can't thank you enough for all your love, care and support throughout this journey – and for lifting my spirits to keep me going when the map making felt endless.

My deepest gratitude goes to Peilei Fan for inspiring me and trusting me with this project. Thank you for your guidance and care throughout the process. To Mary Davis, thank you for believing in this thesis from the very beginning and for always asking the right questions. This research and my COP29 experience in Baku are the two defining milestones of my time at UEP, and neither would have been possible without your unwavering support — for which I will always be grateful to you both. Thank you also to Shubham Singh for your support and patience in the making of this thesis.

I would like to thank Sumeeta Srinivasan, Erin Coughlan de Pérez, Shomon Shamsuddin and Julie Schaffner, whose teaching and classrooms offered invaluable guidance, clarity, and the space I needed to explore and develop the ideas that shaped this thesis. Thank you for your support and for the generosity with which you shared your knowledge with me. And to Kristin Skrabut, my academic advisor—thank you for your guidance, your friendship, and for always giving me the extra push I needed to make this journey truly meaningful.

To all my UEP peers and friends, it has been an enormous pleasure learning and growing alongside you!

This thesis is part of the project "Climate, Land, & (Health) Outcome of Dengue Fever (CLOUD)" of the Global Urban Environmental and Socioeconomic Sustainability (GUESS) Lab, led by PhD Peilei Fan (PI), funded by National Aeronautics and Space Administration (NASA).

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Chapter 1: Introduction

Dengue is a viral infection that spreads from mosquitoes (mainly the *Aedes aegypti*) to people and is considered a public health issue around the world. The dengue virus (DENV) can present as an asymptomatic or symptomatic infection, and in some cases it can be lethal (Amaya-Larios et al., 2020). This vector-borne disease is more common in tropical and subtropical climates. However, dengue has been expanding geographically into more remote regions and to higher latitudes and altitudes, challenging the historical perception of dengue as mainly a disease of tropical cities (Alghsham et al., 2023; Gibb et al., 2023; Zeng et al., 2021). Just in the last two decades global incidence of dengue has increased from 505,430 cases in 2000 to 5.2 million in 2019 (WHO, 2024).

In recent years, Peru has observed an unprecedented increase in the incidence of dengue fever, putting Peruvian authorities and the population on alert. In 2023, the National Center for Epidemiology, Disease Prevention and Control (CDC) reported 273,684 cases of dengue, with a national cumulative incidence of 808.9 cases per 100,000 inhabitants (Ministerio de Salud del Perú, 2024). By February 2024, CDC reported a sustained increase of 97.88% in dengue cases nationwide, compared to the same period in 2023, with several regions exceeding the national cumulative incidence (Ibid.).

Amongst them is Piura, a northwestern coastal department – equivalent to a state in the US- characterized by a predominantly hot desert climate with some subtropical highland areas (World Bank Climate Change Knowledge Portal, 2021b). In 2023, Piura reported 34,252 cases, accounting for approximately 30% of the national total (Defensoría del Pueblo, 2023).

According to the epidemiological alert of the Government of the Piura Region, by the end of 2023, the number of cases surpassed 70,000, which was 6.6 times higher than in 2022 (Gobierno Regional Piura, 2024). By the end of 2024, Piura was found amongst the departments with higher dengue incidence per 100 thousand habitants. Now, Piura and a handful of other departments -Loreto, Tumbes and Ucayali- are preparing to be national pioneers in applying a vaccination against dengue (Dirección Regional de Salud Piura, 2024).

A large body of literature has explored the roles of temperature and precipitation as main drivers of dengue incidence. In 2023, the Intergovernmental Panel on Climate Change (IPCC) reported a global increase in the prevalence of vector-borne diseases, including dengue, and estimated further widespread in a global warming climate (Calvin et al., 2023). Urbanization is another factor cited as a major contributor to the increasing dengue occurrence globally (Gubler, 2011). Yet, urbanization trends and human mobility have rarely been quantitatively analyzed as drivers of dengue expansion (Colón-González et al., 2023). Recent research has shown that urban infrastructure factors, such as sanitation, water supply, and urban growth, can predict local spatial patterns of dengue incidence (Gibb et al., 2023). Other variables, such as prevention policies, or access to healthcare and warning systems of epidemics, have been widely unexplored as drivers or mitigators of dengue incidence.

Research Questions

In this study, I examine the effects of climate variability, built environment features and the interactions amongst these – as hypothesized drivers of increased incidence in the region- on dengue incidence at the district level in Piura, Perú, one of the regions with the highest dengue incidence in Peru. I intend to address the following main research questions in this thesis:

1. What is the historical trend of dengue incidence in Piura, Peru, (from 2000-2023) and how is it spatially distributed across districts? How does it compare to national averages?
2. What is the relationship between climate variables and dengue incidence at the districts of Piura? How are these relationships modified by urban features?
   - What is the seasonality of dengue incidence and its relationship with climate variability (temperature, precipitation, and relative humidity) at the district level in Piura?
   - How does the relationship between climate variability and dengue incidence differ during ENSO and non-ENSO years/seasons?
   - How does access to piped water and sewage systems modify the effect of climate variability on dengue incidence?
3. How does the spatial relationship between climate and environmental variables and dengue peaks shifts across districts through different epidemic years?

This study contributes to the academic literature on climate change and its impacts on human health in urban contexts in the Global South, particularly those related to potential changes in the distribution, abundance and transmission of vector-borne diseases. The methodology and results can help inform national and local authorities in the formulation of early warning systems that can trigger timely and effective anticipatory action for vector control in a changing climate.

Study Area

The study area for this research is the department of Piura, located in the northwestern part of the country, politically composed of 8 provinces and 65 districts. Piura is bordered on the north by Tumbes-Perú and the Republic of Ecuador; on the east by Cajamarca-Perú and Ecuador; on the south by Lambayeque-Peru; and on the west by the Pacific Ocean. Its capital and political and administrative center is the city of Piura located on the coast of this territory (Municipalidad Provincial de Piura, 2025).

Figure 1 Study Area: Piura, Peru

The department of Piura is made up of 2,599 population centers, of which 96.1% are rural - having less than 2,000 inhabitants (Presidencia del Consejo de Ministros, 2024); 20.7% of the population of the department of Piura lives in rural population centers while 79.3% lives in urban centers (Ibid.). According to the National Service of Meteorology and Hydrology of Peru (SENAMHI), Piura's climate is classified as arid or semi-arid with moisture deficiency in all seasons of the year, with only a minority of semi-dry or temperate and humid areas inland, on the eastern slopes (SENAMHI, 2020) . Rainfall is scarce, except when the El Niño phenomenon occurs, years in which rainfall is abundant. During the extraordinary El Niño years, average temperature during the summer exceeds 35°C (95 °F) and can reach up to 40°C (104 °F) (Banco Central de Reserva del Perú, 2011), while anomalies in precipitation can bring up to 3000 mm of rainfall between September and May (SENAMHI, 2014).

This thesis is structured as follows. The next chapter presents a **literature review** to inform the selection of the hypothesized drivers of dengue incidence used in the analysis. The subsequent **methods and data** chapter outlines the data sources and processing steps used to construct the panel dataset, along with an overview of the analytical approaches employed in each chapter. **Chapter 4** addresses the first research question, examining historical trends, seasonality, and spatial clustering of dengue incidence in Piura, Peru. **Chapter 5** explores the relationship between climate variability, urban characteristics, El Niño events, and dengue outbreaks over the study period with the use of data visualization and econometric modeling. **Chapter 6** investigates how the effects of climate and environmental factors on dengue incidence vary spatially across districts during peak epidemic years using geographically weighted regression maps. Each chapter includes a detailed description of methods, analysis, results, and discussion. The **conclusions** chapter summarizes the key findings, discusses their policy implications in the context of Piura and beyond, acknowledges the study's limitations, and suggests avenues for future research.

Chapter 2: Literature Review

This section provides an overview of commonly explored drivers of dengue incidence in urban contexts and how these have been measured to determine their significance in exacerbating or mitigating the disease. This review was limited to peer-reviewed journal articles, searched via Jumbo Search and Google Scholar. Findings on drivers of dengue incidence are grouped in four categories to help orient the analysis further: Climate, Built Environment, Socioeconomic, and Policy.

2.1 Climate Drivers

One growing concern of the effects of climate change globally is the emergence of vector-borne diseases and the burden on healthcare systems as a result. Climate variability, particularly precipitation and temperature changes, play a key role in spreading waterborne and water-related diseases as they increase the area of land with a climate suitable for dengue fever transmission (Ahmed et al., 2020; Hales et al., 2002; Lin et al., 2024).

In this sense, Peru has observed a change in distribution of average mean surface air temperature from 16.95 °C -19.05 °C in the 1951-1980 period, to 17.82 °C- 19.70°C in the 1991-2020 period (World Bank Climate Change Knowledge Portal, 2021c). While the distribution of precipitation moved from 1580-2516 mm in the 1951-1980 period to 1750-2561 mm in the 1991-2020 period (Ibid.).

In Piura, projections under the 3-7.0 Shared Socioeconomic Pathway (SSP) scenario – in which global warming is expected to reach 2.0°C to 3.7°C above pre-industrial levels by 2100- estimate an increase of mean surface temperature in the range of 0.84 and 1.77 °C and high levels of uncertainty regarding changes in precipitation, ranging from a decrease of -72 mm to a large increase up to 250 mm, by 2060 (Ref. Period: 1995-2014) (World Bank Climate Change Knowledge Portal, 2021a). According to the literature, these changes could be influencing a higher incidence of dengue in this area that was previously considered unsuitable for vector-borne disease proliferation.

Lee et. al found that increased temperature suitability has contributed to the expansion of the dengue transmission in Brazil by calculating the number of months per year each municipality lay within the suitable temperature ranges (between 16.2℃ and 34.5℃) (Lee et al., 2021). A large body of experimental literature supports that increasing temperatures result in higher infection, dissemination, and transmission of viruses such as chikungunya, dengue, and Zika viruses (Delrieu et al., 2023). Common to most studies is that temperature effects on dengue are highly non-linear (Descloux et al., 2012). Temperature has also been found to influence dengue outbreak seasonality and transmission season length (Colón-González et al., 2023; van Panhuis et al., 2015). And although Gibb et. al argue (2023) that there is little evidence of how warming may have shaped recent dengue distribution and expansion trends, other scholars sustain that future warming temperatures are projected to significantly expand dengue transmission suitability worldwide (Messina et al., 2019). Estimates from a systematic review on more than a hundred studies and a meta-analysis of about 50 suggest that each 1 °C increase in high temperatures is associated with a 13% increase in risk of dengue infection (Damtew et al., 2023).

Precipitation patterns are consistently analyzed to understand dengue transmission. A recent study conducted in Arizona examined the *Aedes aegypti* abundances and daily precipitation, with results suggesting that precipitation may explain 90% of mosquitoes abundance, with anthropogenic water sources supporting mosquitoes during long, precipitation-free periods (Newman et al., 2024).

Although precipitation patterns influence the creation and flush-away of vector breeding sites, their relationship to dengue transmission may be nonlinear, delayed, and determined by how seasonality and extremes interact with local socio-environmental factors (Caldwell et al., 2021). In their study on the interactions between climate change, urban infrastructure and mobility as drivers of dengue emergence in Vietnam, Gibb et. al estimated monthly precipitation as well as deviations from historical average hydrometeorological conditions for the reference period 1981–2020 using the Standardized Precipitation Evapotranspiration Index (SPEI), from short- to long timescales, as a more sensitive approach to local context than simple precipitation (Gibb et al., 2023). They found that dengue risk increased under either short-term heavy rainfalls or long-term droughts, with water supply improvements mitigating drought-associated risks in non-extreme conditions (Ibid.).

The academic literature suggests that high humidity shortens incubation and blood-feeding intervals, favoring mosquito longevity and thus dengue transmission. According to Descloux et. al, this may explain why a sustained high humidity in the months leading to the outbreak were associated with a higher risk of dengue (Descloux et al., 2012).

A group of scholars performed an analysis of the nonlinear and delayed effects of drought and extreme rainfall on dengue risk in Barbados from 1999 to 2016. Their findings show that drought conditions positively influenced dengue risk at long lead times of up to five months, while excess rainfall increased the risk at shorter lead times between one and two months (Lowe et al., 2018). Descloux et al. developed an early warning system using a long-term data set (39 years) including dengue cases and meteorological data, including mean, minimum and maximum temperature, relative humidity (RH), precipitation and El Niño-Southern Oscillation (ENSO) indices in New Caledonia. Contrasting with Lowe's result, they found no significant correlation of dengue incidence with annual mean RH and precipitation for the 1971–2010 period, while evapotranspiration was found to be significantly higher during the epidemic years (Descloux et al., 2012). Yet another study conducted in Metro Manila, Philippines with climate data from 1996 to 2005, found that rainfall was significantly correlated to dengue incidence, while no significant correlation between dengue incidence and temperature was established (Su, 2008).

Finally, extreme hydrometeorological events, such as tropical storms, extreme rainfall, floods, and droughts, are thought to increase risk of water- and mosquito-borne diseases, with different delays between urban and rural settings (Lowe et al., 2018). In the context of Peru, scholars have studied the effect of ENSO on the risk for dengue outbreaks. A time-series analysis at the district-month level, found positive and significant effects of temperature and ENSO, but not from precipitation (Dostal et al., 2022). However, this study does not account for humidity, population growth or any urban infrastructure-related variables.

2.2 Built environment

Amongst the most cited drivers of dengue and other vector-borne diseases are infrastructure features. Piped water access has been consistently classified as a determinant for dengue outbreaks. Recent studies suggest that, while precipitation may explain mosquitoes abundance, anthropogenic water sources support mosquitoes during long, precipitation-free periods (Newman et al., 2024). This is because the main vector of dengue viruses, the *Aedes* *aegypti*, often breeds in water storage containers used by households without tap water supply. Therefore, scholars argue that adequate water supply may reduce the propensity to store water around homes, reducing vector breeding sites and thus transmission (Gibb et al., 2023). However, interruptions in water supply caused by increasing climate variability, drought, precipitation changes, or urbanization, have made water storage practices a necessity for many households (Chen et al., 1994; Ortega & Montes-Mata, 2024; Trewin et al., 2021), creating favorable conditions for the survival of the *Aedes aegypti*, and thus transmission of DENV.

Having adequate water supply (tap or piped water) was associated with lower DENV infection in Ecuador and Paraguay (Power et al., 2022). Researchers in Vietnam conducted an individual-level cohort study during two epidemics based on dengue hospital admissions. This study showed that areas with adequate water supply did not experience severe outbreaks compared to those without, and that after controlling for wealth, education and population density, the risk of dengue was higher in rural areas than in urban areas, largely explained by lack of piped water supply in the study area (Schmidt et al., 2011).

However, the presence of a public water supply system alone, or lack thereof, is not enough to explain dengue propensity. Scholars from Brazil found that water storage and differences in water supply irregularity between privileged and under-privileged areas can also explain differences in exposure to DENV. For example, dwellings in privileged areas that are not connected to the public water system may instead have a private pump system, whereas inhabitants in under-privileged areas tend to buy water from horse-drawn carts, motorized tanks or from people who walk around the streets with large cans of water, leading them to store water in diverse containers (Caprara et al., 2009). Although the sealing of water tanks is a practice that has been implemented as a dengue control mechanism, not all dwellings have tanks with lids or mesh (Caprara et al., 2009), and attitudes or practices towards water storage in uncovered containers behaviors remain (Nguyen-Tien et al., 2021).

Several strategies related to water containers have been implemented to control for dengue outbreaks. In Taiwan, incidence of dengue fever cases decreased after the implementation of a waste recycling system and the promotion of breeding site reduction campaign for waste management, including the release of fish in water containers to prevent larvae breeding (Chen et al., 1994). In Veracruz, Mexico and Trujillo, Venezuela, the use of window curtains and water container covers treated with insecticide in 18 urban sectors resulted in the reduction on the number of containers with immature stages per 100 houses, although no significant differences were found between control and intervention groups (Kroeger et al., 2006). Regulatory approaches, such as compliance with properly sealing rainwater tanks in Brisbane, Australia, have been found to reduce tank infestation and population spread of the vector (Trewin et al., 2021).

Water storage for human consumption is not the only water-related risk factor for dengue incidence. A study conducted in Guangzhou, China, found that increasing the water surface areas in the city through the construction of urban artificial lakes was strongly associated with increased number of dengue cases by about 30-50% in 2014, since larger surface water areas provide more breeding habitats and thus more contact opportunities between vectors and hosts (Tian et al., 2016).

Similar to water supplies, sewage systems are said to play a significant role in reducing or increasing risk of DENV. Improvements in sanitation systems can reduce the risk of infection by reducing the density of water storage containers, however, if not well treated, drains and septic tanks can be conducive mosquito breeding sites (Charlesworth et al., 2022; Gibb et al., 2023). A study conducted in Puerto Rico found that ill maintained septic tanks are common in suburban and rural areas and that these contribute significantly to dengue transmission, even during dry seasons (Barrera et al., 2008). The findings of this study suggest that repairing septic tanks or replacing them with sewage systems can reduce the dengue burden.

Paradoxically, Oliveira et. al's (2023) research in the Midwest region of Brazil found that as water and sanitation improvement actions are implemented in the city, such as piped water and sewerage, the cross-correlation between rainfall and dengue increases (Oliveira et al., 2023). This is thought to be explained by the fact that the continuous availability of water in sewage drains and septic tanks make permanent habitats for vector reproduction and better quality of water reservoirs is preferred by the mosquitoes for breeding (Ibid.). Charlesworth et al. proposes the use Sustainable Drainage Systems (SuDS), consisting of installing structures to encourage infiltration of contaminated surface water into the ground to reduce breeding opportunities for mosquitoes. However, this is not a straightforward solution in low-income countries where existing drainage infrastructure is either insufficient or totally lacking (Charlesworth et al., 2022).

Several articles attribute dengue outbreaks to *urbanization*. These arguments also trace back to inadequate water and sewage infrastructure in rapidly urbanizing contexts – mainly driven by population growth (Colón-González et al., 2023) and its close association with suitable breeding environments near crowded populations. Gubler (2011) argues that "the dramatic global geographic expansion and the increased incidence of epidemic dengue coincided exactly with urban growth and globalization" (Gubler, 2011, p. 5). Research shows that cities in the global South face significant challenges in providing adequate sanitation infrastructure and services to keep pace with population growth (Beard et al., 2022), while poor and low-income populations are particularly affected as they face acute water stress and daily struggles to secure access to potable water (Beard & Mitlin, 2021; Khan & Arshad, 2022; Sultana, 2020). Population growth and accelerating urbanization have historically widened the gap between urban water demand and supply (Dos Santos et al., 2017), with informal settlements being disproportionately impacted (Adams et al., 2022; Hernández Aguilar et al., 2021; Hoelzel, 2024; Mehta et al., 2014). Evidence suggests that areas with unreliable access to water supply are highly susceptible to dengue outbreaks, particularly after a drought (Lowe et al., 2021).

In addition to water supply access and sewage infrastructure, the effects of *urbanization* on the rise of dengue patterns have been explored through different approaches. Tiong et. al report that increasing land development, decreased vegetation, and population growth – characteristics of urban sites in Malaysia- coincide with increased human presence and activities, and thus higher dengue prevalence (Tiong et al., 2015). In a different approach, Wu et.al (2009) explored the relationship between cumulative incidence of dengue fever, climatic and non-climatic factors in Taiwan. The level of urbanization was measured as a compounded factor including average population density, percentage of service occupation, percentage of agriculture occupation, household ownership, number of clinics per 10,000 person, and median income (Wu et al., 2009). The study found that higher levels of urbanization were strongly associated with increasing risk on the occurrence of dengue fever at township level (Ibid.).

In Ouagadougou, Burkina Faso, Fourtnet et. Al (2016) analyzed the apparent prevalence of flavivirus infections according to urbanization patterns, including land tenure, building density of the districts, water access, waste management, as well as individual (sex, age) and household features (education, socioeconomic level, house appearance) from a sample of previously infected children. This analysis found that the lack of householder's education, neglected house appearance and building density were associated with past flavivirus infection, while socioeconomic level and type of water supply did not influence flavivirus prevalence. The authors hypothesize that the latter is due to water being scarce in Ouagadougou and, thus not stored for a long time since containers are being regularly emptied (Fournet et al., 2016). Another interesting finding of this study is that good practices of waste management had the unexpected consequence of increasing risk of infection, associated with an increase in the availability of municipal dumpsters (Ibid.).

Emerging research employing machine learning techniques and predictive model approaches suggest that the geographic expansion of DENV to more remote areas and higher latitudes and altitudes is driven by increasing human mobility. Gibb et. al argue that higher mobility can contribute to maintenance of dengue transmission in areas where epidemic fade-outs are more likely, such as with lower population densities or seasonally transient climatic suitability (Gibb et al., 2023). In their study conducted in five major municipalities in Vietnam, they measured human mobility through per-capita road travel rates and predicted mobility fluxes. Results found these mobility metrics to be positively associated with dengue risk, particularly in northern areas where climatic conditions might not be suitable to support local transmission, yet higher connectivity facilitates DENV reintroductions (Ibid.). Lee et.

al. also found that highly connected cities within urban networks in Brazil had greater odds of dengue outbreaks (Lee et al., 2021).

Similarly, Colón-Gonzáles et. al (2023) projected changes in dengue incidence in eight countries across Southeast Asia based on different future scenarios of determinants of dengue risk, including within-country human mobility and international air travel volume (Colón-González et al., 2023). Results show that international air travel increase dengue risk, consistent with other studies in Brazil and Asian countries where aerial transportation networks are found to influence the spread of DENV (Nunes et al., 2014; Tian et al., 2017).

An innovative approach conducted by Wesolowski et. al (2015) measured the dynamics between a dengue outbreak in Pakistan from 2013 and human mobility using mobile phone information. Researchers found that mobile phone-based mobility estimates can help predict the geographic spread and timing of epidemics in both recently epidemic and emerging locations (Wesolowski et al., 2015).

2.3 Socioeconomic Factors

Lower income has been thought to be a risk factor for dengue infection, however there is little empirical evidence on the matter. Vanlerberghe and Verdonck argue that the burden of dengue is higher amongst the poor due to a lower rate in use of vector-human barrier methods, and because interventions tend to be less effective in disadvantaged populations due to less awareness, less compliance by suppliers and end-users, and less access or coverage (Vanlerberghe & Verdonck, 2013). They also argue that dengue can lead to greater inequality due to loss of income related to absence from work and high health costs, further exacerbating poverty in some already impoverished households (Ibid.). In contrast, Suárez et. al consider the poverty-tropical illness relationship, particularly in the case of dengue, to be a stigmatizing and reductionist approach to the complexity of dengue fever. Their argument is that the biopsychosocial space of this disease cannot be reduced to marginal urban, rural or poverty contexts given that dengue has expanded and adapted to the social organization of modern contexts (Suárez et al., 2004).

Some assessments of the relationship between poverty or social vulnerability and arboviral infection have been based on household income, socioeconomic categories or per capita income quartiles or quintiles (Power et al., 2022). Yet evidence for poverty as a determinant of dengue is not well established or inconsistent (Mulligan et al., 2015; Power et al., 2022). A study conducted in Brazil found that urban slum communities with high levels of absolute poverty had increased risk of dengue transmission (Kikuti et al., 2015). A different study in Malaysia showed that high seroprevalence – number of people tested positive for dengue virus- was significantly associated with low household income (Abd-Jamil et al., 2020). In contrast, a spatial analysis conducted by Barcellos et. al found that sectors with dengue cases present high income characteristics, including the predominance of houses and good sanitation infrastructure (Barcellos et al., 2005). Similarly, an analysis of different arbovirus outbreaks in French Guiana found that DENV affected richer population and richer areas, unlike Chikungunya virus (CHIKV) (also transmitted by the A. aegypti) which affected poorer districts (Bonifay et al., 2017). Researchers speculate that a possible explanation for this difference is that CHIKV outbreak followed that of DENV and thus richer districts may have had better and more effective control measures, particularly in the midst of elections that made richer neighborhoods more "politically interesting" areas (Ibid.).

One last dimension related to poverty and social vulnerability has been health vulnerability. A study in Belo Horizonte, Brasil found that high dengue seroprevalence rates were associated with the type of dwelling (apartment or house/shed, with apartment being a protective factor) and with a high health vulnerability index – composed of socioeconomic and environmental variables - in the place of dwelling, (Pessanha et al., 2010). Kikuti et. al found that, besides socioeconomic factors, residential proximity to a health care facility was associated with improved case detection (Kikuti et al., 2015). Similarly, a spatial analysis conducted in Purwosari District, Indonesia found that distance, duration of travel time, and the number of doctors in health facilities play a significant role in the health facility selection by dengue fever patients (Susianti et al., 2023).

However, access to healthcare goes beyond proximity to medical centers. The study in French Guiana examined healthcare coverage status in relation to CHIKV and DENV infection, finding that a lack of private health insurance was associated with higher CHIKV infection (Bonifay et al., 2017). An interview-based study with mothers of children infected with dengue in eastern Cambodia found that quality of healthcare varies substantively depending on ability to pay, and that inadequate health insurance and health systems, along with high rates of hospitalization and mortality from dengue fever amongst children reflect the difficulties that communities and families face when having to cover for emergencies, diagnosis and treatments of dengue (Khun & Manderson, 2008).

2.4 Policy: Early Warnings, Risk Perception and Communication

Anticipatory action initiatives are increasingly designed to address extreme climate and weather events. However, the COVID-19 pandemic triggered the need to look beyond climate and weather-related hazards to include epidemics and to consider the compounding and exacerbating impacts on vulnerabilities when multiple hazards coincide (German Red Cross et al., n.d.). Early detection of emerging outbreaks has been found to be crucial for efficient and cost-effective local responses to infectious diseases (Hussain-Alkhateeb et al., 2018; Lowe et al., 2014). In this sense, the Special Programme for Tropical Disease Research and Training of the WHO introduced the Early warning and response system (EWARS) together with national dengue control services and academia in partner countries to address the need for an alarm system for dengue outbreaks.

Early warning systems rely on accurate and timely surveillance to develop predictive models to help visualize, understand and combat infectious diseases in anticipation to an outbreak. As it has been described in this literature review, many studies have improved modeling of outbreaks or transmission patterns based on serologic, socioeconomic, biophysical data. Yet, the design of an early warning system for vector borne diseases are especially complex due to the involvement of various factors originating from the human, animal and insect sector as well the disease itself (Racloz et al., 2012).

Lessons from anticipatory action for climate change adaptation suggest that, beyond accurate data and surveillance, early warning systems depend on risk perception from the population (Eitzinger et al., 2018; Meyer et al., 2014) and the means of communication to encourage early action (Al Mamun et al., 2013), such as preventive measures and practices to mitigate dengue transmission. On risk perception, a cross-sectional study in Havana, Cuba found a statistically significant relationship between economic status, knowledge on dengue, risk perception and practices and underlying determinants, but only knowledge on dengue had a significant, direct, positive, effect on decreased risk practices for dengue (Castro et al., 2013).

Similarly, findings from a systematic review of literature on the risk perceptions, attitudes, and knowledge of chikungunya suggest that lack of knowledge is an important barrier for motivating community level interventions and personal protection against mosquitoes (Corrin et al., 2017).

Regarding risk communication, several studies conclude that the role of media coverage positively influences the public's familiarity, knowledge, and behavior towards disease prevention (Gamboa & Rodriguez Lesmes, 2018; Ndii, 2022; Ophir & Jamieson, 2020). A study conducted in Brazil shows that danger alerts are important in risk situations, yet the involved communicators lack skills to convey the information, while communities demand targeted informative and educational strategies for preventing arboviruses (Jesus et al., 2021). The results from a quasi-experimental study conducted in Thailand suggest that health literacy programs can bring desired changes with respect to dengue fever prevention (Padchasuwan et al., 2024). Liu et. al (2021) suggest that communication interventions should target to improve the perceived susceptibility and the perceived severity of dengue fever among the population, even when there is sound knowledge on dengue prevention practices (Liu et al., 2021).

Chapter 3: Data Sources and Methods

Building on insights from the literature review and the availability of spatially and temporally resolved data, this thesis examines the effects of climate variability, built environment characteristics, and their interactions on dengue incidence at the district level in Piura, Peru. This section is organized into two parts: the first details the sources, resolution, and preprocessing steps applied to both spatial and non-spatial datasets; the second outlines the methodological approaches used to address each of the study's research questions, including both spatial and econometric approaches.

3.1 Data Description

3.1.1 Geographic ID

Peru uses a code system known as *ubigeo* to identify each administrative unit in the country. As of September 2023, there were 1,891 districts, including 65 in the Piura department (Secretaría de Gobierno Digital, 2023). However, many of these districts were created after 1993 through redrawing of administrative boundaries, which also altered their corresponding ubigeos over time. To ensure geographic consistency across the study period (2000–2023), all data were harmonized to match the most recent political boundary definitions, represented by the 1,891-districts shapefile. This required adjusting earlier census and population data—originally aligned with outdated ubigeo codes—to correspond with the current administrative divisions. These adjustments were only made for Piura districts.

District *Veintiséis de Octubre* was created in 2013 from the original Piura district. Since no data existed for this district prior to 2017, estimates for census data of earlier years (1993, 2005, 2007) were derived using proportional allocation based on the 2018 population. The share of Veintiséis de Octubre's population in 2018 relative to the combined total of Piura and Veintiséis de Octubre was calculated and assumed constant across earlier years. This proportion was then applied to (re)estimate values for accessed to piped water, sewage systems, health insurance coverage and monetary poverty for both Veintiséis de Octubre and Piura. Districts within the Sechura province (Sechura, Bellavista de la Unión, Bernal, Cristo Nos Valga, Rinconada-Llícuar, and Vice) had data available for all census years. Their ubigeo codes changed over time—from being part of Piura province (e.g., codes starting with 20011...) to becoming part of Sechura province (codes starting with 200800). Their ubigeos were recoded to their corresponding "200800" identifier across all data points. All climate and land use data were extracted through zonal statistics based on this 1,891-district version of the shapefile to ensure spatial consistency.

3.1.2 Dengue and Population

This research employs data on the notification of dengue cases to the Peruvian public health surveillance system. This information is managed by the National Center for Epidemiology, Prevention and Disease Control (CDC PERU). The data come from the National Epidemiology Network (RENACE), which is comprised of 10,232 health facilities of the Ministry of Health, EsSalud and others in the sector at the different levels of Peru's Regional Health Directorates (Plataforma Nacional de Datos Abiertos, 2024). The dataset was downloaded on January 25, 2025, with the lates version available (2024-12-11). The original dataset includes a historical series from 2000 to 2023. It classifies cases by diagnosis (with and without alarm signs and serious dengue), and type (probable, confirmed, and suspected), and includes district of residence, age, sex, date of initial symptoms, date of diagnosis, and date of notification. For this study, all cases were grouped by month and year per district, with a final dataset of 757,890 cases reported from 2000 to 2023 in 622 of the 1891 districts. Population data for the years 2000, 2005, 2010, and 2015 were derived from satellite data (European Commission, JRC, GHS-POP R2023A, 2023). Population data for 2018 through 2022 were collected from INEI (2022). Missing values between known years were filled using linear interpolation in R, and values outside the known range (2023) were forward filled with data from 2022, so that all months in the same year had the same population value. Incidence was calculated per 100,000 habitants, based on a given year's population.

3.1.3 Access to Piped Water and Sewage System

Data on access to piped water was downloaded from Sistema de Consulta de Base de Datos (REDATAM) of Peru National Census for the years 1993, 2005, 2007 and 2017 (INEI, 1993, 2005, 2007, 2017). For access to piped water, data was collected at the district level for the census question on the types of water supply in the house (*Abastecimiento de agua en la vivienda*). The latest Peru Census classifies access to water supply in nine different categories: Public network inside the dwelling; Public network outside the dwelling, but inside the building; Pylon or pool for public use; Truck - cistern or other similar; Well (subway water); Spring or pond; River, ditch, lake, lagoon; Other; Neighbor. INEI considers only the first three categories as water for human consumption coming from the public network. That is inside the dwelling, outside the dwelling, but inside the building or public use pylon, while other categories are considered as no public water supply (INEI, 2020). For this research, only those three categories were considered to estimate the percentage of households with access to piped water system by districts in Piura.

Similarly, data on access to public sewage was downloaded from REDATAM for the same Census years under housing categories for sewage system in the house (*Servicio higiénico que tiene la Vivienda*). For this variable, Peru Census classifies sewage services in the following categories: Public sewage system inside the dwelling; Public sewage system outside the dwelling, but inside the building; Septic tank, septic tank or biodigester; Latrine (with treatment); Cesspool or cesspit; River, ditch, canal or similar; Open field or outdoors; Other. In this case, access to the public sewage system includes only dwellings with access inside the house or outside the house, but inside the building (INEI, 2020). For this research, only those two categories were considered to estimate the percentage of households with access to public sewage.

Given that census data was only available for 1993, 2005, 2007 and 2017, values for 2000 were set equal to the 1993 values. After visually confirming an average upward trend in the distribution of these data, the remaining missing values between known years were filled using linear interpolation, while data from 2018 to 2022 were backfilled with the latest known data point (2017) in R Studio.

3.1.4 Climate Data

The climate data for this analysis includes Precipitation (PR), Relative Humidity (RH), and Near-Surface Air Temperature (T2m- 2 meters above the ground) from 2003-2023. Monthly PR and RH were sourced from TerraClimate, because of the availability of monthly data and higher resolution compared to other products (Abatzoglou et al., 2018), which is better in the context of this local-level research. Monthly rasters for PR represent the aggregated value (in millimeters (mm) per month unit) over all days in each month. Relative Humidity rasters were derived using the ratio of actual vapor pressure (vap) to saturation vapor pressure (e_s), following the formula:

$$RH = (vap / e\_s) * 100$$

Where:

vap = actual vapor pressure (from TerraClimate dataset, in kPa after multiplying by 0.001)

e_s = saturation vapor pressure (calculated using TerraClimate average temperature) in kPa. The saturation vapor pressure e_s is estimated using the August-Roche-Magnus equation (Lawrence, 2005), which is commonly used in meteorology:

$$e\_s = 0.6108 * \exp((17.27 * T) / (T + 237.3)) \text{ kpa}$$

Therefore, each monthly raster of RH represents the average relative humidity for that month, in percentage (%) of the maximum possible water vapor the air held during that month, which provides an indication of the overall moisture content of the air for each month.

The spatial mean, maximum and minimum values of PR and RH were extracted from each monthly raster for every district using the terra package in R Studio, to align the gridded climate data with Piura's administrative units.

Additionally, Near-Surface Air Temperature was collected from KNMI Climate Explorer, using the ERA5 monthly reanalyses dataset from 2003 to 2023 with coordinates -81.328230--68.652279E_-0.038606--18.350928N for Peru (KNMI, 2025). The spatial mean of T2m values was extracted to Piura boundaries using the terra package in R. All raster data were projected to EPSG:5839- Peru96UTM17, matching the projected coordinate system of the 1891-districts shapefile.

3.1.5 Land Use Data

Annual raster values for land cover type data were obtained from MCD12Q1.061 MODIS at a 500m resolution for years 200, 2005, 2010, 2015 and 2020. Each raster dataset was reclassified using ArcGIS Pro into three categories: vegetated (0), water bodies (1), and built-up/non-vegetated areas (2). The total pixel area (in square meters) of each class was calculated using the Tabulate Area tool. In R, the total district area was computed to derive the percentage of built-up and water area per district-year. Missing values for 2000, intermediate years and post-2020 years, were estimated using the average annual growth rate of built-up area by district, applying it recursively to project and complete the time series of built-up percentages across the full 2000–2023 period.

3.2 Methods

3.2.1 Significance Tests and Spatial Statistics

To identify the historical trend of dengue incidence in Piura, Peru, and how incidence has been spatially distributed across districts (Research Question 1. See Chapter 4), this research used weekly surveillance data on dengue cases from 2000 to 2023 and calculated incidence per 100,000 habitants by month of each year under analysis. Using R Studio, annual and monthly average dengue incidence in Piura were plotted against national averages to identify overall differences, similarities and seasonality. Significance test (T-test and Mann-Whitney U Test) were employed to evaluate the statistical significance of the differences in annual mean incidence between Piura and the national level. Additionally, a Modified Mann-Kendall was performed to identify and compare long-term trends in dengue incidence in Piura and at the national level. Monthly average incidence across all years at the province level was graphed using a heatmap.

Finally, a Space Time Cube using ArcGIS Pro was created to conduct spatial cluster analysis of dengue outbreak trends at national and Piura level. This enabled the performance of Emerging Hot Spot Analysis (EHSA) and Local Outlier Analysis (Local Moran's I) to detect which regions in Peru, and which districts in Piura are statistically significant clusters rather than random occurrences, as well as determine whether dengue incidence at the district level in Piura is randomly distributed or spatially clustered. In both cases, the analysis was run at both 3- and 6-month time steps, using the queen's case (contiguity edges corners), such that spatial units that share a boundary are considered neighbors.

3.2.2 Ordinary least squares (OLS) and Fixed Effects (FE) Regressions

To understand the relationship between dengue incidence, climate variability and urban features at the district level in Piura (Research Question 2. See Chapter 5), the dataset was adjusted to match the extent of the climate variables' available data (from 2003 to 2023). This panel dataset consisted of 544,608 observations: each one corresponding to a year-month-district combination. Chapter 5 used exploratory data analysis and visualization of seasonality trends using ggplot2 package of R studio, as well as statistical modeling.

First, a series of visualizations was run to better understand the functional form of each climate variable in relation to dengue incidence. Annual averages of the three climate variables under analysis– PR, RH, T2m (means) - were visualized using line plots, showing average annual trends across the 65 districts of Peru. Identifiers were used to visualize possible interactions during El Niño Southern Oscillation years, based on the classification of the Índice Costero El Niño (ICEN) by Peru's Multisectoral Commission for the Study of the El Niño Phenomenon (ENFEN). These were labeled by intensity and plotted against climate and incidence trends to explore temporal coincidence.

To understand the bivariate relationship between dengue incidence and climate variables, this study employed scatterplots to visualize every individual (monthly) observation of dengue incidence and mean PR, RH, T2m (correspondingly). Additionally, monthly trends of climate variables across the study period were plotted using facets and seasonal trend lines to understand seasonality of climate variables.

As a first approach to assessing the degree of statistical association between dengue incidence and climatic conditions, a linear regression model was estimated using lm() in R. Following Ren et al., (2017) and Acharya et al., (2018) methods, the dependent variable (raw incidence based on the ratio of cases per population count of a given year), was transformed using the Empirical Bayes Rates methods to smooth out extreme fluctuations in incidence caused by the diverse size of the populations by district, and allow for more accurate and stable estimates (Bakshi, 2024). A log transformation was applied to the raw smoothed incidence to allow for a closer-to-normal distribution of the data.

The model selection process was guided theoretical expectations based on the literature review, exploratory data analysis using ggplot2 visualizations, and evaluation of goodness-of-fit metrics (mainly Adjusted R^2). Initially, an Ordinary Least Squares (OLS) model was run including climate (mean temperature, relative humidity, precipitation), urban infrastructure (access to piped water, sewage, percentage of built-up land area, and percentage of water bodies), and extreme weather events (ENSO dummy) predictors. Interaction, quadratic and lagged terms were added incrementally to the model to evaluate statistical significance of the predictors and changes in goodness-of-fit of the model. Finally, a final version of the OLS model was selected and run using Fixed Effects estimations in R.

Recognizing the likelihood of spatial heterogeneity and non-linearity in the dynamics between climate and dengue, the third chapter explores the use of Geographically Weighted Regression (GWR) as a semi-parametric, more flexible modeling approach.

3.2.3 Geographically Weighted Regression (GWR)

To investigate the spatial variability of climatic and built environment influences on dengue incidence in Piura, Peru (Research Question 3. See Chapter 6), this research conducted a GWR analysis in ArcGIS Pro, using continuous (Gaussian) model type, based on number of neighbors within an optimal distance determined via the golden search method. The dependent variable was the average log Empirical Bayes (EB)-smoothed dengue incidence during the peak transmission season (March–August, as identified in the previous chapters), aggregated at the district-year level. Given that this model is highly sensitive to multicollinearity, the GWR excluded highly multicollinear variables. The final GWR specification estimates include average temperature, its squared term, relative humidity, precipitation, the interaction between precipitation and piped water access, access to piped water, percent built-up area, and surface water coverage. These variables were selected based on their theoretical relevance and model diagnostics steaming from the literature review and Chapter 5, including adjusted R^2 and Akaike Information Criterion (AIC) scores. The analysis was limited to select years (2009, 2010, 2016, 2021, 2022, and 2023) in which Piura experienced heightened dengue incidence compared to national averages, and further distinguished years based on the presence or absence of El Niño events. Maps and graphs were used to visualize the changing temporal and spatial distribution and significance of each variable's coefficients, with maps specifically depicting differences between two epidemic years, one no-ENSO (2021) and another ENSO (2023) year.

Chapter 4. Dengue on the Rise in Piura, Peru

This chapter employs data visualization, statistical tests and spatial analysis tools to explore the temporal and spatial trends and patterns of dengue incidence in Piura from 2000-2023, to identify whether Piura's recent dengue peaks reflect a rare occurrence, in both space and time, or if Piura is a consecutive dengue hotspot at the national level.

Research Question: What is the historical trend of dengue incidence in Piura, Peru, and how is it spatially distributed across districts? How does this compare to national averages in incidence?

4.1 Introduction and Study Context

Given that the aedes aegypti is considered the main vector of dengue fever, the Pan American Health Organization (PAHO) implemented an ae. aegypti eradication program in 1947, resulting in the Americas being an almost dengue-free zone by the late 1950s (Tapia-Conyer et al., 2012). However, the deterioration of this program in the late 1960s facilitated its reintroduction from areas that had failed to eliminate it, and today, most countries in Latin America have ae. aegypti infestation (Cabezas et al., 2015; More et al., 2018; Tapia-Conyer et al., 2012).

In Peru, the reintroduction of this mosquito was detected in 1984 in Loreto, which then spread to neighboring regions such as San Martín and the central jungle (More et al., 2018). In 1990, a dengue epidemic affected major cities in the Amazon region. Today, dengue cases have been reported across nearly all areas of Peru, with all four dengue serotypes circulating in the country (Cabezas et al., 2015).

Over time, dengue has progressively expanded into regions at increasingly higher altitudes, surpassing 1,700 meters above sea level—an elevation where ae. aegypti presence has rarely been documented (Requena-Zúñiga et al., 2016). For instance, in 2015 ae. aegypti was reported in Chulqui, a locality in the district of Churubamba, at an altitude of 1,900 meters. Additionally, the highest recorded presence of ae. aegypti in Peru was recorded in Cayrán, Huánuco province, at 2,227 meters above sea level (More et al., 2018).

In Piura, the expansion of ae. aegypti to higher altitudes follows the broader national trend of dengue vector adaptation to new environments. While early reports placed the highest detection of ae. aegypti in Piura at 1,319 meters in Jilili district (Ayabaca province) in 2005, more recent findings in Huancabamba at 1,959 meters suggest that the mosquito is progressively establishing in areas previously considered unsuitable for transmission (More et al., 2018). These findings suggest an upward expansion of the dengue vector, possibly driven by environmental and / or climatic changes – the subject matter of this thesis-, which could increase the risk of transmission in areas that were once considered low-risk.

4.2 Findings

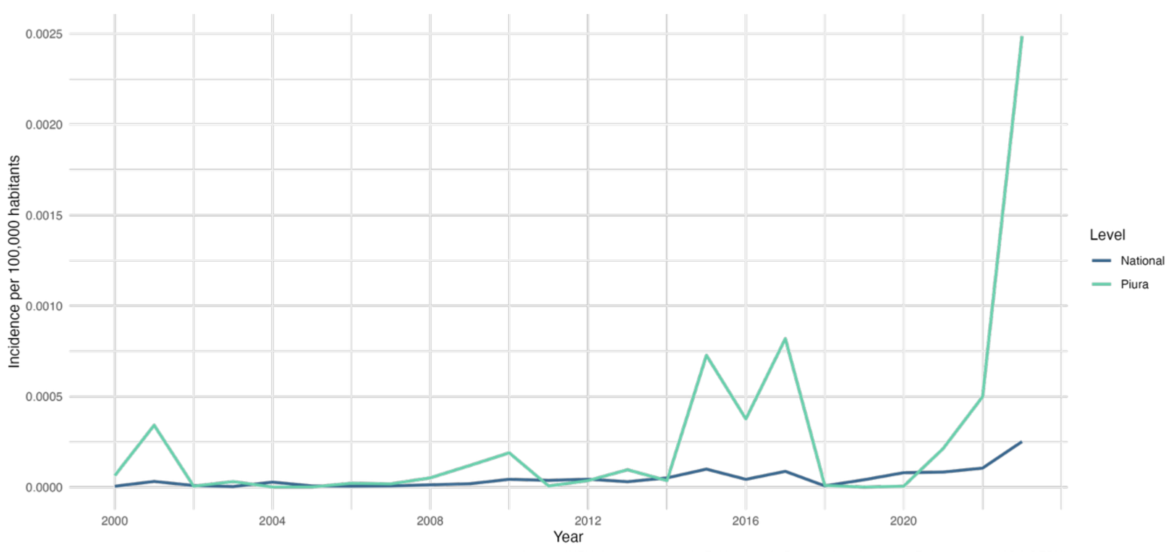
This section presents the key findings on the temporal evolution and spatial distribution of dengue incidence in Piura between 2000 and 2023. Through a combination of trend analysis, significance tests, and spatial clustering methods, this chapter evaluates how Piura’s dengue incidence compares to national patterns and whether dengue outbreaks in the region are becoming more frequent, intense, or geographically clustered. The results highlight Piura's distinct epidemic profile, including its seasonal dynamics, its emergence as a sporadic hotspot, and the significant spatial heterogeneity in incidence across its districts.

4.2.1 Time Trend and Significance Tests

Dengue incidence in Piura is higher than the national average and rising

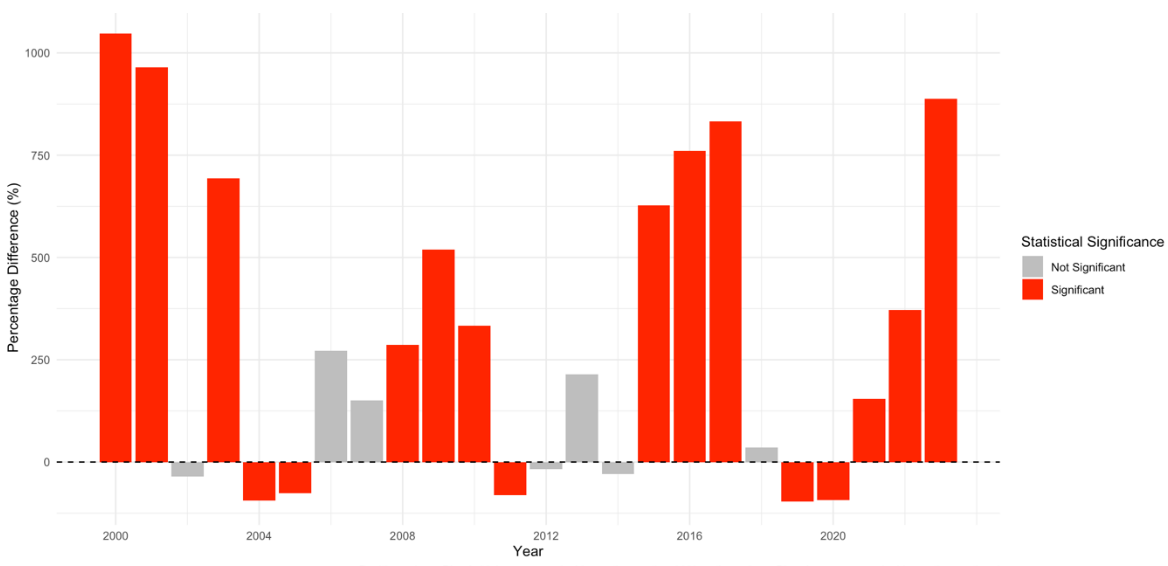
To begin understanding the evolution of dengue outbreaks in Piura, this section looks at changes in dengue incidence (measured as cases per 100,000 habitants) from 2000 to 2023 in the Piura region and at the national level. It should be noted, however, that these figures reflect reported cases by RENACE-CDC Peru, which are subject to underreporting and improvements in surveillance over time; therefore, trends may reflect changes in case detection and reporting capacity. Figure 1 shows the average annual dengue incidence trends at the district level from 2000 to 2023, illustrating how dengue incidence in Piura has evolved over time compared to Peru's average. It can be observed that Piura's incidence trend generally follows a similar pattern to the national average, with some exceptions in 2001, 2015, 2017 and 2023, when Piura's incidence was considerably higher.

Figure 2. Dengue Incidence Trends: Piura vs. National (2000-2023)



A significance test comparing the overall annual mean dengue incidence in Piura and the national average reveals a statistically significant difference between these means, with Piura's average incidence being overall higher (about 5.4 times) than the national average (National mean: 4.767026×10^{-05}, Piura's mean: 2.568977×10^{-04}; p-value $< 2.2 \times 10^{-16}$). However, a year-by-year analysis paints a more nuanced picture. Figure 2 shows how much higher, or lower, Piura's average incidence was compared to the national average in percentage difference terms. When the t-test is applied to each year individually, Piura's dengue incidence was statistically significantly lower than the national mean in 2004, 2005, 2011, 2019, and 2020. In contrast, Piura experienced significantly higher incidence in other years, such as 2000, 2001, 2015, 2016, 2017, 2022, and most recently in 2023. In that year, the mean incidence in Piura (0.00249) was almost ten times the national average (0.000252), with a highly significant difference (p-value = 4.28×10^{-29}), highlighting an exceptional outbreak, like the one in 2000.

Figure 3. Percentage Difference in Dengue Incidence: Piura vs. National (2000-2023)



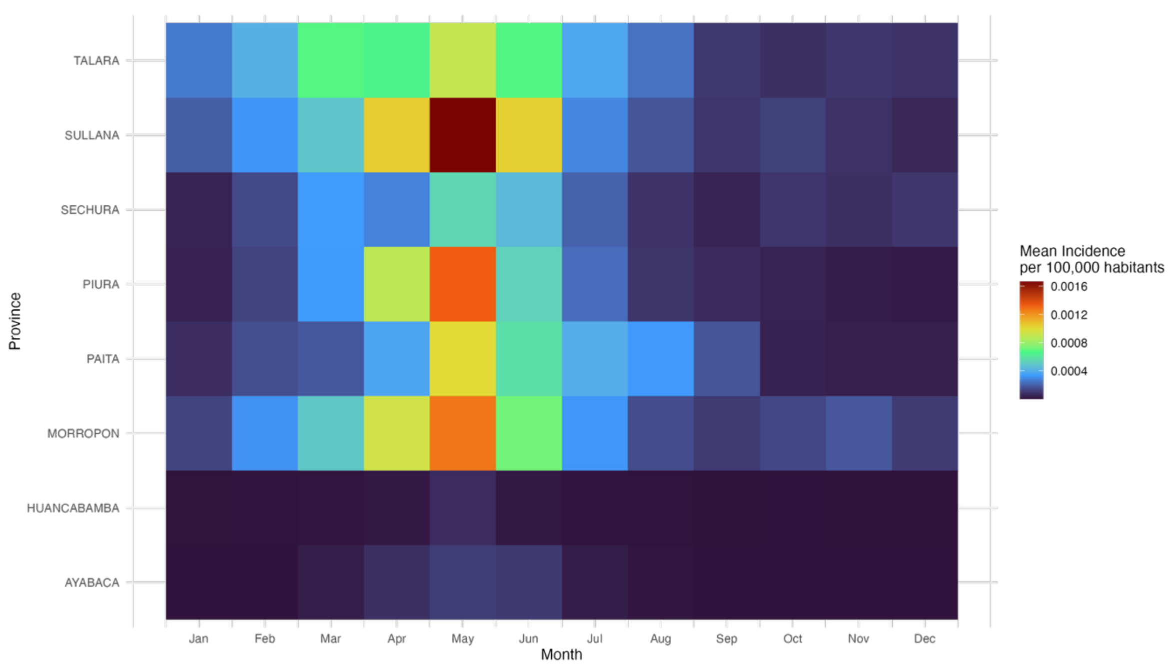
When relaxing the assumption that the dengue surveillance data is normally distributed, a Mann-Whitney U Test, also called Wilcoxon test in R, can help identify whether dengue incidence levels in Piura are significantly different from the national average (McClenaghan, 2024; Yadav et al., 2023). After visually confirming that the distribution of dengue incidence in both groups (Piura and National levels) deviates from normality, a Wilcoxon test was performed using the ggstatsplot package in R. The results confirm that there is a statistically significant difference in mean annual incidence between the two groups ($W = 4,247,061,028$, p-value $< 2.2 \times 10^{-16}$). A negative rank-biserial correlation (-0.14) suggests that the National level has a lower incidence of dengue compared to the Piura's average (Soetewey, 2020).

To further detect whether or not a dengue incidence trend exists within this data, a Mann-Kendall test was employed to assess long-term changes in dengue incidence in Piura, comparing the results to those at the national level (Mandal & Mondal, 2024; Zheng et al., 2023). A positive but not significant Z statistic suggests a weak upward trend in dengue incidence in Piura over time ($Z = 1.7115$, p-value = 0.08699). In contrast, at the national level the test suggests there is a significant upward trend of dengue incidence ($Z = 4.2416$, p-value $= 2.22 \times 10^{-05}$). Considering that this time series data has not been randomly selected and can be influenced by serial correlation, Mandal & Mondal's (2024) methodology suggests the use of Modified Mann-Kendall test for more reliable significance levels in the estimation of dengue incidence trends. Interestingly, after adjusting for autocorrelation Piura presents a highly significant upward trend (corrected Z statistic= 3.2260). The large correction suggests that there was autocorrelation in the data, possibly due to persistent outbreak dynamics in Piura, or because of difference in sample size between groups. At the national level, Z values stayed the same, showing no statistically significant trend, just as in the original MMK test.

Dengue in Piura follows a seasonal pattern

When exploring the seasonal distribution of dengue incidence at the provincial level in Piura, it is possible to identify seasonality of outbreaks. Figure 3 presents a heatmap of the average incidence per month across all years in the dengue sample (2000-2023), aggregated by the eight provinces of Piura. Thus, each square represents the average incidence in each month (per 100,000 habitants). The color grading indicates the average intensity of dengue surges in that month, with dark red signaling largest levels of incidence and dark blue close to zero incidence. For example, the province of Sullana, located in the arid sub-region of Piura, shows the highest average intensity (.0016) in the month of May, along with the provinces of Piura and Morropon. This figure shows a concentration of the highest incidence levels between March and August in all provinces, and a pronounced decrease starting in August.

Figure 4. Average Monthly Dengue Incidence (Piura Provinces, 2000-2023)



4.2.2 Emerging Hotspot and Local Outlier (Moran’s I) Analysis Results

Piura is a *sporadic* dengue hotspot in Peru

Given that this research is based on the constructed timeseries dataset, two Space Time Cubes were created using the Space time Cube From Defined Locations tool in ArcGIS Pro to analyze spatial and temporal cluster patterns. The space time cubes were created using the 1891 districts shapefile for the national level analysis and the 65 districts shapefile for Piura analysis; in both cases the time step interval was set to one month. The space time cubes enabled the use of cluster analysis tools, such as the emerging hotspot analysis (EHSA) and the Local Outlier Analysis (Moran’s I).

The EHSA tool in ArcGIS Pro helps identify trends in the clustering of counts or values (in this case dengue incidence per month in each district) and classifies each spatial unit (the districts) in one of eight specific hot or cold spot trends: new, consecutive, intensifying, persistent, diminishing, sporadic, oscillating, and historical. This tool is based on a space-time implementation of the Getis-Ord Gi* statistic, which considers the value for each bin (monthly dengue incidence) in the context of the values for neighboring bins (ESRI, 2024d).

The analysis was conducted using both 3-month and 6-month time steps for the national dataset and for the Piura region. This means that, for each district (or bin), the tool considers the values of all adjacent districts, as well as their corresponding values from the previous three (or six) time intervals (Ibid.). Thus, the tool incorporates a space-time neighborhood that includes both spatial neighbors (boundary-sharing districts) and temporal neighbors (earlier time steps, in this case months), allowing for the detection of patterns and trends in dengue incidence over the specified time and space (monthly time steps from 2000 to 2023).

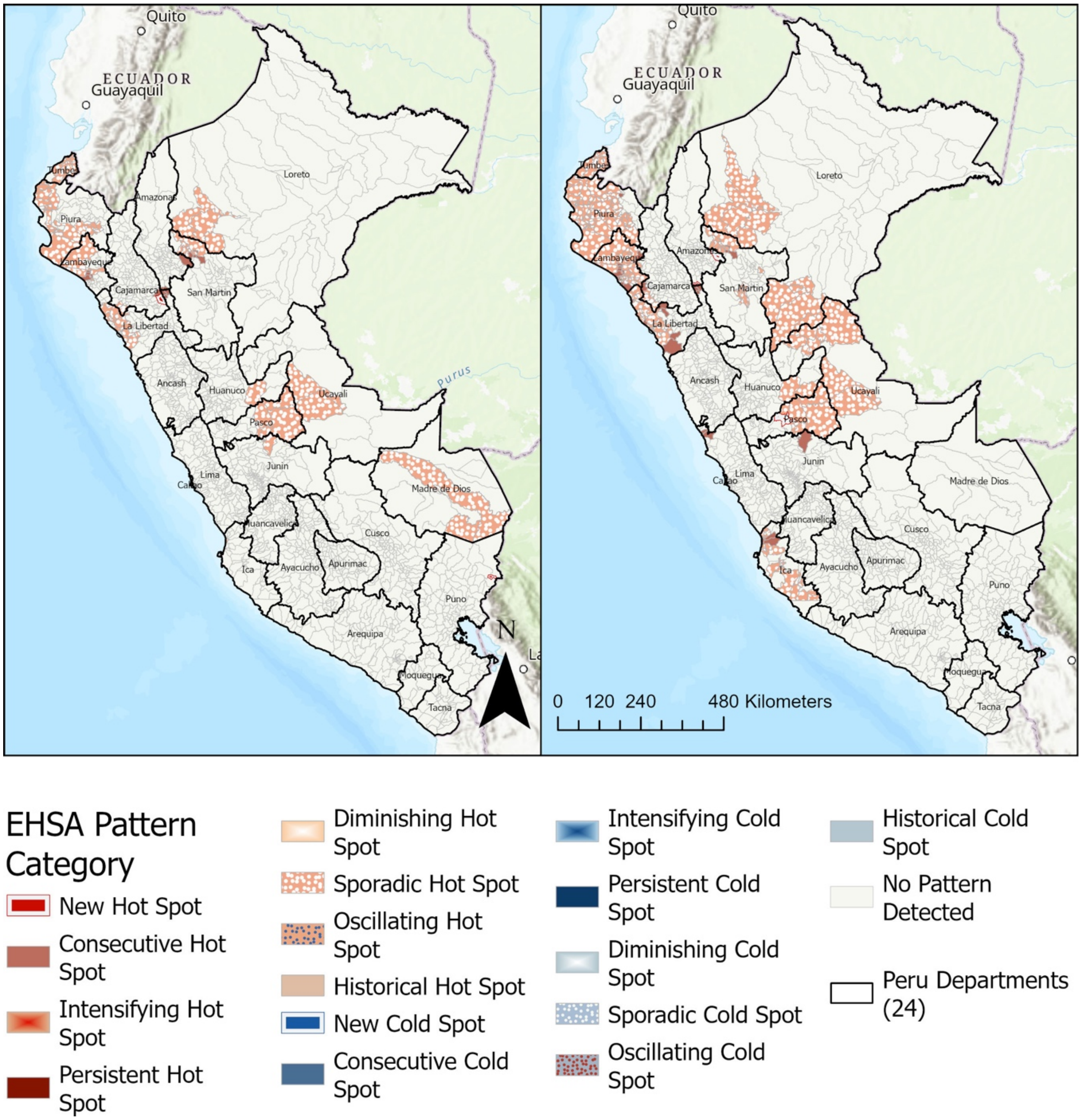
The EHSA tool applied to all Peru districts across the twenty-three years in the panel dataset revealed “Sporadic Hotspots” in Piura region (Fig. 4). These sporadic hotspots extend into neighboring district in Tumbes and Lambayeque departments. According to ESRI’s definitions, a sporadic hotspot pattern indicates that, across the timeseries dataset, only in some of the time step intervals is Piura a hotspot of dengue. More specifically, less than 90 percent of the time-step intervals have been statistically significant hot spots and none of the time-step intervals have been statistically significant cold spots (ESRI, 2024a).

This means that district in Piura can be experiencing significant clustering of high dengue incidence at some intervals over time, but with no consistent pattern. This result is contrasting with the MMK tests that suggested upward trends in the data. The EHSA tool offers a more detailed picture by reflecting incidence with respect to temporal and spatial neighbors, being able to identify a specific pattern in each district. This result could be echoing the annual significance tests, where Piura presented higher incidence only in a handful of years.

In Figure 4, the 3-month time step map on the left reflects short-term trends and is more sensitive to seasonal variation, revealing sporadic hotspots in the coastal arid and dry districts of Piura. In contrast, the 6-month time step map on the right is capturing sporadic hotspots over a longer period, revealing an extended area in all the dry and arid regions in Piura and further south along the coast of Peru. This shows that, in a 6-month time step analysis, all district in the dry and arid regions of Piura present a statistically significant hot spot for the final time-step interval (December 2023) with a history of also being an on-again and off-again hot spot (ESRI, 2024a). That is, high dengue incidence has emerged intermittently over time in Piura’s districts but has become significant in the most recent time period of the dataset.

When performed only at the Piura level (65 districts), the EHSA suggests the presence of sporadic hotspots again in near-coastal districts in the 3-month time step, with only Bernal district as a consecutive hotspot. Based on ESRI's terminology, Bernal showed a statistically significant hotspot pattern consistently in the final time periods, without being a hotspot earlier in the time series, and without more than 90% of all time steps showing significant clustering (ESRI, 2024a). This means that a consecutive hotspot is a district where high levels of dengue cases have only recently started appearing in a sustained way.

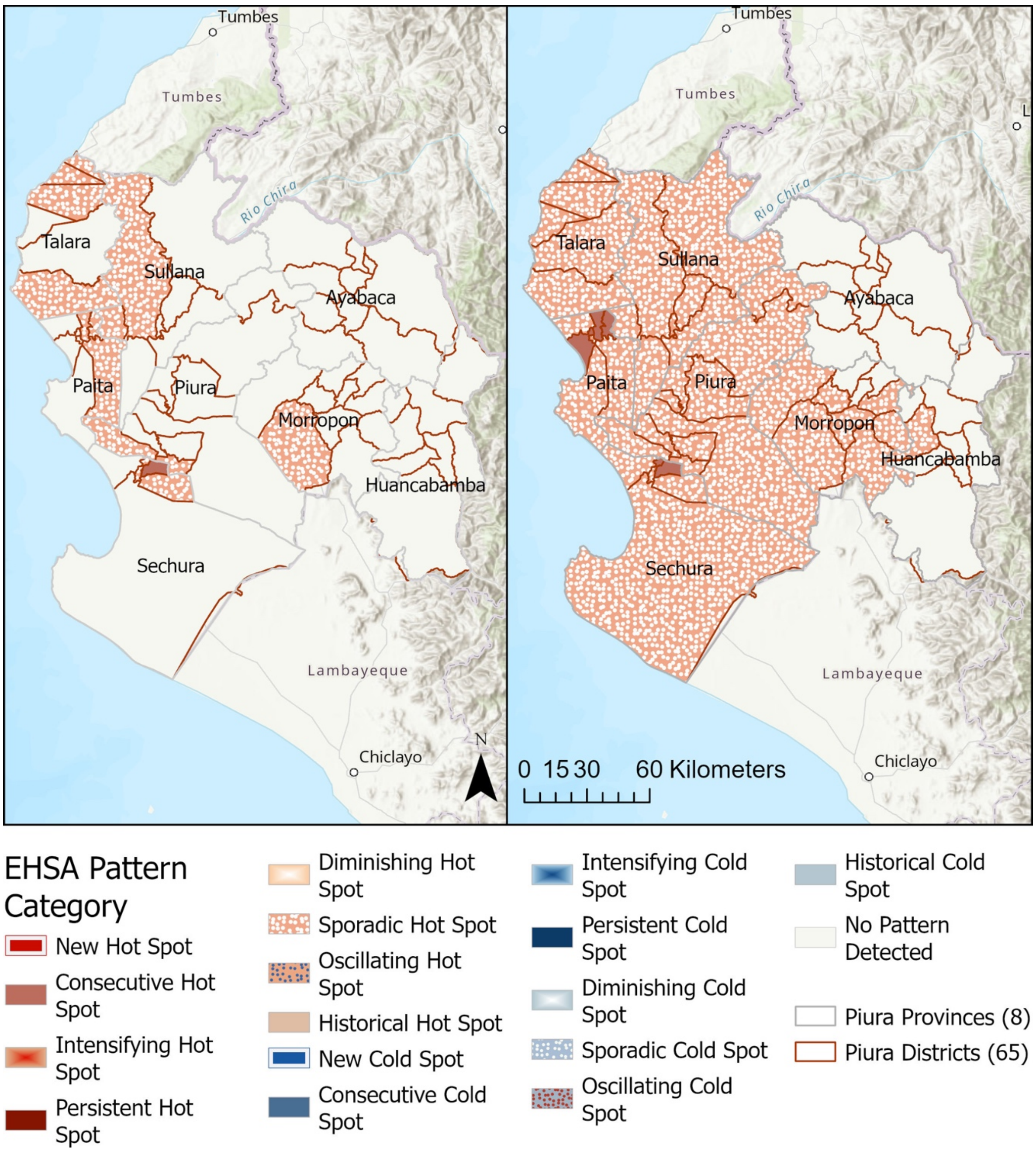
Figure 5. Emerging Hotspot Analysis at 3-month (left) and 6-month (right) time steps at national level



The 6-month time step shows an expanded area inland, including four new districts as consecutive hotspots: Colán, Amotape, Tamarindo and Bellavista de la Unión (Figure 5). These results suggest that recent and persistent increases in dengue incidence are emerging in new areas in Piura (and in other regions in Peru), emphasizing the need for targeted and localized surveillance and control efforts.

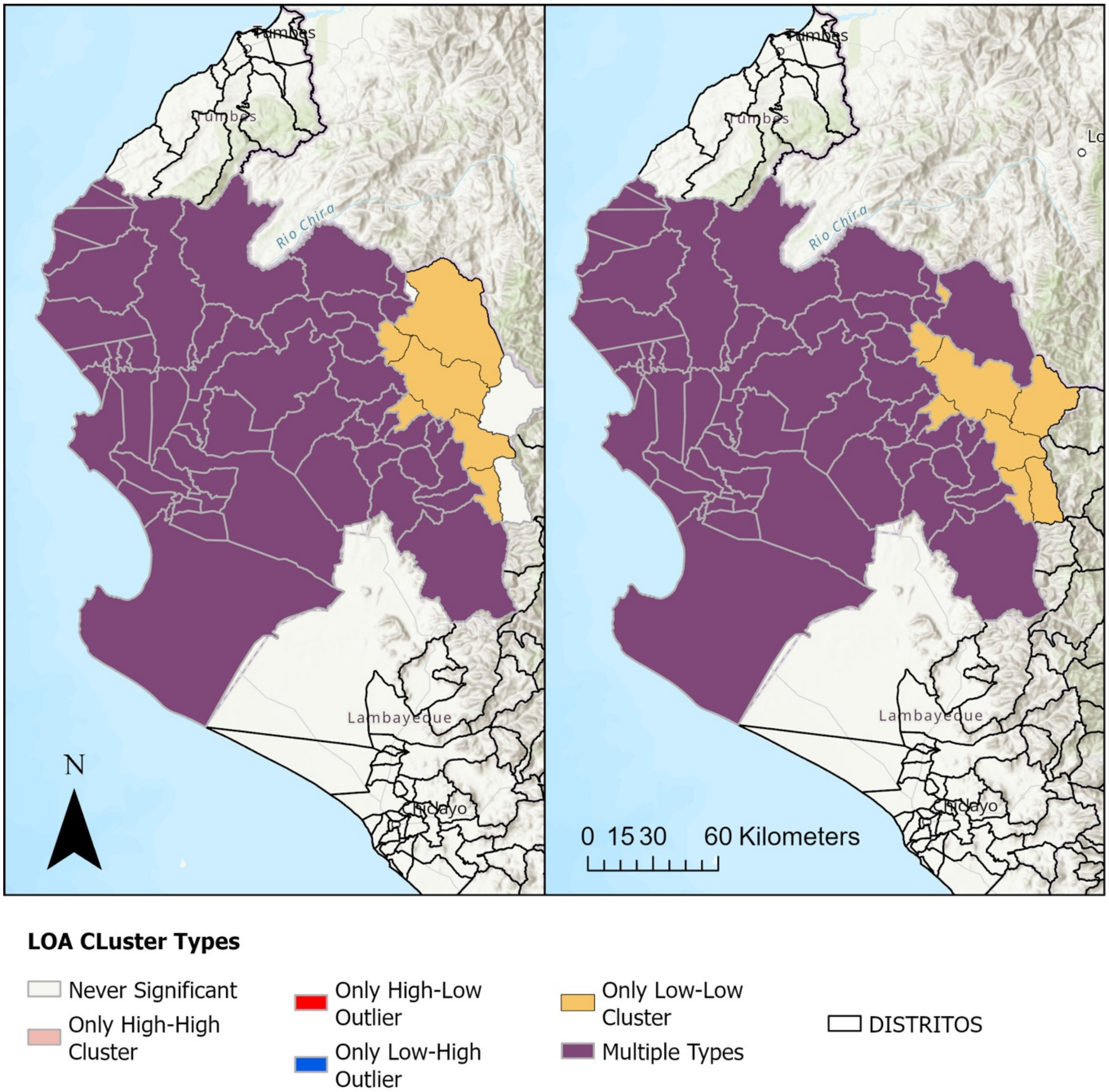
The area identified as sporadic hotspot in the 6-month time step covers mostly all the of the arid and semi-arid climate districts of Piura, while no sporadic hotspots are identified in the temperate and humid areas of Piura (refer to Annex 1 for Climate Typology of Piura).

Figure 6. Emerging Hotspot Analysis at 3-month (left) and 6-month (right) time steps in Piura districts



Finally, the Local Outlier Analysis (LOA) - a method employed to study the spatial clustering of dengue incidence at the district level in Piura- revealed high levels of spatial heterogeneity. The LOA too in ArcGIS Pro identifies statistically significant clusters and outliers in the context of both space and time by implementing the Anselin Local Moran's I statistic (ESRI, 2024c). Spatial heterogeneity means that in the study area, there are not many significant clusters of high (or low) incidence districts surrounded by high (or low) incidence districts. In fact, as observed in Figure 6, only districts located in the more temperate and humid regions of Piura showed a significant level of Low-Low Clustering (low-incidence districts surrounded by other low-incidence districts). The rest of the region show as “Multiple Types”, meaning that in these districts there has been multiple types of statistically significant cluster and outlier types throughout the timeseries (for example, during some time periods the location has been a Low-High Outlier, and during other time periods it has been a High-High Cluster) (ESRI, 2024b).

Figure 7. Local Outlier Analysis at 3-month (left) and 6-month (right) time steps



According to Ren et al. (2017), such high spatiotemporal heterogeneity of dengue incidence rates suggests that the hypothesized drivers may be affecting the epidemic in different ways and to various degrees, which is motivation to analyze these relationships using geographically weighted regression (GWR) model (see Chapter 3).

4.3 Conclusions

In sum, the results presented in this chapter confirm that Piura not only exhibits higher average dengue incidence than the national level but also shows signs of increasingly intense and spatially variable outbreaks over time. While only some districts are beginning to display persistent clustering of cases, most are experiencing sporadic and spatially inconsistent surges, particularly in the arid and semi-arid subregion of Piura. This spatiotemporal heterogeneity—observed through both significance tests and spatial analysis tools—underscores the need for localized approaches to understanding the underlying drivers of outbreaks and, consequently, context-specific public health responses. The emergence of new hotspots in recent years further motivates exploring the effect of changes in climate and the built environment as potential drivers of dengue risk into previously unaffected areas, which the next chapters explore more in depth.

Chapter 5. Climate And Built-Environment Drivers Of Dengue Incidence

In this chapter I use ggplot2 package in R for data visualization and econometric modeling to explore the form of the relationship between climate variables – temperature, humidity and precipitation- and dengue incidence at the district level in Piura. Because climate data was collected only from 2003 to 2023, this chapter used the dengue surveillance period only for those twenty years.

Research Question: What is the relationship between climate variables and dengue incidence at the district level in Piura? How are these relationships modified by urban features?

5.1 Introduction and study context

First, I examine how these key climate variables have behaved and evolved over the study period, with respect to the dengue outbreaks and trends, with special attention to seasonality. I further explore if the relationship between the climate variables and dengue incidence differs depending on whether outbreak coincide with ENSO months. Based on the findings, I built an OLS regression model by incrementally adding the climate and built environment variables and their corresponding transformations.

To assess the potential modifying effect of built environment features I used piped water access, piped sewage systems, built-up/non vegetated area by district as covariates, and an interaction terms between piped water access and precipitation. The model selection for interpretation was based on goodness of fit metrics. A Fixed Effect version of the OLS model was also run to compare the global effects assumption underlying OLS coefficients to within district changes estimated through FE.

5.2 Findings

5.2.1 Climate Data Analysis

Annually aggregated trends mask local climate–dengue dynamics

As mentioned previously in the literature review, the vast majority of Piura's climate is considered arid or semi-arid with moisture deficiency in all seasons of the year, with only some semi-dry or temperate and humid areas inland (SENAMHI, 2020) (see Annex 1 for Piura’s climate map). The fact that sporadic and consecutive hotspots identified in Chapter 1 are predominantly found in the dry areas of Piura challenges the perception that dengue is a tropical cities’ disease and motivates the study of the climate and built environment dynamics that could be enabling the expansion of dengue into these areas.

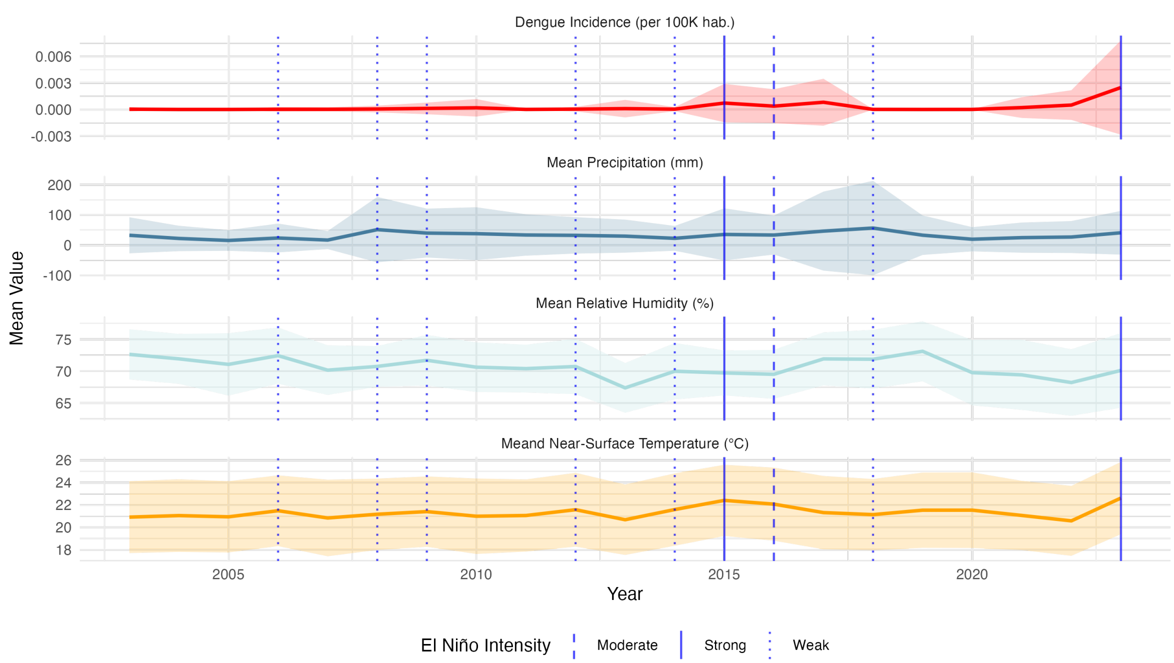
To understand the context in which dengue outbreaks have occurred in Piura, it is helpful to examine how key climate variables have evolved over study period. Figure 7 presents the mean annual trend of these key variables, with bandwidths showing the range of variation across all 65 Piura’s districts for each year in the study period. Vertical lines for ENSO years categorized by intensity, allow to assess whether climate extremes and dengue peaks correspond with ENSO events.

Identifiers for EL Niño years and their intensity (labelled as weak, moderate or strong) are added based on and very strong on the Índice Costero El Niño (ICEN), which is calculated as the three-month moving average of the sea surface temperature anomaly off the Peruvian coast (Comisión Multisectorial del ENFEN, 2025; Instituto del Mar del Perú (IMARPE),

2025) especially between Paita and Chicama, with respect to the climatology for the period 1981-2010.

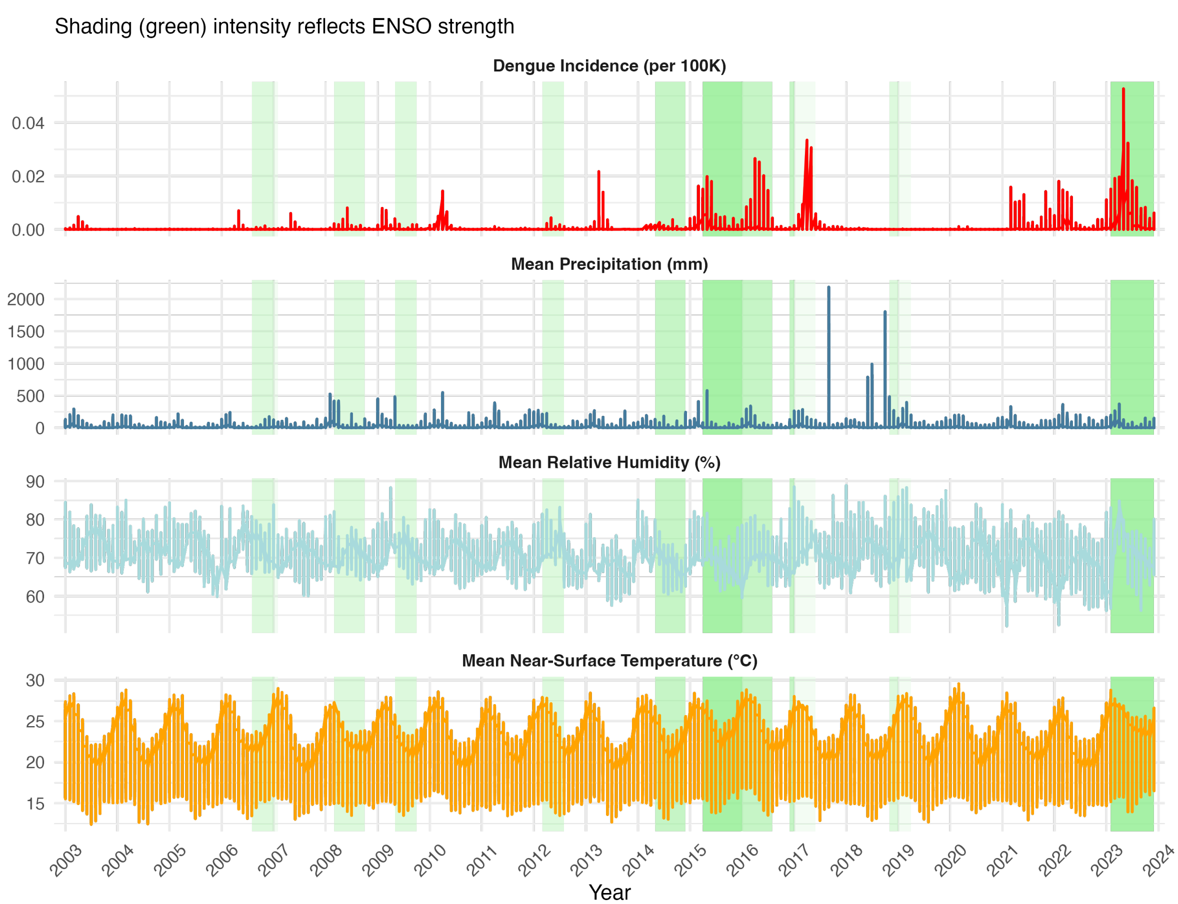
This graphic does not reveal any major shifts in the behavior of the climate variables over time. It is worth noting the slight increase in dengue incidence in 2015, which coincided with rising temperatures during a “strong” El Niño year. Similarly, 2022 shows a notable increase in incidence, leading to the exceptional outbreak in 2023, accompanied by higher temperatures, increased humidity, and another “strong” ENSO event. However, the wide standard deviation bands for the three climate variables in all ENSO years indicate substantial variation across districts, suggesting that this aggregated view is masking important local-level differences. This points to the need for more granular analyses to better capture the spatial heterogeneity of climate–dengue dynamics—such as incorporating an ENSO dummy variable at the district–month–year level to account for shifts in baseline climate conditions during ENSO events.

Figure 8. Average Climate and Dengue Incidence Trends (2003-2023) Across Piura



When maintaining the original monthly resolution of the data rather than aggregating by year, as observed in Figure 8, it is easier to identify the seasonal patterns of dengue outbreaks, climate variability and ENSO intensity. This graph shows the range of values for each climate variable across all 65 districts by month from 2003 to 2023. Some dynamics are noteworthy, including the wide range of precipitation observed in 2017 and 2018, followed by near-zero dengue incidence levels across all districts. Although the graph does not indicate which specific districts experienced these extreme precipitation events, the pattern may support the idea that precipitation has a complex relationship with dengue incidence, as intense rainfall can wash out mosquito breeding sites, potentially reducing DENV transmission. Interestingly, these precipitation extremes do not coincide with ENSO months.

Figure 9. Monthly Time Series of Climate Variables and Dengue Incidence



Maximum climate values do not necessarily coincide with ENSO years or dengue peaks

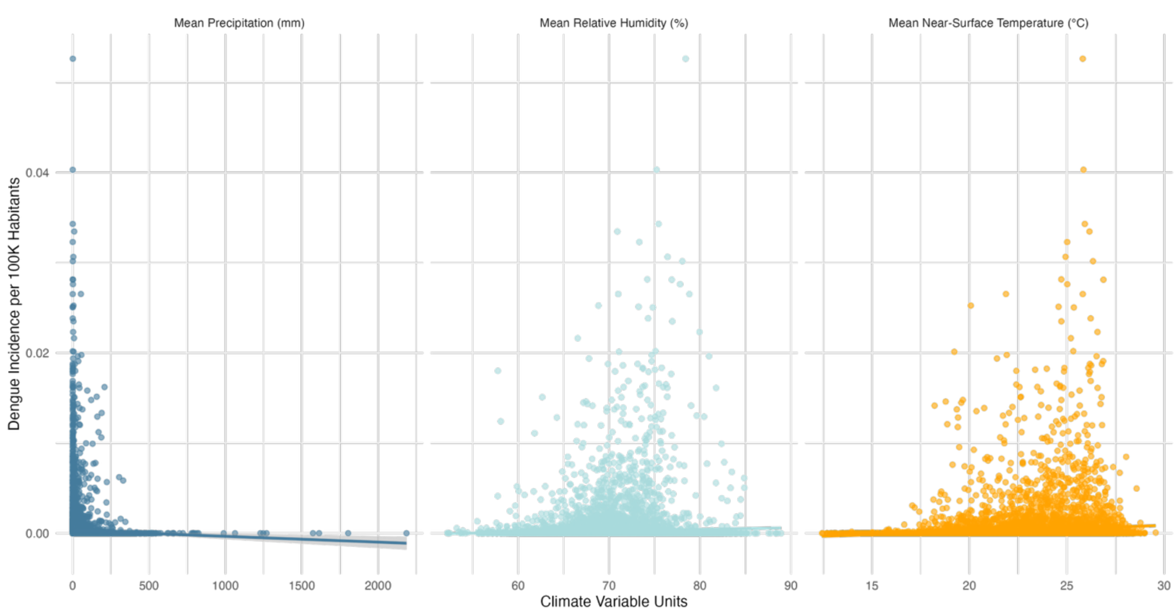
Compared to mean annual trends, plotting maximum annual values amongst all districts for each climate variable and dengue incidence offers an opportunity to observe if extreme climate conditions act as triggers for dengue outbreaks, and whether these extremes are associated with El Niño years. Figure 9 shows no consistent association between climate or dengue extremes and ENSO events. For example, the 2015 increase in dengue incidence coincides with a slight increase in maximum precipitation, a slight decrease in maximum relative humidity, and stable maximum temperatures. The 2023 outbreak, by contrast, aligns with rising maximum values for both temperature and humidity. Still, the wide standard deviation bands in humidity and temperature emphasize the need for more granular analysis to capture district-level variation and better understand how ENSO may modify the relationship between climate variables and dengue incidence. It is worth noting, however, that variation in maximum precipitation values remains relatively limited across most years.

Figure 10. Maximum Climate and Dengue Incidence Trends (2003-2023) Across Piura

Relationships between dengue incidence and climate variables are not linear

The following scatterplots (Figure 10) were created to explore the relationship between dengue incidence and each of the climate variables considered in this chapter. As can be observed, none of these variables shows a clear linear relationship with dengue incidence. In the case of temperature and relative humidity, the graphs suggest that high levels in these variables could be correlated with greater concentration of dengue incidence observations, however, beyond a certain threshold, further increases in these variables appear to correspond with a decrease in the concentration of incidence observations. The high incidence peaks and outliers tend to fall within this threshold too, which suggests a non-linear relationship between these variables and dengue incidence. In contrast, no clear relationship is observed between precipitation and dengue incidence. The shape of these relationships motivates the transformation of variables to quadratic or logarithmic forms, or the use of alternative statistical models beyond OLS to relax the linearity and normally distributed residuals assumptions.

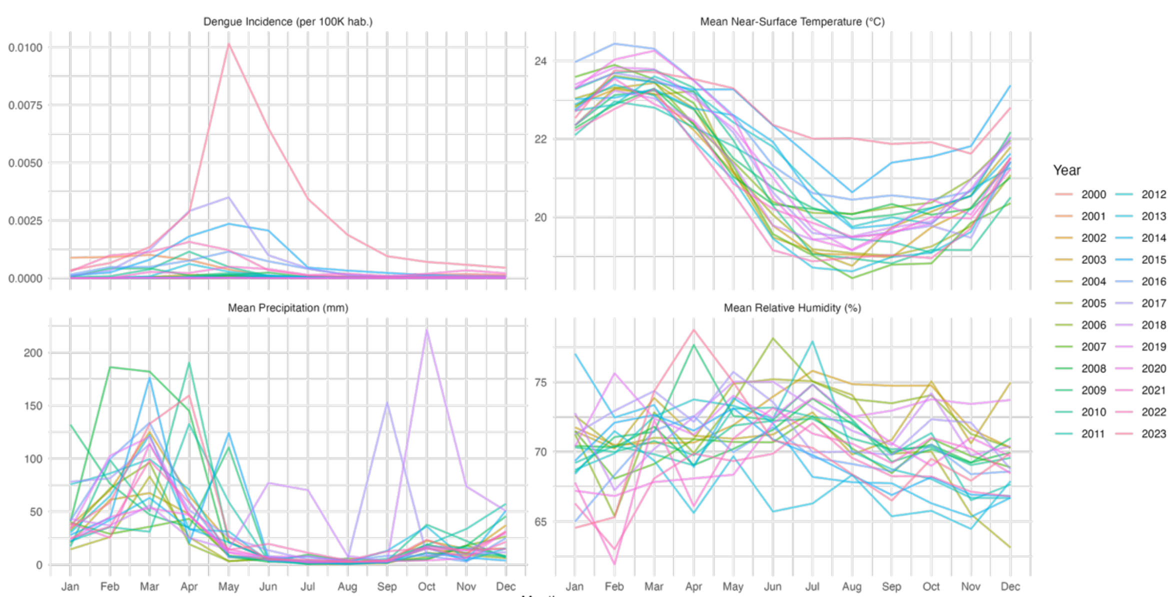
Figure 11. Bivariate Relationships of Dengue Incidence and Climate Variables



Dengue outbreak peaks coincide with the end of the warm period and onset of precipitation

Figure 11 provides an overview of the seasonal (monthly average) relationship between climate variables and dengue incidence. Consistent with the heatmap presented in Chapter 1, dengue incidence peaks tend to occur between March and August, with a clear peak in the month of May. This period aligns with the transition from the warmest months in Peru (January to March) into cooler months, as well as the onset of declining precipitation. In contrast, the seasonal relationship with relative humidity is rather unclear. These findings, along with the scatterplots discussed earlier, suggest the importance of incorporating lag effects in the analysis of climate variables to better capture the delayed influence of climate variables on dengue incidence dynamics.

Figure 12. Seasonal Trends of Monthly Climate Variables and Dengue Incidence



Through the regression model specification, it is possible to evaluate whether these seasonal patterns may be amplified during ENSO months, when expected elevated temperatures and anomalous rainfall can potentially extend the dengue transmission window.

5.2.2 Ordinary Least Squares (OLS) Model Specification

To assess the hypothesized climate and built environment drivers of dengue incidence, a series of multiple linear regression were run using an incremental approach to select the best explanatory model, based on goodness of fit. As noted in the methods section, the dependent variable (raw incidence [cases per 100,000 habitants] calculated based on the ratio of monthly cases per population count of a given year), was transformed using the Empirical Bayes Rates technique - following Ren et al., (2017) and Acharya et al., (2018) methodology to smooth out extreme fluctuations in incidence caused by the diversity of population size across districts. This allows for more accurate and stable estimates (Bakshi, 2024). Additionally, the smoothed incidence was log- transformed to allow for a closer-to-normal distribution of the data. All models were run using the logarithmic value of empirical bayes smoothed incidence rates as the dependent variable.

The multiple linear regression is used to estimate how changes in the explanatory variables (climate and built environment drivers) are associated with changes in the dependent variable (empirical bayes smoothed dengue incidence rates), while holding all other predictors constant. This model aims to isolate the average effect of each individual factor—such as temperature, precipitation, or access to piped water—on dengue incidence. The general form of the regression model used is:

$$\log(EBR_{it}) = \beta_0 + \beta_1 X_{1,it} + \beta_2 X_{2,it} + \cdots + \beta_n X_{n,it} + \varepsilon_{it}$$

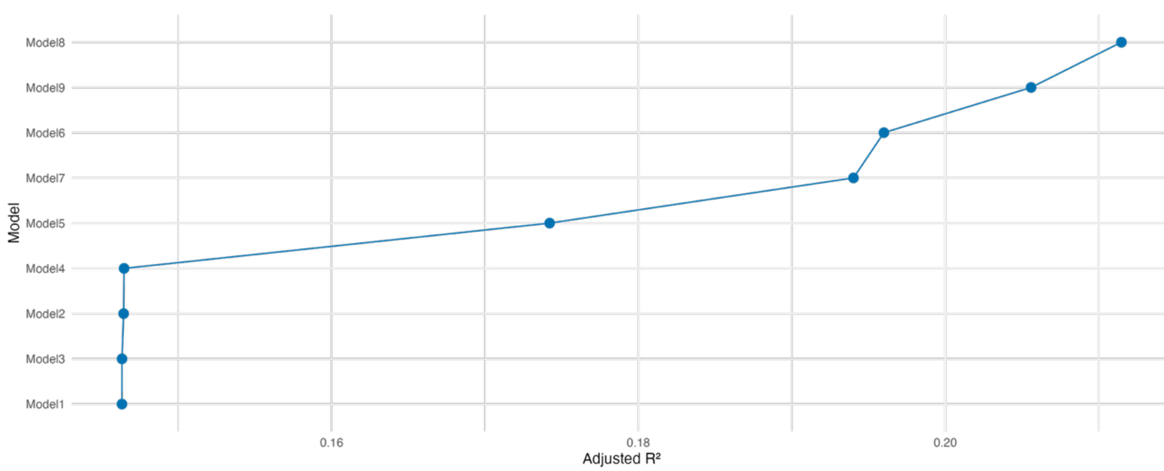
where $\log(EBR_{it})$ represents the log-transformed Empirical Bayes Rate of dengue incidence in district *i* at time *t*; β_0 is the intercept; $X_1 \ldots X_n$ are the climate and built environment covariates; $\beta_1 \ldots \beta_n$ are their respective coefficients; and ε_{it} is the error term. The use of the *it* subscript only reflects the panel structure of the data, thus the coefficients the coefficients reflect average marginal effects of a one-unit change in any of the explanatory variables on the log EB dengue incidence rate across all districts and months in the panel, holding the rest of variables constant. While some variables in this timeseries may be correlated, the model can still yield valid estimates as long as there is no perfect multicollinearity among predictors. This was verified in this using the Variance Inflation Factor (VIF) in car R package. Considering the sample size (16,380 observation), near perfect multicollinearity was not a criterion for eliminating covariates in the model.

The baseline model included key climate variables—temperature, precipitation, and relative humidity—alongside built environment covariates such as access to piped water, piped sewage coverage, land cover (percentage built/non-vegetated area and water bodies by district), and an ENSO dummy variable. Subsequent models introduced quadratic terms for temperature and humidity (Models 2–4) to capture the non-linear relationships identified above (Figures 10 and 11), followed by adding the interactions between ENSO and climate variables to assess differential effects of climate-dengue relationships during ENSO events (Model 5).

The first lag (1 month) of climate variables was then introduced to account for short-term delayed impacts on dengue transmission (Model 6), followed by an interaction term to test the hypothesis that during low precipitation months, districts with larger access to piped water systems have reduced water storage practices, thus reduced risk of dengue incidence (Models 7). Finally, a comprehensive model incorporated multiple monthly lags for all three climate variables up to six months (based on Gibb et al., 2023 and Lowe et al., 2018) to better capture the temporal dynamics of dengue outbreaks (Model 8) (See Annex 2).

Figure 12 illustrates the incremental changes in model fit based on the Adjusted R^2 of each model. Unlike the standard R^2, the Adjusted R^2 accounts for the number of predictors in the model, providing a more reliable basis for comparing goodness of fit across. This metric indicates the proportion of the variation in the dependent variable —log-transformed, Empirical Bayes smoothed dengue incidence—that is explained by the set of covariates. As it can be observed, the addition of the quadratic terms for temperature and relative humidity alone and jointly, did not improve the model's explanatory power (only about 15% of the variation in average log EBR dengue incidence) and produced coefficients that were not statistically significant.

Figure 13 . Adjusted R^2 Comparison Across OLS Models



Larger gains in goodness of fit presented when introducing the interaction terms of temperature, precipitation and relative humidity, with ENSO in Model 5, explained over 17% of the variation in the dependent variable (Adjusted R^2 of 0.1742). In this scenario, both relative humidity and its quadratic term remained insignificant, while temperature and squared temperature showed high significance at the 0.0 level of confidence. Mean precipitation showed statistical significance, with a very low positive coefficient. All three ENSO interaction terms had high levels of significance, with the interaction of ENSO and temperature having the largest positive effect (β= 0.2207680), meaning that during ENSO months, a one-degree Celsius increase in mean temperature is associated with an approximate 24.7% increase in smoothed dengue incidence rates, while holding other variables constant. The interaction between ENSO and relative humidity also showed a modest but significant positive effect (β = 0.0896, or nearly 9.4% increase per one percentage point increase in humidity during ENSO months). Precipitation had a small negative effect (β = -0.0023), suggesting a slight decrease in dengue incidence per additional millimeter of rainfall during ENSO months.

Another major improvement in model fit came with the inclusion of a one-month lag, which captures the delayed effects of temperature, precipitation, and relative humidity on dengue incidence (Model 6, Adj. $R^2 = 0.196$). Under this model specification, lagged temperature (β = 0.308, $p < 0.001$) and lagged precipitation (β = 0.0017, $p < 0.001$) yielded highly significant and positive coefficients, suggesting that warmer temperatures and increased rainfall in the previous month contribute to higher transmission risks in the current month. The lagged relative humidity effect was smaller, it was also statistically significant ($p = 0.015$), suggesting a modest but meaningful delayed influence. Model 6 continued to yield strong significance for other covariates, including the ENSO interactions—particularly the interaction between ENSO and temperature (β = 0.213, $p < 0.001$)—and built environment factors such as access to piped water (β = 1.30) and sewage coverage (β = 0.75).

In contrast, incorporating the interaction term for Precipitation × Piped Water (Models 7) led to a slight decrease in model fit, with the adjusted R^2 falling to 0.194. Although when adding the interaction term the coefficient was statistically significant (β = -0.00198, $p = 0.034$), its practical contribution to explaining variation in dengue incidence was small. The negative sign in the coefficient suggests that in areas with greater access to piped water, the positive effect of precipitation on dengue incidence is slightly reduced—possibly due to improved drainage or reduced water storage practices, which can serve as mosquito breeding grounds. Other key variables, including lagged temperature ($\beta = 0.313$) and ENSO-related variables, remained highly significant and consistent with prior specifications, emphasizing the importance of climate variability and urban infrastructure on dengue dynamics.

To strengthen the lag analysis, particularly considering research highlighting the delayed effects of extreme events (e.g., heatwaves, droughts, and heavy rainfall) on vector-borne disease dynamics, I expanded the model to include lag terms up to 6 months in Model 8. This adjustment yielded the second-largest improvement in explanatory power, increasing the adjusted R^2 to 0.2115. Several lagged climate variables showed as statistically significant, indicating a complex temporally distributed influence of climate on dengue incidence. Notably, temperature showed both positive (lags 1 and 3) and negative (lags 4 and 6) effects over time, while precipitation lag effects from 1 to 6 months were consistently positive and significant. This supports the idea that accumulated rainfall can contribute to favorable breeding conditions over an extended period.

A Pearson correlation matrix revealed strong correlation between access to sewage systems and access to piped water, as well as between the Precipitation × Piped Water interaction term and mean precipitation in Model 8. To reduce unnecessary noise around the regression line for the final model, a last model was run (Model 9) removing access to piped sewage systems. The interaction term was kept for its theoretical relevance based on the literature review. This slightly reduced the explanatory potential of the model (Adj. $R^2 = 0.2056$) but improves model parsimony. Resulting estimates from model 9 can be found in Figure 13 below.

Figure 13. OLS Regression Coefficients Table

Effects on Log EB Smoothed Dengue Incidence

Variable	Estimate	Std. Error	t value	P-Value	95% CI (Lower)	95% CI (Upper)
(Intercept)	5.1045	2.6572	1.9210	0.0548	−0.1040	10.3130
Mean temperature (°C)	0.0791	0.0764	1.0345	0.3009	−0.0708	0.2289
Mean temperature²	-0.0046**	0.0017	−2.6876	**0.0072**	−0.0080	−0.0012
Mean precipitation (mm)	0.0021***	0.0006	3.7677	**0.0002**	0.0010	0.0032
Mean relative humidity (%)	-0.1218	0.0743	−1.6384	0.1014	−0.2675	0.0239
Mean relative humidity²	0.0006	0.0005	1.0557	0.2911	−0.0005	0.0016
ENSO × Precipitation	-0.0026***	0.0005	−5.1650	**0.0000**	−0.0036	−0.0016
ENSO × Relative humidity	0.0770***	0.0080	9.5873	**0.0000**	0.0613	0.0928
ENSO × Temperature	0.2128***	0.0115	18.5892	**0.0000**	0.1904	0.2353
Temp lag 1 mo	0.1250**	0.0392	3.1861	**0.0014**	0.0481	0.2019
Temp lag 2 mo	0.0361	0.0399	0.9045	0.3658	−0.0421	0.1142
Temp lag 3 mo	0.0966*	0.0404	2.3913	**0.0168**	0.0174	0.1758
Temp lag 4 mo	-0.0881*	0.0405	−2.1745	**0.0297**	−0.1675	−0.0087
Temp lag 5 mo	0.0441	0.0396	1.1131	0.2657	−0.0336	0.1218
Humidity lag 5 mo	-0.0133*	0.0062	−2.1273	**0.0334**	−0.0255	−0.0010
Temp lag 6 mo	-0.0524*	0.0236	−2.2185	**0.0265**	−0.0987	−0.0061
Humidity lag 1 mo	-0.0032	0.0063	−0.5056	0.6131	−0.0154	0.0091
Humidity lag 2 mo	0.0024	0.0063	0.3838	0.7011	−0.0099	0.0147
Humidity lag 3 mo	-0.0005	0.0062	−0.0815	0.9350	−0.0127	0.0117
Humidity lag 4 mo	-0.0114	0.0063	−1.8215	0.0685	−0.0237	0.0009
Humidity lag 6 mo	-0.0318***	0.0054	−5.8791	**0.0000**	−0.0424	−0.0212
Precip lag 1 mo	0.0006*	0.0003	2.2308	**0.0257**	0.0001	0.0011
Precip lag 2 mo	0.0008**	0.0003	3.0738	**0.0021**	0.0003	0.0013
Precip lag 3 mo	0.0008**	0.0003	3.0435	**0.0023**	0.0003	0.0013
Precip lag 4 mo	0.0006*	0.0003	2.2179	**0.0266**	0.0001	0.0011
Precip lag 5 mo	0.0006*	0.0003	2.4600	**0.0139**	0.0001	0.0012
Precip lag 6 mo	0.0006*	0.0002	2.4525	**0.0142**	0.0001	0.0011
Precipitation × Piped water	-0.0032***	0.0009	−3.3428	**0.0008**	−0.0050	−0.0013
% Households with piped water	1.9384***	0.0826	23.4711	**0.0000**	1.7765	2.1003
% Built-up land	-0.0019**	0.0006	−2.8949	**0.0038**	−0.0031	−0.0006
% Water bodies	-0.0705***	0.0066	−10.6691	**0.0000**	−0.0834	−0.0575
ENSO dummy	-9.0697***	0.6360	−14.2596	**0.0000**	−10.3165	−7.8230

Statistical Significance: *p < 0.05, **p < 0.01, ***p < 0.001

5.2.3 Fixed Effects (FE) Model Specification

Model 9 OLS can provide valuable insights into the average effects of temporal and climatic drivers of dengue incidence across Piura's districts. However, it relies on two major assumptions. The first is that the estimated coefficients represent global effects across all district-month pairs in the panel dataset. As seen in the Local Outlier Analysis in Chapter 1, this assumption may not hold, given the heterogeneity in the temporal patterns and spatial clustering of dengue incidence across districts. Moreover, this chapter has shown that there is considerable variability variation in the historical levels and effects of temperature, humidity, and precipitation across space and time, suggesting that a single coefficient may mask important local dynamics.

The second key assumption is that the model is correctly specified, meaning all relevant factors affecting dengue incidence are either included as covariates or are uncorrelated with the included predictors – meaning their effect is not being picked up in the error term. Based on the literature reviewed, this assumption is likely violated in the context of dengue incidence. Many unobserved district-specific characteristics—such as land elevation, access and quality of local health infrastructure, prevention communication efforts, vector control programs, behavioral factors related to water storage, or baseline urban infrastructure—may systematically influence incidence and be correlated with the included variables in Model 9. In this case, the error term of the model absorbs their influence, leading to omitted variable bias.

For these reasons, this section explores a fixed effects version of Model 9 as an attempt to control for unobserved, time-invariant factors specific to each district. This approach aims to improve the internal validity of the estimates by isolating within-district variation over time.

The fixed effects model specification is derived from the original base model

$$\log(EBR_{it}) = \beta_0 + \beta_1 X_{1,it} + \beta_2 X_{2,it} + \cdots + \beta_n X_{n,it} + \boldsymbol{\beta_k Z_i} + \varepsilon_{it}$$

Where now Z_i represents those time-invariant, omitted variables that are specific to each district. This variable(s) has no time subscript as it is assumed to be constant over time for any given district. Using the first difference estimation approach to eliminate the omitted variable bias, we can estimate a regression of the change in log(EBRit) on the change in the values of the covariates within each district. This is done by subtracting log(EBRit) for month 1 from $\log(EBR_{it})$ for month 2 and so on across all months in the pane, as the example below:

$$\Delta \log(EBR_i) = \Delta \log(EBR_{i2}) - \Delta \log(EBR_{i1})$$

$$= \beta_1(X_{i2} - X_{i1}) + \cancel{\boldsymbol{\beta_k(Z_i - Z_i)}} + (\varepsilon_{i2} - \varepsilon_{i1})$$

Because Z_i does not vary over time, it drops out of the differenced equation. The Fixed-effects OLS estimation in the feols package in R can perform this change estimation for several periods of time (in this case, the 252 months in the panel) (DataCamp, 2024). The model was run using cluster standard errors to address potential serial autocorrelation and heteroskedasticity in the error terms within districts over time.

Figure 14. Fixed Effects Regression Coefficients Table

Effects on Log EB Smoothed Dengue Incidence (District FE)

Variable	Estimate	Std. Error	t value	P-Value	95% CI (Lower)	95% CI (Upper)
Mean temperature (°C)	0.3189	0.2043	1.5607	0.1235	−0.0893	0.7271
Mean temperature²	-0.0050	0.0045	−1.1106	0.2709	−0.0139	0.0040
Mean precipitation (mm)	0.0012**	0.0004	2.7525	**0.0077**	0.0003	0.0021
Mean relative humidity (%)	-0.0221	0.0926	−0.2390	0.8119	−0.2072	0.1629
Mean relative humidity²	-0.0003	0.0006	−0.4295	0.6690	−0.0016	0.0010
ENSO × Precipitation	-0.0022***	0.0006	−3.6594	**0.0005**	−0.0033	−0.0010
ENSO × Relative humidity	0.0826***	0.0117	7.0865	**0.0000**	0.0593	0.1058
ENSO × Temperature	0.2008***	0.0208	9.6299	**0.0000**	0.1591	0.2424
Temp lag 1 mo	0.0667**	0.0250	2.6660	**0.0097**	0.0167	0.1166
Temp lag 2 mo	0.0342	0.0197	1.7412	0.0864	−0.0050	0.0735
Temp lag 3 mo	0.1422***	0.0200	7.0918	**0.0000**	0.1021	0.1822
Temp lag 4 mo	-0.0765**	0.0226	−3.3901	**0.0012**	−0.1216	−0.0314
Temp lag 5 mo	0.0137	0.0208	0.6609	0.5110	−0.0278	0.0552
Temp lag 6 mo	0.1463***	0.0288	5.0841	**0.0000**	0.0888	0.2038
Humidity lag 1 mo	-0.0098*	0.0038	−2.5449	**0.0134**	−0.0174	−0.0021
Humidity lag 2 mo	-0.0016	0.0041	−0.3948	0.6943	−0.0098	0.0066
Humidity lag 3 mo	-0.0056	0.0040	−1.3776	0.1731	−0.0136	0.0025
Humidity lag 4 mo	-0.0156***	0.0040	−3.9092	**0.0002**	−0.0235	−0.0076
Humidity lag 5 mo	-0.0144**	0.0042	−3.4175	**0.0011**	−0.0228	−0.0060
Humidity lag 6 mo	-0.0506***	0.0077	−6.5906	**0.0000**	−0.0659	−0.0352
Precip lag 1 mo	0.0007***	0.0002	4.0877	**0.0001**	0.0004	0.0011
Precip lag 2 mo	0.0010***	0.0003	3.7937	**0.0003**	0.0005	0.0016
Precip lag 3 mo	0.0011***	0.0003	3.6213	**0.0006**	0.0005	0.0017
Precip lag 4 mo	0.0008***	0.0002	4.4036	**0.0000**	0.0004	0.0011
Precip lag 5 mo	0.0006***	0.0002	3.4735	**0.0009**	0.0003	0.0010
Precip lag 6 mo	0.0006**	0.0002	2.8533	**0.0058**	0.0002	0.0011
Precipitation × Piped water	-0.0016	0.0008	−1.9447	0.0562	−0.0032	0.0000
% Households with piped water	1.0966***	0.2527	4.3396	**0.0001**	0.5918	1.6014
% Built-up land	-0.0148***	0.0031	−4.8442	**0.0000**	−0.0209	−0.0087
% Water bodies	-0.0863**	0.0316	−2.7361	**0.0080**	−0.1494	−0.0233
ENSO dummy	-9.4228***	1.1287	−8.3485	**0.0000**	−11.6776	−7.1680

Statistical Significance: *p < 0.05, **p < 0.01, ***p < 0.001

5.3 Discussion: OLS and FE Regression Interpretation

The logarithmic transformation of empirical Bayes smoothed dengue incidence implies that the estimated parameters from Model 9 have an exponential effect on plain dengue incidence. Estimated coefficients tell by what proportion does dengue incidence rises given a one unit increase in any of the covariates. This means that positive coefficients reflect an estimated average rise in dengue incidence at an increasing rate, while negative coefficients reflect an inverse relationship where dengue incidence exponentially decreases. The results from the OLS model reflect the average effects across all districts and months in the panel dataset, while the FE model how changes in a climate or built-environment variable within the same district over time influence dengue incidence — while controlling for all unchanging district-level characteristics. Both offer interesting insights into the climatic and built-environment factors driving dengue incidence across districts in Piura (refer to Figures 13 and 14 above).

For instance, compared to the initial OLS model, the Adjusted R^2 of 0.323 in the FE model suggests that this specification has a fit to the observations in the panel, explaining about 32.3% of the variance in the log of EB-smoothed dengue incidence.

The current mean temperature in original OLS was found to have a positive but not significant association with dengue incidence rates. While the estimate is larger in the FE, it remained insignificant at the 5% level of confidence. However, the coefficient of the quadratic term (negative, and significant in the OLS) confirms the non-linear relationship with dengue incidence and the hypothesis that dengue increases with temperature up to a threshold beyond which vector survival or virus transmission may decline. This is consistent with existing literature on the effects of temperature on DENV dissemination. For example, findings from Lee et. al (2021) in Brazil, where increased temperature was found as contributor to the expansion of the DENV transmission (Lee et al., 2021). These results also align with most studies in that temperature effects on dengue are non-linear (Descloux et al., 2012).

Mean precipitation showed a weak but highly significant relationship, as well as all its lagged values (1–6 months) in both the OLS and FE. These results possibly reflects the delayed role of rainfall in creating breeding sites and influencing mosquito population dynamics. By contrast, current humidity was not found as a statistically significant driver in either model, and, in fact, its coefficient is negative, while the quadratic term was positive in the OLS model and negative in the FE, suggesting that the relationship might not have been well captured in either of the models. This echoes the complexity of precipitation and humidity as drivers of dengue. For example, Descloux et al., (2012) found that sustained high humidity in the months leading to an outbreak in New Caledonia was more strongly associated with a higher risk of dengue than precipitation (Ibid.). Similarly, Gibb et. al incorporated both monthly precipitation and Standardized Precipitation Evapotranspiration Index (SPEI) as a more sensitive approach to local context, measuring deviations from historical average hydrometeorological conditions for the reference period 1981–2020, both tested at lags of 0 to 6 months to capture delayed effects (Gibb et al., 2023). Their findings suggest that dengue risk increases in either short-term precipitation excess or long-term drought, but improvements in water supply mitigate drought-associated risks except under extreme conditions (Ibid.)

In terms of access to piped water services, both models show a large positive and highly significant association with dengue incidence. According to the estimated parameters, a one percentage point increase in the proportion of households with piped water access is correlated with approximately 193% increase in the proportion of dengue incidence across districts-month pairs in the timeseries for OLS, approximately 109% increase within a given district when holding all other time-varying factors constant. This large estimate could reflect the widely cited phenomenon in which piped water infrastructure is unreliable or intermittent, leading households to store water in containers that become breeding grounds for mosquitoes. In this regard, studies have found that adequate water supply services help mitigate DENV infections in Ecuador and Paraguay (Power et al., 2022), and Vietnam (Schmidt et al., 2011).

Both models shed light on dengue seasonality and the role of ENSO. Strongly significant coefficients for ENSO × Temperature and ENSO × Relative humidity interactions indicate that during ENSO months, higher temperatures and humidity significantly increase dengue risk, intensifying the baseline climatic effects of these two variables on dengue incidence. In contrast, the ENSO × Precipitation interaction shows a negative effect, possibly suggesting a wash-out of breeding sites during heavy rainfalls in ENSO months. Meanwhile, the ENSO dummy itself is considerably large and significantly negative. This could be a sign that this variable is capturing other effects happening during ENSO months that lead to a decrease in incidence.

Regarding variables for land use, higher proportions of built-up areas and surface water bodies were negatively associated with incidence in the panel in both models. Contrary to the hypothesis that increasing land development and decreased vegetation are associated with increased dengue prevalence (Tiong et al., 2015), these results suggest that less vegetated areas are associated with reduce DENV risk. Also contrasting with literature supporting that water surface areas are associated with increased number of dengue cases (Tian et al., 2016) the models suggest that the presence of water bodies in a district is associated with reduced incidence. This could indicate that standing water bodies may not necessarily contribute to breeding if not coupled with other urban or climatic features.

5.4 Conclusion

This chapter explored the climate-dengue relationship in Piura by applying regression modeling and climate data analysis at the district level. The findings highlight that temperature and precipitation, particularly when interacting with ENSO events and when lagged over time, are significant predictors of dengue incidence. Temperature was found to have a positive effect in dengue surges, and significant at time lags and during ENSO months. Precipitation was found to be positively and significantly associated with dengue surges, but the relationships became negative and significant during heavy rainfall events (ENSO), reinforcing the hypothesized wash-out effect of mosquito breeding sites, thus reducing transmission risk.

These results underscore the importance of incorporating time lags, non-linear effects, and interaction terms to better model the complex transmission dynamics of dengue. In particular, the strong effect of lagged temperature and rainfall, as well as their amplified effects during ENSO months, point to the potential value of climate-based early warning systems as policy and planning tools to anticipate dengue outbreaks weeks or months in advance.

Furthermore, the marked and consistent increase in dengue risk associated with piped water access raises important concerns about the reliability of water services in Piura and their contribution to vector breeding. While literature typically finds that improved water access is correlated with lower dengue risk - on the assumption that households with piped water store less water-, these findings could be reflecting that access alone does not suffice. Intermittent, unreliable or poor-quality water services may still be leading to water storage practices and create favorable conditions for mosquito breeding.

Together, these results suggest that both climate-informed planning and investments in urban infrastructure - especially water service delivery and drainage- must be prioritized as part of an integrated dengue prevention strategy, particularly under increasingly variable climate conditions.

Finally, Fixed Effects model showed that even after controlling for unobserved, time-invariant characteristics at the district level, the relationships between climate, infrastructure, and dengue incidence remains statistically significant. However, it is important to recognize that these models estimate uniform, average effect across all districts, which may obscure important local variations, such as the spatiotemporal heterogeneity in dengue outbreaks found in Chapter 4. This represents a key limitation, given the considerable differences in local weather conditions and infrastructure across Piura's districts. The next chapter addresses this constraint by introducing an alternative, more spatially sensitive modeling approach.

Chapter 6: Spatiotemporal Variation Of Dengue Incidence Drivers

6.1 Introduction

Building on the findings from the previous chapters, which demonstrated significant but spatially and seasonally aggregated effects of climate and infrastructure variables on dengue incidence, this chapter investigates how such relationships vary across space and time within each district in Piura. In contrast to the previous chapter, in which OLS analysis assumes linear relationships between the dependent and independent variables - and considering the non-linear associations identified in Chapter 5- this chapter explores the localized associations between the selected covariates using Geographically Weighted Regression (GWR) on the log-transformed empirical Bayes (EB) smoothed dengue incidence rates.

This analysis focuses on a subset of months identified as the high peak transmission season (March–August, as discussed in previous chapters) and includes only selected years from the time series: ENSO years (2009, 2016, 2023) and non-ENSO years (2010, 2021, 2022), all of which showed significantly higher dengue incidence in Piura compared to national averages (as established in Chapter 1).

Research Question: How does the spatial relationship between climate and environmental variables and dengue outbreaks shifts across districts in different epidemic years?

The results provide spatially explicit insights into how climatic and infrastructural factors influence dengue risk, highlighting local heterogeneity that is hardly captured by traditional regression models. This approach is particularly relevant for informing the design of targeted dengue prevention strategies in the context of increasing climate variability and urban expansion at the local level.

6.2 Method: Geographically Weighted Regression model specification

Because the GWR tool in ArcGIS Pro is highly sensitive to multicollinearity, the explanatory variables in this model were selected based on Model 9 of Chapter 5, including only temperature, its squared term, relative humidity, precipitation, access to piped water, percent built-up area, and surface water coverage. The ENSO interaction terms with the climate variables, the lag terms, as well as the interaction between precipitation and water were removed from the model due to multicollinearity issues, which impeded the GWR to run in ArcGIS.

It is important to note that ArcGIS Pro's GWR requires a single shapefile where each spatial unit (districts) has only one value per variable. Therefore, the variables in the GWR derive from estimating the average value of each variable during the high transmission season for each district (65), resulting in one shapefile per year of analysis. Considering these methodological differences is important since the GWR estimated coefficients presented in this chapter are not directly comparable to the linear models discussed in Chapter 5. However, some general comparisons are possible in terms of overall model fit, such as R^2 values.

The geographically weighted regression (GWR) model is an extension of the traditional multiple linear regression that allows regression coefficients to vary by location (Acharya et al., 2018; Ren et al., 2017), producing a set of local parameter estimates for each spatial unit

(65 districts). These parameters are estimated based on the values of neighboring spatial units, with greater weight assigned to closer neighbors (for example, districts sharing boundaries) and less to more distant ones (Acharya et al., 2018; ESRI, 2025b). Based on Ren et al., 2017, the GWR model can be specified as follows:

$$y_i=\beta_0\,(u_i,v_i) + \sum^{n}{}_{k=1}\,\beta_k(u_i,v_i)x_{ik} + \varepsilon_i$$

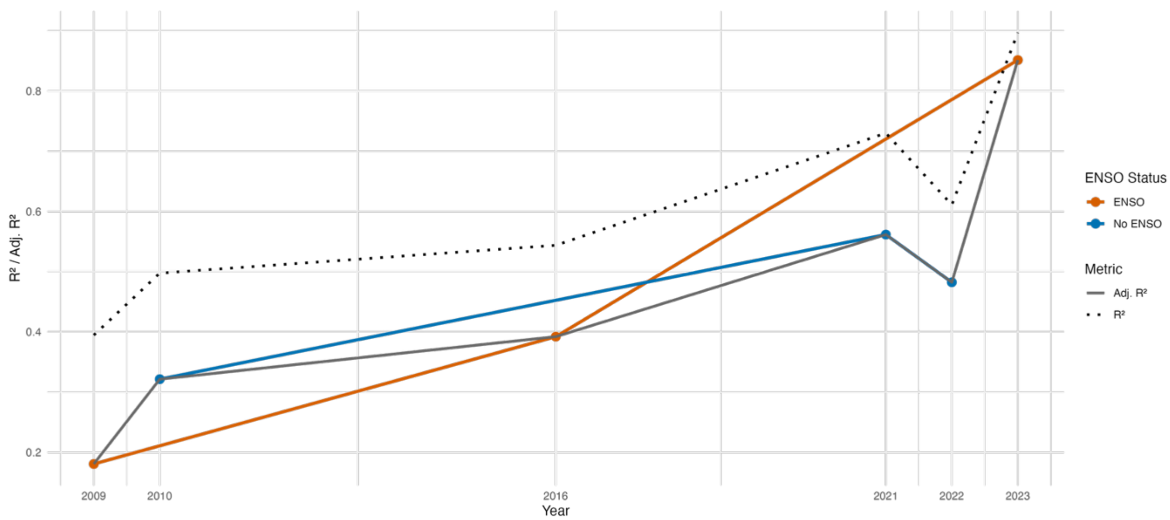
where y_i is the log-transformed EB-smoothed dengue incidence rate at district *i ;* x_{ik} is the k'th independent variable at district *i* (in this case the sum of the coefficients for temperature, its squared term, relative humidity, precipitation, access to piped water, percent built-up area, and surface water coverage); (u_i,v_i) is the coordinates for each the centroids of each district; β_k represents the location-specific coefficient for variable x_k; β_0 is the intercept for district i; and ε_i is the error term.

Given the continuous nature of the dengue incidence data and the approximately normal distribution of the dependent variable after the log-transformation and Empirical Bayes smoothing, a Gaussian GWR model was selected for the GWR. The neighborhood type was specified as number of neighbors, as opposed to a fixed distance setting. This is to allow that closer districts are weighted more heavily than those farther away. According to ESRI, in locations where many districts are close together, the bandwidth will be small, so only very close neighbors (like those that share boundaries) will influence the regression. In more sparser areas, the bandwidth expands to ensure enough neighbors are included (ESRI, 2025a). Finally, the golden search selection method allows the model to find maximum and minimum distances, in search for the lowest AIC metric at various distances between them (Ibid.).

6.3 Findings (GWR Interpretation)

Overall, the GWR models ran for each year showed a better performance compared to the OLS model in terms of Adjusted R^2. Interestingly, the variables in this model show an increasing explanatory potential, from a 0.1806 Adj. R^2 for the 2009 model, a nearly 90% of variation explained in the 2023 model (Figure 15). It should be noted, however, that each GWR regresses the variables on the log EB dengue incidence on 65 observations for each variable, corresponding to each district each year, which inevitably introduces risks of overfitting.

Figure 16. Comparison of GWR Model Fit Over Time

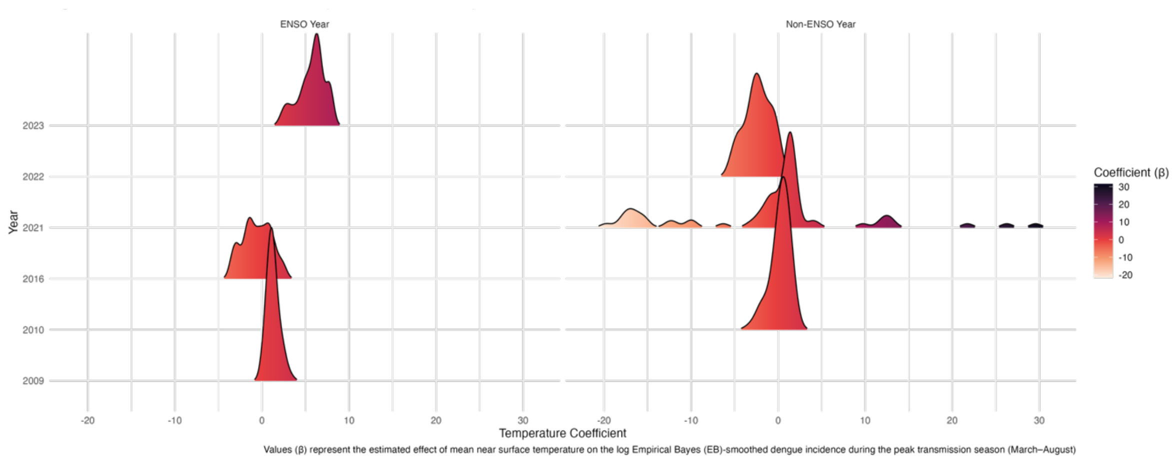


Temperature is strongly and positively associated with dengue during ENSO years

Figure 16 presents the overall distribution of temperature coefficients for each district in the three ENSO years, compared to the three non-ENSO years. Each ridge in the graph represents the density distribution of the GWR coefficients (β) for temperature in a specific year, with the x-axis showing the range of coefficient values and the y-axis stacked by year. Taller and narrower ridges indicate that a larger number of districts had similar coefficient values, meaning the effects were more concentrated around a specific estimate. Conversely, wider and flatter ridges reflect more variability in the estimated effects across districts.

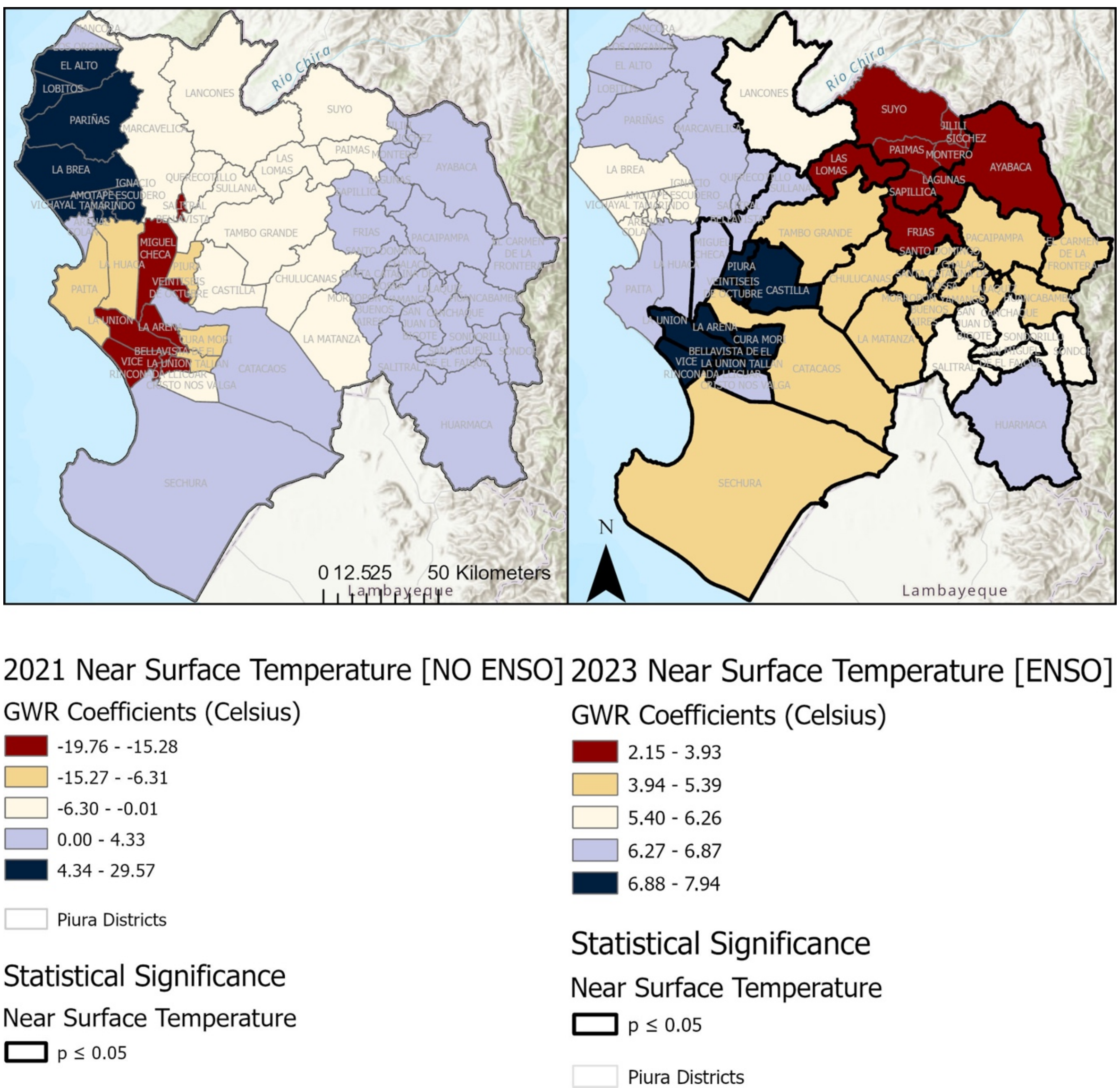
In most years the coefficients tend to concentrate near zero, suggesting either weak associations or effects that are not statistically significant in many districts. However, in 2021 the estimated effects of a one unit increase in temperature on the log EB rate incidence of dengue are sparsely distributed from a -20 up to 30 values of β, indicating substantial variability in how temperature influences dengue incidence across districts. The sharp peaks near zero within this ranges implies many of these effects may not be statistically significant. By contrast, in 2023, an ENSO year, the distribution displays more compact and skewed toward positive values, implying that the effect of temperature on dengue incidence was both more consistent and more strongly positive across most districts during that year.

Figure 17. Distribution of Near Surface Temperature Coefficients by Year and ENSO Status



Taking advantage of GWR's ability to reveal spatial variations in relationships at the district level Figure 17 shows the association between temperature and dengue incidence varied across Piura in 2021 and 2023. In 2021, the relationship was predominantly negative across most districts, meaning that an increase of 1°C in that year was associated with a negative (but not significant) decrease in incidence. By contrast, in 2023, all the coefficients for temperature became positive and many were statistically significant. This included several arid districts such as Piura and Castilla, and more humid, temperate districts like Frias and Santo Domingo, reinforcing the finding on a stronger and more spatially consistent association between temperature and dengue incidence during ENSO.

Figure 18. Map of Estimated Effects of **Temperature (°C)** on Dengue Incidence

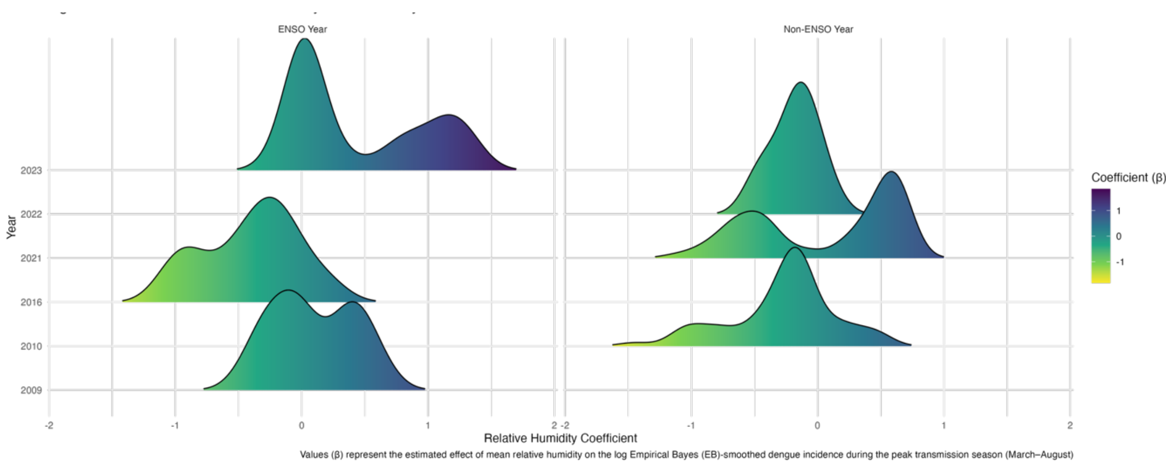


Note (Figure 17): GWR Coefficients represent the estimated effect of mean annual temperature (interpreted in terms of percentage change) on the log Empirical Bayes-smoothed dengue incidence rates during peak transmission season (March-August).

Moisture effects vary by local climates and years

The annual distributions of relative humidity's effect on the log of EB incidence show a noticeable shift toward positive values in 2023. However, the difference between the other ENSO and No-ENSO years is only slightly different towards the positive values (Figure 18).

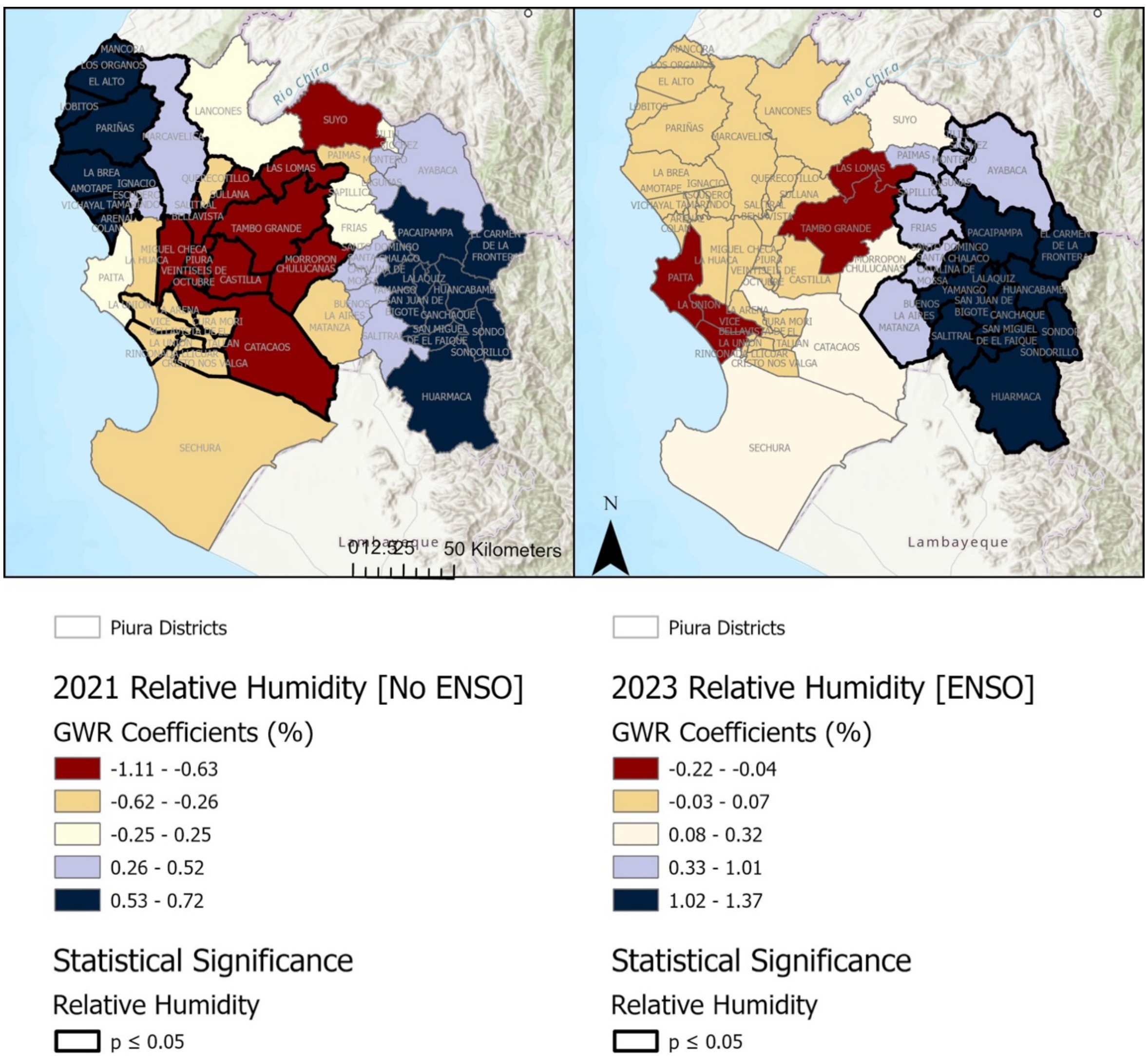
Figure 19. Distribution of Relative Humidity Coefficients by Year and ENSO Status



In terms of spatial variation, districts located in the temperate and humid highlands of Piura presented a consistent positive association between moisture and dengue incidence, with statistically significant effects observed only during the ENSO year (2023). By contrast, there is no clear pattern of influence on dengue incidence in districts across the sporadic dengue hotspot areas along Piura's arid coast (Figure 19). For example, the northwestern coastal districts of Pariñas and Marcavelica showed a positive and significant association in 2021, meaning a one unit increase in moisture in these arid districts was correlated with an increase in dengue incidence. However, in 2023, the same districts displayed a negative—but not statistically significant—association. Conversely, the southern coastal district of Sechura shifted from a negative to a positive association between humidity and dengue incidence, although the change was not statistically significant.

Notably, neighboring districts often displayed contrasting associations. For instance, Paita consistently presented negative but insignificant association across years, while its neighboring district, Colán, showed a positive and statistically significant relationship in 2021. These localized contrasts underscore the importance of studying microclimates and the spatially diverse impacts of weather events like ENSO, which reinforces the value of geographically weighted approaches in climate-health analyses.

Figure 20. Map of Estimated Effects of **Relative Humidity (%)** on Dengue Incidence

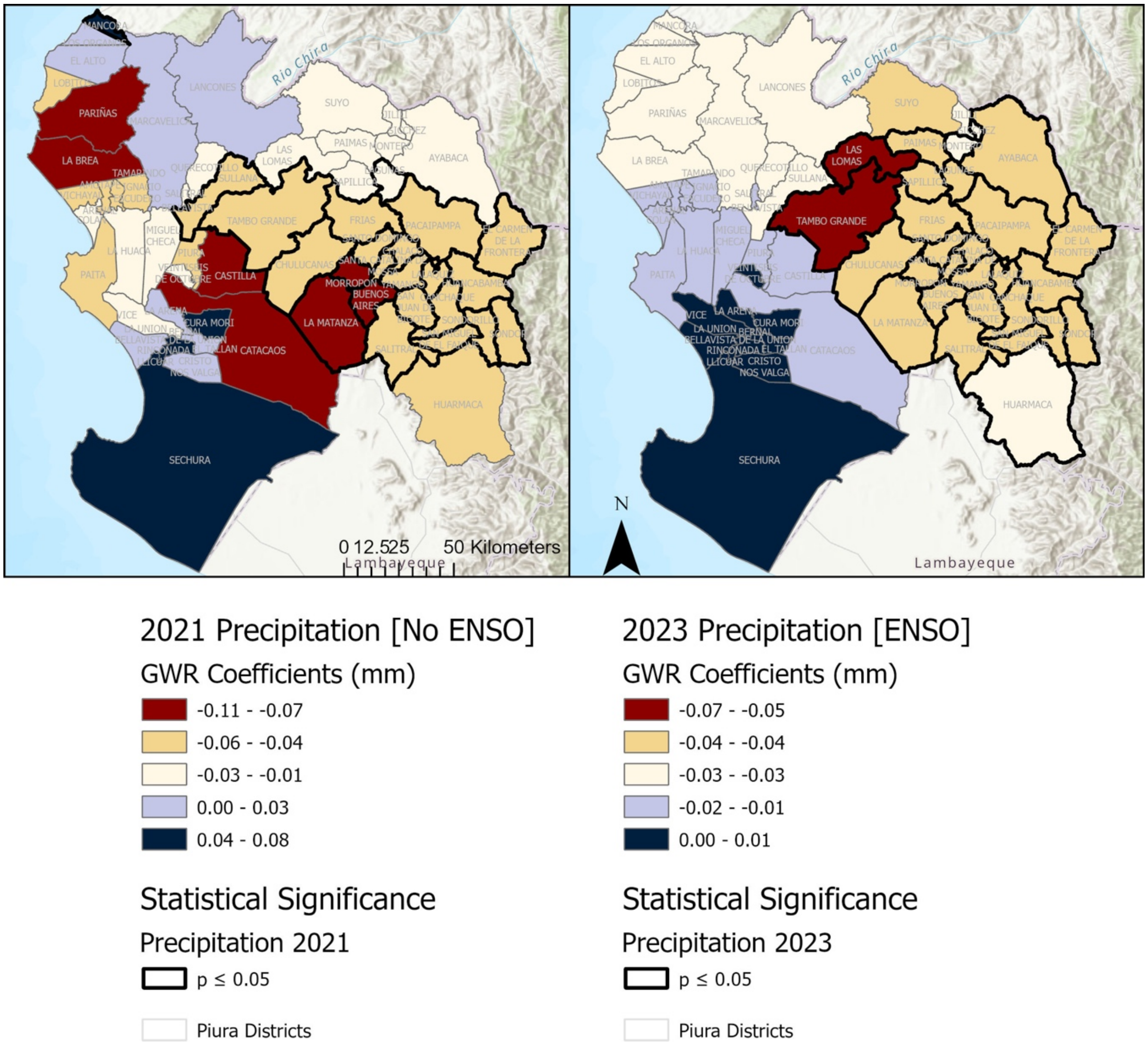


Note (Figure 19): GWR Coefficients represent the estimated effect of mean annual relative humidity (interpreted in terms of percentage change) on the log Empirical Bayes-smoothed dengue incidence rates during peak transmission season (March-August).

Precipitation has locally varying effects on dengue incidence in Piura hotspots

Spatial patterns of precipitation's effect on dengue incidence in Piura differ between ENSO and non-ENSO years, as observed in Figure 20 below. In 2021 (the No-ENSO year), GWR coefficients for precipitation indicate a wide range of estimated effects, including both negative and positive associations, from a –11 % to 8% change in the log EB dengue incidence in Piura districts. Notably, districts in the semi-arid, temperate and rainy highlands, exhibited significant and negative association, suggesting that increases in precipitation may decrease dengue risk in these wet regions. In contrast, the 2023 ENSO year displayed a narrower coefficient range, with associations from a -7% to .5% change, with most values skewing toward negative associations. Despite this general shift, statistical significance of these negative associations remained concentrated in the same eastern region, reinforcing the idea that heavy rainfalls can wash out mosquitoes breeding sites, diminishing its transmission. The reduced variation and overall more negative values of β in 2023 suggest that during ENSO years, the relationship between precipitation and dengue incidence may become more uniform.

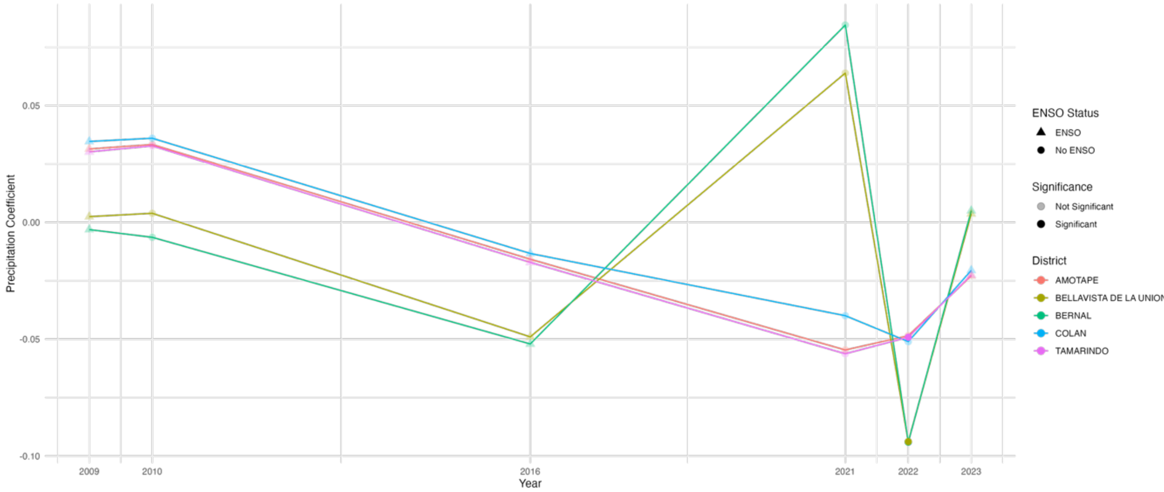
Figure 21. Map of Estimated Effects of **Precipitation (mm)** on Dengue Incidence



Note (Figure 20): GWR Coefficients represent the estimated effect of mean annual precipitation (interpreted in terms of percentage change) on the log Empirical Bayes-smoothed dengue incidence rates during peak transmission season (March-August).

In districts identified as consecutive hotspots under the EHSA analysis in Chapter 4 in the arid regions of Pira (Bernal, Amotape, Colan, Tamarindo and Bellavista De La Union), the GWR coefficients for precipitation showed fluctuations over time. In Figure 21, the shape and opacity of each data point communicate ENSO status and statistical significance. A filled triangle (high opacity, ENSO year) indicates a statistically significant association during ENSO, while a faded circle reflects a non-significant estimate in a non-ENSO year.

Figure 22. Precipitation Coefficient Over Time in Consecutive Hotspot Districts



Note (Figure 21): Values (β) represent the estimated effect of a one unit increase in precipitation (mm) on the log Empirical Bayes (EB)-smoothed dengue incidence during the peak transmission season (March–August).

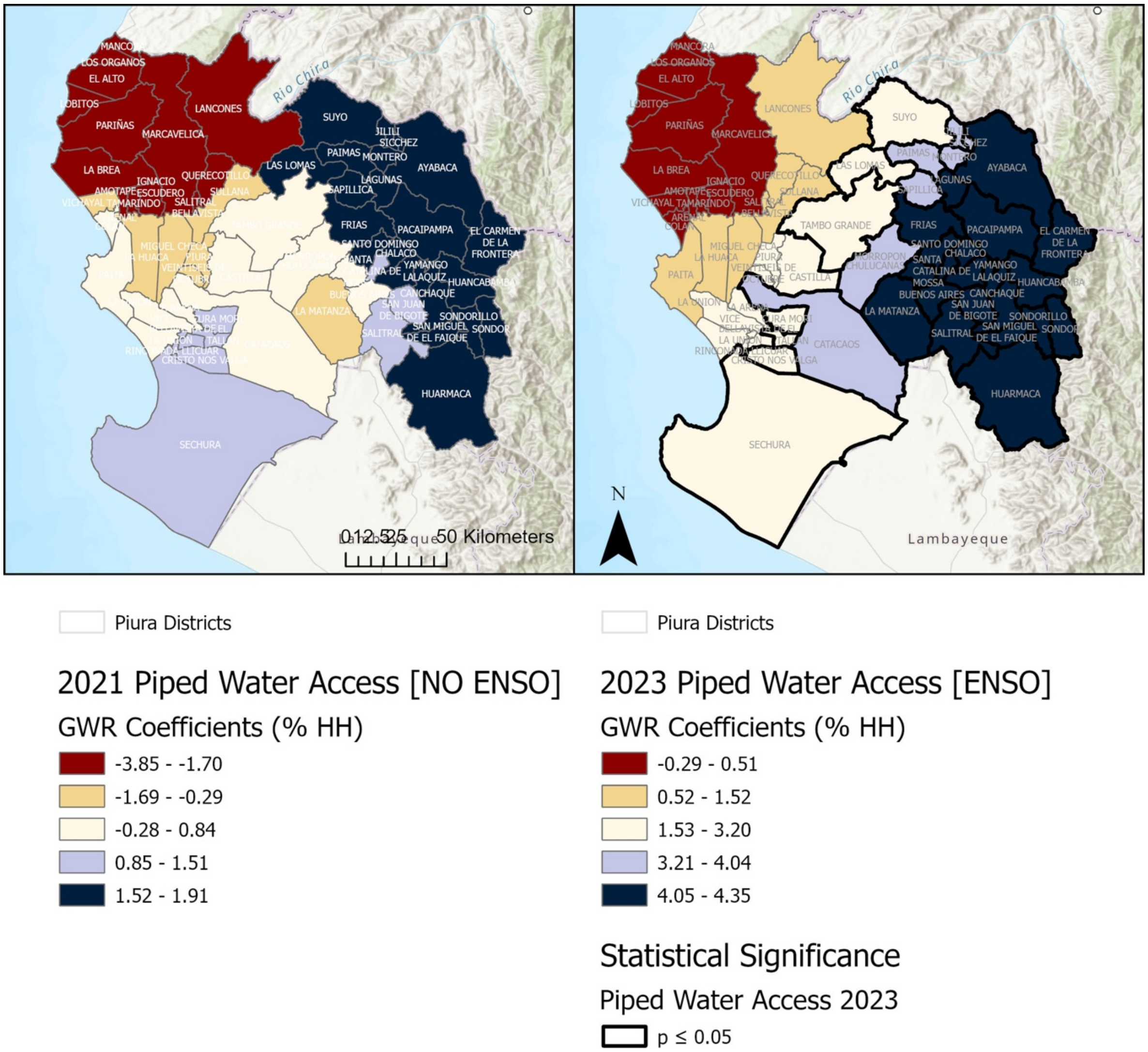
Based on this graph we observe that the precipitation coefficients in Colan, Tamarindo and Amotape follow a very similar pattern. These three districts are close neighbors in the arid province of Paita in Piura. A one-unit increase (mm) in precipitation was associated with a significant increase in dengue incidence by about 3% in the log EB dengue incidence of all three districts in 2010 (a No-ENSO year). In contrast, Bellavista de la Union and Bernal, two district neighbors of the southern province of Sechura in Piura, showed a close to zero effect in that year. However, in 2021 the effects of precipitation increased dramatically to suggest a more than 5% increase in dengue incidence. Considering this was not an ENSO year and it is a moisture deficient region; it could be argued that water storage practices during low precipitation seasons could have led to an increase dengue transmission. However, the associations in that year here were not statistically significant and precipitation levels in 2021 showed no evident difference compared to other years (refer to Figure 2.2).

The effects of precipitation only show a statistically significant inverse effect in 2022, a no ENSO year, for Tamarindo, Bellavista de la Union and Amotape. This temporal variation suggests that precipitation plays a local and context-dependent role in dengue dynamics. However, the overall results do not provide strong evidence that precipitation is consistently correlated with high or low incidence of dengue in the arid regions of Piura.

Piped water access shows as temporally dynamic dengue risk factor

The GWR results reveal a contrasting spatial and temporal relationship between piped water access and dengue incidence during ENSO and non-ENSO years. In 2021, coefficients ranged from strongly negative to moderately positive, with no statistically significant relationships observed. However, in the 2023 ENSO year, statistically significant positive coefficients emerged in the eastern half of Piura—mainly in the provinces of Piura, Ayabaca, Huancabamba, and Morropón (the four most densely populated), as well as Sechura (the least densely populated) (Figure 22). Districts in these provinces showed large positive coefficients, ranging from 1.5 to 4.35, indicating that a 1% increase in household piped water access was associated with a significant exponential rise in dengue incidence, approximately equivalent to 100*β percent. This shift suggests that, under ENSO conditions, piped water access correlates with dengue in in spatially different ways.

Figure 23. Map of Estimated Effects of **Piped Water Access (% households)** on Dengue Incidence



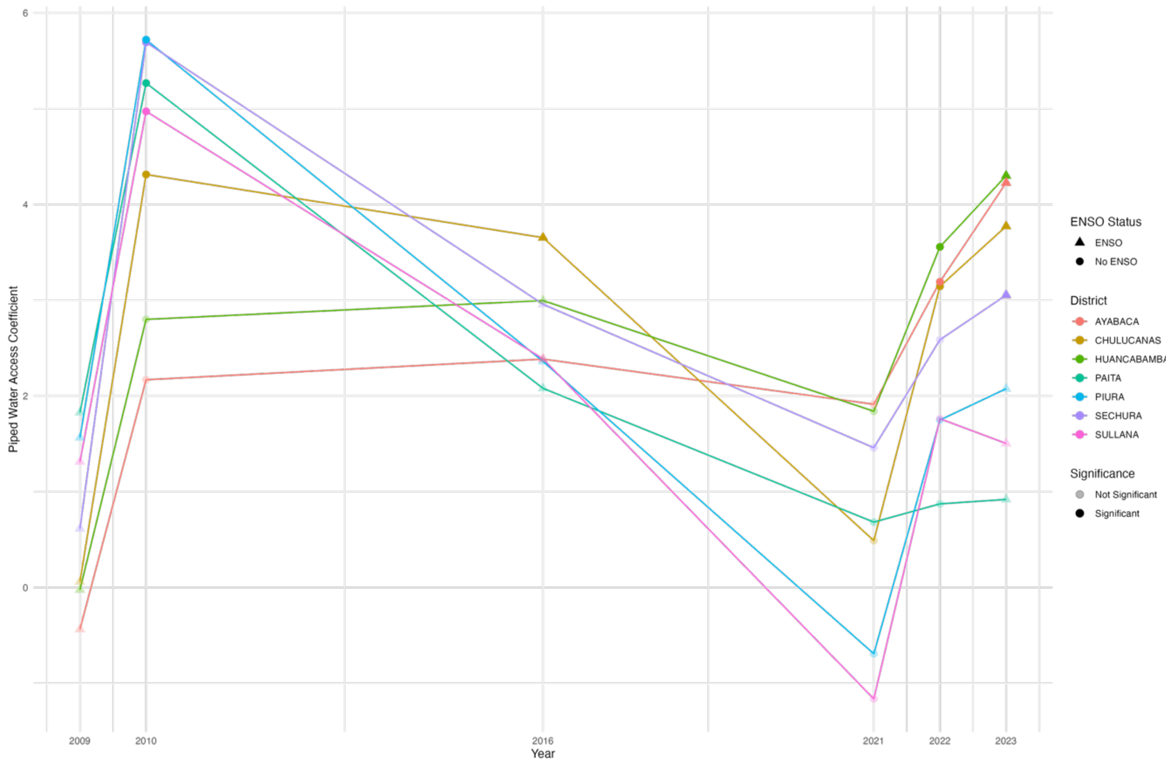
Note (Figure 22): GWR Coefficients represent the estimated effect of mean annual % of households with piped water access (interpreted in terms of percentage change) on the log Empirical Bayes-smoothed dengue incidence rates during peak transmission season (March-August).

There are several possible explanations to this relationship. For instance, unreliable piped water service can lead to water storage practices that create mosquito breeding habitats (Caprara et al., 2009; Nguyen-Tien et al., 2021). This behavior may intensify during ENSO years, when previous or current erratic rainfall patterns may encourage water hoarding. The concentration of human activities and interactions in urban spaces could also be a transmission factor (Tiong et al., 2015); however, this cannot entirely explain the 2023 pattern, as only Piura and Sechura provinces are predominantly urbanized (over 85% urban, INEI 2018), while Ayabaca and Huancabamba remain largely rural (INEI, 2018).

A time series perspective of the evolution of the coefficients of piped water access on dengue incidence show that, across districts the pattern of the effect is similar. Figure 23 presents trends for the capital districts of the eight provinces in Piura. All districts included showed a strong positive effect in 2010 a No-ENSO year, with significant effects in Chulucanas, Morropon; Piura, Piura and Sullana, Sullana. Despite the climatic diversity amongst them, these districts consistently exhibit large positive associations between piped water access and dengue incidence during that year. In the following years, the strength of this relationship weakened, with coefficients declining gradually through 2022. This could reflect improvements in water infrastructure across the region, which could have initially created conditions conducive to mosquito breeding (Oliveira et al., 2023).

Nevertheless, the resurgence of piped water's influence in 2023 remains paradoxical. It could be reflecting continued unreliability of existing water and sewerage systems (Chen et al., 1994; Ortega & Montes-Mata, 2024; Trewin et al., 2021), combined with persisting poor water management and storage practices (Nguyen-Tien et al., 2021). This supports the idea that piped water access, while often cited as a protective factor from dengue risk, can under certain conditions become a proxy for urban infrastructure limitations and behavioral adaptation, and climate-related vulnerability under a changing climate scenario.

Figure 24. Piped Water Access Coefficients Over Time in Capital Districts



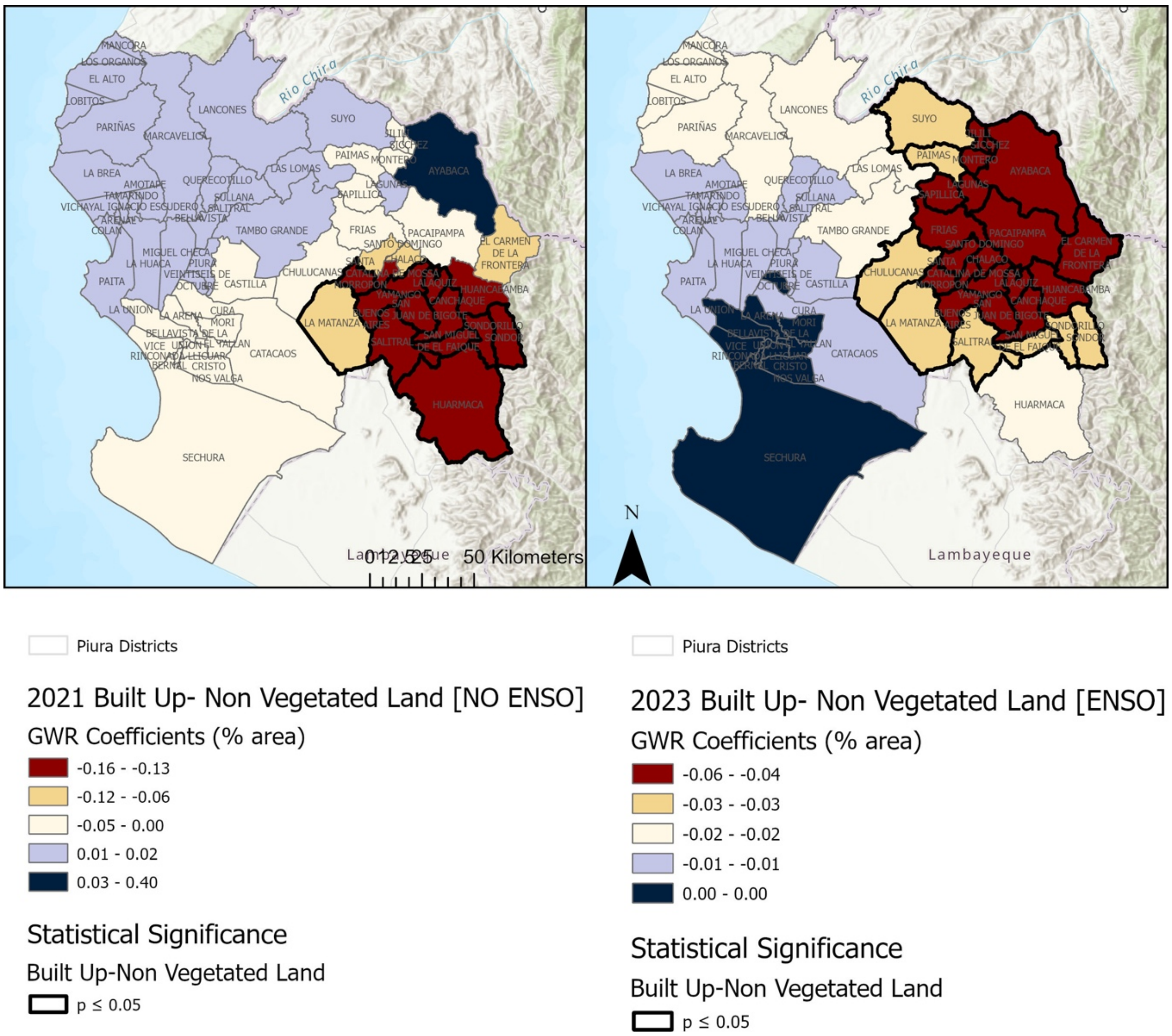
Note (Figure 23): Values (β) represent the estimated effect of a one unit increase in piped water access (%) on the log Empirical Bayes (EB)-smoothed dengue incidence during the peak transmission season (March–August).

Built-Up and Non-Vegetated area is weak, locally varying predictor of dengue incidence

Figure 24 illustrates the geographically weighted effects of built-up or non-vegetated land—measured as the percentage of district area—on dengue incidence during a non-ENSO year (2021) and an ENSO year (2023). In both years, most coefficients are negative or close to zero, suggesting a generally weak or inverse relationship between urban land cover and dengue incidence across districts in Piura. In 2021, statistically significant negative coefficients are concentrated in the highland provinces of Morropon and Huancabamba, where increases in the percentage of built-up or non-vegetate land by district were associated with lower dengue incidence.

By 2023, this pattern extends to districts in Ayabaca province. The magnitude of the coefficients in 2023 ranges narrowly from -0.056 to -0.001, reinforcing the idea that the built-up land factor has a small influence on dengue incidence, and is primarily localized in rural or semi-urban contexts.

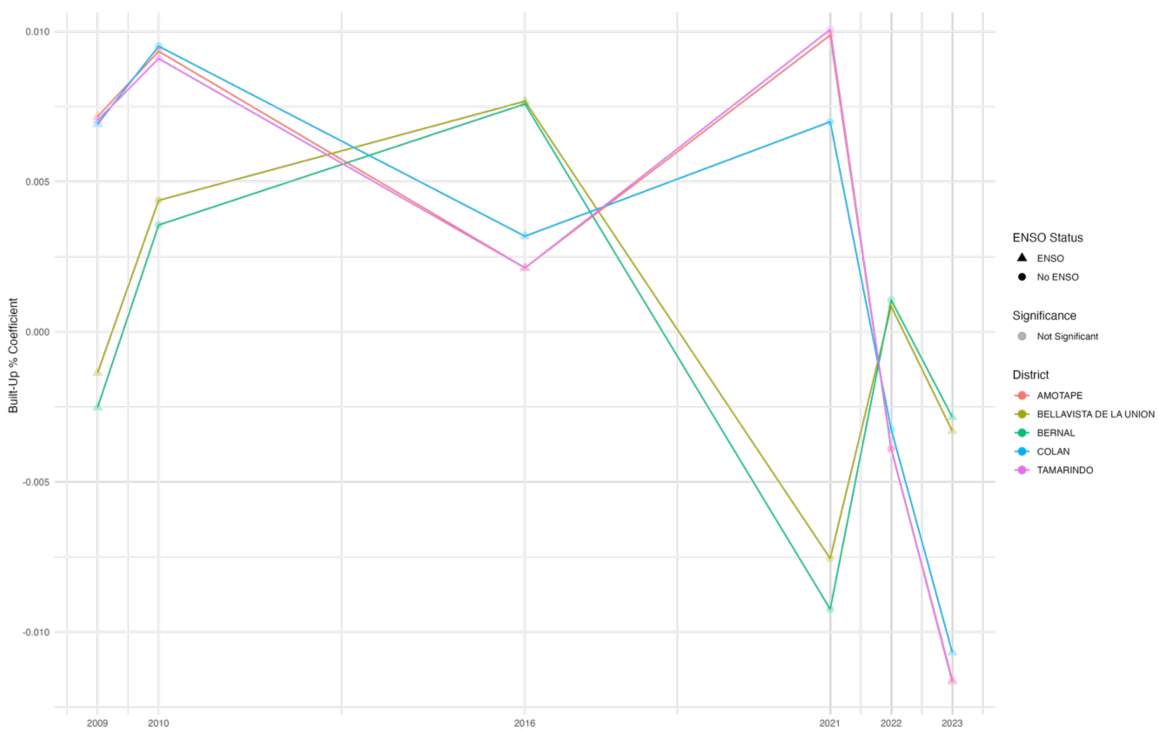
Figure 25. Map of Estimated Effects of **Built Up/Non-Vegetated (%) Land** on Dengue Incidence



Note (Figure 24): GWR Coefficients represent the estimated effect of mean annual % of district area which land use type is classified as built-up or non-vegetated (interpreted in terms of percentage change) on the log Empirical Bayes-smoothed dengue incidence rates during peak transmission season (March-August).

When tracking the evolution of GWR coefficients across five persistent dengue hotspot districts in the coastal and semi-coastal zone, coefficients are statistically insignificant in both ENSO and non-ENSO years (Figure 25). However, some degree of spatial clustering can be observed. Colán, Tamarindo, and Amotape's coefficients remain close to zero but follow a similar pattern: positive peaks in 2010 and 2021, followed by sharp declines toward 2023. Meanwhile, Bernal and Bellavista show contrasting trend, with both districts presenting positive coefficients in 2016, followed by a sharp decrease in the estimated effect by 2021, with Bernal reaching below -0.05, meaning a one percent increase in the proportion of Bernal's land classified as built-up or non-vegetated was correlated with a decrease in dengue incidence. Despite statistical insignificance, these patterns point to localized and temporally related influences of urban land expansion on dengue dynamics.

Figure 26. Built Up / Non-Vegetated Land Coefficient Over Time in Consecutive Hotspot Districts



Note (Figure 25): Values (β) represent the estimated effect of a one unit increase in the percentage (%) of district area classified as built-up or non-vegetated on the log Empirical Bayes (EB)-smoothed dengue incidence during the peak transmission season (March–August).

6.4 Conclusion

This chapter provides evidence that the relationships between climate, infrastructure, and dengue incidence in Piura are not uniform; instead, the associations vary considerably across districts and years. This analysis does not allow for definitive conclusions about differences between ENSO and non-ENSO periods -due to its focus on six selected years and a relatively small sample size of 65 observations per year. However, the use of GWR does allows to identify localized effects of each variable. For instance, that temperature was more consistently and positively associated with dengue incidence during the most recent ENSO year (2023), while the effects of precipitation and humidity were more context-dependent, varying sub-regionally or even among neighboring districts in different years. Piped water access showed dynamic and spatially divergent effects, shifting from a protective to a risk-enhancing factor depending on the year and district - possibly reflecting variation in infrastructure reliability and behavioral responses to climate stressors, such as heavy rainfalls or droughts.

These findings underscore the limitations of relying on global models to inform public health interventions and stress the importance of incorporating spatial variation into epidemiological and climate-related risk analyses. As climate change intensifies and urban systems evolve, localized strategies can support dengue risk mitigation policies. The insights from this chapter point to the need for localized surveillance - ideally at a finer resolution than the one used here- and for urban infrastructure planning that accounts for the spatially varying and often non-linear, interactions between climate variables, urban form, and vector-borne disease transmission.

Chapter 7: Conclusions and Policy Implications

This exploratory analysis sought to understand the evolution of dengue incidence in Piura, Peru and some underlying climate and built-environment drivers using spatial statistics and econometric tools. By evaluating the role of climate variability, ENSO events, and urban features through spatial trend analysis and three different panel regression approaches, this thesis highlights the complex interrelation between climate, infrastructure and public health, and thus the importance of employing these tools in the design of targeted and localized disease prevention strategies and climate-resilient urban planning. In particular, district-specific effects during ENSO years and the relevance of lagged climate variables revealed that dengue transmission dynamics are not only seasonal, but also sensitive to prior environmental conditions and exposure to climate hazards, reinforcing the need for early warning systems and comprehensive anticipatory action frameworks at the local level.

The trend analysis and statistical tests of Chapter 4 confirmed that the Piura case challenges the perception of dengue as a tropical disease and has in fact experienced a significant upward trend in the last twenty-three years. However, the spatial statistics also indicate that Piura is overall a sporadic rather than consecutive or new hotspot of dengue incidence in Perú, with remerging incidence during past few years. This calls for special attention to the factors driving such increases in dengue incidence.

The findings support the hypothesis that dengue incidence in Piura is closely linked to non-linear and lagged effects of temperature and precipitation. Temperature was found to follow an inverted U-shaped relationship with dengue, while precipitation's effect was more prominent at lags of one to six months, suggesting a delayed role in creating suitable breeding habitats for mosquitoes. Although relative humidity showed less consistent effects, its interaction with ENSO was significant, as well as that of temperature and precipitation, highlighting that climate–dengue relationships shift during months of extreme weather events. Still, the GWR results suggest that climate effects on local dengue incidence are highly heterogeneous and temporally varying, in some cases from year to year. These results underscore the need for climate-informed planning in the region. For example, designing early intervention policies in the months following climate anomalies, such as ENSO events, could help reduce the dengue burden. This could include proactive vector control measures, public health campaigns, and water management interventions targeted at high-risk districts during and immediately after anomalous climate periods.

Access to piped water was found to be positively associated with dengue incidence across models (OLS, FE and GWR – to a different degree in location and time), suggesting that areas with greater coverage of piped water systems may still experience elevated risk—possibly due to storage practices or intermittence in the service. On the other hand, it may indicate that piped water access is correlated with other urban characteristics—such as higher population density, concentration of services, or better disease surveillance—that also influence reported incidence. By contrast, the negative interaction between precipitation and piped water access in both OLS and Fixed Effects models indicates that precipitation-driven increases in dengue incidence are less pronounced in areas with better piped water coverage. This suggests that piped water infrastructure plays a moderating role in reducing vulnerability to rainfall-induced mosquito breeding. From a policy perspective, this finding emphasizes the importance of proper water infrastructure as a critical component of climate-resilient public health strategy. Investing in reliable, continuous piped water systems—particularly in flood-prone or high-precipitation districts—could reduce the environmental suitability for dengue vectors and help prevent outbreaks during the rainy season.

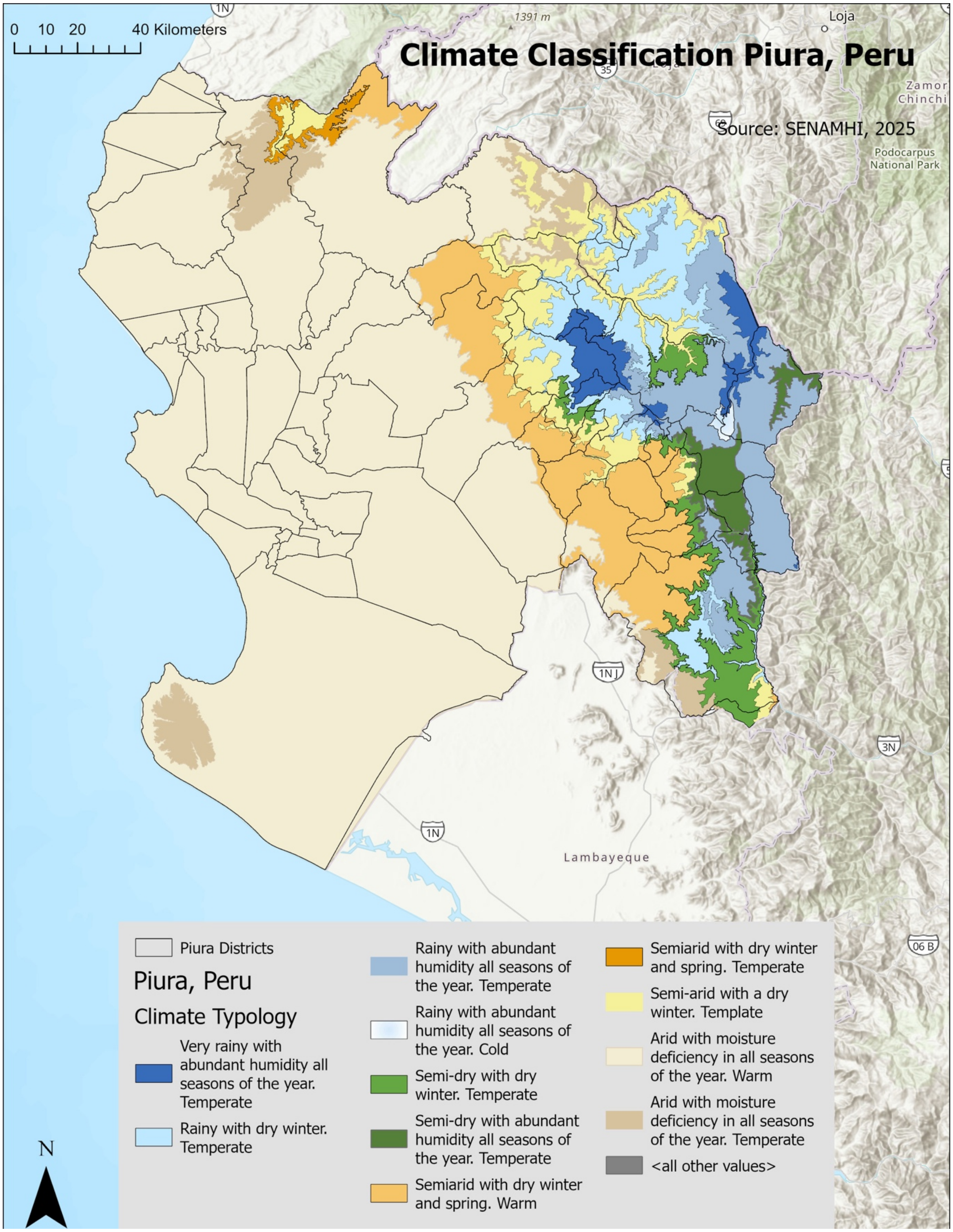
As climate change is expected to increase the frequency and intensity of ENSO-like events, these findings highlight the need for proactive, climate-informed health planning in Piura and similar regions vulnerable to dengue outbreaks.

Given the complex dynamics and non-linear relationships observed between climate variables, infrastructure, and dengue incidence, future research should explore alternative non-parametric and machine learning approaches to better capture these interactions. Modeling approaches such as the Bayesian statistical approaches are increasingly cited techniques due to their capacity to incorporate these complex relationships and integrate more potential explanatory variables. For example, future studies could consider the inclusion of factors recently cited as strong predictors of dengue incidence, such as human mobility (Gibb et al., 2023), cities connectivity (Lee et al., 2021) and international air travel (Colón-González et al., 2023, Nunes et al., 2014; Tian et al., 2017).

In terms of spatial and temporal analysis, future research could benefit from some improvements. For instance, expand the application of spatial statistics tools to evaluate the spatial mean center and standard distance of dengue incidence on a year-by-year case to identify how the spatial distribution of dengue burden changes over time (Isnan et al., 2021). Likewise, conducting a similar analysis at finer spatial units (e.g., “centros poblados” in Peru or neighborhoods), or expanding it to cover all districts in Piura (n = 1890), could address model overfitting limitations in geographically weighted regressions.

Additionally, more advanced spatial modeling tools such as Multiscale Geographically Weighted Regression (MGWR) and Geographically and Temporally Weighted Regression (GTWR) could help account for spatial heterogeneity and time-specific effects simultaneously. Finally, further research could benefit from expanding the historical coverage beyond 20 years to strengthen the ability to detect climate change signals and make stronger attribution claims.

ANNEX 1: Climate Typology of Piura



ANNEX 2: OLS and FE Regression Covariates

Annex 2. Variables Included in Each Model

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Mean temperature (°C)	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mean temperature²		✓		✓	✓	✓	✓	✓	✓
Mean precipitation (mm)	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mean relative humidity (%)	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mean relative humidity²			✓	✓	✓	✓	✓	✓	✓
ENSO × Precipitation					✓	✓	✓	✓	✓
ENSO × Relative humidity					✓	✓	✓	✓	✓
ENSO × Temperature					✓	✓	✓	✓	✓
Temp lag 1 mo						✓	✓	✓	✓
Temp lag 2 mo								✓	✓
Temp lag 3 mo								✓	✓
Temp lag 4 mo								✓	✓
Temp lag 5 mo								✓	✓
Temp lag 6 mo								✓	✓
Humidity lag 1 mo						✓	✓	✓	✓
Humidity lag 2 mo								✓	✓
Humidity lag 3 mo								✓	✓
Humidity lag 4 mo								✓	✓
Humidity lag 5 mo								✓	✓
Humidity lag 6 mo								✓	✓
Precip lag 1 mo						✓	✓	✓	✓
Precip lag 2 mo								✓	✓
Precip lag 3 mo								✓	✓
Precip lag 4 mo								✓	✓
Precip lag 5 mo								✓	✓
Precip lag 6 mo								✓	✓
Precipitation × Piped water							✓	✓	✓
% Households with piped water	✓	✓	✓	✓	✓	✓	✓	✓	✓
% Households with sewage	✓	✓	✓	✓	✓	✓	✓	✓	
% Built-up land	✓	✓	✓	✓	✓	✓	✓	✓	✓
% Water bodies	✓	✓	✓	✓	✓	✓	✓	✓	✓
ENSO dummy	✓	✓	✓	✓	✓	✓	✓	✓	✓

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