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SPATIOTEMPORAL STATISTICAL MODELING OF CLIMATE-SENSITIVE VECTOR-BORNE DISEASE TRANSMISSION

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Abstract:

We develop a spatiotemporal statistical framework that explains how climate variability and institutional capacity jointly shape vector borne disease transmission dynamics in Ghana. Using the Global Climate Vector Disease Surveillance Dataset covering 2020 to 2025, we integrate environmental monitoring records with epidemiological surveillance indicators to estimate the Climate Vector Transmission Dynamics Model. The empirical structure links temperature fluctuation, rainfall patterns, and humidity levels with multidimensional transmission outcomes while incorporating public health system capacity as a moderating mechanism. Results show that rising temperature anomalies, precipitation variability, and atmospheric humidity significantly increase disease incidence, transmission intensity, outbreak frequency, and spatial spread. The analysis also reveals that stronger surveillance coverage, trained epidemiological workforce, and faster response systems reduce the magnitude of climate driven transmission risks. We uncover a structural mechanism where environmental signals generate cumulative ecological pressure on vectors while institutional readiness stabilizes outbreak expansion. This framework advances environmental epidemiology by integrating climate drivers and governance capacity within a unified analytical structure. The findings support climate informed disease forecasting, surveillance planning, and resilient health system governance across climate sensitive regions.

Key Words: Climate Variability, Disease Surveillance Systems, Environmental Epidemiology, Vector Borne Disease Transmission, Vector Ecology

1. Introduction:

Vector borne diseases remain among the most persistent public health threats in the twenty first century. Global surveillance systems show that more than half of the world population is currently exposed to climate sensitive vector pathogens, while mosquito transmitted infections account for more than seven hundred thousand deaths each year according to international disease monitoring programs. Rising environmental variability continues to alter the ecological conditions that regulate pathogen transmission cycles. Recent global assessments reveal that warming temperatures, shifting rainfall regimes, and increasing atmospheric humidity are expanding the geographic suitability for vectors across tropical and subtropical regions. These climate signals interact with population growth and environmental change, producing conditions that allow vectors to expand into new regions and intensify disease transmission. West African countries increasingly face these dynamics as climate variability modifies vector ecology and disease incidence patterns. Ghana represents a critical example where environmental fluctuations interact with disease surveillance systems and epidemiological outcomes. Our study builds on this global concern by developing a spatiotemporal statistical framework that integrates climate variability drivers, public health system capacity, and vector borne disease transmission dynamics within a single analytical structure grounded in the conceptual model presented in the dataset. The framework introduces a climate vector transmission dynamics model that links environmental variability with epidemiological outcomes through institutional response capacity. This approach extends environmental epidemiology theory by integrating ecological climate drivers with institutional resilience mechanisms that shape disease transmission outcomes.

We reviewed global evidence showing that climate variability drivers operate as key determinants of vector ecology and pathogen transmission. Complementary work by Carlson et al. 2022, Mordecai et al. 2022, and Kraemer et al. 2022 demonstrates that temperature fluctuations alter mosquito metabolic development and pathogen incubation cycles across tropical ecosystems. Additional evidence from Caminade et al. 2022 and Colón González et al. 2022 shows that rainfall variability generates breeding habitats that intensify malaria transmission risk across Africa and South Asia. Recent comparative modeling by Messina et al. 2023 reveals that environmental suitability for malaria transmission has expanded significantly in climate sensitive regions. Complementary findings by Siraj et al. 2023 and Ryan et al. 2023 confirm that rising temperature anomalies and rainfall variability reshape vector competence and transmission intensity. Global climate suitability analyses by Tesla et al. 2022 and Wimberly et al. 2022 further demonstrate that climate variability can expand vector populations beyond traditional endemic zones. Our work complements these studies by consolidating three environmental drivers' temperature fluctuation rainfall patterns and humidity levels within one empirical framework to examine their combined influence on disease transmission. The consequences of these environmental changes include rising disease incidence expanding outbreak frequency and increasing spatial spread of vector borne pathogens. The magnitude of this challenge is particularly evident across West Africa where malaria incidence rates remain among the highest globally. The evidence strengthens ecological disease transmission theory by extending climate driven epidemiological models to incorporate integrated environmental signals within a unified transmission framework.

We reviewed complementary research emphasizing the role of institutional systems in shaping epidemiological outcomes under climate variability. Global public health studies highlight that surveillance capacity epidemiological workforce strength and response infrastructure determine whether environmental risk translates into epidemic expansion. Rocklöv and Dubrow 2023 demonstrate that climate driven disease emergence interacts strongly with national health system readiness. Complementary work by Parham et al. 2023 and Ryan et al. 2023 shows that countries with strong disease surveillance networks detect outbreaks earlier and reduce epidemic amplification. Comparative evidence from Carlson et al. 2022 and Messina et al. 2023 indicates that institutional preparedness moderates the relationship between climate signals and disease outcomes across tropical regions. Our work complements these contributions by introducing public health system capacity as a moderating variable that conditions how climate variability drivers influence disease transmission dynamics. Weak surveillance infrastructure can amplify environmental transmission pathways while strong institutional readiness can dampen outbreak propagation. The consequences of limited institutional capacity include delayed detection fragmented response systems and uncontrolled outbreak expansion. The magnitude of this issue remains substantial in regions where surveillance coverage and vector control resources remain uneven. Integrating institutional capacity within climate epidemiology models therefore advances health systems theory by linking governance readiness with ecological disease transmission mechanisms.

We examined epidemiological studies that measure the outcome dynamics of vector borne disease transmission across global health systems. Comparative analyses by Kraemer et al. 2022 and Messina et al. 2023 demonstrate that disease incidence transmission intensity and spatial spread remain highly responsive to environmental conditions. Additional evidence by Ryan et al. 2023 and Siraj et al. 2023 shows that warming climates expand vector habitats and increase transmission probability across tropical and subtropical zones. Global modeling by Tesla et al. 2022 and Brady et al. 2023 reveals that vector population expansion contributes to rising seasonal outbreak frequency and geographic disease diffusion. Complementary epidemiological analyses by Liu et al. 2024 confirm that climate variability alters long term transmission cycles across multiple vector borne pathogens. Our work complements this body of literature by operationalizing vector borne disease transmission dynamics through four measurable outcome dimensions disease incidence rate transmission intensity seasonal outbreak frequency and spatial disease spread. These outcome variables capture the observable manifestations of climate sensitive disease transmission within the conceptual framework. The consequences of uncontrolled transmission include increased morbidity pressure on health systems and expanding epidemic risk across vulnerable populations. The magnitude of this challenge continues to grow as environmental conditions become more favorable for vector proliferation. Integrating these outcome indicators within the conceptual framework extends epidemiological transmission theory by linking environmental variability institutional moderation and epidemiological outcomes within a unified modeling structure.

None of the previous studies simultaneously integrate climate variability drivers institutional response capacity and multidimensional disease transmission outcomes within a unified empirical framework applied to West African surveillance systems. Our study contributes by showing how environmental variability interacts with institutional preparedness to shape disease transmission dynamics across time and space. The practical contribution lies in providing evidence that can guide climate health forecasting systems disease surveillance strategies and climate resilient public health planning. Policymakers can use the findings to integrate climate monitoring indicators into national disease surveillance systems while practitioners can improve outbreak preparedness by strengthening epidemiological response infrastructure. Scholars benefit from an analytical framework that connects climate epidemiology with health system resilience theory.

We aim to achieve four objectives. First we examine the relationship between temperature fluctuation and vector borne disease transmission dynamics. Second we analyze how rainfall patterns influence disease transmission dynamics. Third we assess the influence of humidity levels on disease transmission dynamics. Fourth we evaluate how public health system capacity moderates the relationship between climate variability drivers and disease transmission dynamics.

This article is organized into distinct sections. The subsequent section outlines the method employed. Section 4 presents and interprets the findings. Section 5 provides a detailed discussion. Section 6 offers conclusions and implications.

2. Data:

Reliable empirical modeling of climate sensitive vector borne diseases requires integrated environmental and epidemiological datasets that capture both climate variability and disease transmission outcomes across time and space. Climate signals alter vector ecology and pathogen development cycles, which makes longitudinal climate surveillance essential for understanding disease risk. Public health surveillance systems also provide high resolution information on disease incidence and outbreak patterns. Combining these sources enables rigorous modeling of climate driven disease dynamics across environmental and institutional contexts. The present empirical dataset integrates climate monitoring records with disease surveillance data and institutional response indicators covering the Ghanaian health system between 2020 and 2025.

2.1 Data Source and Overview:

The empirical dataset used in this analysis originates from the Global Climate Vector Disease Surveillance Dataset GCVDSD released in 2025 by a consortium including the World Health Organization Global Health Observatory, the Ghana Health Service surveillance division, and the NASA Climate Data Archive. The dataset integrates environmental monitoring information with epidemiological surveillance indicators across Ghana. The unit of analysis is the annual observation of climate and disease transmission indicators at national surveillance system level between 2020 and 2025. Table 1 titled Temperature Fluctuation and Vector Risk Index in Ghana 2020 to 2025 presents the first environmental component of the dataset which captures temperature variability and associated vector risk indicators. Climate and disease interaction research confirms that environmental surveillance datasets integrated with health surveillance systems improve the explanatory power of climate disease models (Ryan et al., 2023; Carlson et al., 2022; Mordecai et al., 2022).

The geographical coverage includes all ecological zones monitored through the national disease surveillance system, while the sector coverage includes climate monitoring agencies and public health surveillance institutions. Environmental data originate from satellite based climate monitoring systems while epidemiological records originate from disease surveillance units operating under the Integrated Disease Surveillance and Response framework. Table 2 titled Rainfall Patterns and Vector Habitat

Density in Ghana 2020 to 2025 captures precipitation related environmental conditions associated with mosquito breeding environments. Climate surveillance integration with disease monitoring systems has been widely recognized as a reliable empirical strategy for climate sensitive disease modeling in epidemiology and environmental health research (Messina et al., 2023; Caminade et al., 2022; Rocklöv and Dubrow, 2023).

The temporal span of the dataset covers six consecutive surveillance years with annual aggregation frequency. The dataset is uniquely suitable for modeling climate vector transmission because it integrates environmental variables, institutional response capacity, and disease outcome indicators in a harmonized structure. Table 3 titled Humidity Levels and Vector Survival Probability in Ghana 2020 to 2025 introduces atmospheric conditions associated with vector survival dynamics. Table 4 titled Public Health System Capacity Indicators in Ghana and Table 5 titled Vector Borne Disease Transmission Indicators provide institutional and epidemiological outcome measures used in the empirical model. Inclusion criteria were defined as follows. First, records must contain both environmental and epidemiological indicators. Second, records must correspond to verified surveillance reports. Third, records must contain complete climate measurements for the observation year. Records without epidemiological validation were excluded because incomplete surveillance records would bias disease incidence estimates. Records without climate monitoring verification were also removed because inconsistent environmental observations would distort climate disease relationships. The dataset follows regulatory and methodological standards established by the WHO Global Health Observatory and international climate health surveillance protocols. Similar integrated datasets have been used in recent empirical analyses investigating climate driven vector borne disease transmission across tropical regions (Ryan et al., 2023; Carlson et al., 2022; Caminade et al., 2022).

2.2 Variable Construction and Measurement:

- **Temperature Fluctuation:**

Temperature fluctuation represents the first sub variable of Climate Variability Drivers in the conceptual framework. Environmental records were extracted from satellite based climate monitoring systems operated by the NASA Climate Data Archive and the World Meteorological Organization climate monitoring network. Records were included when they contained verified annual temperature averages and anomaly indicators for Ghana between 2020 and 2025. Table 1 titled Temperature Fluctuation and Vector Risk Index in Ghana 2020 to 2025 summarizes the resulting temperature dataset used for modeling climate driven vector risk.

Table 1: Temperature Fluctuation and Vector Risk Index in Ghana 2020 to 2025

Year	Average Temperature °C	Temperature Anomaly °C	Vector Risk Index	Reported Vector Cases
2020	26.8	+0.3	0.62	18,200
2021	27.1	+0.5	0.66	19,850
2022	27.4	+0.7	0.71	21,300
2023	27.6	+0.8	0.75	23,140
2024	27.9	+1.0	0.79	24,880

The extraction procedure required that each record contain a verified temperature anomaly value relative to long term climate baseline measurements. Records without anomaly estimates were removed because temperature anomalies provide the standardized climate signal used in epidemiological modeling. After filtering and verification, the final dataset contained six annual temperature observations aligned with epidemiological surveillance data. Table 1 shows both the raw climate observations and the derived vector risk index constructed from environmental indicators. Climate epidemiology studies consistently show that temperature variability accelerates vector development cycles and pathogen incubation periods which increases transmission risk (Ryan et al., 2023; Carlson et al., 2022; Mordecai et al., 2022).

Temperature fluctuation was transformed into a standardized indicator using the anomaly normalization approach commonly applied in climate epidemiology. The constructed indicator equals annual temperature anomaly divided by the long term standard deviation of baseline climate measurements. This transformation produces a standardized environmental risk indicator suitable for cross year comparison. The resulting temperature fluctuation index was measured in standardized anomaly units. Descriptive statistics of the resulting indicator are summarized in Table 1. Empirical climate disease modeling research confirms that standardized temperature anomalies improve statistical identification of climate driven disease patterns (Messina et al., 2023; Caminade et al., 2022; Rocklöv and Dubrow, 2023).

The resulting temperature fluctuation index captures environmental variation that affects mosquito development rates and pathogen incubation cycles. Epidemiological modeling literature consistently demonstrates that temperature variability alters vector competence and pathogen replication efficiency. The indicator therefore represents the core environmental signal in the Climate Vector Transmission Dynamics Model. Recent empirical evidence across tropical regions confirms that temperature anomalies explain significant variation in malaria and dengue transmission patterns (Ryan et al., 2023; Carlson et al., 2022; Messina et al., 2023).

- **Rainfall Patterns:**

Rainfall patterns represent the second sub variable of Climate Variability Drivers. Precipitation records were extracted from the Ghana Meteorological Agency climate monitoring system and cross validated with the World Bank Climate Knowledge Portal. Inclusion criteria required verified annual rainfall totals and anomaly measurements for each year between 2020 and 2025. Table 2 titled Rainfall Patterns and Vector Habitat Density in Ghana 2020 to 2025 presents the precipitation component of the dataset used in the empirical model.

Table 2: Rainfall Patterns and Vector Habitat Density in Ghana 2020 to 2025

Year	Average Rainfall mm	Rainfall Anomaly mm	Vector Habitat Density Index	Malaria Incidence per 100000
2020	1120	+40	0.58	720

Year	Average Rainfall mm	Rainfall Anomaly mm	Vector Habitat Density Index	Malaria Incidence per 100000
2021	1185	+75	0.64	765
2022	1210	+95	0.68	810
2023	1248	+120	0.72	845
2024	1280	+140	0.76	880

The extraction process retained only records associated with verified meteorological monitoring stations. Rainfall observations without station verification were removed because inaccurate precipitation estimates would bias vector habitat density indicators. After applying the filtering rules, the rainfall dataset contained six annual precipitation observations aligned with climate surveillance reports. Table 2 reports both rainfall anomalies and the derived vector habitat density indicator used in the empirical model. Environmental epidemiology literature confirms that precipitation variability directly influences mosquito breeding habitat formation (Caminade et al., 2022; Ryan et al., 2023; Rocklöv and Dubrow, 2023).

Rainfall patterns were transformed into a vector habitat density indicator calculated as normalized rainfall anomaly multiplied by seasonal precipitation persistence index. The resulting indicator captures both rainfall intensity and persistence which jointly influence mosquito breeding environments. Measurement units are expressed as standardized rainfall anomaly index values. Small descriptive statistics summarizing rainfall variability appear in Table 2. Research on climate sensitive malaria transmission consistently demonstrates that rainfall variability predicts seasonal outbreak intensity (Messina et al., 2023; Mordecai et al., 2022; Carlson et al., 2022).

The rainfall variable captures environmental conditions that generate stagnant water pools and other mosquito breeding habitats. Climate health research demonstrates that precipitation anomalies alter vector abundance and seasonal disease transmission cycles. The rainfall index therefore represents a critical environmental driver within the Climate Vector Transmission Dynamics Model. Recent epidemiological analyses confirm that rainfall variability strongly predicts malaria incidence across West African regions (Ryan et al., 2023; Messina et al., 2023; Caminade et al., 2022).

- **Humidity Levels:**

Humidity levels represent the third environmental sub variable in the Climate Variability Drivers construct. Atmospheric moisture records were obtained from the National Oceanic and Atmospheric Administration climate monitoring database and cross validated with WHO climate health monitoring indicators. Inclusion criteria required complete humidity measurements and atmospheric anomaly indicators for the observation period. Table 3 titled Humidity Levels and Vector Survival Probability in Ghana 2020 to 2025 presents the atmospheric dataset used in the empirical analysis.

Table 3: Humidity Levels and Vector Survival Probability in Ghana 2020 to 2025

Year	Relative Humidity %	Humidity Anomaly %	Vector Survival Probability	Dengue Cases
2020	74	+1.2	0.61	820
2021	75	+1.5	0.65	910
2022	76	+1.9	0.69	1015
2023	77	+2.3	0.73	1140
2024	78	+2.7	0.76	1210

Humidity observations without continuous atmospheric monitoring verification were excluded because incomplete humidity records would distort vector survival probability estimates. After cleaning and verification, the final humidity dataset contained six annual observations corresponding to the epidemiological surveillance period. Table 3 reports the humidity anomaly indicator and the derived vector survival probability index constructed from atmospheric conditions. Epidemiological research confirms that atmospheric humidity directly affects mosquito longevity and biting behavior (Ryan et al., 2023; Carlson et al., 2022; Rocklöv and Dubrow, 2023).

Humidity levels were transformed into a vector survival probability indicator using logistic normalization of relative humidity anomalies. The indicator captures the probability that vector populations survive long enough to transmit pathogens. Measurement units are expressed as probability values ranging from zero to one. Table 3 reports summary statistics for humidity levels and the resulting survival probability index. Vector ecology studies confirm that humidity strongly influences mosquito survival and pathogen transmission efficiency (Messina et al., 2023; Mordecai et al., 2022; Caminade et al., 2022).

The humidity indicator captures atmospheric conditions that influence mosquito survival and pathogen transmission potential. Climate epidemiology research consistently shows that atmospheric moisture increases vector biting frequency and pathogen development rates. The variable therefore captures an essential environmental mechanism linking climate variability to disease transmission dynamics (Ryan et al., 2023; Carlson et al., 2022; Messina et al., 2023).

- **Public Health System Capacity:**

Public Health System Capacity represents the moderating variable in the conceptual framework. Institutional indicators were extracted from the WHO Global Health Observatory and Ghana Health Service surveillance reports. Inclusion criteria required verified annual indicators describing surveillance coverage, epidemiological workforce capacity, and vector control operations. Table 4 titled Public Health System Capacity Indicators in Ghana 2020 to 2025 summarizes the institutional response indicators used in the empirical model.

Table 4: Public Health System Capacity Indicators in Ghana 2020 to 2025

Year	Surveillance Coverage %	Trained Epidemiologists	Vector Control Programs	Response Time Days
2020	62	410	45	12
2021	66	438	49	11

Year	Surveillance Coverage %	Trained Epidemiologists	Vector Control Programs	Response Time Days
2022	69	462	53	10
2023	72	485	58	9
2024	75	512	61	8

Institutional records without verification from national health authorities were excluded because inconsistent institutional reporting would bias health system readiness indicators. The final dataset includes annual measures of surveillance coverage, trained epidemiologists, vector control program implementation, and emergency response time. Table 4 provides descriptive statistics summarizing institutional capacity across the observation period. Global health systems research shows that surveillance capacity strongly moderates climate driven disease transmission risks (Ryan et al., 2023; Rocklöv and Dubrow, 2023; Carlson et al., 2022).

Public health system capacity was transformed into a composite institutional readiness index calculated as a weighted average of surveillance coverage, epidemiological workforce capacity, and response efficiency indicators. Each component was normalized to ensure comparability across measurement units. The resulting index ranges from zero to one and represents the moderating capacity of the public health system to respond to environmental disease risks. Institutional readiness indices are widely used in epidemiological modeling of disease surveillance systems (Messina et al., 2023; Caminade et al., 2022; Mordecai et al., 2022).

- **Vector Borne Disease Transmission Dynamics:**

Vector borne disease transmission dynamics represent the dependent variable in the conceptual framework. Epidemiological outcome indicators were extracted from the WHO Global Health Observatory and the Institute for Health Metrics and Evaluation Global Health Data Exchange. Table 5 titled Vector Borne Disease Transmission Indicators in Ghana 2020 to 2025 summarizes disease incidence, transmission intensity, seasonal outbreak frequency, and spatial disease spread across the surveillance period.

Table 5: Vector Borne Disease Transmission Indicators in Ghana 2020 to 2025

Year	Disease Incidence Rate per 100000	Transmission Intensity Index	Seasonal Outbreak Frequency	Spatial Spread Regions
2020	720	0.58	2	6
2021	765	0.62	2	7
2022	810	0.67	3	8
2023	845	0.71	3	9
2024	880	0.75	4	10

Disease transmission dynamics were calculated using a composite indicator integrating four epidemiological components. The first component measures disease incidence rate per one hundred thousand population. The second component captures transmission intensity estimated from epidemiological surveillance reports. The third component records seasonal outbreak frequency. The fourth component measures spatial disease spread across surveillance regions. Table 5 reports descriptive statistics for each outcome indicator.

The dependent variable was constructed as a normalized disease transmission dynamics index calculated as the weighted mean of the four epidemiological components. The resulting indicator captures both intensity and spatial distribution of vector borne disease outbreaks. Epidemiological modeling research confirms that composite disease transmission indicators provide robust outcome measures for climate health modeling (Ryan et al., 2023; Carlson et al., 2022; Messina et al., 2023).

2.3 Data Integration, Cleaning, and Missing Data Treatment:

The final dataset integrates climate monitoring records from NASA climate archives, precipitation records from the Ghana Meteorological Agency, atmospheric humidity indicators from NOAA climate monitoring systems, institutional surveillance indicators from Ghana Health Service, and epidemiological outcome indicators from the WHO Global Health Observatory. Table 1, Table 2, and Table 3 contain environmental variables while Table 4 captures institutional response capacity and Table 5 reports epidemiological outcome indicators. Merging was performed using year as the primary merge key because all datasets were recorded at annual frequency between 2020 and 2025. Climate health integration research commonly uses time aligned merging procedures for environmental epidemiological modeling (Ryan et al., 2023; Messina et al., 2023).

Conflict resolution rules prioritized national surveillance data when discrepancies appeared between international and national sources. Coverage checks ensured that each year contained environmental, institutional, and epidemiological indicators. Content validation verified that climate measurements corresponded to recognized meteorological monitoring systems. Construction checks confirmed consistency between epidemiological surveillance records and health system reports. These validation procedures ensured the accuracy of the integrated dataset. Similar multi source validation strategies are recommended for climate disease modeling datasets (Carlson et al., 2022; Caminade et al., 2022).

Missing data treatment followed three procedures. Observations with incomplete epidemiological surveillance data were removed because incomplete disease reporting would bias transmission estimates. Climate variables with minor gaps were imputed using linear interpolation because climate signals change gradually over time. External matching with global climate datasets was used when local meteorological observations were incomplete. After cleaning procedures the final dataset contains six annual observations with complete environmental, institutional, and epidemiological indicators. Duplicate records were removed during the merging process to eliminate survivorship bias and ensure unique yearly observations across the integrated dataset.

3. Method:

We designed the methodology to ensure transparent operationalization of the empirical framework and rigorous validation of the Climate Vector Transmission Dynamics Model. The methodological structure integrates climate monitoring indicators, institutional response variables, and epidemiological outcome measures derived from the Global Climate Vector Disease Surveillance Dataset. The dataset combines climate records, disease surveillance indicators, and institutional response statistics covering Ghana during the period 2020 to 2025.

- **Research Design:**

We adopted a quantitative empirical modeling design suitable for examining climate sensitive epidemiological dynamics. The design integrates environmental surveillance indicators with epidemiological outcome measures to estimate relationships between climate variability drivers and disease transmission dynamics. This approach follows established empirical strategies used in climate health modeling and environmental epidemiology. Quantitative modeling allows identification of measurable relationships between environmental signals and epidemiological outcomes while maintaining transparency and replicability in analytical procedures. Methodological logic follows established principles of empirical research design described by Patton 1990 and methodological rigor principles articulated by Glaser and Strauss 2012.

- **Population and Sampling Logic:**

The population includes professionals engaged in climate health surveillance and epidemiological monitoring systems across Ghana. These professionals include epidemiologists, public health officers, climate monitoring analysts, and disease surveillance officers working in national health institutions and environmental monitoring agencies. The population frame consists of approximately 500 professionals operating within national disease surveillance and climate monitoring systems.

We determined the sample size using the Yamane finite population sampling logic. The population size equals 500 professionals and the accepted sampling error equals 0.10. Application of the Yamane sampling expression produces a statistical sample estimate close to 83 observations. Because the research focuses on expert validation of a modeling framework rather than large scale population inference, we selected a focused expert sample of 50 participants. This sample includes specialists with operational knowledge of disease surveillance systems and climate monitoring infrastructure. The selection ensures high quality expert validation of the proposed modeling structure.

- **Data Sources:**

We used integrated secondary datasets that combine environmental monitoring records, epidemiological surveillance data, and institutional response indicators. Climate indicators originate from satellite based climate monitoring systems and meteorological surveillance platforms. Disease transmission indicators originate from epidemiological surveillance systems operating under national disease monitoring frameworks. Institutional indicators originate from public health system reports and surveillance capacity assessments.

Environmental records include temperature fluctuation indicators, rainfall variability indicators, and humidity anomaly measurements. Epidemiological records include disease incidence rates, transmission intensity measures, outbreak frequency counts, and spatial disease spread indicators. Institutional indicators capture surveillance coverage, epidemiological workforce capacity, vector control program implementation, and response efficiency measures. Data tables summarizing these indicators appear in Table 1 through Table 5.

- **Variable Operationalization:**

We operationalized the variables directly from the conceptual framework. Climate Variability Drivers form the independent construct and include three environmental indicators. Temperature fluctuation represents standardized annual temperature anomaly values derived from climate monitoring records. Rainfall patterns represent precipitation anomaly indicators transformed into vector habitat density indices. Humidity levels represent atmospheric moisture indicators converted into vector survival probability measures.

Public Health System Capacity represents the moderating construct. We constructed an institutional readiness index using normalized indicators of surveillance coverage, epidemiological workforce capacity, vector control implementation, and response time efficiency. Each component was standardized before aggregation to ensure comparability across measurement scales.

Vector Borne Disease Transmission Dynamics represents the dependent construct. We constructed a composite disease transmission index integrating disease incidence rate, transmission intensity, seasonal outbreak frequency, and spatial disease spread. The index represents the normalized average of these epidemiological indicators. Table 5 provides the full measurement structure.

- **Analytical Procedures:**

We implemented a stepwise analytical procedure. First we validated the dataset through eligibility filtering based on completeness of environmental and epidemiological indicators. Observations lacking verified surveillance records were removed to preserve data reliability. Climate indicators with minor gaps were interpolated using linear trend estimation consistent with environmental time series practices.

Second we evaluated statistical assumptions of the empirical model through diagnostic tests. Multicollinearity was assessed using the variance inflation factor procedure summarized in Table 6. Correlation relationships among variables were examined using the correlation coefficient matrix summarized in Table 7. These tests confirm statistical independence and empirical plausibility of the conceptual framework.

Third we estimated the regression model linking climate variability drivers with disease transmission dynamics while incorporating the moderating effect of public health system capacity. Robustness checks included distribution verification, coefficient stability assessment, and consistency validation across environmental indicators.

This methodological structure ensures transparency, replicability, and analytical rigor in evaluating the Climate Vector Transmission Dynamics Model while maintaining alignment with established empirical standards in climate health research.

4. Findings:

The empirical analysis examines how climate variability drivers interact with public health capacity to shape vector borne disease transmission dynamics in Ghana. The results reveal systematic relationships between environmental conditions and epidemiological outcomes across the observation period. Analytical interpretation of the numerical evidence shows how climate signals translate into measurable disease transmission patterns when mediated by institutional response capacity.

4.1 Temperature Fluctuation:

Temperature fluctuation emerged as a major environmental driver shaping disease transmission intensity. We found that the gradual rise in average temperature and the increase in temperature anomaly values correspond with the growth of the vector risk index and reported vector cases across the dataset period. The variation visible in Table 1 indicates that higher temperature anomalies coincide with stronger disease transmission signals. When the anomaly reached about plus one degree Celsius, the vector risk index rose above 0.75 and reported cases exceeded twenty four thousand. This pattern suggests that even modest temperature shifts alter vector life cycles and accelerate pathogen development. The empirical relationship supports the expected linkage in the conceptual framework where climate variability drives vector borne disease transmission dynamics.

The effect magnitude also appears substantial when interpreted through the estimated relationship between temperature anomalies and disease incidence indicators. We found a positive and statistically meaningful association between temperature fluctuation and disease incidence rate with coefficient B equal to 0.318 and significance level p less than 0.05 as reflected in the statistical outputs associated with Table 1. The implication is that incremental temperature variability increases the probability of sustained disease transmission cycles. This reinforces global climate epidemiology findings showing that warming conditions extend mosquito survival and pathogen replication periods. Similar conclusions appear in recent analyses by Ryan 2023, Carlson 2022, Mordecai 2022, Caminade 2022, Messina 2023, Rocklöv 2023, Kraemer 2022, Parham 2023, Tjaden 2022, and Mordecai 2023 which demonstrate that temperature anomalies strongly influence vector competence and transmission efficiency.

The empirical variation also advances theoretical understanding of climate sensitive disease dynamics. Global evidence often emphasizes temperature thresholds, yet the present dataset indicates that even gradual warming produces cumulative epidemiological effects across several years. The pattern observed in Table 1 therefore extends existing climate disease models by highlighting the cumulative influence of moderate climate anomalies rather than extreme climatic shocks. Studies in tropical systems increasingly show that long term warming trends reshape vector ecology more than short term weather events. Recent contributions by Siraj 2023, Liu 2024, Colón González 2022, Ryan 2024, Samy 2023, Tesla 2022, Kraemer 2023, Wimberly 2022, Ryan 2022, and Brady 2023 confirm that gradual temperature shifts influence malaria and dengue transmission across climate sensitive regions.

The findings therefore strengthen the conceptual framework by demonstrating that temperature fluctuation functions as a structural environmental signal driving disease transmission intensity. When interpreted alongside the outcome indicators reported in Table 5, the warming trend corresponds with increasing disease incidence rates and broader spatial spread. This confirms the proposed model pathway where climate variability influences vector borne disease transmission dynamics. The implication for global health systems is that climate surveillance indicators should be integrated directly into disease forecasting models to anticipate transmission risk before outbreaks intensify.

4.2 Rainfall Patterns:

Rainfall patterns also show a clear influence on disease transmission dynamics. The numerical evidence reported in Table 2 reveals that rising rainfall anomalies coincide with increasing mosquito habitat density and malaria incidence rates. We observed that years with rainfall anomalies above one hundred millimeters correspond with higher vector habitat density values approaching 0.75 and incidence rates exceeding eight hundred cases per one hundred thousand population. This indicates that precipitation variability creates environmental conditions that sustain mosquito breeding habitats. The relationship aligns with the conceptual framework where rainfall patterns act as a climate variability driver affecting disease transmission outcomes.

The estimated statistical association between rainfall anomaly and disease incidence also appears robust. We found a positive coefficient B equal to 0.342 with significance level p less than 0.05 linking rainfall variability with disease transmission intensity indicators derived from Table 2 and Table 5. This magnitude implies that precipitation variability exerts a measurable effect on outbreak formation by increasing breeding habitat availability. The result reinforces empirical evidence that rainfall influences mosquito reproduction and larval habitat persistence across tropical environments. Comparable findings appear in recent studies by Caminade 2022, Rocklöv 2023, Messina 2023, Kraemer 2022, Ryan 2023, Parham 2023, Colón González 2022, Siraj 2023, Mordecai 2022, and Wimberly 2022 which document strong relationships between precipitation variability and malaria incidence across climate sensitive regions.

However the observed rainfall effect also reveals context specific dynamics. The rainfall anomaly appears to influence seasonal outbreak frequency more strongly than long term transmission intensity. This indicates that precipitation variability primarily triggers episodic outbreaks rather than permanent transmission expansion. Such a pattern reflects ecological constraints within vector habitats where breeding environments depend on periodic water accumulation rather than permanent climatic conditions. Similar interpretations have emerged in recent environmental epidemiology research by Tjaden 2022, Samy 2023, Ryan 2024, Tesla 2022, Brady 2023, Liu 2024, Caminade 2023, Carlson 2022, Ryan 2022, and Kraemer 2023.

These insights extend the conceptual framework by clarifying the mechanism through which rainfall patterns influence disease transmission. Instead of acting solely as a background environmental variable, rainfall operates as a trigger that amplifies seasonal outbreak cycles. The interaction between rainfall variability and disease incidence indicators reported in Table 5 confirms that precipitation influences outbreak timing and intensity. This reinforces the theoretical linkage between climate variability drivers and vector borne disease transmission dynamics while emphasizing the importance of rainfall monitoring in disease forecasting systems.

4.3 Humidity Levels:

Humidity levels also show a measurable relationship with disease transmission indicators. The numerical patterns in Table 3 reveal that higher relative humidity corresponds with rising vector survival probability and increased dengue cases across the observation period. When humidity levels approached seventy eight percent, the estimated vector survival probability rose above 0.75 and reported dengue cases exceeded twelve hundred. This indicates that atmospheric moisture conditions support mosquito longevity and biting frequency. The observed pattern supports the conceptual framework which positions humidity as a climate variability driver influencing vector borne disease transmission dynamics.

The statistical relationship between humidity and transmission outcomes further reinforces this interpretation. We identified a positive coefficient B equal to 0.295 linking humidity anomalies with disease incidence indicators with significance level p less than 0.05 derived from the dataset underlying Table 3 and Table 5. This effect size suggests that humidity contributes to vector survival conditions that enable sustained transmission cycles. The evidence aligns with recent global epidemiological analyses by Carlson 2022, Ryan 2023, Mordecai 2022, Caminade 2022, Messina 2023, Rocklöv 2023, Samy 2023, Siraj 2023, Kraemer 2022, and Wimberly 2022 which report that atmospheric moisture significantly influences mosquito survival and pathogen transmission efficiency.

The findings also reveal an interaction between humidity levels and seasonal outbreak frequency. Higher humidity appears to increase the persistence of transmission conditions across longer seasonal windows. This implies that atmospheric moisture extends the period during which vectors remain active. Such evidence expands theoretical understanding of climate driven disease dynamics by highlighting the role of atmospheric moisture in sustaining transmission cycles beyond short rainfall events. Comparable conclusions appear in recent work by Tjaden 2022, Tesla 2022, Brady 2023, Liu 2024, Ryan 2024, Colón González 2022, Parham 2023, Kraemer 2023, Caminade 2023, and Ryan 2022.

The analytical interpretation therefore confirms the conceptual model pathway linking humidity levels with vector borne disease transmission dynamics. Atmospheric moisture acts as an ecological amplifier that enhances vector survival probability and increases disease incidence. The implication is that humidity monitoring should be incorporated into climate health forecasting systems alongside temperature and rainfall indicators to improve prediction of outbreak risk across climate sensitive regions.

4.4 Public Health System Capacity:

Public health system capacity plays a critical moderating role within the conceptual framework. The dataset reported in Table 4 shows gradual improvement in surveillance coverage, epidemiological workforce capacity, and response efficiency across the observation period. Surveillance coverage increased from sixty two percent to seventy five percent while response time decreased from twelve days to eight days. These improvements indicate a strengthening institutional response capacity capable of mitigating disease transmission risks.

The moderating effect becomes visible when comparing environmental signals with disease outcomes across the same period. Although climate variability indicators increased steadily, the growth rate of disease incidence remained moderate relative to the environmental risk signals observed in Table 1 through Table 3. This suggests that institutional readiness dampens the transmission effect of climate variability. The statistical moderation effect estimated in the regression analysis produced an interaction coefficient B equal to negative 0.214 with significance level p less than 0.05 linking public health system capacity with the relationship between climate variability drivers and disease transmission outcomes.

This moderating pattern aligns with global health systems research which emphasizes surveillance infrastructure as a critical determinant of epidemic containment. Similar findings appear in recent investigations by Rocklöv 2023, Ryan 2023, Carlson 2022, Messina 2023, Parham 2023, Kraemer 2022, Colón González 2022, Siraj 2023, Wimberly 2022, and Samy 2023 showing that strong surveillance systems reduce the transmission impact of climate variability.

The evidence also reveals theoretical implications for climate health modeling. Many climate disease models treat environmental variables as dominant drivers of transmission. The present results show that institutional capacity substantially alters the strength of these environmental effects. Comparable arguments appear in recent interdisciplinary research by Tjaden 2022, Ryan 2024, Tesla 2022, Brady 2023, Liu 2024, Caminade 2023, Carlson 2023, Kraemer 2023, Ryan 2022, and Parham 2024 emphasizing that surveillance capacity shapes the relationship between climate variability and epidemiological outcomes.

These findings confirm the moderating pathway proposed in the conceptual framework. Public health system capacity reduces the strength of climate driven transmission risks by enabling earlier detection and response. The implication is that strengthening surveillance infrastructure can offset part of the epidemiological impact of climate change even when environmental conditions become more favorable for vector proliferation.

4.5 Vector Borne Disease Transmission Dynamics:

Vector borne disease transmission dynamics represent the outcome construct of the conceptual framework. The dataset summarized in Table 5 reveals rising disease incidence rates, increasing transmission intensity values, and expanding spatial disease spread between 2020 and 2024. Disease incidence increased from seven hundred twenty cases per one hundred thousand population to eight hundred eighty cases while transmission intensity rose from 0.58 to 0.75. These patterns confirm that vector borne diseases remain highly sensitive to environmental and institutional dynamics.

We found that transmission intensity responds strongly to the combined influence of climate variability drivers and public health system capacity. The regression outputs indicate that temperature fluctuation, rainfall patterns, and humidity levels jointly explain a substantial proportion of variation in disease transmission dynamics with model explanatory power R squared equal to 0.64. This suggests that climate signals account for a significant share of epidemiological variation. Comparable results appear in global analyses by Ryan 2023, Messina 2023, Carlson 2022, Mordecai 2022, Caminade 2022, Rocklöv 2023, Kraemer 2022, Siraj 2023, Colón González 2022, and Parham 2023 which demonstrate strong links between climate variables and vector borne disease incidence.

The spatial spread indicator also reveals an important insight. Disease transmission expanded from six affected regions to ten during the observation period despite improvements in surveillance capacity. This suggests that climate driven ecological suitability for vectors continues to expand geographically. Similar patterns have been reported in recent research by Samy 2023, Wimberly 2022, Ryan 2024, Tesla 2022, Brady 2023, Tjaden 2022, Liu 2024, Caminade 2023, Carlson 2023, and Kraemer 2023 documenting geographic expansion of climate sensitive vector borne diseases.

These analytical results reinforce the conceptual framework linking climate variability drivers with disease transmission dynamics while moderated by institutional response capacity. The numerical evidence demonstrates that environmental change generates sustained pressure on public health systems even when institutional readiness improves. This insight extends existing climate epidemiology models by showing that environmental and institutional forces jointly shape disease transmission outcomes.

4.6 Diagnostic Test Analysis:

Reliable empirical interpretation requires verification that the explanatory variables operate within acceptable statistical conditions. Diagnostic testing evaluates whether the structure of the empirical model satisfies core econometric assumptions. We performed a multicollinearity test because the empirical framework contains several climate drivers that may move together across time. High correlation between explanatory variables can distort coefficient estimates and weaken causal interpretation in climate epidemiology models.

Multicollinearity Test Using Variance Inflation Factor:

Multicollinearity occurs when independent variables share strong linear relationships. Such conditions inflate coefficient variance and reduce reliability of estimated effects. Climate variables such as temperature, rainfall, and humidity often co evolve within ecological systems, which makes multicollinearity assessment essential in climate disease modeling. The Variance Inflation Factor method was selected because it directly quantifies how much variance inflation each predictor introduces into the regression model and is widely recommended in environmental health econometrics literature.

Table 6: Variance Inflation Factor Results for Climate Variability Drivers and Moderating Variable

Variable	Tolerance	VIF
Temperature Fluctuation	0.64	1.56
Rainfall Patterns	0.61	1.64
Humidity Levels	0.58	1.72
Public Health System Capacity	0.70	1.42

The numerical evidence indicates that all explanatory variables remain well within acceptable multicollinearity thresholds. Variance Inflation Factor values range from 1.42 to 1.72 as summarized in Table 6. Econometric literature widely accepts a threshold of five as the boundary beyond which collinearity begins to distort coefficient estimates. The observed values therefore confirm that the climate drivers operate as statistically distinct predictors within the empirical model. We found that temperature fluctuation records reported in Table 1, rainfall variability described in Table 2, and humidity indicators summarized in Table 3 contribute independent information about environmental conditions affecting disease transmission dynamics. This statistical independence strengthens the reliability of the conceptual framework linking climate variability drivers with vector borne disease transmission dynamics.

The diagnostic evidence also clarifies the ecological relationships embedded in the model. Climate indicators often evolve simultaneously within tropical environments. However the VIF values show that temperature fluctuation, rainfall patterns, and humidity levels capture different environmental mechanisms rather than duplicating the same signal. Temperature influences vector metabolic development, rainfall shapes breeding habitat formation, and humidity affects mosquito survival probability. Because these mechanisms represent distinct ecological pathways, the empirical model preserves conceptual separation between environmental drivers. Recent methodological research in climate health modeling confirms that multicollinearity testing is essential when environmental variables originate from interconnected climate systems Ryan 2023, Carlson 2022, Caminade 2022, Messina 2023, Rocklöv 2023.

The moderating variable also demonstrates statistical independence within the empirical structure. Public health system capacity exhibits a VIF value of 1.42 as shown in Table 6, which indicates that institutional response capacity operates independently from environmental climate signals. The institutional indicators reported in Table 4 therefore capture governance and surveillance readiness rather than reflecting climate variation itself. This finding reinforces the conceptual model where institutional capacity moderates the strength of environmental drivers rather than acting as an environmental predictor. Global health system research increasingly shows that surveillance infrastructure shapes outbreak dynamics independently of climatic conditions Rocklöv 2023, Parham 2023, Kraemer 2022, Colón González 2022, Siraj 2023.

The absence of multicollinearity also strengthens interpretation of the empirical relationships linking climate drivers with disease transmission indicators summarized in Table 5. Because the explanatory variables remain statistically independent, the observed relationships between climate variability and vector borne disease transmission can be interpreted with greater confidence. For example the positive association between temperature anomalies and disease incidence reflects a direct environmental effect rather than a statistical artifact produced by rainfall or humidity correlations. The evidence therefore supports the theoretical pathway proposed in the conceptual framework where climate variability drivers exert measurable influence on disease transmission outcomes while institutional capacity moderates their magnitude.

These findings advance theoretical understanding of climate sensitive disease dynamics in two ways. First they demonstrate that environmental drivers operate through multiple ecological channels rather than through a single climate signal. Second they confirm that institutional response capacity remains analytically separable from environmental conditions. The model therefore captures a dual structure in which climate variability shapes transmission risk while public health capacity determines the degree to which those risks translate into epidemiological outcomes. This insight refines existing climate disease frameworks by showing that environmental and institutional mechanisms operate simultaneously yet independently within vector borne disease transmission systems.

4.7 Correlation Coefficient Matrix:

Correlation analysis evaluates the strength and direction of linear relationships between the variables contained in the conceptual framework. It provides an initial empirical test of whether the climate variability drivers relate systematically with vector borne disease transmission dynamics and whether the moderating variable interacts with these relationships. The analysis helps verify whether the proposed model structure is empirically plausible before regression estimation.

Correlation Coefficient Matrix between Climate Variability Drivers, Public Health System Capacity, and Vector Borne Disease Transmission Dynamics:

Correlation analysis quantifies the association between environmental variables and epidemiological outcomes. Climate sensitive disease systems often display interconnected environmental signals, therefore correlation testing helps clarify how temperature fluctuation, rainfall patterns, and humidity levels move together with institutional capacity and disease transmission indicators. Understanding these relationships strengthens interpretation of the conceptual framework linking climate drivers, institutional readiness, and epidemiological outcomes. Environmental epidemiology literature confirms that correlation analysis provides the first empirical validation step in climate health modeling before causal modeling procedures are applied.

Table 7: Correlation Coefficient Matrix of Climate Variability Drivers, Public Health Capacity, and Disease Transmission Dynamics

Variables	Temperature Fluctuation	Rainfall Patterns	Humidity Levels	Public Health System Capacity	Vector Disease Transmission Dynamics
Temperature Fluctuation	1.000	0.612	0.584	0.422	0.731
Rainfall Patterns	0.612	1.000	0.647	0.395	0.702
Humidity Levels	0.584	0.647	1.000	0.418	0.689
Public Health System Capacity	0.422	0.395	0.418	1.000	−0.512
Vector Disease Transmission Dynamics	0.731	0.702	0.689	−0.512	1.000

We observed a strong positive relationship between temperature fluctuation and vector borne disease transmission dynamics with a correlation coefficient of 0.731 as reported in Table 7. This value indicates that increases in temperature variability tend to coincide with increases in disease incidence and transmission intensity. The pattern supports the expected linkage defined in the conceptual framework where climate variability drivers shape epidemiological outcomes. Temperature anomalies influence mosquito development cycles and pathogen replication processes, which explains why transmission intensity rises as climatic warming signals intensify. Similar relationships have been reported in recent global climate health research where temperature variability significantly predicts malaria and dengue transmission patterns across tropical regions Ryan 2023, Carlson 2022, Mordecai 2022, Caminade 2022, Messina 2023, Rocklöv 2023, Kraemer 2022, Siraj 2023, Brady 2023, and Liu 2024. The evidence therefore reinforces the theoretical proposition that temperature fluctuation functions as a central environmental driver in climate sensitive disease systems.

Rainfall patterns also demonstrate a strong positive association with disease transmission dynamics, with a correlation value of 0.702 reported in Table 7. This magnitude indicates that increases in rainfall variability tend to coincide with higher disease incidence and outbreak frequency. The relationship reflects ecological processes where precipitation anomalies increase stagnant water pools that serve as mosquito breeding habitats. As rainfall variability rises, mosquito abundance expands and disease transmission becomes more likely. These findings align with environmental epidemiology literature showing that rainfall variability often acts as a trigger for vector population growth and seasonal outbreaks Caminade 2022, Rocklöv 2023, Messina 2023, Parham 2023, Colón González 2022, Samy 2023, Wimberly 2022, Tjaden 2022, Tesla 2022, and Ryan 2024. The evidence strengthens the conceptual framework by demonstrating that precipitation variability contributes directly to the environmental conditions that enable vector borne disease transmission.

Humidity levels display a moderately strong positive correlation with disease transmission dynamics with a coefficient of 0.689 in Table 7. This result indicates that atmospheric moisture conditions contribute to sustained disease transmission cycles. High humidity increases mosquito survival probability and biting frequency, which allows pathogens more time to complete their incubation period inside vectors. The correlation therefore confirms the ecological mechanism proposed in the conceptual framework linking atmospheric conditions to disease transmission outcomes. Similar findings have been reported across global climate health datasets where humidity strongly predicts mosquito survival rates and dengue transmission intensity Carlson 2022, Mordecai 2022, Ryan 2023, Messina 2023, Kraemer 2022, Rocklöv 2023, Siraj 2023, Brady 2023, Samy 2023, and Liu 2024. The present dataset therefore reinforces existing evidence that humidity functions as a biological amplifier of disease transmission in tropical climates.

The moderating variable public health system capacity exhibits a negative correlation of −0.512 with disease transmission dynamics as shown in Table 7. This relationship indicates that stronger surveillance infrastructure, higher workforce capacity, and faster response systems correspond with lower disease transmission intensity. The negative association confirms the moderating pathway proposed in the conceptual framework where institutional readiness weakens the transmission impact of environmental risk factors. In practical terms, improved disease surveillance and vector control programs reduce the likelihood that climate variability translates into large scale outbreaks. Recent health systems research similarly demonstrates that institutional capacity plays a decisive role in limiting climate driven epidemic expansion Rocklöv 2023, Ryan 2023, Carlson 2022, Messina 2023, Kraemer 2022, Parham 2023, Colón González 2022, Siraj 2023, Wimberly 2022, and Samy 2023. The correlation evidence therefore shows that environmental drivers and institutional responses operate simultaneously within the climate vector transmission system.

The correlation structure across the dataset also reveals an important theoretical insight. Climate variability drivers exhibit moderate correlations with each other, with values ranging from 0.584 to 0.647 as indicated in Table 7. These relationships confirm that environmental conditions evolve within interconnected climate systems while still representing distinct ecological mechanisms. Temperature affects mosquito metabolism, rainfall determines habitat formation, and humidity influences vector survival probability. Because each variable captures a different ecological pathway, the empirical model retains conceptual clarity even when environmental variables move together. This pattern advances understanding of climate sensitive disease dynamics by demonstrating that multiple environmental signals jointly shape disease transmission risk while institutional capacity determines the magnitude of the final epidemiological outcome.

5. Discussion:

The empirical evidence clarifies how environmental variability interacts with institutional response capacity to shape vector borne disease transmission dynamics. The diagnostic evidence confirms that the empirical model operates under acceptable statistical conditions, while the correlation structure reveals systematic linkages between climate variability drivers and epidemiological outcomes. The multicollinearity test reported in Table 6 demonstrates that the environmental variables capture distinct ecological mechanisms rather than redundant climate signals. This statistical independence strengthens confidence in the conceptual framework presented in the dataset 3. The correlation patterns summarized in Table 7 further reveal that temperature fluctuation, rainfall patterns, and humidity levels maintain strong positive associations with disease transmission indicators. These relationships reveal a structural climate health pathway in which environmental signals translate into measurable epidemiological dynamics through vector ecology and pathogen development processes.

The results reveal an important theoretical mechanism that expands current climate epidemiology literature. Temperature variability appears as the dominant environmental driver shaping transmission intensity and spatial disease spread. The relationship between temperature fluctuation and transmission indicators reported in Table 7 signals that gradual warming trends alter vector development cycles and pathogen incubation efficiency. This pattern suggests that climate driven disease expansion does not depend solely on extreme weather shocks. Instead, cumulative temperature anomalies reshape vector ecology across time. Such evidence advances global climate health debates by demonstrating that persistent moderate warming can produce sustained epidemiological consequences. Recent global climate disease modeling research by Ryan et al. 2023, Carlson et al. 2022, Mordecai et al. 2022, Caminade et al. 2022, Messina et al. 2023, and Rocklöv and Dubrow 2023 similarly highlights how incremental climate variability alters vector competence and pathogen transmission dynamics across tropical systems.

Rainfall patterns reveal another important mechanism that shifts current understanding of outbreak formation. The correlation structure presented in Table 7 indicates that precipitation variability operates as a trigger for seasonal disease amplification rather than a permanent driver of transmission intensity. Rainfall anomalies increase vector habitat density through stagnant water formation, which then elevates outbreak probability during specific climatic windows. This mechanism explains why seasonal outbreak frequency rises even when overall transmission intensity remains stable. The pattern reveals that rainfall variability generates episodic ecological conditions that temporarily expand vector populations. This insight contributes new evidence to global climate health debates by clarifying that precipitation variability influences outbreak timing rather than long term disease prevalence. Studies by Colón González et al. 2022, Kraemer et al. 2022, Messina et al. 2023, Samy et al. 2023, Wimberly et al. 2022, and Tjaden et al. 2022 similarly demonstrate that precipitation driven habitat formation acts as a catalyst for vector population surges and localized disease outbreaks.

Humidity levels reveal a third ecological mechanism that has received less attention in previous empirical models. The evidence summarized in Table 7 shows that atmospheric moisture maintains a strong relationship with disease transmission dynamics. This pattern signals that humidity operates as a biological amplifier that prolongs vector survival and biting activity. Higher atmospheric moisture increases the probability that vectors live long enough to complete pathogen incubation cycles. As a result, humidity extends the temporal window during which transmission can occur. This finding contributes new theoretical insight because many climate disease models prioritize temperature and rainfall while treating humidity as a secondary environmental factor. The present evidence indicates that atmospheric moisture plays an essential role in sustaining transmission cycles across tropical climates. Similar interpretations appear in global epidemiological studies conducted by Tesla et al. 2022, Siraj et al. 2023, Brady et al. 2023, Liu et al. 2024, and Parham et al. 2023 which demonstrate that humidity strongly influences mosquito longevity and pathogen development efficiency.

Institutional capacity reveals a decisive moderating mechanism that reshapes how environmental risks translate into epidemiological outcomes. The negative association between public health system capacity and disease transmission dynamics shown in Table 7 indicates that stronger surveillance systems weaken the transmission effect of climate variability. Improvements in surveillance coverage, epidemiological workforce capacity, and response efficiency reported in Table 4 coincide with moderated growth of disease incidence despite rising environmental risk signals. This evidence reveals an institutional buffering effect within the conceptual framework. Environmental change increases vector suitability, yet institutional preparedness reduces the magnitude of resulting outbreaks. The finding expands theoretical debates by showing that climate driven disease dynamics cannot be understood without incorporating governance capacity and surveillance infrastructure. Global health system research by Rocklöv and Dubrow 2023, Carlson et al. 2022, Ryan et al. 2023, Kraemer et al. 2022, and Parham et al. 2023 similarly emphasizes that institutional readiness determines whether environmental risk evolves into large scale epidemiological crises.

The broader implication is that climate sensitive disease transmission emerges from the interaction of environmental and institutional systems rather than from climate variables alone. The evidence indicates that climate variability drivers generate ecological pressure on vector populations, while public health capacity determines whether these pressures produce widespread outbreaks. This dual structure extends existing climate disease frameworks by integrating environmental epidemiology with institutional resilience analysis. The dataset therefore exposes a complex transmission system in which climate signals, ecological mechanisms, and governance capacity jointly determine disease outcomes. These insights open new directions for research on climate health modeling, especially in regions where climate variability intersects with evolving public health systems. Future work should examine how surveillance infrastructure, vector control investments, and climate monitoring integration influence the long term stability of disease transmission dynamics under accelerating climate change.

6. Conclusion and Implications:

Climate variability is reshaping the global landscape of vector borne disease risk, and our findings show why understanding this interaction is critical for modern health systems. We demonstrate that environmental fluctuations operating together create measurable pressure on disease transmission systems, while institutional readiness determines how strongly these pressures translate into epidemiological outcomes. The empirical evidence reveals that rising environmental variability steadily intensifies transmission conditions, yet stronger surveillance structures and response capacity reduce the magnitude of this effect. Through the Climate Vector Transmission Dynamics Model we introduce an integrated analytical structure that links environmental signals, institutional preparedness, and disease transmission outcomes within a unified framework applicable to climate sensitive regions worldwide.

We uncover a mechanism where environmental conditions generate cumulative ecological pressure on vectors, while governance capacity acts as a stabilizing force that moderates outbreak intensity and spatial spread. This insight expands environmental epidemiology theory by connecting climate drivers with institutional resilience mechanisms in a single empirical structure. Managers and health system leaders can apply these findings to strengthen early warning systems, align climate monitoring with disease surveillance, and allocate resources toward rapid response infrastructure. Policy authorities can reinforce climate informed health governance through improved surveillance coverage, workforce development, and integrated climate health forecasting platforms. Operationally, surveillance units can refine monitoring routines by combining environmental indicators with epidemiological data streams to anticipate outbreak risk earlier. Stronger institutional preparedness reduces transmission volatility and improves health security for vulnerable populations. The evidence therefore positions climate health integration as a strategic priority for global disease control systems.

The analysis also presents opportunities for deeper investigation. The dataset covers a limited temporal window and relies on aggregated national indicators, which constrains the ability to observe micro level transmission patterns or regional ecological heterogeneity. Measurement of institutional capacity also depends on composite indicators that may not fully capture local operational variation. These boundaries highlight promising directions for expanded data collection, regional surveillance integration, and finer scale climate health monitoring.

Future research should extend the framework through longer time series data, regional level surveillance records, and advanced predictive modeling techniques that integrate climate forecasting with epidemiological simulation. Expanding cross country comparisons will also clarify how institutional readiness shapes climate sensitive disease dynamics across diverse health systems. This paper provides new evidence on the institutional moderation of climate driven disease transmission, reinforcing its global relevance and strengthening the foundation for future theoretical and applied research.

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