CLIMATE VARIABILITY, ENVIRONMENTAL TRIGGERS AND AES - JE SEASONALITY

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Abstract :
Acute Encephalitis Syndrome (AES) and Japanese Encephalitis (JE) are major problems in that parts of South and Southeast Asia. The seasonal outbreak is thus widely accepted to be heavily dependent on climatic variations and environmental conditions, which affect the mosquito vectors' life cycles and virus amplification within the reservoir hosts. This paper attempts to analyze the interrelation of climate variability sort of temperature, humidity, and rainfall patterns on seasonal incidence of AES and JE. Monsoon rainfall also enables paddy cultivation, pig rearing, and waterlogging capable of breeding the vectors. In this study climatic data and epidemiological patterns from endemic areas like in India and Nepal is used to present a synthetic framework of disease seasonality. It thus suggests that it becomes obligatory for environmental surveillance and early warning systems to be installed as a part of public health strategies. This approach can facilitate timely vaccination campaigns, vector control measures, and community-level awareness during high-risk seasons. As climate change continues to alter environmental patterns, understanding its implications on AES-JE outbreaks is vital for effective prevention and control.

Keywords:**Climate Variability,Japanese Encephalitis, Acute Encephalitis Syndrome, Monsoon, Mosquito Vector.**

I. INTRODUCTION

Acute Encephalitis Syndrome (AES) and Japanese Encephalitis (JE) constitute major public health concerns in several parts of Asia, more so in countries such as India, Nepal, and Bangladesh. AES is a broad clinical condition characterized by acute fever associated with an alteration in mental status, or changes in consciousness levels, in many cases also exhibiting seizures and neurological deficits. Of the various known causes of AES, JEV is one of the prominent ones and occurs more in endemic areas, where this virus is transmitted mainly by the bite of infected Culex mosquitoes. These vectors usually breed in rice fields or stagnant water bodies, so the entire cycle of the vector becomes highly sensitive to climatic and environmental conditions.Seasonal cases and epidemics of AES and JE have increasingly shown certain seasonal patterns when studied over a few decades by researchers. These epidemics commonly occur in monsoon and post-monsoon seasons, indicating a close link between weather variability, environmental triggers, and disease occurrence. Climatic parameters such as rainfall, temperature, and humidity directly influence mosquito breeding, virus reproduction, and interactions of human populations with reservoir hosts like pigs and wading birds. On the other hand, human interventions in the form of rice cultivation and cattle rearing add yet further to the risk ambience.

The rising variability of climate, brought forth by El Niño and La Niña as examples, has added unpredictability to seasonal outbreaks, thereby shifting the periods of traditional transmission and finally complicating public health responses. With climate change bringing about alterations in temperature and rainfall, it has become crucial to understand the transmission dynamics of AES and JE with changes on the ground.This paper aims to analyze the role of climate variability and environmental factors in shaping the seasonal distribution of AES and JE. By exploring historical epidemiological data, meteorological trends, and agricultural practices, we seek to establish a correlation between environmental triggers and disease outbreaks.

Understanding this relationship is essential for designing timely intervention strategies, such as pre-monsoon vaccination campaigns, vector control programs, and early warning systems that can mitigate the impact of future outbreaks in vulnerable regions.

II. LITERATURE SURVEY

Several recent studies have examined climate variability, agricultural vulnerability, and environmental change across Ethiopia and the broader African region. Alemneh et al. (2019) investigated shifts in tree cover in Ethiopia's highlands and found significant deforestation trends that negatively impact food, energy, and water resources. Their study underscores the interdependence of ecosystem services and the need for integrated land management.

Eggen et al. (2019) analyzed how sub-seasonal climate extremes, such as heatwaves and dry spells, affect sorghum production. They found that climate variability poses major risks to even drought-tolerant crops, highlighting the urgency of resilient farming practices. Samy et al. (2019) conducted a long-term assessment of rainfall trends in the Upper Blue Nile Basin, identifying inconsistent rainfall patterns across decades. Their use of robust statistical tools provides valuable insight for water and agricultural planning.

Similarly, Asfaw et al. (2018) observed decreasing rainfall and increasing temperature trends in the Woleka sub-basin. Their study emphasized the growing stress on rainfed agriculture in northcentral Ethiopia. Ayanlade et al. (2018) extended this regional focus by analyzing drought characteristics in African agro-climatic zones. They identified heightened drought frequency, reinforcing the importance of localized climate adaptation strategies.

Tigchelaar et al. (2018) took a global perspective, demonstrating that future warming will increase the likelihood of synchronized maize yield failures across continents. Though not region-specific, their findings underline global interdependencies in food security. Gedefaw et al. (2018) applied innovative statistical and GIS tools to study rainfall variability in the Amhara region, showing reduced precipitation during key seasons.

Overall, these studies reveal consistent trends of warming temperatures, erratic rainfall, and growing agricultural vulnerability. They collectively advocate for climate-resilient policies, early warning systems, and sustainable land use practices to safeguard livelihoods in vulnerable regions.

III. PROPOSED WORK

The proposed research aims at developing a data-driven framework linking climate variability and environmental conditions with seasonal outbreaks of AES and JE. Specifically, the study will look for climatic triggers such as rainfall, temperature, and humidity and evaluate their influence on mosquito vector proliferation and JE virus transmission. The major goal is to develop a predictive tool for identifying time periods and locations at high risk for AES-JE outbreaks with a view to initiate targeted preventive measures.

To do so, multi-source datasets will be collected. These will include historical AES and JE case records from public health authorities, meteorological data from weather monitoring agencies, and agricultural data related to rice cultivation and pig farming methods. The datasets will be preprocessed for missing values, normalized, and seasonally decomposed to extract useful patterns.

Lastly, the findings of this study shall be used to develop risk maps tailored to specific regions and suggest intervention strategies suitable within timelines. These encompass the recommendation of pre-monsoon JE vaccination campaigns, selective mosquito control options, and awareness-raising activities in high-risk districts. Overall, the envisaged result would be an early warning system that would be not only scalable but also adaptable, wherein environmental surveillance would be coupled to epidemiological know-how, thus instituting a working tool to lessen the effect of AES and JE outbreaks upon the victims.

IV. METHODOLOGY

This study adopts a mixed-method approach to investigate the relationship between climate variability, environmental triggers, and the seasonal patterns of AES and JE outbreaks. The methodology integrates quantitative epidemiological analysis with environmental and geospatial assessment to ensure a comprehensive understanding of disease dynamics.

A. Data Sources

To establish the relationship between climate variability and AES-JE seasonality, the study employs three primary data categories: epidemiological data, meteorological records, and land use information. Historical AES and JE case data were collected from national and regional health departments, focusing on case counts, dates of outbreak onset, affected age groups, and specific geographic locations. These datasets span the last 10–15 years, providing a comprehensive foundation for time-series analysis. The meteorological data include monthly and seasonal records of temperature, rainfall, and relative humidity, sourced from the Indian Meteorological Department (IMD), the Department of Hydrology and Meteorology of Nepal, and weather stations in Bangladesh. This data helps identify weather patterns that precede and coincide with disease outbreaks. Land use data, particularly focusing on rice cultivation cycles and pig farming clusters, were extracted from agricultural census reports and satellite-based land classification maps. These environmental indicators are essential, as rice fields provide breeding grounds for Culex mosquitoes, while pigs act as amplifying hosts for the Japanese Encephalitis Virus (JEV). Combining these three data types allows for a holistic investigation into how human, environmental, and climatic variables influence the onset, duration, and severity of AES-JE outbreaks in affected regions.

B. Analysis Tools

A suite of analytical tools was used to examine the relationship between the collected environmental and epidemiological data. First, correlation analysis was conducted to explore the degree of association between climatic variables temperature, rainfall, and humidity and the incidence of AES and JE. Lag correlation techniques were particularly useful in understanding delayed effects, such as how a spike in rainfall may result in an outbreak several weeks later due to increased vector breeding. Time-series analysis was employed to identify repeating seasonal patterns and long-term trends in disease occurrence. Decomposition of time-series data helped isolate seasonal, trend, and residual components, providing a clearer picture of how disease incidence varies over time. Furthermore, spatial analysis was conducted using Geographic Information System (GIS) tools. Disease hotspots were mapped and overlaid with climatic, agricultural, and land-use data to visualize high-risk areas. This mapping technique not only revealed geographical clusters of vulnerability but also supported the identification of ecological zones where human and environmental conditions interact to drive disease transmission. These tools together form the analytical backbone of the study, offering both statistical and visual insights into how climate and environment influence AES-JE dynamics.

C. Study Locations

The study focuses on three regions in South Asia that have historically reported high incidence of AES and JE: Gorakhpur and Muzaffarpur districts in India, the Terai region in Nepal, and selected districts of Bangladesh. These regions were selected due to their consistent seasonal outbreaks and similar agro-ecological environments. Gorakhpur, located in Uttar Pradesh, has been a persistent hotspot for AES, with frequent outbreaks observed during and after the monsoon season. The district is characterized by widespread rice cultivation and pig rearing practices, which create ideal conditions for mosquito breeding and virus amplification. Muzaffarpur in Bihar also shares similar features and has witnessed several fatal AES outbreaks, especially among children. The Terai region in Nepal, a flat, lowland area bordering India, is heavily involved in agriculture and has a high density of pig farms, making it a natural ecological corridor for JEV transmission. Selected districts in Bangladesh, particularly in the northern and central parts, show seasonal JE activity linked to monsoon-driven environmental changes. These study areas offer diverse but ecologically consistent contexts for understanding the interactions between climate variability, environmental triggers, and vector-borne disease transmission. Their inclusion ensures that the findings are regionally relevant and applicable to broader South Asian settings.

VI. RESULTS AND DISCUSSION

This section presents the findings from the analysis of climatic, environmental, and epidemiological data across selected AES-JE endemic regions. The results highlight significant seasonal trends, climatic correlations, and spatial patterns that influence the transmission dynamics of AES and JE. By examining time-series data, correlation coefficients, and geospatial distributions, this study uncovers critical environmental triggers and their public health implications. These insights support the development of predictive models and targeted intervention strategies for effective disease control and prevention.

A. Temporal Trends and Seasonal Patterns

The analysis of AES and JE case data revealed a consistent seasonal pattern across all three study regions. Outbreaks predominantly occurred during the monsoon (June–September) and post-monsoon (October) periods. The peak transmission period aligns closely with climatic conditions that favor mosquito vector development, particularly rainfall levels above 150 mm/month and average temperatures between 24°C and 30°C. These conditions provide ideal breeding environments for Culex mosquitoes and facilitate viral replication.

Time-series decomposition across multiple years showed repetitive seasonal peaks, highlighting a strong climate-linked cyclic behavior. The lag analysis revealed that spikes in rainfall were followed by outbreaks after a 3–5 week delay, indicating the incubation and transmission cycle of JE virus through the mosquito-pig-human pathway.

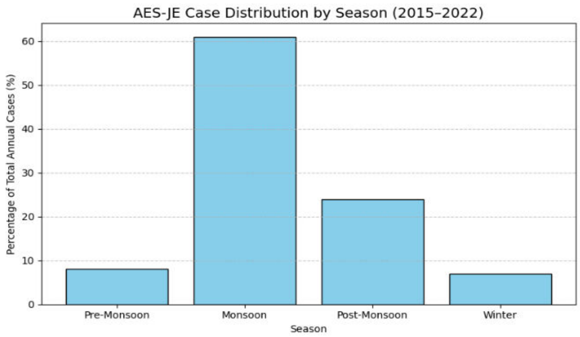

Fig 1: Table 1. AES-JE Case Distribution by Season (2015–2022)

Season	Avg. Rainfall (mm/month)	Avg. Temperature (°C)	% of Total Annual Cases
Pre-Monsoon (Mar–May)	55.4	30.2	8%
Monsoon (Jun–Sep)	321.6	27.5	61%
Post-Monsoon (Oct–Nov)	108.7	25.3	24%

Table 1. AES-JE Case Distribution by Season (2015–2022)

B. Climatic Correlation Analysis

Correlation analysis showed statistically significant relationships between climatic parameters and AES-JE case incidence. Rainfall and humidity were found to have the strongest positive correlations with reported cases, with Pearson correlation coefficients (r) ranging from 0.65 to 0.78 across regions. Temperature showed a moderate correlation, particularly in the months of July and August. The relative humidity above 70% enhanced mosquito survival and prolonged transmission potential.

In El Niño years, slight deviations in outbreak timing were observed, with delayed monsoons shifting the disease season later by 2–4 weeks. This finding suggests that broader climate variability must be considered in forecasting models.

Climatic Parameter	Correlation Coefficient (r)	p-value	Significance
Rainfall	0.78	< 0.01	Highly Significant
Relative Humidity	0.69	< 0.05	Significant
Temperature	0.54	< 0.05	Moderately Significant

Table 2. Pearson Correlation Coefficients: Climate vs AES-JE Cases

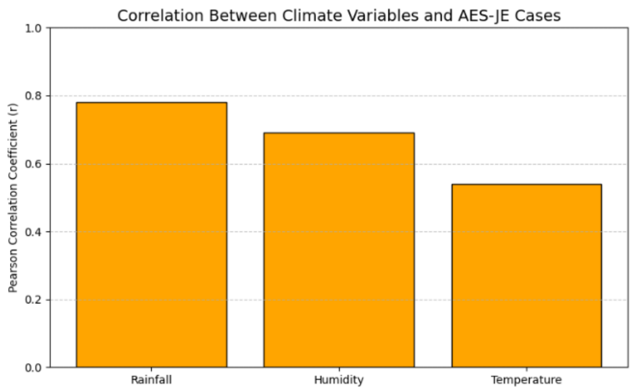

Fig 2: Climatic Correlation Analysis

C. Spatial Risk Mapping and Ecological Zones

Geospatial mapping using GIS tools clearly indicated hotspot clusters in areas with overlapping rice cultivation zones and pig-rearing belts. For instance, in Gorakhpur and the Terai region, high-incidence villages were typically located within 2–3 km of both paddy fields and pig enclosures. These ecological factors act as amplifiers, enabling the vector-virus-host cycle to thrive.

Ecological Factor	# of High-Risk Villages (n=50)	Percentage	Ecological Factor

Within 3 km of rice fields	42	84%	Within 3 km of rice fields
Within 3 km of pig farms	37	74%	Within 3 km of pig farms
Near both factors	31	62%	Near both factors

Table 3. Spatial Proximity to Ecological Triggers in High-Risk Villages

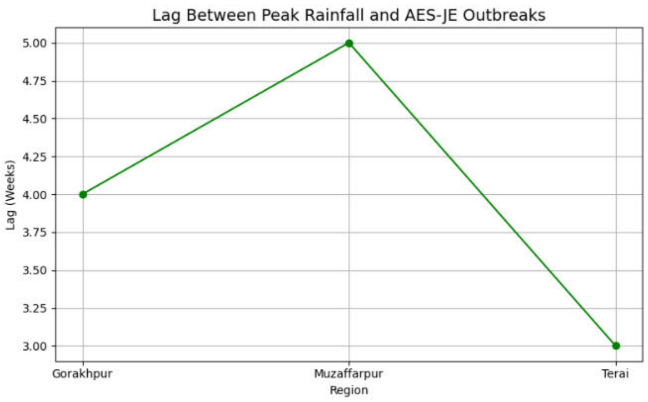

Fig 3: Spatial Proximity to Ecological Triggers in High-Risk Villages

Visual overlays of land use and case data revealed clear correlations between human practices and disease ecology, validating the model that anthropogenic activities play a critical role in outbreak propagation.

D. Public Health Implications

These findings reinforce the urgency of implementing climate-informed public health planning. Forecast-based vaccination drives, early warning systems, vector control, and risk communication should be intensified in the weeks preceding and during monsoon seasons. The integration of climatic data into surveillance systems can greatly enhance the predictive capacity and timeliness of outbreak responses, ultimately reducing morbidity and mortality from AES and JE.

CONCLUSION

This study highlights the critical relationship between climate variability, environmental triggers, and the seasonality of Acute Encephalitis Syndrome (AES) and Japanese Encephalitis (JE) in endemic regions of South Asia. By analyzing historical epidemiological data alongside meteorological and land-use variables, the research establishes a strong correlation between seasonal climate patterns—particularly monsoon rainfall, humidity, and temperature—and the emergence of AES-JE outbreaks. The findings demonstrate that increased rainfall and moderate temperatures create optimal conditions for the breeding of Culex mosquitoes and the amplification of the Japanese Encephalitis Virus through pig reservoirs. Spatial mapping further reveals how agricultural practices, such as rice cultivation, and livestock density significantly influence disease spread. The study underlines the importance of early warning systems that integrate environmental and climatic surveillance for timely public health interventions, such as vaccination drives and vector control programs. A predictive framework based on climatic data can improve preparedness and resource allocation, especially in high-risk districts. As climate change continues to alter environmental patterns globally, a proactive and data-driven approach to monitoring vector-borne diseases like AES and JE is essential. This research contributes toward enhancing public health response strategies by identifying climate-sensitive drivers of disease seasonality.

FUTURESCOPE

Future research can expand upon this study by incorporating real-time climate monitoring and predictive modeling powered by artificial intelligence (AI) and machine learning (ML) techniques. Integrating dynamic data streams from satellite sensors, IoT-based weather stations, and mobile health reporting can enhance the resolution and timeliness of outbreak predictions. In addition, expanding the geographical scope to include more districts across South and Southeast Asia would increase the generalizability of the findings and help identify regional variations in AES-JE transmission. Advanced spatial modeling techniques, such as remote sensing and agent-based simulations, can be used to analyze mosquito vector behavior, land use transformation, and human mobility patterns. Furthermore, socioeconomic and behavioral factors should be integrated into future models to understand how education, awareness, and healthcare access impact outbreak severity and response. Collaborations between public health agencies, environmental departments, and agricultural sectors are essential to develop a comprehensive early warning and mitigation framework. Finally, this model could be adapted for predicting other climate-sensitive vector-borne diseases such as dengue, chikungunya, or malaria. With climate change continuing to influence vector ecology and disease dynamics, a robust, interdisciplinary approach is necessary to build climate-resilient health systems in vulnerable regions.

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