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ARTIFICIAL INTELLIGENCE–DRIVEN SPATIAL PREDICTION OF CLIMATE-SENSITIVE INFECTIOUS DISEASE HOTSPOTS IN PAKISTAN

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Abstract

Climate change is altering the spatial and temporal dynamics of infectious diseases through changes in temperature, precipitation, humidity, ecological conditions, and vector suitability. Pakistan is particularly vulnerable because of climatic diversity, rapid urbanization, population density, recurrent flooding, and uneven public-health infrastructure. This study proposes an artificial intelligence (AI)-driven geospatial framework for predicting climate-sensitive infectious-disease hotspots in Pakistan. District-level epidemiological records are integrated with climatic, environmental, demographic, geographic, and remotely sensed variables. Random Forest, XGBoost, Support Vector Machine, and Artificial Neural Network models are compared using temporal and spatial validation. Explainable-AI techniques are used to identify influential predictors, and the best-performing model is used to generate district-level risk maps. The framework is designed to capture nonlinear and interacting relationships and to support climate-informed surveillance, targeted prevention, and risk-based public-health resource allocation. Because the source manuscript does not contain empirical model outputs, numerical findings are not fabricated; the proposed analytical and interpretive framework is retained for completion after dataset analysis.

1. INTRODUCTION

Climate change influences infectious-disease transmission by modifying temperature, rainfall, humidity, vector ecology, pathogen development, and human exposure. These effects can change the geographical distribution, seasonality, and intensity of transmission. Vector-borne diseases such as dengue are particularly climate-sensitive because mosquito survival, breeding, biting behaviour, and pathogen replication respond to environmental conditions.

Pakistan provides an important setting for climate-health research because it contains arid and semi-arid areas, humid plains, mountainous regions, densely populated cities, agricultural zones, and flood-prone environments. Rapid urbanization, population growth, inadequate sanitation, environmental degradation, and climate-related disasters further increase vulnerability. Previous studies in Pakistan have shown that climate change can shift dengue transmission suitability and that local dengue prevalence is associated with meteorological, land-use, water-body, and population characteristics.

Conventional statistical approaches may not adequately capture nonlinear interactions, spatial heterogeneity, and temporal lags among climate, environmental, demographic, and epidemiological variables. AI and machine learning can process multidimensional datasets and identify complex patterns. When combined with GIS and remote sensing, these methods can

Frontier in Medical & Health Research

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produce geographically explicit risk estimates rather than only national or temporal forecasts.

The present study therefore develops an integrated AI-GIS framework for identifying climate-sensitive infectious-disease hotspots in Pakistan. Its primary focus is dengue, with extension to other climate-sensitive diseases considered where sufficiently consistent data are available. The study emphasizes spatially actionable predictions, robust temporal and spatial validation, and explainability.

2. Problem Statement

Climate-sensitive infectious-disease risk in Pakistan is spatially heterogeneous and arises from interactions among climate, environment, population, geography, and previous disease transmission. Existing Pakistani studies have provided valuable evidence but have often focused on individual diseases, cities, conventional statistical relationships, or descriptive GIS mapping. Climate datasets, surveillance information, remote sensing, and demographic data are also frequently analysed separately.

A major gap is the limited availability of a nationally integrated, AI-driven framework that combines these data sources and produces operationally meaningful hotspot predictions. Accuracy alone is insufficient for public-health use; models must generalize to unseen periods and locations, explain important predictors, and translate outputs into geographically targeted intervention priorities. This study addresses these methodological and practical gaps.

3. Research Questions

- RQ1: What are the spatial and temporal patterns of climate-sensitive infectious diseases across Pakistan?
- RQ2: Which climatic, environmental, demographic, geographic, and epidemiological variables are the strongest predictors of disease hotspots?
- RQ3: How accurately can AI and machine-learning models predict spatial disease hotspots?
- RQ4: Which AI model provides the strongest predictive performance?
- RQ5: How do climate variables interact with environmental and demographic conditions in determining spatial risk?
- RQ6: How can AI-generated risk maps support targeted surveillance and prevention?

4. Research Objectives

General objective: To develop and evaluate an AI-driven spatial prediction framework for identifying climate-sensitive infectious-disease hotspots in Pakistan.

- Characterize the spatial and temporal distribution of selected climate-sensitive diseases.
- Quantify relationships between disease occurrence and climatic, environmental, demographic, geographic, and epidemiological predictors.
- Develop and compare AI/ML models for spatial disease-risk prediction.
- Evaluate model performance using appropriate temporal and spatial validation metrics.
- Identify influential predictors using feature-importance and explainable-AI techniques.
- Generate spatial risk maps showing differentiated levels of disease risk.
- Assess the potential use of predictions for climate-informed surveillance and resource allocation.

5. Significance of the Study

The study contributes to climate-health and spatial epidemiology by integrating epidemiology, climatology, GIS, remote sensing, and AI within a unified framework. Theoretically, it conceptualizes disease risk as a multidimensional spatial phenomenon and extends the practical application of One Health through predictive analytics. Methodologically, it combines heterogeneous secondary datasets with nonlinear machine-learning models and spatially separated validation. Practically, the resulting risk maps could support vector control, surveillance, diagnostic preparedness, environmental management, public awareness, emergency planning, and risk-based allocation of health resources.

Frontier in Medical & Health Research

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The framework also has policy relevance because climate-sensitive disease risk crosses administrative and institutional boundaries. Effective implementation would require coordination among health, meteorological, environmental, disaster-management, and local-government institutions.

6. Literature Review

6.1 Climate Change and Infectious Disease

Temperature, precipitation, humidity, flooding, drought, land-use change, and ecological disruption can modify vector abundance, pathogen survival, vector competence, and human exposure. Climate-sensitive disease risk therefore varies across space and time and is shaped by environmental and socioeconomic conditions in addition to climate.

6.2 Climate-Sensitive Disease in Pakistan

Pakistan-specific evidence indicates that climate change can alter dengue transmission suitability across time and geography. Spatial studies in Lahore have linked dengue prevalence with precipitation, land-surface temperature, water bodies, population density, vegetation, and land-use characteristics. These findings support models that preserve geographical heterogeneity rather than relying on national averages.

6.3 Spatial and Environmental Determinants

Disease occurrence can differ between neighbouring areas because of differences in land cover, elevation, vegetation, water bodies, urban form, population density, sanitation, mobility, and healthcare access. GIS and remote sensing can provide spatially continuous information, including land-surface temperature, vegetation indices, water indicators, land cover, and elevation.

6.4 AI and Machine Learning

Machine-learning models are increasingly used for infectious-disease forecasting because they can represent nonlinear relationships and interactions. Random Forest, XGBoost, Support Vector Machines, and neural networks are relevant candidates. However, model complexity does not guarantee superiority; out-of-sample temporal and spatial validation is essential to avoid overfitting and overly optimistic estimates.

6.5 Research Gap

The literature reveals geographical, methodological, integration, validation, interpretability, and operational gaps. Pakistan-specific research has established climate-disease relationships, but a nationally integrated AI framework combining epidemiological, climate, environmental, demographic, remote-sensing, and spatial information remains comparatively underdeveloped. The present study addresses these gaps through integrated modelling, explainable AI, and spatially actionable outputs.

7. Theoretical Foundation

The study is grounded in the One Health framework, which recognizes the interdependence of human, animal, plant, and ecosystem health. Climate-sensitive infectious-disease risk can be conceptualized as: Climate factors → environmental conditions → vector/ecological suitability → human exposure → disease occurrence → spatial risk. AI serves as the analytical mechanism for learning complex relationships across these interconnected domains.

The theoretical model is therefore: Climate + Environmental + Demographic + Geographic + Epidemiological factors → AI model → Predicted disease risk → Spatial hotspot identification → Climate-informed intervention.

8. Hypotheses

- H1: Higher temperature is positively associated with predicted disease risk.
- H2: Higher precipitation is positively associated with predicted disease risk.
- H3: Higher relative humidity is positively associated with predicted disease risk.
- H4: Higher population density is positively associated with predicted disease risk.
- H5: Greater environmental suitability for vector breeding is positively associated with predicted risk.
- H6: Previous disease incidence is positively associated with subsequent spatial risk.

Frontier in Medical & Health Research

ISSN: (e) 3007-1607 (p) 3007-1593

- H7: Integrated AI models outperform climate-only models.
- H8: Integrated AI models outperform conventional statistical models in hotspot identification.
- H9: Climate variables interact with environmental and demographic factors in determining disease risk.
- H10: The predictive importance of climate variables varies geographically across Pakistan.
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9. Conceptual Framework

Climate factors (temperature, precipitation, humidity, extreme weather) → Environmental/geographic factors (land use, vegetation, water bodies, elevation, land-surface temperature) → Demographic/epidemiological factors (population density, urbanization, historical incidence, spatial connectivity) → AI/ML modelling → Predicted disease risk → Spatial hotspot classification → Climate-informed surveillance and targeted intervention.

10. Methodology

10.1 Research Design and Study Area

A quantitative, retrospective, longitudinal, and spatial-predictive design is used. The analytical unit is the district-month observation. The study covers Pakistan, including Punjab, Sindh, Khyber Pakhtunkhwa, Balochistan, and Islamabad Capital Territory, subject to data availability. Dengue is the principal disease because of its climatic sensitivity and public-health relevance.

10.2 Population, Sampling, and Study Period

The target population comprises all spatially identifiable district-level disease observations during the study period. A census-based strategy is used: all eligible district-month observations with adequately matched disease and predictor data are included rather than selecting a sample of districts. The planned study period is January 2015–December 2024, providing up to 120 monthly observations per eligible district. The final number of observations must be reported only after data integration and quality screening; the source manuscript explicitly notes that inventing a final sample size would be inappropriate.

10.3 Data Sources and Variables

Epidemiological data are obtained from authenticated public-health surveillance sources. Monthly incidence is standardized per 100,000 population. Climate variables are obtained from ERA5 and include temperature, precipitation, humidity/moisture, anomalies, and selected lagged measures. Environmental and remote-sensing predictors include land-surface temperature, NDVI, surface-water indicators, land use/land cover, elevation, urbanization, and proximity to water bodies. Demographic data include population density and urban population indicators, with district-level information aligned to the 2023 Pakistan Census. Geographic boundary data are harmonized to common spatial identifiers.

10.4 Data Integration and Preprocessing

Datasets are merged by district and month-year. Processing includes duplicate removal, standardized geographic identifiers, date correction, unit harmonization, missing-value treatment, outlier assessment, spatial alignment, aggregation of gridded variables to districts, normalization where appropriate, lag construction, and final feature-matrix development. Predictor redundancy is assessed before modelling.

10.5 Dependent and Independent Variables

The primary outcome is dengue risk, represented by monthly incidence per 100,000 population and a binary hotspot classification based on a predefined epidemiological threshold. Sensitivity analyses can use alternative thresholds. Predictors cover four domains: climate (temperature, precipitation, humidity and anomalies), environment (NDVI, land-surface temperature, water bodies, land cover and urbanization), geography (elevation and spatial location), and demography/epidemiology (population density and previous incidence).

Frontier in Medical & Health Research

ISSN: (e) 3007-1607 (p) 3007-1593

10.6 AI Models and Validation

Random Forest, XGBoost, Support Vector Machine, and Artificial Neural Network models are compared. LSTM may be considered where temporal data are adequate. A temporal hold-out strategy separates earlier observations for training from more recent observations for testing. Spatial validation is also used where feasible by withholding selected geographical units. This reduces leakage and provides a more realistic assessment of generalization.

10.7 Performance Evaluation

Classification performance is assessed using accuracy, sensitivity, specificity, precision, F1-score, AUC-ROC, and AUC-PR. Continuous prediction is evaluated using MAE, RMSE, MAPE where appropriate, and R^2. Sensitivity and AUC receive particular attention because failure to identify high-risk locations may have greater public-health consequences than false-positive classification.

10.8 Spatial Analysis and Explainability

GIS is used to map observed incidence and predicted risk. Risk categories may include very low, low, moderate, high, and very high. Spatial autocorrelation and local clustering can be examined where appropriate. Feature importance and SHAP-based explainability are used to identify influential predictors, directionality, nonlinear patterns, interactions, and geographical variation in predictor importance.

10.9 Reliability, Validity, Quality Assurance, and Ethics

Reliability is strengthened through authenticated sources, standardized cleaning, consistent spatial and temporal identifiers, documented missingness, and reproducible preprocessing. Predictive validity is assessed using observations not used for model training, with temporal and spatial validation. A data dictionary documents variable definitions and transformations. The study uses aggregated secondary data and excludes personally identifiable patient information; data are handled according to applicable access and confidentiality requirements.

11. Data Analysis and Results Framework

The source manuscript does not contain actual empirical dataset outputs. Accordingly, this shortened version does not report fabricated means, correlations, AUC values, p-values, model rankings, hotspot counts, or hypothesis decisions. The final results should be populated after the merged dataset has been analysed.

11.1 Descriptive and Correlation Analysis

Descriptive statistics should summarize disease incidence, temperature, precipitation, humidity, land-surface temperature, NDVI, population density, elevation, and previous incidence. Pearson or Spearman correlations may be used as exploratory diagnostics. VIF and tolerance statistics should be examined where appropriate to identify excessive predictor redundancy.

11.2 Model Comparison

The models should be compared using out-of-sample classification and regression metrics. The preferred model should be selected on the basis of consistent performance across multiple metrics and validation periods rather than a single accuracy statistic.

11.3 Feature Importance and SHAP

Feature-importance analysis should identify the predictors contributing most strongly to predictions. SHAP or an equivalent method should then clarify whether high or low predictor values increase or decrease predicted risk and whether relationships are nonlinear. Importance scores should be interpreted as predictive contributions, not causal effects.

11.4 Hotspot Mapping and Hypothesis Testing

The best-performing validated model should generate district-level risk probabilities and hotspot maps. Observed and predicted hotspots should be compared spatially. Hypotheses concerning individual predictors can be evaluated using model evidence, while comparative hypotheses should be assessed through predictive-

Frontier in Medical & Health Research

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performance differences. Statistical significance should not be treated as sufficient evidence of practical predictive importance.

12. Discussion

The study framework indicates that climate-sensitive infectious-disease risk should be understood as an integrated spatial phenomenon rather than a simple function of climate alone. Temperature, precipitation, and humidity are expected to contribute to risk, but environmental conditions, population characteristics, previous incidence, and geography can modify these relationships. This interpretation is consistent with Pakistan-specific evidence showing spatially differentiated dengue suitability and associations with geo-climatic characteristics.

The integrated AI approach extends earlier climate-suitability and city-level mapping studies by combining multiple predictor domains and emphasizing spatially and temporally validated prediction. Historical incidence may provide strong predictive information because it captures persistent ecological, behavioural, reporting, and transmission conditions, but heavy reliance on historical patterns can also reduce generalizability. Spatial validation is therefore essential.

Remote sensing provides valuable environmental information where ground observations are incomplete, while explainable AI improves transparency by showing which predictors drive model outputs. Nevertheless, AI should remain a decision-support technology rather than a substitute for epidemiological expertise. Predicted hotspots should be interpreted probabilistically and alongside field surveillance, vector indices, reporting quality, and local public-health information.

13. Conclusion

The study provides an integrated AI-GIS framework for predicting climate-sensitive infectious-disease hotspots in Pakistan. By combining epidemiological, climatic, environmental, demographic, and geographic information, the framework is designed to capture nonlinear relationships and spatial heterogeneity that may be missed by simpler approaches. Temporal and spatial validation and explainable AI are central to ensuring that predictive performance is both generalizable and interpretable.

The resulting district-level risk maps have potential to support anticipatory, climate-informed disease surveillance and targeted public-health action. However, because the source manuscript does not provide empirical model outputs, the numerical performance and hypothesis-testing conclusions remain to be completed from the actual dataset.

14. Implications

- Integrate disease surveillance with climate, environmental, and geospatial information.
- Use AI-generated risk maps to prioritize vector surveillance, diagnostics, sanitation, awareness, and emergency preparedness.
- Develop climate-health early-warning platforms linking health and meteorological institutions.
- Promote data sharing among health, meteorological, environmental, disaster-management, and research institutions.
- Use explainable AI so public-health officials can understand why areas are classified as high risk.
- Maintain expert epidemiological oversight of AI-generated predictions.

15. Recommendations

- Establish a national AI-based climate-health early-warning system.
- Strengthen disease surveillance at district and sub-district levels.
- Integrate meteorological, environmental, remote-sensing, demographic, and health data.
- Allocate preventive resources according to predicted risk as well as historical burden.
- Integrate vector surveillance, including mosquito abundance and breeding-site indicators, where available.
- Develop provincial and district GIS dashboards showing risk, trends, climate

Frontier in Medical & Health Research

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conditions, uncertainty, and surveillance priorities.

- Regularly recalibrate models as climate, disease ecology, population behaviour, and surveillance systems change.

16. Limitations and Future Directions

The principal limitation is the quality and completeness of secondary epidemiological data. Under-reporting, asymptomatic infections, diagnostic differences, and healthcare-seeking behaviour may bias observed incidence. District-level analysis may also conceal within-district heterogeneity and cannot establish individual-level relationships. Gridded climate products introduce additional uncertainty, while climate and environmental predictors do not fully represent human mobility, sanitation, housing, healthcare access, vector-control activities, or behaviour.

Future research should use finer spatial units where data permit, incorporate vector and biological surveillance, compare multiple climate datasets, model extreme events such as floods and heatwaves, evaluate future climate scenarios, and combine AI with mechanistic or causal models. Multi-disease prediction and near-real-time dynamic risk mapping are also important. Ultimately, real-world evaluations should determine whether AI-supported hotspot information improves early detection, reduces disease burden, or improves resource efficiency.

17. Overall Research Contribution

The principal contribution is an integrated framework combining climate science, spatial epidemiology, remote sensing, artificial intelligence, and public-health decision support for Pakistan. The framework advances existing work by emphasizing national spatial prediction, multidimensional predictors, explainable AI, and temporal/spatial validation. Its practical value lies in converting complex climate-health information into geographically actionable intelligence for more anticipatory and climate-resilient infectious-disease surveillance.

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