

SENTINEL-Dengue ASEAN-11: An AI-Powered Climate–Geospatial Intelligence System for Dengue Early Warning and Surveillance Prioritization Across Southeast Asia

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Abstract

Dengue remains a major climate-sensitive vector-borne disease in tropical and subtropical regions, particularly across Southeast Asia where rainfall variability, temperature suitability, vegetation dynamics, urbanization, surface water, and population exposure interact to shape transmission risk. Conventional dengue surveillance is often reactive and administratively aggregated, limiting its usefulness for early warning, targeted vector control, and regional preparedness. This study develops SENTINEL-Dengue ASEAN-11, an artificial intelligence and climate–geospatial intelligence framework for dengue early warning and surveillance prioritization across Brunei Darussalam, Cambodia, Indonesia, Lao PDR, Malaysia, Myanmar, the Philippines, Singapore, Thailand, Timor-Leste, and Viet Nam. The framework integrates publicly available dengue case-count data, climate reanalysis, remote-sensing vegetation indices, gridded population exposure, surface-water indicators, administrative boundaries, explainable artificial intelligence, spatial block cross-validation, temporal validation, and uncertainty mapping. A harmonized Admin-1month geospatial panel dataset is proposed for 2010–2023. Dengue alert outcomes are defined using within-area historical baselines to reduce misleading country-level comparison. Statistical models, Bayesian spatiotemporal smoothing, Random Forest, XGBoost, and explainable AI are used to estimate dengue alert probability and identify influential climate environmental predictors. The final output is an ASEAN-11 surveillance-priority framework that distinguishes high-risk/high-confidence, high-risk/high-uncertainty, moderate-risk, low-risk, and data-insufficient areas. SENTINEL-Dengue ASEAN-11 advances dengue geoinformatics beyond retrospective hotspot mapping toward interpretable, scalable, and policy-relevant epidemic intelligence for climate-sensitive public-health preparedness.

Keywords: Artificial Intelligence, Dengue, Early Warning, Geoinformatics, Southeast Asia

1. Introduction

Dengue is a mosquito-borne viral disease affecting tropical and subtropical regions. Its transmission is influenced by climate suitability, mosquito ecology, rainfall, temperature, urbanization, human exposure, and surveillance capacity. In 2024, dengue reached unprecedented global transmission levels, with 14,434,584 reported cases and 11,201 reported

deaths worldwide [1]. Southeast Asia is an important region for dengue early warning because monsoon variability, rapid urbanization, dense settlements, ecological suitability, and population movement create persistent conditions for transmission. This study defines the regional scope as ASEAN-11, consisting of Brunei Darussalam, Cambodia,

Indonesia, Lao PDR, Malaysia, Myanmar, the Philippines, Singapore, Thailand, Timor-Leste, and Viet Nam. Timor-Leste is admitted as the 11th Member State of ASEAN in 2025 [2].

Open-data infrastructure makes it possible to develop regional dengue geospatial intelligence. OpenDengue version 1.2 contains more than 56 million dengue case records from 102 countries between 1924 and 2023, with more than 95% of records reported at weekly or monthly temporal resolution and subnational data available for 40 countries [3]. This makes it suitable as a core secondary dengue surveillance layer for ASEAN-11 analysis. Geographic Information Systems have become important tools for dengue detection, surveillance, and control. Recent dengue geoinformatics research has shown that GIS can support dengue detection, spatial surveillance, and operational decision-making [4]. Applied studies have demonstrated the use of GIS for dengue hemorrhagic fever prevention, local surveillance support, and spatio-temporal dengue analysis [5] and [6]. GIS-based dengue surveillance modelling in Thailand has also supported local public-health planning [7].

Beyond dengue, geospatial health studies have supported disease surveillance, preparedness planning, spatial epidemiology, and community-based health analysis. GIS-based surveillance frameworks have been applied to health preparedness and ASEAN-level public-health analysis [8] and [9]. Related studies have demonstrated the importance of geocoding reliability and participatory GIS for spatial epidemiological interpretation [10] and [11]. GIS-based disease modelling and health-service coverage analysis further demonstrate the value of geoinformatics for prevention planning and service-area assessment [12] and [13]. Machine learning is increasingly relevant to geoinformatics because it can support nonlinear pattern detection, spatial prediction, and decision-support modelling. Previous studies have applied machine learning to GIS data generalisation [14]. Related GIS-machine learning studies have also been applied to environmental susceptibility prediction and land suitability analysis [15] and [16]. These applications suggest that AI-based geoinformatics can be extended to dengue early warning when supported by appropriate data harmonization, spatial validation, and interpretable outputs.

Despite these advances, four research gaps remain. First, many dengue GIS studies focus on retrospective hotspot mapping rather than early-warning probability. Second, climate-lag effects are often insufficiently represented, despite delayed

relationships among rainfall, temperature, mosquito breeding, infection, diagnosis, and reporting. Third, AI models may overestimate predictive performance when random validation is applied to spatially autocorrelated data. Fourth, risk maps are rarely paired with uncertainty maps, increasing the risk of overinterpretation by public-health decision-makers.

The objective of this study is to develop “SENTINEL-Dengue ASEAN-11” as an AI-powered climate-geospatial intelligence system for dengue early warning and surveillance prioritization across Southeast Asia. To achieve this, the project was first harmonize open dengue surveillance data, climate reanalysis, remote-sensing indicators, surface-water variables, population exposure data, and administrative boundaries into a unified ASEAN-11 Admin-1 monthly geospatial panel dataset. This foundational data was utilized to identify lagged climate and environmental predictors associated with dengue alert risks across the region. Leveraging these insights, the study developed and validated AI-based models for estimating dengue alert probabilities using spatially responsible validation methods. Ultimately, these models generated ASEAN-11 dengue risk-uncertainty surveillance-priority maps designed to provide critical actionable intelligence for early warning, vector control planning, and public-health decision support.

2. Materials and Methods

2.1 Study Area

The study area includes 11 ASEAN Member States: Brunei Darussalam, Cambodia, Indonesia, Lao PDR, Malaysia, Myanmar, the Philippines, Singapore, Thailand, Timor-Leste, and Viet Nam (Figure 1). The spatial unit of analysis is the first-level administrative unit, hereafter referred to as Admin-1. Admin-1 units include provinces, states, regions, municipalities, or equivalent subnational divisions. The temporal unit of analysis is month.

2.2 Study Design

This study applies a retrospective, secondary-data, spatiotemporal geoinformatics design. The analytical unit is the Admin-1 month. The proposed study period is 2010-2023, corresponding to the availability of standardized OpenDengue data and overlapping climate, remote-sensing, population, surface-water, and administrative-boundary datasets. The study follows four objective-based analytical phases: data harmonization, climate-environmental lag feature engineering, AI model development and validation, and risk-uncertainty surveillance-priority mapping.



Figure 1: Sentinel-dengue ASEAN-11 study area context map

Table 1: Secondary data inventory for SENTINEL-Dengue ASEAN-11

No.	Data layer	Dataset	Main variables	Function
1	Dengue surveillance	OpenDengue	case counts, date, location	outcome layer
2	Climate	ERA5-Land	rainfall, temperature	climate predictors
3	Vegetation	MODIS MOD13Q1	NDVI, EVI	environmental suitability proxy
4	Surface water	JRC Global Surface Water	water occurrence, seasonality	breeding-site proxy
5	Population	WorldPop	gridded population	denominator and exposure
6	Administrative boundaries	geoBoundaries, GADM, national open data	Admin-1 polygons	spatial harmonization
7	Urban environment	GHS-L GHS-BUILT-S	built-up surface, built-up fraction	urban exposure proxy

2.3 Data Used

Table 1 shows the secondary data inventory for SENTINEL-Dengue ASEAN-11. All datasets were harmonized to the Admin-1 month analytical unit. Dengue surveillance data were used as the outcome layer, while climate, vegetation, surface water, population, built-up surface, and administrative-boundary datasets were used as explanatory and harmonization layers. OpenDengue was used as the core dengue surveillance dataset because it provides publicly available dengue case-count data with spatial and temporal attributes [3]. ERA5-Land was used to extract rainfall and temperature predictors suitable for monthly climate feature construction [17]. MODIS MOD13Q1 was used to extract NDVI

and EVI vegetation indices as environmental suitability proxies [18]. WorldPop was used to estimate gridded population exposure and incidence denominators [19]. JRC Global Surface Water was used to derive surface-water occurrence and seasonality variables as breeding-site proxies [20]. geoBoundaries was used as the primary source for administrative-boundary harmonization, while GADM and national open boundary data was used for cross-checking and boundary reconciliation [21] and [22]. GHS-L GHS-BUILT-S was used to derive built-up surface and built-up fraction as urban exposure proxies [23].

2.4 Outcome Definition

The first outcome is monthly dengue incidence per 100,000 population as presented in Equation 1:

$$DI_{i,t} = \frac{C_{i,t}}{P_{i,t}} \times 100,000$$

Equation 1

Where:

- i is the Admin-1 unit
- t is the month
- $C_{i,t}$ is the case numbers
- $P_{i,t}$ is the population numbers

The second outcome is a binary dengue alert variable. If the dengue incidence exceeds the historical 75th or 90th percentile for the same Admin-1 unit and calendar month, the outcome is assigned as 1, and 0 for otherwise.

2.5 Feature Engineering

Climate and environmental predictors was transformed into current-month and lagged variables. Rainfall was tested at 0-, 1-, 2-, and 3-month lags. Temperature was tested at 0-, 1-, and 2-month lags. NDVI and EVI was tested at 0-, 1-, and 2-month lags. Surface-water indicators was treated as static and seasonal environmental predictors. Climate anomaly was calculated using Equation 3:

$$Ano_{i,t} = X_{i,t} - \bar{X}_{i,m}$$

Equation 3

Where $Ano_{i,t}$ is climate anomaly, $X_{i,t}$ is the observed climate or environmental value in Admin-1 unit i and month t , and $\bar{X}_{i,m}$ is the long-term mean value for the same Admin-1 unit and calendar month

Climate and environmental predictors were transformed into current-month and lagged variables

to capture delayed relationships between environmental conditions and dengue transmission. Rainfall variables were tested at 0-, 1-, 2-, and 3-month lags. Temperature, humidity proxy, and vegetation variables were tested at 0-, 1-, and 2-month lags. Surface-water variables were treated as static and seasonal predictors, while population and built-up variables were used to represent human exposure and urban environmental conditions. Historical dengue baseline variables were included to control for local seasonality and recurring transmission patterns. The predictor domains, variables, and lag structures used in this study are shown in Table 2.

2.6 AI Models

SENTINEL-Dengue ASEAN-11 was compare statistical, spatial, and machine-learning models. Logistic regression was used as a transparent baseline for dengue alert classification. Negative binomial regression was used where count outcomes show overdispersion. Bayesian spatiotemporal models were used for smoothed risk and uncertainty estimation. Random Forest and XGBoost was used for nonlinear prediction. The AI prediction target is presented in Equation 4:

$$P(\text{Alert}_{i,t} = 1 | X_{i,t})$$

Equation 4

Where $X_{i,t}$ includes lagged climate, vegetation, surface-water, population, urban, seasonal, and spatial predictors.

Explainable AI was used to interpret model outputs. SHAP values, permutation importance, and partial dependence plots were used to identify influential predictors and support interpretation of dengue alert probability [22].

Table 2: Predictor and lag structure

No.	Predictor domain	Variable	Lag structure
1	Rainfall	total rainfall, rainfall anomaly	0, 1, 2, 3 months
2	Temperature	mean, minimum, maximum temperature	0, 1, 2 months
3	Vegetation	NDVI, EVI, vegetation anomaly	0, 1, 2 months
4	Surface water	occurrence, seasonality	static and seasonal
5	Population	population density	annual
6	Urban environment	built-up fraction	annual or static
7	Seasonality	calendar month, monsoon period	current month
8	Historical dengue baseline	previous incidence, historical percentile	local baseline

2.7 Model Validation

Random cross-validation was used only as a baseline comparison. Spatial block cross-validation was used as the primary validation method because neighbouring areas may share similar climate, environmental, demographic, and dengue transmission patterns. Temporal holdout validation was used to test early-warning performance in unseen years. Country-exclusion sensitivity analysis was used to assess regional robustness. Model validation was designed to assess both predictive performance and spatial generalizability. Random cross-validation was used only as a baseline comparison because it may overestimate model performance when nearby areas share similar climate, environmental, demographic, and epidemiological characteristics.

Spatial block cross-validation was used as the primary validation strategy to evaluate whether the model can generalize across spatially separated areas. Temporal holdout validation was used to assess early-warning performance in unseen time periods. Country-exclusion and data-completeness sensitivity analyses were included to evaluate regional robustness and the influence of missing or incomplete surveillance data. The validation strategies and their purposes are shown in Table 3.

Spatial block cross-validation was prioritized because dengue observations from neighboring Admin-1 units may not be statistically independent. Temporal holdout validation was used to evaluate whether the model can support early warning beyond the training period. Country-exclusion sensitivity analysis was used to assess whether model performance depends heavily on specific data-rich countries. Data-completeness sensitivity analysis was used to examine whether missing or incomplete

dengue records affect model stability. The overall AI modelling and spatially responsible validation framework.

2.8 Risk-Uncertainty Classification

Final outputs were classify Admin-1 units into five surveillance-priority classes as illustrates in Table 4. The final priority score ($P_{i,t}$) is defined as in Equation 5:

$$P_{i,t} = f(R_{i,t}, U_{i,t}, C_{i,t}) \quad \text{Equation 5}$$

Where $R_{i,t}$ is predicted dengue alert probability, $U_{i,t}$ is model or data uncertainty, and $D_{i,t}$ is the completeness of dengue surveillance and geospatial covariates.

The final decision-support output was designed as a risk-uncertainty surveillance-priority classification rather than a deterministic dengue outbreak map. Predicted dengue alert probability represented the risk dimension, while model uncertainty and data completeness represented the uncertainty dimension. This structure allows high-risk/high-confidence areas to be prioritized for immediate public-health action, whereas high-risk/high-uncertainty areas can be prioritized for both intervention and surveillance strengthening.

2.9 Ethical Considerations

This study uses publicly available secondary data. No individual-level identifiable human data were used. The analysis does not rank countries, attribute dengue transmission to any political jurisdiction, or infer cross-border responsibility. All outputs were interpreted as surveillance-priority and data-strengthening layers, not deterministic outbreak predictions.

Table 3: Model validation strategy

No.	Validation type	Purpose
1	Random cross-validation	baseline comparison
2	Spatial block cross-validation	spatial generalizability
3	Temporal holdout validation	early-warning performance
4	Country-exclusion sensitivity analysis	regional robustness
5	Data-completeness sensitivity analysis	missingness robustness

Table 4: Risk-uncertainty surveillance-priority matrix

Class	Risk	Uncertainty	Interpretation
1	High	Low	high-confidence surveillance priority
2	High	High	surveillance and data-strengthening priority
3	Moderate	Low/Moderate	routine monitoring with climate watch
4	Low	Low	baseline surveillance
5	Low/Unknown	High	data-insufficient area

3. Results and Discussion

3.1 Results According to Objective 1

Month geospatial panel dataset is technically feasible. Climate, vegetation, surface-water, population, built-up environment, and administrative-boundary layers are available from global or near-global open-data systems. These layers can be spatially aggregated or harmonized to Admin-1 units and temporally aligned to monthly dengue surveillance records. The main limitation is not the availability of geospatial covariates, but the heterogeneity of dengue surveillance completeness across countries, reporting systems, and time periods. OpenDengue provides a suitable foundation for the disease outcome layer because it contains publicly available dengue case-count data with spatial and temporal attributes [3]. However, dengue reporting systems differ across countries and years. Therefore, data extraction, spatial reconciliation, temporal aggregation, duplicate checking, missingness assessment, and country-specific completeness verification are required before model development. The preliminary source-readiness matrix is shown in Table 5. The regional source-readiness concept is illustrated in Figure 2. The map shows the 11 ASEAN study countries included in the SENTINEL-Dengue ASEAN-11 framework and distinguishes between broadly available geospatial covariates and dengue surveillance layers that still require extraction and completeness verification. Green square symbols indicate that key geospatial covariates, including administrative boundaries, population, climate, vegetation, and surface-water layers, are available for harmonization. Orange circular symbols indicate that dengue surveillance

records are available as a candidate outcome layer but require country-specific extraction, cleaning, temporal aggregation, spatial reconciliation, and completeness assessment before model development. Figure 2 confirms that the proposed ASEAN-11 spatial framework is feasible from a geospatial data perspective. The distribution of markers across mainland and maritime Southeast Asia indicates that all ASEAN-11 countries can be included in the regional harmonization workflow. However, the figure also emphasizes that dengue surveillance data are not treated as immediately complete model-ready data. Instead, they require verification before being converted into an Admin-1 month analytical panel. This distinction is important because apparent low dengue burden in some areas may reflect reporting incompleteness rather than true low transmission risk.

3.2 Results According to Objective 2

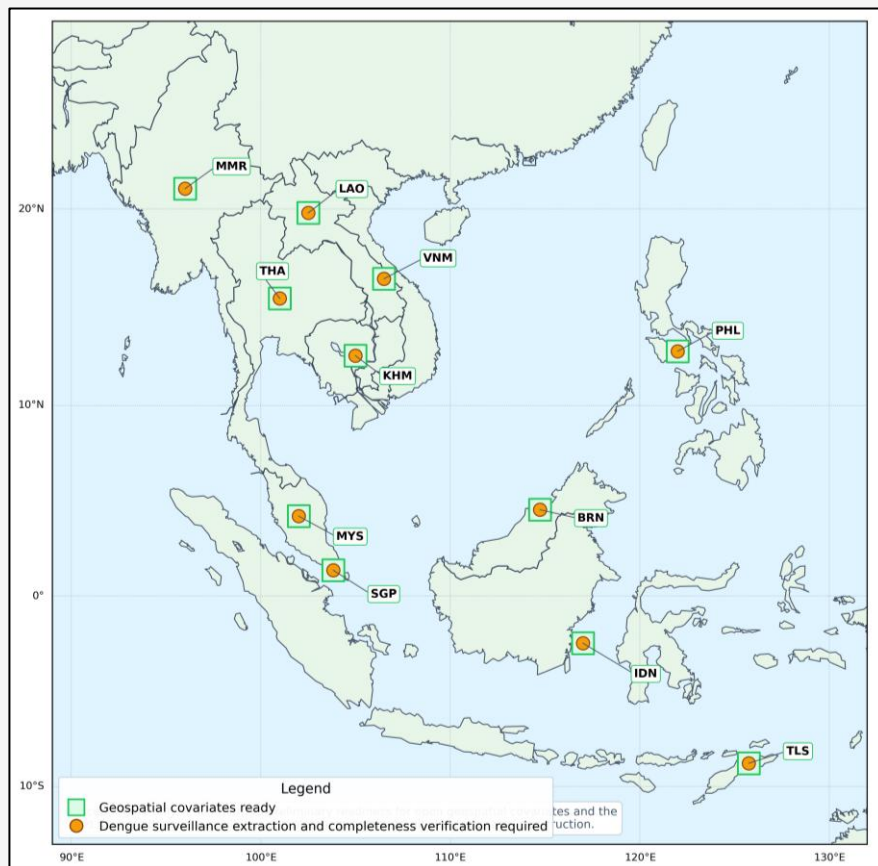
The preliminary feature-engineering assessment indicates that dengue alert risk across ASEAN-11 should be modelled as a climate-sensitive, lagged, nonlinear, and spatially heterogeneous process. Based on the data inventory and predictor structure described in Table 2, rainfall, temperature, humidity proxy, vegetation indices, surface water, urban exposure, population density, seasonality, and historical dengue baseline were retained as candidate predictors for dengue alert probability. Rainfall was assigned the longest lag structure because it can create or refresh mosquito breeding sites, while dengue alerts may occur several weeks later due to mosquito development, viral incubation, human infection, diagnosis, and reporting.

Table 5: Preliminary ASEAN-11 source-readiness matrix (con't next page)

No.	Country	Dengue surveillance	Boundary	Population	Climate	MODIS	Surface water	Preliminary source readiness
1	Brunei Darussalam	Available, pending extraction and completeness verification	Available for harmonization	Available for harmonization	Available for extraction	Available for extraction	Available for extraction	Moderate
2	Cambodia	Available, pending extraction and completeness verification	Available for harmonization	Available for harmonization	Available for extraction	Available for extraction	Available for extraction	Moderate
3	Indonesia	Available, pending extraction and completeness verification	Available for harmonization	Available for harmonization	Available for extraction	Available for extraction	Available for extraction	Moderate
4	Lao PDR	Available, pending extraction and completeness verification	Available for harmonization	Available for harmonization	Available for extraction	Available for extraction	Available for extraction	Moderate
5	Malaysia	Available, pending extraction and completeness verification	Available for harmonization	Available for harmonization	Available for extraction	Available for extraction	Available for extraction	Moderate

Table 5: Preliminary ASEAN-11 source-readiness matrix (con't from previous page)

No.	Country	Dengue surveillance	Boundary	Population	Climate	MODIS	Surface water	Preliminary source readiness
6	Myanmar	Available, pending extraction and completeness verification	Available for harmonization	Available for harmonization	Available for extraction	Available for extraction	Available for extraction	Moderate
7	Philippines	Available, pending extraction and completeness verification	Available for harmonization	Available for harmonization	Available for extraction	Available for extraction	Available for extraction	Moderate
8	Singapore	Available, pending extraction and completeness verification	Available for harmonization	Available for harmonization	Available for extraction	Available for extraction	Available for extraction	Moderate
9	Thailand	Available, pending extraction and completeness verification	Available for harmonization	Available for harmonization	Available for extraction	Available for extraction	Available for extraction	Moderate
10	Timor-Leste	Available, pending extraction and completeness verification	Available for harmonization	Available for harmonization	Available for extraction	Available for extraction	Available for extraction	Moderate-Low
11	Viet Nam	Available, pending extraction and completeness verification	Available for harmonization	Available for harmonization	Available for extraction	Available for extraction	Available for extraction	Moderate

**Figure 2:** Objective 1 source-readiness concept map for SENTINEL-Dengue ASEAN-11

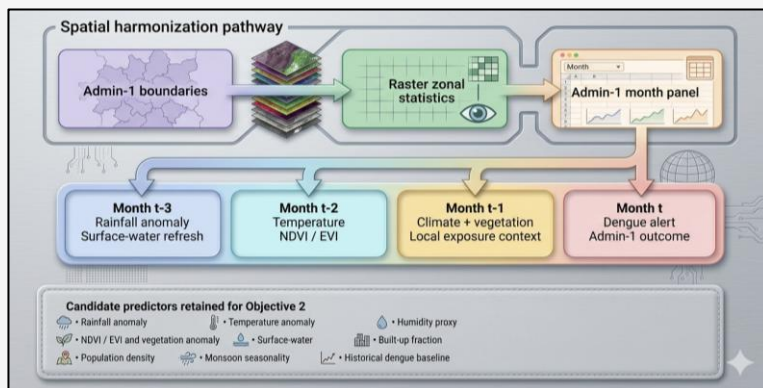


Figure 3: Objective 2 climate-geospatial lag feature engineering framework

Temperature variables were retained because they influence mosquito survival, biting activity, and dengue virus replication. Humidity proxy variables were included because moisture conditions may affect vector survival and habitat suitability. Vegetation indices and surface-water indicators were treated as environmental proxies rather than direct measurements of mosquito abundance, but they are useful for representing ecological suitability and potential breeding environments [1]. The proposed lag structure does not assume that all predictors have the same effect across all ASEAN-11 countries. Rainfall, temperature, vegetation, surface water, urban exposure, and population density may operate differently across mainland and maritime Southeast Asia because climate regimes, urbanization patterns, ecological conditions, vector dynamics, and surveillance systems vary by location. Therefore, lagged predictors should be evaluated through model validation and explainable AI rather than interpreted as universal linear drivers. The climate–geospatial lag feature engineering framework is illustrated in Figure 3. The figure shows how climate and environmental variables from previous months are transformed into lagged predictors and harmonized into an Admin-1 month analytical panel for dengue alert modelling. Figure 3 supports Objective 2 by showing that dengue early warning requires temporal feature construction before model development. The framework links lagged rainfall, temperature, vegetation, surface-water, population, urban, seasonal, and historical baseline predictors to the dengue alert outcome at month t . This structure allows the model to capture delayed environmental effects while preserving the Admin-1 month unit of analysis.

3.3 Results According to Objective 3

The preliminary model-design assessment supports a comparative AI modelling strategy rather than

reliance on a single prediction model. Transparent statistical models, including logistic regression and negative binomial regression, were retained as interpretable baseline models. Bayesian spatiotemporal models were retained to support smoothed risk estimation and uncertainty assessment. Random Forest and XGBoost were retained to capture nonlinear relationships among climate, environmental, population, urban, seasonal, and historical dengue predictors. Explainable AI was included to support interpretation of modelled dengue alert probability and to identify influential predictors. The AI modelling and spatially responsible validation framework is illustrated in Figure 4.

Spatial block cross-validation was identified as the primary validation strategy because dengue observations from neighbouring Admin-1 units may be spatially autocorrelated. Random cross-validation was retained only as a baseline comparison because it may overestimate predictive performance when spatial dependence is present. Temporal holdout validation was retained to assess whether the model can support early warning in unseen years. Country-exclusion sensitivity analysis was included to evaluate whether model performance depends heavily on specific data-rich countries, while data-completeness sensitivity analysis was included to examine the influence of incomplete surveillance records. The expected result of Objective 3 is a spatially validated dengue alert modelling framework rather than a single deterministic prediction output. Model performance was reported using discrimination, calibration, false-alert burden, spatial transferability, and temporal transferability indicators. This structure allows SENTINEL-Dengue ASEAN-11 to evaluate whether AI-based dengue alert prediction is robust across space, time, and surveillance-data conditions.

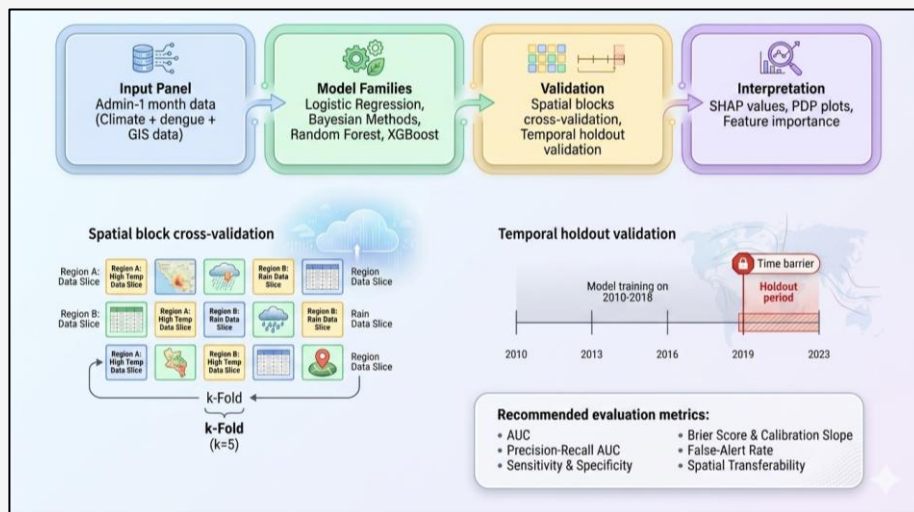


Figure 4: Objective 3 AI modelling and spatially responsible validation framework

3.4 Results According to Objective 4

The preliminary decision-support assessment indicates that dengue risk maps alone are insufficient for ASEAN-11 surveillance planning. Because dengue surveillance completeness may vary across countries, years, and reporting systems, predicted low risk may reflect weak surveillance or incomplete reporting rather than true low transmission risk. Therefore, the final decision-support output should combine dengue alert probability, model uncertainty, and data-completeness information. The expected output of Objective 4 is an ASEAN-11 risk uncertainty surveillance-priority map rather than a deterministic dengue outbreak map. High-risk/low-uncertainty areas should be interpreted as high-confidence action-priority areas for vector control, community warning, clinical preparedness, and resource allocation. High-risk/high-uncertainty areas should be interpreted as dual-priority areas requiring both public-health intervention and surveillance strengthening. Moderate-risk areas should be used for routine monitoring and climate-watch activities. Low-risk/high-uncertainty areas should not be interpreted as safe areas; they should be interpreted cautiously as data-insufficient or uncertainty-sensitive areas. The proposed risk uncertainty surveillance-priority classification template is illustrated in Figure 5. The figure supports Objective 4 by translating model outputs into operational surveillance categories. The risk dimension represents predicted dengue alert probability, while the uncertainty dimension represents model uncertainty and data-completeness limitations. This classification structure allows SENTINEL-Dengue ASEAN-11 to separate areas requiring immediate

action from areas requiring improved surveillance, field verification, or data strengthening.

The key contribution of Objective 4 is the transformation of dengue early-warning outputs into an interpretable public-health decision-support layer. Instead of producing a single risk surface, the framework produces a priority map that distinguishes action-ready areas, uncertainty-sensitive areas, routine monitoring areas, baseline surveillance areas, and data-insufficient areas. This approach reduces the risk of overinterpreting model predictions and strengthens the policy relevance of regional dengue geoinformatics. The risk uncertainty classification framework was further translated into a browser-based operational dashboard prototype. The prototype was designed to demonstrate how dengue alert probability, uncertainty score, source freshness, data completeness, and surveillance-priority class can be displayed for public-health decision support. The interface includes an ASEAN-11 command map, high-risk area analyzer, live source registry, AI ingestion pipeline, and risk-uncertainty matrix. This dashboard should be interpreted as an operational prototype and system-interface demonstration, not as a validated real-time surveillance product. The proposed dashboard interface is shown in Figure 6. Figure 6 demonstrates how the SENTINEL-Dengue ASEAN-11 framework can be operationalized beyond static map production. The dashboard supports source-status review, priority-area inspection, risk-uncertainty interpretation, and surveillance-readiness monitoring. This interface is consistent with the study objective of translating AI-based dengue early warning into surveillance prioritization and public-health decision support.

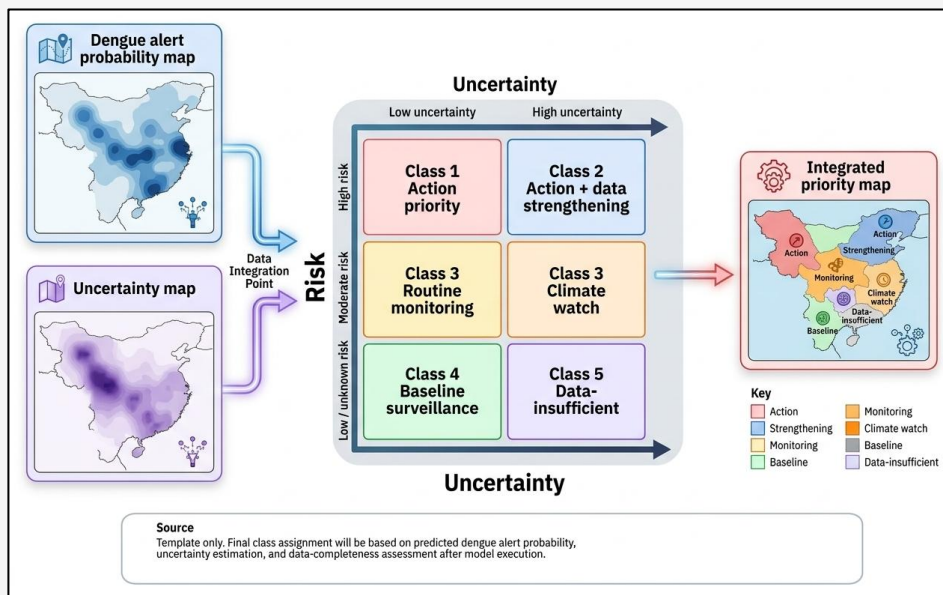


Figure 5: Objective 4 risk–uncertainty surveillance-priority classification template

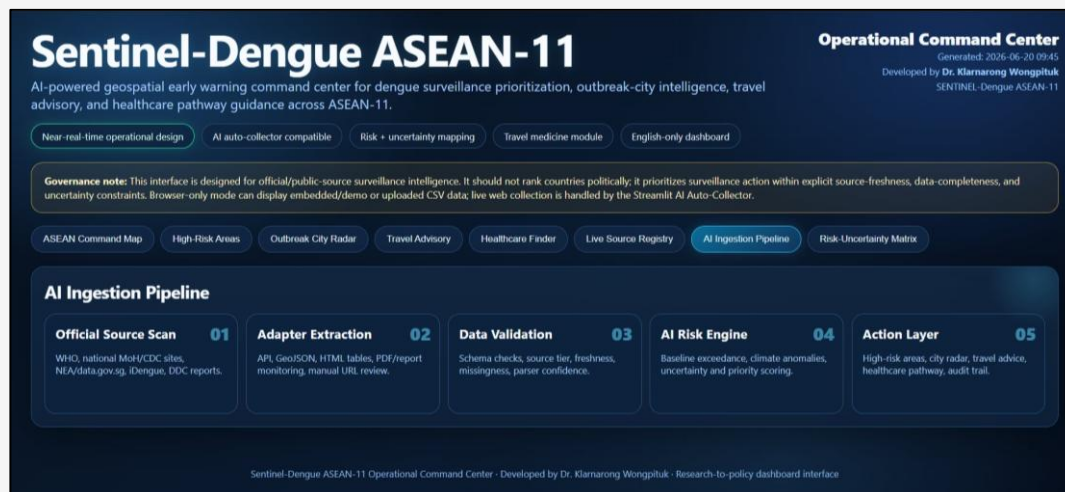


Figure 6: SENTINEL-Dengue ASEAN-11 operational dashboard prototype

The framework also extends broader geospatial health applications into a regional dengue early-warning architecture. GIS-based surveillance studies have shown the relevance of geoinformatics for health preparedness and ASEAN-level public-health analysis [8] and [9]. Related spatial epidemiology studies have highlighted the importance of geocoding reliability, participatory GIS, disease modelling, and health-service coverage assessment [10][11][12] and [13]. In this study, these concepts are extended into an ASEAN-11 system that integrates dengue surveillance, climate reanalysis, remote sensing, population exposure, administrative-boundary harmonization, and built-up environment indicators. The main methodological contribution is the integration of climate-lag feature engineering,

remote sensing, population exposure, machine learning, explainable AI, spatial validation, and uncertainty mapping into one regional surveillance architecture. ERA5-Land, MODIS MOD13Q1, WorldPop, JRC Global Surface Water, geoBoundaries, GADM, and GHSL GHS-BUILT-S provide the core geospatial and environmental layers required for harmonized feature construction [17][18][19] and [20]. Administrative-boundary reconciliation and built-up surface information further support spatial harmonization and urban exposure assessment [21][22] and [23].

A second contribution is the use of spatially responsible validation. Random cross-validation may overestimate predictive performance when observations are spatially or temporally structured.

Spatial block cross-validation is therefore more appropriate for assessing model transferability across new spatial units or regions [24]. This is important for ASEAN-11 dengue modelling because neighbouring Admin-1 units may share similar rainfall regimes, land-cover conditions, mobility patterns, vector ecology, and surveillance practices. A third contribution is the use of explainable AI to strengthen interpretability. Machine-learning models can capture nonlinear relationships among climate, environmental, population, urban, seasonal, and historical dengue predictors, but their outputs require interpretation for public-health use. SHAP provides a framework for assigning feature-attribution values to model predictions and can support interpretation of influential predictors in complex AI models [25]. In SENTINEL-Dengue ASEAN-11, explainable AI is used to identify whether rainfall anomaly, temperature, vegetation, surface water, population density, built-up fraction, seasonality, or historical baseline contributes strongly to dengue alert probability.

The decision-support contribution is the integration of risk, uncertainty, and data completeness. Dengue risk maps alone may be misleading when surveillance completeness varies across countries and time periods. A predicted low-risk area may reflect incomplete reporting rather than genuinely low transmission. Therefore, the proposed risk–uncertainty surveillance-priority map separates high-confidence action areas from areas requiring surveillance strengthening, data verification, or cautious interpretation. The major limitation is reliance on secondary data. Dengue surveillance data may differ by country, temporal completeness, administrative resolution, diagnostic practice, and public availability. Remote-sensing and climate variables are proxies rather than direct measurements of mosquito abundance. These limitations were addressed through data-completeness assessment, sensitivity analysis, spatial validation, explainable AI interpretation, and conservative use of the dashboard as an operational prototype rather than a fully validated real-time system.

4. Conclusions

SENTINEL-Dengue ASEAN-11 provides an AI-powered climate–geospatial intelligence framework for dengue early warning and surveillance prioritization across Southeast Asia. The proposed system is designed to harmonize open dengue surveillance data, climate reanalysis, remote-sensing indicators, surface-water variables, population exposure data, built-up environment data, and administrative boundaries into an ASEAN-11 Admin-1 month geospatial panel dataset.

The framework supports the identification of lagged climate and environmental predictors associated with dengue alert risk. It also proposes a spatially responsible AI modelling and validation workflow that integrates statistical baseline models, machine-learning models, Bayesian spatiotemporal smoothing, explainable AI, spatial block cross-validation, temporal holdout validation, and data-completeness sensitivity analysis. The expected decision-support output is a risk–uncertainty surveillance-priority map that combines predicted dengue alert probability, uncertainty, and data completeness.

The principal contribution of this study is the transformation of dengue geoinformatics from retrospective hotspot mapping into interpretable regional epidemic intelligence. Rather than producing only a static risk map, SENTINEL-Dengue ASEAN-11 provides a structured pathway for converting climate, environmental, surveillance, and geospatial data into operational surveillance-priority information. The system is designed to be reproducible, politically neutral, and scalable. It does not rank countries or infer cross-border responsibility. Instead, it supports early warning, vector control planning, surveillance strengthening, data-quality improvement, and regional public-health preparedness across ASEAN-11. Future work should proceed with full dengue data extraction, Admin-1 boundary reconciliation, monthly panel construction, model training, spatial validation, explainable AI interpretation, uncertainty estimation, and operational dashboard refinement before real-time or near-real-time public-health deployment.

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