Strengthening Vector-Borne Disease Surveillance in a Changing Climate



National Centre for Disease Control

Council on Energy, Environment, and Water

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Abbreviations

AdaBoost	Adaptive Boosting
AI	Artificial Intelligence
ARTPARK	AI and Robotics Technology Park
ASHA	Accredited Social Health Activist
BI	Breteau Index
CatBoost	Categorical Boosting
CEEW	Council on Energy, Environment and Water
CI	Container Index
CSIR	Council of Scientific and Industrial Research
CSD	Climate-Sensitive Diseases
DL	Deep Learning
EIS	Epidemic Intelligence Service
EWARS	Early Warning and Response System
EWS	Early Warning System
GIS	Geographic Information System
GPM	Global Precipitation Measurement
HI	House Index
IDSP	Integrated Disease Surveillance Programme
IHF	India Health Fund
IHIP	Integrated Health Information Platform
IICT	Indian Institute of Chemical Technology
IIT	Indian Institute of Technology
IITM	Indian Institute of Tropical Meteorology
IMD	India Meteorological Department

IMERG	Integrated Multi-satellite Retrievals for GPM
JSI	John Snow India
LST	Land Surface Temperature
MAE	Mean Absolute Error
ML	Machine Learning
MODIS	Moderate Resolution Imaging Spectroradiometer
MoHFW	Ministry of Health and Family Welfare
NCDC	National Centre for Disease Control
NCVBDC	National Centre for Vector-Borne Disease Control
NCVBDCP	National Centre for Vector-Borne Disease Control Programme
NDVI	Normalised Difference Vegetation Index
NIMR	National Institute of Malaria Research
NPCCHH	National Programme on Climate Change and Human Health
PHC	Primary Health Centre
PHFI	Public Health Foundation of India
RF	Random Forest
RFR	Random Forest Regression
RMSE	Root Mean Square Error
S2S	Sub-seasonal to Seasonal
SAFETYNET	South Asia Field Epidemiology and Technology Network
SHAP	Shapley Additive Explanations
SVM	Support Vector Machine
TERI	The Energy and Resources Institute
TS	Time Series

VBD	**Vector-Borne Disease**
VPD	**Vapour Pressure Deficit**
WHO	**World Health Organisation**
XGBoost	**Extreme Gradient Boosting**

Executive Summary

In India, climate change is becoming an important factor in the spread and distribution of vector-borne diseases. These climate–disease relationships are non-linear and vary across regions, depending on rainfall patterns, temperature, and humidity. The increase in temperature, shift in rainfall, flooding and other extreme weather events are conducive to the spread of diseases like dengue, malaria, Japanese encephalitis, and other climate-sensitive diseases. The shifting disease trends underscore the importance of enhancing current surveillance systems by including climate and environmental data to inform timely public health responses.

In response to this need, the **National Centre for Disease Control (NCDC) along with the Council on Energy, Environment and Water (CEEW),** hosted a consultation on "Strengthening Vector-Borne Disease Surveillance in a Changing Climate" in the presence of **the National Centre for Vector Borne Diseases Control.** The consultation convened stakeholders from government institutions, research organizations, academic institutions, international agencies, technology partners, and public health experts to share their views on new approaches to strengthening climate-informed disease surveillance and developing robust Early Warning Systems (EWS) for vector-borne diseases.

The consultation centered on the increasing importance of predictive modelling, artificial intelligence, machine learning, climate science, and geospatial technologies for disease surveillance and outbreak preparedness. Diverse operational experiences and models were presented, demonstrating the potential of using epidemiological, climatic, environmental, and entomological data to produce timely disease forecasts and identify high-risk areas before outbreaks occur. Around eight models were presented to illustrate how these EWS models are used in practice to support public health planning and decision-making.

Predictive models should complement, not replace, current surveillance systems, which was a recurring theme in the discussions. Participants noted the importance of using high-quality surveillance data, combining multiple data sources and frequent model validation for reliable forecasting. Forecasting models should be locally calibrated and continually updated with new surveillance data as disease patterns differ by region because of climate, ecology, population, and vector behaviour.

The consultation further explored the opportunities and challenges in operationalising climate-informed early warning systems within existing public health programmes and surveillance. The need for greater cooperation between various agencies and organisations, such as health departments, the meteorological department, research institutions, and technology partners, to facilitate the sharing of data and coordinated decision-making was emphasised. The importance of interoperable digital platforms, standardised data management practices and long-term institutional collaborations for the implementation of predictive surveillance systems was further highlighted.

The compendium features important technical presentations by experts from various organisations, such as the **Indian Institute of Tropical Meteorology (IITM), AI and Robotics Technology Park (ARTPARK), Khushi Baby, the National Institute of Malaria Research (NIMR), IIT Bombay, the World Health Organisation (WHO), Swasti Health Catalyst, Lurio University (Mozambique), and CEEW**. The presentations highlighted various modelling techniques such as statistical models, machine learning algorithms, hybrid forecasting models, and AI-driven disease forecasting and decision-making support systems for diseases like dengue, malaria, scrub typhus, and typhoid. These experiences collectively show the increasing possibilities of climate-informed forecasting to improve disease preparedness and response in various epidemiological contexts.

The consultation identified several priority actions to integrate environmental parameters to strengthen vector-borne disease surveillance in India, based on technical deliberations and expert discussions. These include enhancing the quality and availability of surveillance information, incorporating climate and environmental indicators into regular disease surveillance, making surveillance platforms interoperable, building capacity at the institutional level to support predictive analysis, testing forecasting models in a variety of geographical contexts, and defining procedures for using the early warning information to take public health action. The participants also noted the need for a national guidance that is standardised and flexible for adaptation at the state level.

The consultation highlighted the need for a more proactive and anticipatory public health system through EWS. The inclusion of climate information, disease surveillance, and predictive analysis can help identify potential disease threats at an earlier stage, facilitate targeted response measures, help allocate resources, and help enhance preparedness for climate-sensitive vector-borne diseases. The recommendations in this report aim to support the development of a national framework for climate-informed vector-borne disease surveillance, inform the pilot implementation of predictive early warning systems, and contribute to the evidence-based development of policies and programmes to build resilient public health systems in a changing climate.

1. Background

India is increasingly exposed to the health risks associated with climate change, including rising temperatures, extreme weather events, prolonged dry spells, intense rainfall and flooding. These climatic changes can alter the distribution, seasonality and transmission dynamics of climate-sensitive diseases (CSDs). Evidence from South Asia, including India, highlights associations between climatic variables and the incidence of infectious diseases, particularly vector-borne, water-borne and zoonotic diseases (Asaaga et al., 2024).

In this context, NITI Aayog's *Vision 2035: Public Health Surveillance in India* emphasises strengthening the responsiveness and preparedness of public health surveillance systems across all levels. The integration of advanced data analytics, data science, artificial intelligence (AI), machine learning and health informatics presents opportunities to enhance the predictive capabilities of surveillance systems and improve the early identification of climate-sensitive disease risks. Achieving this vision requires greater integration of environmental and meteorological intelligence with epidemiological surveillance, enabling a transition from reactive disease management towards proactive, risk-informed, and anticipatory public health action.

Aligned with the priorities of the National Mission on Climate Change and Human Health and the National Vector Borne Diseases Control Programme, the development and application of climate-informed predictive models for diseases such as malaria, dengue, and Japanese encephalitis are important for strengthening early warning and response capacities. Such models can support state and district health authorities in anticipating potential disease outbreaks, identifying high-risk geographies and populations, and implementing timely, targeted public health interventions. This approach is particularly important in climatically vulnerable regions, where populations may face a disproportionate burden of climate-sensitive diseases alongside constraints in health system capacity. Strengthening the use of predictive analytics within existing surveillance and response mechanisms can therefore contribute to improved preparedness, more efficient resource allocation and enhanced resilience of public health systems to climate-related health risks.

2. Objectives

The national-level consultation, co-organised by the National Centre for Disease Control (NCDC), and Council on Energy, Environment and Water (CEEW) aims to bring together knowledge partners and key stakeholders from public health, climate science, environmental management, disaster management, and digital innovation sectors to share knowledge and evidence, facilitate dialogue, and develop an integrated framework for assessing the interlinkages between climate impacts and vector-borne disease outbreaks and spread in the country. Document case studies and lessons learned from key stakeholders in designing localised models of predictive analysis and their outcomes in supporting public health outcomes.



3. Consultation Overview

Keynote Address

Dr. Ranjan Das, Director, NCDC, in his keynote address, observed that India, along with the rest of the world, is witnessing a fundamental shift driven by climate change. He noted that geographical areas that were previously unaffected by certain climate-sensitive diseases and health risks are now increasingly experiencing their impacts, altering established patterns of disease transmission and public health challenges. This evolving scenario, he emphasised, calls for a structural upgrade of existing public health programmes, moving beyond conventional reactive approaches towards more proactive and anticipatory systems. In this context, he highlighted the growing relevance of predictive modelling as a critical tool for strengthening preparedness, enabling early identification of emerging risks, and supporting evidence-based decision-making. He expressed confidence that the consultation would provide an opportunity for leading experts, climate scientists, and public health practitioners to present their work and share insights on the application of predictive models for climate-sensitive diseases.

Dr. Das further outlined the key expectations from the consultation and stressed the need for translating discussions into actionable outcomes. He stated that **the consultation should contribute towards three major deliverables: 1) The development of a framework document to guide the integration of predictive modelling into disease surveillance and response systems; 2) A pilot roadmap to support the testing and operationalisation of such approaches in selected settings; and 3) A policy note to inform decision-makers and facilitate institutional adoption.** He noted that these outputs could help bring about structural changes within NCDC and support the development of formal guidelines for incorporating predictive and climate-informed approaches into public health programmes. Emphasising the importance of collective action, he underscored the need for collaboration among institutions and stakeholders rather than duplication of efforts, highlighting that a coordinated and synergistic approach would not only strengthen public health preparedness in India but also contribute to broader global efforts to address the health impacts of climate change.



Source: PATH

Table 1: Session Summary from Speakers

S.No.	Speaker	Organisation	Disease targeted	Type of model used	Pilot State/City
1	**Dr Roxy Mathew Koll** (Climate Scientist and IPCC lead Author)	IITM Pune	Dengue	Machine learning-based dengue forecasting model using Random Forest Regression (Pune), XGBoost (Kerala) and Bhopal (not mentioned).	Pune, Kerala, Bhopal
2	**Dr Raunaq Pradhan** (Product Manager) **Mr Harish Nalawade** (Programme Lead in Health and Climate)	ARTPARK	Dengue	Ensemble of statistical and ML models (geographically gated)	Andhra Pradesh, Karnataka, Odisha
3	**Dr Haya Khan** (Specialist Infectious and One Health) **Ms Anuja Venkatachalam** (Data Scientist)	Khushi Baby Association	Dengue	Negative Binomial Regression Model	Rajasthan
4	**Dr. Ramesh C. Dhiman** (Former Scientist G, ICMR-NIMR & Technical lead, TCI Foundation) **Dr. Himmat Singh**	ICMR-NIMR	Malaria	Climate-based hybrid malaria forecasting models combining Time Series–Random Forest, Time Series–Support Vector Machine (SVM), and Time Series–Extreme Gradient	Kullu (HP), Hoshiarpur (Punjab), Mokokchung (Nagaland), North Goa (Goa), Surat (Gujarat), Keonjhar (Odisha)

	(Scientist E) **Dr. Jaspreet Kaur** (Scientist D)			Boosting (XGBoost) models.	
5	**Dr. Raghu Murtugudde** (Emeritus Professor, UMD and Visiting Professor, IITK)	IIT Bombay	Dengue	Hybrid dengue forecasting model integrating climatic, epidemiological, vulnerability, and exposure factors within a Ready–Set–Go early warning framework.	Model under development
6	**Mr. Vaibhav Chugh** (AI Tech Lead) **Mr. Neeraj Patel** (ML Analyst) **Dr. Saru Gupta** (Consultant) **Mr. Ankit Sharma**	CEEW	Dengue	Two-stage ensemble machine learning model comprising a classification stage followed by a regression stage, using AdaBoost, CatBoost, and XGBoost.	Madhya Pradesh
7	**Dr. Badri Thapa** (Team Lead for Communicable Diseases and Health Emergencies)	WHO	Climate-Sensitive Diseases	Shewhart method—a method that adopts systematic control charts, using the historical mean and standard deviation of the outcome variable to define states of 'in-control' and 'out-of-control' throughout the model evaluation process	17 Countries

8	**Ms. Purnima Ranawat** (Senior Technical Specialist) **Mr. Aditya Pangaria** (Senior Associate-Data Science)	Swasti Health Catalyst	Scrub Typhus, Dengue, Malaria, Typhoid	Hyper-local, climate-informed time-series disease forecasting models	Tamil Nadu, Meghalaya, Andhra Pradesh
9	**Dr. Micanaldo Ernesto Francisco** (GIS Consultant)	PhD (Lurio University), Mozambique	Dengue	Hybrid qualitative–quantitative machine learning dengue forecasting framework for zero-inflated dengue data, Conditional Inference Forest (CIF), Random Forest (RF), Support Vector Machine (SVM), Neural Network (NN), and Extreme Gradient Boosting (XGBoost).	Cimahi City, Indonesia

4.1 Climate Drivers and Early Warning Systems, IITM Pune

Title of Presentation: *Climate Drivers and Early Warning Systems*

Presenter: Dr. Roxy Mathew Koll

States: Maharashtra (Pune), Kerala and Bhopal

Type of Model: Climate-informed machine learning-based dengue forecasting model using Random Forest Regression (Pune), multiple AI/ML models including XGBoost (Kerala) and Bhopal (not mentioned)

Data Used (Source): Meteorological data from the India Meteorological Department (IMD) and health data from the Directorate of Health Services (DHS), Kerala, and the Health Department, Pune Municipal Corporation.

Model Findings – Sensitivity, Specificity, Accuracy: For Pune, the dengue prediction model based on Random Forest Regression demonstrated good predictive performance with a correlation coefficient (r) of 0.77 and a Normalised Root Mean Square Error (NRMSE) of 0.522 at a two-month lead time, accounting for the lagged relationship between climatic variables and dengue incidence. Meanwhile, for Kerala, the dengue prediction model based on XGBoost showed better skill than Random Forest Regression.

Summary Findings of Model Implemented/Used: The presented framework integrates epidemiological surveillance data with key climatic variables, including temperature, rainfall, relative humidity, wind speed, and vapour pressure, to develop climate-informed dengue forecasting models. Statistical analyses are used to identify region-specific climatic predictors, followed by the development and validation of machine learning models. The framework ranks the relative importance of climatic variables, enabling identification of the major environmental drivers influencing dengue transmission in different regions. When combined with future climate projections to estimate future dengue burden, the projections for Pune indicate increased dengue mortality under all emission pathways. The presentation highlighted that climate–disease relationships vary considerably across geographies; consequently, model performance differs by region, with **Random Forest Regression** performing well in Pune and **XGBoost** yielding better results in Kerala. The findings underscore the importance of localised model development, validation, and improved integration of high-quality health and climate data to support operational early warning systems.

Advantages

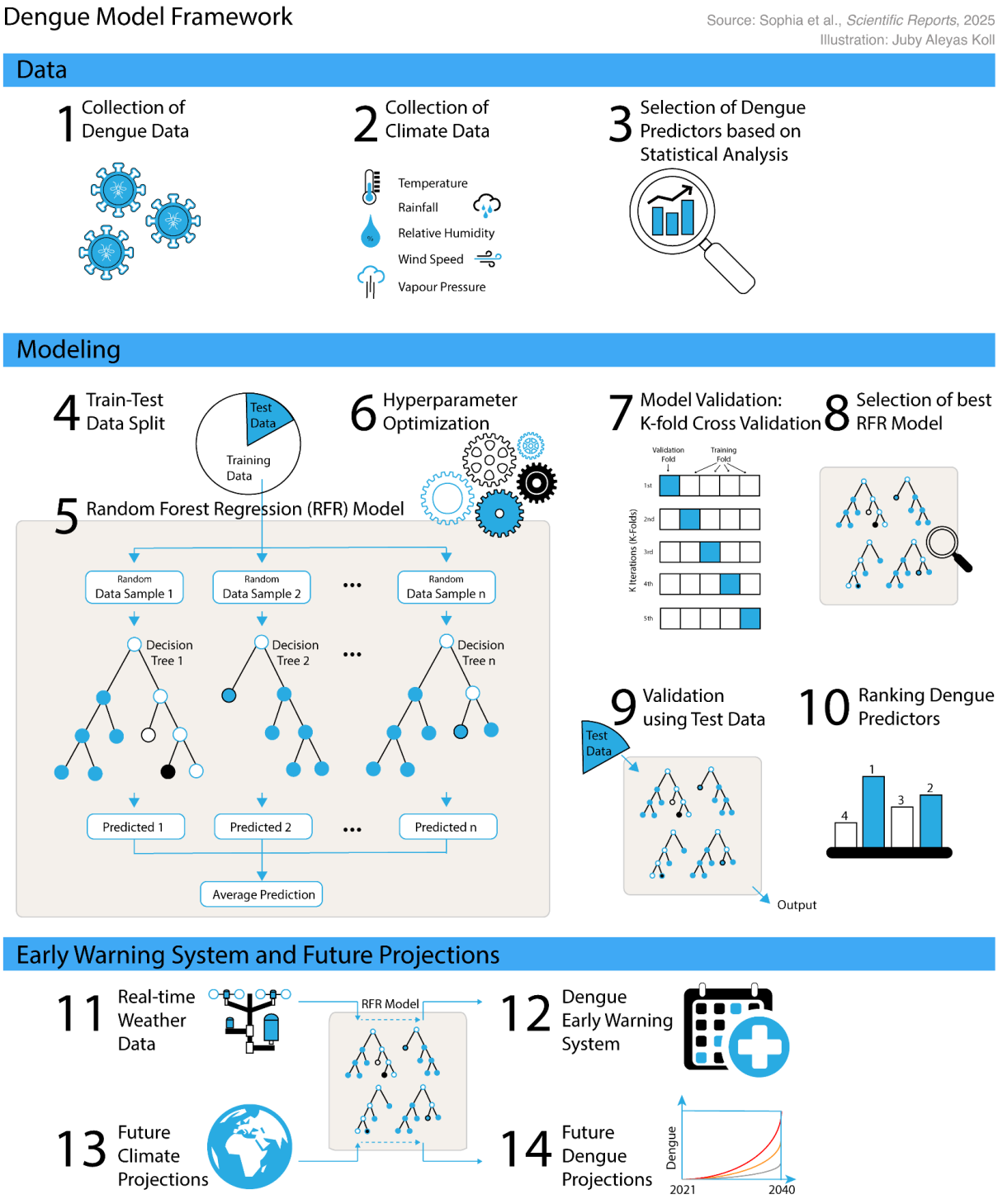
- Captures **non-linear interactions** between climate and health variables.
- Identifies the **relative importance of climate variables** influencing health outcomes.
- Provides **advance signals** for early preparedness and timely response.

Limitations

- Implementation needs **tighter coordination between IITM and respective health departments**, particularly for **real-time data flow**.
- Adaptation to other regions requires **local data training, recalibration, and validation**; the Pune model cannot be transferred directly.

Future plan: Future work should use longer and more reliable weekly dengue incidence datasets, develop disease- and region-specific predictors, undertake external validation, and link forecast categories to predefined public-health actions. The outputs should initially be treated as experimental decision-support information rather than as stand-alone operational warnings.

Figure 1: Dengue Model Framework (IITM)



Source: Presentation by Dr. Roxy. Sophia et al. Scientific Reports, 2025.

4.2 Collaborative Innovation in Dengue Surveillance ARTPARK

Title of Presentation: *Collaborative Innovation in Dengue Surveillance*

Presenter: Dr Raunaq Pradhan and Mr Harish Nalawade

States: Andhra Pradesh, Karnataka, and Odisha

Type of Model: Ensemble-based climate-informed dengue forecasting framework integrating **statistical and machine learning models** with geographically gated model selection and weekly retraining.

Data Used:

1. Epidemiological Data: Integrated Health Information Platform (IHIP), State National Vector Borne Disease Control Program (NVBDCP) registries, and direct line lists from partner state health departments (Karnataka, Odisha, and Andhra Pradesh)
2. Climatic Data: Openmeteo (ERA5-land)
3. Real-Time & High-Frequency Signals: Google News
4. Google research /pdfm /geospatial (exploratory, not used in production)

Model Findings – Sensitivity, Specificity, Accuracy: The framework achieved 86% risk categorisation accuracy for one-week forecasts and 61% accuracy for four-week forecasts. It demonstrated over 71% outbreak detection accuracy overall and more than 82% during peak transmission periods. Forecast reliability was enhanced through a gatekeeping mechanism that withheld low-confidence predictions.

Summary Findings of Model Implemented/Used: The framework integrates epidemiological, climatic, environmental, and entomological data into a continuous weekly forecasting cycle that converts surveillance data into actionable intelligence. It employs an ensemble of statistical and machine learning models, with geographically gated model selection to ensure the most appropriate model is used for local conditions. The system incorporates confidence-based gatekeeping, fallback rules, and geography-specific outbreak thresholds (WHO thresholds for Karnataka and Odisha; ICMR quartile-based thresholds for Andhra Pradesh) and is retrained weekly as new surveillance data become available. Operationally, the framework has been implemented through varying levels of integration across Andhra Pradesh, Karnataka, and Odisha, resulting in a dashboard-based decision-support system that provides real-time risk maps, hotspot identification, dengue forecasts, larval indices, alerts, and intervention tracking. The model shifts dengue surveillance from retrospective

reporting to proactive, real-time decision support, enabling targeted interventions and strengthening outbreak preparedness.

Progress:

1. The framework has been operationally deployed across varying levels of integration in Andhra Pradesh, Karnataka, and Odisha
2. Successfully developed and deployed an interactive dashboard-based decision-support system capable of providing risk maps, hotspot identification, four-week advance dengue forecasts, and intervention tracking
3. Conducted one round of user research in Odisha and the Greater Bengaluru Area (GBA), which provided key insights to improvise the platform and build the "Action Taken" tracking feature directly in the dashboard.
4. Established a continuous weekly retraining cycle that updates automatically as new health surveillance data is received.

Advantages:

- **High Local Accuracy:** Geographically gated model selection ensures that the chosen algorithm matches specific local historical, epidemiological and climatic conditions.
- **Actionable Outputs:** Converts raw multi-source surveillance data directly into real-time decision support (risk maps, hotspot identification, alerts).
- **High Peak Accuracy:** Achieves over 82% accuracy in predicting outbreaks during critical peak transmission seasons
- **Shift from Reactive to Proactive Planning:** Predictive window gives state and district health authorities sufficient lead time to pre-position testing kits, arrange hospital beds, allocate medical staff, and initiate early vector control actions

Limitations:

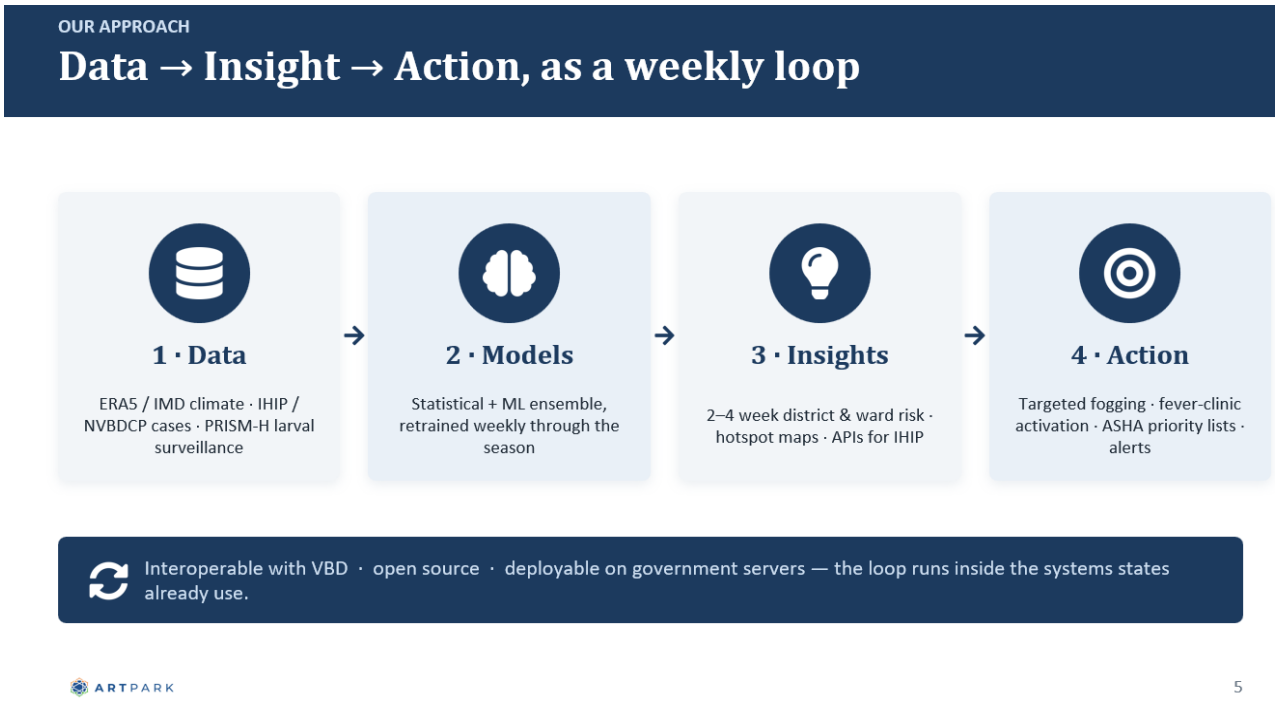
- **Lead-Time Decay:** Accuracy drops from 86% for 1-week advance forecasts to 61% for 4-week forecasts
- **Data Dependency:** Relies heavily on consistent, high-quality and timely submission of weekly IHIP data from the field
- **Weekly Processing Cycle:** The platform generates predictions on a weekly basis rather than continuously updating in real time. Mid-week disease spikes or sudden localized micro-climatic events

Future plan:

1. Extend operationalisation and model deployment across all the districts of Odisha and other additional states.
2. Integrate the Samastha real-time larval survey directly into the dashboard for enhanced vector monitoring.

3. Establish regular automated risk alerts sent directly to concerned healthcare providers and local administrative personnel.

Figure 2: Early Warning System Approach (ARTPARK)



Source: Presentation by ARTPARK

4.3 Vector-Borne Diseases: Data to Action in Rajasthan: Khushi Baby

***Title of Presentation**: Vector-Borne Diseases: Data to Action in Rajasthan*

Presenter: D*r. Haya Khan and Ms. Anuja Venkatachalam*

States: Rajasthan (42 districts; 377 blocks)

Type of Model: Climate-informed Dengue Early Warning System (EWS) using Negative Binomial Regression

Data used: Environmental variables (Mean temp, Min temp, Max temp, Rainfall, Wet weeks, Flush count, Diurnal Temperature Range, Humidity) , Seasonal indicators (Week of year, annual dengue seasonal pattern), Block population, Case history (4 week rolling mean and t-2 weeks), Spatial indicators (District level fixed effect)

Model Findings – Sensitivity, Specificity, Accuracy: The Negative Binomial Regression model was implemented across 377 blocks in 42 districts of Rajasthan to generate block-level dengue outbreak forecasts up to two weeks in advance. During validation, the model correctly identified 70.3% of outbreak weeks (459 of 653 block-weeks), , and captured approximately 72% of dengue cases within alerted weeks. Performance was highest during the peak transmission season (weeks 35–40), with outbreak miss rates reduced to 0–7%. Expert-driven manual override further improved outbreak detection to 85–90%.

Summary Findings of Model Implemented/Used:
The Negative Binomial Regression-based Dengue Early Warning System (EWS) generates block-level dengue outbreak forecasts up to two weeks in advance, enabling anticipatory public health action. The model combines climate, seasonal, epidemiological, and demographic factors to estimate outbreak risk and produce actionable forecasts at the block level. A key strength of the framework is its ability to support proactive preparedness by identifying high-risk areas before outbreaks occur, rather than relying on reactive surveillance. The system also incorporates an expert-driven manual override mechanism for low-performing blocks or seasons, improving forecast reliability and supporting more effective targeting of surveillance, vector control, and resource allocation.

Progress:

1. Expanded historical surveillance datasets to **five years of epidemiological data**, enabling improved modelling of **seasonal and interannual transmission patterns**.
2. Continued **model refinement** using expanded historical datasets.
3. Conducted consultations with **state, district, and frontline health officials** to understand surveillance and response workflows.

4. Identified **decision-making needs** and co-designed mechanisms for integrating the EWS into **routine programme implementation**.
5. Developed the **Spark Action feature** to digitise **response planning and intervention tracking** following an EWS alert.
6. Technical consultations with **IITM** informed the selection of **disease- and region-specific climatic predictors** and **biologically plausible lag structures**.
7. Incorporated **block-level climatic and epidemiological heterogeneity**, while addressing **sparse and under-reported surveillance data** and the need for **operational validation**.

Advantages

- Generates forecasts at **district and block levels**, aligning with **surveillance, vector control, and resource deployment** decisions.
- Enables **block-level risk stratification** for more targeted allocation of interventions.
- Avoids treating an entire district as **uniformly high risk**.
- Incorporates an **expert review mechanism**, allowing public health officials to **override model predictions** based on local intelligence.
- Improves **operational reliability** and supports **outbreak detection in challenging settings**.

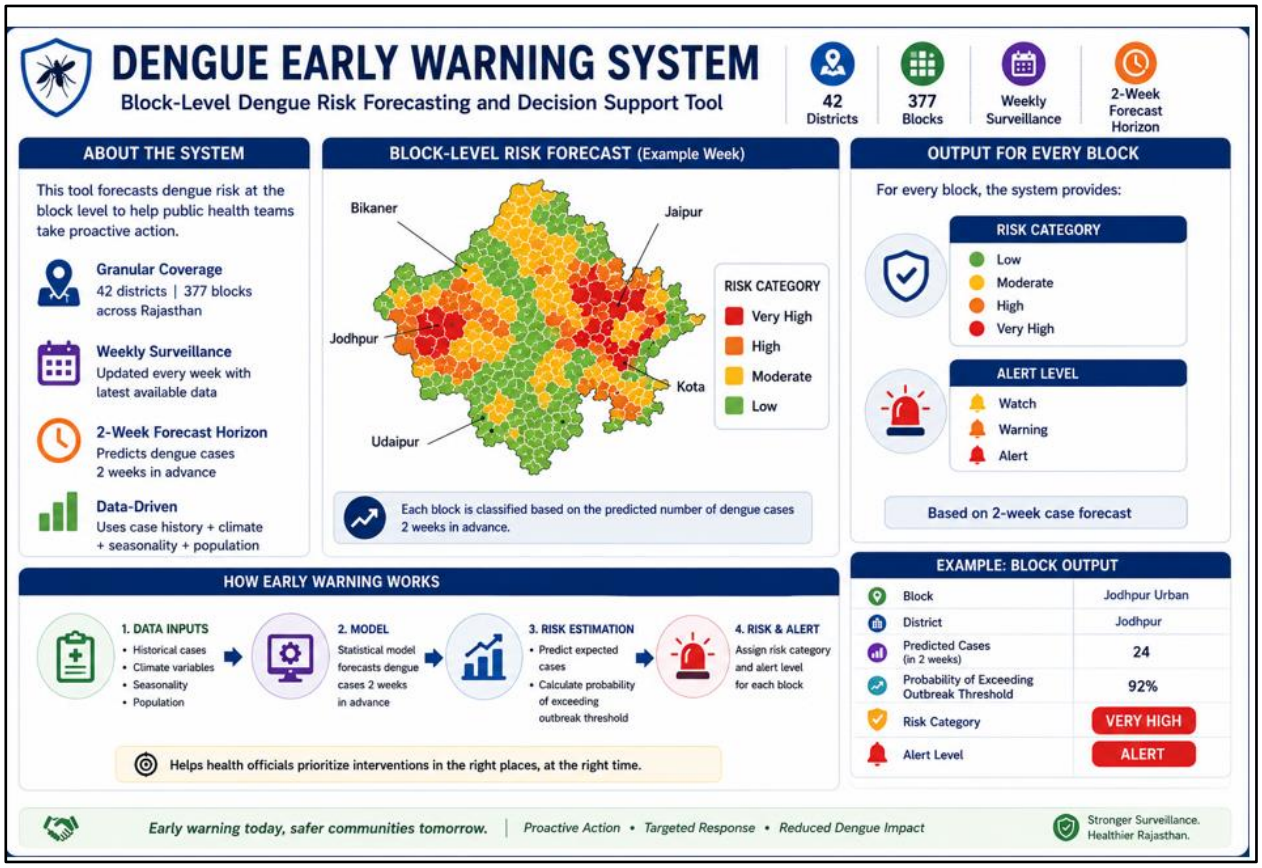
Limitations

- Forecast performance depends on the **quality, completeness, and consistency of surveillance data**.
- Reduced dengue incidence has limited **outbreak observations for model training**, particularly in **low-incidence blocks and early/late transmission periods**.
- Requires continued **model refinement and validation** using **longer historical datasets and prospective implementation data**.
- Limited historical observations may affect **generalisability and operational performance**.

Future plan:

The next phase will focus on prospective implementation and evaluation of the Early Warning System during routine dengue programme operations. The system will be deployed in collaboration with the Government of Rajasthan to support risk-informed planning in 2026, while the Spark Action feature will capture the timing and intensity of interventions undertaken following alerts. This will enable systematic evaluation of whether earlier, forecast-informed public health action leads to improved outbreak containment, generating implementation evidence to refine the model and inform wider adoption of climate-informed dengue early warning systems.

Figure 3: Dengue Early Warning System (Khushi Baby)



Source: Presentation by Khushi Baby

4.4 Predictive Modelling of Vector-Borne Diseases for Strategic Planning: ICMR-NIMR

Title of Presentation: *Predictive Modelling of Vector-Borne Diseases for Strategic Planning: Opportunities and Challenges*

Presenter: Dr Ramesh C. Dhiman, Dr Himmat Singh and Dr Jaspreet Kaur

States: Kullu (HP), Hoshiarpur (Punjab), Mokokchung (Nagaland), North Goa (Goa), Surat (Gujarat), Keonjhar (Odisha)

Type of Model: Climate-based hybrid malaria forecasting models combining Time Series–Random Forest, Time Series–Support Vector Machine (SVM), and Time Series–Extreme Gradient Boosting (XGBoost) models.

Data Used: Environmental variables (Mean monthly temperature, Rainfall, humidity), population under risk , number of VBD cases, entomological parameters (monthly mosquito and larval densities and infectivity, etc.), Spatial indicators

Model Findings – Sensitivity, Specificity, Accuracy: Hybrid forecasting models were developed and evaluated across multiple districts in India, with model performance assessed using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). Different hybrid model combinations demonstrated superior predictive performance in different ecological settings, indicating that no single model consistently outperformed others across all regions. Sensitivity, specificity, and classification accuracy were not reported.

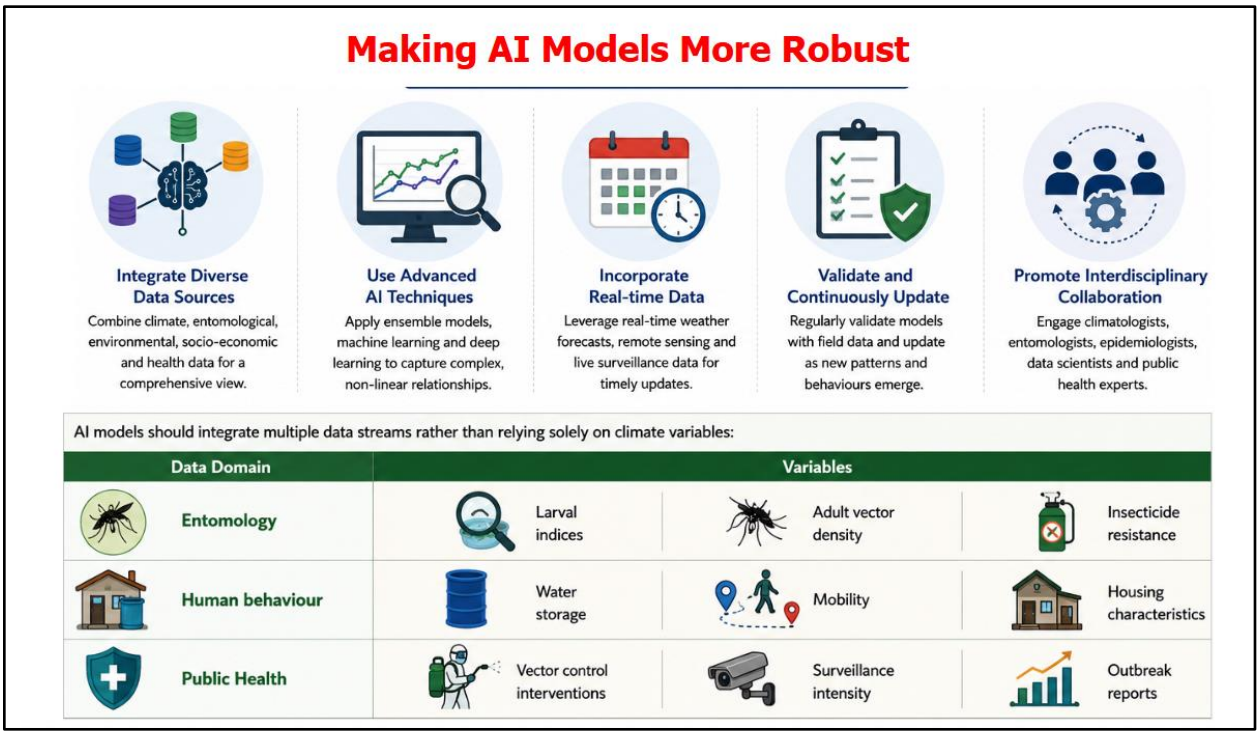
Summary Findings of Model Implemented/Used: The framework develops region-specific hybrid malaria forecasting models capable of predicting malaria incidence one to three months in advance. It evaluates multiple statistical, machine learning, deep learning, and time-series approaches, selecting the most appropriate model based on local climatic, ecological, and epidemiological conditions. Variable selection is performed using multicollinearity assessment and SHAP (Shapley Additive Explanations), while grid search is used for hyperparameter optimisation and bootstrapping to estimate forecast uncertainty. By combining complementary modelling approaches, the hybrid framework improves forecasting robustness and supports geographically tailored early warning systems for strategic public health planning.

Progress: The model has been tested with the data from NCVBDC and trained. In addition to this, it will be checked for feasibility with the IHIP platform after validation.

Advantages and Limitations: According to the training data of meteorological data and cases, prediction can be for 3-6 months.

Future plan: Integration with national portal/platforms and expansion of the same to other VBDs.

Figure 4: Framework for Developing Robust AI Models for Malaria Forecasting (ICMR NIMR)



Source: Presentation by NIMR

4.5 Initial Dengue Modelling and Early Warnings IIT Bombay

***Title of Presentation**: Initial Dengue Modelling and Early Warnings at IIT Bombay*

Presenter: Dr. Raghu Murtugudde

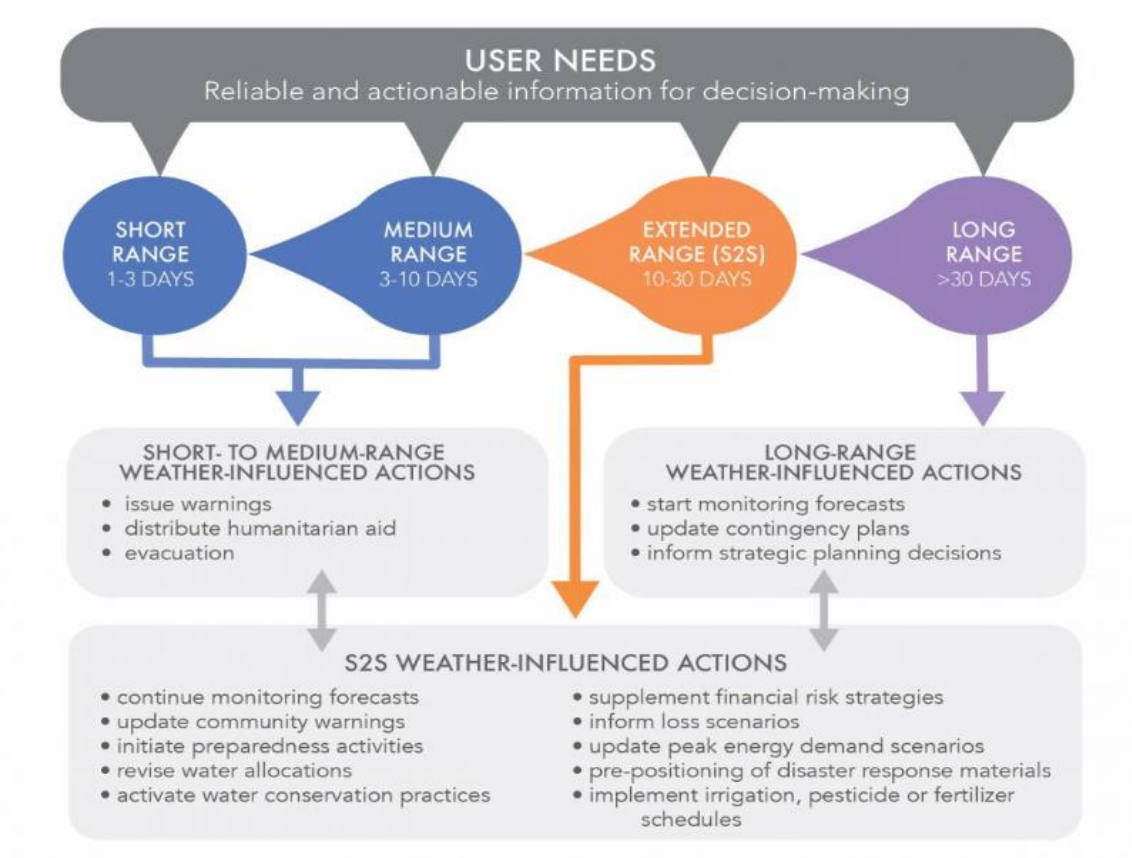
States: Not implemented in any state, as the model is still under development

Type of Model: Hybrid dengue forecasting model integrating climatic, epidemiological, vulnerability, and exposure factors within a Ready–Set–Go early warning framework.

Model Findings – Sensitivity, Specificity, Accuracy:
Model still under development

Summary Findings of Model Implemented/Used: The proposed framework seeks to improve dengue forecasting by integrating climate, epidemiological, vulnerability, exposure, entomological, and human mobility factors, rather than relying solely on climate variables or artificial intelligence models. It adopts the Ready–Set–Go framework, which combines seasonal, extended-range, and short-term forecasts to support preparedness and response across multiple time horizons. The approach also emphasises hyperlocal downscaling of climate forecasts and continuous user feedback to improve forecast calibration and operational relevance. By incorporating multiple transmission pathways and vulnerability dimensions, the framework aims to provide more robust and actionable early warnings for targeted public health interventions and resource allocation.

Figure 5: Framework for Forecast-Informed Decision-Making (IIT Bombay)



Source: Presentation by IIT Bombay

4.6 Early Warning System for Vector-Borne Diseases, CEEW

Title of Presentation: *Early Warning System for Vector-Borne Diseases – Dengue*

Presenter: Mr Vaibhav Chugh, Mr Neeraj Patel Dr Saru Gupta and Ankit Sharma

States: Madhya Pradesh

Type of Model: Two-stage ensemble machine learning model comprising a classification stage followed by a regression stage, using AdaBoost, CatBoost, and XGBoost.

Model Findings – Sensitivity, Specificity, Accuracy: The ensemble model was evaluated on unseen 2024 data, achieving an R^2 of 0.52, an MAE of 4.03, and an RMSE of 8.97. It achieved 87% precision, 84% sensitivity (recall), and 85% specificity, correctly identifying 765 of 916 dengue case-weeks and 682 of 800 non-outbreak weeks.

Data Used:

- Epidemiological data: District-wise weekly dengue cases from Madhya Pradesh government weekly surveillance reports, all 51 districts, 2017 to 2025. This is the target variable.
- Laboratory surveillance data: Weekly samples tested and test-positivity rate from the same surveillance reports (2017 to 2025), used both as a model input and as a data-quality signal.
- Climate data: IMD gridded rainfall, temperature (mean, maximum, minimum) and relative humidity, 2017–2025, aggregated to district–week. IMD was chosen over ERA5 after benchmarking both against ground-station readings; the two are near-identical on temperature (1–2°C) and humidity (4–6%), but IMD is much closer on rainfall (0–1 mm/day vs 2–5 mm/day for ERA5), and rainfall is the deciding variable for dengue.
- Environmental data: Satellite-derived NDVI (vegetation greenness) via Google Earth Engine, 2021–2024, as a proxy for mosquito habitat.
- Demographic data: District population (Census and projections, 2021–2024), used to convert case counts into incidence rate per 100,000 so that large and small districts are comparable during training.

Summary Findings of Model Implemented/Used: The framework employs a two-stage explainable ensemble machine learning approach, where the first stage identifies potential dengue transmission weeks and the second stage estimates the expected number of cases. Following evaluation of six model configurations (M1–M6), a final ensemble combining AdaBoost, CatBoost, and XGBoost was selected for its overall better performance. The model integrates climate variables, historical dengue trends, and surveillance indicators and uses Tweedie loss distribution and asymmetric mean absolute error to improve predictions during transmission weeks. SHAP-based explainability analysis indicated that the model explains approximately 52% of the observed variation in dengue cases, with past case history (26%) and climate variables (14%) emerging as the most influential predictors, followed by

population (6%) and testing (6%) indicators. The remaining unexplained variation highlights the potential value of incorporating factors such as serotype circulation, water supply and stagnation, and entomological (larval) surveillance to further improve model performance. The presentation also emphasised that AI-based disease forecasting systems require long-term partnerships with government agencies, rather than standalone technology solutions, to ensure sustained operational use and impact.

Progress:

1. Built a complete district–week dataset for all 51 districts of Madhya Pradesh, 2017–2025, combining surveillance, laboratory, climate, NDVI and population data.
2. Developed and compared six ML model configurations (M1–M6) on the same held-out 2024 data. M6 - 56 features, quality-weighted, with all seasonal calendar features removed, performed best.
3. Established that the two-stage architecture is the right choice. On the same data and features, a plain Random Forest scored R^2 –0.07 and plain XGBoost 0.05, against 0.52 for the two-stage Tweedie design. Finally, we have a classification stage followed by a regression stage, using XGBoost, LightGBM and CatBoost.
4. Extended the model from a single 4-week forecast to an eight-horizon system, producing forecasts 1 to 8 weeks ahead for every district, every week.
5. Operationalised the model as a REST API and an interactive dashboard (ews.tools.ceew.co.in), giving a district-level view (forecast, risk level, severity class, actual-versus-predicted trend) and a state-level view ranking all districts by risk for the chosen week.
6. Proposed an indicative action mapping so each severity band translates into a response level — routine watch (0 cases), awareness drive (1–5), larvicide and survey (6–20), fogging and ASHA mobilisation (>20).

Advantages

- The two-stage design fits the data. About 76% of district weeks have zero cases and true outbreaks are a thin 2.8% tail. Splitting "will there be cases?" from "how many?" stops the model settling on a safe low number everywhere, right most weeks, but missing every spike.
- Tuned to catch outbreaks, not to look good on average. The alert threshold is set at 0.35 rather than 0.5, outbreak weeks are up-weighted 2–6× in training, and under-prediction is penalised twice as heavily as a false alarm, a missed outbreak costs more than an unnecessary alert.
- It works with imperfect data rather than discarding it. Down-weighting unreliable district-years keeps all ~17,200 training rows; hard-filtering to clean data alone left 2,110 rows, and accuracy collapsed (R^2 0.18 against 0.52).

- It does not lean on the calendar. Removing all week-of-year and monsoon flags improved accuracy (R^2 0.43 → 0.52), confirming predictions are earned from climate and case signals, not from knowing it is September.
- It is explainable and operationally practical. SHAP shows why a district was flagged, and the model needs only one week of weather forecast, well inside IMD's reliable range, so it can run every week for all 51 districts.

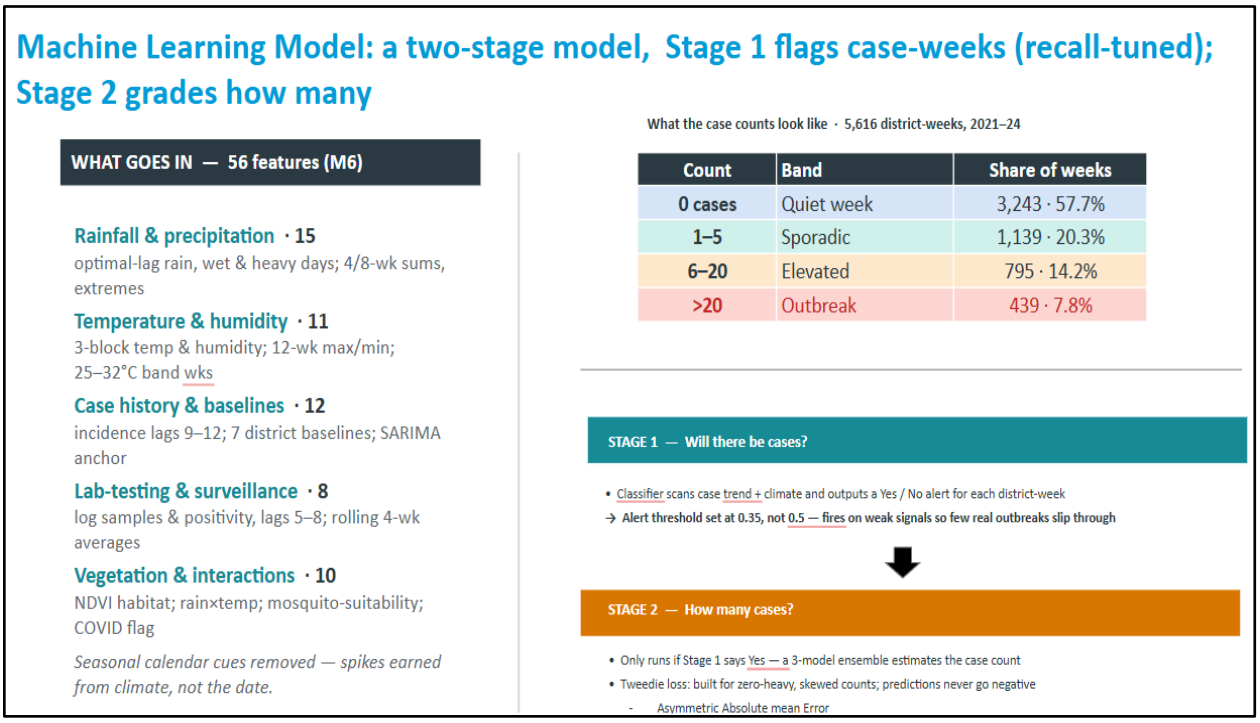
Limitations

- It explains about half the variation (R^2 0.52). The rest needs data not currently collected — serotype circulation, water supply and stagnation, and larval surveillance. This is a data ceiling, not a modelling one.
- Forecast quality is bounded by surveillance quality. An unreported week looks identical to a genuinely quiet week.
- District and weekly resolution is still too coarse for the last mile, an alert cannot yet tell a team which ward to fog. We need disease data at a subdistrict level to make the EWS more useful.
- Accuracy declines with lead time; 6–8-week forecasts should be read as trend indicators, not case counts. Unusual years remain hard: MP's 2021 and 2024 spikes are only partly explained by climate.
- Validation so far is on a held-out year (2024), not on a live season with the health department.

Future plan

- Go finer in space, from district to block and ward, so alerts point to where the response actually happened. This depends on reporting at that granularity.
- Close the missing half of the signal by adding serotype surveillance, water supply and stagnation data, and vector surveillance. Adding even one should improve the forecast more than any change to the algorithm.
- Validate prospectively with the state health department during a live season, with each severity band linked to a named action and a responsible level.
- Extend to other states, work has begun on Kerala, using daily IDSP reports that are more granular and more frequent than the MP data.
- Sustain it as a partnership, not a product, AI forecasting needs long-term engagement with government agencies to stay calibrated and actually used.

Figure 6: Dengue Machine Learning Model Framework (CEEW)



Source: Presentation by CEEW

4.7 Early Warning and Response System for Climate-Sensitive Diseases (EWARS-csd) WHO

Title of presentation: Early Warning and Response System for Climate-Sensitive Diseases (EWARS-csd) and Experience for Dengue Outbreak

Presenter: Dr Badri Thapa (WHO India)

States: Implemented in 17+ countries

Type of Model: WHO-developed EWARS-csd early warning and response system using automated model calibration with meteorological, epidemiological, and entomological data.

Data Used: Weekly epidemiological data (dengue cases) & mean temperature, humidity and precipitation. Potential to use entomological data.

Model Findings – Sensitivity, Specificity, Accuracy: The WHO EWARS-csd tool has been implemented in more than 17 countries and demonstrated strong predictive performance for dengue outbreaks. It generates 4–12-week advance forecasts through automated calibration, which selects the most suitable predictive model and alarm thresholds for the local context. Quantitative metrics such as sensitivity and positive predictive values are calculated to calibrate the most appropriate predictive model.

Summary Findings of Model Implemented/Used: The EWARS-csd framework combines meteorological, epidemiological, and entomological data to generate dengue outbreak forecasts and automatically calibrates the most appropriate predictive model and alarm thresholds for local settings. It produces both central-level dashboards for monitoring predicted and observed incidence, endemic channels, and alarm thresholds, and peripheral-level dashboards that provide weekly outbreak risk assessments and recommended response actions. The system links forecasts directly to predefined public health interventions through a four-tier response framework (no response, initial response, early response, and late/emergency response). It also quantifies forecast uncertainty using 95% confidence intervals, supporting risk-informed decision-making. The framework is designed to be adaptable across different diseases and country contexts, with successful implementation dependent on strong institutional collaboration and effective sharing of health, climate, and vector surveillance data.

Progress

1. Developed, used, and validated since 2012 across 17+ countries in five WHO regions.
2. Close to full implementation in national surveillance platforms of Colombia, the Dominican Republic, Mexico, and Thailand.
3. Demonstrates potential for application to climate-sensitive diseases beyond dengue.

Advantages

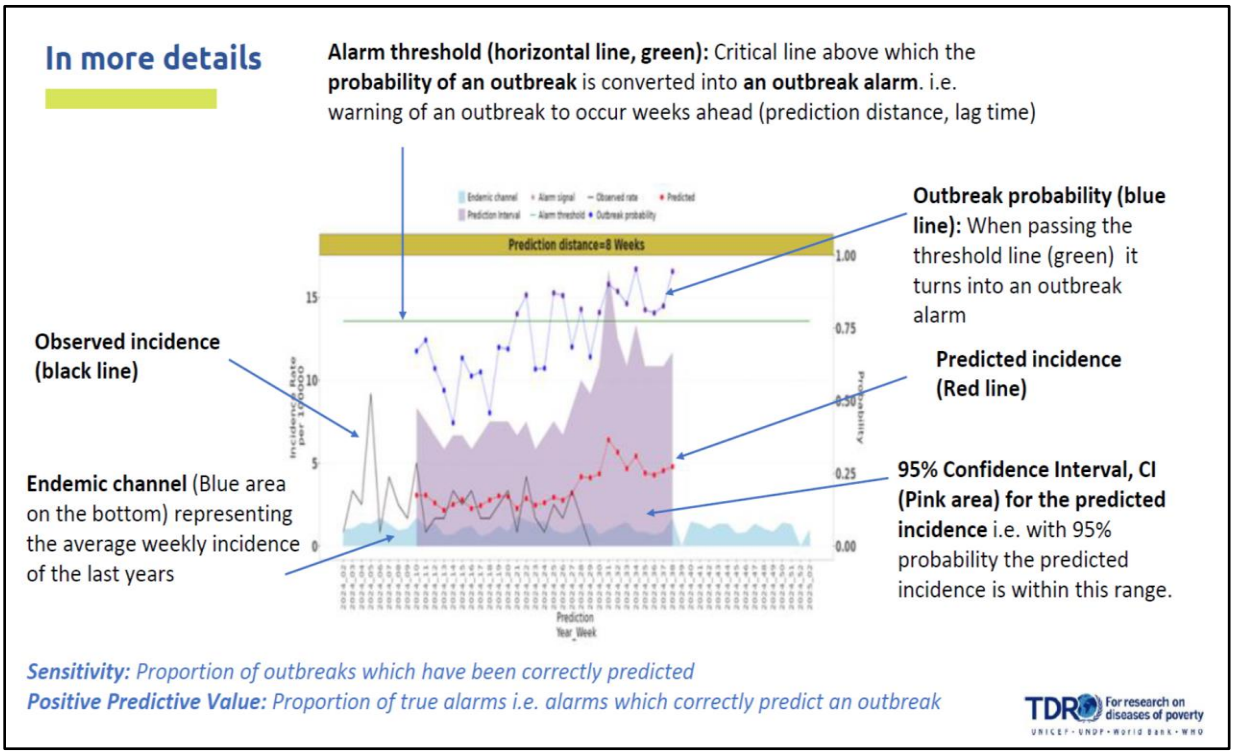
- **Validated and rolled out in 17+ countries**, demonstrating wider applicability.
- Can be **installed on local servers** and configured in the **local language**.
- Integrates **routine data** without adding substantial workload to overstretched national control programmes.
- Provides a **user-friendly interface** for operational use.
- Enables **local ownership, data control, and data security** through local server hosting.
- Can be made **interoperable with DHIS-2 and other systems**.

Limitations

- Requires **weekly mean meteorological data flow** into the software for effective operation.

Future plan: WHO can demonstrate using local data and provide on-site hand-holding support to integrate EWARS-cds tool in national surveillance system.

Figure 7: EWARS-csd outbreak prediction approach (WHO)



Source: Presentation by WHO

4.8 Predicting Disease Outbreaks Before They Happen Swasti Health Catalyst,

Title: Predicting Disease Outbreaks Before They Happen

Presenter: Ms Purnima Ranawat and Mr Aditya Pangaria

States: Tamil Nadu, Meghalaya, and Andhra Pradesh

Type of Model: Hyper-local, climate-informed time-series disease forecasting models for scrub typhus, dengue, malaria, and typhoid, developed using disease-aware feature engineering and integrated climate–health datasets.

Data Used: The forecasting framework integrates multi-source epidemiological, climatic, environmental, and geospatial datasets to capture the drivers of disease transmission. The primary datasets include:

- Historical disease surveillance data (weekly confirmed cases) from state surveillance systems.
- Climate variables including rainfall, temperature (minimum, maximum and mean), relative humidity, dew point, soil moisture and other meteorological indicators derived from IMD observations and global climate reanalysis products.
- Environmental and land-use variables including elevation, vegetation indices, land cover, water bodies, urbanisation, and other ecological characteristics influencing vector or pathogen survival.
- Administrative and spatial datasets for district, block and village boundaries enabling hyper-local modelling.
- Derived epidemiological features including lagged disease incidence, moving averages, seasonal components
- All datasets are harmonised spatially and temporally through a unified climate-health data integration pipeline before model development.

Model Findings – Sensitivity, Specificity, Accuracy: The scrub typhus forecasting model was implemented at the block level in Tamil Nadu, achieving 92% recall, 83% precision, 97% volume match between predicted and observed cases, and providing 2–4 weeks of lead time before outbreak escalation. Validation also demonstrated strong performance for scrub typhus in Meghalaya (81% recall, 77% precision), typhoid in Meghalaya (91% recall, 80% precision), and typhoid in Andhra Pradesh (98% recall, 80% precision). Validation of dengue and malaria models is ongoing.

Summary Findings of Model Implemented/Used: The framework follows a structured modelling pipeline comprising data sourcing, data integration and harmonisation, disease-aware feature engineering, time-series forecasting, and model validation. It integrates climate and epidemiological datasets to generate hyper-local disease forecasts tailored to local ecology, transmission dynamics,

and data availability. The framework is designed to provide warnings of disease risk, identify emerging hotspots, and support targeted surveillance and preparedness through dashboard-based visualisation of disease risk and climate trends. Its modular design enables adaptation across multiple climate-sensitive diseases and geographic settings, demonstrating the scalability of hyper-local forecasting approaches for strengthening anticipatory public health action.

Progress:

1. Successfully developed and operationalised hyper-local forecasting models across multiple states including Tamil Nadu, Meghalaya and Andhra Pradesh.
2. Demonstrated consistently high predictive performance across independent state validations, with recall exceeding 80–90% for multiple diseases while maintaining strong precision.
3. Developed a modular forecasting pipeline that has been successfully adapted across different diseases (scrub typhus, typhoid, dengue and malaria) and diverse ecological settings with minimal changes.
4. Integrated forecasting outputs into government decision-support platforms, including the Real-Time Governance Society (RTGS) ecosystem of Andhra Pradesh and public health decision-support systems in Tamil Nadu, enabling routine operational use.
5. Established continuous model monitoring through regular validation exercises, review meetings with state surveillance teams, and comparison of forecasts with observed disease trends to ensure sustained operational performance.
6. Built an end-to-end decision intelligence workflow that not only generates forecasts but also supports hotspot identification, surveillance prioritisation and evidence-based public health action.

Advantages and Limitations:

- **Modular and scalable forecasting framework:** The modelling pipeline is highly modular and can be rapidly adapted to new diseases and geographies with minimal redevelopment. However, disease-specific calibration and sufficient historical surveillance data remain essential for achieving optimal predictive performance.
- **Epidemiologically informed and climate-driven modelling:** The framework combines disease transmission dynamics with climatic, environmental and historical epidemiological patterns through disease-aware feature engineering, enabling scientifically meaningful forecasts rather than purely statistical predictions. Nevertheless, important drivers such as vector density, population mobility, intervention coverage and healthcare-seeking behaviour are not consistently available across all regions.
- **Rigorous validation and operational deployment:** Models undergo rolling time-series validation, independent testing, continuous monitoring and regular review with state surveillance teams. The forecasting framework has also been operationalised through decision-support platforms such as the Andhra Pradesh RTGS ecosystem and public health

systems in Tamil Nadu. However, model performance can be influenced by changes in surveillance practices, reporting delays and variations in diagnostic capacity across districts.

- **Early identification of emerging disease risk:** By integrating climate and historical transmission signals, the framework identifies regions with elevated outbreak risk even when reported case counts remain low, thereby supporting early surveillance and targeted interventions while helping identify potential surveillance or testing gaps. However, forecasts remain dependent on the quality, completeness and timeliness of underlying surveillance and climate datasets.
- **Hyper-local decision intelligence for public health action:** The framework generates district- and block-level forecasts that support hotspot identification, resource prioritisation and anticipatory public health action through interactive dashboards. While the approach has demonstrated consistent performance across multiple diseases and states, rare outbreak events and abrupt ecological or policy changes remain challenging to capture because of limited historical examples and evolving transmission dynamics.

Future plan:

- Expand forecasting to additional climate-sensitive infectious diseases across multiple states.
- Incorporate near real-time climate forecasts and seasonal weather predictions to extend forecasting horizons.
- Integrate additional data streams including vector surveillance, mobility, environmental sensing and health system indicators to improve predictive performance.
- Strengthen uncertainty estimation and probabilistic forecasting to better support risk-based decision making.
- Establish a unified Decision Intelligence Platform integrating disease forecasting, risk stratification, intervention tracking and outcome monitoring.

Figure 8: Predictive Model Development Approach (Swasti Health Catalyst)

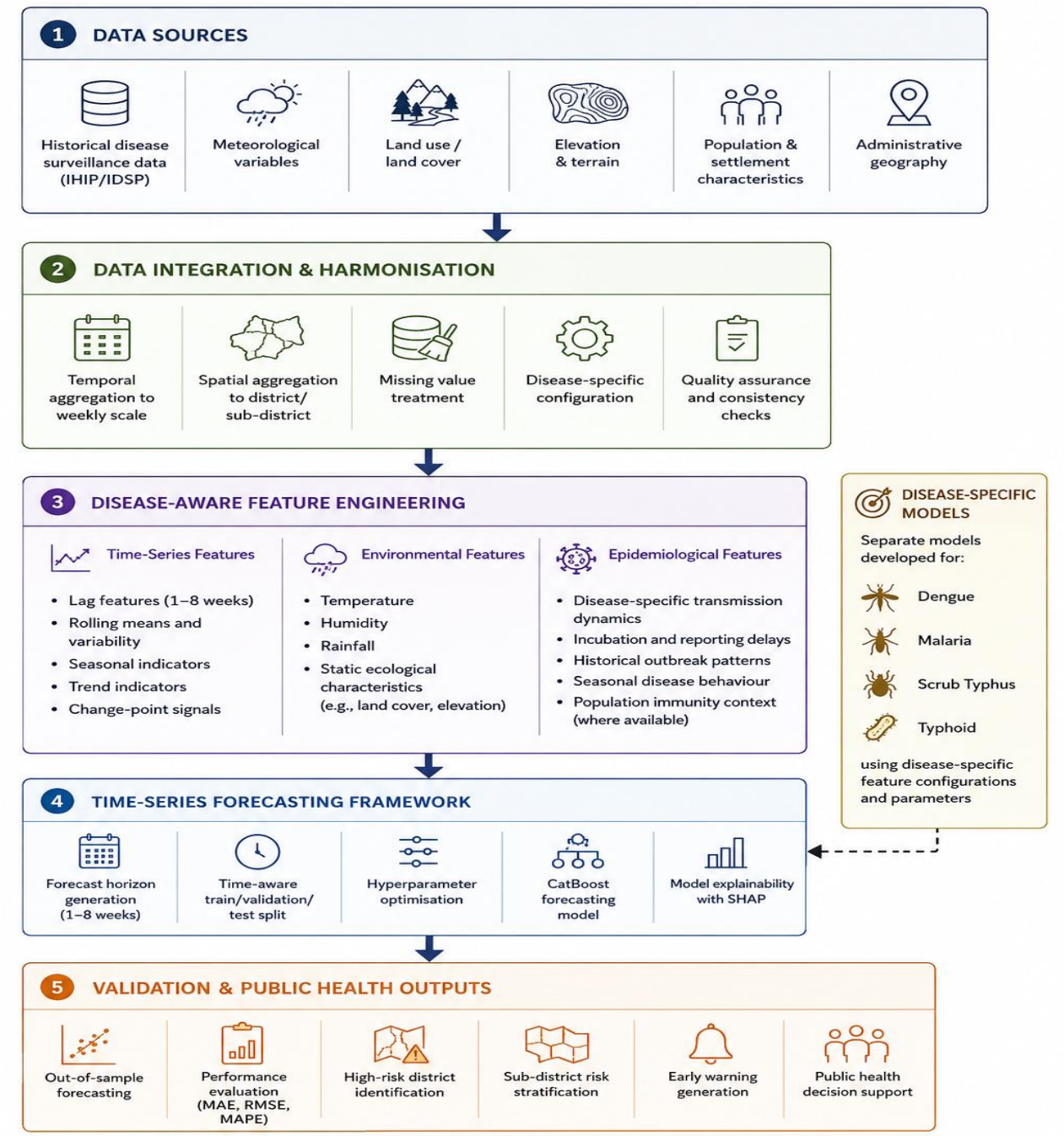


Figure 1. Overview of the disease-aware forecasting framework.
Historical surveillance, meteorological, ecological, and demographic datasets were integrated and harmonised to generate disease-specific temporal and environmental features informed by epidemiological knowledge. Time-series forecasting models were trained using time-aware validation procedures and produced district- and sub-district-level risk predictions to support early warning and public health decision-making.

Source: Presentation by Swasti Health Catalyst

4.9 Strengthening Vector-Borne Disease Surveillance in a Changing Climate Lurio University, Mozambique

Title: Strengthening Vector-Borne Disease Surveillance in a Changing Climate

Presenter: Dr. Micanaldo Francisco

States: Study region not specified

Type of Model: Hybrid qualitative–quantitative machine learning dengue forecasting framework for zero-inflated dengue data, integrating landscape and satellite-derived climate variables with machine learning algorithms including Conditional Inference Forest (CIF), Random Forest (RF), Support Vector Machine (SVM), Neural Network (NN), and Extreme Gradient Boosting (XGBoost).

Data Used: Data from 2009 to 2012 was used for training, and data from 2013 were used for model validation with quantitative and qualitative dengue variables.

Model Findings – Sensitivity, Specificity, Accuracy: The hybrid modelling framework consistently outperformed standalone models across all evaluated algorithms. Conditional Inference Forest (CIF) achieved the highest Hybrid Accuracy Index (HAI) of 0.771, followed by Random Forest (0.599) and XGBoost (0.591). The framework enabled reliable qualitative outbreak prediction at the village level while substantially improving quantitative forecasting performance.

Summary Findings of Model Implemented/Used: The study developed a hybrid two-step forecasting framework to overcome the challenge of zero-inflated dengue datasets, where weeks with zero reported cases dominate the data. The framework first performs qualitative prediction (outbreak vs. no outbreak) and subsequently quantitative prediction (number of dengue cases), improving forecasting accuracy compared with standalone models. It integrates landscape characteristics (land use, road networks, flood risk) with satellite-derived climate variables (NDVI, land surface temperature, and precipitation) to generate fine-scale dengue forecasts. The framework demonstrated that aggregating data across space and time further improves model performance and that the hybrid approach is particularly effective for village-level forecasting. The methodology is also generalisable to other applications involving zero-inflated continuous data, making it a promising approach for strengthening climate-informed vector-borne disease surveillance.

Progress

1. Developing a new version of the hybrid model focused purely on **forecasting accuracy**, rather than the mechanistic inference approach used previously.
2. The model incorporates **lagged climate and dengue variables**, including the number of dengue cases reported in the previous month, average relative humidity from one month before, total precipitation from two months before, and average temperature from three months before.
3. The model also incorporates **dengue temporal features**, including measures of monotonic dengue trend and trend magnitude over time, long-term trend, seasonal pattern, residual variation after removing trend and seasonality, cyclic features derived from the dominant Lomb–Scargle frequency, and local oscillation strength at approximately 3-, 6-, and 12-month scales.
4. These variables **substantially improve model accuracy** and its ability to predict dengue cases **one month in advance**.

Advantages

- A **two-step modelling approach** first classifies villages according to their likelihood of dengue occurrence and then predicts the magnitude of dengue cases.
- Improves the accuracy of **dengue case magnitude prediction** in the second stage.
- Helps address the challenge of **zero-inflated dengue data**.
- Incorporates both **climate drivers and temporal patterns** in dengue transmission.

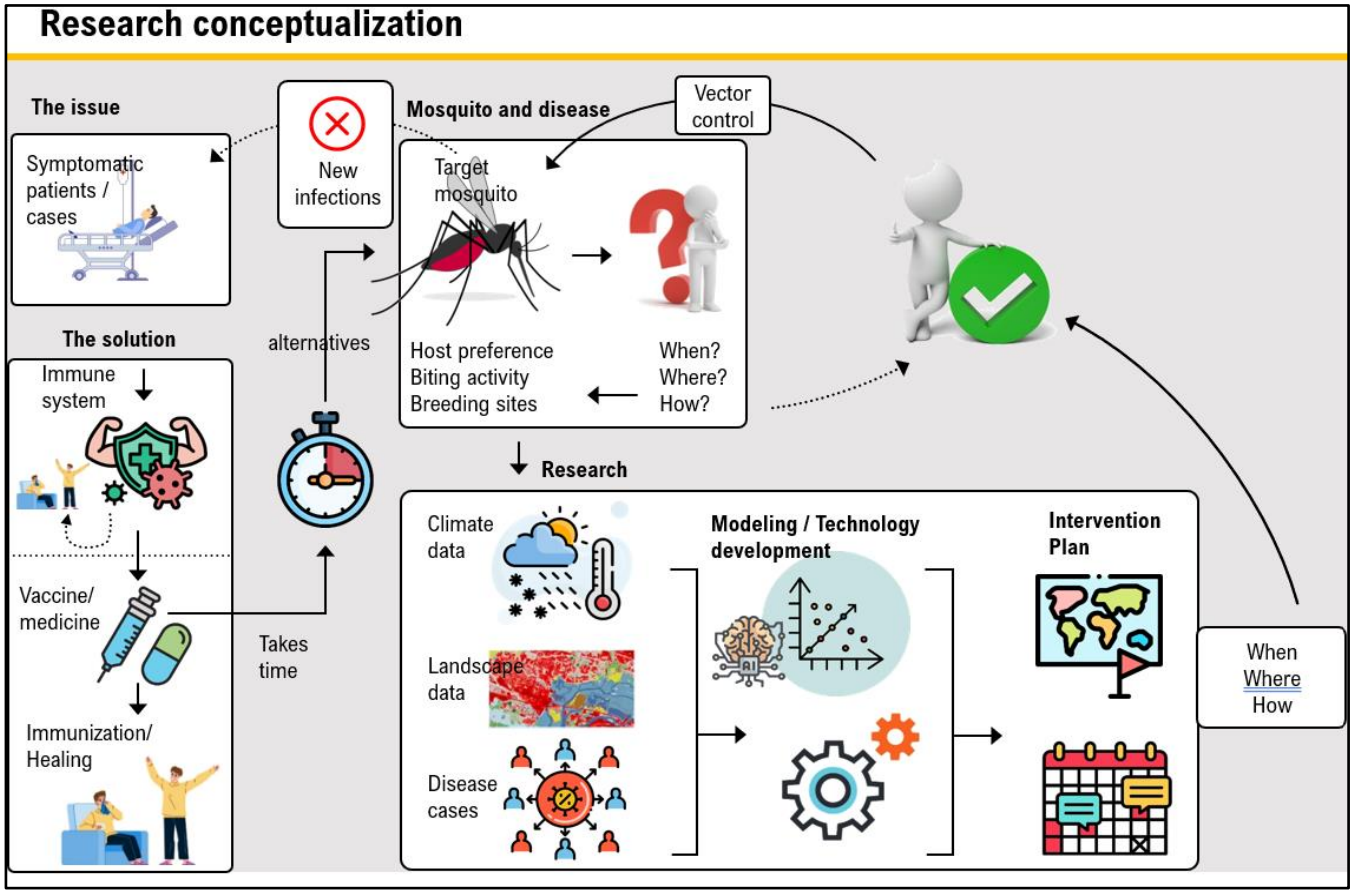
Limitations

- **False-negative villages** in the first-stage classification cannot be predicted in the second stage.
- Errors in the first-stage classification can therefore **propagate to the second stage**.

Future Plan

- Deploy the model in **Cimahi City, Indonesia**.
- Use model outputs by **health authorities to support dengue control and prevention**.
- Share model outputs, along with other relevant information, openly with the public through a **mobile application**.

Figure 9: Climate-Informed Early Warning System: Research Framework (*Lurio University, Mozambique)*



Source: Presentation by Dr Micanaldo

5. Key Recommendations and Expert Insights

The report highlights eight cross-cutting recommendations that emerged to strengthen the operationalisation of predictive modelling for disease surveillance and response.

1. **Strengthen availability of granular health data**: Experts highlighted the need for routine availability of weekly ward-level health data, as finer spatial and temporal resolution can significantly improve the accuracy and usefulness of predictive models. Historical data is important for training and validating the models, and real-time data is important for running the model in operational mode. Reliance on aggregated district-level data may mask local disease hotspots and delay targeted interventions.
2. **Build capacity at the local level:** There is a need to strengthen capacities at the ward and field levels to interpret model outputs and act upon model-generated recommendations. Predictive systems can only be effective when local health functionaries are equipped to translate forecasts into timely preparedness and response actions.
3. **Establish a digital platform for knowledge sharing and institutional learning:** A shared digital platform could be developed to connect model developers, public health institutions, programme implementers, and other relevant stakeholders. The platform could enable institutions to share updates on ongoing work, modelling approaches, tools, implementation experiences, challenges, lessons learned, and best practices. It could also provide a repository of relevant resources and facilitate peer learning and collaboration across jurisdictions. Such a platform would help reduce duplication of effort, promote adaptation of successful approaches, and support continuous improvement of predictive modelling systems.
4. **Establish robust feedback mechanisms:** Experts recommended instituting a clear feedback loop between model developers and programme implementers. Regular feedback on model performance, field realities, and operational challenges can help refine model assumptions, improve predictive accuracy, and enhance usability over time. The proposed digital platform could serve as an important mechanism for documenting and communicating this feedback.
5. **Standardise spatial scales for modelling and decision-making:** Participants noted considerable variation in the geographical units used across different models and jurisdictions. Given that districts vary substantially in size and population across the country, there is a need to develop uniform and context-appropriate spatial scales to improve comparability, interpretation, and operational application of model outputs.
6. **Promote a portfolio of modelling approaches**: Experts cautioned against relying on a single predictive model for all contexts. Different diseases and climatic conditions may require different analytical approaches, and therefore a suite of complementary models should be considered rather than adopting a one-size-fits-all framework.
7. **Expand data inputs beyond routine surveillance systems:** While routine surveillance platforms such as IHIP provide an important foundation, experts emphasised that predictive models should incorporate a broader range of determinants, including climatic, environmental,

entomological, demographic, and socio-economic factors, to better capture disease transmission dynamics and improve forecasting performance.

8. **Connect each warning to a predefined action**: Risk categories should be linked to named actions, responsible agencies and timelines for surveillance, testing, vector control, community communication and resource mobilisation.

Overall, experts underscored that predictive modelling should be viewed as part of a broader decision-support ecosystem, requiring high-quality data, local implementation capacity, standardised methodologies, and continuous learning to effectively support climate-sensitive disease surveillance and response.

6. Conclusion

The consultation provided a valuable platform to review the current landscape of climate-informed disease forecasting and vector-borne disease surveillance in India. It highlighted the significant progress made by research institutions, technical agencies, and state governments in developing predictive models and decision-support tools for public health. While several initiatives have demonstrated promising results, most models are currently at varying stages of development, validation, and operationalisation, with implementation largely concentrated at the district level.

The discussions underscored the growing potential of integrating climate information into routine disease surveillance and public health planning. Experiences shared by states implementing forecasting models demonstrated the value of evidence-based decision-making for enabling timely preparedness, targeted vector control measures, efficient resource allocation, and early public health response. At the same time, participants recognised the need to strengthen data quality, improve interoperability across surveillance systems, standardise methodologies, and generate stronger operational evidence to facilitate wider adoption.

A recurring theme throughout the consultation was the importance of sustained collaboration among government agencies, research organisations, technical partners, and development institutions. Continued knowledge exchange, sharing of implementation experiences, and coordinated efforts towards model validation, capacity building, and institutional integration were identified as essential for scaling climate-informed forecasting systems. Building on the insights and recommendations generated during the consultation, strengthening partnerships and translating emerging evidence into operational public health practice will be critical for developing robust, scalable, and sustainable forecasting systems that enhance India's preparedness and resilience against climate-sensitive vector-borne diseases.

7. Way Forward

The consultation identified several priority actions to strengthen climate-informed disease forecasting and enhance coordination among stakeholders. A key recommendation was the establishment of a common platform for knowledge exchange to facilitate the sharing of methodologies, technical innovations, operational experiences, and emerging best practices among organisations working in this domain. Such a platform would promote continuous learning, strengthen technical collaboration, and support the wider dissemination of evidence and implementation experiences.

Regular sharing of progress updates by organisations developing forecasting models was also identified as an important step towards improving awareness of ongoing work. Periodic updates on the status of model development, key technical advancements, and implementation experiences would enable stakeholders to remain informed about progress across different initiatives. Complementing this, a mechanism to document, track, and showcase forecasting initiatives being undertaken across states would improve the national visibility of ongoing efforts and provide a clearer understanding of the evolving landscape of climate-informed disease forecasting in India.

The consultation further highlighted the important coordinating role of national institutions such as the National Centre for Disease Control (NCDC) and the National Centre for Vector-Borne Disease Control (NCVBDC) in facilitating collaboration across states and technical partners. These institutions can support the documentation and dissemination of forecasting initiatives, promote knowledge exchange and cross-state learning, and provide a national platform for sharing implementation experiences and emerging best practices. Such coordination would help reduce duplication of efforts, strengthen alignment across ongoing initiatives, and accelerate the adoption of effective forecasting approaches.

The consultation also emphasised the importance of promoting cross-state learning by encouraging states that have successfully operationalised forecasting tools to share their implementation experiences, lessons learnt, and effective strategies. This would enable other states to benefit from proven approaches while adapting them to their local epidemiological and operational contexts.

The consultation further underscored the need for continuous strengthening and refinement of forecasting models through validation, incorporation of additional evidence, and adaptation to local disease dynamics and climatic conditions. Sustained model enhancement was recognised as essential for improving the reliability, applicability, and operational utility of forecasting systems.

Finally, strengthening collaboration among government agencies, research institutions, technical partners, and state governments was identified as critical for building a coordinated ecosystem for climate-informed disease forecasting. Leveraging complementary expertise, fostering long-term partnerships, and sustaining knowledge exchange would help accelerate the development, operationalisation, and wider adoption of forecasting systems to support evidence-based public health decision-making across the country.

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ANNEXURES

Annexure I: Consultation Agenda

10:00 - 10:05	**Welcome Address and Agenda Setting** Dr Aniket Chowdhury, Deputy Director, NCDC
10:05 - 10:15	**Round of Introduction and Context Setting** Dr OP Singh, Head of Public Health, CEEW
10:15 - 10:20	**Opening Remarks** Dr Aakash Shrivastava, Additional Director, NCDC
10:20-10:25	**Key Address** Dr Tanu Jain, Director, NCVBDC
10:25-10:30	**Key Address** Dr Ranjan Das, Director, NCDC
10:30-10:45	**Tea Break & Group Photo**
10:45 - 13:00	**VBD Surveillance—Presentations by Partners, Researchers, Institutions** *Presentation for insights and learnings, sharing on Dengue Model (9 x 15 min each), tentative- 9 participants* **Moderator:** Dr Saru Gupta, CEEW
13:00- 13:30	**Q & A Discussion from the stakeholders**
13:30-13:40	**Summarisation of Consultation From NCVBDC**
13:40- 13:50	**Way Forward** Dr Aakash Shrivastava, NCDC
13:50 - 14:00	**Vote of Thanks** CEEW/NCDC
14:00-14:30	**Lunch**

Annexure II: List of Participants

S.No.	Name	Organization/Description
1	**Dr. Sophia Yacob**	Indian Institute of Tropical Meteorology (IITM), Pune
2	**Prof. Sagnik Dey**	Indian Institute of Technology (IIT), Delhi
3	**Dr. Tavpritesh Sethi**	Indian Institute of Technology (IIT), Delhi
4	**Dr. Karuppusamy Balasubramani**	Central University of Tamil Nadu
5	**Dr. Rajib Chattopadhyay**	India Meteorological Department (IMD), Pune
6	**Prof. Siuli Mukhopadhyay**	Indian Institute of Technology (IIT), Bombay
7	**Prof. Harish C. Phuleria**	Indian Institute of Technology (IIT), Bombay
8	**Dr Srinivasa Rao Mutheneni**	CSIR–Indian Institute of Chemical Technology (IICT)
9	**Ms. Monisha Balasubramaniyan**	Bharathidasan University, Tiruchirappalli, Tamil Nadu
10	**Dr. Sukanya Das**	The Energy and Resources Institute (TERI)
11	**Dr Mackwin Kenwood Dmello**	Nitte Institute of Allied Health Sciences (NIAHS), NITTE University, Mangaluru, Karnataka
12	**Dr. Roop Kumari**	CARAH Women Foundation A public health expert with over three decades of experience in vector-borne disease control, health systems strengthening, and health surveillance
13	**Dr. Kalpana Baruah**	National Centre for Vector-Borne Disease Control (NCVBDC)
14	**Dr. Amit Katewar**	National Centre for Vector-Borne Disease Control (NCVBDC)

15	**Dr. Gavendra Singh**	National Centre for Vector-Borne Disease Control (NCVBDC)
16	**Dr. P. K. Srivastava**	Former Joint Director NCVBDC
17	**Dr. S. N. Sharma**	Former Joint Director NCVBDC
18	**Dr. Akilesh**	India Meteorological Department (IMD)
19	**Dr. Neeraj Agrawal**	Wadhwani AI
20	**Dr Raj Shankar Gosh**	Public Health Foundation of India (PHFI)
21	**Dr. Poornima**	Ashoka University
22	**Ms. Sonalini Khetrapal**	Asian Development Bank (ADB)
23	**Dr. Guru Jammy**	World Bank
24	**Mr. Raghavendra Rao**	India Health Fund (IHF)
25	**Dr. Swati Mahajan**	Scope Impact
26	**Mr. Aniket Choudhary**	Scope Impact
27	**Dr. Anoop**	Indian Council of Medical Research (ICMR)
28	**Dr. Jatin**	PATH
29	**Dr. Tikesh Bisen**	JSI
30	**Dr. Farah Yesmin**	Jhpiego
31	**Dr. Aparna Chaudhary**	Wadhwani AI
32	**Ms. Simonti**	Civic DataLab
33	**Dr. Sanjay Pattenshetty**	NIMS University
34	**Dr. Nivethiha N**	SAFETYNET, India

Annexure III: Photo Glimpses




Dengue
Climate Drivers
and Early Warning Systems


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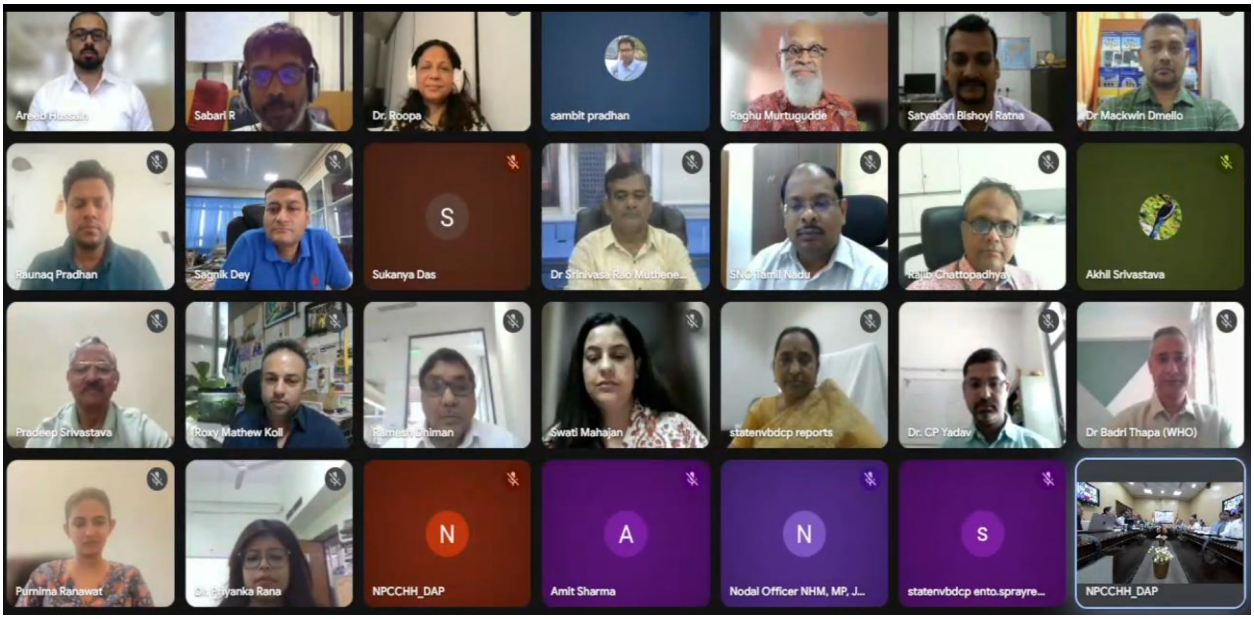
EN
Roxy Mathew Koll (Presenting)
Dengue and Global South
Dengue is the fastest-spreading vector-borne disease.
...with South Asia, Southeast Asia, and tropical Latin America being the most severely affected regions.
Attributed to climate change, vector transmission, and population mobility.
Dengue occurrence exhibits a distinct seasonal cycle and interannual variability over most of the regions
GBD 2021, Nakase et al. Scientific Data 2023, Zhang et al. PLOS Neglected Tropical Diseases 2025
Ramesh Dhiman
Pradeep Srivastava
Dr Srinivasa Rao Mutha...
Amit Sharma
Dr Mackwin Dmello
Shashank Molakalapalli
26 others
NPCCHH_DAP


Dr. Akash Shrivastava
Vaibhav Chugh
AI Tech Climate Lead CEEW


Sabari R
Dr. Roopa
sambit pradhan
Raghu Murtugudde
Satyaban Bishoyi Ratna
Dr Mackwin Dmello
Raunaq Pradhan
Sagnik Dey
Sukanya Das
Dr Srinivasa Rao Muthene...
SNO Tamil Nadu
Akhil Srivastava
Pradeep Srivastava
Roxy Mathew Koll
Swati Mahajan
statenvbdcp reports
Dr. CP Yadav
Dr Badri Thapa (WHO)
Purnima Ranawat
NPCCHH_DAP
Amit Sharma
Nodal Officer NHM, MP, J...
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NPCCHH_DAP


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sambit pradhan
Sukanya Das
Satyaban Bishoyi Ratnaj
Aishi Srivastava
Swati Mahajan
Dr Badri Thapa (WHO)
Purnima Ranawat
NPCCHH_DAP
Amit Sharma
Kajok Engtipi
Nodal Officer NHM, MP, JANM...
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2024


YOGA
Vaibhav Chugh
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