A PROPOSED FRAMEWORK FOR SURVEILLANCE OF DENGUE DISEASE AND PREDICTION

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ABSTRACT:

Recurring outbreaks of dengue during past decades have affected public health and burdened resource constraint health systems across the world. Transmission of such diseases is a conjugation of various complex factors including vector dynamics, transmission mechanism, environmental conditions, cultural behaviours, and public health policies. Modelling and predicting early outbreaks is the key to an effective response to control the spread of disease. In this study, a comprehensive framework has been proposed to model dengue disease by integrating significant factors using different inputs, such as remote sensing, epidemiological data, and health infrastructure inputs. This framework for Dengue Disease Monitoring (DDM) model provides a conceptual architecture for integrating different data sources, visualization and assessment of disease status, and prediction analysis. The developed model will help forewarn the public health administration about the outbreak for planning interventions to limit the spread of dengue. Further, this forecasting model may be applied to manage the existing public health resources for medical and health infrastructure, also to determine the efficacy of vector surveillance and intervention programmes.

1. INTRODUCTION

1.1 BACKGROUND

Dengue is the fastest-spreading vector-borne diseases with a growth rate of 8 times in the last two decades (WHO, 2021). The highest burden is observed in tropical and sub-tropical regions (Fig 1). With about 128 countries currently at risk of infection, 70% of the burden is contributed by Asia for 2019. For dengue prevention is the only measure to reduce the health burden as no specific therapeutics are defined (WHO,2021). Therefore, there is a need to undertake a holistic approach and adopt adequate measures to control the onset of such a disease. Developing a disease surveillance system that has the capability to detect disease outbreaks may provide proactive and effective control measures during the onset of the outbreak. Further, it should be able to monitor the trends of incidences including temporal and geographic distribution of cases, but also be able to assess and confirm the possibility of an outbreak considering various aspects of the surrounding environment and demographic factors, geo-spatial physiographic features, entomological, epidemiological and serological evidence by aiding an Early warning system (EWS).

1.2 DETERMINANTS OF DENGUE TRANSMISSION

The ecology of the dengue vector has been widely studied and modelled using weather dependency as its occurrence is highly seasonal (Jayaraj et al., 2019; Nuraini et al., 2021). In addition, complex dynamics of dengue is governed by the interaction of multiple agents i.e. humans (host), mosquitoes (vector) and dengue virus over time and space. Despite complexities, an analysis involving identified dengue cases linked with significant factors, analysing and modelling their dependence for predicting future cases, may be used to analyse the impact of public health and vector intervention measures opted for disease control. For efficient planning, implementation and evaluation of the interventions to reduce dengue transmission, equal emphasis on the virus, vector, and their interaction with humans along with environmental factors is required. Well-timed and reliable estimates of dengue emergence, including location, time, and intensity, may enhance proactive disease management.

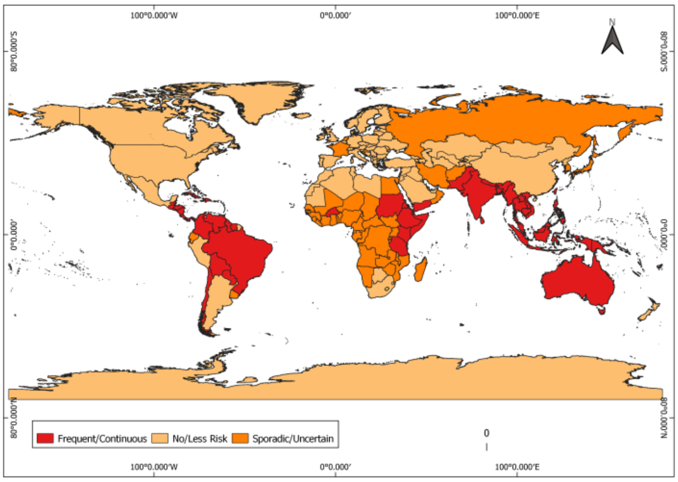

Fig 1: Geographic distribution of dengue cases (Data Source: CDC, 2021)

Dengue is extremely sensitive to weather conditions as the vectors hence its highly seasonal. However, this seasonality is not uniform across the globe. It varies with geographical location, macro and micro climatic patterns like draught cycle, and trend of rainfall. The geographical range in which vectors' movement occurs along with their habitat preferences increases the exposure of humans to vectors(Vanwambeke et al., 2007). In addition, the growth, and development of the viruses in vectors and hosts occur under specific environmental conditions. The geographical shift in the distribution of dengue cases across the globe owing to climate change is being widely studied. It has been observed under warmer conditions, the extrinsic incubation period of the dengue virus may be shortened, which may lead to increased efficiency of viral transmission by mosquitoes. In contrast, extreme conditions like very high temperatures and low temperatures may hinder mosquito growth as it may lead to high mosquito mortality or hinder the development of the virus, therefore decreasing the risk(Sirisena et al., 2017). Rainfall, on the other hand, is necessary to create and maintain breeding sites for Aedes mosquitoes and therefore has a strong influence on vector distribution. The major governing factors for dengue transmission identified in various studies are summarised in Table 1.

Table 1: Major contributing factors for dengue occurrences

Determinant Factor	Author	Impact/Magnitude
Built-up	Machault et al., 2014	Maximum dengue cases were found in the built-up area with a 300-m radius buffer.
	(Dom et al., 2016)	High levels of dengue cases were reported within a buffer of 600 m around residential areas.
	(Zahouli et al., 2017)	Development time of larvae in urban areas is significantly shorter than that in rural and sub-urban areas due to comparatively warmer temperatures.
	(Ferraguti et al., 2016)	Vector abundance were higher in vegetated and rural areas as compared to urban areas.
Water Bodies	(Ferraguti et al., 2016)	High mosquito distribution is found in wetland areas.
Vegetation Density	(Sarfraz et al., 2012)	Land cover consisting of orchards, rangeland and deciduous forests contributed more towards vector growth. Standing water in paddy fields and swamp forests upto 2.5 cm to 30 cm in depth are observed as most common habitats for the dengue vector
Temperature	Wu et al., 2007	Every 1 °C increase in average monthly temperature above 18°C increased the risk for dengue transmission by 1.95 times.
	(Xiao et al., 2018)	It was observed the biting activities of mosquitoes were restricted to temperatures between 15 °C and 35 °C.
Season	(Appawu et al., 2006)	A high number of cases in the dry season is due to the increase in the storage of water.
	(Sirisena et al., 2017; Zahouli et al., 2017)	Bimodal rainfall patterns corresponded to two peaks in dengue distribution noted on an annual scale.
	(Captain-Esoah et al., 2020)	Unimodal rainfall pattern corresponded to a single peak in dengue case distribution
Elevation	(Gyawali et al., 2020)	The suspected elevation limit for Aedes spp. was found to be up to 2100 m. However, an increased incidence of dengue was found to be in cities located above 1300 m of elevation compared to cities in the same elevation due to urban heat island effects.

The major risk components of dengue transmission are classified into exposure, sustainability and adaptive capacity (Fig 2). Exposure determines the vector-human interaction in an environment while susceptibility governs the proneness of a community to be infected by dengue. The adaptive capacity provides the ability to the community to deal with the disease. It may be enhanced by enhancing the quality of healthcare facilities, vector control measures, and spreading awareness among the public.

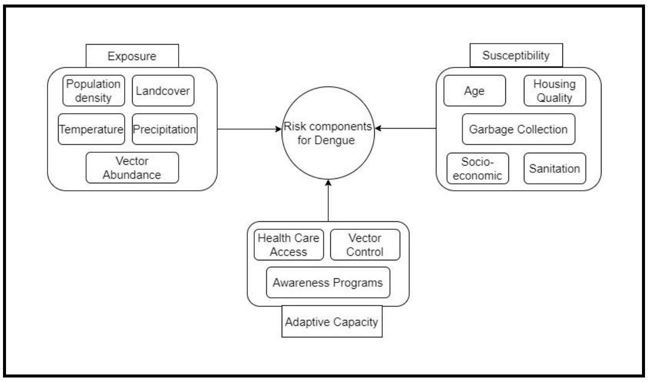

Fig 2: Factors affecting dengue risk and susceptibility

1.3 DENGUE INCIDENCE MODELLING

The high global burden of dengue led to much research across the globe depending upon the severity of the problem and varying from studying the distribution of cases, assessing contributing factors, determining the population at risk and predicting future incidences. A variety of statistical and machine learning methods are applied to model dengue transmission and produce risk maps. While plotted disease incidence may facilitate the allocation of public health resources, but also there is a need for methods that allows an assessment of interventions over time and space. Disease modelling utilizes existing estimates of disease incidence to predict impact depending on the expected changes in population demographics, environmental and climatic conditions. It is crucial to plan the resources, create emergency

SOPs, task allocation and most important restrict the disease in case of occurrence. While most of the studies undertaken in the past decade used different statistical models to analyse contributing factors to dengue or to carry out prediction. However, the latest researches are more focused on using advanced methods like the use of machine learning or deep learning tools in order to predict disease occurrences. The various significant modelling techniques along with contributing variables for dengue used across the globe are shown in Table 3.

Table 3: Modelling Techniques used for dengue prediction

Model Name	Developed By	Parameters Used
Logistic Regression	Joseph Berkson,1944 (Cramer, 2002)	Land use, vegetation density, slope, aspect, distance from open areas and gold mining sites along with malaria incidence data.
Generalised Linear Model	John Nelder and Robert Wedderburn (Nelder et al., 1972)	Temperature, humidity, and the total number of dengue cases per week. Remote sensing-derived products like NDVI, NDWI, Daytime Temp, Night-time Temp, and Precipitation in both urban and rural areas are used as a proxy for environmental conditions, mosquito population
Analytical Hierarchy Process	T.L. Saaty (1971-1975) (Saaty, 1987)	Dengue data, land use, housing type, residential buffering, elevation, population density, Land Surface Temperature
Support Vector Machine	Cortes and Vapnik (Cortes and Vapnik, 1995)	Dengue incidence data, mean temperature, rainfall, relative humidity, vector density, elevation, remote sensing derived products like NDVI and NDBI as a proxy for vegetation and urban density
Poisson Regression	Simon Poisson, 1837	Weekly dengue cases, Oceanic Ni˜no Index (ONI), temperature, rainfall, humidity, sunshine hours, wind speed, built-up and vegetation density.
Auto-Regressive Integrated Moving Average	Box and Jenkins (Wilson, 2016)	Temperature, rainfall, humidity, dengue cases, vector density, wind speed and direction
Gradient Boosting	Jerome H. Friedman (Friedman, 1999)	Confirmed dengue incidence data, Land surface temperature, precipitation, LULC, population density, urban accessibility, wind speed and direction
Random Forest	Leo Breiman (Breiman, 2001)	Minimum temperature, maximum temperature, precipitation, NDVI, relative humidity, urbanicity, population density, urban accessibility, vector data, land surface temperature
Generalised Additive Model	Trevor Hastie and R. Tibshirani (Hastie and Tibshirani, 2005)	Dengue incidence data mean temperature, average relative humidity and rainfall, and population density.

The advantage of using a statistical model against a machine learning model is that a statistical model may be easily interpreted, and the governing factors may be assessed and may be understood by public health managers (Mudele et al., 2021). Moreover, it may be further integrated into real-life health systems and aid robust decision-making. Another advantage is the ease of processing and visualization which in contrast, for machine learning methods specialized libraries are required, followed by parameter tuning and long training cycles. However, machine learning algorithms may help by determining hidden patterns by combining different variables, which is not possible in statistical analysis. Overall it is observed that ARIMA, GAM, regression, RF and BRT have got maximum accuracy while modelling dengue transmission. However, these models have not been simultaneously applied to the same datasets for a region. Therefore, it is proposed to verify the suitability of the such model for a given region after a comparative analysis.

2. DENGUE DISEASE MONITORING MODEL

2.1 CONCEPTUAL FRAMEWORK

Lack of data availability in many under-developed countries led to the development of frameworks like the Water Associated Disease Index, Analytical Hierarchical Process, and Spatial Multi-Criteria Evaluation. Such frameworks worked on determining highly vulnerable areas based on a set of criteria like risk factors, and computing pair-wise comparisons and lacked maintaining consistency itself. Very few studies incorporated the socio-environmental aspects of dengue transmission including their spatial association and relative risk concerning neighbourhood regions. Moreover, the risk associated with neighbourhood regions and the non-availability of the medical facility on dengue occurrences has not been studied. Thus, this study aims to overcome these limitations and aims to bring together a conceptual framework that may assist in modelling and predicting dengue cases and addresses how the dynamics of DENV transmission are modulated by significantly identified factors. Therefore, this study proposes a framework model which provides a comprehensive support for exploratory analysis, spatiotemporal analysis, risk analysis and prediction depending upon the level of analysis required at the time of the outbreak. The framework aims at (i) identifying hotspots and rate of disease spread, (ii) determining risk zones that may be prone to future outbreaks and (iii) predicting the occurrences of dengue in time and space. Based on the findings

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from the various literature, the conceptual framework is presented in Fig 3.

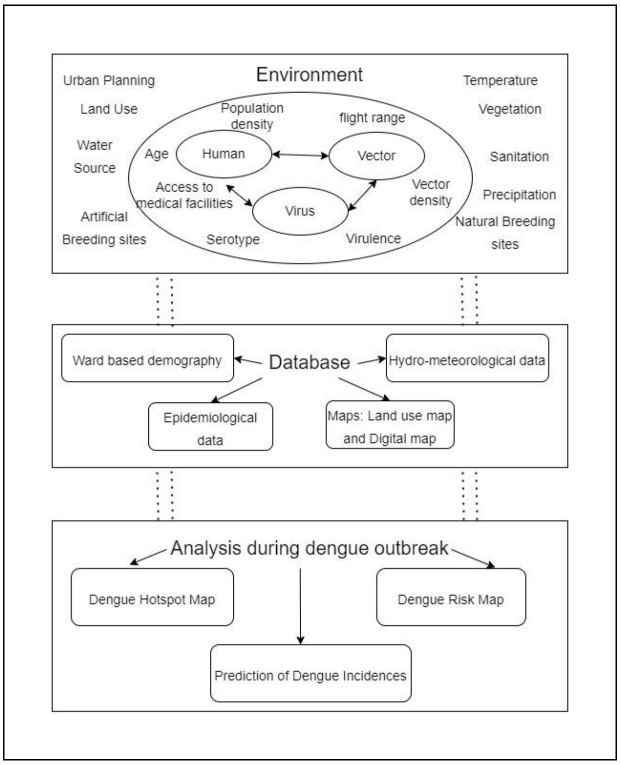

Fig 3. Conceptual framework of the proposed model for dengue disease monitoring

This framework integrates the three important aspects of dengue transmission i.e. environmental component, the database containing disease-related information and analysing of the dengue outbreak. The base layer consists of integrating all the factors associated with dengue incidence. Thereafter, the database consisting of dengue illness, the demography of the study region and its geographic information is integrated to model the existing situation of the outbreak. The final layer consists of the outputs based on the type of support required depending on stages of the disease outbreak viz disease occurrence, spread, and fall. For robust prediction, the such model will be trained to predict dengue occurrences in the region over time. The analysis may provide graphical output in terms of hotspot maps, risk maps and prediction of dengue incidence. The advantages of having graphical output are interpretation, ease of data sharing, and communication across various sectors and levels of administration including public communication. DDM may be further used for developing an early warning system which may alarm public health administrators to take preventative measures to minimize the further spread of the outbreaks by enforcing required interventions.

2.2 PROPOSED WORKFLOW:

The workflow followed for the DDM model is summarised in Fig 4. Overall it consists of input, processing and output blocks. The input block includes data harvesting processes from different sources like remote sensing, station data, ground-truth data, and surveying. A database will be generated containing geo-coded reported cases with supplementary information about the patient details, demographic information and the area/ward from which the patient belongs. The standard and homogeneous form of such data are required such database will contain epidemiological data of at least 5 years or the latest available data, whichever is earliest. The datasets for environmental parameters like vegetation density, built-up, and water bodies and hydro-meteorological parameters like temperature, rainfall, and humidity will be collected. The preliminary data processing carried out at the input block includes data aggregation, homogenisation, storing, filtering and visualisation. The data aggregation process as a part of data governance will integrate structured, semi-structured and unstructured data coming from various sources after homogenisation based on the spatial resolution of acquired data. Thereafter the dataset will be processed and analysed in a processing block using a set of algorithms and equations to determine the trend, regions of dengue risk, and predicted dengue occurrences. The processing block of the DDM model is further divided into three distinct modules, with further descriptions of these modules provided in subsequent subsections.

Module I: Dengue Spread Model

Spatio-temporal patterns of DF cases will be determined to study the variation of DF cases over time and geographical regions. Surface Trend Analysis will be used to determine the rate and direction of outbreak spread. Such analysis is useful for Public Health administration by planning preventative/control measures to limit the further spread by enforcing interventions. The geo-coded epidemiological data will be first converted from a daily scale to a weekly scale in the respective wards of the municipal boundary. The rate of disease spread will be estimated using polynomial regression models (Tutt-gu et al., 2021; Zinszer et al., 2015). The rate of change (in weeks/km) of dengue incidences will be obtained based on the best fit linear model, using partial derivatives with respect to x and y. The vectors will then be converted for determination of magnitude and direction.

Cluster Analysis is used to determine significant clusters of DF outbreaks. Such analysis is useful for planning a medical facility or for additional resource allocation as a mitigation measure to control an outbreak. The discrete Poisson Model will be used to identify overlapping spatiotemporal and spatial clusters. The temporal unit may be selected depending on the incidence of DF cases in the region. For example, in case the incidence is low, an annual DF occurrence per municipality per year will be selected (Tutt-gu et al. 2021) and the case it is highly seasonal variation per municipality may be considered (Henry and Mendonça 2020).

Relative Risk (RR) will be calculated for each significant cluster providing risk within that cluster relative to that of the outside cluster and calculated as per equation (1)

$$RR = c/E(c)(C-c)/(C-E(c)) \ldots\ldots\ldots \quad (1)$$

Where, c= observed cases within the cluster, E(c) expected number of cases, C= total number of cases in the dataset.

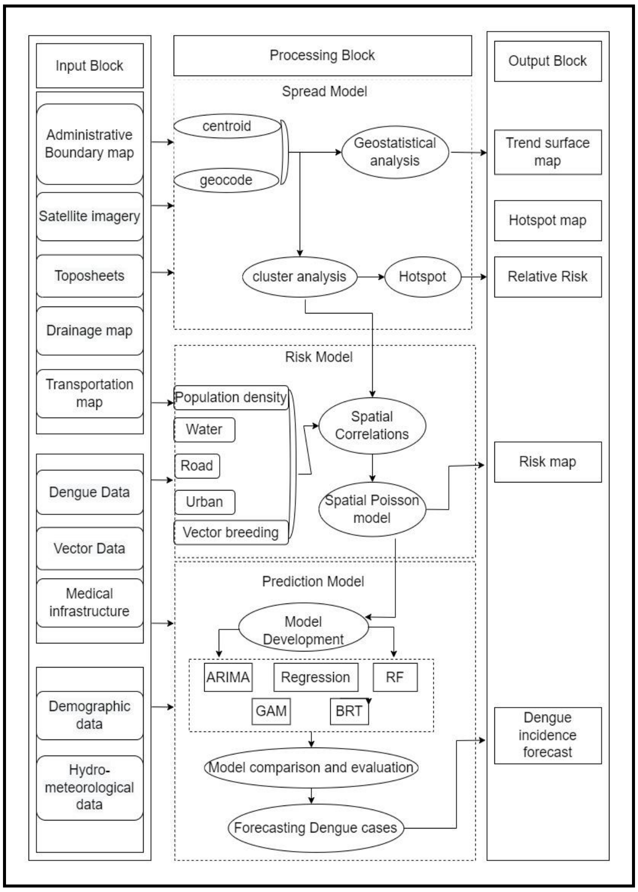

Fig 4 Workflow of the DDM model

Module 2: Dengue Risk Model

A multivariate temporal approach will be used to identify vulnerable regions prone to DF outbreaks. A risk model along with a spatial Poisson point process model will be generated using individual layers of epidemiological data consisting of patient locations, land-use maps, roads, and total buildings in high-risk areas determined in the first objective. Raster layers will be developed separately for patient data, breeding places and road map layers using the kernel density function and the euclidean distance function will be used to calculate distances of roads, water bodies, and buildings. Spatial correlations between DF case locations in each high-risk area and other layers will be determined using Pearson's product correlation coefficient (Mala and Jat, 2019; Withanage et al., 2021). The risk values will be ranked for each layer depending upon their contribution to DF occurrence in the range of 0(minimum) to 10(maximum). The resulting risk map may help healthcare workers and decision-makers in taking preventative measures in vulnerable areas.

Mathematical modelling of patient cases with developed layers: Spatial Poisson point process model will be used to determine high-risk localities using patient locations as a function of raster layers created from breeding places, road maps, water bodies and buildings.

$$\ln(i) = \alpha + \beta 1 \text{ Breeding Places-} + \beta 2(\text{Roads}) + \beta 3(\text{water bodies}) + \beta 4(\text{buildings})\ldots \qquad (2)$$

where (i) is the modelled point pattern intensity for dengue incidences at location "i", α is the base intensity derived from the multivariate model and β_1 to β_4 are the estimated coefficients for each respective variable. Thereafter, model outputs will be used to plot the predicted intensity of dengue in the areas to identify high-risk localities.

Module III: Dengue Prediction Model

The disease data will be split into 2:1 for training and testing. Different statistical- machine learning models will be developed and compared to forecast the dengue outbreaks based on the epidemiological data and predictive variables such as monthly rainfall, rainy days and temperature. Different models will be generated using ARIMA, GAM, regression, Random Forest and Boosted Regression Trees. The best model will be selected based on the lowest Akaike's information criterion (AIC), Bayesian Information criterion (BIC), R-squared (R^2), root mean square errors (RMSE), mean absolute errors(MAE) and mean absolute percentage error (MAPE) of prediction and will be used for analysing dengue disease data for prediction.

The processed output will be presented to the users in the form of a graphical representation using a web application. By using a graphical user interface the user experience may be enhanced and allow for eased data communication and sharing. Based on a detailed literature review on dengue surveillance and modelling, this proposed framework provides an overview and foundation for a new approach to handling public health problems.

3. CONCLUSION

This framework provides different stages of analysis depending upon the severity of the situation which may provide information about the location, timing, and intensity of infectious diseases that will help public health stakeholders in taking proactive disease containment and management efforts. This framework includes comprehensive, end-to-end support for exploratory analysis, spatiotemporal analysis, disease spread modelling and prediction. It provides an architecture for epidemiologists to break up disease management into sub-problems and solve the sub-problems with appropriate modelling approaches. The framework supports the integration of structured data (disease incidents, environmental conditions, demographics, health status, and other data. The study will provide support to the different stages of the disease viz disease occurrence, spread, and fall which will allow public health administrators to better planning and preparedness.

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