A Central Hub to predict the effects of Climate Change on Vector Borne Diseases

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Video Demostration

***Abstract*—Current evidence suggests that inter-annual and inter-decadal climate variability have a direct influence on the epidemiology of vector-borne diseases. This evidence has been assessed at the continental level in order to determine the possible consequences of the expected future climate change. By 2100 it is estimated that average global temperatures will have risen by 1.0-3.5 degrees C, increasing the likelihood of many vector- borne diseases in new areas.**

From Fig.1 it is evident that the risk of vector borne disease outbreaks has been steadily increasing over the years. The risk is even greater for equatorial countries. This calls for international remedies against these rising trends.

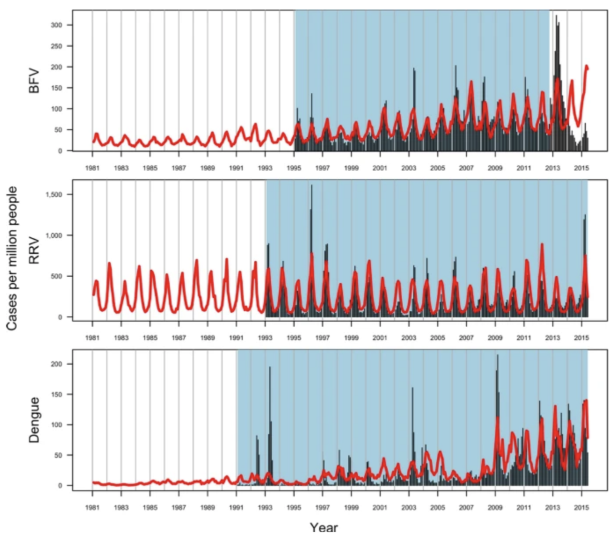


Fig. 1. Rising Deaths due to Vector Borne Diseases

I. Literature Review

Title	Review	Year
Genetics of Major Insect Vectors	Vector-borne diseases are responsible for a substantial portion of the global disease. Control of insect vectors is often the best and sometimes the only way to protect the population from these destructive diseases. This chapter reviews vector genetics of three of the most important vector-borne diseases that have much to contribute to understanding vector-borne disease epidemiology and to designing successful control methods.	2011
Detection and Attribution of Climate Change Effects on Infectious Diseases	Infectious agents whose life cycle includes a life stage or extended periods exposed to ambient weather conditions (including time within vectors or hosts)are sensitive to climate variability. Anthropogenic (or human-induced) climate change will alter the patterns of many human infectious diseases, because the development rates, lifespan and reproductive capacity of climate-sensitive infectious agents, their vectors and hosts are influenced by higher temperatures and increased climate variability.	2015
Climate change and human infectious diseases: A synthesis of research findings from global and spatio-temporal perspectives	The life cycles and transmission of most infectious agents are inextricably linked with climate. Geographically, regions experiencing higher temperature anomalies have been given more research attention; unfortunately, the Earth's most vulnerable regions to climate variability and extreme events have been less studied. From local to global scales, agreements on the response of infectious diseases to climate change tend to converge.	2017
System and method for detecting, collecting, analyzing, and communicating event related information	A system and method involves detecting operational social disruptive events on a global scale, assigning disease event staging and warnings to express data in more simplistic terms, modelling data in conjunction with linguistics analysis to establish responsive actions, generating visualisation and modelling capabilities for communicating information, and modelling disease propagation for containment and forecasting purposes.	2018

Title	Review	Year
Impact of climate change on human infectious diseases: Empirical evidence and human adaptation	Climate change refers to long-term shifts in weather conditions and patterns of extreme weather events. It may lead to changes in health threat to human beings, multiplying existing health problems. This review examines the scientific evidences on the impact of climate change on human infectious diseases. It identifies research progress and gaps on how human society may respond to, adapt to, and prepare for the related changes.	2016
Vector-Borne Infections	Vector-borne infections are caused by diverse pathogens transmitted to humans by arthropod vectors. Vector-borne diseases are responsible for a substantial portion of the global disease burden causing about 1.4 million deaths annually. Vector-borne infections, such as malaria, yellow fever, dengue, Japanese encephalitis, filariasis, and others, have an important place in morbidity and mortality from infectious diseases worldwide.	2022

II. Dataset Review

- Local Epidemics of Dengue Fever
- Dengue Cases in Brazil w/ Temperature
- Year wise spatial distribution of Vector-borne diseases in India
- Monitoring of Mosquito Vectors of Disease
- Seasonal Climate Forecast
- Historical, current, and future climate conditions around the globe.
- Distribution and diversity of mosquito-associated viruses and their related mosquito vectors in china
- State/UT-wise Details of Dengue Cases in India

III. Objectives

- Predict the stats based on location, population and general climatic factors specific to the location. Predict the precautionary measures and their scale as well.
- Indicate alarming instances for the international governments and public for awareness.
- Either designing mathematical models or employing neural networks for prediction.

IV. Work Plan

- 1st Review - Define scope of work, identify and gather datasets, device preprocessing algorithms.
- 2nd Review - Preprocess datasets, train model, test results, perform comparative studies.
- 3rd Review - Deploy a scalable, public API to automate the training and testing procedures.

V. Detailed Methodology

- Time-series forecasting is achieved using TensorFlow. It builds a few different styles of models including Convolutional and Recurrent Neural Networks (CNNs and RNNs).

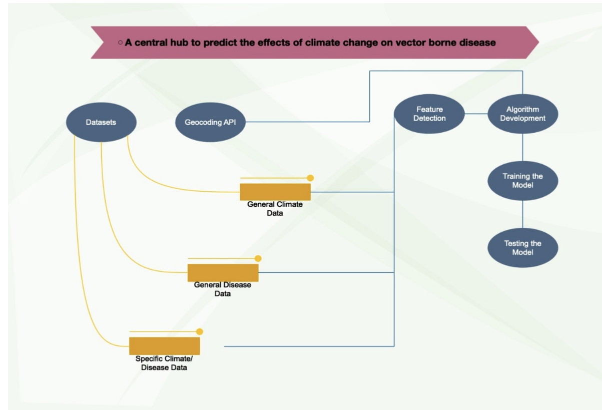


Fig. 2. Block Diagram

- The model is trained preserving Temporal Resolution and Spatial Resolution and is then tested with the currently available data.
- Extrapolating the results to geolocations with similar climate can be explored.
- An API is developed using GraphQL to consume the predicted results and develop further public applications.

A. Description of Modelling

We aim to accomplish time series-forecasting of vector-borne disease against the historical trends of the disease in the area and the climate variables. This can be accomplished in the following ways:

- Forecast for a single time step
  - A single feature
  - All feature
- Forecast multiple steps
  - Single-shot: Make the predictions all at once.
  - Autoregressive: Make one prediction at a time and feed the output back to the model.

B. Detailed Procedure

- Weather Data and Vector Borne Disease Data for a place is collected.
- Time Series Predictions are made for Weather Data to overlap the temporal domain of climatic features and cases.
- Dense Multi Variable Regressor is used with Stochastic Gradient Descent Optimiser and Mean Squared Error as the error calculation function.
- An API is built on GraphQL and Node.js to allow users to input their datasets and train/test the developed model.

C. Working Mechanism

- Our primary prediction model is deep multiple regression model with stochastic gradient descent as the optimizer and mean squared error as the loss calculation function. We have considered 2 major features i.e. Temperature and Humidity to predict one major response i.e. Cases in the given temporal domain.

- The data predicted by the model is fed into an API for public accessibility. The API is built on Node.js and express frameworks and implements the Apollo GraphQL standard.

D. Preliminary Visualisations

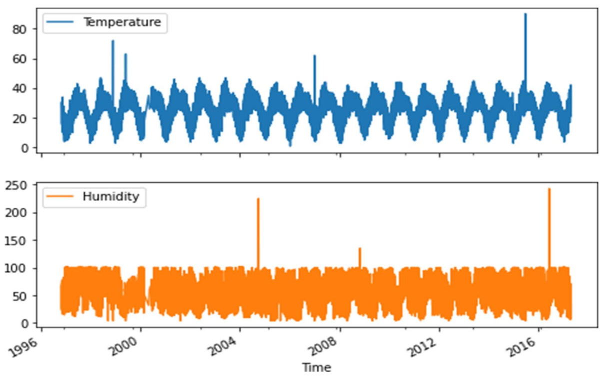


Fig. 3. Evolution of Temperature and Humidity over time

	count	mean	std	min	25%	50%	75%	max
Humidity	100233.0	57.909481	23.807771	4.0	39.0	59.0	78.0	243.0
Temperature	100317.0	25.451269	8.482859	1.0	19.0	27.0	32.0	90.0

Fig. 4. Data Statistics

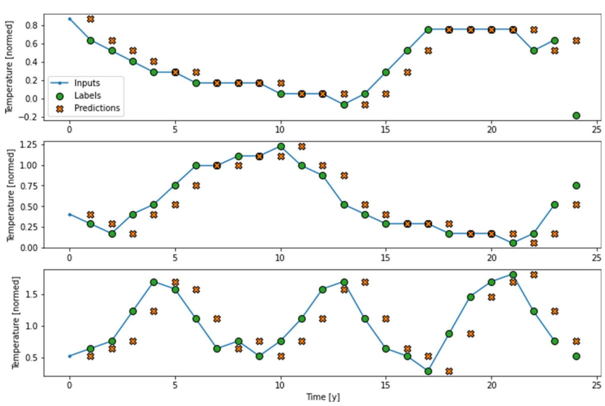


Fig. 5. Final Predicted Temperatures and Corrected Output

VI. Outcomes

A. Expected Outcomes

- Climate and Disease datasets with coherent spatial and temporal resolutions.
- Time series forecasting model.
- API to allow automated training/testing.

B. Results

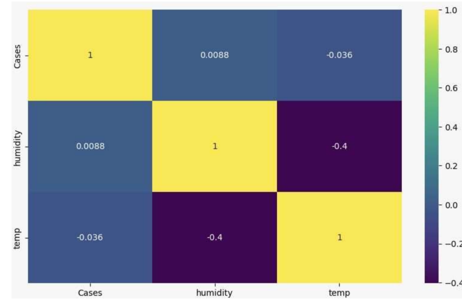


Fig. 6. Correlation of Features from Antwerp Data

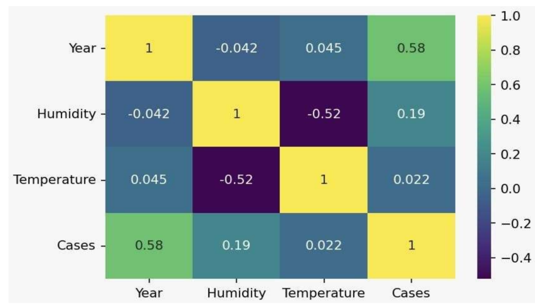
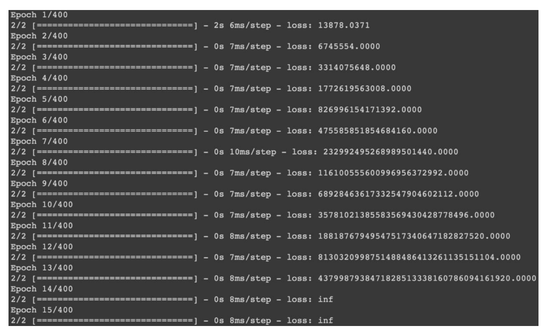


Fig. 7. Correlation of Features from Delhi Data



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Epoch 1/400
2/2 [==============================] - 2s 6ms/step - loss: 13878.0371
Epoch 2/400
2/2 [==============================] - 0s 7ms/step - loss: 6745554.0000
Epoch 3/400
2/2 [==============================] - 0s 7ms/step - loss: 3314075648.0000
Epoch 4/400
2/2 [==============================] - 0s 7ms/step - loss: 1772619563008.0000
Epoch 5/400
2/2 [==============================] - 0s 7ms/step - loss: 826996154171392.0000
Epoch 6/400
2/2 [==============================] - 0s 7ms/step - loss: 475585851854684160.0000
Epoch 7/400
2/2 [==============================] - 0s 10ms/step - loss: 232992495268989501440.0000
Epoch 8/400
2/2 [==============================] - 0s 7ms/step - loss: 116100555600996956372992.0000
Epoch 9/400
2/2 [==============================] - 0s 7ms/step - loss: 68928463617332547904602112.0000
Epoch 10/400
2/2 [==============================] - 0s 7ms/step - loss: 35781021385583569430428778496.0000
Epoch 11/400
2/2 [==============================] - 0s 8ms/step - loss: 18818767949547517340647182827520.0000
Epoch 12/400
2/2 [==============================] - 0s 7ms/step - loss: 8130320998751488486413261135151104.0000
Epoch 13/400
2/2 [==============================] - 0s 8ms/step - loss: 4379987938471828513338160786094161920.0000
Epoch 14/400
2/2 [==============================] - 0s 8ms/step - loss: inf
Epoch 15/400
2/2 [==============================] - 0s 8ms/step - loss: inf
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Fig. 8. Model cannot converge since the features are not correlated

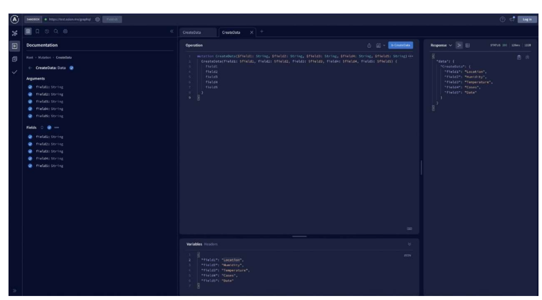

Fig. 9. Developed API

C. Conclusion

We conclude that for the given Temporal and Spatial Domains, there exists no correlation between temperature and humidity and cases of vector borne disease. Thought this conclusion only holds true for Delhi and Antwerp for the chosen time period. Predictions for other spatial and temporal domains are still worth exploring.

VII. Social Impacts

- Allows government or relief organisations to plan remedial efforts in advance.
- Establishes time series patterns, allowing for discovery of key factors of outbreaks.
- Provides a quantitative analysis of the results incurred by remedial efforts.

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