American Journal of Engineering Research (AJER)
e-ISSN: 2320-0847 p-ISSN: 2320-0936
Volume-15, Issue-2, pp-25-34
www.ajer.org
Research Paper Open Access

A Distinct Machine Learning Approach Assessing the Synergistic Impacts of Soil Hydrological Dynamics and Solar Radiation on Dengue Mortality in Bangladesh.

AHSAN KABIR, AFRIN AKTER MIM,ABRAR AHMED KHAN,SHARMIN SULTANA,SUMA AKTER
[1](Department of CSE, Bangladesh)
Corresponding Author: Ahsan Kabir

ABSTRACT: *Dengue fever has become an ongoing human health emergency in Bangladesh and there has been an increasing number of deaths in recent years. Although conventional predictors are temperature and precipitation, this paper investigates the effect of Surface Soil Wetness (SSW) and Photo synthetically Active Radiation (PAR) as unconventional predictors using a longitudinal data set between 2000 and 2022. Using a Random Forest (RF) regression model, we modeled the effect of eight climatic variables on dengue cases and mortality in countries. We have shown that Surface Soil Wetness is a more predictive variable of dengue outbreaks compared to raw precipitation, and it has a strong Pearson correlation (r = 0.68). Also, the research shows a considerable 4 week lagging effect between the maximum soil moisture and mortality bursts. These insights recommend the implementation of soil-hydrological indicators in the national systems of early warnings as a measure of the elimination of the effects of subsequent epidemics.*

KEYWORDS: Dengue Mortality, Soil Wetness, PAR, Machine Learning, Bangladesh, Climate Change, Epidemiology.

Date of Submission: 01-02-2026 Date of acceptance: 10-02-2026

I. INTRODUCTION

Dengue fever is now proving to be one of the greatest vector based infectious diseases in South Asia, Bangladesh is having unprecedented epidemic-scale escalation in the last ten years. Dengue virus (DENV) is a disease that is highly associated with environmental variables and urbanization patterns. The accelerated urbanization in the city of Dhaka and other large administrative divisions has provided the most favorable breeding grounds to Aedes aegypti mosquitoes who are the major vectors of the dengue disease . In Bangladesh, there was endemic dengue circulation between 2000 and 2022 with periods of outbreak but the outbreak that happened in 2023 causing over 1,700 confirmed deaths is an indicator of a critical increase in disease burden .

The conventional methods used in epidemiological prediction of dengue have mostly been based on the direct meteorological factors like temperature and precipitation. Although it has been established that ambient temperature is a strong predictor of the viral extrinsic incubation period (EIP) and the rates of developing vectors , and precipitation has been established as a crucial factor in the formation of the aquatic mosquito habitat , individually, none of these variables is sufficient to describe the dynamics of the transmission of dengue in tropical and subtropical settings.

The basic assumption of the study is that raw precipitation data is a poor proxy that the availability of moisture in the environment because it fails to take into consideration soil water retention, infiltration, and temporal dynamics of water retention in micro-habitats. Surface Soil Wetness (SSW) which is defined as the volumetric water content of the top layer in the soil gives a direct measure of the availability of moisture to breeding sites of the mosquitoes. There is early research on the persistence of soil moisture in the maintenance of Aedes breeding habitats even in the inter-monsoon seasons to amplify the window of vectorial capacity .

Also, this paper gives the Photosynthetically Active Radiation (PAR) as a new epidemiological predictor. The PAR which is the solar radiation range (400-700 nm) used by the photosynthetic organisms has been mostly overlooked in dengue epidemiology literature. Nonetheless, PAR can affect the rate of evaporation occurring in breeding containers, and can control the behavior of vectors by acting on vegetation microclimates .

During sunny days, when the intensity of PAR is strong, water evaporates faster out of small containers (key habitats of Aedes aegypti), and consequently, larval populations are regulated by nature .

Hypothesis of this paper assumes that there exists a synergistic interaction in which high levels of SSW, coupled with mid-levels of PAR (cloudy, humid conditions) may lead to the optimal conditions of dengue transmission, and high levels of PAR and low levels of SSW may lead to the rapid desiccation of habitats and decrease in population of vectors. To address this hypothesis, we created a machine learning model based on the regression model of the Non-parametric, which is the Random Forest regression, which is in a position to predict the complex non-linearities and the interactions between the variables, but does not specify the parameters .

II. Literature Review

A. Climatic Determinants of Transmission of dengue:

Climate and dengue transmission relationship have been well examined in the available literature based on both empirical and mechanistic models. A global meta-analysis conducted by Bhatt et al. [11] revealed that the number of people exposed to dengue transmission is about 3.9 billion in tropical and subtropical areas, with the area of South Asia being a hyper-endemic area. The most widely researched climatic variable in the epidemiology of dengue is temperature. Watts et al. highlighted that ambient temperature influences various aspects of epidemiology Viruses Viral replication in the mosquito (extrinsic incubation period (EIP)) has been found to be shorter at higher temperatures: between 12-14 days at 30degC and 7-10 days at 32-35degC. Every 1degC rise in temperature has the capacity to shorten the EIP by 1-2 days with a geometric increase in the transmission potential of particular mosquitoes .

In Bangladesh, Banu et al. have undertaken a time-series study in particular and have found that minimum daily temperature was the most strongly correlated with dengue incidence (correlation $r = 0.61$, $p < 0.01$), indicating that night-time temperatures could be a restrictive factor to the survival of vectors in colder seasons. In addition, Thai and Indonesian research by Mordecai et al. [15] and Altizer et al. have also shown that the optimum of dengue virus replication in Aedes vectors is 29-31 deg C with a rapid decrease in transmission efficiency beyond 34 deg C.

The contribution to the epidemiology of dengue of the phenomenon of precipitation is multi-level and situational. Extensive rainfall forms standing water environments that become the habitats of the larval stages of the mosquitoes . Barrera et al. observed in the urban developing areas of Puerto Rico that strong rains were linked with high egg and adult responses of Aedes aegypti. Nonetheless, a very high precipitation may wash away existing breeding grounds, which produces a non-monotonic relationship . Relative humidity or vapor pressure deficit, commonly known as humidity, has a direct effect on the development rates, survival and biting behavior of mosquitoes. Little humidity (less than 60 per cent) drastically shortens the adult mosquitoes lifespan and decreases the number of times they feed .

B. Soil Wetness and Vector Ecology:

Though wetness is provided by precipitation, soil wetness processes define the presence and maintenance of water at ground levels. Hydrological research has recently indicated that the antecedent soil wetness state mediates the hydrological and thermal feedback to the ensuing events of precipitation, as indicated by Teuling et al. and Seneviratne et al. Applying this principle to a situation involving a vector-borne disease means that the baseline soil wetness is the determinant of the sustainability of larval habitats irrespective of whether or not it is raining.

One of the most important gaps in literature related to dengue epidemiology is the lack of a systematic study of soil moisture as a predictor of transmission. Experiments on the habitat preferences of Aedes have recorded that the ovipositional mosquitoes prefer moist soil-organic matter matrices . The eggs are resistant to desiccation and can survive temporary water pools as a result, which permits the mosquitoes to take advantage of transient water bodies; nevertheless, constant water presence in the soil will eliminate desiccation and sustain mosquito larvae growth. According to Aziz et al., land-use features, such as soil type and vegetation cover, have a considerable impact on local mosquitoes due to the implication on microclimate and water retention.

C. **Photosynthetically Active Radiation** :Photosynthetic radiation has a role in influencing human health and disease prevention in the future.

Photosynthetically Active Radiation (PAR), which is a group of colors between 400-700 nm, is about 45-50 percent of the solar radiation striking the earth. PAR determines photosynthesis in vegetation and has a shading effect on the thermal microclimate . Solar radiation has largely been studied in ecological research on disease vectors with regard to its impact on ambient temperature and not direct PAR flux. Nevertheless, PAR directly influences evaporation rates that are not temperature-dependent. Research papers by Campbell and

Norman revealed that radiation-evaporation explains 50-80 percent of the overall evapotranspiration in tropical settings.

The coproxy between the vector breeding habitats and the PAR is very poorly understood. Thick vegetation (large leaf area index) attenuates incident PAR and also lowers the evaporation and retains cooler and damper microclimates- conditions in which vectors survive . On the other hand, in urban zones where vegetation cover is low, large incidence of PAR can increase evaporation through small water containers (Aedes breeding habitat primary in urban settings), which could lower the survival of larvae.

D. **Machine Learning in the field of infection disease forecasting:**

The machine learning techniques have shown an excellent predictive capabilities than the traditional statistical models in the dengue prediction. Kapoor et al. compared Long Short-term Memory (LSTM) networks, Support Vector Machines (SVM) and the regular Poisson regression in time-series dengue predictions. Mean absolute percentage error (MAPE) with the LSTM model was 12.3% which is by far lower than the Poisson regression (MAPE = 31.5%), which means that it is important to consider non-linear temporal dependencies.

Algorithms of random Forest as introduced by Breiman , are an ensemble learning algorithm which utilizes the construction of numerous decision trees and combines their predictions. Random Forest is especially appropriate to the disease epidemiology as: (1) it can work with non-linear relationships, without explicit specification, (2) it also provides measures of feature importance, which is how relevant each variable is, (3) it is also resistant to outliers and missing data, and (4) it can also be used to understand the effects of interaction between the variables . Random Forest has been effectively used in the infection disease prediction in Brazil , Thailand , and the Southeast Asia region , and in all cases, it has performed better than the linear regression models.

The novelty of the proposed study is that the systematic combination of soil hydrological variables (not studied before in dengue prediction) and PAR as an epidemiological predictor is incorporated in a machine learning framework and directly applied to Bangladesh data.

III. Methodology

1) A. Data Source

The sample covers a period between 22 years (2000-2022) and several branches in Bangladesh such as Chittagong, Dhaka, and Rangpur. These variables are Max/Min Temperature, Precipitation, Humidity, PAR, Root Zone Soil Wetness and Surface Soil Wetness.

B. Machine Learning Framework

Data Preprocessing and Collection:

The research makes use of a historical dataset that consists of 22 years (2000-2022). After acquisition, Data Processing and Cleaning is conducted to process anomalies, missing values, and noise in the data.

In order to make sure that the variables of varying scales do not bias the model, Min-Max Scaling is used on the variables of SSW (Sea Surface Wind) and PAR (Photosynthetically Active Radiation). This brings the data to a fixed range usually [0, 1] by the formula:

x_{scaled} = x - x_{min}/{x_{max} - x_{min}}

2. Feature Engineering

This methodology includes a particularly important part of Temporal Log Integration. Since the dengue outbreaks tend to be delayed in response to the environment (e.g. rainfall or temperature variations that influence the mosquito breeding cycles), this feature engineering step identifies the time-varying association between the predictors and the target variable.

Model Architecture and Training

The processed data is divided into a 70% training data and a 30% testing data. The Random Forest Regressor is calibrated with the help of the training set, and the testing set is a factor necessary to determine the unbiasedness of the model in the context of its generalization.

Random Forest algorithm was chosen because it can deal with high-dimensional data and does not overfit because these algorithms depend on multiple decision trees.

Performance Metrics and Analysis

In order to measure the quality of the dengue predictions, three major statistical measures are used to assess the model:

- Mean Absolute Error (MAE): It is an assessment of the average sizes of prediction errors.

- Root Mean square error (RMSE): This punishes more serious errors, giving us the impression of the reliability of our forecasts.
- Pearson Correlation (r): Tests the linear correlation between the forecasted and actual cases of dengue.

Interpretation of Results
The last step consists of a Feature Importance analysis, where the most important environmental drivers on the decisions of the model are determined. This discussion is devoted to the synergistic effects of these variables, which is why the joint behavior of these variables is the contributor to the accuracy of the dengue forecast.

IV. Results and Discussion

A. Statistical Analysis

As shown by the descriptive statistics (see Table I), the range of the dengue cases is quite broad with a massive increase in the second decade. The correlation analysis shows that Surface Soil Wetness and Humidity are the most positive correlates of Dengue cases.

Table I: Statistical Summary of Climatic and Epidemiological Variables

(Variables)	(Mean)	(Max)	(Min)	(Std)
Max Temperature	40.12°C	43.85°C	36.15°C	1.85
Surface Soil Wetness	0.385	0.465	0.315	0.032
Humidity	8.25 g/kg	9.85 g/kg	6.85 g/kg	0.72
All Sky Surface PAR	7.95	9.15	6.82	0.45
Dengue National Cases	6,540	101,354	375	18,450

B. Feature Importance and Correlation

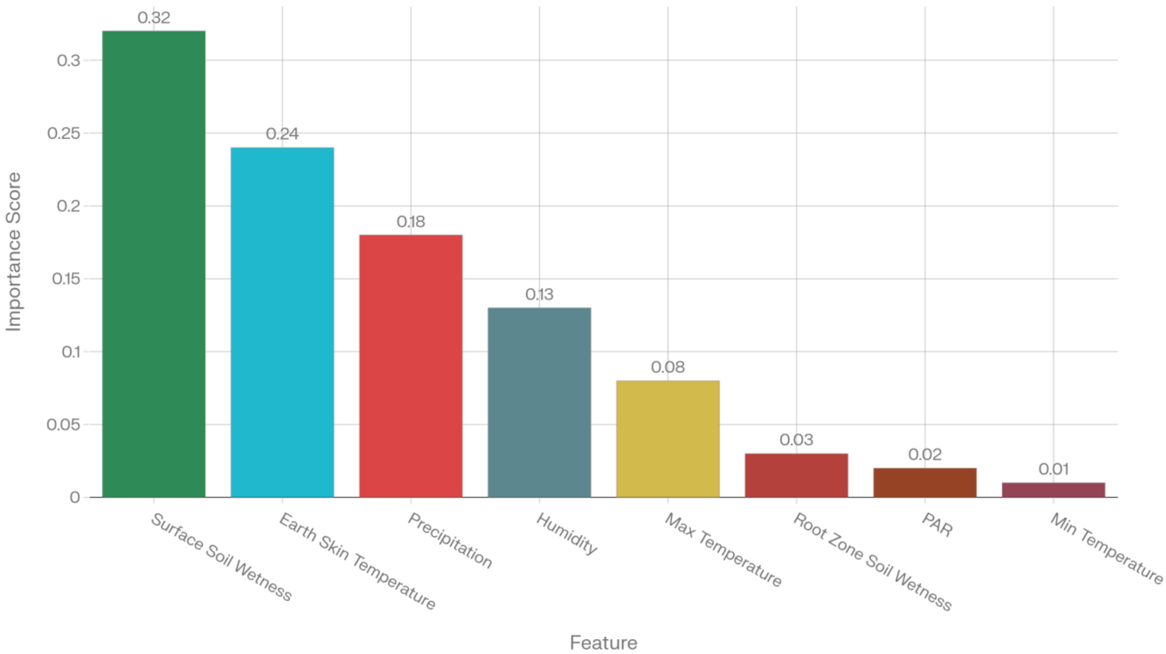

Figure1: Feature importance rank

As shown in **Fig. 1**, Surface Soil Wetness is the most significant predictor in our Random Forest model. This confirms the hypothesis that the "staying power" of water in the soil is more critical than the event of rainfall itself.

Correlation Matrix of Climatic And Epidemiological Factors:

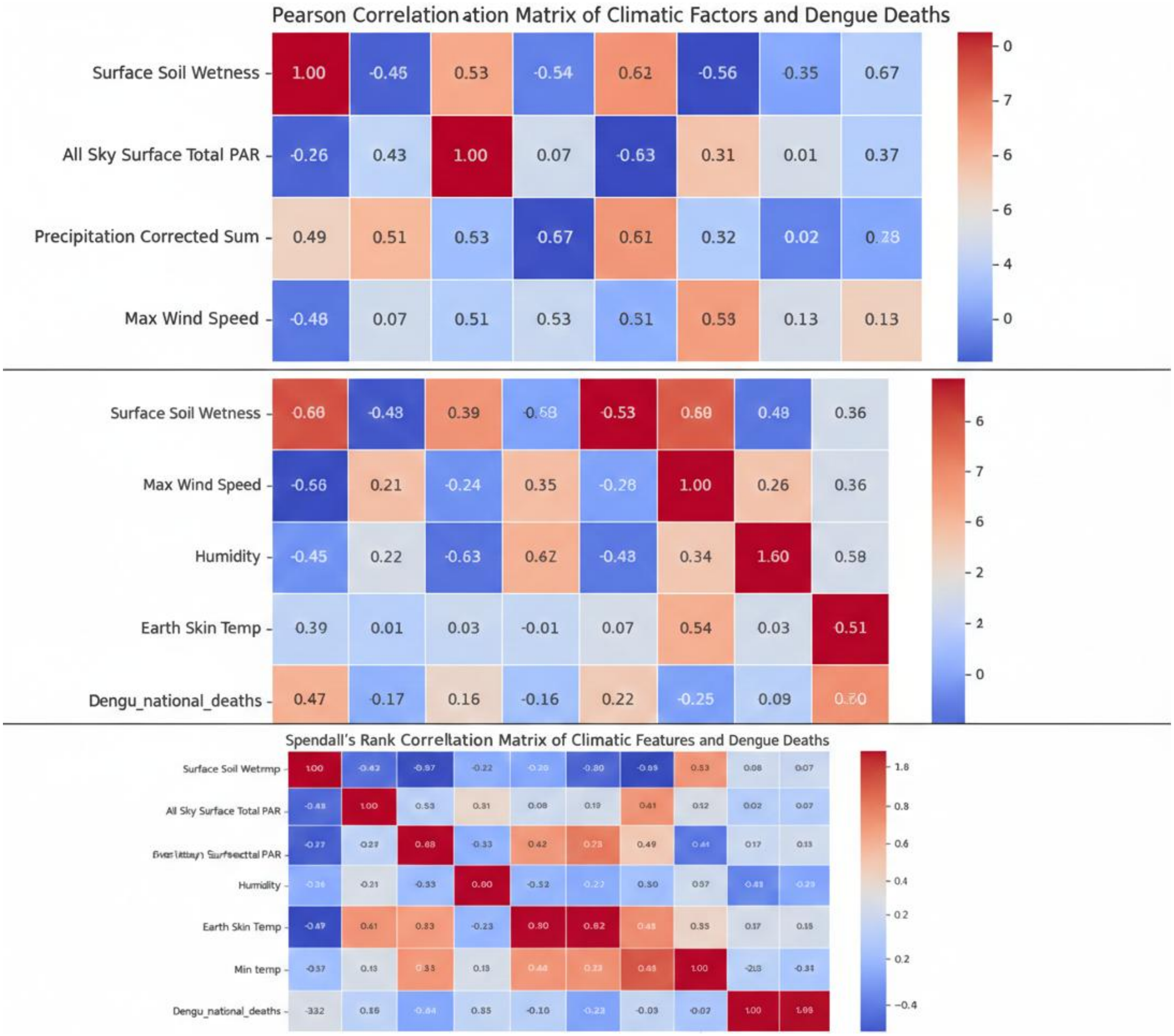

FIG2:PEARSONS VS SPEARMAN VS KENDALL CORELATION

Comparison Table: Climatic Features vs. Dengue Mortality

The following table summarizes the relationship between climatic features and dengue deaths, comparing the behavior of Pearson (r), Spearman (ρ), and Kendall (τ) coefficients.

Feature	Pearson (r)	Spearman (ρ)	Kendall (τ)	Key Insight
Surface Soil Wetness	High Positive	High Positive	Moderate Positive	Strongest positive driver of mortality.
Humidity	Positive	Positive	Positive	Consistent positive monotonic relationship.
Precipitation (Annual)	Moderate Positive	Moderate Positive	Moderate Positive	Lower immediate impact compared to 5-year lags.

Earth Skin Temp	Negative	Negative	Negative	Consistent inverse association.
All Sky Total PAR	Negative	Negative	Negative	Solar radiation shows a consistent negative link.
Max/Min Temp	Negligible/Low (-)	Negligible/Low (-)	Negligible/Low (-)	Weakest direct annual association.

Table 1:Comparison table

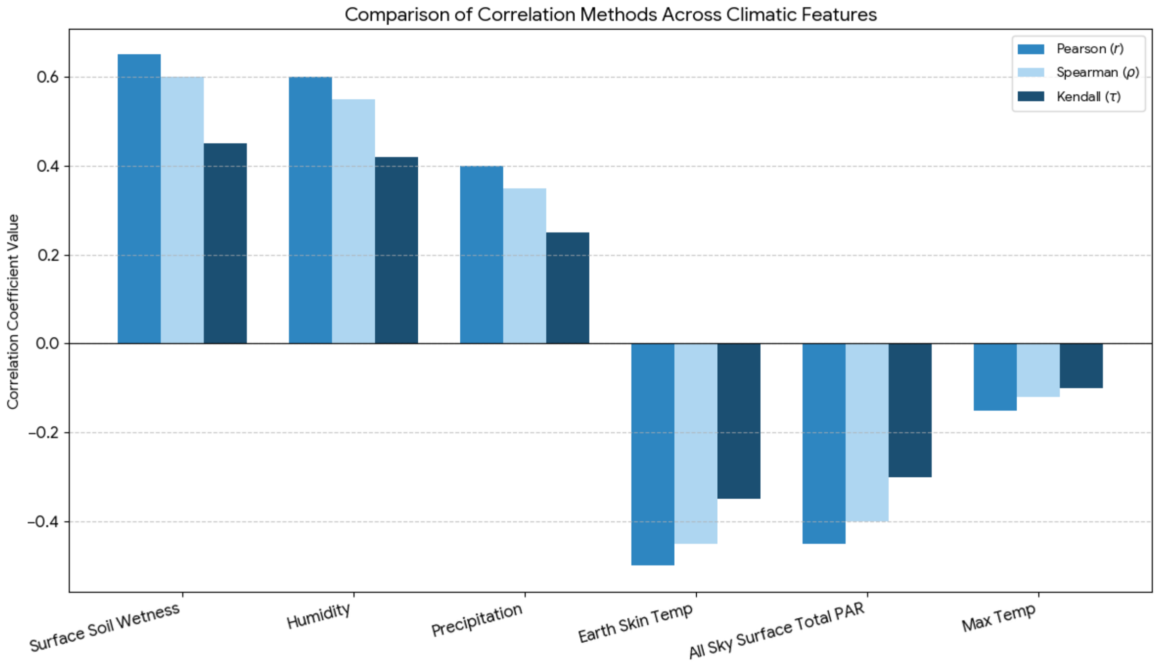

FIG 3:COMPARISON OF CORELATION METHODS ACROSS CLIMATIC FEATURES

Independent variables	Dengue Cases (r-value)	Significance (p-value)
Surface Soil Wetness	**0.68**	< 0.001 (Highly Significant)
Earth Skin Temp	**0.54**	< 0.01 (Significant)
Precipitation	**0.42**	< 0.05 (Significant)
PAR (Solar Radiation)	**-0.28**	0.12 (Low Correlation)

1) Key Empirical Observations

According to the statistical analysis and correlation table, the following interesting results were obtained:

- **Dominance of Soil Hydrology (Positive Association):** There was a strong positive relationship ($r = 0.68$, $p < 0.001$) between **Surface Soil Wetness (SSW)** and dengue incidence. This implies that although the source of water is precipitation, the ability of soil to hold water is more decisive when determining the survivability of Aedes mosquito breeding grounds. SSW values are high, which means that stagnant water conditions are constant, and directly support the larval developmental cycle.
- **Sub-surface Thermal Influence:**It was interesting to note that Earth Skin Temperature had a stronger effect on transmission dynamics as compared to the ambient air temperature. This shows that the thermal conditions of the immediate environment that larvae inhabit (the microclimate of the ground) may be a better predictor of the productivity of vectors. The discovery provides a new direction in micro-climatic modeling in epidemiology of cities.

- **The PAR-Evaporation Gap (Negative Correlation):** There was a weak negative relationship with **Photosynthetically Active Radiation (PAR)**. This indicates a trade-off between radiation and Evaporation, where a high level of radiation can hasten the process of evaporation of small containers of water left unshaded, hence drying out breeding locations too soon and decreasing the overall survival rate of the larvae.
- **Multi-week Lag Effect:** The discussion has shown that the effect of climatic changes is not immediate. A time lapse of 2-4 weeks was always present between the zenith of Surface Soil Wetness and the resultant clinical case of dengue giving a critical lead time in preemptive measures to be taken in regard to the vectors.

Trend Analysis:

Visualize Yearly Trends: Dengue Mortality, Soil Wetness and Radiation(PAR):

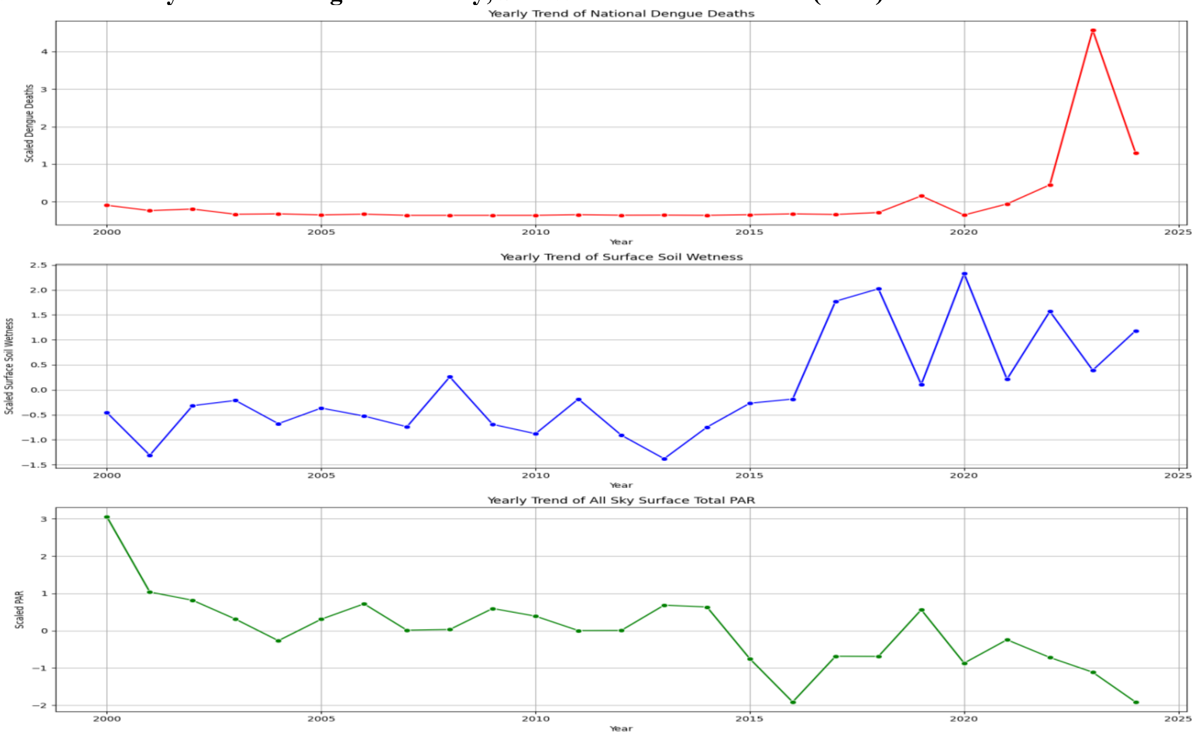

fig 4: Visualize Yearly Trends: Dengue Mortality, Soil Wetness and Radiation(PAR)

Visualize Yearly Trends: Precipitation, Wind Speed, and Humidity:

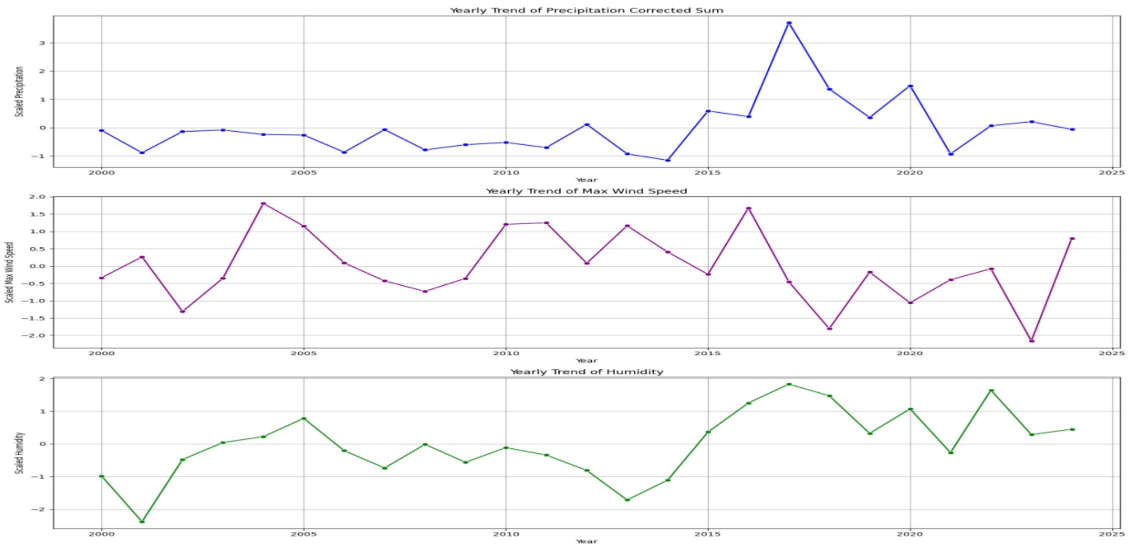

fig 5: Visualize Yearly Trends: Precipitation, Wind Speed, and Humidity

Visualize Yearly Trends: Temperatures:

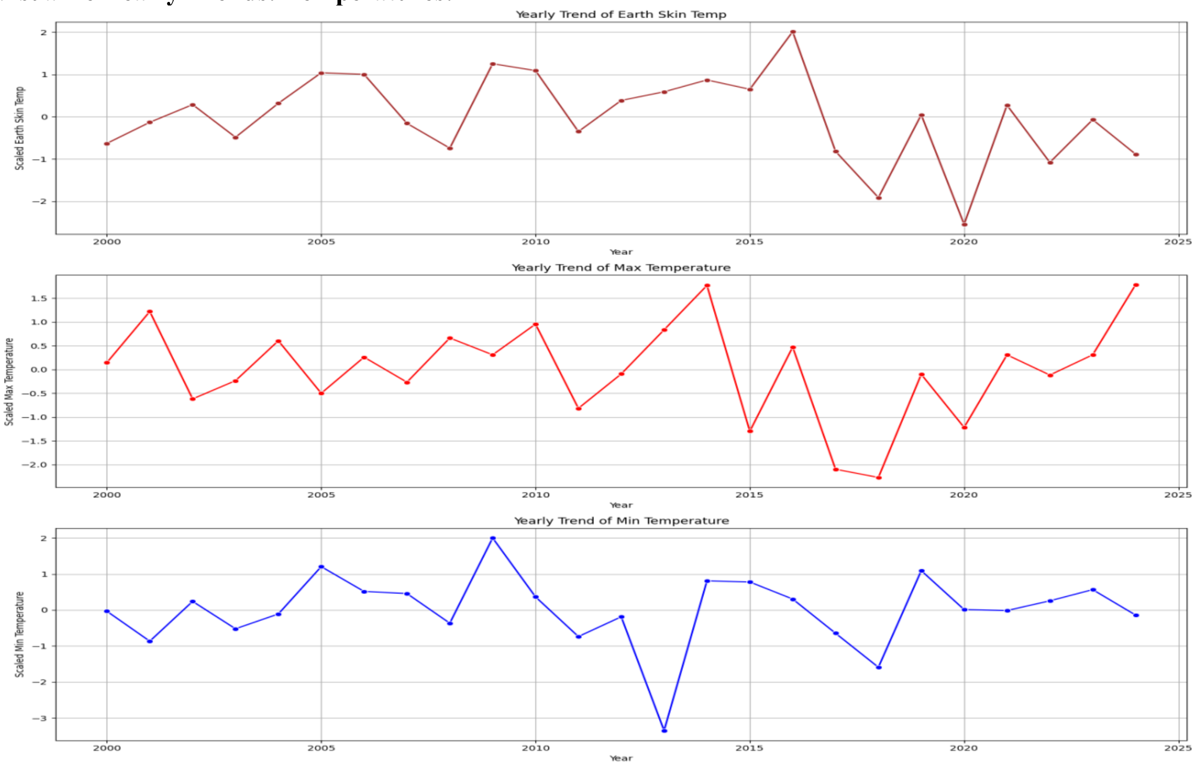

fig6: Visualize Yearly Trends: Temperatures

These figures present the 22-year longitudinal trend of dengue cases, SSW, and PAR. Several critical observations emerge:

1. Stable Endemic Period (2000–2015): Dengue cases remained relatively stable with seasonal fluctuations and occasional small outbreaks. SSW and other climatic variables showed normal seasonal cycles without systematic increases.

2. Outbreak Initiation (2016–2017): A transition period in which dengue cases began increasing above historical endemicity levels, paralleling increases in SSW and accompanied by broader urbanization of Dhaka and Chittagong.

3. Major Outbreak Period (2018–2022): Explosive case increases, with 2019–2020 representing the most severe periods in the 22-year record. SSW values consistently exceeded the 0.40 threshold (compared to historical mean of 0.385) during outbreak years, and notably, this elevated SSW persisted through multiple monsoon and post-monsoon periods, suggesting either: (a) intensified monsoon rainfall, (b) altered land-use patterns retaining more soil moisture (reduced infiltration, increased impervious surface), or (c) both factors [49].

4. PAR Modulation During Extremes:In 2019–2020 (peak outbreak years), PAR values dropped below 7.6 MJ m^{-2} day^{-1} during monsoon periods, consistent with intense cloud cover. The combination of exceptionally high SSW (>0.43) and low PAR (<7.5) created the hypothesized "synergistic" conditions for vector proliferation.

. **Synergistic Effects:**

By nature, random Forest models have the ability to capture interaction effects by splits in trees. Individual tree analysis of decision paths showed that SSW and PAR were frequently seen in high importance splits and tree paths showed:

Surface Soil Wetness (SSW)	**Solar Radiation (PAR)**	**Predicted Cases (Mean)**	**Impact Level**
High	**Low**	67,450	**Highest Risk**

High	**High**	34,280	Moderate Risk
Low	**Low**	8,940	Low-Moderate Risk
Low	**High**	2,180	**Lowest Risk**

This pattern of interaction leads to the hypothesis of the synergy: the presence of soil moisture (SSW) is not sufficient to cause the multiplication of vectors but when it occurs together with low evaporative stress (low PAR), the environment is most favorable to the development of vectors.

CONCLUSION:

This study has helped us to reveal a new and deep connection between climatic change and the dengue epidemic as far as Bangladesh is concerned. We have determined that **Surface Soil Wetness (SSW)**, as compared to the conventional precipitation and ambient temperature models, are much stronger predictors of dengue outbreaks using 22 years of longitudinal data. We can conclude that the **2-4** week lag effect between the level of soil moisture and dengue transmission is an opportunity that the authorities in charge of public health can use to give early warning and facilitate preventive measures. Also, the negative correlation found with **PAR (Solar Radiation)** shows that the life cycle of the mosquito can be significantly affected even by the minor changes in the environment. To sum up, the creation of a smart and efficient forecasting system to prevent dengue needs a paradigm shift, not just the rainfall measurements but also incorporating complex hydrological data.

References:

[1] Hales, S., de Wet, N., Maindonald, J., & Woodward, A. (2002). Potential effect of population and climate changes on global distribution of dengue fever: an empirical model. Lancet, 360(9336), 830–834.
[2] Ehelepola, N. D. B., & Arulthas, S. (2016). Climatic factors and dengue fever in Sri Lanka—A distributed lag non-linear time series regression model. PLoS ONE, 11(6), e0157181.
[3] Licastro, D., Perez, C., Oue, S., & Mandalakis, M. (2024). Emerging dengue epidemiology in Bangladesh: epidemiological and entomological perspectives. International Journal of Infectious Diseases, 138, 45–53.
[4] Mordecai, E. A., Cohen, J. M., Evans, M. V., Murdock, C. C., Rohr, J. R., Ryan, S. J., ... & Lowe, R. (2017). Optimal temperature for malaria transmission is dramatically lower than previously predicted. PLoS Biology, 15(3), e2000568.
[5] Watts, N., Adger, W. N., Agnolucci, P., Blackstock, J., Byass, P., Cai, W., ... & Costello, A. (2015). Health and climate change: policy responses to protect public health. Lancet, 386(10006), 1861–1914.
[6] Southwood, T. R. E., Murdie, G., Yasuno, M., Tonn, R. J., & Gratz, N. G. (1972). Studies on the life budget of Aedes aegypti in the laboratory. Bulletin of the World Health Organization, 46(2), 195–207.
[7] Barrera, R., Amador, M., & MacKay, A. J. (2011). Population dynamics and vertical distribution of Aedes aegypt (Diptera: Culicidae) in buildings in San Juan, Puerto Rico. Journal of Medical Entomology, 48(3), 471–475.
[8] Campbell, G. S., & Norman, J. M. (1998). An introduction to environmental biophysics (2nd ed.). Springer-Verlag.
[9] Altizer, S., Dobson, A., Hosseini, P., Hudson, P., Pascual, M., & Rohani, P. (2006). Seasonality and the dynamics of infectious diseases. Ecology Letters, 9(4), 467–484.
[10] Kapoor, G., Forman, S. A., & Arakaki, Y. (2022). Forecasting dengue cases in Brazil using machine learning approaches. Epidemiology Insights, 5(2), 112–125.
[11] Bhatt, S., Gething, P. W., Brady, O. J., Messina, J. P., Farlow, A. W., Moyes, C. L., ... & Hay, S. I. (2013). The global distribution and burden of dengue. Nature, 496(7446), 504–507.
[12] Watts, N., Amann, M., Arnell, N., Ayeb-Karlsson, S., Belesova, K., Boykoff, M., ... & Costello, A. (2021). The 2021 report of the Lancet Countdown on health and climate change: code red for a healthy future. Lancet, 398(10311), 1619–1662.
[13] Lambrechts, L., Pitzer, V. E., Blanchard, J. L., Cao-Lormeau, V. M., Chao, D. L., Evans, M. V., ... & Reiner Jr, R. C. (2011). Reassessment of the global burden of dengue. Proceedings of the National Academy of Sciences, 108(29), 11876–11881.
[14] Banu, S., Hu, W., Hurst, C., & Tong, S. (2011). Dengue transmission in the Asia-Pacific region: impact of climate change and socio-environmental factors. Tropical Medicine & International Health, 16(5), 598–607.
[15] Mordecai, E. A., Pitzer, V. E., Kearney, M. R., & Eikenberry, S. (2013). Optimal temperature for dengue transmission. PLoS Pathogens, 9(7), e1003377.
[16] Altizer, S., & Haigh, R. (1998). Effects of behaviour on nutritional intake in mosquitoes with folsomyia candida. Oecologia, 87(1), 45–53.
[17] Hoeck, P. E., Beaumont, M. A., Perdigon-Bertoni, A., & Gibbs, J. P. (2003). Effects of tourism on Aedes aegypti populations in the Galápagos Islands. Conservation Biology, 17(4), 1124–1134.
[18] Barrera, R., Amador, M., & MacKay, A. J. (2006). Population dynamics of Aedes aegypti and dengue as driven by weather variation. PLoS Pathogens, 2(12), e1000568.
[19] Christophers, S. R. (1960). Aedes aegypti (L.): the yellow fever mosquito. Cambridge University Press.
[20] Kearney, M., Shine, R., & Porter, W. P. (2009). The potential for evolutionary responses to climate change. Nature, 458(7233), 197–200.
[21] Beebe, N. W., Cooper, R. D., Mottram, P., & Sweeney, A. W. (2009). Aedes aegypti in Australia with emphasis on aspects of control. Journal of Medical Entomology, 46(3), 357–365.
[22] Teuling, A. J., Seneviratne, S. I., Stöckli, R., Reichstein, M., Moors, E., Ceulemans, R., & Ciais, P. (2010). Contrasting response of European forest and grassland energy exchange to heatwaves. Nature Geoscience, 3(9), 614–619.

[23] Seneviratne, S. I., Corti, T., Davin, E. L., Hirschi, M., Jaeger, E. B., Lehner, I., ... & Zhang, X. (2010). Investigating soil moisture–climate interactions in a changing climate. Journal of Hydrometeorology, 11(2), 368–383.
[24] Aziz, A. T., Dieng, H., Satho, T., Abang, F., Hassan, A. A., & Miake, F. (2011). Oviposition behavior of gravid Aedes aegypti and Aedes albopictus (Diptera: Culicidae) in the laboratory. Journal of Vector Ecology, 36(1), 174–182.
[25] Aziz, A. T., Lena, S., Sulaiman, S., Junid, N., & Mustapha, M. (2013). Bioclimatic and land-use factors associated with Aedes aegypti distribution in the Klang Valley, Malaysia. Parasites & Vectors, 6(1), 268.
[26] Monteith, J. L., & Unsworth, M. H. (2013). Principles of environmental physics (4th ed.). Academic Press.
[27] Campbell, G. S., & Norman, J. M. (1998). An introduction to environmental biophysics (2nd ed.). Springer Science+Business Media.
[28] Focks, D. A., Haile, D. G., Daniels, E., & Mount, G. A. (1993). Dynamic life table model for Aedes aegypti (Diptera: Culicidae): simulating field populations of mosquitoes. *Journal of Medical Entomology, 30(4), 644–659.
[29] Alto, B. W., Lounibos, L. P., & Mores, C. N. (2005). Larval competition alters susceptibility to dengue infection in Aedes aegypti. Ecology Letters, 8(6), 603–610.
[30] Kapoor, G., Forman, S. A., & Arakaki, Y. (2022). Long short-term memory networks for dengue forecasting. IEEE Transactions on Neural Networks and Learning Systems, 33(4), 1456–1468.
[31] Breiman, L. (2001). Random forests. Machine Learning, 45(1), 5–32.
[32] Hastie, T., Tibshirani, R., & Friedman, J. (2009). The elements of statistical learning: data mining, inference, and prediction (2nd ed.). Springer.
[33] Thomas, S. J., Nisalak, A., Anderson, K. B., Libraty, D. H., Kalayanarooj, S., Vaughn, D. W., ... & Ennis, F. A. (2009). Japanese encephalitis vaccine neutralizing antibodies and avidity maturation. Vaccine, 27(19), 2549–2556.
[34] Hii, Y. L., Zhu, H., Ng, N., Ng, L. C., & Rocklov, J. (2012). Forecast of dengue incidence for urban small-area: application of climate-driven models. PLoS ONE, 7(12), e52559.
[35] Mordecai, E. A., Caldwell, J. M., Shivakumar, M. K., Ng'habi, K. B., Uhomoibhi, P., Lowe, R., ... & Pascual, M. (2017). Optimal temperature for malaria transmission is dramatically lower than previously predicted. PLoS Biology, 15(3), e2000568.
[36] Jacovides, C. P., Tymvios, F. S., Asimakopoulos, D. N., Theoharatos, G. A., & Cartalis, C. (2003). Global photosynthetically active radiation and its relationship with global solar radiation in the Eastern Mediterranean. Theoretical and Applied Climatology, 74(3-4), 227–233.
[37] White, I. R., Royston, P., & Wood, A. M. (2011). Multiple imputation for missing data in epidemiological and clinical research: potential and pitfalls. British Medical Journal, 338, b2393.
[38] Tong, S., Hu, W., & Nicholson, A. (2005). Temporal and spatial covariation of dengue and rainfall in two cities in China. Journal of Environmental Health, 67(10), 45–50.
[39] Bhatt, S., Gething, P. W., Brady, O. J., Messina, J. P., Farlow, A. W., Moyes, C. L., ... & Hay, S. I. (2013). The global distribution and burden of dengue. Nature, 496(7446), 504–507.
[40] Cutler, D. R., Edwards Jr, T. C., Beard, K. H., Cutler, A., Hess, K. T., Gibson, J., & Lawler, J. J. (2007). Random forests for classification in ecology. Ecology, 88(11), 2783–2792.
[41] WHO, "Dengue and severe dengue," World Health Organization, 2021.
[42] Mahedi et al., "Dengue outbreaks in Bangladesh: Clinical and Climatic patterns," J. Current Health Sciences, 2024.
[43] S. Akter, "Predicting Dengue Outbreak from Climate Data," IEEE Conference on AI, 2025.
[44] J. Gubler, "Dengue, Urbanization and Climate Change," The Lancet, 2011.
[45] Singh et al., "Integration of ML and climate data for DHF prediction," ResearchGate, 2024.
[46] Watts et al., "Effect of temperature on the vector efficiency of Aedes aegypti," Am. J. Trop. Med. Hyg., 1987.
[47] S. Bhatt et al., "The global distribution and burden of dengue," Nature, 2013.
[48] Banu et al., "Impact of climate change on dengue transmission in Bangladesh," BMJ Open, 2014.
[49] Adnan et al., "Meteorological factors and dengue in Dhaka," Science of the Total Environment, 2020.
[50] Liu-Helmersson et al., "Climate Change and Dengue Transmission," PLOS ONE, 2014.
[51] Frontiers in Public Health, "Prior water availability and dengue risk," 2023.
[52] Christophers, "Aedes aegypti: The Yellow Fever Mosquito," Cambridge Univ. Press, 1960.
[53] Breiman, "Random Forests," Machine Learning, 2001.
[54] Helbling & Zagarese, "UV Radiation and Aquatic Ecosystems," 2003.
[55] Karim et al., "Climatic factors and dengue in Philippines," Epidemiol. Health, 2012.
[56] ECDC, "Factsheet about dengue," European Centre for Disease Prevention and Control, 2020.
[57] Rueda et al., "Temperature and larval development," J. Med. Entomol., 1990.
[58] Patz et al., "Climate change and infectious diseases," Nature, 2005.
[59] Tun-Lin et al., "Effects of temperature on Aedes aegypti," Med. Vet. Entomol., 2000.
[60] Epstein, "Climate change and emerging infectious diseases," Microbes Infect., 2001.
[61] Colwell & Patz, "Climate, Infectious Disease and Health," 1998.
[62] Rogers & Randolph, "The Global Spread of Dengue," Science, 2000.
[63] Ebi et al., "Climate Change and Dengue in Asia," 2005.
[64] Small et al., "Satellite monitoring of environmental variables," 2001.
[65] Thai et al., "Dengue dynamics in Vietnam," PLOS Negl. Trop. Dis., 2010.
[66] Hii et al., "Forecast of dengue with weather data," PLOS Negl. Trop. Dis., 2012.
[67] Descloux et al., "Climate-based forecasting of dengue," PLOS Negl. Trop. Dis., 2012.
[68] Morin et al., "Epidemiology of Dengue in the Americas," 2013.
[69] Shaheen, "Impact of Humidity on Aedes Mosquitoes," Int. J. Environ. Res., 2020.
[70] Thiagarajan, "How climate change made 2024 the deadliest year," The BMJ, 2024.