

# Impact of climatic factors on acute bloody diarrhea, dengue and influenza-like illness incidences in the Philippines

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**Abstract.** The effect of climate variability on the weekly incidence of acute bloody diarrhea, dengue and influenza-like illness in the 17 regions of the Philippines is examined using correlation, mutual information and transfer entropy. Results show that the correlations between climate variables and disease incidences differ from one region to another. Interestingly, the diseases are directly correlated to each other for each region. This is explained by their common driving climate factors which are shown by large transfer entropy values. This work is important in further understanding the role of climate variability to the temporal dynamics of disease incidences.

**Keywords.** Time series analysis; Statistics; Information theory

## 1 Climate Change and Human Health

Climate change affects human health. Several endemic human diseases are linked to climate variability from cardiovascular and respiratory disease fluctuations influenced by heatwaves, transmission of communicable diseases by adaptation of vectors, to malnutrition caused by crop shortage [7, 8]. Philippines is the third most disaster-prone nation in the world. It is susceptible to many environmental upshots due to active volcanoes, rich biodiversity and regular typhoon occurrences [9]. It is therefore important to examine the effects of climate variability on health. Evidence and expectancy of the harmful effects will improve preemptive policies and adaptive solutions [3].

This work investigates the impact of climate variables on acute bloody diarrhea, dengue and influenza-like illness in the 17 regions of the Philippines using time series analysis. Statistical and information theoretic measures known as correlation, mutual information and transfer entropy are used to determine important relationships between the climate variables and disease incidences.

## 2 Methodology

The National Epidemiology Center (NEC) of the Philippines [5] provided the number of reported cases of acute bloody diarrhea, dengue and influenza-like illness from January 1, 2012 to May 4, 2013. The climate variables include average, maximum and minimum air temperature, diurnal temperature range ( $^{\circ}\text{C}$ ), relative humidity (%), dew or frost point temperature ( $^{\circ}\text{C}$ ), rainfall (mm/day) and wind speed (m/s). These daily data, obtained from National Aeronautics and Space Administration Prediction of Worldwide Energy Resource (NASA POWER) [4], are converted to mean weekly time series to be consistent with the frequency of the disease data.

Three techniques in time series analysis are applied to evaluate the impact of climate variables on the disease incidences. For two time series  $X$  and  $Y$  with measured observations  $X = \{x_1, x_2, \dots, x_N\}$  and  $Y = \{y_1, y_2, \dots, y_N\}$ , respectively, the correlation coefficient  $r$  or Pearson's  $r$  determines the extent of how  $X$  and  $Y$  follow each other's path through time [1]. It is a measure of linear association but does not immediately imply causality [10]. Moreover, mutual information measures the similarity between the pair of time series by measuring the amount of information common to them. Unlike Pearson's  $r$ , mutual information can detect nonlinear dependencies. It is mathematically expressed as

$$I(X, Y) = \sum_i p_{X,Y}(x_i, y_i) \log \left( \frac{p_{X,Y}(x_i, y_i)}{p_X(x_i)p_Y(y_i)} \right) \quad (1)$$

where  $p_{X,Y}(x, y)$  is the joint probability distribution of  $X$  and  $Y$  and  $p_X(x)$  and  $p_Y(y)$  are the corresponding marginal probabilities [1]. Finally, transfer entropy determines the magnitude and directionality of information exchange between  $Y$  and  $X$ . Such tool is non-symmetric under information exchange which makes it capable to quantify the influence of  $Y$  on the evolution of  $X$  [2]. It is given by

$$T_{Y \rightarrow X} = \sum_k p(x_{k+1}, x_k, y_k) \log_2 \frac{p(x_{k+1} | x_k, y_k)}{p(x_{k+1} | x_k)} \quad (2)$$

where  $p(x|y)$  are conditional probabilities. It can determine whether two systems are similar because another system influences the first two. [1].

## 3 Results and Discussion

Figure 1 presents the regional map of the Philippines and the spatial distribution of the mean weekly number of the diseases in the country. On the average, there were 46 reported acute bloody diarrhea cases, 83 dengue cases and 7 influenza-like illness cases nationwide every week from January 1, 2012 to May 4, 2013. Region III (Central Luzon) has the lowest mean number of acute bloody diarrhea cases which suggests that it is the least vulnerable region to the said disease. On the other hand, Region II (Cagayan Valley) has the highest mean number of cases. Region X (Northern Mindanao) and Region IX (Zamboanga Peninsula) are the least and most vulnerable regions to dengue, respectively. Furthermore, Region III is the least vulnerable to influenza-like illness while CAR (Cordillera Administrative Region) is the most vulnerable.

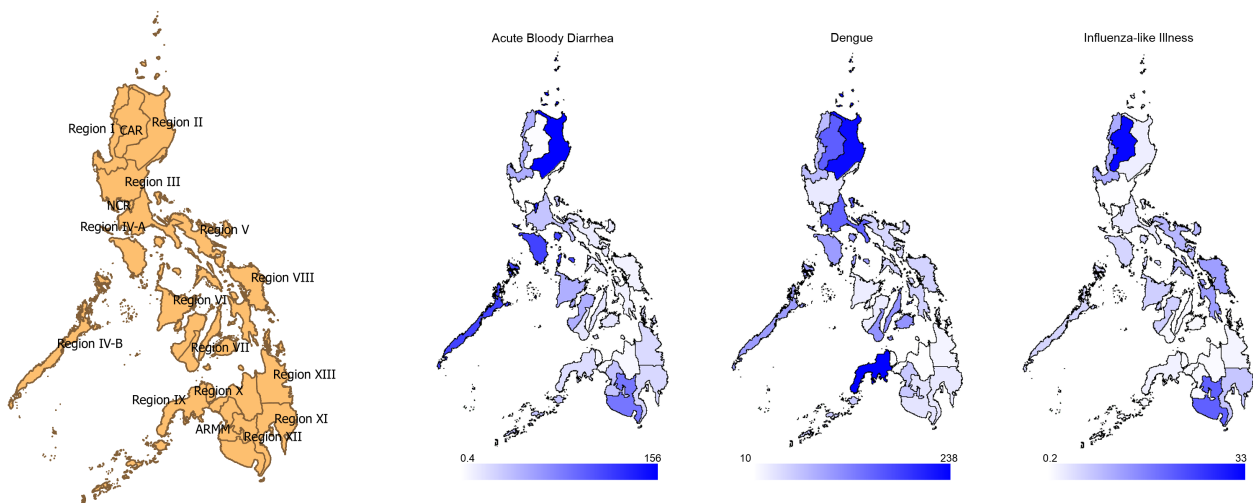


Figure 1: Regional map (orange) of the Philippines and mean weekly number of acute bloody diarrhea, dengue and influenza-like illness reported cases (blue) in the country.

Figure 2 summarizes the temporal associations between the diseases and climate variables in Region I by presenting the correlation, mutual information and transfer entropy values between the datasets. Correlation is significant when  $|r| > 0.2352$  by two-tailed student's t-test at 0.05 level of significance [6, 10]. From Figure 2a, dengue is inversely correlated to maximum temperature and changes in temperature and is directly correlated to humidity, dew or frost point temperature and rainfall fluctuations in Region I. It can also be observed from Figure 2b that acute bloody diarrhea is not mutually dependent to any climate variable. On the other hand, dengue, influenza-like illness and all the climate variables are mutually dependent despite the fact that majority of these relationships are not detected by linear correlation.

Information transfer patterns by transfer entropy imply that acute bloody diarrhea, although not correlated with any climate variable, together with dengue are driven by changes in temperature as shown by their large transfer entropy values. It can also be observed that there are significant linear correlations between the three diseases. Detected correlations can therefore be explained by their common driving elements.

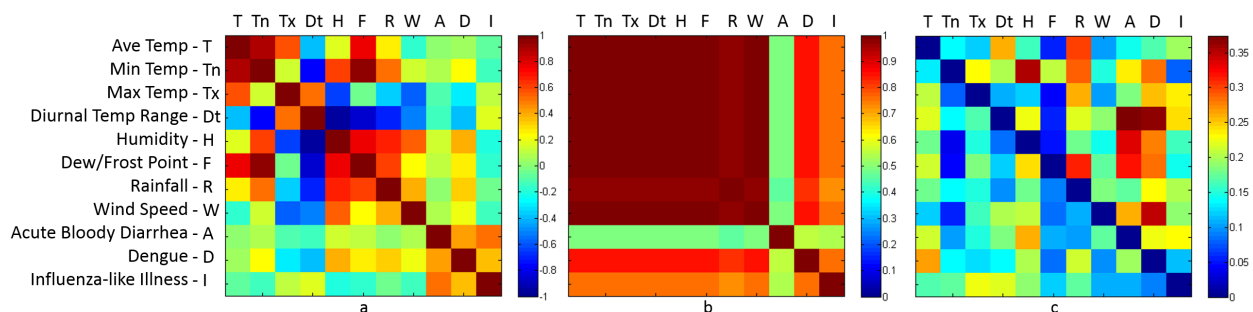


Figure 2: (a) Correlation, (b) mutual information and (c) transfer entropy between the climate variable and diseases in Region 1 (Ilocos Region).

The corresponding correlation, mutual information and transfer entropy plots of the remaining 16 regions were also generated. In general, the three diseases are directly correlated to each other for each region. The linear and nonlinear associations can be explained by the common driving climate variables. Moreover, the relationships between the diseases and climate variables differ from one region to another. Such dissimilarities can be accounted for the differences in geography, population and other features of the regions of the Philippines.

## 4 Conclusion

The extent of the effects of climate variables on the incidence of acute bloody diarrhea, dengue and influenza-like illness vary from one region to another as manifested by the calculated correlation, mutual information and transfer entropy values. However, linear correlations between the diseases are consistently observed for each region. The dissimilarities can be accounted for the disparate geography, population and other attributes of each region. The linear and nonlinear associations, on the other hand, can be explained by the common driving climate variables. Improving the length and the resolution of the datasets could reveal more information about the relationship between the diseases and climate variables. This work is important in further understanding the role of climate variability to the temporal dynamics of disease incidences. It can be used to mitigate disease outbreaks and to employ practical solutions to climate-related health problems.

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