The Use of Spaceborne and Oceanic Sensors to Model Dengue Incidence in the Outbreak Surveillance System

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Abstract. This research focuses on the development of a computational data-driven modeling method to be used in the dengue outbreak surveillance system. The outbreak-level forecasting is based on the estimation of dengue fever cases in Thailand using both statistical and data mining techniques. Major statistical techniques used in this research are linear regression and generalized linear model. The data mining algorithms used in our study are chi-squared automatic interaction detection (CHAID), classification and regression tree, artificial neural network, and support vector machine. The input data are from four sources, which are remotely sensed indices from the NOAA satellite to represent vegetation health and other related weather conditions, rainfall, the oceanic Niño index (ONI) for justifying climate variability affecting amount of rainfall, and historical dengue cases in Thailand to be used as the modeling target. In the modeling process, these data are lagged from 1 up to 24 months to observe time-series effect. On comparing performances of models built from different algorithms, we found that CHAID is the best one yielding the least error on estimating dengue cases. From the CHAID models to forecast dengue cases in Bangkok metropolitan and Nakhon Ratchasima in the northeast of Thailand, the high level of ONI is the most important factor. The large amount of rainfall is significant factor contributing to dengue outbreak in Chiang Mai in the north and Songkhla in the south.

Keywords: Dengue outbreak surveillance system · Incidence modeling · Remote sensing · Oceanic index · Chi-squared automatic interaction detection · CHAID

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1 Introduction

Dengue is the viral infectious disease that does not spread directly from people to people, but it transmits to people through the female mosquito in the *Aedes* species. The sign of dengue infection is like the flu illness. The common symptoms are mild fever, severe headache, muscle ache, and join pain [1, 2]. Patients with mild dengue fever can recover within a week under appropriate treatment. For some patients, the infection can develop into a fatal severe dengue, called dengue haemorrhagic fever, that causes severe complications such as plasma leakage, internal bleeding, and organ impairment leading to deadly internal bleeding.

Dengue outbreak is a serious public health problem occurring every year in many tropical countries such as Thailand, Malaysia [3], Singapore [4, 5], Vietnam, and Philippines [6]. Recently, some other areas including Australia [7], Saudi Arabia [8], Central Mexico [9], and southern part of China [10] also reported the dengue epidemic. In Thailand, during the past decade there are almost hundred deadly cases from dengue infection each year [2]. A large number of researchers in public health community have tried to study the epidemic patterns of dengue fever in several regions of Thailand using either ground-based [11, 12] or satellite-based data [13–16].

The dengue outbreak situation in Thailand is in the peak period during the rainy season. Rainfall and some other related factors such as temperature and humidity are thus expected to be the important causes for dengue transmission. But the reported correlation of temperature and humidity to the dengue incidence in Thailand is quite low. On the contrary, rainfall has been concluded as a determinant factor for dengue transmission. The reports from other countries also show the common observation that rainfall is significantly correlated with dengue incidence.

In our previous work [17], we found that some satellite based indices such as vegetation health index can be used to infer the recent rainfall and subsequently employed to estimate the possibility of dengue outbreak. In this research, we thus adopt the satellite indices with other data sources such as climate variability to build a model for estimating the dengue cases across Thailand. The modeling module is to serve as the incidence predictor in our surveillance system to monitor the dengue outbreak event. The input from satellite and oceanic sensors incorporating with historical dengue cases are used to build a predictive model for estimating the number of dengue cases in the outbreak surveillance system.

The intuitive idea of designing a dengue outbreak surveillance system is according to the concern of the World Health Organization (WHO) that currently dengue has become a major intensified epidemic that expands rapidly across more than hundred countries and threatening more than three billion people worldwide [1]. The control and prevention of dengue epidemic is important for countries in tropical region such as Thailand and other ASEAN countries. Prevention through immunization is not an effective strategy because the dengue vaccine is still in an early stage and it needs careful pre-vaccination screening [1]. The main strategy to control the dengue virus transmission is the efficient prevention of adult mosquitoes to lay eggs. For disease control, active monitoring and surveillance of dengue case incidence should also be carried out.

We thus propose the outbreak surveillance system with the modeling process as a core module of the system. Detail of modeling process as well as the data sources of spaceborne and oceanic sensors are explained in Sect. 2. The built model and the model assessment results are shown in Sect. 3. We finally conclude this work in Sect. 4.

2 A Dengue Incidence Modeling Method

2.1 Study Area

In this research, we consider dengue cases across Thailand in the four regions: central, north, northeast, and south. The representative areas for each region are that Bangkok metropolitan in the central part of the country, Chiang Mai province in the north, Nakhon Ratchasima province in the northeast, and Songkhla province in the south. The locations of the four provinces are shown in Fig. 1.

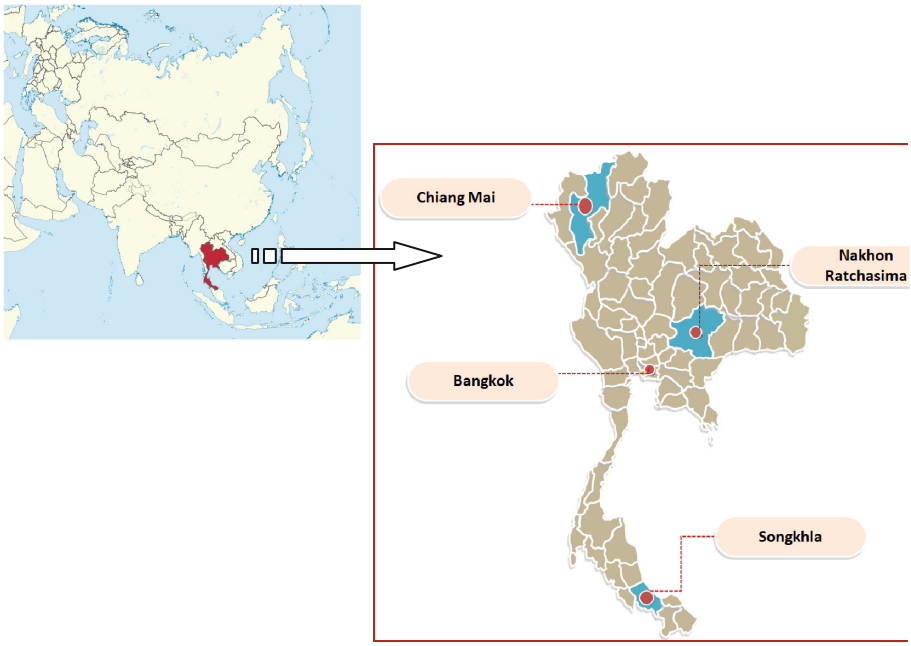


Fig. 1. Areas of study: Chiang Mai in the north, Nakhon Ratchasima in the northeast, Bangkok metropolitan at the central, and Songkhla in the south of Thailand.

Upon visually investigate the coincidence of dengue infection incidence and amount of rainfall in each of the four provinces, we found that the co-occurrence of the two events are subtle as shown by the plots of dengue cases (with dashed line) and rainfall amount (solid line) in Fig. 2. From this preliminary observation, we thus consider adopting other factors to build an accurate model to capture dengue outbreak events. The information used for model building is mainly the indices from remote sensing and the oceanic Nino index computed from the equatorial Pacific sea surface temperature anomaly to capture climate variability.

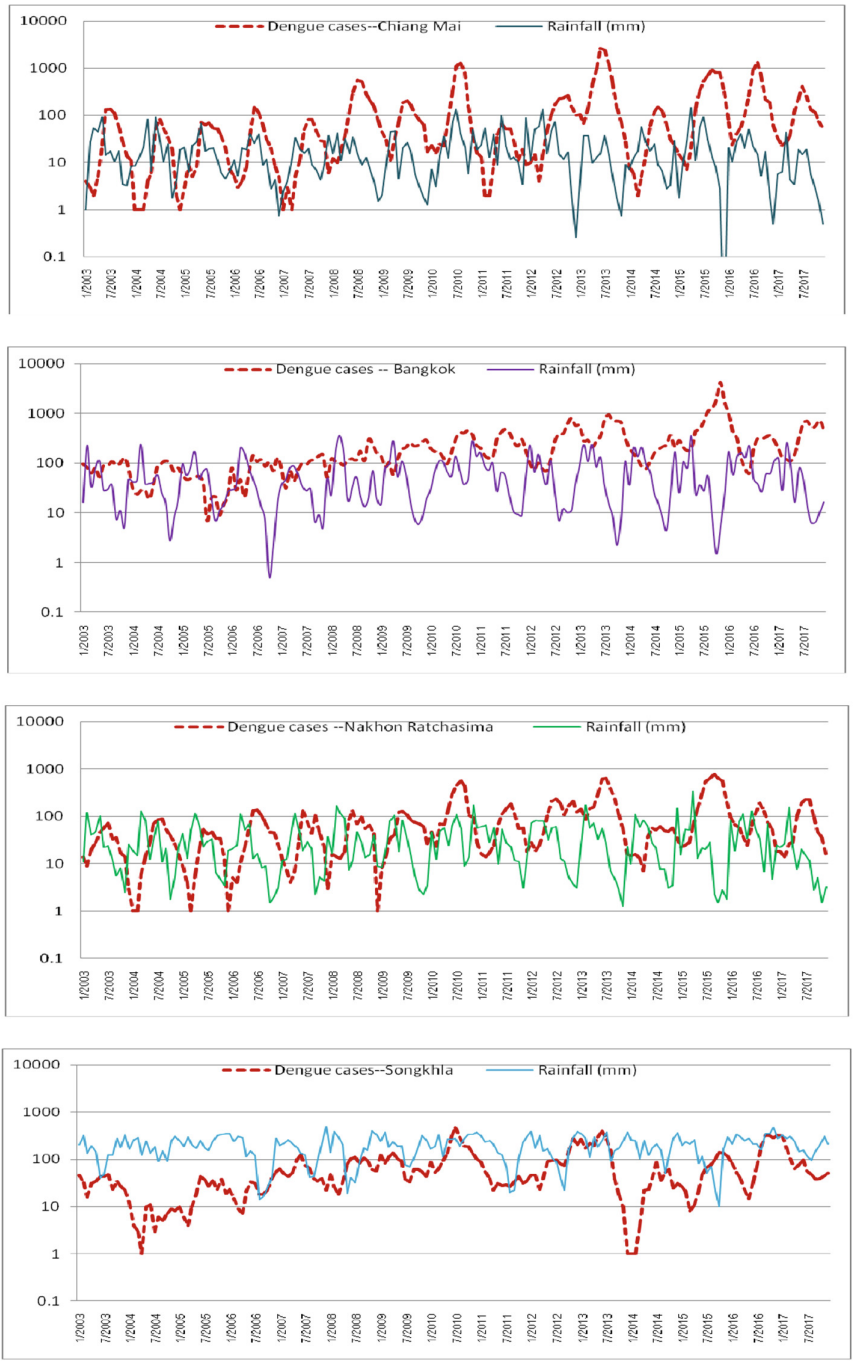


Fig. 2. The plots showing subtle co-occurrence of dengue incidence and amount of rainfall in the four provinces: Chiang Mai, Bangkok, Nakhon Ratchasima, and Songkhla.

2.2 Remote Sensing and Oceanic Nino Index Data

From the preliminary observations that predicting dengue incidences based on rainfall [18] as a sole factor is not accurate enough for planning an efficient outbreak control, we thus consider adopting other factors to build a model for an early warning for the dengue outbreak events. In this work, we use five remote sensing indices that can be a proxy to characterize vegetation greenness [19–21]. These indices are vegetation health index (VHI), smoothed and normalized difference vegetation index (SMN), smoothed brightness temperature index (SMT), vegetation condition index (VCI), and temperature condition index (TCI). These remotely sensed data are made available by the National Oceanic and Atmospheric Administration (NOAA) of the United States [22]. The NOAA satellites are equipped with the advanced very high resolution radiometer (AVHRR) to detect moisture and heat that are radiated from the Earth surface [23, 24]. Several visible and infrared radiated channels are detect from the 4 km spatial resolution and used to compute the indices that are helpful for crop monitoring. The SMN index is used for estimating the greenness of vegetation. SMT is the index to estimate the thermal condition in vegetation. High SMT refers to the dry condition of vegetation. VCI captures the anomaly in vegetation greenness. TCI represents the thermal condition required by plants; the higher TCI, the more favorable condition. VHI is the combined estimation of moisture and thermal conditions appropriate for vegetation; the higher is the better.

Besides the remote sensing indices to reflect rainfall impacts and subsequently the dengue incidences, we also consider the influence of climate variability on the anomaly of rainfall in each region of the country by incorporating Oceanic Nino index (OCI) as another important factor for our model creation process. The ONI is computed [25] from the anomaly of sea surface temperature (SST) at the region called Niño3.4 in the Pacific Ocean at the equator line (5°N–5°S and 170°–120°W), as shown in Fig. 3. The SST is collected each month to compute ONI by averaging from the 3-month periods: the current one, the previous, and the following month. This 3-month average value is then compared to a thirty-year average [26] to check temperature deviation. For instance, to compute ONI of April, the SST anomalies in March, April, and May are to be averaged.

If the ONI values observed in five consecutive months are +0.5 °C or higher than the normal value averaging from the thirty-year period, then the phenomenon called El Niño (the warm event) is announced. On the contrary, if the ONI values in five consecutive periods are –0.5 °C or lower than the normal value, the opposite phenomenon called La Niña (the cold event) is announced. Examples of ONI values are shown in Table 1 with the cold period in bold italic font and the warm in bold.

The El Niño and La Niña are the opposite events of the Pacific climate pattern known as the El Niño-Southern Oscillation, or ENSO. The major side effect of El Niño to the Southeast Asian area is higher temperature and less precipitation than normal, whereas the occurrence of La Niña causes excessive rainfall than usual. Temperature and rain are important factors to the rapid spread of mosquito that causes dengue fever. We thus include ONI as the representative of the ENSO events in our modeling process.

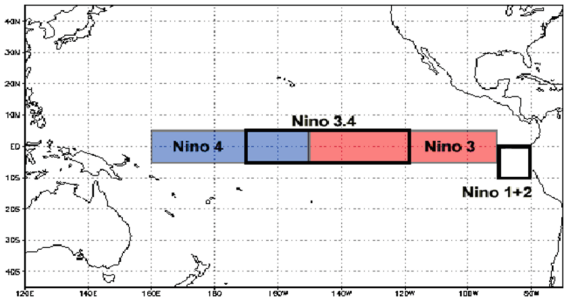


Fig. 3. Location of the Niño3.4 region for measuring sea surface temperature. (source: https://www.ncdc.noaa.gov/teleconnections/enso/indicators/sst/)

Table 1. ONI values during the past five years (2014 to 2018).

	2014	2015	2016	2017	2018
January	–0.4	**0.6**	**2.5**	–0.3	***–0.9***
February	–0.4	**0.6**	**2.2**	–0.1	***–0.8***
March	–0.2	**0.6**	**1.7**	0.1	***–0.6***
April	0.1	**0.8**	**1.0**	0.3	–0.4
May	0.3	**1.0**	**0.5**	0.4	–0.1
June	0.2	**1.2**	0.0	0.4	0.1
July	0.1	**1.5**	–0.3	0.2	0.1
August	0.0	**1.8**	***–0.6***	–0.1	0.2
September	0.2	**2.1**	***–0.7***	–0.4	0.4
October	0.4	**2.4**	***–0.7***	***–0.7***	**0.7**
November	**0.6**	**2.5**	***–0.7***	***–0.9***	**0.9**
December	**0.7**	**2.6**	***–0.6***	***–1.0***	**0.8**

2.3 Modeling Process

The proposed dengue outbreak surveillance system (as shown in Fig. 4) is composed of four main modules: data entry, data exploration, model building, and visualization modules. The focus of this paper is the dengue incidence modeling, which is a core module of our outbreak surveillance system. The steps in data access, extraction, preparation, model induction and evaluation, which are the parts from data entry to model building modules, are graphically illustrated in Fig. 5.

Operational details in model building can be explained as follows. The first step is for data access and extraction. In this work, we use data from four main sources. Three of them are remote sensing indices, rainfall measures, and SST anomaly (or ONI) are from the NOAA websites [18, 22, 25]. The fourth source is from the Bureau of Epidemiology, Thailand [27] that reports dengue cases from all provinces. We collect cases during the years 2003–2017 from the four targeted provinces. These data sources

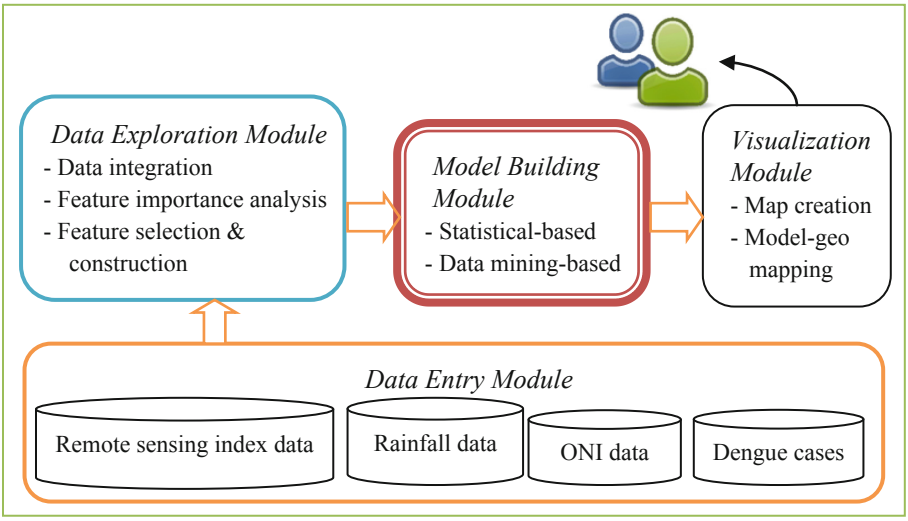


Fig. 4. A framework of dengue outbreak surveillance system.

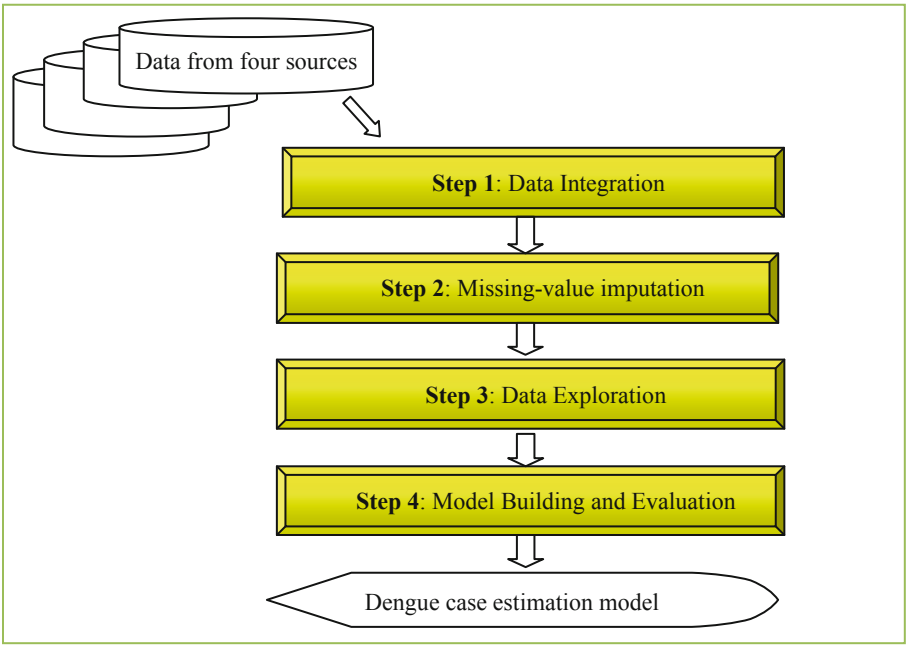
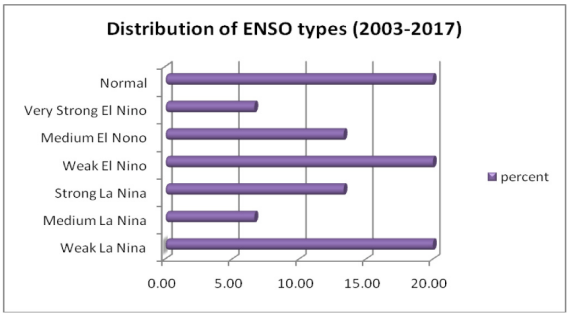


Fig. 5. Proposed model building method to estimate dengue incidences.

provide their open data in various formats and different time-frame units. We thus have to unify the data into a single format using the unique monthly time-frame (step 1 in Fig. 5).

We found that some data records from the satellite sensors are missing. This might be the case from the cloudy condition over Thailand region on those days. We then perform imputation (step 2) with the nearest-neighbor technique. At this step, the numeric ONI values are also categorized into different degrees of intensities in terms of SST anomaly in degree Celsius [28] as shown in Fig. 6.



ENSO events (SST anomaly)

- normal (±0.0°C to ±0.4°C)
- weak El Niño (+0.5°C to +0.9°C)
- medium El Niño (+1.0°C to +1.4°C)
- strong El Niño (+1.5°C to +1.9°C)
- very strong El Niño (≥ +2.0°C)
- weak La Niña (-0.5°C to -0.9°C)
- medium La Niña (-1.0°C to -1.4°C)
- strong La Niña (-1.5°C to -1.9°C)
- very strong La Niña (≥ -2.0°C)

SMN	SMT	VCI	TCI	VHI	Rain	Case	Death
0.035	0.144	0.077	-0376	-0.233	-0.096	0.056	0.030
strong	strong	strong	strong	strong	strong	strong	strong

Fig. 6. Distribution of ENSO types in each category (top) with Pearson correlations (bottom) to other indices and dengue cases and deaths.

Based on our data records, there exist three levels of El Niño (weak, medium, very strong) and three levels of La Niña (weak, medium, strong). The distribution of ENSO events (in percentage) during the years 2003 to 2017 and their correlations to other data attributes are shown in Fig. 6. From the total of 180 months, the normal sea surface temperature, the weak El Niño, and the weak La Niña had occurred also equally at around 20% of the time. In our specific purpose of using ONI as a factor to analyze dengue incidence in Thailand, we found that ONI has strong correlations to other remote sensing indices and positively correlated to dengue cases and number of deaths from severe dengue, as shown at the bottom part of Fig. 6.

On step 3, we analyze importance of each attribute (or feature) with statistical technique based on the reduction in variance of the dengue incidence, which is the target of our modeling process. The purpose of feature importance analysis is to select only attributes contributing the most to the accurate prediction of dengue incidences. At this step, we also perform data lagging from 1 month up to 24 months. This is for the observation of the impact from historical data on estimating the future dengue cases.

We then build different kinds of predictive models and evaluate forecasting performances of those models. The algorithms used in model building are linear regression (LR), generalized linear model (GLM), support vector machine (SVM), artificial neural network (ANN), classification and regression tree (CART), and chi-squared automatic interaction detection (CHAID).

In our experimentation, we apply around 50 percents of data for training the algorithm to build model. On tuning algorithm parameters to achieve the best predictive performance, we use another validation set of data (approximately 20%). To assess the model performance, we employ the remaining 30% of data as a test set.

3 Model Evaluation and Results

On the preparation of training data sets, we prepare two kinds of training data: the data set with lagging periods from 1 up to 24 months, and the data set with no lagging. This is the preliminary step prior to building the final models. The main purpose of this step is for observing the impact of time series events on predicting the dengue incidences.

The measurements that we used for selecting the best scheme on data preparation are mean absolute error (MAE) and correlation. The MAE is the error of the model on predicting dengue cases. Correlation measures the association between predictive features and the target attribute. Therefore, we are looking for the training data set that yields lower MAE but higher correlation (Table 2).

Table 2. Comparative results of models built from the lagged and non-lagged data.

Province/Region	24-month lagged data		Non-lagging data	
	MAE	Correlation	MAE	Correlation
Bangkok/Central	156.064	0.510	146.406	0.474
Chiang Mai/North	135.555	0.815	165.679	0.621
Nakhon Ratchasima/Northeast	62.368	0.565	79.741	0.091
Songkla/South	49.001	0.823	57.119	0.623
Average	**100.747**	**0.678**	**112.236**	**0.452**

The output we observed from the experimental results is that the 24-month lagging data set yields the predictive model with lower MAE and higher correlation to the target attribute than the data set with no lagging. We thus choose the data set with attribute lagging to build the model. The six classification algorithms are then applied with the 24-month lagging data set and the results are summarized in Table 3.

It turns out that CHAID is the best forecasting model for all four provinces. Compared to other modeling algorithm, CHAID uses less predictive features and produces the most correlated model with less error. The CHAID algorithm generates a tree-based model with conditional events on the left-hand-side of the tree, and other additional conditions to be co-considered are displayed with indentation on the

Table 3. Performance of the models built from the 24-month lagged data.

Province	Algorithm	No. variables	Correlation	Relative error
Chiang Mai	**CHAID**	12	**0.881**	**0.223**
	GLM	30	0.640	0.590
	LR	29	0.611	0.627
	ANN	30	0.532	0.718
	CART	30	0.000	1.001
	SVM	30	0.412	1.115
Bangkok	**CHAID**	8	**0.852**	**0.275**
	LR	30	0.634	0.598
	SVM	30	0.432	1.034
	CART	17	0.731	0.491
	GLM	30	0.634	0.598
	ANN	30	0.364	0.901
Nakhon Ratchasima	**CHAID**	11	**0.856**	**0.268**
	GLM	30	0.717	0.487
	LR	29	0.635	0.597
	CART	9	0.557	0.692
	ANN	30	0.489	0.762
	SVM	30	0.532	1.065
Songkhla	**CHAID**	7	**0.856**	**0.268**
	GLM	30	0.643	0.587
	LR	29	0.642	0.587
	ANN	30	0.454	0.800
	CART	30	0.000	1.002
	SVM	30	0.453	1.015

following lines. Forecasting target is the estimated number of dengue patients displayed as number in red bold fonts. The highest three cases are stressed with underlines. We show the CHAID models built from the 24-month lagging data of Bangkok metropolitan area in Fig. 7.

The three most serious cases of dengue outbreak in each province are illustrated in Table 4 with the predictive factors at each outbreak level displayed on the right hand side. For instance, the number of dengue infected patients in Chiang Mai province can reach 1,748 if all of the following three factors occur:

- amount of rainfall in the past eighth month is more than 0.1 inches
- amount of rainfall in the past seventh month is less than 0.1 inches
- amount of rainfall in the past fifteenth month is more than 1.98 inches

In Bangkok, the predictive factors are different. The number of dengue patients in Bangkok can be as high as 3,084 if the following two factors occur:

- the ONI is higher than 1
- amount of rainfall in the current month is less than 0.3 inches

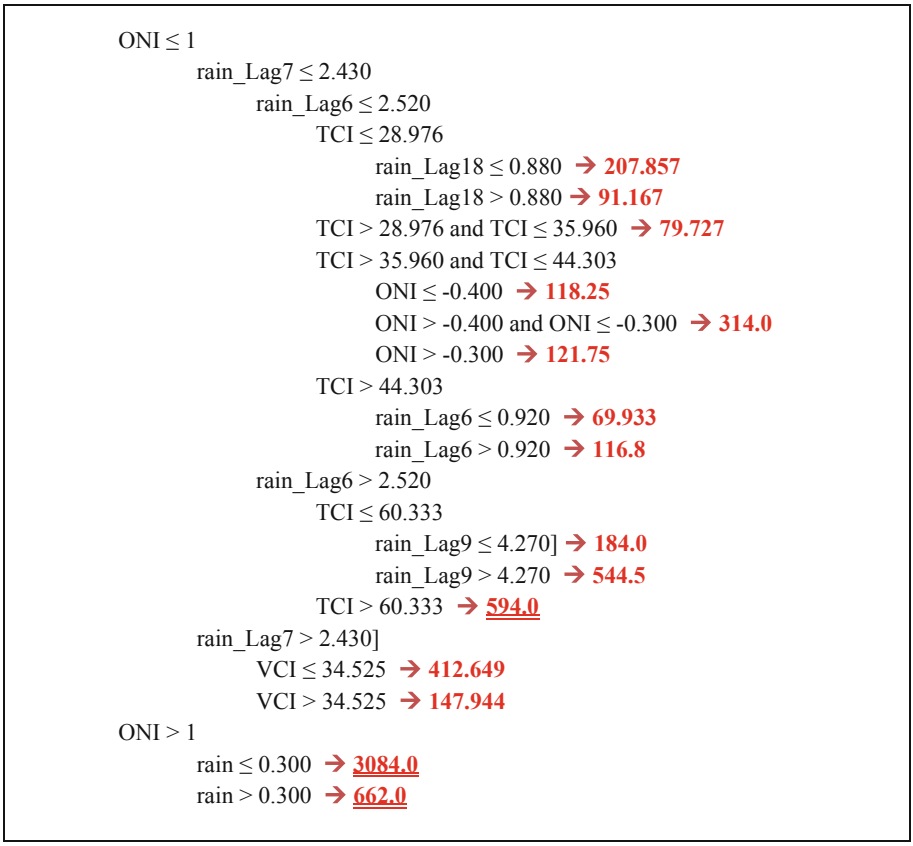


Fig. 7. The CHAID model to estimate dengue incidences in Bangkok. (Color figure online)

The oceanic Nino index (ONI) is also the most important factor to be considered for dengue outbreak estimation in Nkahon Ratchasima province. But in Songkhla area, the amount of rainfall in the current month is the best predictor for dengue cases.

4 Conclusion

This research work presents the application of sensor data obtained from the NOAA-AVHRR that had been used to compute indices such as VHI, VCI, TCI, SMN, SMT to reflect greenness of vegetation on the global surface. Besides these spaceborne indices, we also apply the index computed from the sea surface temperature (SST) anomaly in the equatorial Pacific region Niño3.4. The SST anomaly is the temperature deviation measurement to identify either the normal, warm, or cold events occurred in the Pacific ocean climate.

The warm events are those months that the SST are +0.5 °C or higher than the normal long-term temperature. The cold events occur when the SST anomaly are –0.5 °C or lower than the norm. The warm episodes are called El Niño, whilst the cold ones are

Table 4. The top-3 cases of CHAID model to estimate dengue outbreak in each province.

Province	Outbreak Estimation	Predictive Factors
Chiang Mai	Dengue cases ≈ 1748	rain_Lag8 > 0.1 inch & rain_Lag7 ≤ 0.1 inch & rain_Lag15 > 1.98 inch
	Dengue cases ≈ 1653	rain_Lag8 ≤ 0.1 inch & rain_Lag16 > 1.98 inch
	Dengue cases ≈ 1195	rain_Lag8 ≤ 0.1 inch & rain_Lag16 ≤ 1.98 inch & TCI is in the range (19.63, 30.425]
Bangkok	Dengue cases ≈ 3084	ONI > 1 & rain in current month ≤ 0.3 inch
	Dengue cases ≈ 662	ONI > 1 & rain in current month > 0.3 inch
	Dengue cases ≈ 594	ONI ≤ 1 & rain_Lag7 ≤ 2.43 inch & rain_Lag6 > 2.52 inch & TCI > 60.33
Nakhon Ratchasima	Dengue cases ≈ 653	ONI > 1 & rain_Lag18 > 2.03 inch
	Dengue cases ≈ 421	ONI > 1 & rain_Lag18 ≤ 2.03 inch & rain_Lag22 ≤ 0.28 inch
	Dengue cases ≈ 416	ONI ≤ 1 & rain_Lag16 > 2.49 inch & rain_Lag17 is in the range (2.49, 3.60] inch
Songkhla	Dengue cases ≈ 351	rain in current month ≤ 10.55 inch & VHI > 54.053 & rain_Lag21 ≤ 1.68 inch
	Dengue cases ≈ 349	rain in current month > 10.55 inch & rain_Lag11 ≤ 4.2 inch
	Dengue cases ≈ 233	rain in current month > 10.55 inch & rain_Lag11 > 4.2 inch & rain_Lag21 is in the range (7.57, 10.01] inch

called La Niña. Both cold and warm episodes are the natural phenomena called the El Niño-Southern Oscillation, or ENSO.

The scientists and climatologists from the NOAA, U.S.A., devise the measurement based on the SST anomaly and call the metric as the Oceanic Nino Index (ONI) to capture variability of sea surface temperature in the Pacific Ocean. On the first week of each month, the updated ONI values are announced. We employ this ONI value together with the NOAA-AVHRR indices as important oceanic and remote-sensing factors to predict number of infected dengue patients in Thailand.

From the experimental results, we found that ONI is the most important factor and it is the first condition that the CHAID algorithm considers for building tree models for Bangkok and Nakhon Ratchasima provincial areas. Other important factors appeared in the models of these two provinces are TCI, VCI, and amount of rainfall in the current month and in the past up to 18 months. In Chiang Mai, ONI has no role in the dengue incidence forecasting. Amount of rain in the past, TCI, and SMN are predictive factors appeared in the model. To predict dengue cases in Songkhla, rain in current month, VHI, VCI, and ONI are important factors.

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