Combining Traditional Data Sources, Unmanned Aerial Vehicle Derived Data and Statistical Relational Learning to Improve Dengue Surveillance

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Abstract

We present a machine learning-based methodology capable of providing real-time (nowcast) and forecast estimates of dengue prediction in the Thailand by leveraging data from multiple data sources including: survey data, hospital visit records and drone derived data. Our main contribution consists of (a) addressing the limitations of the method for traditional data sources by combining it with the data derived using unmanned aerial vehicles (UAVs); and (b) understanding epidemiology using statistical relational learning techniques (SRLs).

Our methodology enables... We evaluate the predictive ability.. Our approach demonstrates several advantages: (1)...(2)..

Keywords: Dengue Foreccasting, Statistical Relational learning, Probabilistic Relational Modeling, Bayesian Epidemiology, Disease Surveillance, Unmanned Aerial Vehicles.

1. Introduction

Dengue, a mosquito borne viral disease, has been a significant cause of death and hospitalization among children in developing countries such as India, Thailand etc.

Despite this, the surveillance for diagnosing dengue has been limited which makes it difficult to generate detailed information on its epidemiology.

Dengue fever and dengue hemorrhagic fever (DF/DHF) result from infection by any of four serotypes of dengue viruses (DENV 14). The infection by one type usually gives lifelong immunity to that type, but only short-term immunity to the others. Transmission occurs through the bite of infected Aedes mosquitoes, principally Aedes aegypti. This kind of mosquito prefers to breed in areas of stagnant water, such as flower vases, uncovered barrels, buckets, and discarded tires, but the most dangerous areas are wet shower floors and toilet tanks, as they allow the mosquitoes to breed inside the residence. The number of cases of dengue fever has increased dramatically since the 1960s, with between 50 and 528 million people infected yearly. Hundreds of thousands of cases of dengue are reported each year in tropical regions of the Americas, Africa, Asia, and Oceania. Globally, more than 2.5 billion people are at risk [1]. The World Health Organization (WHO) estimates that more than 50 million dengue virus (DENV) infections and 20,000 dengue disease-related deaths occur annually worldwide [2, 3], and a recent disease distribution model estimated that were 390 million DENV infections in 2010, including 96 million apparent infections. Overall, 70% of these apparent infections occurred in Asia [4]. In 2015, there were 111,826 reported cases in Thailand [5].

There have been numerous urban outbreaks of dengue with significant health and economic impact [6, 7, 8, 9]. Studies in Thailand and Brazil have shown that the social and economic impact is equivalent to that of malaria in these countries [10, 11]. Dengue also poses a risk to those who travel to endemic areas and is increasingly being reported in travelers returning from trips to endemic countries [12]. However, globally, dengue research has not received the same level of funding as other tropical infectious diseases. There are currently no available drugs and no licensed vaccine. The main mosquito control methodology: reducing the habitat and the number of mosquitoes and limiting exposure to bites is currently the best method for disease prevention.

This research will focus on analyzing captured data from UAVs sensors such as image to classified land-type, landmark, and weather for estimating infection factors from Aedes mosquito combined with population statistics in the target area to predict risk of dengue outbreak.

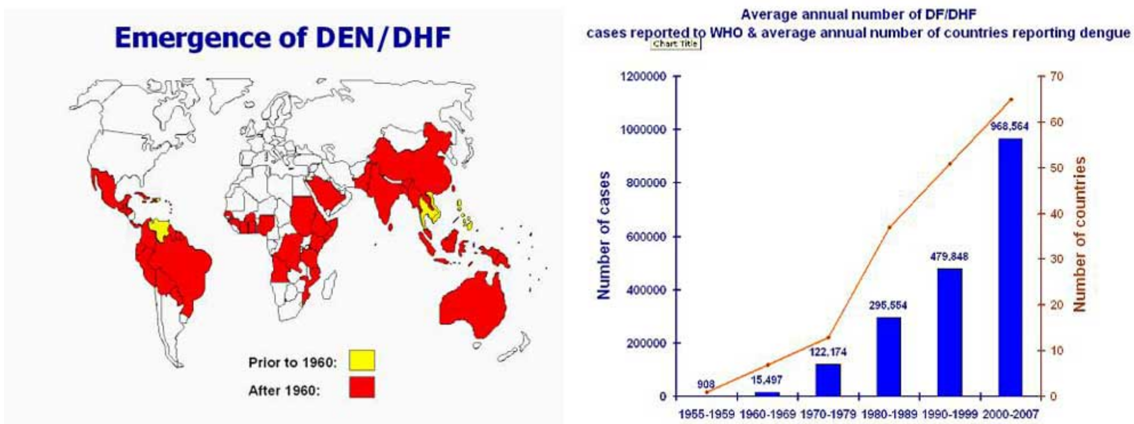

Figure 1: The figure show the increase of incidence rate of dengue from 1970-2007. Before 1970, there are only 9 countries that experienced DHF cases. But in twenty-first century, the incident rate is increase dramatically and the disease is now endemic in more than 100 countries. Up to 50 million infections occur annually with 500 000 cases of DHF and 22,000 deaths mainly among children. The virus became the most important mosquito-borne viral disease in the world. Reprinted from the website of [13].

The risk of epidemic dengue transmission is determined by a combination of factors that include level of human immunity to virus serotypes, virulence characteristics of the virus strain, abundance of Aedes mosquitoes, weather, and population statistics in target area [14]. Several potential predictive indicators for outbreaks have been described but further study is needed [15, 16, 17, 18]. Difference researches have identified different factors; those models need to be compared on common data sets. Furthermore, the appearance of a new dengue serotype can be used as an early warning sign for a possible outbreak but the association between the introduction of a new serotype and outbreak occurrence remain unknown [19]. The complexity and interdependence of the factors make prediction of the risk of a dengue outbreak very hard to estimate over short time scales.

The main factors related to the abundance of Aedes mosquitoes in an area are related to the environment in the target area. The environment is continually changing depending on weather and human action. To gain environment data, satellite imagery is common and extremely useful tool for observing the area. However, a satellite imagery has long repeat times and low spatial resolution,we can never know with certainly the current environment of target area, and we lose detail. In order to gain fresh current data from a target area towards creating a high accuracy prediction, I will explore the use of UAVs to observe target areas to gain real time, high detail data for extraction of environment factors predictive of dengue outbreak.

In this research we:

1. Identify the environmental factors of dengue fever by environments of patients house and UAVs sensor data.

2. Analyze the causes and consequences of existing dengue fever factors to calculate the possibility of dengue fever outbreaks in target area.

3. Build a new prototype system able to integrate data from multiple sensor platforms and data sources in order to measure the inputs to the model describes in objective above automatically.

4. Evaluate of the prototype combined with prediction model by surveying one village in Bangkok.

2. Related Work

There are several environmental factors related to dengue outbreak that have been identified from case studies in Southeast Asia [20, 17, 18, 21]. There are many research conclude that most dengue cases are occurred in urban areas due to various contributing factors such high population density, inadequate housing, and inappropriate human behavioral practices [22, 23, 24].

2.1. Vector surveillance

Surveillance of Aedes mosquito density is important for construction models of dengue transmission, in order to prioritize areas and seasons for vector control. Selection of appropriate surveillance strategies is based upon the desired outcome or objective, also taking into consideration time, available resources, and infestation levels.

Additionally, continued vector surveillance (as frequently as every seven days) is required to sustain the control measures and detect any increase in vector density. The 80% of larvae or pupa in house are from Aedes mosquito. The most used indicators for vector surveillance are:

Larval surveys: Estimating presence of larvae and/or pupae of Aedes mosquitoes by surveying water-holding containers.

House index (HI): Percentage of houses infested with larvae and/or pupae.

$$HI = \frac{\text{Number of houses positive for mosquito larvae or pupa}}{\text{Total number of houses surveyed}} \times 100 \tag{1}$$

Container index (CI): Percentage of water-holding containers infested with larvae or pupae.

$$CI = \frac{\text{Number of wet containers found positive for mosquito larvae or pupa}}{\text{Total number of wet containers surveyed}} \times 100 \tag{2}$$

Breteau index (BI): Number of positive containers per house inspected.

$$BI = \frac{\text{Number of wet containers found positive for mosquito larvae or pupa}}{\text{Total number of houses surveyed}} \times 100 \tag{3}$$

Adult Aedes mosquitoes surveys: Estimating adult Aedes mosquito population density using ovitraps, sticky traps, human landing collections [25], or similar traps.

2.2. Environmental factors and incidence of dengue fever and dengue haemorrhagic fever in urban Southern Thailand

[17] analyze the spatial pattern of DF/DHF incidence at the district block level in Songkhla province, Thailand, to test the hypothesis that district block characteristics affect the incidence of the disease. There were 20,745 households with a population of 60,127 people. The main occupations of the population include trading, fishing, and government service. The municipality is divided into 146 districts, each containing about 140 houses and 400 residents. They aqquired data on the population, average number of people per house, children in each age group, and location data in Songkhla

from the National Statistics Office, which had conducted a population census survey in 1997. Approximately 10% of all the houses in each district were selected for the study of housing data which included: housing type, construction material, presence of water drainage, availability of window screens, waste disposal, and BI.

The total number of houses visited was 1996. The overall percentages of infected people inhabiting shop-houses, single houses, buildings, slums and empty houses were 39%, 37%, 3%, 5.4% and 15.6% respectively. The proportions of houses in which included people lived made of bricks, a mixture of brick and wood, wood, corrugated iron and others materials were 42%, 28%, 24%, 3%, and 2%, respectively.

The results of the analysis housing factors vs. district incidence of DF/DHF: DF/DHF incidence per block had a positive correlation with the percentages of *shop-houses, empty houses, brick-made houses and houses with poor garbage disposal*. A comparison of poor garbage disposal rate with DF/DHF is as shown in figure **??**. DF/DHF had a negative correlation with *the average number of people per house, percentages of single houses, slum dwellings, wood-made houses and the BI*.

2.3. Near real-time characterization of urban environments: a holistic approach for monitoring dengue fever risk areas: A city of Phitsanulok Province, Thailand

[18] extract land-use types using object-based and spatial metric approaches to explore dengue incidence in relation to the surrounding environment in near real-time using Google and Advanced Land Observation Satellite images. Geospatial analysis on public health data indicated that most of the dengue cases were found in densely populated areas *surrounded by dense vegetation*. Dense vegetation can facilitate the invasion of Aedes mosquitoes by providing abundant resting sites.

Figure **??** shows the incidence of dengue cases in the city of Phitsanulok in 2010 in relation to important landmarks, for example, a hospital, market, temple and school. A positive relationship between dengue cases and neighborhoods was observed based on proximity and spatial analysis. *Proximity analysis* indicated that most of the dengue cases were around *institutions (40%), religious places (18%), and markets (15%)*. The study also reports that dengue incidence was more prevalent in people of 5-24 years of age (67%), while in terms of occupation, mostly *students, the unemployed, laborers,* *and farmers (88%)* were affected.

2.4. An information value based analysis of physical and climatic factors affecting dengue fever and dengue haemorrhagic fever incidence: Sukhothai province, Thailand.

[21] explores empirical relationship of climatic factors rainfall, temperature and humidity with the DF/DHF incidences using multivariate regression analysis. Sukhothai province located in the northern Thailand, was selected as the study area for this work. The province has a population of about 521,219. Climate of this area is subtropical with extreme high temperatures rising to 42°C in April and dipping low up to 13.2°C in December. Medical data were collected from the Provincial Health Office, Thailand, which collects monthly district level data.

The purpose of the multiple regressions was to learn more about the relationship between several independent or predictor variables and the dependent or criterion variable (number of DF/DHF cases). In general, multiple regression procedures estimate a linear equation of the form:

$$Y = (B_0) + (B_1)(X_1) + (B_2)(X_2) + ... + (B_k)(X_k) \tag{4}$$

Where k is the number of predictors. Rainfall (R), temperature (T), and relative humidity (H) were considered as the independent variables. There are many related studies also conclude that climate is related to dengue outbreak [26, 27, 28, 29, 30]. The realtime at time T relationship (ER) between number of DF/DHF cases and the climatic data (T_t, R_t and H_t) at time *t* during 5 years is listed in ER-1, ER-2, and ER-3 equations. Multiple regression analysis is employed to develop an empirical model to predict the dengue incidences by using the occurrence of DF/DHF cases and monthly climatic data of 5 years (1997−2001).

2.5. Impact of daily temperature fluctuations on dengue virus transmission by Aedes aegypti.

The diurnal temperature range (DTR) is the difference between the daily maximum and minimum temperature. [31] show that DTR affects two important parameters underlying dengue virus (DENV) transmission by Aedes mosquito.

They evaluated experimentally the effect of DTR on the potential for DENV transmission by Aedes mosquito females under three temperature. Each experiment had the same average temperature (26 C), but a different amplitude of daily temperature variation; control (DTR = 0°C), moderate (DTR = 10°C), and large (DTR = 20°C). In two independent experiments using different DENV serotypes (DENV-1 and DENV-2), mosquitoes were less susceptible to virus infection and died faster under larger DTR (20°C). A thermodynamic model predicted that at mean temperatures ¡18 °C, DENV transmission increases as DTR increases, whereas at mean temperatures ¿18 °C, larger DTR reduces DENV transmission.

Infection analysis is divided in to two experiments. In the first experiment, rates of infection by a DENV-2 isolate were measured in a total of 525 Aedes mosquito females (175 in each of the three temperature regimes). Result of the first experiment is 97.1%, 94.9%, and 78.9% of females were DENV-2 infected under DTRs of 0 C, 10 C, and 20 C, respectively. In the second experiment, rates of infection by a DENV-1 isolate were measured in 227 Aedes mosquito females (132 in each of the two temperature regimes: low and large DTR regime) Result of the second experiment is, 97.0% and 88.4% of females were DENV-1 infected under DTRs of 0 C and 20 C, respectively.

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$$Y = (B_0) + (B_1)(X_1) + (B_2)(X_2) + ... + (B_k)(X_k) \tag{8}$$

Where k is the number of predictors. Rainfall (R), temperature (T), and relative humidity (H) were considered as the independent variables. There are many related studies also conclude that climate is related to dengue outbreak [26, 27, 28, 29, 30]. The realtime at time T relationship (ER) between number of DF/DHF cases and the climatic data (T_t, R_t and H_t) at time t during 5 years is listed in ER-1, ER-2, and ER-3 equations. Multiple regression analysis is employed to develop an empirical model to predict the dengue incidences by using the occurrence of DF/DHF cases and monthly climatic data of 5 years (1997−2001).

ER-1 equation:

$$D_t = 1408.318 + 0.151(R_t) - 4.368(T_t) - 12.798(H_t) \tag{9}$$

The coefficient of determination (R^2) of ER-1 was 0.43. Multiple regression analysis was carried out for the occurrence of DF/DHF cases for the rainy season.

ER-2 equation:

$$D_t = -13.893 + 0.377(R_t) + 1.3444(T_t) - 0.276(H_t) \tag{10}$$

The coefficient of determination (R^2) of ER-2 was 0.62.

According to the development period from a mosquito egg to the human disease, there is a time lag of about one month that leads to DF/DHF cases occurring in 7 - 45 days. The duration of larvae stages is 7 to 12 days, and the lifespan of the female mosquito is about 8 to 15 days. In the meantime, the virus develops in the mosquito for a period of 810 days. By the time a person infected with dengue virus develops fever, the infection is usually widely disseminated to many people. The virus is found in serum or plasma, in circulating blood cells and in selected tissues, especially those of the immune system, for approximately 27 days, roughly corresponding to the period of fever. Thus, DF/DHF cases at time t (in month e.g. May) depend on others factors at time t-1 (i.e. one month before month).

The Empirical Relationship-3 (ER-3) with a one-month time lag as shown below offered a coefficient of determination (R^2) as 0.81. Therefore, the ER-3 was selected to model the DF/DHF incidence in Sukhothai as the closest output to the actual data during rainy season and the results were validated with 1998 data, as shown in Figure **??**.

ER-3 equation:

$$D_t = 621.824 + 0.345(R_{t\text{-}1}) - 0.609(T_{t\text{-}1}) - 6.321(H_{t\text{-}1}) \tag{11}$$

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3. Methodology

3.1. Study area

The dengue outbreak in Bangkok can affect to dengue situation for the whole country, because Bangkok is a very crowded city locate at the center part of Thailand. In the 2010 census, Bangkok had a population of 8.28 million, although just 5.7 million were registered residents. Much of the daytime population commutes from surrounding areas in the region, bringing the total population to 15 million [32]. During winter season, temperature in Bangkok still high around 28-35 degree Celsius and there is rain in every season [33]. Figures 2 and 3 show the average temperature and rain of the Bangkok. This makes the city is very suitable for Aedes mosquito to breeding making dengue virus spread from Bangkok in every season. Moreover, many people who live in Bangkok travel to other provinces frequently, so these people may be the main carriers and multipliers of the virus that cause dengue outbreak in other part of Thailand.

Figure 4 shows the relationship between incidences of dengue per one hundred thousand people in Thailand versus Bangkok. The dengue incident rate in Bangkok is nearly the same as the whole country. So, if we could reduce dengue incident rates in Bangkok, the rate in Thailand will be reduce too because there will be fewer dengue carriers who travel from Bangkok to other parts of Thailand.

3.2. Bangkok districts

The Bangkok city covers an area of 1,568.737 square kilometres and it is subdivided into 50 districts , which are further subdivided into 169 sub-districts. Total

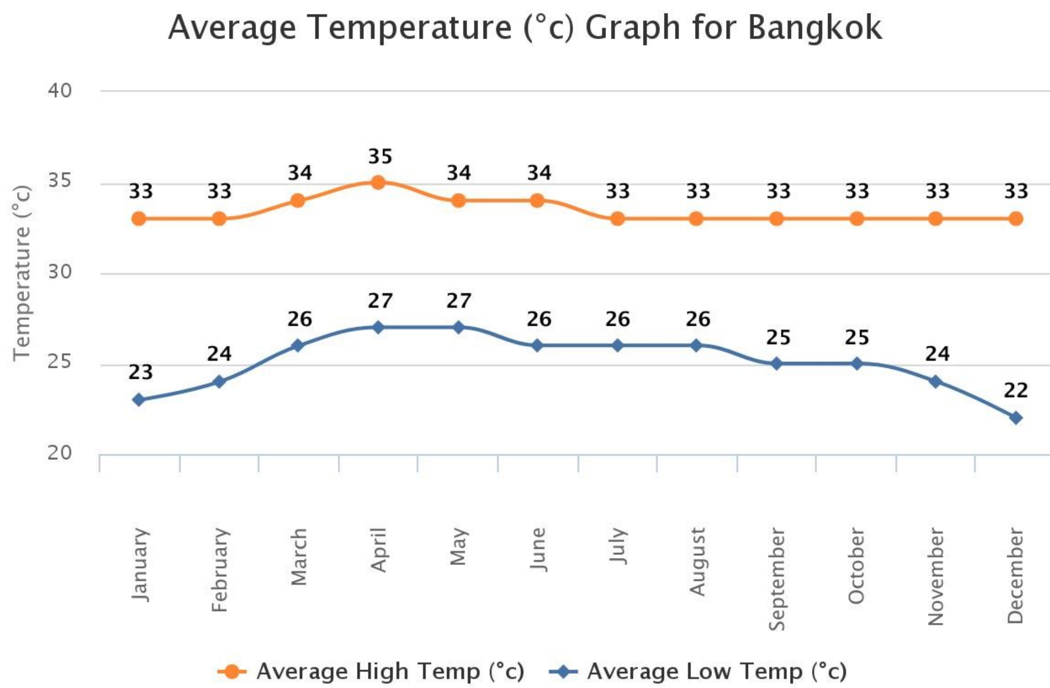


Figure 2: Average high and low temperature in Bangkok from 2000-2012. Reprinted from [33].

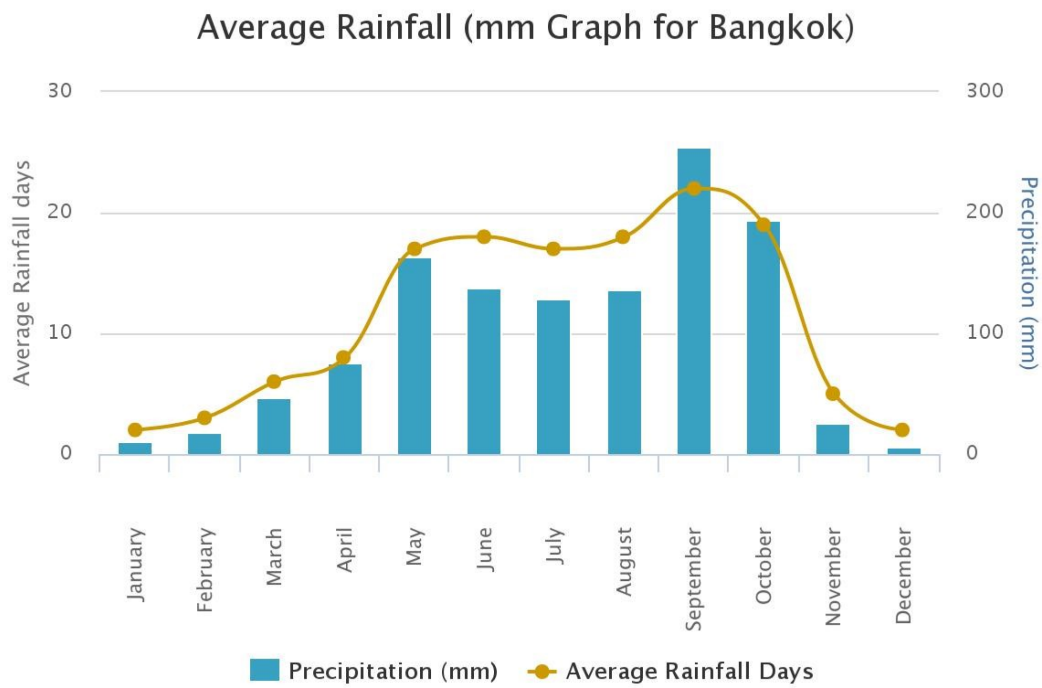


Figure 3: Average rainfall in Bangkok from 2000-2012. Reprinted from [33].

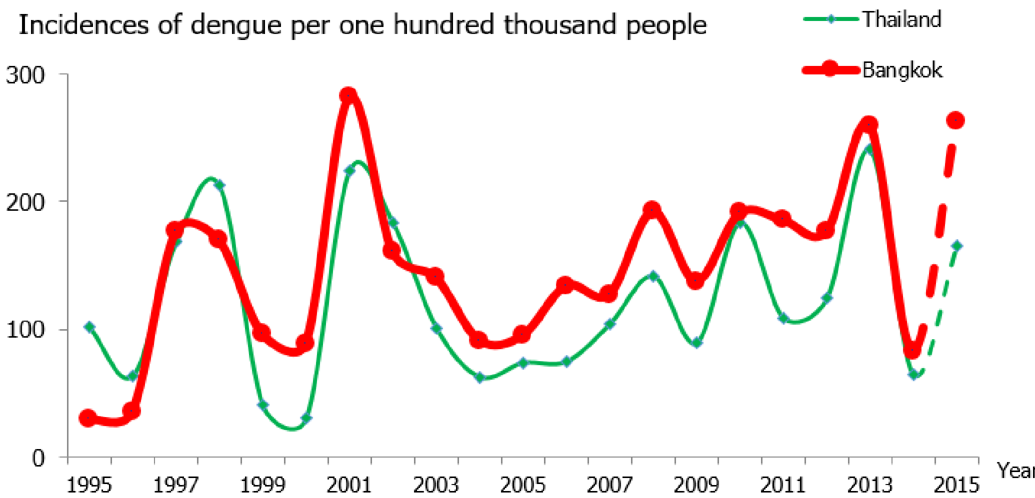


Figure 4: Relationship between incidences of dengue per one hundred thousand people in Thailand versus Bangkok from 2005 - 2014.

population who registered in Bangkok is 5,693,884 and more than three million people are live in Bangkok without registered. Table 3.2 and figure 5 show district name, map and population statistic in each area. The average registered population of Bangkok districts in 2014 is 113845. The highest population district is Saimai (194,511) and the lowest population district is Samphanthawongse (26359). But the highest and lowest population density district are Phranakhon (157791 men/km 2) and Thawiwatthana (2948 men/km 2). Data of Bangkok statistics described more later in subsection "Prediction variable".

3.3. Dengue fever in Bangkok district

Figure 6 (a) shows the increase of dengue cases in Bangkok up to 2015. The average number of dengue cases in Bangkok from 2005 until 2015 is around 10,758 cases per year. The highest number of dengue cases in Bangkok is 28,177 cases which happened in 2015. Figure 6 (b) shows changes in dengue serotypes from 2005 to 2015. The percentage of dengue serotypes DENV 1 - 4 in the central part of Thailand changed every year, making people who already have immunity to one serotype susceptible to

ID Map	District Name	Population	Area	Density
1	Phranakhon	55373	5.536	157791
2	Bangbon	107140	34.745	3084
3	Chomthong	156030	26.265	28111
4	Bangrak	46472	5.536	42529
5	Bangkhae	191966	44.456	18428
6	Bangkapi	148964	28.523	10853
7	Patumwan	51557	8.369	28172
8	Pom prap	49280	1.931	127030
9	Prakanong	92448	13.986	6610
10	Minburi	139771	63.645	4619
11	Don muang	168197	36.803	14759
12	Yannawa	80843	16.662	9651
13	Samphanthawongse	26359	1.416	55837
14	Payathai	72203	9.595	7525
15	Thung khru	119349	30.741	7861
16	Bangkok yai	70003	6.18	27711
17	Huai khwang	80002	15.033	16746
18	Thawiwatthana	77121	50.219	2948
19	Taling chan	105857	29.479	26455
20	Suanluang	118371	23.678	4999
21	Lat Krabang	168309	123.859	10304
22	Dindaeng	127260	8.354	15233
23	Nongkhaem	153175	35.825	8572
24	Radburana	84881	15.782	10678
25	Bangplad	96787	11.36	34173
26	Bangsue	128995	11.545	22359
27	Bung kum	145514	24.311	17772
28	Watthana	83520	12.565	18145

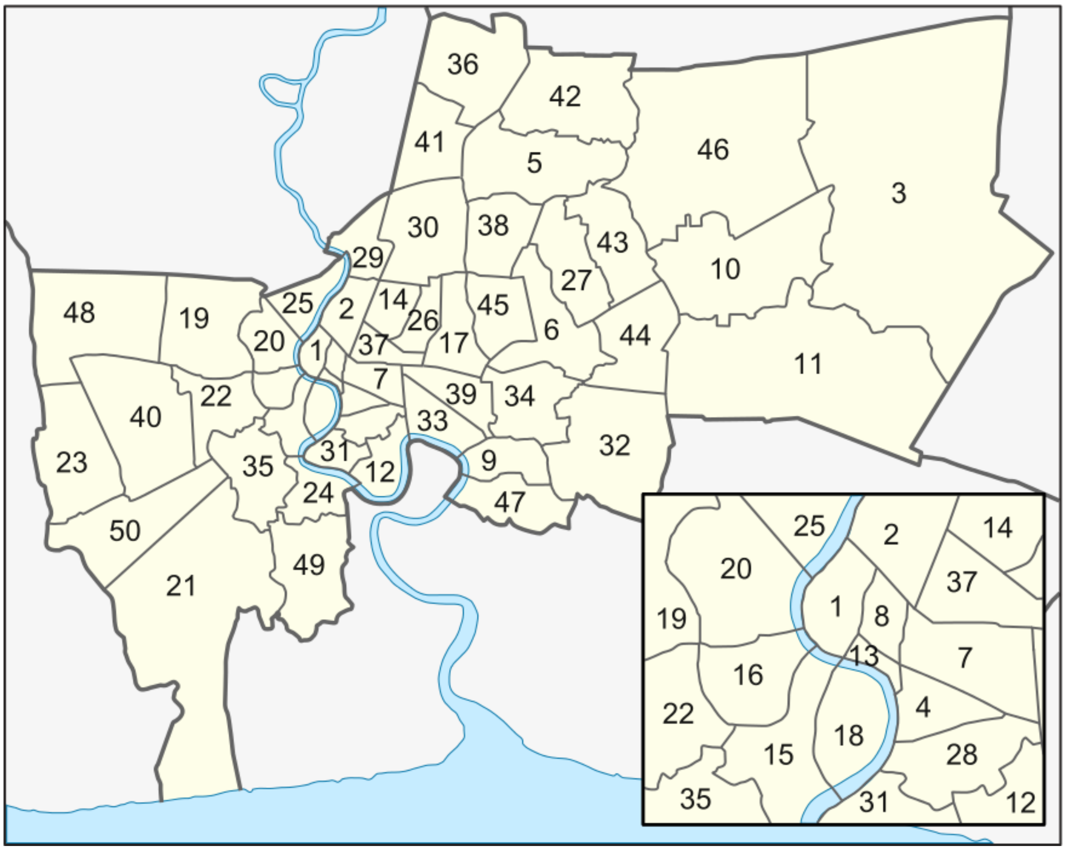
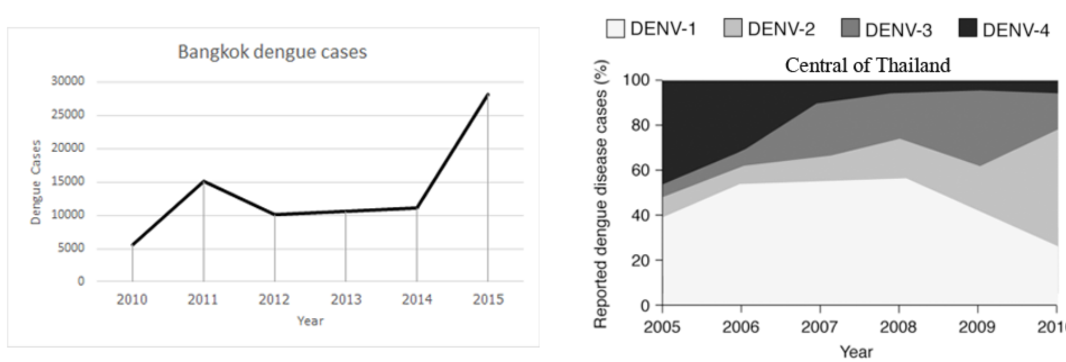


Figure 5: Bangkok districts, Reprinted from [34].

infection with another serotype in the following year. Figure 7 shows the effect of season on dengue cases. In rain season (mid May - October), dengue cases rise dramatically, and then they decrease suddenly in summer season (February - mid May). The reason that November has the highest number cases is that dengue virus in patients need 4 - 10 days for the incubation period. So most dengue patients in November are infected in rain season (October).



(a) Dengue cases

(b) Dengue virus serotype

Figure 6: (a) Dengue cases from 2010 - 2015 in Bangkok. (b) Dengue serotypes from 2005 - 2010 in central Thailand. Data from Department of Disease Control 13th Division and [35].

3.4. Prediction variable and data collection

According to Dr Sonpon and Dr Nicholas, there are three main factors that affect to dengue incidence cases: other cases of dengue virus, presence of Aedes mosquitoes, and various human factors. Dengue fever cannot spread to humans from other animal; mosquitoes are mainly carries. Typically, people infected with dengue virus are asymptomatic (80%) or have only mild symptoms , such as an uncomplicated fever [36, 37]. In Bangkok's case, dengue fever and dengue hemorrhagic fever were reported in each season, mean, dengue virus is always present in human too. Once infected, *humans* become the main carriers and multipliers of the virus, serving as a source of the virus for uninfected *Aedes mosquitoes* to carry. All prediction variables that I choose are related to these three main factors.

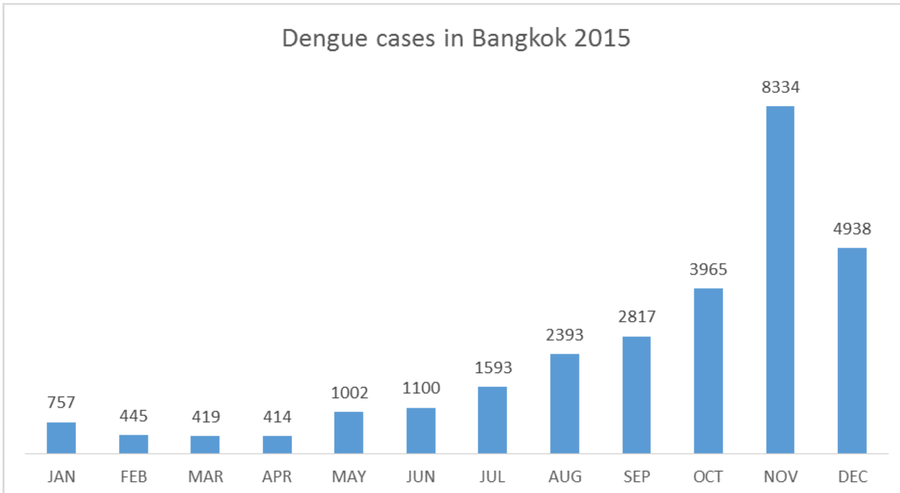


Figure 7: Monthly dengue cases in Bangkok 2015. Data from Department of Disease Control 13th Division.

3.4.1. Dengue virus prediction variable

I selected 2 prediction variables related to dengue virus factors:

1. **Monthly DF/DHF incidents in the district** represents the number of dengue virus report in the target district.

2. **Monthly DF/DHF incident in the nearby districts** represents the number of dengue virus reports which may affect to the target district

All DF/DHF case data are provided by the Department of Disease Control, Bangkok.

3.4.2. Aedes mosquito prediction variables

I selected 2 prediction variables related to the Aedes mosquito factor:

1. **Monthly rainfall in district** represents the density of Aedes mosquitoes in the target district.

2. **Monthly average diurnal temperature range (DTR) in Bangkok** represents the health of the dengue virus in Aedes mosquito. Higher DTR means lower health of dengue virus in Aedes mosquito, deceasing infection rates.

Rainfall data is provided by Department of Drainage and Sewerage, Bangkok ,and temperature data is provided by Meteorological Department, Thailand.

3.4.3. Human prediction variables

I selected 3 prediction variable that related to human factor:

1. **Population with age less than 35 in the district** represents the proportion of the district population that has a high risk for dengue fever.

2. **Population age 35+ in the district** represents the proportion of the district population that has a low risk for dengue fever.

3. **Number of communities in the district** represents how large the group are, make it more of less convenient transmission of dengue virus by Aedes mosquito.

Bureau of Epidemiology, Thailand reports that 80% of dengue patient from 1993 - 2013 are in the age range between 5 - 35 years old. So I divide the population into two groups: population with age less than or equal to 35 as high risk group and those older than 35 as low risk group. Population and community data are provided by the Department of Social Development, Bangkok.

I did a basic analysis of dengue case data and human prediction variable in Bangkok in Microsoft Excel. I determined the relationship between average dengue incidence rate from 2005-2015 and the number of communities in each individual district. Figure 8 shows that fewer communities district may have higher dengue than district with a large number of communities.

3.5. Data preparation and prediction methodology

3.5.1. Multiple linear regression model

For the first prediction model in this research, we will use multiple linear regression. **Dengue virus prediction variables**

MDR_x = Monthly DF/DHF incident rate in district X

$MNDR_x$ = Monthly DF/DHF incident rate in the Nearby district X

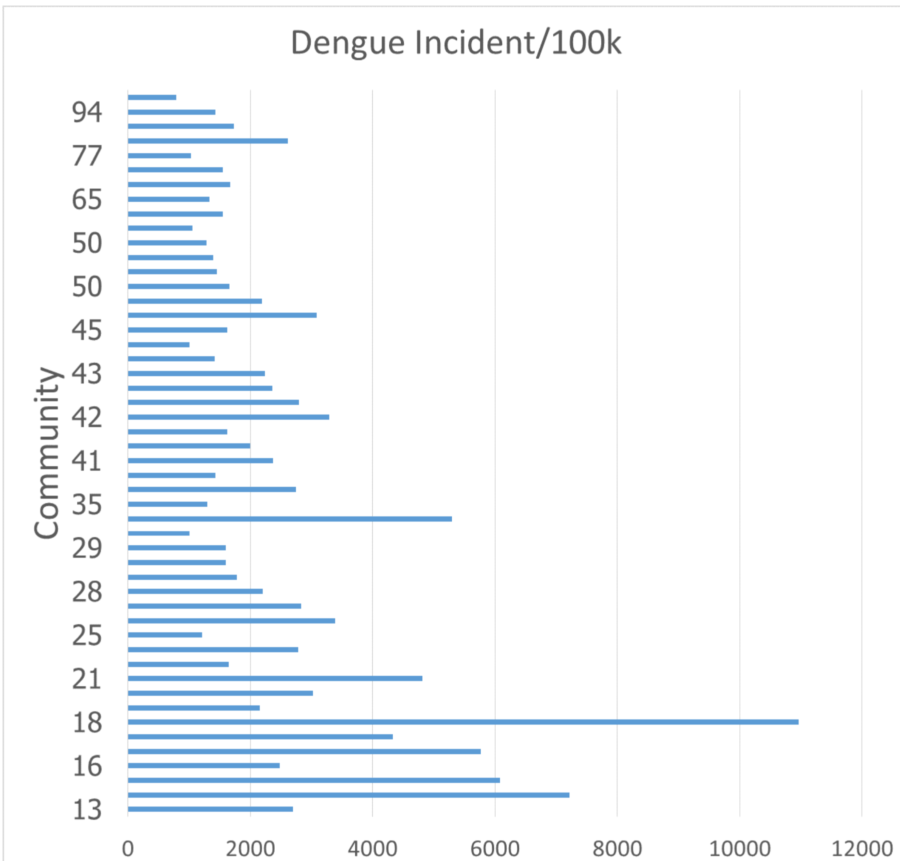


Figure 8: Average dengue rates per 100,00 people from 2005-2015 and number of communities in individual district of Bangkok. Dengue cases data from Department of Disease Control 13th division and Community data from Department of Social Development, Bangkok.

Aedes mosquito prediction variables

MR_x = Monthly Rainfall in district X

$MDTR_b$ = Monthly average Diurnal Temperature Range (DTR) in Bangkok

Human prediction variables

$P35_x$ = Population who age $\leqslant 35$ in district X

$P35+_x$ = Population who age > 35 in district X

C_x = Number of Communities in district X

Prediction model

At first, I begin with predicting dengue incident rate in the next month by using dengue virus prediction variables and Aedes mosquito prediction variables as the inputs of multiple regression model.

DR_x = DF/DHF incident rate in district X

$$DR_x = b_0 + b_1 MDR_x + b_2 MNDR_x + b_3 MR_x + b_4 MDTR_x$$

Dengue-Community impact

Then, to calculate dengue−community impact, I will use human prediction variable and dengue virus prediction variable of each district from the previous month to calculate the calculate community by using multiple Logistic Regression model. The community impact will tell the effect of district structure to dengue virus outbreak.

DCI_x = Dengue−community impact in district X

$$DCI_x = [1 + exp(\alpha X)]^{-1}$$

$$\alpha X = b_0 + b_1 MDR_x + b_2 C_x$$

Immunity estimation

As I described in Section 3.4, 80% of people infected with dengue virus are asymptomatic. To approximate how many people have dengue virus immunity,the number of DF/DHF cases must be extrapolated to estimate the actual number of infected people in the target district.

DC_x = DF/DHF cases in district X

PM_x = Number of people who immune to dengue virus in district X (people who already infected dengue virus in previous six months)

$$PM_x = DC_x \times 100\%/20\%$$

Estimate actual dengue cases

Lastly, I will combine both predictor variables by dividing the population into two groups: the high risk population (age $\leqslant 35$) and the low risk population (age > 35). Then I will multiply the result with denguecommunity impact to calculate the DF/DHF cases in the target district.

PH$_x$ = Population that has a high risk for dengue fever in district X

$PH_x = P35_x - PM_x \times 80\%$

PL$_x$ = Population that has a Low risk for dengue fever in district X

$PL_x = P35+_x - PM_x \times 20\%$

$$DC_x = (1 + DCI_x) \times ((80\% \times DR_x) \times PH_x + (20\% \times DR_x) \times PL_x)$$

To evaluate the prediction model, I will compare the result (DF/DHF cases in the target district) with prediction model that use only DF/DHF cases to predict and also compare it with the actual dengue cases.

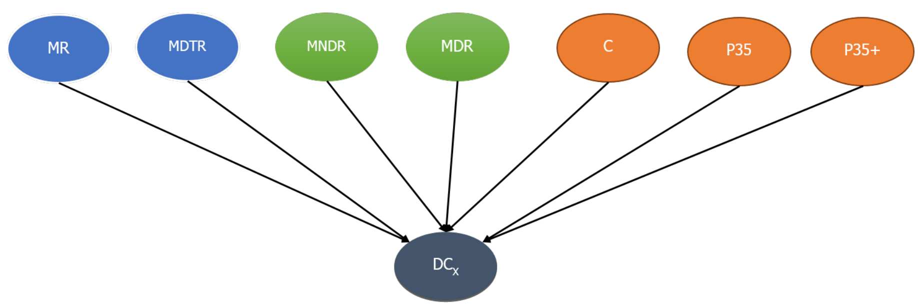


Figure 9: Multiple regression model of dengue outbreak prediction.

3.5.2. Multiple logistic regression model

As a second model for comparison I will use a multiple logistic regression model to predict the probability that dengue virus will outbreak in the target district. This model will help to warn official in districts outbreaks tend to occur in next month. Based on the prediction, the public health officer and citizen in the district can prepare themselves.

This model will use the same input variable as 3.5.1

Estimate percentage of people who infected dengue virus

DOS_x = Dengue Outbreak status in district X (Percentage of population infected, 0 = None, 1 = 100% infected)

$DOS_\text{x} = [1 + exp(\beta X)]^{-1}$

$\beta X = b_0 + b_1 MDR_\text{x} + b_2 MNDR_\text{x} + b_3 MR_\text{x} + b_4 MDTR_\text{x}$

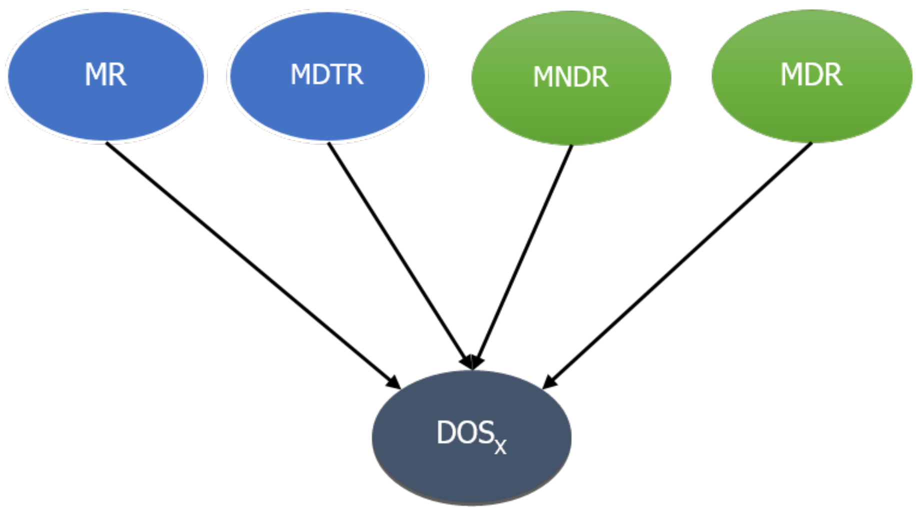


Figure 10: Multiple Logistic Regression model of dengue outbreak prediction.

3.5.3. Bayesian network model

The are many variables in the Bayesian network model that I designed DF/DHF incident rate prediction based on my literature reviews and expert interviews. I divide the Bayesian network into 2 parts.

The first part is a Bayesian network model to predict mosquito density in the target area. There are three categories of mosquito density: Low, Moderate, and High. I believe this variable can be predicted from density of outdoor likely breeding spots, density of indoor likely breeding spots and diurnal temperature range. Figure 11 depicts the directed acyclic graph for the Bayesian network, and table **??** describes the conditional probability distributions of variables in model.

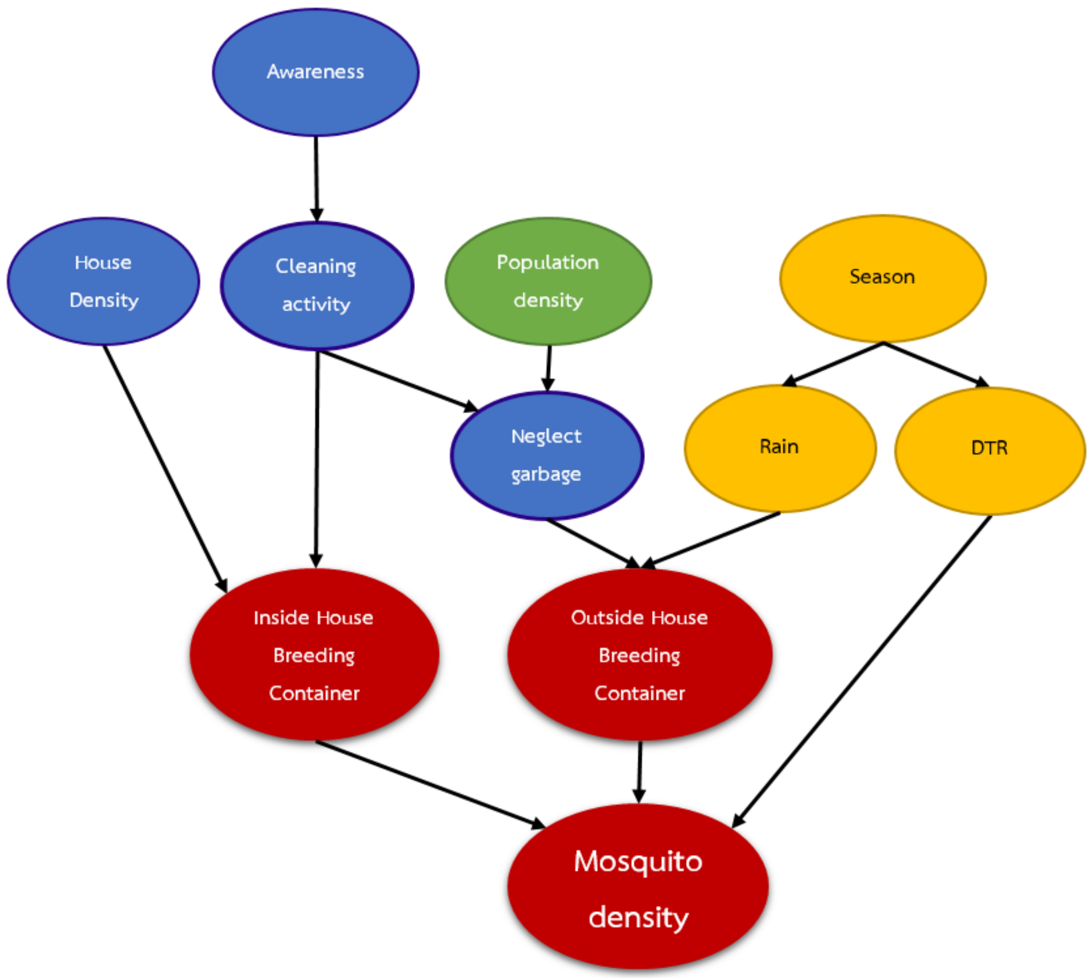


Figure 11: Directed acyclic graph of Mosquito density Bayesian network model

Name	Abbreviation	Predict possibilities output	Parents (Pa)
Mosquito density	MD	MD_0: Low MD_1: Moderate MD_2: High	Outside house breeding container Inside house breeding container Diurnal temperature range
Outside house breeding container	OB	OB_0:Low OB_1:High	Neglect garbage Rain
Inside house breeding container	IB	IB_0:Low IB_1:High	Cleaning activity House type
Neglect garbage	NG	NG_0:Low NG_1:High	Cleaning activity Population density
Cleaning activity	CA	CA_0:Low CA_1:High	Awareness
Rain	R	R_1:Low R_1:Moderate R_2:High	Season
Diurnal temperature range	DTR	DTR_0:Low DTR_1:High	Season
House Density	HT	HT_0:Low HT_1:High	
Awareness	A	A_0:Low A_1:High	
Season	S	S_0:Summer S_1:Winter S_2:Rain	
Population density	PD	PD_0:Low PD_1:High	

Table 2: Value of each variables in Mosquito density Bayesian network model

Pattern			P(MD_0 | PA)	P(MD_1 | PA)	P(MD_2 | PA)
OB_0	IB_0	DTR_0	1	0	0
OB_0	IB_0	DTR_1	1	0	0
OB_0	IB_1	DTR_0	0	0.7	0.3
OB_0	IB_1	DTR_1	0.2	0.6	0.2
OB_1	IB_0	DTR_0	0	0.3	0.7
OB_1	IB_1	DTR_0	0	0	1
OB_1	IB_0	DTR_1	0	0.5	0.5
OB_1	IB_1	DTR_1	0	0	1

Table 3: Conditional probability distribution of mosquito density

Pattern		P(OB0 | PA)	P(OB1 | PA)
NB_0	R_0	1	0
NB_0	R_1	0.4	0.6
NB_0	R_2	0.2	0.7
NB_1	R_0	0.9	0.1
NB_1	R_1	0.2	0.8
NB_1	R_2	0	1

Table 4: Conditional probability distribution of density of outside house breeding spot

Pattern		P(IB0 | PA)	P(IB1| PA)
CA0	HT0	0.6	0.4
CA0	HT1	0	1
CA1	HT0	1	0
CA1	HT1	0.4	0.6

Table 5: Conditional probability distribution of density of inside house breeding container

Pattern		P(NG0 | PA)	P(NG1 | PA)
CA0	PD0	0.4	0.6
CA0	PD1	0	1
CA1	PD0	0.9	0.1
CA1	PD1	0.6	0.4

Table 6: Conditional probability distribution of neglect garbage

Pattern	P(CA0 | PA)	P(CA1 | PA)
A0	1	0
A1	0	1

Table 7: Conditional probability distribution of cleaning activity

Pattern	P(R0 | PA)	P(R1 | PA)	P(R2 | PA)
S0	1	0	0
S1	0.4	0.6	0
S2	0	0.2	0.8

Table 8: Conditional probability distribution of rain

Pattern	P(DTR0 | PA)	P(DTR1 | PA)
S0	0	1
S1	1	0
S2	0.9	0.1

Table 9: Conditional probability distribution of Diurnal temperature range

Name	Abbreviation	Predict possibilities output	Parents (Pa)
Actual report DF/DHF Cases	ARDC	ARDC0:Under report ARDC1:Moderate report ARDC2:Active report	Hospital Awareness Dengue rate
Dengue rate	DR	DR0:Low DR1:Moderate DR2:High	Infected Mosquitos Immune Dengue People
Density of infected Mosquitos	IM	IM0:Low IM0:Moderate IM1:High	Dengue Cases Dengue Case of nearby district Diurnal temperature range Mosquito density
Immune Dengue People	IP	IP0:Low IP1:Moderate IP2:High	Dengue Cases
Diurnal temperature range	DTR	DTR0:Low DTR1:High	Season
Dengue Cases	DC	DC0:Low DC1: Moderate DC2:High	
Dengue Case of nearby district	DCN	DCN0:Low DCN1: Moderate DCN2:High	
Mosquito density	MD	MD0: Low MD1: Moderate MD2: High	
Hospital Awareness	HA	HA0: Low HA1: High	
Population Density	PD	PD0: Low PD1: High	
Season	S	S0:Summer S1:Winter S2:Rain	
Awareness	A	A0:Low A1:High	

Pattern		P(ARDC 0 | PA)	P(ARDC 1 | PA)	P(ARDC2 | PA)
HA0	DR0	1	0	0
HA0	DR1	0.7	0.2	0.1
HA0	DR2	0.3	0.5	0.2
HA1	DR0	0.7	0.3	0
HA1	DR1	0.3	0.5	0.2
HA1	DR2	0	0.2	0.8

Table 10: Conditional probability distribution of Actual report DF/DHF Cases

Pattern		P(DR0 | PA)	P(DR 1 | PA)	P(DR 2 | PA)
IM0	IP x	1	0	0
IM1	IP 0	0	0.3	0.7
IM1	IP 1	0.1	0.4	0.5
IM1	IP 2	0.1	0.5	0.4
IM2	IP 0	0	0	1
IM2	IP 1	0	0.1	0.9
IM2	IP 2	0	0.3	0.7

Table 11: Conditional probability distribution of dengue incident rate (DF/DHF cases)

Pattern	P(IP0 | PA)	P(IP1 | PA)	P(IP2 | PA)
DC0	1	0	0
DC1	0	1	0
DC2	0	0	1

Table 12: Conditional probability distribution of immune dengue people

Pattern				P(IM0 | PA)	P(IM1 | PA)	P(IM2 | PA)
DC0	DCN 0	MD0	DTRx	1	0	0
DC0	DCN 0	MD1	DTRx	0.9	0.1	0
DC0	DCN 0	MD2	DTR0	0.7	0.3	0
DC0	DCN 0	MD2	DTR1	0.8	0.2	0
DC0	DCN 1	MD0	DTRx	1	0	0
DC0	DCN 1	MD1	DTR0	0.7	0.3	0
DC0	DCN 1	MD1	DTR1	0.8	0.2	0
DC0	DCN 1	MD2	DTR0	0.3	0.7	0
DC0	DCN 1	MD2	DTR1	0.4	0.6	0
DC0	DCN 2	MD0	DTRx	0.9	0.1	0
DC0	DCN 2	MD1	DTR0	0.2	0.8	0
DC0	DCN 2	MD1	DTR1	0.3	0.7	0
DC0	DCN 2	MD2	DTR0	0	0.8	0.2
DC0	DCN 2	MD1	DTR1	0.6	0.9	0.1
DC1	DCN 0	MD0	DTR0	0.8	0.2	0
DC1	DCN 0	MD0	DTR1	0.9	0.1	0
DC1	DCN 0	MD1	DTR0	0	0.9	0.1
DC1	DCN 0	MD1	DTR1	0.1	0.9	0
DC1	DCN 0	MD2	DTR0	0	0.3	0.7
DC1	DCN 0	MD2	DTR1	0	0.4	0.6
DC1	DCN 1	MD0	DTRx	0.7	0.3	0
DC1	DCN 1	MD1	DTR0	0	0.6	0.4
DC1	DCN 1	MD1	DTR1	0.2	0.5	0.3
DC1	DCN 1	MD2	DTR0	0	0.2	0.8
DC1	DCN 1	MD2	DTR1	0	0.3	0.7
DC1	DCN 2	MD0	DTRx	0.2	0.8	0
DC1	DCN 2	MD1	DTR0	0	0.4	0.6
DC1	DCN 2	MD1	DTR1	0	0.6	0.4
DC1	DCN 2	MD2	DTRx	0	0	1
DC2	DCN 0	MD0	DTR0	0.7	0.2	0.1
DC2	DCN 0	MD0	DTR1	0.8	0.2	0
DC2	DCN 0	MD1	DTR0	0	0.3	0.7
DC2	DCN 0	MD1	DTR1	0	0.4	0.6
DC2	DCN x	MD2	DTRx	0	0	1

Table 13: Conditional probability distribution of density of infected mosquitoes

The second part is a Bayesian network model to predict dengue incident rate in the target area. There are three possibilities for the dengue incident rate: Low, Moderate, and High. I believe this variable can be predicted from density of infected mosquitos and dengue-immune people. Figure 12 depicts the directed acyclic graph, and table **??** describes the conditional probability distribution of each variable in the dengue incident rate Bayesian network model.

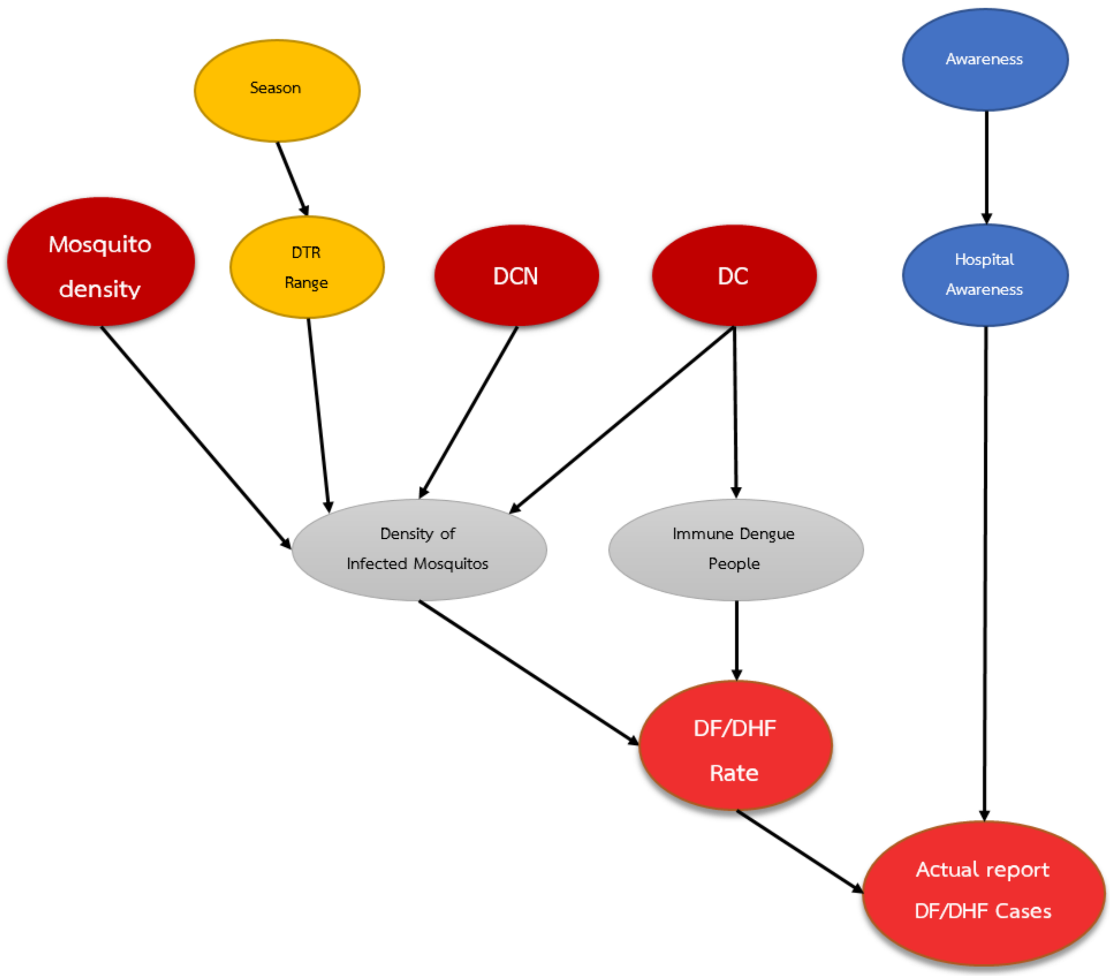


Figure 12: Directed acyclic graph of dengue incident rat Bayesian network model

Lastly, I combine both models into one model as shown in Digure 13.

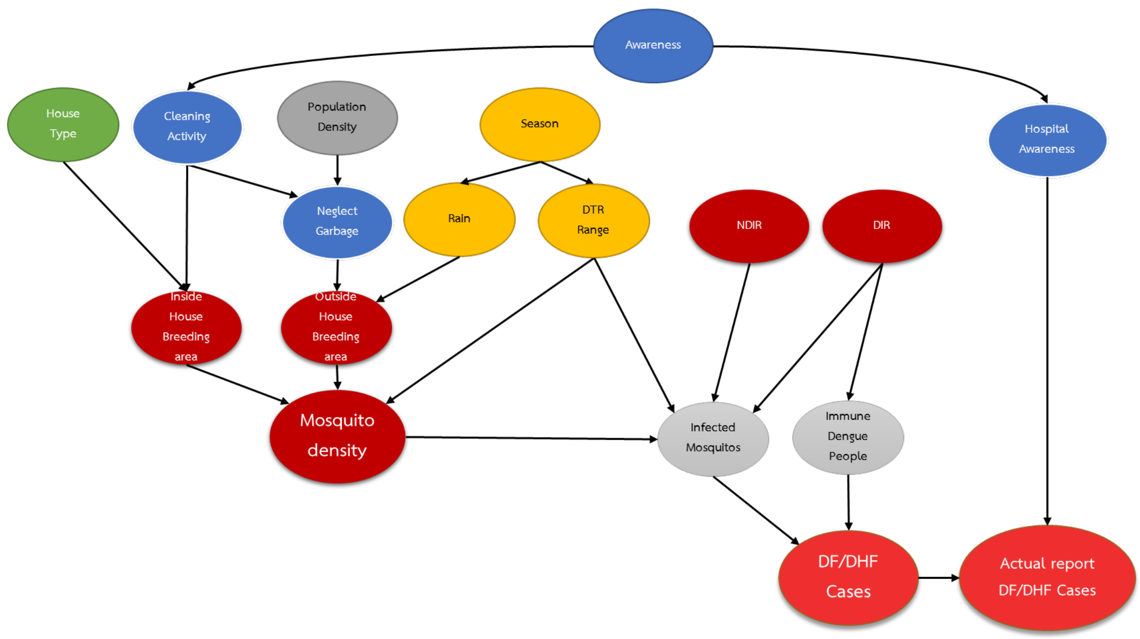


Figure 13: Combined directed acyclic graph of dengue incident rate and mosquito density Bayesian network model

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