ASIA-PACIFIC NETWORK FOR
GLOBAL CHANGE RESEARCH

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Utilizing geospatial technology to assess health vulnerability to climate change for rural population in Vietnam and Philippines

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Project Overview

Project Duration	**:**	30 months (10/07/2015-10/7/2016) –(10/11/2016 -10/5/2018)
Funding Awarded	**:**	US$ 35.314,81 for Year 1; US$ 40000,00 for Year 2
Key organisations involved	**:**	- Vietnam National Space Center (changed from Vietnam National Satellite Center: Dr. Pham Thi Thanh Nga, Mr. Nguyen Tien Cong, Ms. Nguyen Thi Thu Thuy - The University of Santo Tomas, Philippines: Dr. Maria Ruth B. Pineda-Cortel - National Institute of Hygiene and Epidemiology (NIHE), Vietnam: Dr. Vu Trong Duoc - Dokkyo University, Japan: Prof. Nakamura - Philippine Atmospheric Geophysical and Astronomical Services Administration: Mr. Joseph Quilang Basconcillo

Project Summary

Vietnam and Philippines are recognized as the most vulnerable to climate change due to regular flooding and frequent typhoons and therefore an increased burden of climate change related diseases. Changes in temperature and precipitation are likely to alter the incidence and distribution of vector-borne diseases such as dengue and malaria. The objective of the project is to improve the knowledge of the above vector-borne diseases and their vulnerability to climate variability for rural population in both countries by using advanced geospatial technology. The study covered a period of 2000-2016 years over disease exposure areas. We developed a geospatial database on dengue including temperature, precipitation, land cover, socio-environmental conditions; Data analyses helped in identifying trends in epidemiological patterns, high-risk locations and factors, and mapping vulnerability to dengue. In addition, 2 mathematical approaches were applied to predict dengue in the most disease exposure regions in two countries. Finally, the outputs of the project including the database of climate related diseases with the analyses and maps of vulnerability to dengue are accessed at the webGIS of http://apn-climateandhealth.com/. The project results are expected to contribute to building science-based knowledge for adaption planning and decision making in health sector via informing risk and vulnerability.

Keywords:

Dengue incidence, remote sensing data, vulnerability to dengue, climate variables, modelling

Project outputs and outcomes

<u>Project outputs:</u>

- A geospatial database of climate change related malaria and dengue diseases
- Published results on vulnerability of malaria and dengue diseases to climate change variable projections

- GIS-based website presents project results
- 02 Dissemination Workshops
- 08 International conference presentations/ posters and 05 journal peer-review papers have submitted and under review

Project outcomes:

- Enhance application of remote sensing for public health in developing countries
- Improve basic knowledge for developing early technologies that can predict dengue outbreaks and map the vulnerability using climate and non-climate information.
- Support policy-makers and public health institutions in formulating strategies for dengue prevention taking into consideration environmental/climatic variables in Vietnam and Philippines

Key facts/figures

- Geospatial database of climate-related disease for the period of 2000-20016 for Vietnam and Phillipines
- The WebGIS for online access to the geospatial dataset for dengue studies with dengue vulnerability maps.
- Two dissemination workshops were held in Vietnam and the Philippines with over 20 participants each from different organisations including Vietnam General Department of Preventive Medicine, The health environmental management department – Vietnam Ministry of health, National institute of hygiene and epidemiology, Pasteur Institute of Ho Chi Minh City and Nha Trang of Vietnam, and different institutes.
- In this project were involved 9 young scientists working on different aspects ranging from data collection, field surveys, database development, modelling and mapping to WebGiS development.

Potential for further work

- Downscaling study on influences of combined exposure and susceptibility at district and commune levels for both countries is one subject for the further vulnerability mapping.
- Epidemiology modelling could be more reliable if incorporating ecology of vectors for virus transmission, therefore the further improvement of modelling with mosquito's ecology is one of future direction.
- At regional scale, this project could be expanded to other ASEAN countries, such as Laos and Cambodia, where similar studies were not reported.

Publications

- Poster presentation titled "Mapping health vulnerability to climate change for rural population in Vietnam and Philippines using geospatial technology" by Pham Thi Thanh Nga, Nguyen Thi Thu Thuy at "International Conference on Livelihood Development and Sustainable Environment Management in the Context of Climate Change" - LDEM 2015 / 13-15/11/2015, Thai Nguyen, Vietnam
- Pham T.T. Nga, Nguyen Tien Cong, and Nguyen Thi Thu Thuy (2016). Correlation of Dengue Disease and Climate Variables using Geospatial Data for Vietnam. Asia Oceania Geosciences Society (AOGS) 2016 Proceedings. Beijing, IG04-A004. (http://www.asiaoceania.org/aogs2016/public.asp?page=abstract.htm)
- Pham T.T. Nga (2016). Modelling Dengue disease with climate variables using geospatial data

for Vietnam and Philippines. *The 23rd Session of the Asia-Pacific Regional Space Agency Forum (APRSAF-23)*, Manila, the Philippines, November 15-18, 2016. https://aprsaf.org/annual_meetings/aprsaf23/working_groups_sawg.php

- Pham T.T. Nga, Nguyen Tien Cong, and Nguyen Thi Thu Thuy (2017). Correlation of dengue disease and climate variables using geospatial data for Vietnam. "*Impact of Changing Regional Environment on Global Health*", 65th Annual Convention of the Philippine Association for the Advancement of Science and Technology and 8th Asian Heads of Research Councils Joint Symposium, Philippines, 22 to 23 September 2016.
- Maria Ruth B. Pineda-Cortel et al. (2016). Prediction Model for Dengue and Malaria Cases in the Philippines: A Preliminary Study. "*Impact of Changing Regional Environment on Global Health*", 65th Annual Convention of the Philippine Association for the Advancement of Science and Technology and 8th Asian Heads of Research Councils Joint Symposium, Philippines, 22 to 23 September 2016.
- Pham T.T. Nga, Nguyen Tien Cong, and Nguyen Thi Thu Thuy (2017). Modelling Dengue disease with climate variables using geospatial data for Vietnam and Philippines. *Asia Oceania Geosciences Society (AOGS) 2017 Proceedings*. Singapore, IG03-A00. (https://www.meetmatt-svr3.net/aogs/aogs2017/mars2/pubViewAbs.asp?sMode=session&sId=11&submit=Browse+Abstracts)
- Nguyen Tien Cong, Pham Thi Thanh Nga, Vu Duoc (2017). Mapping vulnerability to dengue in Mekong Delta region, Vietnam from 2002 to 2014 using geospatial data by water-associated disease index approach. *Impacts World 2017 symposium*, Germany, 10-13 Oct. 2017.
- Maria Ruth B. Pineda-Cortel, Benjie Clemente, Joseph Q. Basconcillo, Nguyen Tien Cong and Pham Thi Thanh Nga (2017). Analysis of the effect of temperature, rainfall, and humidity on dengue cases in the Philippines from 2008 – 2015. *ASEAN Medical Laboratory Science and Public Health Education Stakeholders Summit and Research Conference*, Philippines Nov 29-Dec 01, 2017.

Papers under review

- Damien Philippon, Thi Thanh Nga Pham, Alexis Drogoul, and Thi Thuy Nguyen. Modeling Dengue over Mekong Delta Region of Vietnam (No ACBI-D-17-00041R1), (First submission June 29, 2017), re-submitted to *Acta Biotheoretica* (ISSN: 0001-5342), now under revision.
- Nga T. T. PHAM, Cong T. NGUYEN, Duoc T. VU, Kenji NAKAMURA. Remote sensing-based mapping of vulnerability to dengue in the Mekong Delta region of Vietnam using a water-associated disease index approach, submitted to *APN Bulletin* (ISSN 2185-761X).
- Maria Ruth B. Pineda-Cortel, Joseph Q. Basconcillo, Benjie Clemente, Nguyen Tien Cong, and Pham Thi Thanh Nga. Analysis of the effect of temperature, rainfall, and humidity on dengue cases in the Philippines from 2008 – 2015, submitted to *Asia Pacific Journal of Medical Laboratory Science* (ISSN 2244-6249).
- Damien Philippon, Nga Thi Thanh Pham, Alexis Drogoul, and Thuy Thi Thu Nguyen. Modelling Land Cover and Weather influences on Dengue Fever in the Mekong Delta Region of Vietnam using remote sensing data, Submitted to GeoHealth (ISSN: 2471-1403)
- Nga T. T. Pham, Cong T. Nguyen, Maria Ruth B. Pineda-Cortel. Time-series Modelling of Dengue over the Mekong Delta Region of Vietnam Using Remote Sensing Data, submitted to *Western Pacific Surveillance and Response* (WHO) (ISSN: 2094-7321)

Awards and honours

First place for Oral Research Presentation at 2017 ASEAN Medical Laboratory Science and Public Health Education Stakeholders Summit and Research Conference presented by the Commission on Higher Education in coordination with the Philippine Association of Schools of Medical Technology and Public Health.

Pull quote

"Developing countries have big problem in health. Industrialization and expansion of cities cause vulnerability to diseases. In addition, the climate change make difficult to predict future health conditions. In this context, the project aims to develop skills to investigate the epidemic, such as, the expansion of dengue fever. Since ground survey is difficult for developing countries, utilization of satellite remote sensing data, such as, temperature, precipitation, land cover, etc. is a powerful and effective way to cope with this matter. The project showed fruitful results that confirm the satellite remote sensing data have big potential for grasp the epidemics. The results gave a good base for the prediction of epidemics. Though the results are limited in Vietnam and Philippine, the results are very important in Vietnam and Philippines, and also they become part of global data. In this sense, I evaluate that the project is very successful" - *Prof. Kenji Nakamura, Dokkyo University, Soka, Japan. An advisor for the project.*

"Today, we were able to listen to the talk of our distinguished speakers on an important topic and we certainly have understood that as the incidence of dengue continues to increase, and as climate change continues to become one important driver of the current distribution of dengue, and as the geographic ranges of the primary vectors, the Aedes aegypti mosquitoes continue to expand, it is but certain that the greater burden of dengue and malaria shall be on the low and middle income countries. Thus, new prevention and control efforts are needed to counter the potential effects of climate change on the geographical range and incidence of dengue and malaria. However, I believe that closing remarks shall always be the remarks of thanksgiving. So on behalf of the Faculty of Pharmacy, Department of Medical Technology, let me express my profound gratitude to our speakers... Dr. Pham Thi Thanh Nga, Ms. Kim Carmela Co, Asst. Prof. Ma. Gina M. Sadang, and Asst. Prof. Maria Ruth Pineda-Cortel…Thank you very much…for you insights and sharing which did not only impress us but the montage of how important this topic is to us was effectively cascaded, reminding, motivating, and inspiring us to reflect and to act on the important issues of dengue, malaria, and climate change." – *Ass. Prof. Ma. Frieda Z. Hapan, Assistant Dean of the Faculty of Pharmacy, University of Santo Tomas at the project workshop in Philippines, Nov 24, 2017.*

"In the context of climate change and burden dengue, while a vaccine for dengue is still not applicable in Vietnam, this contributed to providing science-based evidence on climate variability role in dengue, one of important vector-born diseases and identifying a gap in researches needed for early warning of dengue under influence of climate change on community health" – *Ass prof. Pham Thanh Binh, Head of Vietnam Vaccine Administration Office, Ministry of Health.*

Acknowledgments

1) Institute of Hygiene and Epidemiology, Vietnam Ministry of Health for providing disease data.
2) IRD (Institut de recherche pour le développement) in Vietnam, Dr Alexis Drogoul, Representative of IRD in Vietnam and Philippines; http://en.vietnam.ird.fr for his encouragement for modelling study by GAMA platform.
3) Prof Nakamura Kenji for his valuable advisor for the project implementation.

1. Introduction

Emerging of vector-born disease related to climate variables over the Asian region, including Vietnam and Philippines

According to the WHO (2012), Vietnam and Philippines are among the top ten countries of high reported dengue cases in the world with 91,321 and 54,639 cases; meanwhile, the number of reported confirmed cases of malaria in Vietnam and Philippines in 2012 are 19,638 and 7,133, respectively. A total of 1,117,142 dengue cases were reported in the Philippines from 2008 to 2015, with approximately 0.48% of the cases led to death, while in Vietnam from 2007, dengue has been recorded in 55 of the 63 provinces, increasing from the north to the south with the Mekong Delta experiencing the highest accounting for approximately 30-50% of total cases. WHO also identified both nations as countries with ongoing malaria transmission and resistant to chloroquine, the long-used drug in the treatment or prevention of malaria. Studies have shown that dengue epidemics in Vietnam follow a cycle of 3-5 years and reach a peak almost every 10 years (large outbreaks were recorded in 1987, 1998 and 2009) while in Philippines, epidemics of dengue occur every 3–4 years (Sia Su, 2008; Vu, 2014). Peak dengue period in Vietnam and Philippines both occurs in rainy season from June to November (Sia Su, 2008). Malaria is also recorded generally higher during the rainy season in Philippines, while in Vietnam malaria transmission is highest during transition periods between dry and rainy seasons (Wannapa et al. 2013). Only remote mountainous regions are recorded with most malaria incidence in both countries.

With the impact of global climate change on human health, there has been an increasing number of infectious disease cases (Patz et al. 2005), including mosquito-borne diseases such as dengue, one of the most climate-sensitive diseases. Climate factors, in addition to multiple human, biological, and ecological determinants, influence the emergence and re-emergence of infectious diseases (Patz & Balbus, 1996). In Southeast Asia, a study by Sia Su (2008) has shown that there was a significant correlation between rainfall and dengue incidence in metropolitan Manila, the Philippines, from 1996 to 2005. Promprou et al. (2005) also found a correlation of dengue incidence with temperature and rainfall and in Southern Thailand using multiple regression analysis. On a regional scale, a review of the impacts of climate change on human health by Patz et al. (2005) provided more evidence of the burden of climate change-attributable diseases and emphasized the uncertainty in attributing diseases to climate change, owing to a lack of long-term and high-quality data. However, climate change is certainly not the only factor. The land cover of the area might also have an impact on dengue fever. Cheong et al. (2014) showed an important correlation between the number of dengue cases and land cover, with human settlements and water body types having higher probabilities of infection than other land types.

Dengue disease impact on economics and society and the measure for controlling

Dengue fever is a vector borne disease with four different serotypes, the infection of human beings is possible thanks to the vector of the dengue fever: the mosquitoes of Aedes species. Duong et al. (2015) shown that nearly three cases on four is asymptomatic or mid-asymptomatic, which means that people could be infected without knowing it, but could still infect mosquitoes. Furthermore, if someone infected with a serotype get infected by another serotype, the risk for this person to suffer from severe dengue increases, which could lead to death. The burden of the dengue is both economic and social: people who must be hospitalized are a cost for countries, they cannot work for a certain amount of time and the death of human beings is still a sad event for the society. In Vietnam, the average cost for a family to hospitalize a child infected with dengue is about 61 USD, with the greatest expenses being visits to the general practitioner, hospitalization, and lost income of the parents (Harving and Ronsholt, 2007). The population of the provinces in the south of Vietnam, the most affected by the dengue fever, represents millions of inhabitants, which represents millions of susceptible human beings. Dengue treatment in Can Tho, one of the provinces in the Mekong River Delta, is approximately 167 USD for a child, which could represent a consequent burden if an outbreak occurred.

The countries have the possibility to control the dengue outbreak by applying control policies or health policies. Targeting the vector directly is one of the best way to control the dengue dynamics. The different means used by the countries and organizations to reduce the risk coming from the vector is to kill the mosquitoes, by introducing natural predators of the larvae or the adults mosquitoes (putting guppy fishes inside the water tanks to eat the larvae for instance), using pesticides and other chemicals (BTI briquettes which can kill larvae) or simply reducing the population by introducing sterile male mosquitoes (Wilke, et al. 2009). However, it is also possible to control the dengue fever dynamics by informing the population, training them to wear wide shirts or remove stagnant water inside flower pots. Recently, a vaccine produced by Sanofi Pasteur called Dengvaxia has been experimented in Mexico and Philippines, and is now used by different countries to fight against the severe dengue (WHO, 2015).

Range of study approaches

Several important studies of dengue fever have been performed in recent years in an effort to understand the dynamics of the disease and the influences of environmental factors on the disease, as well as to be able to predict outbreaks. A range of approaches, including statistical modelling, mathematical modelling, and spatial analysis and indices have been applied to demonstrate a relationship between dengue and climate variables and to predict dengue outbreak and occurrence from this relationship (Louis, 2014, Pham et al. 2016). The characteristics of each approach, such as input and output, geographic area, and scales, as well as its advantages and disadvantages, were reviewed by Louis (2014). The most popular approach is statistical modelling with two main methods, regression and time-series (Pham et al, 2016). There were several studies to investigate the associations among climate variables, demography and dengue incidence in Vietnam. For example, Thai et al. (2010) and Cuong et al. (2013) used a wavelet time series analysis, Coudeville & Garnett (2012) developed a mathematical model representing the transmission dynamics of the four dengue serotypes. Recently, Phung et al. (2015) used three different regression models, the standard multiple regression model (SMR), the autoregressive integrated moving average model (ARIMA), and the Poisson distributed lag model (PDLM), to examine the association between climate factors and dengue incidence in the Can Tho province of Mekong Delta Region of Vietnam. The conclusion was that the PDLM performs the best in predicting dengue incidence over 6-, 9-, and 12-month periods and in diagnosis of an outbreak; however, the ARIMA model provides a better prediction of dengue incidence for a 3-month period. Additionally, Phung et al. (2016) applied a Poisson generalized linear model (GLM) and distributed lag model (DLM) to predict infectious diseases in relation with climate variables at different time-lags in Mekong Delta provinces. The results produced from above statistical models cannot predict the time and place of a dengue outbreak precisely. However, they provided the quantitative association of rainfall, temperature, and humidity with dengue epidemics at certain geographic area with specific time-lag. Mathematical model including human mobility and entomological data is considered better than statistical model in precisely quantitative prediction of dengue transmission and outbreak (Louis 2014, Pham et al. 2016). Nevertheless, dengue prediction models can vary due to their complexity and methodology and are dependent on the type of data collected and the nature of the variables, and no universal models exist for global analysis and prediction (Racloz et al. 2012).

An analysis of vulnerability has popularly been applied to assess health hazards related to climate change (Patz & Balbus, 1996, Dickin et al. 2013). Mapping health vulnerability to climate change with three components of exposure, sensitivity and adaptive capacity is a popular assessment approach, which includes 3 phases: problem formulation, analysis, and integration (Kovats et al. 2003). Patz & Balbus (1996) proposed a framework for the assessment of health vulnerability due to climate change. Dickin et al. (2013) developed the Water-Associated Disease Index (WADI) approach to provide a "practical tool" and vulnerability map in support of dengue prevention and control in Southeast Asia and South America and on a global scale. Khormi & Kumar (2011) reviewed and highlighted the advantages of geospatial data and techniques in the issue of mapping mosquito-borne diseases where satellite images provide good data with high temporal and spatial resolution to estimate various parameters (rainfall, temperature, soil moisture, land cover type, etc.) to identify mosquito habitats. GIS will merge such information with socio-economic factors and disease incidence, applying spatial statistical analysis to map and model diseases with high accuracy. The flexibility of the WADI framework allows the ability to adapt multi-dimensional data at different scales and geographic places, which can be applied with geospatial data (Louis et al. 2014). The literature review shows that there are still limited studies being able to collect and integrate epidemiological spatial and temporal data to map vulnerability of vector-borne diseases to climate change for Southeast Asia region.

The study objective

Viet Nam and Philippines are recognized as the most vulnerable to climate change, affecting human health in both direct and indirect ways, increasing burden of climate change related diseases. However, literature review reveals a knowledge gap in applying geospatial data and techniques in studying disease vulnerability. Thus, the proposed study will be an attempt to fulfil the gap in climate related health data and improve the knowledge of disease dynamics to climate and environmental variability specific for two developing countries in ASEAN region.

2. Methodology

Assuming that there exists a strong relationship among factor groups of mosquito-borne disease incidence, characteristics of vectors, climate parameters (temperature and precipitation), land-use, land-cover, and socio-environmental conditions, this study will focus on describing this relation in both temporal and spatial scales and identifying the risk under this influence. We developed a conceptual framework for project activities as in Figure 1. Following the framework, firstly, 3 groups of data including climate and environmental variables; Disease incidences; and socio-economic data were collected for inputting to the study. The second activity is data analysis, in which we applied spatial and temporal analysis methods to identify correlation among variables with dengue and distribution patterns of dengue by applying cluster and hot-pot analysis. These analyses helped in defining the high-risk dengue regions to focus on with two approaches: modelling and mapping. We decided to try with both approaches rather than only mapping because both approaches have advantages and limitations in their application. Nevertheless, it is worth to carry out this study in both directions with a support from huge set of remote sensing data. The rest of this section will describe data, mapping approach, and modelling approach in more detail.

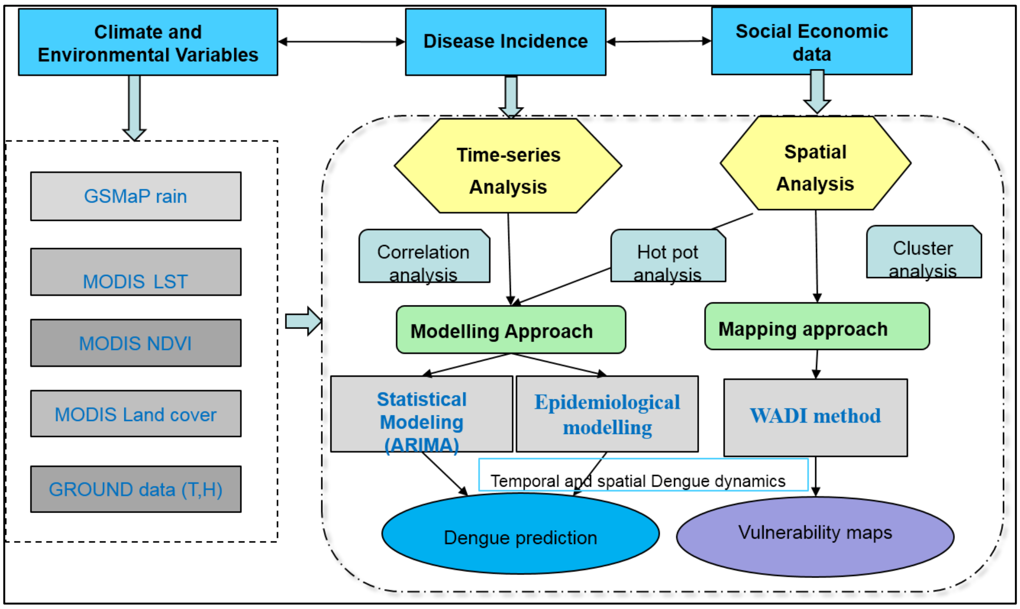

Figure 1. Study framework of the project

Data

Disease data

Monthly data on numbers of reported cases vector-born diseases for Vietnam were provided from database of National Institute of Hygiene and Epidemiology (NIHE) and for Philippines from the regional and national offices of the Department of Health (DOH). The exploration of all data revealed that for the last ten years, malaria occurred very occasionally with few cases reported in remote provinces of both countries. This is not significant for statistical analysis, therefore, we decided to focus on dengue, which was gathered from 2000 to 2016 for Vietnam and from 2008 to 2015 for Philippines. Dengue case detection is based on the World Health Organization criteria and collected through the disease surveillance systems from Provincial Preventive Medicine Centres to Regional and National Centres accordingly to the regulation of the Ministry of Health.

GSMaP rainfall and MODIS Land surface temperature

In the condition of sparse and manual surface observations, the climate variables of temperature and rainfall over the region are very limited for the mapping. In attempt of extensive use of remote sensing data with their advantages of spatial coverage with high resolution and temporal availability, we used GSMaP (Global Satellite Mapping of Precipitation) data as alternative for surface rainfall measurement. The daily GSMaP/MVK (version 6) data of spatial resolution of 0.1x0.1 Ushio et al. (2009) were extracted for the MRD correspondingly and accumulated to monthly amount. We used monthly Land Surface Temperature data from MODIS LST (MOD11A2) with a 1 km spatial resolution (Wan, 2007) as a proxy for air temperature of night and day. An example of those data presented in Figure 2.

In addition to climate variables, one of most commonly used remote sensing-derived environmental variables, the normalized difference vegetation index NDVI from MODIS (MOD13Q1) with a 250 m spatial resolution was also used for modelling its influence on dengue. Depending on the requirement, these remote sensing-based parameters were also aggregated to compute mean monthly variable for each province.

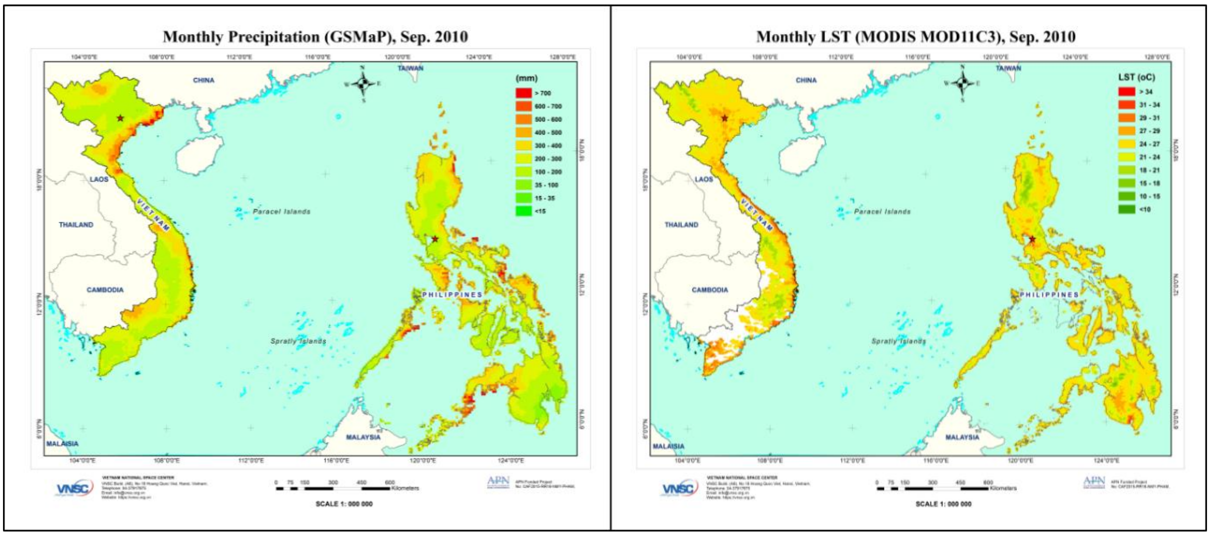

Figure 2. Examples of GSMaP and LST data for Vietnam and Philippines

MODIS Land Cover Data

Change of the environment also contributes to exposure by providing mosquito breeding habitats favourable for dengue transmission. Distribution of dengue-carrying mosquitoes associates with different type of land cover/land use (Cheong et al. 2014). They clarified the most important land use factors to dengue disease are human settlements, followed by water bodies. In this study, land cover data were extracted from satellite-based secondary product, MODIS Land Cover Type Yearly L3 Global (MCD12Q1) products (Friedl et al. 2010) and mapped with areas of standard Land Use Map of 2010 year with the scale of 1:100.000 provided by the Ministry of Natural Resources & Environment (MONRE). Spatial resolution of data is 500 m x 500 m, and the data covers the period from 2001-2013. The MODIS data has four different type land cover classifying results. We found the result of type 3 classification mostly fitted to the Vietnam 2010 national land use dataset. In this map, there are 7 main classes of Water, Bare soil, Shrubs, Mixed horticulture, Water, Cereal/ paddy field, and Urban for calculating the exposure (Figure 3). It is clearly seen in Figure 3 that the majority of land is covered by agriculture, urban lands concentrate in few areas in each province, while rural lands are scattered within the agriculture lands. Thresholds were adapted from the works of Dickin et al. (2013) and modified according to important contribution of land use to dengue disease in the study of Cheong et al. (2014) to this MODIS land cover class.

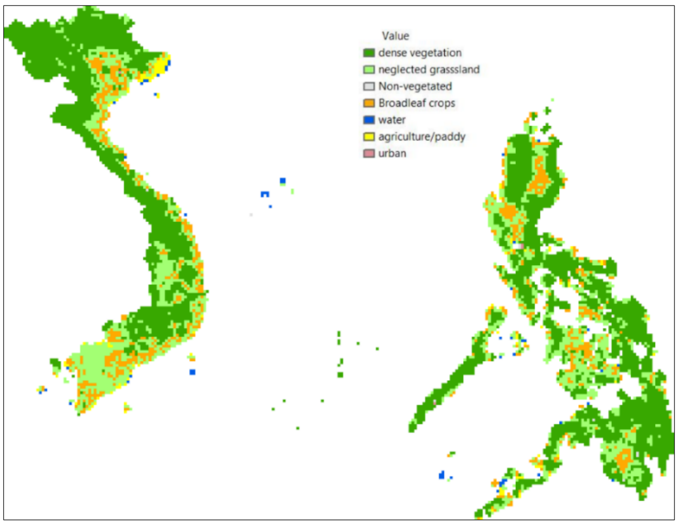

Figure 3. Land cover data from MODIS (MCD12Q1) for Vietnam and Philippines (2010)

Mapping approach

This study applies the WADI conceptual framework, which was developed by Dickin et al. (2013) and is described in Figure 4. In this framework, the vulnerability index is composed of only the exposure and susceptibility indicators, where the exposure describes conditions that are conducive to the survival and transmission of dengue in the environment. Susceptibility describes the existing sensitivity of a population to dengue. The susceptibility indicator also includes conditions that impact resilience, a concept described as the capacity to prevent, respond to and cope with disease.

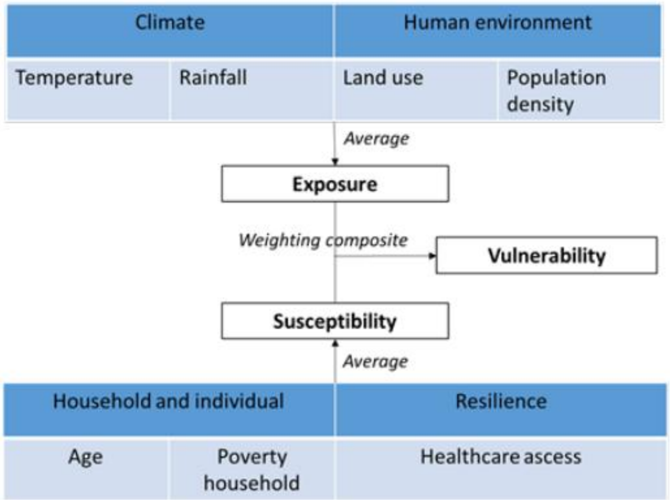

Figure 4. The WADI framework following Dickin et al. (2013)

Following Dickin et al. (2013), in this study we use two components of climate and human environment for the exposure indicator, while the susceptibility composes of components indicating the age, poverty, and healthcare access (Figure 4). The climate factor includes two important variables of temperature and rainfall and human environment consists of land cover and population density. It is noted that exposure and susceptibility scores were scaled between 0 and 1, representing a range from low to high exposure or susceptibility and were based on proposed threshold of Dickin et al. (2013) with modification by Cheong et al. (2014) for land use as summarized in Table 1.

Table 1. Summary of the exposure components and calculation threshold

Component	Data sources	Threshold	Value	Threshold source
Land cover	MODIS Land Cover Type Yearly L3 Global 500m (MCD12Q1) using classification type 3	Forest	0	Cheong et al. (2014), Dickin et al. (2014)
		Bare soil	0.2	
		Shrubs	0.17	
		Mixed horticulture	0.25	

		Water	0.3	
		Cereal agriculture/ paddy field	0.45	
		Urban	1	
Population density (thousand/km^2)	General statistic office	<0.1	0	Dickin et al. (2013)
		>0.1-<0.25	0.25	
		>0.25-<0.5	0.5	
		>0.5-<1	0.75	
		>1	1	
Temperature	MODIS LST	Monthly daytime LST (1 months lag)	20^{0}C to 34^{0}C: linear increase in exposure up to 1; out of range (20-34^{0}C): 0 exposure	Dickin et al. (2013)
Rainfall	GSMaP data	Monthly cumulative precipitation (2 months lag)	<300 mm precipitation: linear increase in exposure up to 1; >300 mm monthly precipitation: 0 exposure	Dickin et al. (2013)

The susceptibility indicator needs to include a range of socio-economic and demographic components that increase sensitivity to dengue transmission when exposure conditions are favourable (Patz and Balbus, 1996). Dickin et al. (2013) proposed 5 components including population age, housing quality, water and sanitation, health care access, and Female education level. However, based on the availability of collected data we were able to use 3 of them as listed in table 2. Louis et al. (2014) reviewed the 26 published papers on mapping dengue risk and found that age and income are two of the most commonly used factor using to predict dengue risk. This is agreeable with reported dengue incidence in Mekong delta region showing a high rate of patient of less than 15 years old (Coudeville and Garnett, 2012). In other hand, poverty contributes to lessen resilience to dengue, especially poor people in urban and rural in developing countries spend almost their income to food and house rather than to health care service (Khun and Manderson, 2008). Harving and Ronsholt (2007) showed that dengue fever was socio-economic burden in Southern Vietnam with cost of treating one child is $61, in the meantime the poverty standard applying to rural as Mekong delta was $10,25 of income per month. Until now, the cost of dengue treatment in the Southern Vietnam still increase higher with approximately $200 per case (Pham et al. 2017), meanwhile the new poverty standard is $20. The poverty component is define as percentage of poverty household per each province.

Table 2. Summary of the susceptibility components used for calculation

Component	Data sources	Threshold
Age under 15 years	The General Statistic Office of Vietnam (2009 census dataset)	% population under 15 years by province
Health care access	Annual data from the General Statistic Office of Vietnam	Density health facilities per square km area
Poverty	Annual data from the General Statistic Office of Vietnam	% poverty household per province

Modelling approach

For statistical modelling, in this study we apply the ARIMA model for dengue fever with extensive use of remote sensing data for both countries. We decided to use ARIMA model because it has the ability to cope with stochastic dependence of consecutive data and to account for auto-correlations in time-series as well as seasonality, long-term trends and lags (Racloz et al. 2012).

We used the Box-Jenkins methodology (Dela Cruz al. 2012) to fit ARIMA models to monthly dengue incidence by statistical "forecast" package in RStudio software. To avoid effects from the non-constant variance of dengue counts, they were stabilized by natural log transformation. First, examination of data showed strong seasonality and inter annual variation of dengue incidence and climate and environmental variables (rain, LSTd, LSTn, and NDVI) presented in Figure 5, as examples for Angiang province of Vietnam during the period 2000-2015 and for Central Luzon of Philippines, ensuring the ARIMA model suitable for studying monthly dengue data in each site. The adequacy of the each model for each province was verified by histogram, by autocorrelation (ACF) of the standardized residuals, and by the Ljung-Box test, similar to previous studies (Dela Cruz et al. 2012, Martinez et al. 2011, Johansson et al. 2016, and Wongkoon et al. 2012).

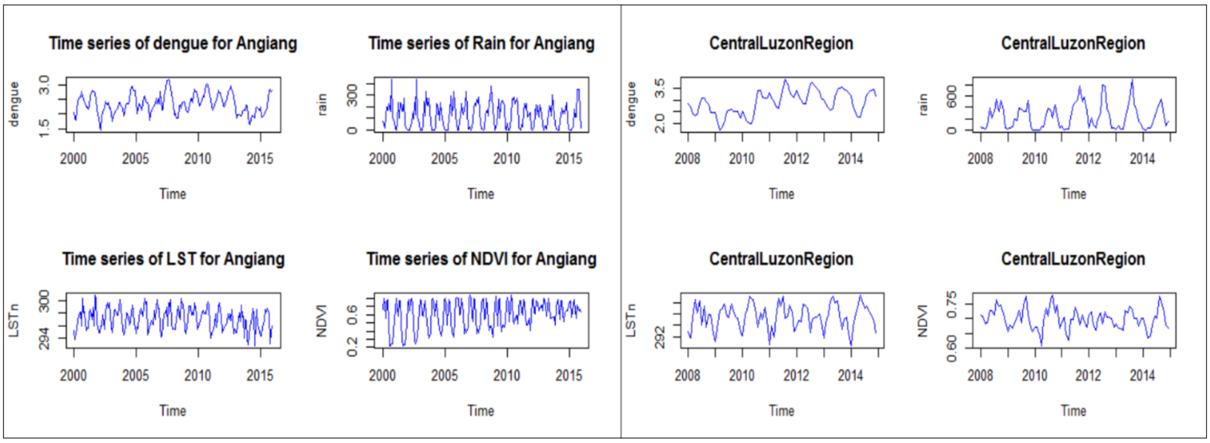

Figure 5. Time series of dengue, rain, LSTn, and NDVI for Angiang province (Vietnam) and for Central Luzon Region (Philippines)

The structure of the model followed the standard form for ARIMA, (p,d,q)(P,D,Q)s, where p is the order of auto-regression; d, the degree of differencing; q, the order of the moving average; P, the seasonal auto-regression; D, the degree of seasonal differences; Q, the seasonal moving average; and s, the seasonal period. Next, different SARIMA model forms (different combinations of p, d, q, P, D, and Q) were tested to fit the log-transformed time series data without environmental covariates. The best ARIMA model was selected as that with the lowest Akaike information criterion (AIC), a measure of the relative goodness of fit of a model across the 12 provinces (Hau Giang province was excluded because of missing data, as it had separated from Can Tho province in 2004). Then, using selected ARIMA components (p, q, P, Q from 0 to 2), multivariate ARIMA models were fitted with log-transformed dengue cases in relation to all the climate variables with time lags, which were chosen by their best correlation with dengue.

In addition to statistical approach, another approach is an agent based model that will answer a problematic question using agents to represent the different entities existing in our world (abstract or concrete entities, such as mosquitoes, human beings but also provinces, geographical entities), their behaviours but also the interactions between them. The main interest was the methodology used to represent the dengue fever dynamics among different locations: using agents to represent the location, and having an Ordinary Differential Equation model among these agents. Phung et al. (2016) developed a climate-based prediction model in order to improve dengue prevention and control in the Mekong Delta Region. The model aims to identify the high-risk clusters considering daily average temperature, daily average relative humidity and daily cumulative rainfall. The model shows that the impact of the average temperature is higher and last longer than the impact of the other climate factors, although all the factors are significantly associated with the change of dengue incidence. The results also indicate that the high-risk clusters in this region are the provinces located at the northeast part of the region. While these articles presented mathematical model, Boosted Regression Tree analysis and agent based model, we decided to use their results and findings to define an agent based model focusing on the impacts of climate and land cover on the dengue fever transmission for one of high dengue-risk region in Vietnam, the Mekong River Delta Region by understanding how the dengue works but also by showing the potential areas that could have a higher-risk of seeing dengue infections. We tried to use an agent based model because it is a good way to represent geographical complex dynamics such as the disparity of the incidence of the dengue but also the weather. We considered the different cells contained in the grids provided by the different data sources as agents to simplify the relations between them. We used GAMA platform (Grignard et al. 2013) to build our model, as it is easy to use even for non-computer scientists and proposes an already built-in environment for modelling. One advantage of this platform is also its facility to integrate GIS data and do spatial operations as spatial overlapping and distance computation.

3. Results & Discussion

In this section, we present the main results from two mentioned approaches. The analyses focus on the target regions after spatial investigation using GIS techniques. Figure 6 showed the results of Local Moran's Index and Getis-Ord Gi^* score from dengue incidence data for both countries in 2014-2015 as examples. By Local Moran's I, we defined some areas of clusters in the northern and southern regions of Vietnam during 2014-2015, and Gi^*score helped in identify hot spot (red) location, which is defined as the highest value surrounded by relatively high values and cold spot (blue) locations, which is defined as the highest value surrounded by relatively low values. Checking through whole the period, we got a consistent hot spot location in the Mekong River Delta region of Vietnam and consistent cold spot in Hanoi. Therefore, further modelling and mapping studies is concentrated on the MRD region in

Vietnam. In Philippines, we got the focused regions including Calabarzon, Central Luzon, Ilocos Region, and National Capital Region by their consistent hot spot results for the enhanced study.

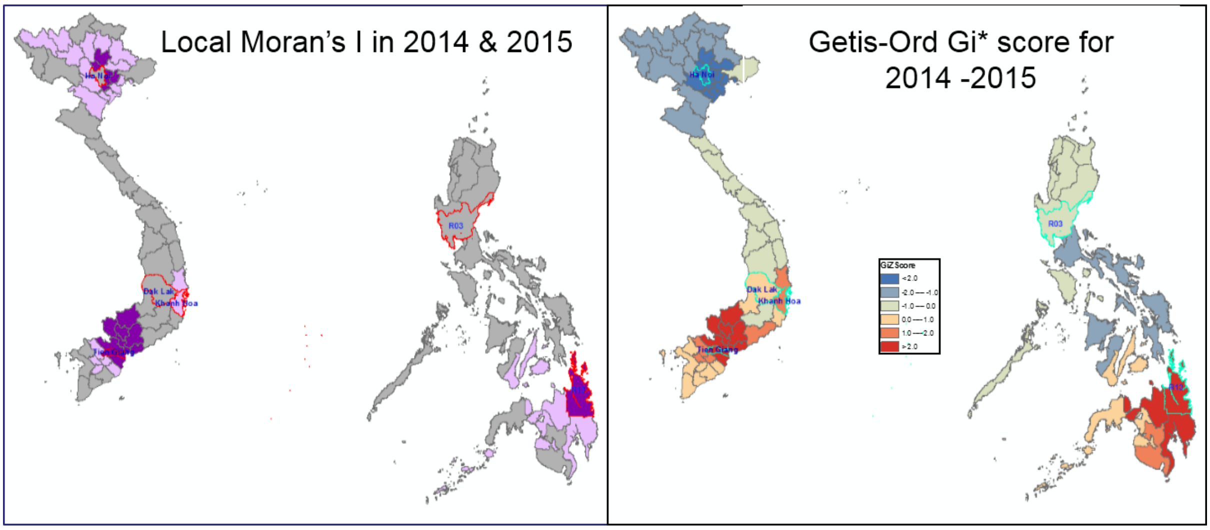

Figure 6. Spatial Analyses of dengue incidence by Local Moran's I and Gi* score

Vulnerability maps

Monthly maps of overall vulnerability were produced by combining raster layers of susceptibility and exposure indicators. The selection of weighting schemes for each indicator to the total vulnerability index was based on an approach in which different weightings were tested to find the best correlation coefficient of the WADI index with monthly dengue rates from 2002 to 2014 for each province. In fact, the vulnerability is more sensitive to exposure than the susceptibility indicator because the climate components clearly show monthly variations, while the others change at a yearly scale. Based on correlation results, we decided to use weightings of 1 for the susceptibility and 3 for the exposure indicator, so that the final vulnerability index was weighted more heavily on the exposure indicator. In addition, monthly data for temperature and rainfall were used in a time-lagged manner based on their best correlation with monthly dengue incidences for each province. This approach is similar to the approach used by Vu et al. (2014), where weather components strongly affected dengue transmission at a lag time of 0 to 3 months, with considerable variation in their influence among different areas in Vietnam due to the delay between the onset of weather conditions and the impact on mosquito populations. Yearly vulnerability maps were produced by aggregating monthly maps, and GIS software was used to combine raster layers to obtain maps by district and provincial administrative boundaries.

Figure 7 showed monthly vulnerability maps of 2010 year for Vietnam and Philippines. The results indicated that vulnerability to dengue over both countries varies greatly across spatial and temporal dimensions. In Vietnam, the highest vulnerability is clearly mainly in the southern region while the lowest vulnerability is observed in the remote and sparse populations covered by forest and bare soil land types. Overall, this finding agrees well with the weighting of land use for calculating the exposure indicator (table 1). We found that aggregated vulnerability concentrated higher in the provinces corresponding to a high-risk cluster of dengue in the Mekong Delta area (Phung et al. 2016). And in Philippines, higher vulnerability was found in the previous identified focused regions.

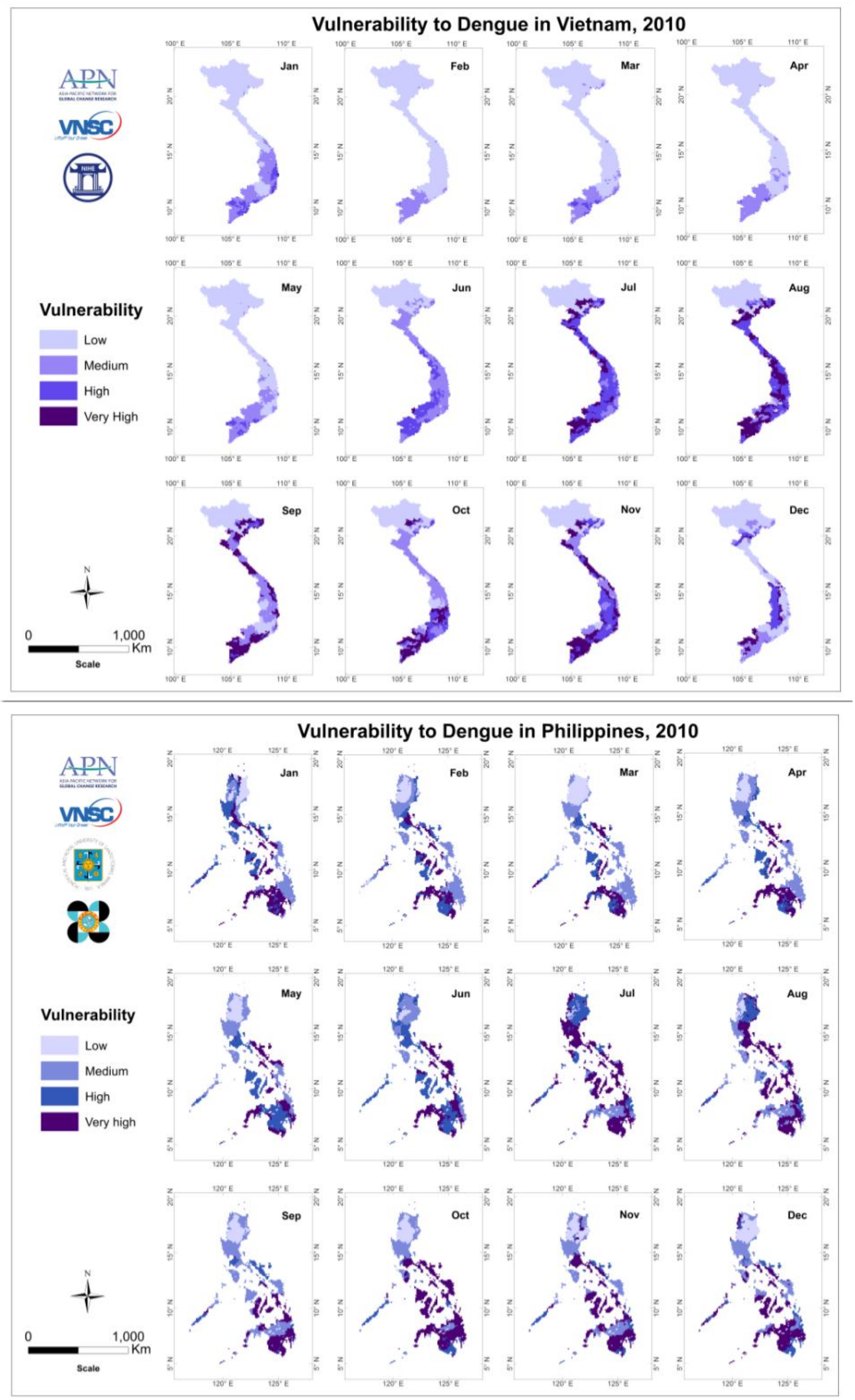

Figure 7. Monthly vulnerability maps in 2010 for Vietnam (a) and Philippines (b)

At a temporal scale, the monthly average data in Figure 7 also clearly show the seasonal variation of vulnerability with the lowest values in February-March, increasing towards the highest values during August to November for both countries. Obviously, this seasonal cycle is mainly affected by the seasonal variation in climate in this region, as other factors remained unchanged throughout the year. Generally, increased temperature and rainfall are associated with increased dengue transmission (Johansson et al. 2009); therefore, higher vulnerability is related to the rainy season during May-November. This trend was widely reported in many regions in Southeast Asia in tropical environments (Wai et al. 2012). Apparently, exposure to dengue heavily varies throughout the year, depending on the changes in climate condition over the region.

ARIMA Model in association with variables

Figure 8 presents an example of ARIMA fitting model plot for An Giang province of Vietnam (a), and the comparison of fitted with reported dengue cases (b), which shows the regression function with its root mean square error value for fitted period of 2000-2015 data. The final model for each province was confirmed by Ljung-box test of the residual with no correlation for fitted data. And Figure 9 presents the similar examples for the Central Luzon region of Philippines.

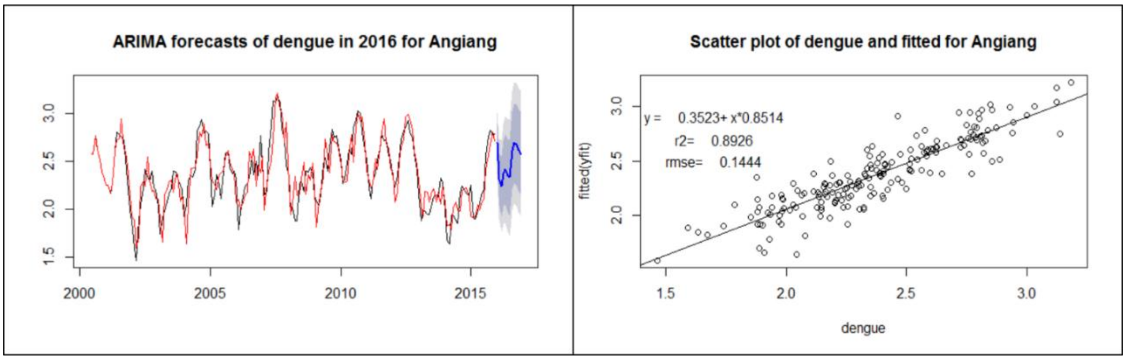

Figure 8. a) Plot of ARIMA fitting model for An Giang province (reported data in black, fitted model in red, and predicted model in blue); b) Scatter plot of fitted and reported dengue cases

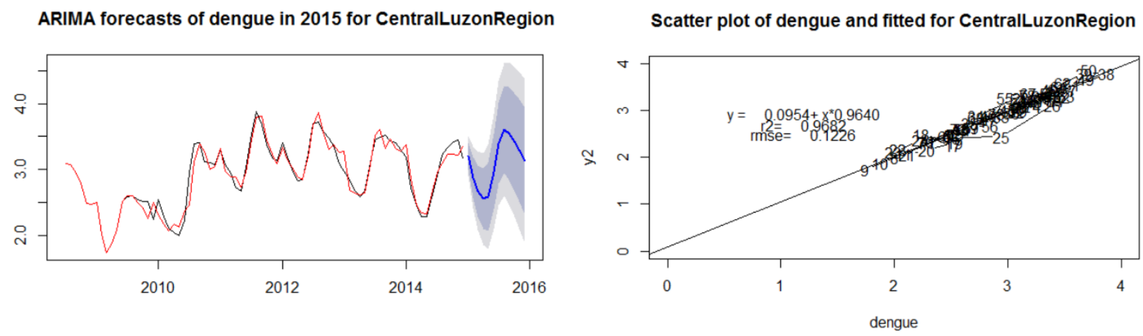

Figure 9. a) Plot of ARIMA fitting model for the Central Luzon of Philippines (reported data in black, fitted model in red, and predicted model in blue); b) Scatter plot of fitted and reported dengue cases

We generated 16 final models that closely fitted dengue incidence for 12 provinces of Vietnam and 4 regions of Philippines in incorporating climate and environment variables as external predictors. After careful screening, those variables with their highest correlation with dengue incidence at specific time lags are kept in the final ARIMA model for each province. In the MRD of Vietnam, dengue had the strongest correlation with rain at a 1-month lag across all provinces, reaching 0.604 at Long An province, while dengue had a comparable correlation with LSTd and LSTn at 1-month to 4-month lags. In addition, it had both positive and negative correlation with NDVI at 4 to 5-month lags. Interestingly, we found a picture of 2 quite different sub-regions in term of climate and environmental influences on dengue based on their correlations and time lags. In provinces in the northern part of the MRD dengue was found to have a higher correlation with rain with a 1-month lag and NDVI with a 5-month lag, and dengue was associated with LSTd mainly with a 4-month lag and LSTn with a 1-month lag. This finding is different to those for provinces in the south-eastern part along the coast of the, where dengue was found to have a weaker correlation with rain and a negative correlation with NDVI with a 4-month lag. The variability in the association between dengue and climate and environmental factors across provinces over the MRD region emphasizes the need for a separate time-series model for each province. For 4 regions of the Philippines, dengue was found in the highest correlation with rain in 1-month lag and with LSTn in 1 or 2-month lag.

Validation results

Assessing the correlation of vulnerability with dengue incidence

For the MRD region of Vietnam, we evaluate an association between monthly vulnerability indicators and dengue incidence by calculating Pearson's correlation for both the training data period of 2001-2014 and the last two years of 2015-2016 data. To avoid variance in dengue counts, the data were stabilized by log transformation to the same scale as vulnerability score. The regressions of vulnerability and dengue for the 2001-2014 training data are presented in Figure 6 for provinces with highly correlated cases. We found that better regressions were associated with provinces with a high dengue rate.

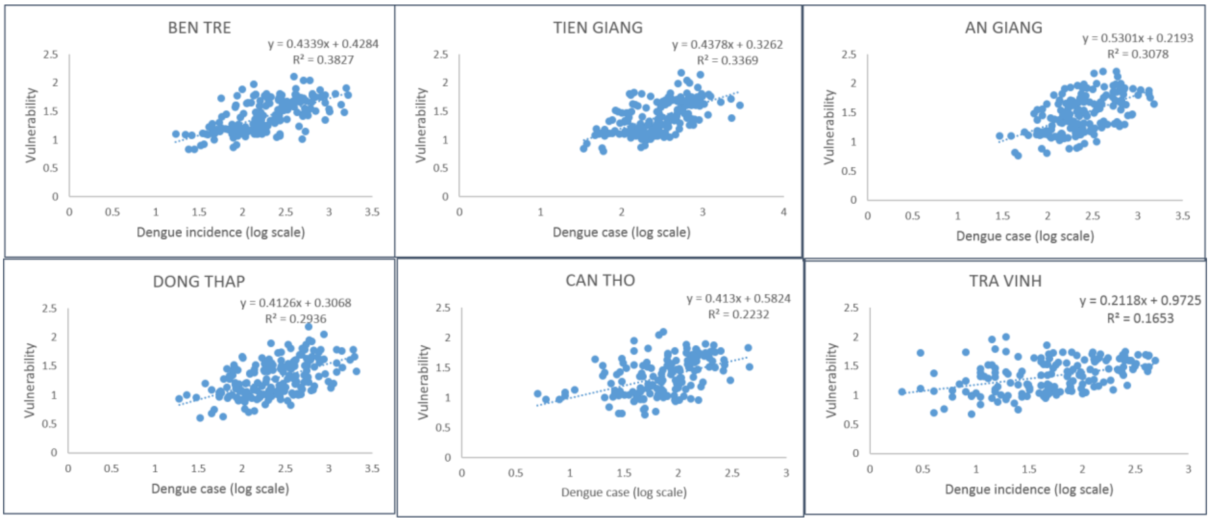

Figure10. Regression between monthly vulnerability and monthly dengue (2001-2014) for higher correlated cases of provinces

The correlation varies significantly from 0.26 to 0.63 (with $p<0.05$) for different provinces, and a high correlation was only found in provinces with a high dengue rate. The most seasonal factor in this region that contributes to the exposure of vulnerability is rainfall; therefore, we also evaluated the association between monthly rainfall amount and dengue incidence for each province with Pearson's correlation. We compared two correlations, as in Figure 11(a), which show a similar trend in their variations: the higher correlation of dengue with rain and the better correlation of dengue with estimated vulnerability. This finding indicates that seasonal trends in exposure are highly sensitive to climate variables, as mentioned in the review of climate change and dengue with the modelling approach by

Naish et al. (2014). Validation result for the 2015-2016 years of data also presented correlation above 0.5 in provinces of high-risk cluster of dengue towards the north-eastern part of the region (Figure 11b).

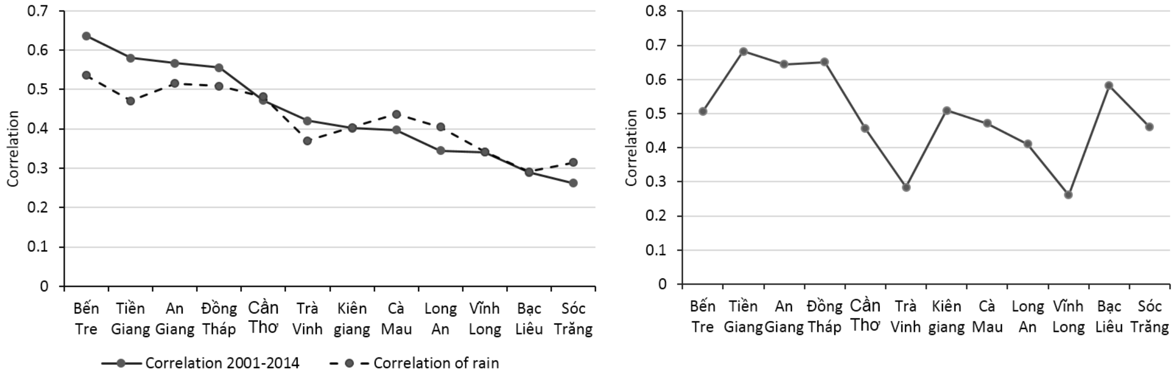

Figure 11. a) Comparison of the correlation of dengue with vulnerability and rain; b) Correlation of dengue with vulnerability for the validation data from the period of 2015-2016

Validation of ARIMA Model

The best time series ARIMA model with final independent variables found for each province was applied to predict dengue during Jan-Dec 2016 for Vietnam and during Jan-Dec 2015 for the Philippines. We compared the predicted dengue with reported cases for each provinces in the MRD region of Vietnam as in figure 12 and for the Philippines in Figure 13. The results showed that in general modelled dengue at every province followed well with the trend of reported data in both countries that is lower incidence during Feb-Apr period, gradually increasing during the rainy season of May-November.

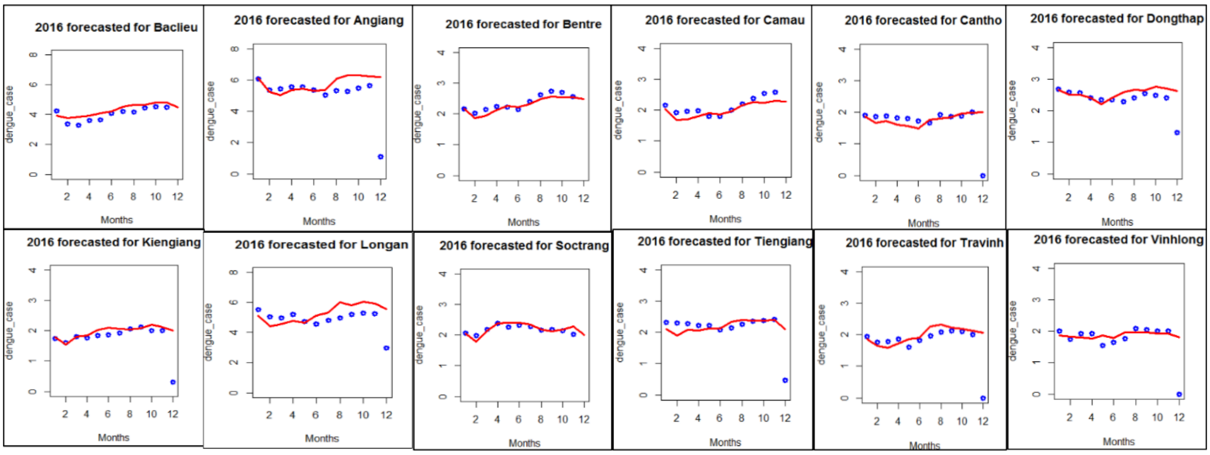

Figure 12. Comparison of predicted (red) and reported (blue) dengue cases for 12 provinces of the RMD Vietnam

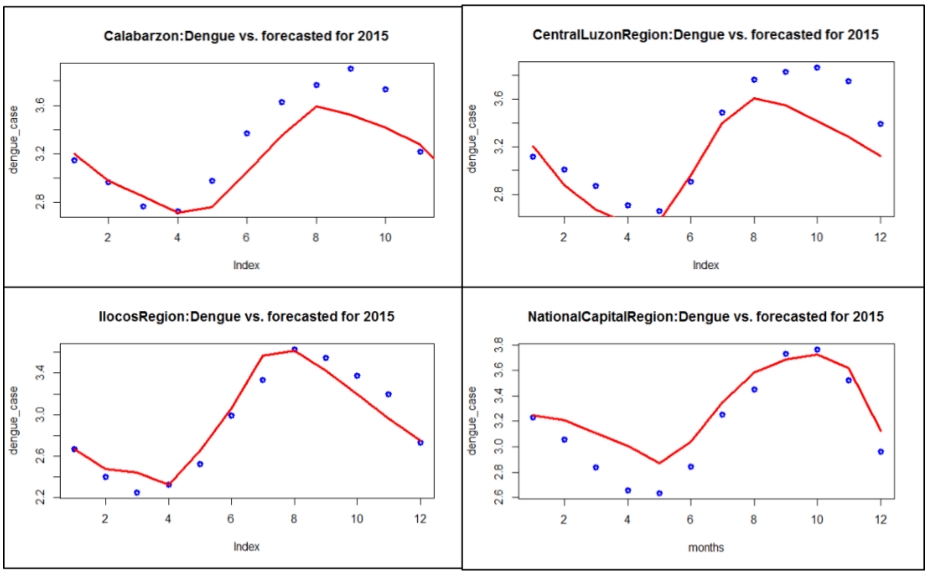

Figure 13. Comparison of predicted (red) and reported (blue) dengue cases for 4 regions of the Philippines

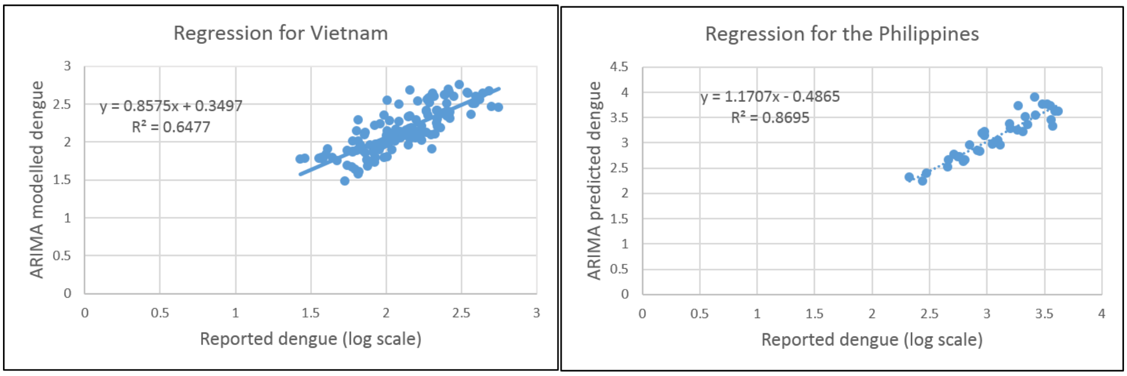

Figure 14. Scatter plot of predicted and reported dengue incidences for Vietnam and Philippines

We also evaluated an association between monthly predicted and reported dengue incidence during Jan-Dec 2016 by calculating Pearson's correlation for the whole MRD of Vietnam and 4 regions of the Philippines. The correlation value was found quite high for the Philippines (R^2=0.695 with $p<0.05$) while it was 0.6477 for Vietnam.

Discussion

With the extensive use of satellite remote sensing data for eco-environmental factors of rainfall, temperature, and land use, we have limited the inconsistency of data sources over the whole region for index calculating. As mentioned before, the vulnerability was weighted more heavily on the exposure indicator; therefore, changes in exposure resulted in greater changes in vulnerability. Because all index approaches are restrained by the weighting selection (Dickin & Schuster-Wallace, 2014), different weighting schemes were tested in this study, and the weight was assigned based on the best correlation of dengue incidence and vulnerability for the training data (2001-2014). Nevertheless, the result of validation showed the different performance of the WADI over the region; a high correlation of vulnerability with dengue incidence was found in provinces with high dengue risk. It is hard to fully explanation this result; however, we anticipate a better correlation of dengue incidence with rain as one possible reason. This phenomenon is only partly explained because vulnerability includes conditions of exposure and susceptibility that can occur without virus transmission (Fekete, 2009).

The vulnerability maps could be constructed in raster grids with a high spatial resolution of environment variables but still be limited in social variables at the provincial and district scale levels. These data had been rasterized into grids comparable to environment variables for the input to WADI calculation. However, the availability of dengue cases at the provincial level limits the validation to that level, providing results in vulnerability relating to large-scale patterns but not processes occurring at smaller scales. Undoubtedly, a combination of socio-environmental factors affects the transmission of dengue disease at different scales: larger scale factors, such as climate, are responsible for the influence of dengue transmission over the region, while local factors relate to community activities to prevent human infection (Thai et al. 2010). Dickin & Schuster-Wallace (2014) considered that a stronger weighting for exposure is attributable to larger scale factors, while susceptibility contributes plays a role at the local level. Therefore, detailed data on social information and dengue reports at community levels are important for studying the combined effects of exposure and susceptibility at regional and local levels.

Importantly, we have limited the inconsistency of data sources over the whole region for dengue modelling using time-series approach. Different combinations of the best ARIMA model's components were obtained for 12 provinces across the MRD of Vietnam and 4 regions of Philippines. For Vietnam, as mentioned before, the result of validation showed the different performance of the ARIMA model over the MRD region; A correlation of predicted with reported dengue during Jan-Dec 2016 was found higher in the second sub-region and lower in the first one. Also, an analysis of NDVI distribution in relation to land cover data over the whole region indicated that lower values of NDVI for provinces in the second sub-region corresponded to more water bodies, shrubs, and mixed horticulture land cover types. Higher NDVI was found for provinces in the first sub-region, which corresponded to more paddy field land cover types. We anticipate this is a possible reason of opposing effects of NDVI on dengue incidence in two sub-regions leading to different performances of the ARIMA model when incorporating climate and environmental variables. This is possible because vegetation type and growth stage may play an important role in determining vector abundance irrespective of their association with rainfall (Ceccato, et al. 2005).

4. Conclusions

This project focused on investigation of climate-environmental influence on dengue fever in two countries of the ASEAN, Vietnam and the Philippines. The geospatial technology was extensively used in the implementation of the project in both mapping and modelling approaches to improve the knowledge of this vector-borne disease in association with climate-environmental variables and the vulnerability. The followings are our main conclusions:

1) Geospatial dataset of disease-related climate-environmental variables was established for both countries from consistent remote sensing data including: GSMaP rainfall, MODIS LST, MODIS NDVI, and MODIS Land cover (MCD12Q1) for period of 2000-2016 for Vietnam and 2008-2015 for the Philippines
2) By spatial analysis we defined the high dengue cluster regions of the Mekong River Delta for focused studies in Vietnam and 4 regions for the Philippines. Time-series analyses convinced that temperature, rainfall, and land use/land cover are important factors to consider in the transmission of dengue in both countries together with other socio-environmental influences. Humidity may play a role in cases of the Philippines, but it is not clear for the MRD region of Vietnam. However, it is important to emphasize that the influence of these variables on dengue significantly varies across regions in both countries and at different time-lags.

3) For vulnerability mapping, we applied the WADI approach to enhance the understanding of dengue burden by exposure and susceptibility components. Monthly and yearly maps of vulnerability to dengue were produced by using extensive remote sensing data for climate and environment variables at high spatial resolution for two countries. The results showed that the regions of higher population density are more vulnerable to dengue in both countries. There is a clear seasonal variation in the vulnerability over the whole region following variability of the climate factor, such that there is the lower vulnerability during the dry season from January to May and higher vulnerability during the rainy season from June to December. The correlation between the estimated vulnerability with dengue incidence significantly varies among MRD provinces, depending on their local condition of climate variables and land cover as well as population distribution. The validation results revealed that the WADI performed better in provinces with a high-risk cluster of dengue, where dengue has a greater correlation with rain. The remote sensing data provide detailed information on climate and environment variables for vulnerability mapping that are advantageous over standard surface observation. However, the challenge of existing approaches in mapping dengue risk is to improve the accuracy in describing the spatially localized dengue distribution influenced by human activities. In addition, the validation of the mapping was limited to the provincial level due to the lack of dengue data at the community level in this study. Influences of combined exposure and susceptibility at regional and local scales is a subject for further research in other regions of Vietnam.
4) To enhance the capacity of dengue prediction under influence of climate-environmental factors, we applied time-series statistical and agent-based modelling approaches. Consistent dataset of GMSaP rain, MODIS LST and NDVI was processed and used in ARIMA models for focused study regions of Vietnam and the Philippines. The identification of these variables, which significantly correlated with dengue incidence, allowed us incorporating them in ARIMA models as external regressors. The result revealed that the remote sensing-based time series model is capable to assess the temporal dependence of dengue incidence for the MRD region in Vietnam and 4 regions in the Philipines. Predicted dengue incidence described well epidemics of dengue occurred highest in a rainny season. Though our model presented a good fit, but its performance was better for the Phillipnes. The results suggested that the higher correlation of dengue with single variable does not assure the better predicted dengue of the model, therefore, validation of the model is crucial for assessing its accuracy. However, the challenge of existing statistical approaches in modelling dengue is to improve the accuracy in describing the dengue incidence influenced by human activities. Therefore, we also tried to use epidemiology model to describe in more detail the process of interaction of virus transmission with population under influence of climate and land cover. Although, the results of this model for the MRD of Vietnam were not presented in the previous section (they were in submitted paper), we found that the model presented well the dynamics of dengue fever over the simulated period of 2006-2013 in comparison with reported data. It was found that the higher correlation of dengue with rain was, the better prediction of dengue by the model simulation. The result also indicated variations in correlation for different regions, better in denser populated provinces and worse in sparser populated. This suggested the need of incorporating other social economic parameters for assessing dengue spatial variations.
5) This is the first effort towards using remote sensing data related to a vector-born disease study for two ASEAN countries providing a foundation for developing early technologies that can predict dengue outbreaks, such as predictive models using climate and non-climate information and for mapping the vulnerability to dengue. The final output of this project is our WebGIS tool at *http:\\www.apn-climateandhealth.com*, which provides the online access to all

geospatial database and results of the project. This work contributes to an enhancement of earth observation data in public health application. Importantly, our results may also guide policy makers and public health institutions in formulating strategies for dengue prevention taking into consideration environmental/climatic variables. Integrating epidemiological studies, vector control programs, climatic studies, and health education would be a good strategy to prevent the rising of vector-borne diseases.

5. Future Directions

The remote sensing data provides detailed information of climate and environment variables for vector-born disease study that have advantages over standard surface observation by its high spatial and temporal resolution. However, the challenge is to improve an accuracy in describing spatially localized dengue distribution influenced by human activities. The collected social information is not compatible with climate and environmental data from remote sensing. Therefore, the validation of the mapping and modelling was limited at provincial levels due to the lack of dengue data at commune levels in both countries. We suggested some possible future directions as follows:

- Downscaling study on influences of combined exposure and susceptibility at district and commune levels for both countries is one subject for the further vulnerability mapping.
- Epidemiology modelling could be more reliable if incorporating ecology of vectors for virus transmission, therefore the further improvement of modelling with mosquito's ecology is one of future direction.
- At regional scale, this project could be expanded to other ASEAN countries, such as Laos and Cambodia, where similar studies were not reported.

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7. Appendix

Conferences/Symposia/Workshops

WORKSHOP 1:

***Title*: Study on dengue in the context of climate change using geospatial data and modelling for Vietnam and Philippines**

Date: 15 September 2017

Venue: Hanoi, Viet Nam

Programme:

Time	Activity	Personel
08.30 – 09.00	Reception	
09.00 – 09.05	Welcome	Dr. Vu Anh Tuan
09.05 – 09.15	Introduce to the APN project, Summarize the results:	Dr. Pham Thi Thanh Nga
09.15 – 09.30	Dengue prevalence in Vietnam	Dr. Vu Trong Duoc
09.30 – 09.45	Dengue prevalence in Philippines	Ms. Kim Carmela
09.45 – 10.00	JAXA Effort of using geospatial data for vector-born disease	Prof. Nakamura
10.00– 10.15	Coffee Break	
10.15– 10.30	Statistical Models for Dengue and Malaria cases in the Philippines	Dr. Maria-Ruth
10.30 – 10.45	Mathematical approach to dengue prediction by using Remote sensing data	Dr. Pham Thi Thanh Nga
10.40 – 11.10	Mapping Vulnerability to dengue in Mekong Delta region Vietnam	Mr. Nguyen Tien Cong
11.10 – 12.00	Project WebGIS sharing	Mr. Nguyen Tien Cong
12.00 - 13.00	Discussion	
13.00-14.00	Lunch and networking	
14.00-17.00	Visit Vietnam National Space Centre at Hoa Lac Hi-tech Part	

Participants list:

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WORKSHOP 2:

Title: **Study on dengue in the context of climate change using geospatial data and modelling for Vietnam and Philippines**

***Date*:** 24 November 2017

***Venue*:** University of Santo Tomas, Malina, Philippines

***Programme*:**

TIME	ACTIVITY	PERSONS INVOLVED

8:00 – 8:30	Registration	
8:30 – 9:00	Opening Ceremony Opening Prayer National Anthem Welcome Remarks	Prof. Aleth Therese L. Dacanay, Ph.D.
9:00 – 9:20	Introduction of APN Project for dengue and malaria	Dr. Pham Thi Thanh Nga
9:20 – 9:35	Dengue prevalence in the Philippines	Kim Carmela Co
9:35 – 10:00	Coffee Break	
10:00 – 10:20	Prevalence of Malaria in the Philippines	Asst. Prof. Ma. Gina M. Sadang, MSMT
10:20 – 10:40	Prediction of Dengue and Malaria Cases in the Philippines	Asst. Prof. Maria Ruth B. Pineda-Cortel, Ph.D.
10:40 – 11:00	Mathematical Approach for dengue prediction by using remote sensing data	Dr. Pham Thi Thanh Nga
11:00 – 11:15	Mapping vulnerability to dengue in Mekong Delta region	Mr. Nguyen Tien Cong
11:15 – 11:50	Discussion, Sharing and Networking	
11:50 – 12:00	Closing Remarks	Assoc. Prof. Ma. Frieda Z. Hapan, Ph.D.
12:00 – 14:00	Lunch and networking	
14:00 – 16:00	Project WebGIS sharing	Mr. Ngo Duc Anh

Participants list:

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Funding sources outside the APN

- Vietnam National Space Center: In-kind support (Administration support and Office& stationary estimated US$14.400,00)
- University of Santo Tomas In-kind support (Administration support and Office& stationary estimated US$2.400,00)

List of Young Scientists

No	*Name*	*Activity*	*Contact detail*	*Messages*
1	Nguyen Thi Thu Hang	- Satellite data processing and spatial analyses - Map vulnerability of mosquito-born diseases to variability of climate	University of Science and Technology of Hanoi (USTH), Vietnam. nthang@vnsc.org.vn	I had to learn spatial analyzing techniques applicable to public health
2	Tran Kim Dung	Data collection and time series analyses	Hanoi University of Science, Vietnam National University trankimdung24071994@gmail.com	This was my opportunity to improve my programming skill in R for time series analysis
3	Loc Thi Thuy Linh	Database and WebGIS development	USTH, Vietnam lttlinh@vnsc.org.vn	I improved my knowledge and skill to work with different kinds of data and to develop the WebGIS
4	Dao Ngoc Mai	Database development	USTH, Vietnam md.maidao@gmail.com	I worked with database development by exploring raster and vector data

5	Damien Philippon	Epidemiology modelling Coupling remote sensing data, spatial analysis and computer modeling to study and possibly forecast the influence of selected weather	UMI UMMISCO IRD/UPMC and ICTLab Hanoi, VIET NAM. damien.philippon.dev@gmail.com	
6	Benjie Clemente	Data collection and processing	bmclemente@ust.edu.ph	This activity enabled me to enhance my analytical and technical skills in handling data. I was involved in the gathering of socio-economic data of the Philippines needed for the research. Gathering this data entails much patience and critical analysis since most of the data available do not conform with the data of other agencies and sometimes contradicting
7	Ronn Javier	Data collection and processing	rjavier@istaff.ph	I was involved in the collection of the socio-economic data of the different regions of the Philippines. Doing this enhanced my communication skills for building connections with different institutions so as to acquire more data of interest
8	John Michael See	Data collection and processing	jmsee12@gmail.com	This activity developed my technical capacities to be more observant and pay attention to every details and specifics needed for a better outcome of the research
9	Kim Carmela Dee Co	Data collection and time series analyses for Philippines	Department of Medical Technology - University pf Santo Tomas – Philippines kdco1@up.edu.ph	It was very good to have huge data for dengue study with time series analysis

Glossary of Terms

ARIMA - Autoregressive Integrated Moving Average model

GSMaP – Global Satellite Mapping of Precipitation

MRD – The Mekong River Delta region of Vietnam

MODIS - Moderate Resolution Imaging Spectroradiometer

NDVI - Normalized Difference Vegetation Index

LST – Land Surface Temperature

WADI - Water-Associated Disease Index