Royal Netherlands
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Ministry of Infrastructure and the Environment

Towards application of a climate-index for dengue

Case study in the Citarum upper river basin Indonesia

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Towards application of a climate-index for dengue incidence

Case study in the Citarum upper river basin Indonesia

Master Thesis

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submitted by

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This Master Thesis has been prepared and written according to the Examination Regulation of the Master Programme TWM at the University Duisburg-Essen and the Examination Regulation of the Master Programme Environmental Sciences at the Radboud University Nijmegen. This includes all experiments and studies carried out for the Master Thesis.

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Declaration

I declare that I have prepared this Master Thesis self-dependent according to § 16 of the Examination Regulation of the Master Programme Transnational ecosystem-based Water Management (TWM) published at 9 August 2005 at the Faculty of Biology and Geography at the University of Duisburg-Essen.

I declare that I did not use any other means and resources than indicated in this thesis. All external sources of information have been indicated appropriately in the text body and listed in the references.

____________________________ __________________________

Essen – Nijmegen, Date Signature of the Student

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Radboud University Nijmegen

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Abstract:

Billions of people are at risk of getting infected with the dengue virus, as the *Aedes* mosquitoes which transmit the virus have dispersed widely over the world by now. Climate is considered to be one of the main factors influencing the distribution of the dengue virus. The goal of this study is the development of a climate variability-based model, called a climate index, for dengue incidence which can be implemented in the climate database SACA&D (Southeast Asian Climate Analysis & Database). Several models were tested for their ability to reveal correlations between dengue incidence and climate parameters in Bandung, Indonesia between 2001 and 2012.

Climate variability is found to have a statistical correlation with dengue virus transmission in the study area. Especially the diurnal temperature range (the difference between the daily minimum and maximum temperature), the amount of rain days and the daily minimum temperature show high correlations with dengue virus transmission. The trends of these climate parameters in Southeast Asia indicate that climate has changed towards a state in which it enables higher dengue virus transmission. A first attempt has been made to construct a climate index for dengue incidence which can be applied in Southeast Asia..

At the moment there are great difficulties in assessing the dengue risk in areas where no data is available. We anticipate that with further development of the introduced model this void can be filled

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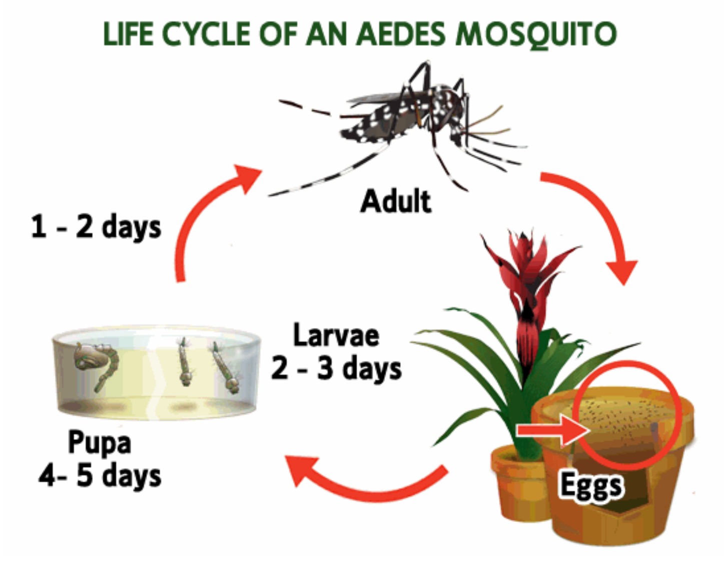
1. Introduction

1. Dengue virus transmission influenced by climate

Dengue fever is an infectious disease caused by the dengue virus (DENV). The disease is carried from human to human by mosquitoes, with *Aedes aegypti* (also called the yellow fever mosquito) and *Aedes albopictus* (also called the Asian tiger mosquito) being the main vectors. The *Ae. aegypti* is the most important vector of the dengue virus. It feeds during daytime and has high deterioration-resistant eggs, which make that it has adapted well to urban areas and has taken a preference to taking blood-meals from humans [1, 2]. *Ae. aegypti* dwells excellently in regions where it has plenty of access to water reservoirs like tires, plant pots and water tanks, where the eggs can be laid.

Figure 1 displays the life cycle of the Aedes mosquitoes. The pupal and larval states of the mosquito will take place in the water reservoir where a female adult mosquito lays her eggs. The duration between the hatching of the egg and development to the adult state takes between one-and-a-half and three weeks [3]. When the vector enters the adult phase it starts taking blood meals. Via blood meals it can get infected with the dengue virus. After a certain time, called the extrinsic incubation period (EIP), which varies between five and twelve days depending on the temperature [4], the mosquito will be able to transmit the dengue virus to hosts from whom it takes a blood meal. This means that it takes between two and five weeks before the mosquito is able to transmit dengue.



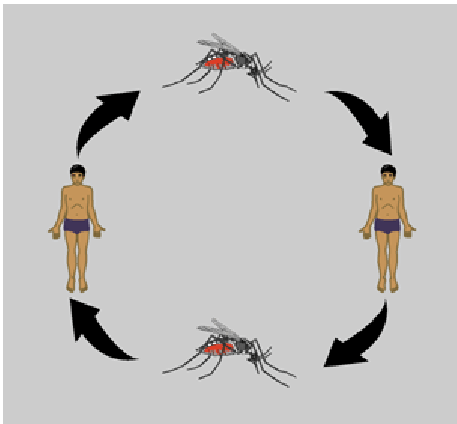


Figure 1: Left; Lifecycle of the Aedes mosquitoes. Right; Transmission from human to human takes place via an adult Aedes mosquito.

1.1 Dengue virus specifications

Dengue is actually caused by four very closely related viruses called DEN-1, DEN-2, DEN-3 and DEN-4 [5]. These four viruses are called the serotypes and despite some genetic variations they cause the same disease and symptoms. Originally the different serotypes were more typical for specific areas, with only Southeast Asia having all serotypes prevalent. By now the different serotypes have spread globally to all dengue vulnerable regions [6].

The general symptoms are high fever, headache and muscle and joint pains. The severe form of dengue is called dengue haemorrhagic fever (DHF) and can present with haemorrhage and abnormal brain and liver function. An estimated amount of 500,000 people with DHF are hospitalized every year, 2.5% of those do not survive [7].

At this moment no vaccines or cures are available to stop the rapid global spreading of this disease. Therefore protection is mainly sought in prevention, where measures are taken like the eradication of breeding sites and the application of insecticides. Despite temporary successes, this approach does not alleviate the threat of dengue on the long term.

1.2 Dengue and climate

In the 2007 IPCC report on climate change a chapter is dedicated to the impact of climate change on human health [8]. On the topic of communicable diseases IPCC states that “Climate change, including changes in climate variability, will affect many vector-borne infections”.

The World Health Organization (WHO) has also recognized climate change as a serious threat to human health. As one of the major health consequences of climate change they identify that changing temperatures and patterns of rainfall will probably affect the geographical distribution of insect vectors responsible for spreading infectious diseases [8].

Estimates of the WHO indicate that up to 100 million people get infected with dengue every year and another 2.5 billion (Figure 2) are at risk of getting infected with dengue [9, 10]. Especially in urban areas there is an upward trend in the cases reported by the WHO [40]. Dengue case numbers have increased dramatically during the past 40 years and different serotypes have invaded new geographical areas [6, 11]. Bhatt et al. challenge the numbers presented by the WHO [12]. In an effort to map the global distribution of dengue risk in 2010, they estimate that there are 390 million dengue infections per year worldwide.

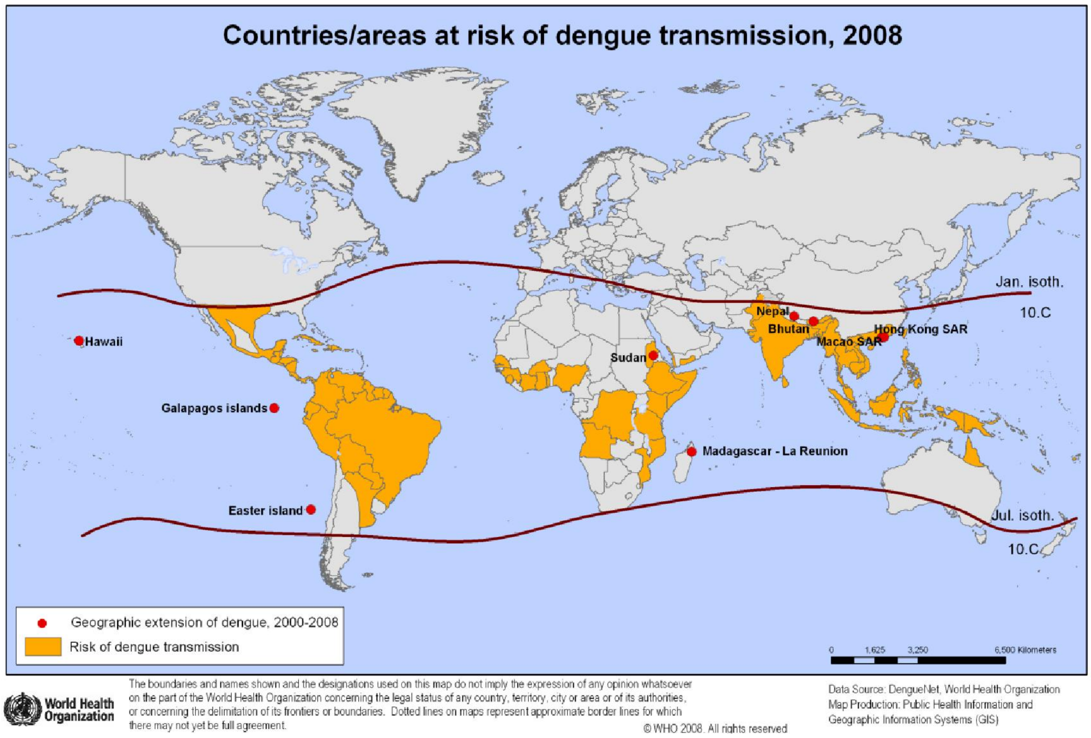


Figure 2: WHO map of the geographic extension of dengue, and the areas at risk. Worldwide 2.5-3 billion people live in areas vulnerable for dengue[9].

The dynamics of dengue are affected by climatological and socioeconomic influence. Rainfall and temperature are considered to be dominant parameters [13]. The impact of climatic parameters on dengue allows the creation of models to predict dengue incidence dependent on weather. But the socioeconomic factors make that modelling of DENV transmission on the basis of climate data only, is bound to be inaccurate (Figure 3).

1.3 Modelling with climate variables

Several previous studies have shown that dengue transmission is influenced by climate [14, 15]. This is caused largely by the influence of climate on the spreading, development and feeding behaviour of the mosquitoes that transmit dengue. Temperature influences the EIP and the survival rate of adults, as well as the mosquito population size and feeding behaviour. Water is necessary for eggs and larvae development [16].

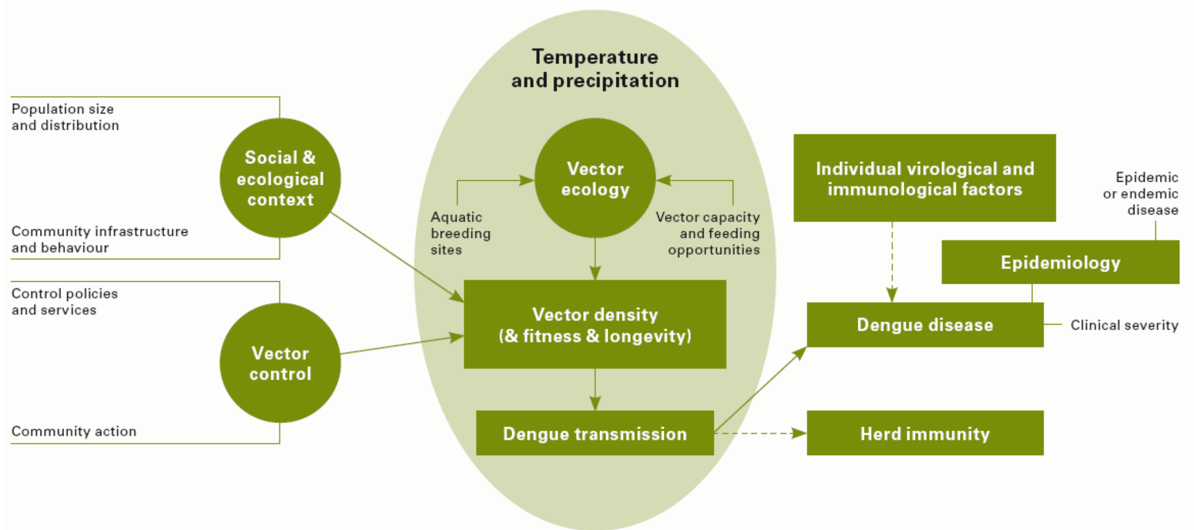


Figure 3: Climate exerts a strong influence on dengue transmission, in interaction with several non-climatic factors [17].

1.4 Dengue in Indonesia

Indonesia is one of the countries where dengue is endemic and a major burden for the public health. The Indonesian government has reported 155000 cases and 1386 deaths for the year 2009 [18]. The first reported outbreak of the dengue virus (DENV) stems from 1968 when there were outbreaks in Surabaya and Jakarta [19]. From then the spreading of dengue caused the incidence rate to develop to over 60 cases/100000 people per year in 2004, due to a large dengue outbreak. For 2011 and 2012 those numbers were 27.7 and 37.3 cases/100000 respectively [18].

Bandung (figure 4), at a height of 768 m above sea-level, is situated in the catchment of the Citarum river and is surrounded by volcanic mountains. It is one of the largest cities of Indonesia on the island Java, lying about 140 kilometres southeast of capital Jakarta. In 2012 the population was almost 2.5 million people [20]. All four serotypes of dengue are prevalent in Bandung [21]. The dengue incidence rate between 1995 and 1998 had an average of 31.7 dengue cases per year [22]. The *Ae. aegypti* and the *Ae. albopictus* are the dominant vector in this area [21].

Figure 4: Left a map of Indonesia and surrounding countries, Bandung is located at the red star. On the right a map of West Java with the position of Bandung is shown.

2. Hypotheses and goals

2.1 SACA&D

SACA&D (Southeast Asian Climate Assessment & Database) is an initiative of the Royal Netherlands Meteorological Institute (KNMI) and the Indonesian Meteorological Institute (BMKG). It encompasses a database with meteorological measurements for 15 countries in Southeast Asia [23]. This database allows users to create climate maps and assess temporal trends and anomalies, based on several climate variables like the minimum, average and maximum daily temperature, rainfall or humidity. It is possible to create a *climate index*, an index created from several climate variables, to monitor certain specific climate events. A straightforward example is the index *RR20*, which indicates the number of days on which more than 20 mm of rain has fallen. Another less obvious index is the "Onset of rainy season (ORS2)", which indicates when the rainy season starts [24].

2.2 Hypotheses and goals

In the context of the influence of climate on DENV transmission, the development of a climate index that can give an estimate of DENV vulnerability on a spatial and temporal scale would open doors for localized and temporally detailed dengue risk assessment. Such an index would allow for the monitoring of year-to-year changes and the effects of climate change on dengue risk. Especially in areas where detailed dengue incidence data is not available, this could provide a helpful tool for scientists and maybe even local governments. SACA&D could be a platform for such an index.

In light of this 12opportunity, the goal of this study is:

- ***the development of a "climate data based dengue index"***

The city Bandung in Indonesia is chosen as the area for a case study. Climate data and dengue incidence data from this area will serve to identify a suitable climate index. In order to reach this goal, some questions need answering.

1. Can a climate signal be distinguished in DENV transmission for Bandung, Indonesia?

Dengue and climate have been linked on a local scale for many different regions, with rainfall and temperature having high correlations with dengue incidence in Singapore, Puerto Rico and New Caledonia respectively [14-16]. However, it has not yet been done in Bandung. The first objective of this study is thus to find out whether climate variability and seasonality can be correlated with DENV transmission.

2. Which climate parameters are most relevant for DENV transmission variability?

Before an eventual dengue transmission index can be developed, the involved climate variables have to be identified.

3. What are the trends for the relevant climate parameters in the southeast Asian region?

Climate change is an on-going process which may push the boundaries of dengue transmissions to new regions. But it is very well possible that climate change also affects the susceptibility for dengue of already endemic regions.

2. Data

1. Health data

Two datasets were acquired that stem from the regency Kota Bandung (the city Bandung) in the west of the island Java. Raw data origins from 71 puskesmas (health centres) located throughout the city where people seek health care. Those puskesmas are obliged to report dengue incidence to the Central Health Office (CHO) of Kota Bandung.

Dataset 1 encompasses the monthly numbers of dengue incidence over the entire regency. All puskesmas report to the CHO when they diagnose a dengue case. This information is summarized to provide an official report of monthly dengue incidence in the Kota Bandung regency. This dataset gives a complete overview of dengue incidence from 2001 until 2012 as it is archived by the CHO (APPENDIX D; Denguedataset1 monthly 2001-2012).

Dataset 2 is collected from the database of the CHO and exists of all single records of patients diagnosed at the puskesmas with dengue. Here the data is reported on a daily basis and also includes the names of the patients and of the puskesmas where the patient was diagnosed. Because there is no specific information about the location where a patient got infected, this spatial information is neglected and instead only the daily reports are summed to generate a database which gives the amount of dengue cases per day in the entire regency Kota Bandung. This dataset ranges from 2005 to 2010 with gaps from May 2006 to December 2006 and from June 2007 to December 2007 (APPENDIX E; Denguedataset2 daily 2005-2010).

All the disease incidence data has been modified for this report to the parameter "cases/100000" (adjusted for population on a yearly basis) (APPENDIX A; Population Bandung 2001-2012) to correct for population growth. The city's population grew from 2,146,360 in 2001 to 2,455,517 in 2012 [20]. In both datasets no distinction between different serotypes of the dengue virus has been made.

1.1 Health data modifications

During the analysis of the health data some inconsistencies surfaced, which forced us to make some modifications to the dataset.

1.1.1 Issues with dengue reports

In the years 2005 and 2006 the patients have not been inserted on a daily routine in database 2. This can be seen in figure 5 where from the daily recording (blue line) it seems like dengue was more prevalent in the years 2005-2006, where a high number of days show more than 80 cases. But after translation of the data into 10ddavg notation, one can see that the actual daily case rate in, for example, 2009 has been higher than in the years 2005 and 2006. To make the dengue incidence data more reliable the 10dd indices have been introduced.

1.1.2 10daysum

Analysis of dataset 2 has been performed by 10 days sums and averages of the data (10ddsum and 10ddavg respectively). This means that for every day the amounts of dengue incidence over that day and the next 9 days was summed or averaged as a representation of dengue incidence on a particular day, in this way a running average of daily dengue fever incidence was created. This measure will make the health incidence more reliable but also less detailed.

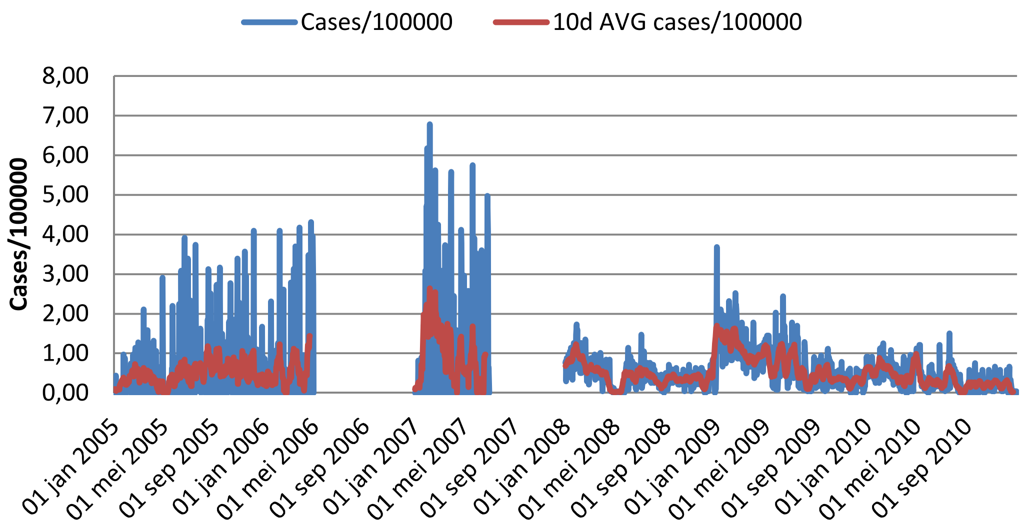


Figure 5: Daily reports of dengue incidence (blue) against the 10ddavg (red) from 2005 to 2010. The daily dengue fever incidence in 2005-2007 gives a poor representation of the actual dengue fever rate.

Errors in registering the dates- In the data we encountered some disease incidence cases dated to 2098, 2020, 2021 and other unlikely years. This data has been deleted.

Organisational inconsistencies - The Kota Bandung regency is divided into 30 sub districts. The 71 puskesmas are all in a specific sub district, making fixed combinations of puskesmas and sub districts. In the disease incidence overview a number of impossible combinations was found. At a governmental level sub district and regency borders have been changed over the years. Together with a changing policy towards decentralization of health affairs this resulted in inconsistency and absence of certain parts of the data (see for example May – December 2006 and the second half of

2007). This effect cannot be quantified which made more detailed spatial analysis impossible and thus all spatial information on sub district and puskesmas level has been discarded.

1.1.3 Underreporting

There are various reasons why people don't seek medical attention when they are infected with the Dengue virus. In Indonesia traditional medicinal practises are still prevalent. A minority of the people depend for medical treatment on traditional alternatives. There are also people that because of a variety of reasons (financial, health related, infrastructure related) are unable to travel to a puskesmas. [25] has conducted a research on underreporting in South East Asia and for the whole of Indonesia they have derived empirically that the absolute number of Dengue cases must lie 2.3 times higher than the reported amount of cases. In urban areas this number is probably lower, but we had no accurate number to correct for underreporting. The data precision can be improved when disease incidence reports are corrected for underreporting.

1.1.4 Limited diagnostic accuracy

Diagnostic tools applied by puskesmas for identifying dengue fever cases have a large uncertainty. This is partly caused by the tools themselves, which are known to have a marginal error rate, but also by limited medical skills of the people who do the diagnostics. Misdiagnosis affects the actual number of dengue cases [26]. No attempts to quantify this effect have been found

2. Climate data

Climate data for the Bandung area has been provided to SACA&D by BMKG, the meteorological institute of Indonesia for weather station Husein – Bandung, WMO number 96781, with coordinates (6:52 ° S; 107:36 ° E).

There is data on daily rainfall (*RR*), minimum temperature(t_n) and maximum temperature(t_x) from 1999 until 2008 (APPENDIX F; Climate data 1999-2008). The daily average temperature (t_g) is calculated by averaging the daily minimum and maximum temperature. Dataset 1 has been compared with monthly climate data. This data is put together by creating values of average t_x, t_g, t_n and the total *RR* per month.

2.1 Accuracy of the climate data

The climate data has been subjected to a quality control to screen for errors which is described elsewhere [27]. The flagged data relate to cases where t_n for a certain day was higher than t_x, and some cases where t_x or t_n had values that are not possible. In those situations this data has been deleted and left out of the analysis.

Daily average temperature, t_g, based on hourly data and provided directly by BMKG was only available for five of the years between 1999 and 2008. Therefore, it was decided not to use this data at all, but to deduce t_g by taking the average of t_n and t_x. This introduces a margin of error in t_g. The estimated t_g has been compared to the observed t_g for the days when t_g was available. It turned out that t_g (estimated) was an average of 0.76 °C too high, with a standard deviation of 0.70 °C.

2.2 Excluded climate variables

2.2.1 Humidity and wind velocity

Lu et al. [28] found that wind velocity and humidity are associated with dengue incidence. However, we had no data on wind velocity available and were hence unable to confirm this finding.

2.2.2 El Nino Southern Oscillation

Earnest et al. [29] make report of a correlation between the Southern Oscillation Index (SOI) and dengue fever incidence in Singapore. On the other hand Johansson et al. [15] suggests that SOI variability has no significant influence. Our major concern with investigating the El Nino Southern Oscillation (ENSO) is that many existing studies treat ENSO as some kind of magic influence which can be seen detached from actual changes in the weather. It is a global phenomenon that changes weather in the tropics and subtropics. So any influence of El Nino on dengue is through variations in precipitation and temperature. Those factors are included in this study.

3. Methodology

1. Statistical analysis and modelling

Coherence analysis was performed with Microsoft Excel by using the Pearson correlation function and the Spearman rank correlation function. If one wants to explore the data it is best to compute both, since the relation between the Spearman (φ) and Pearson (R) correlations will give some information. Briefly, φ is computed on ranks of the data and so depicts monotonic relationships while R is based on true values and depicts linear relationships. Doing both is interesting because if $\varphi>R$ it means that there is a relation that is monotonic but not linear. A linear correlation is favourable, but not always forehanded. With the dual analysis one can thus gain an insight in the nature of the correlations between DENV transmission and climate variability. Significance of the outcomes was determined by using a two-sided *t*-test for the Pearson coherence function, and an F-distribution test has been performed for the Spearman coherence function. Correlation with a *p*-value below 0,05 were taken as being significant, indicating that there is less than a 5% chance of finding that correlation by chance if the null hypothesis was true (no relation between two datasets).

2. Saca&D

The database Saca&D has been used as a platform for the climate indices that seem most interesting after the correlation analysis. The big collection of weather stations with long time series of meteorological data allow the creation of climatologies for a large period over the entire region. This will be used to assess the trend of the dengue indices and to look if there have been anomalies for dengue outbreaks.

3. Standard climate indices

Some general climate indices can be calculated from the available data. They have been obtained from the website of SACA&D [30]. In our study we looked at correlations with the following climate indices:

1. *DTR* – The diurnal temperature range $t_x - t_n$ in °C, averaged over a given period.
2. *RR* – The precipitation sum in mm in a given period.
3. *RR1* – The number of days with RR> 1 mm in a given period.
4. *R20mm* – The number of days with *RR*>20 mm in a given period.
5. *RX1day* – The precipitation in mm for the day with the highest RR in a given period.

During the research some additional climate indices have been introduced inspired by several literature sources. They will be introduced in the next sections of this chapter. In APPENDIX B; climate indices, an overview of all used climate indices is given.

4. Empirically based climate indices

In Wong et al. a model is constructed to predict *Aedes* mosquito abundance in Hong Kong [31]. The *Ae. aegypti* and *Ae. albopictus* are the two most important vectors that transmit DENV in Hong Kong. Under the assumption that the transmission will increase when more vectors are available to transmit the disease, we used the approach of Wong et al. to model dengue fever incidence in Bandung.

Based on Martens et al., it is considered that the abundance of mosquitoes is exponentially dependent on the mean ambient temperature in the previous 22 day period [32]. From Mellor and Leake it is found that abundance of the mosquito has a quadratic dependence on rainfall in the previous 15 day period [33]. Based on this the Climate *Aedes* Mosquito Abundance (CAMA) model is designed:

$$\Phi = e^{\alpha T22}.(\beta {R_{15}}^2 + \gamma R_{15} + \delta). \qquad (1)$$

Where *α, β, γ* and *δ* are empirically obtained to be 7.992 x 10^{-2} °C^{-1},−2.352 × 10^{-5}% mm^{-2}, 2.248 × 10^{-2}% mm^{-1} and 9.820 × 10^{-1}%, respectively.

This was the inspiration to insert a new set of climate indices, that take past time climate variability into account. Those indices are:

6. *Tg22d* - The average t_g of the previous 22 days
7. *Tx22d* - The average t_x of the previous 22 days
8. *Tn22d* - The average t_n of the previous 22 days
9. *DTR22d* - The average DTR of the previous 22 days
10. *RR15d* - The total RR over the previous 15 days
11. *Hum15d* - The average humidity over the previous 15 days
12. *CAMA* - The Climate *Aedes* Mosquito Abundance model expressed by formula *(1)* with *Tg*22d and RR15d filled in

Gomes et al. used cut-off points for the mean temperature to evaluate DENV transmission [34]. They assumed that the optimal temperature for the *Ae. aegypti* to transmit DENV is between 22 and 26

°C. They found significant correlations of the amount of days with t_g under 22 °C and above 26 °C. We have also included those variables in our list.

13. *t_g<22 –* The number of days in a month that t_g lies below 22 °C
14. *22t_g26 –* The number of days in a month that t_g lies between 22 and 26 °C
15. *t_g>26 –* The number of days that t_g lies higher than 26 °C

5. Dynamically based climate indices

Recently Bhatt et al. [12] published a study where a dynamical model has been used to model DENV transmission. They used an index of temperature suitability which has been adapted from an equivalent index for malaria [35]. Where empirical models use regression methods to generate a model which suits the reality, dynamical models use a process based approach to make a model. For example, Focks et al. [36] follow a biological approach to create a dynamic model for dengue incidence which includes parameters that depend on temperature for mosquito breeding, population density, virus serotypes and vertebrate hosts.

Those specific parameters together can determine virus transmission by vectors. Based on the equations presented by Gehting et al. [35], an attempt has been made to model the dynamics of DENV transmission.

Model Description

Vectorial capacity, *V,* has been introduced as a concept to model the contact rate for malaria mosquito's with human hosts [37]. Later it has been adapted for several other vector-transmitted diseases like encephalitis and dengue [38]. It is a function of (a) the vector's density in relation to its vertebrate host *m*, (b) the daily likelihood of a vector biting a human host *a*, (c) the daily probability of vector survival *p*, (d) the duration in days of sporogony *n* (the duration of the period between a vector receiving a pathogen and the moment the vector can transmit the pathogen, also known as the extrinsic incubation time, EIP) and (e) a transmission capability parameter, which represents the probability that a vector gets infected and transmits a pathogen to a susceptible host *b*. All these variables are related to the ambient temperature. This together gives the number of subsequent infectious bites arising from a single person-day of exposure [39]:

$$V = \frac{ma^2p^nb}{-\ln(p)} \qquad (1)$$

Where the dependence of the variables on temperature has been left out in the notation for clarity. Because *m* (the number of mosquitos per human), is not known, a temperature suitability index, *Z,* has been developed which is linearly proportional to *V/b*, and is therefore able to quantify the risk of dengue transmission as a function of temperature [35].

One can express vector survival as the death rate *g* of a mosquito as a function of temperature (°C) with *g* = -ln(*p*) is:

$$g = \frac{1}{(-4.4+1.3\times T-0.0\ 3\times T^2)} \qquad (2)$$

The rate of adult mosquito recruitment λ, is held constant relative to the human population thus,

$$m = \frac{\lambda}{g} \tag{3}$$

This makes that:

$$V = \lambda * \frac{a^2}{g^2} * e^{-gn} \tag{4}$$

a and λ, the feeding rate and adult recruitment of the mosquito are dependent on temperature, but also on a wide range of other environmental factors. As this model is focussed on the direct effect of temperature on the sporogony time and the mosquito survival rate, we can relate V to Z under the assumption that a and λ are independent of temperature, as is done by Gething et al.:

$$Z(T) = \frac{e^{-g(T)n(T)}}{g(T)^2} \tag{5}$$

With $Z(T) \propto V(T)$, since a and λ are unknown.

This formula allows for examination of the relative effect of temperature on vectorial capacity. The probability for a vector to survive the sporogony period can be evaluated by integrating the temperature dependent death rate $g(T(\tau))$ over days τ between the onset of sporogony and its completion n days later, where n can be modelled as has been done by Chan and Johansson and by Bayoh and Linsay [40, 41]. For n some parameters are filled in which determine the development rate of the dengue virus. Those parameters are specific for the virus [42].

The vector competence b is not included in this formula. b is the intrinsic ability of a vector to get infected with the pathogen, and then transmit it further. It is calculated as

$$b = p_i \times p_t \tag{6}$$

With P_i the infection probability and the P_t transmission probability. They are expressed as [39]:

$$p_i(T) = \begin{cases} 0 & T < 12.4\,°C \\ 0.0729T - 0.9037 & 12.4\,°C \le T \le 26.1\,°C \\ 1 & T < 26.1\,°C \end{cases} \tag{7}$$

and:

$$P_t(T) = 0.001044T(T - 12.286)\sqrt{32.461 - T} \tag{8}$$

In formula 7 the relation with Temperature can be explained from the observation that the vectors do not take blood meals below 12.4 °C and thus cannot be infected with the dengue virus.

Furthermore, it has been observed that at temperatures of 26.1 °C or higher the vector always gets infected with the virus. Formula 8 demonstrates a more complex relationship. The transmission probability drops for higher temperatures, even though p_i is stable. The acquired formula has empirically been derived by Lambrechts et al. [39]. These probabilities are calculated using 10-minute intervals over a 24-hours period to describe the diurnal cycle. Due to the absence of 10-minute data, they are estimated by assuming a sinusoidal daily cycle in temperature, banded by the daily minimum and maximum temperatures as provided by the weather station in Bandung.

6. Inclusion of lag times for analysis

The relationship between climate variability and dengue fever incidence has a natural delay. Climatic variability impacts the lengths of the several life stages of the vectors and the incubation period of the virus, which cause this delay. Depradine and Lovell made a study of the optimal lag time for finding a correlation of indices like *tg*, *tx* and *tn*, and also *RR* and humidity, the optimal lag times were 15 weeks, 16 weeks, 12 weeks, 7 weeks and 6 weeks respectively [43]. They did however not give an explanation for these distinctive lag times. This has been tested also by [44] who found that increasing weekly mean temperature and cumulative rainfall are indicative for increased dengue cases after 4-20 and 8-20 weeks respectively. There was also a study in Bangkok over the period between 1966 to 1994 where it was found that the optimal correlations between dengue fever incidence and temperature are after 3 and 4 months [45]. This is why dataset 2 lag times of 10, 20, 30, 40 and 50 days have been examined and for dataset 1 lag times of 1, 2, 3, 4 and 5 months have been studied during the correlation analysis.

7. Analyses of climate indices

The datasets have been tested for correlation with the climate indices in three different ways.

7.1 Average annual cycle

First of all an average annual cycle has been constructed. This has been done for dataset 1 by averaging the DENV cases per month over the entire record, producing average January, February, etc. values. This has also been done for dataset 2 by averaging the DENV cases per day. This way a typical year for dengue incidence is reconstructed. For the climate indices an average annual cycle is constructed as well. This way we can take a look at the typical annual cycle of DENV transmission, related to the typical annual cycle in climate.

7.2 Temporal data analysis

Here we analyse the data per temporal component, thus one on one per date or month. For dataset 1 the monthly DENV transmission data is compared with the monthly climate data. For dataset 2 this is done on a daily scale. This will give us an overview of how monthly and daily climate variability affects DENV transmission.

7.3 Correction for seasonality

A biological study has been conducted by Focks et al. [36]. This study attempts to define the separate biological relations between temperature and *Ae. aegypti* development. However, the writers state that they feel that future studies need to focus on deviations of seasonal patterns in order for predictive models for vector abundance and dengue transmission to be better usable. In the data an annual cycle is visible in the dengue incidence. But in the analysis with correction for this seasonality, we try to discover a relation between dengue and climate outside of this annual cycle. To do this, a dataset is created which is corrected for this seasonality, where the average annual cycle is subtracted from the real-time data. This way the average annual cyclic behaviour is eliminated from the datasets.

4. Results

1. Health data

A first look at the dengue incidence data gives an impression of the complexity of analysis of this data, which can be seen in figure 6. Dataset 1 represents monthly dengue incidence over the period 2001-2012 and dataset 2 represents the 10dd dengue incidence.

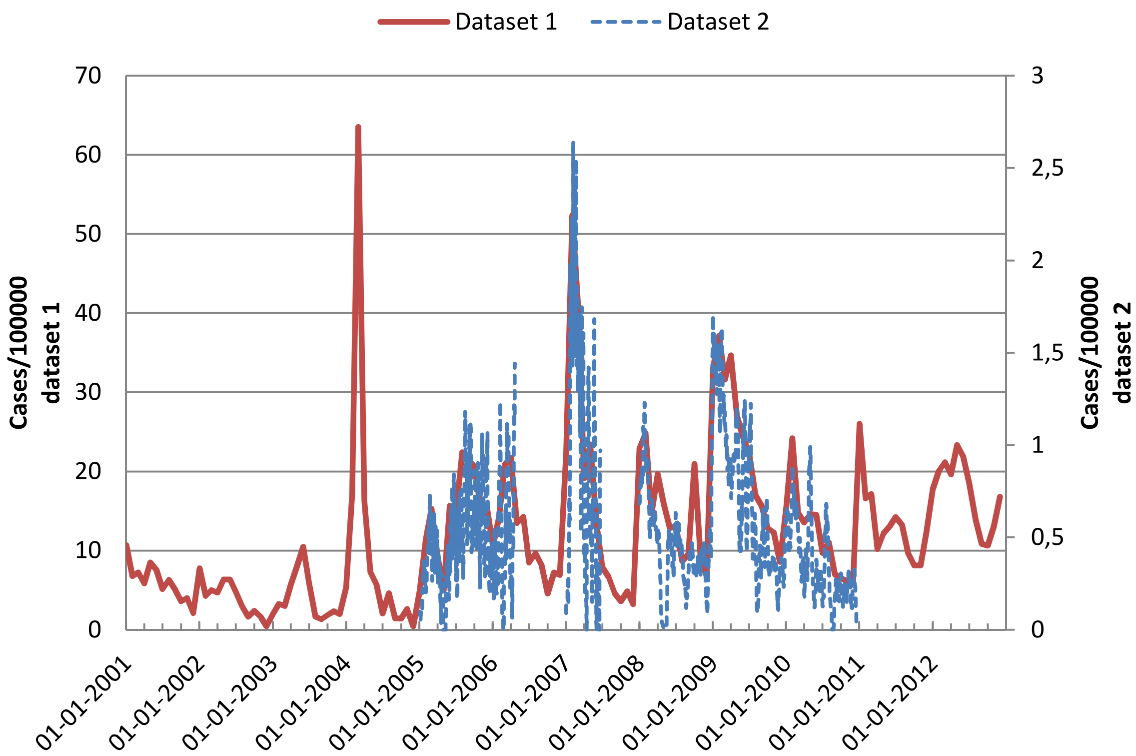


Figure 6: Dataset 1, the monthly dengue incidence over the period 2001 to 2012, projected in red against the left y-axis and dataset 2, the daily dengue incidence from 2005 to 2010, projected in blue against the right y-axis.

Figure 6 shows a strong overlap between dataset 1 and 2, with some bigger fluctuations in dataset 2 because this dataset has a higher temporal resolution. The peak of monthly dengue incidence is 63.5 cases/100000 in march 2004, the peak in daily cases is 2.64 cases/100000 for Febrary 6th in 2007. The peaks of dengue outbreaks occur during the first three months of the year. This gives a first sign that there is seasonality in dengue incidence.

1.1 Average annual cycles of dengue incidence

To get a better indication of seasonality of the data the average annual cycles of dengue incidence for both datasets is determined. They are presented in figures 7 and 8.

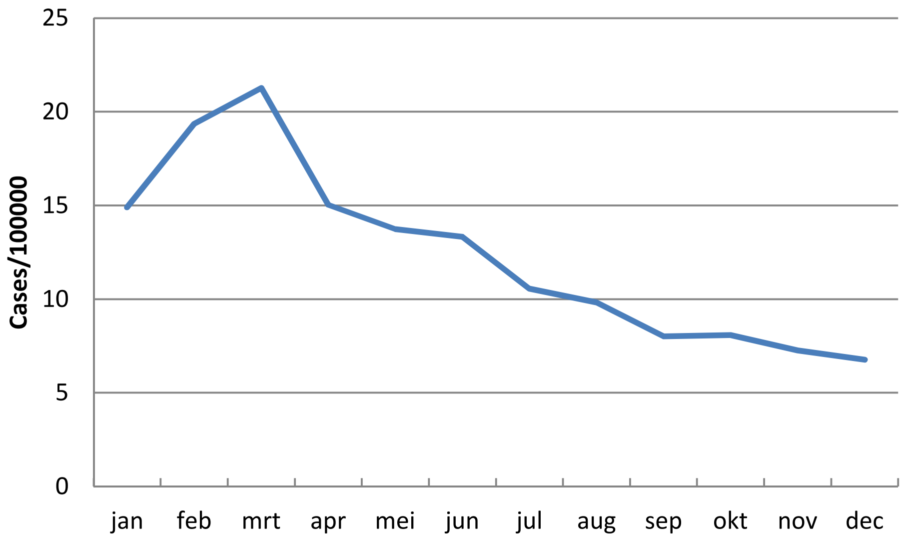


Figure 7: average annual cycle of dengue incidence as described by dataset 1 over 2001-2012, with on the y-as the amount of monthly cases per 100000 people

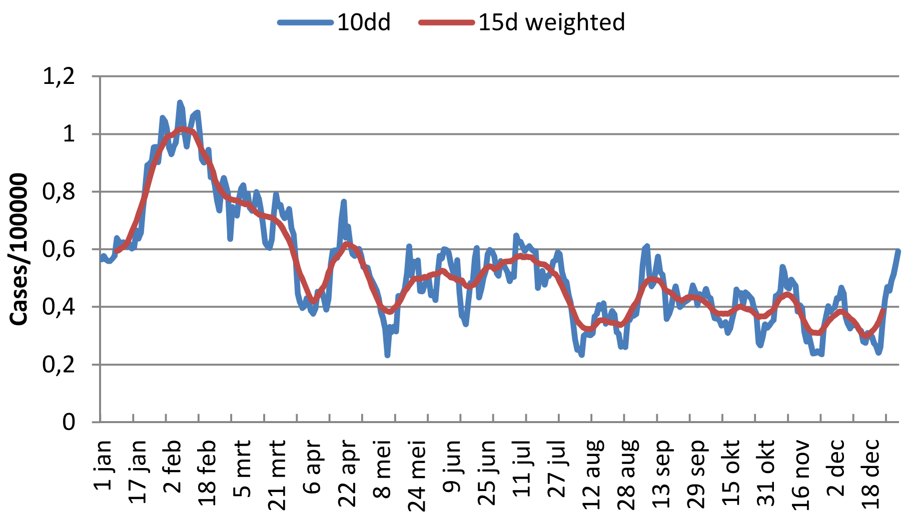


Figure 8: average annual cycle of dengue incidence as described by dataset 2, over 2005-2010, with on the y-as the amount of daily cases per 100000 people.

Dengue outbreaks in Bandung mainly occur during the first months of the year. Dataset 1 shows its highest peak in March (20.27 cases/100000), as shown in figure 7 and dataset 2 peaks at the 6th of February (1.11 cases/100000), as shown in figure 8. These were also the months where the big outbreaks in 2004 (outbreak in March) and 2007 (outbreak in February) occurred, which can be seen clearly in figure 6. In the second half of the year dataset 1 shows a decline with a minimum in December (6.78 cases/100000), see figure 7. Dataset 2 shows no decline but a more or less constant line in the second half of the year with an average of around 0.4 cases/100000 per day, see figure 8. The minimum in dataset 2 lies still above 0.2 cases/100000 because dengue fever is endemic all year round in Bandung. In red a weighted running mean with a window of 15 days through dataset 2 has been plotted. When comparing figure 7 and the running mean in figure 8 one can see that even though the trend of the running mean in figure 8 is more erratic, their trends indicate the same lapse.

1.2 Total yearly dengue cases from 2001 to 2012

Figure 9 demonstrates that the burden of dengue for Bandung is increasing, dengue has become more prevalent over the last 10 years. This is an interesting development which hasn't been explained yet. With the least-squares methods a trend line is produced to illustrate this. From 2005 until 2011 there is a systematic wave, in which there is a peak in dengue incidence every other year, followed by a year with a decrease in dengue cases.

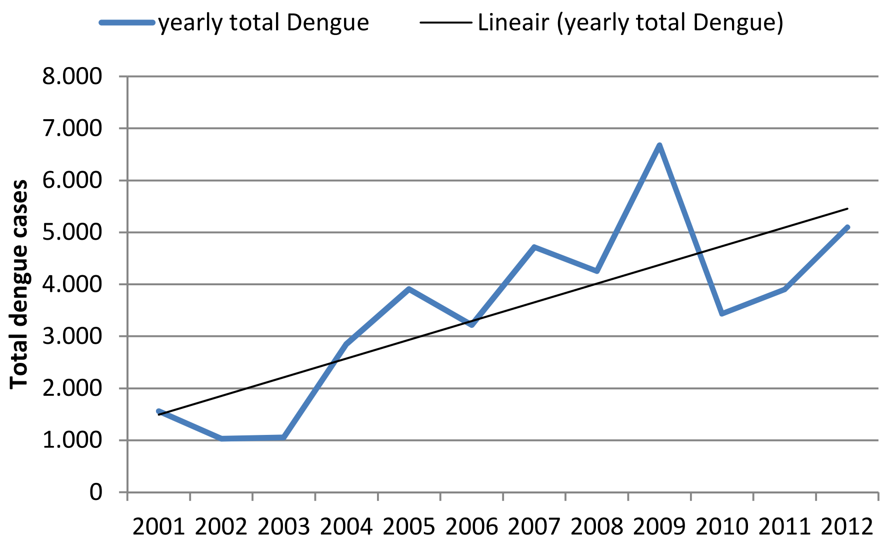


Figure 9: Total yearly dengue cases from 2001 to 2012 and its trend line, pointing to an increase in dengue cases.

2. Climate data

In this paragraph the climate data is presented and explained. In general, the lowest minimum temperature recorded between 1999 and 2008 was 12.6 °C, the highest maximum temperature was 34.9 °C. Daily average temperatures ranged from 19.9 °C to 27.7 °C with a mean average temperature of 24.2 °C. The maximum daily precipitation was 98.0 mm on 23 November 2000. Between the years 1999 and 2008 a total amount of 2093 dry days (*RR0*) and 1560 wet days (*RR1*) were recorded.

Average annual cycle of climate data

Similarly to paragraph 4.1.1, where the annual average cycle for dengue incidence is introduced, the average annual cycles for some climate indices have also been created. The average years for temperature, diurnal temperature range (DTR) and rainfall, as shown in figures 10 to 12, show seasonal patterns in the temperatures and in rainfall. DTR has a minimum in February (7.8 °C), and a maximum in September (11.5 °C), see figure 11. This maximum DTR is related to the relatively low values of t_n around July and August (negative peak of 17.9 °C) and a maximum in t_x (30.2 °C) in September.

The rain season in Bandung is from November to April (maximum average of *RR1* = 18.70 days per month), in the remaining months there is a sharp decrease in *RR1* (minimum of 2.60 days in August), see figure 12. In those months there are also less days with extreme precipitation amounts (*RR20* is lower than 1.30 days per month from July to September). During the rain period DTR is also lower. This can be explained by t_x being lower on rainy days then on dry days (due to the absence of direct solar radiation) and t_n being higher during cloudy nights than during clear nights.

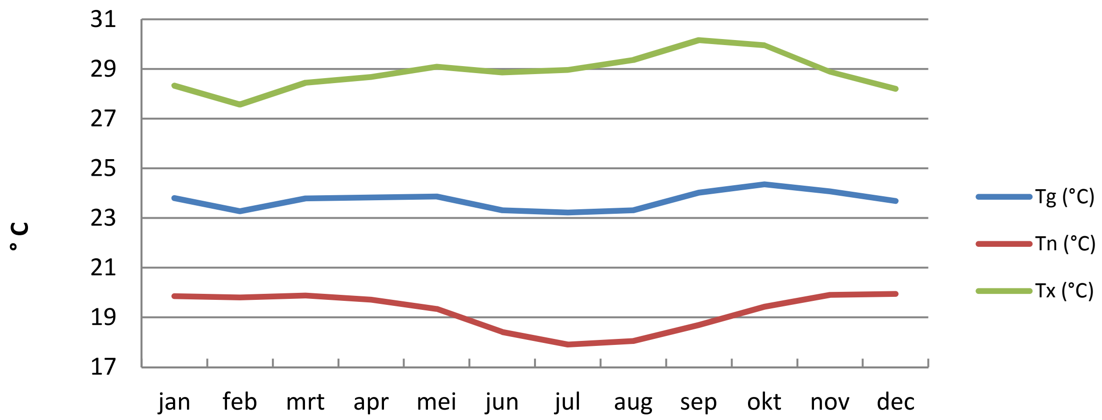


Figure 10: Average annual cycle over 1999-2008 for t_g, t_n, t_x (respectively in blue, red and green) in Bandung.

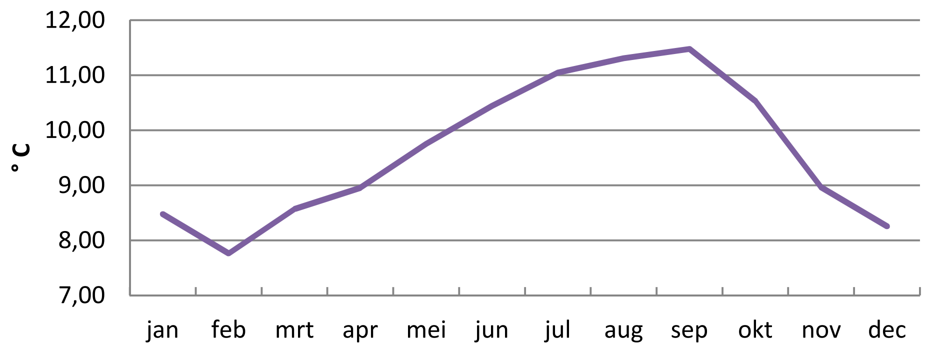


Figure 11: Average annual cycle over 1999-2008 for DTR in Bandung

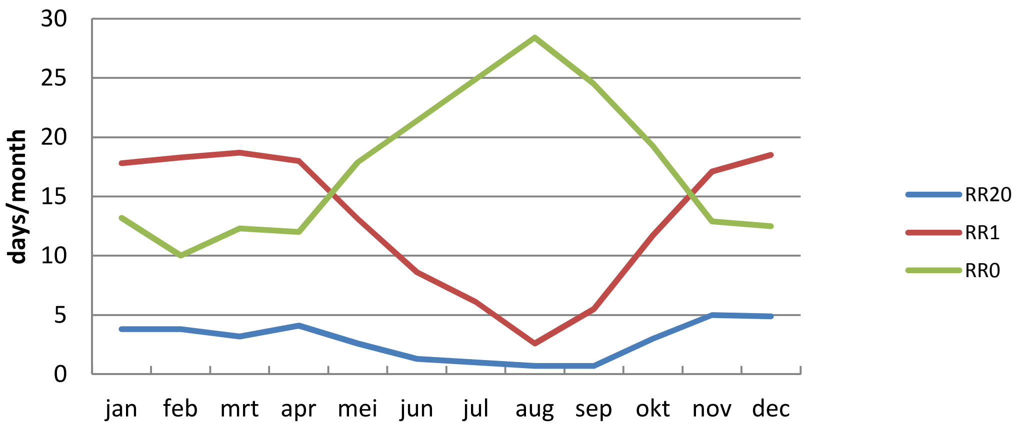


Figure 12: Average annual cycle over 1999-2008 for RR20, RR1 and RR0 (respectively in blue, red and green) in Bandung.

3. Comparison of the average annual cycle

The average annual cycles for rainfall, diurnal temperature range, and the minimum, average and maximum temperature for the period 1999 to 2008 were compared to the annual average cycles of datasets 1 and 2 which contain the dengue data. This analysis gives an insight in the seasonality of dengue incidence with these climatic parameters. Unless noted differently, no lag times are included in the correlation analysis.

3.1 Dataset 1

t_x and DTR have high, negative correlations (R = -0.59 and R = -0.50), for t_n the correlation is weaker (R = 0.29). The fact that the correlations with t_x and DTR are negative means that for higher values of t_x and DTR the dengue incidence gets lower, and vice versa. The average year shows seasonality in dengue incidence with a high peak during the months January, February and March, and a declining trend towards the end of the year. This trend correlates strongest with *RR1* (R=0.80 for $RR1_{2monthlag}$). *RR1*, with two months lag, is compared with the average annual cycle for dengue incidence in figure 13. The dengue incidence data is lagging behind the climate data. For *RR* and *RR20* the correlations were much lower (R = 0.26 and R = 0.11 respectively without lag time). The correlation for *RR1* is highest when a time lag is included.

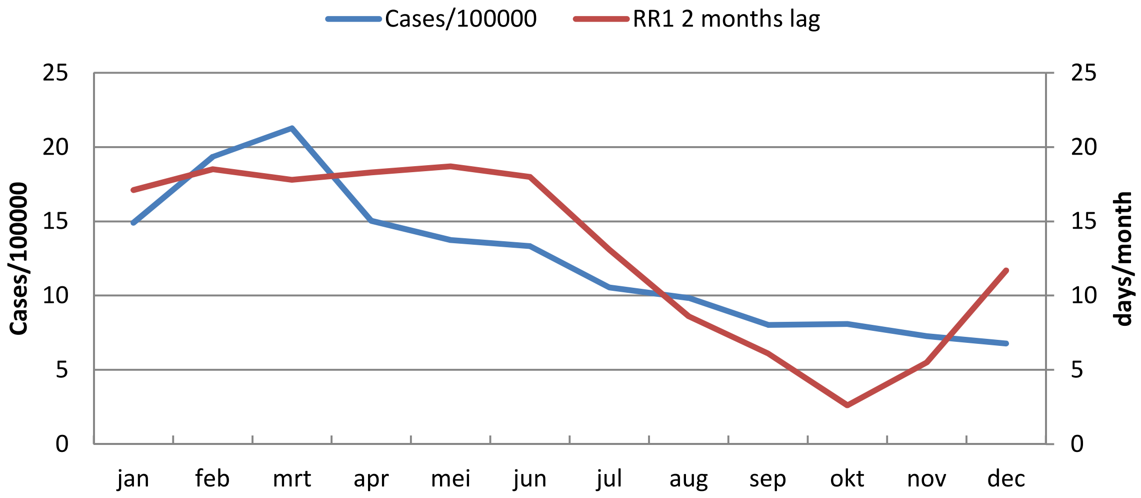


Figure 13: Average year of dataset 1 and $RR1_{2monthslag}$ (R = 0.80).

3.2 Dataset 2

The climatological annual cycle is compared with the average annual cycle of dataset 2. The correlation with t_x was strongest (R = -0.61). The correlation for DTR was in the same range (R = -0.52) and for t_n the correlation was about half as high (R = 0.28). Another strong correlation is found for *RR1* (R = 0.40). The correlation with *RR* is notably lower (R = 0.24). A negative correlation is found for t_g (R = -0.32).

4. Temporal data analysis

In this section the correlations of the several climatic indices with dengue incidence are presented. All climate indices have been analysed for different time lags, see paragraph 3.6. For every climate index the highest correlation and it's corresponding time lag are mentioned. A complete overview of all results will be presented in Appendix C.

4.1 Dataset 1

Datasets 1 has been compared with several climate indices to assess the most useful climate index for describing dengue fever incidence. Per climate index several time lags (dengue incidence lags behind climate) have been applied. Table 1 gives an overview of all the climate indices and the correlations with dengue incidence. Only climate indices with significant correlations are shown (unless specifically mentioned). All the climate indices are described in chapter 2 methodology, a short overview is given in Appendix B.

Climate index	lag time (months)	Spearman (φ)	Pearson (R)
tg	4	0,25	0,32
***tg*<22**	3	0,15	0,06 p = 0,56
22*tg*26	1	0,27	0,17 p = 0,10
***tg*>26**	2	0,07	-0,08 p = 0,46
Pt(31/07/13)	4	0,08 p = 0,41	0,22
Z(T)(31/07/13)	1	0,43	0,32
tn	2	0,48	0,37
tx	1	-0,39	-0,30
***tx*<22**	3	0,51 p = 0,07	0,41
DTR	2	-0,56	-0,39
RR	2	0,36	0,27
RR20	2	0,23	0,22
RR1	2	0,48	0,39
RR0	2	-0,48	-0,39

Table 1: Highest significant correlations of the different climate indices with dataset 1. The climate indices are described in paragraphs 3.2 and 3.3. When for a specific climate index the significance was higher than 0.05 it is displayed in red text.

For Z(T), the dynamical model, there is quite a strong positive correlation (*R = 0.43* and φ = 0.32). P_t, the chance of transmission of dengue, shows a weaker correlation with the Spearman function (φ = 0.22) and no correlation with the Pearson function. The strongest correlation is found for DTR with a lag time of two months (φ = -0.56), this is displayed in figure 14. Also t_n with a two months lag, shows a high correlation. The correlation with t_x (two months lag) is again negative (φ = -0.39), indicating that the higher t_x gets, the dengue cases there are. *RR* is again notably lower (φ = 0.36) again than *RR1* (φ = 0.48). To assess the influence of *RR1* on DTR, their correlation is derived (*R* = -0.76 and φ = -0.85). The remaining other climate indices show considerable lower correlations.

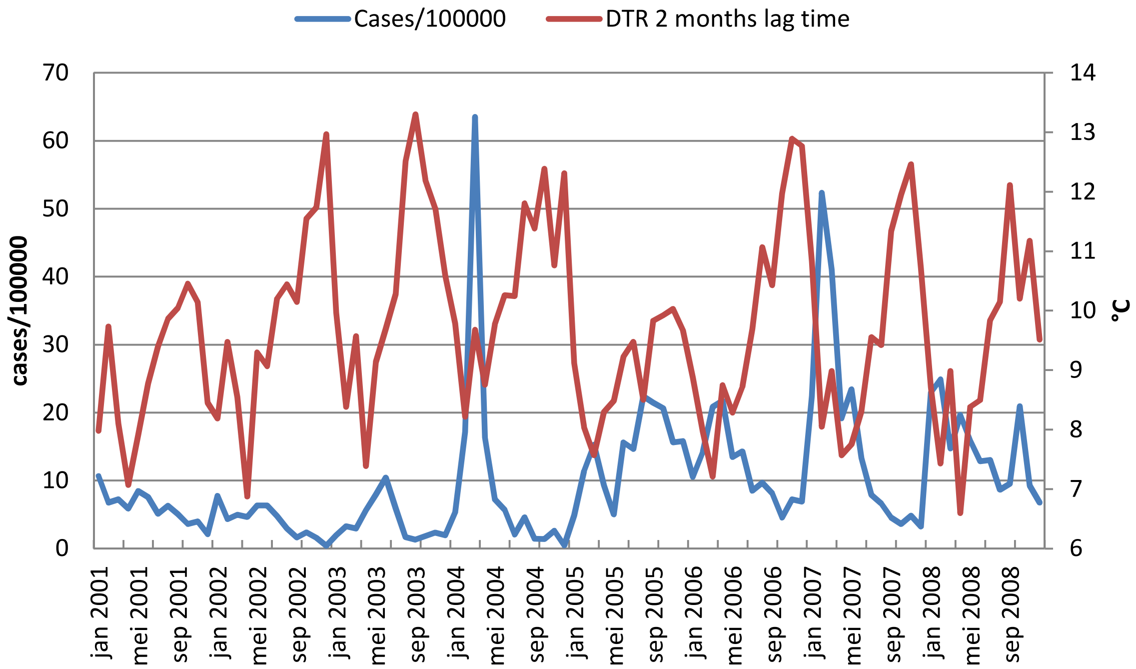


Figure 14: Monthly dengue incidence compared with the average DTR of 2 months earlier.

4.2 Dataset 2

Table 2 gives an overview of the correlations for dengue incidence as described by dataset 2 with the climate indices.

Climate index	lag time (days)	Spearman (φ)	Pearson (R)
tg	0	-0,13	-0,07
Pt(31/07/13)	0	-0,13	-0,11
Z(T)(31/07/13)	50	0,01 p = 0,25	0,30
tn	20	-0,07 p = 0,22	0,14
tx	0	-0,1	-0,14
DTR	20	-0,01 p = 0,13	-0,17
RR	50	-0,08	0,24
RR20	50	0,03 p = 0,29	0,27
RR1	50	-0,11	0,16
RR0	50	0,13	-0,16
Hum	0	-0,01	0,16
30dDTR	20	-0,09	-0,18
45dDTR	10	-0,13	-0,18
30dRR1	50	0,05	0,18
30dZ(T)	20	0,09	0,13
60dDTR	0	-0,13	-0,17
RR10	50	0,09	0,17

Table 2: Highest significant correlations of the different climate indices with dengue incidence as described by dataset 2. The climate indices are explained in paragraphs 3.2 and 3.3.

There are no strong correlations found with both the Pearson and Spearman test. Only for the temperature range climate indices, based on Gomes et al. [34], correlations higher than 0.20 have been found. But those variables are very robust. *Tx*<22 determines whether the maximum temperature of the day stays under 22 °C. As this happened only two times in 3653 data points, it is not useful as a climate index for DENV transmission. This argument also applies for *tg*<22, which occurred 61 out of 3653 days (φ = 0,51).

4.2.1 Analysis of the Climate Aedes *Mosquito Abundance model (CAMA)*

In the analysis of dataset 2 daily climate variables and daily dengue incidence were compared. Wong et al. [31] found by empirical modelling a set of climate indices that may be appropriate for this. In table 3 the correlations of dataset 2 with these indices is given.

Climate index	Lag time (days)	Spearman (φ)	Pearson (R)
22d*tg*	50	0,09 (p = 0,09)	0,15
CAMA	50	0,03	0,30
22d*tn*	20	0,02	0,16
22d*tx*	0	-0,13	-0,13
22dDTR	30	-0,01 (p = 0,13)	-0,17
15dRR	50	- 0,02 (p = 0,63)	0,30
15dHum	50	-0,01	0,15
30dDTR	20	-0,09	-0,18
45dDTR	10	-0,13	-0,18
30dRR1	50	0,05	0,18
60dDTR	0	-0,13	-0,17
RR10	50	-0,18	0,17

Table 3. Highest significant correlations of the time span indices with dataset 2. All correlations have a significance lower than 0.05, expect for the cases when a specific significance is given in red text.

Also here we see big differences between the Spearman rank and Pearson correlations. For the CAMA model we find with Pearson a reasonable correlation (p = 0,30) but this is not confirmed by the Spearman Rank function (φ = 0,07), see also Figure 15.

Additionally some similar climate indices were examined, as has been discussed in paragraph 3.3. They all show relatively low correlations (see table 3).

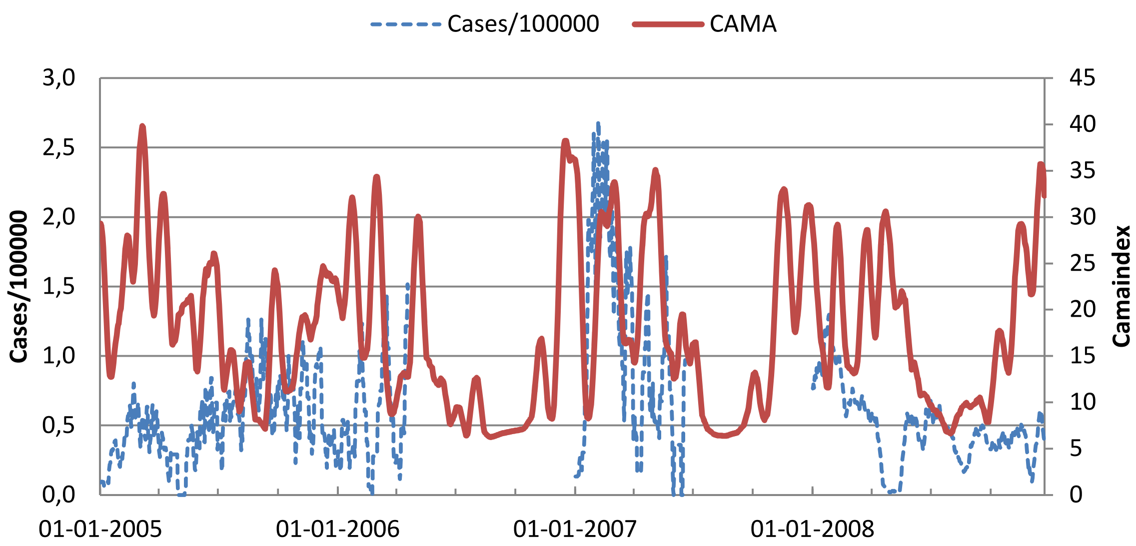


Figure 15: The Climate *Aedes* Mosquito Abundance model, CAMA in red is plotted against the actual DENV transmission in blue. This plot shows that there is a very low correlation.

5. Correction for seasonality

In this section we look at the datasets after the seasonal behaviour has been eliminated, as described in paragraph 3.6. The correlations between the climate indices after correction for seasonality and dengue incidence are expected to be weaker, as the main correlation of dengue transmission following seasonal climatic patterns has been filtered out.

For dataset 2 no correlations higher than 0.10 were found. This correction for seasonality puts a strong focus on small deviations on a specific daily scale. Since the quality of the observations in dataset 2 is not as high as would be required for this test, it was decided to not put any significance to the results of this test.

For dataset 1 the correlations were slightly higher, but only in one case the correlation was significant. For t_n with a lag time of two months we found significant correlations for both Pearson and Spearman Rank (R = 0,25 and φ = 0,27 respectively) (Figure 16).

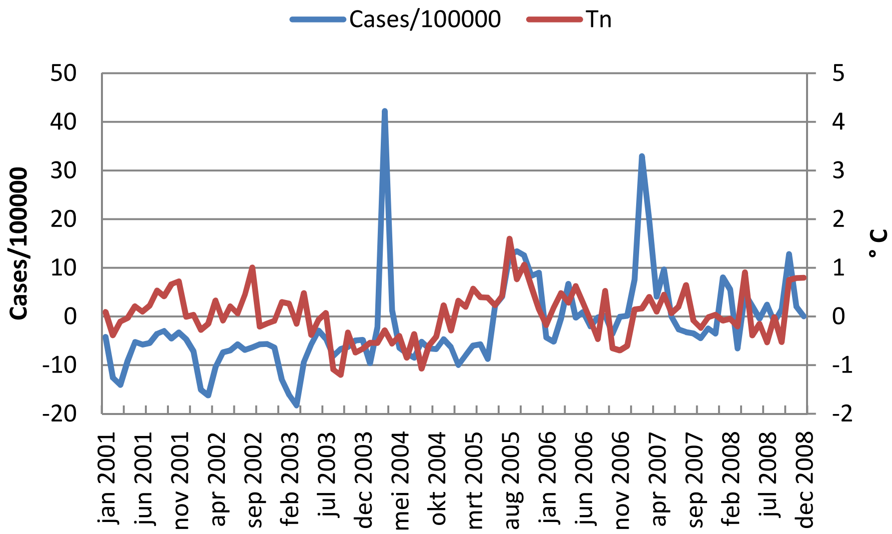


Figure 16: The deviation of t_n with a two month lag from the average annual cycle (in red) plotted against the deviation of monthly DENV transmission cases from the average annual cycle (in blue).

6. Trends and anomalies of the most important climate indices

In figure 9 an increase in yearly dengue cases for Bandung is observed. Besides population growth and other factors, climate variations, possibly related to climate change may partly cause this increase. In order to look into the changes in climate in the Southeast Asian region which may be relevant for the number of dengue cases, a selection of climate indices is analysed. This set of indices are those with the highest scores in the correlation tests with the DENV transmission data, these were t_n (daily minimum temperature), DTR (diurnal temperature range) and *RR1* (Amount of days with *RR*>1mm). On top of that, the trend for the dynamical model, as introduced in paragraph 3.4, is also pictured. For those climate indices we determined the trends over 30 years in the 1981-2010 period and we look at anomalies for Southeast Asia.

6.1 Anomalies

The two strongest outbreaks in dengue occurred in March 2004 and February 2007 (see figure 6). We looked at anomalies of DTR (Figure 17), t_n (Figure 18) and *RR1* (Figure 19) for the months December, January and February preceding these outbreaks. For DTR no corresponding anomalies were found. However it was found that t_n was abnormally high in the weeks preceding both outbreaks. *RR1* was high for the outbreak of 2004, but showed no distinctive anomaly for 2007.

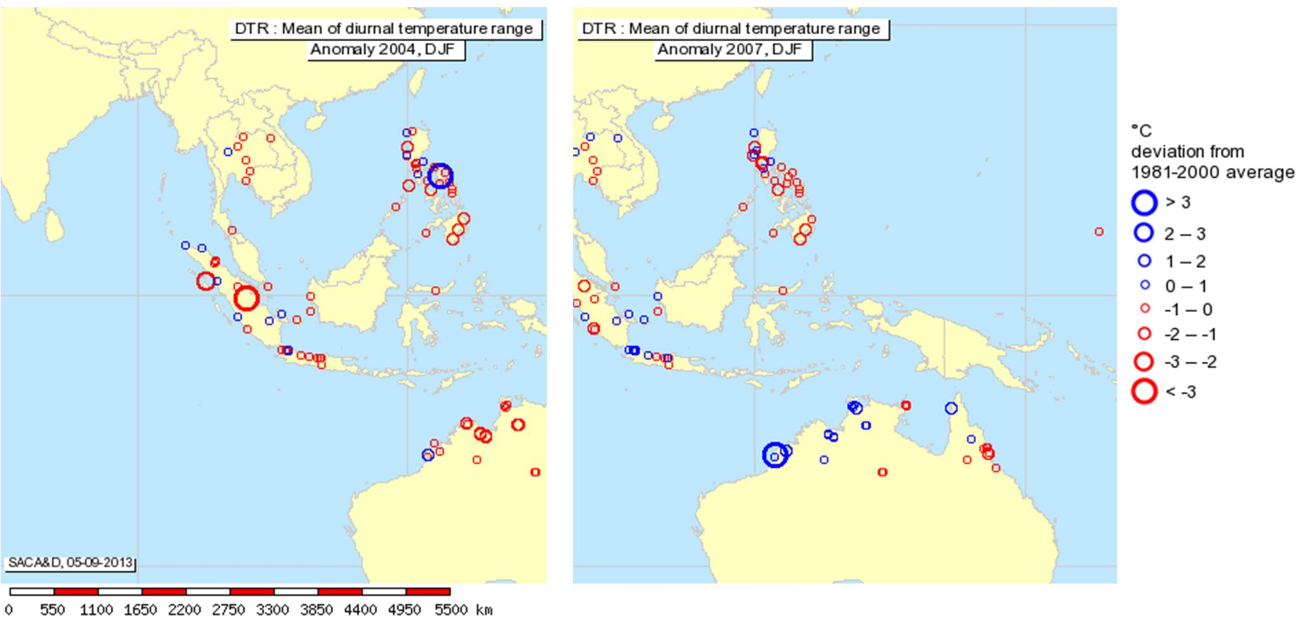


Figure 17: Anomalies of DTR for 2004 and 2007 in the months December to February. The circles indicate how much the DTR in December to February for 2004 and 2007 differs from the average DTR in December to February of the specific years differs from the average DTR over the years 1981 to 2000. Blue gives an increase in DTR, red gives a decrease in DTR.

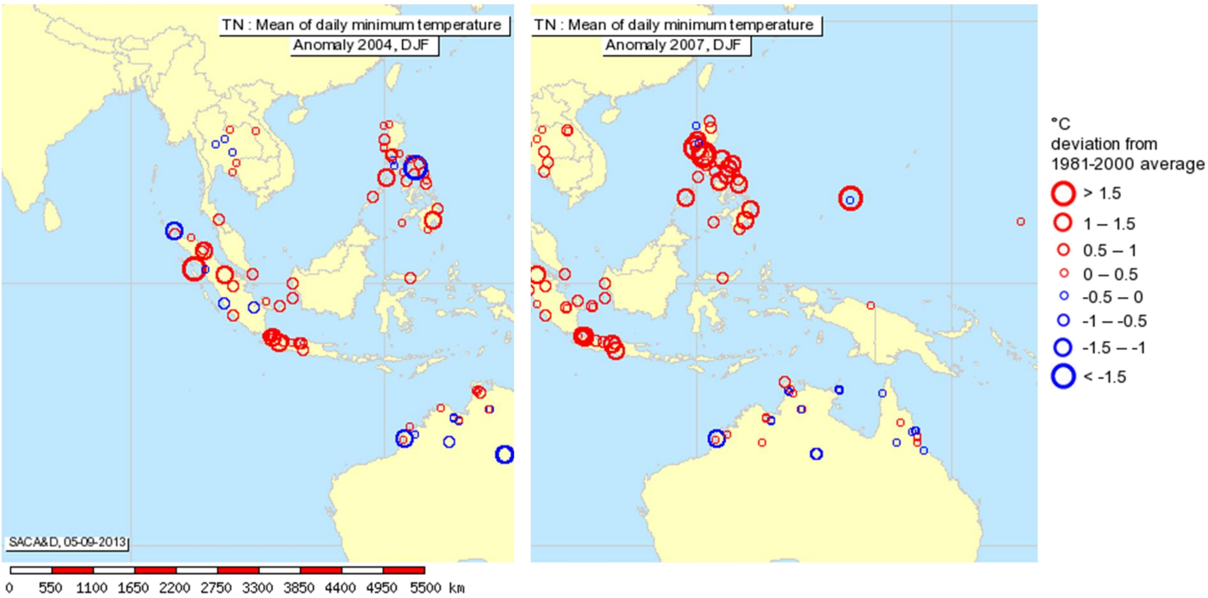


Figure 18: Anomalies for t_n for 2004 and 2007 in the months December to February. The circles indicate how much t_n in December to February for 2004 and 2007 differs from the average t_n in December to February over the years 1981 to 2000. red gives an increase in t_n, blue gives a decrease in t_n.

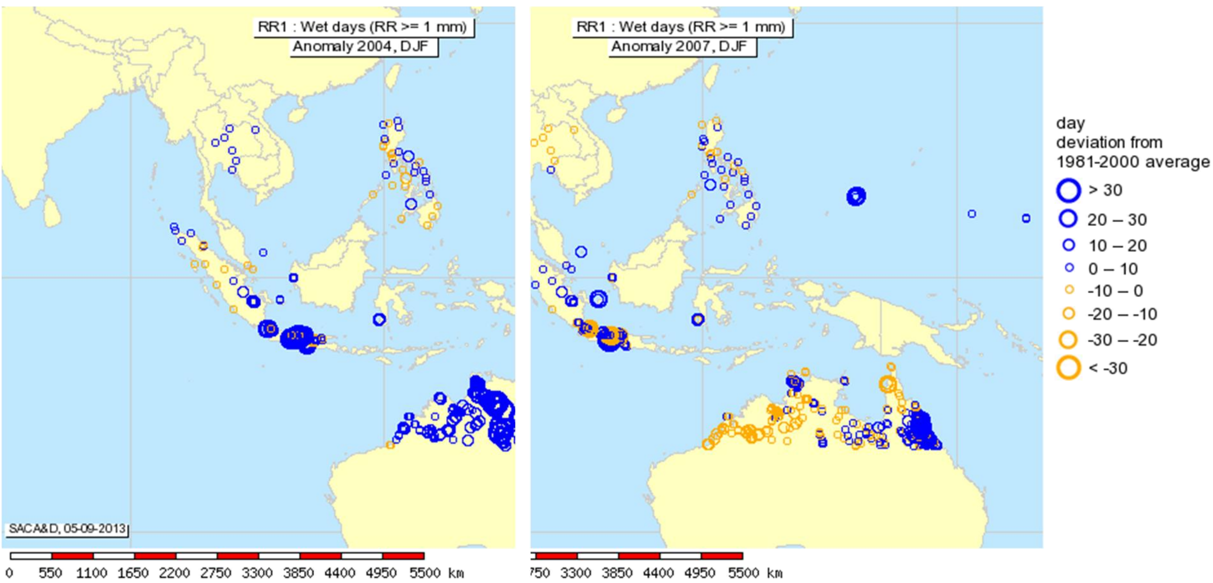


Figure 19: Anomalies for *RR1* for 2004 and 2007 in the months December to February. The circles indicate how much *RR1* in December to February for 2004 and 2007 differs from the average *RR1* in December to February over the years 1981 to 2000. Blue gives an increase in *RR1*, yellow gives a decrease in *RR1*.

6.2 Trends

Trends of DTR, t_n and *RR1* for the months November until February, and for the months December, January and February together (DJF) were considered. They were calculated over the period 1981 until 2010 from the SACA&D database.

DTR

For DTR in the months December until February there is no distinctive decrease in the region Bandung, and only a small decrease for some other stations on Java. However, larger decreases are found in Sumatra, Sulawesi, the Philippines and Northern Australia (Figure 20). For the months February and March this effect is stronger than from November to January. According to the negative correlation found between DTR and DENV transmission, this may have caused an increase in dengue risk.

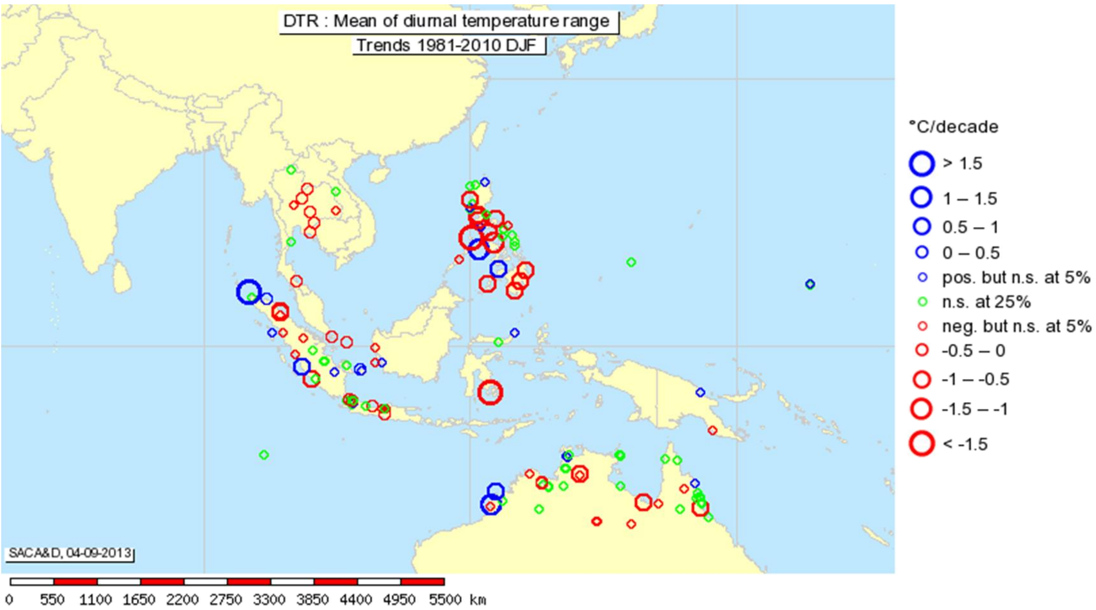


Figure 20: Trends over 1981 to 2010 for the months December, January and February for DTR. The circles indicate per decade how much DTR has changed, related to the conditions in the previous decade. Blue stands for an increase in DTR, red for a decrease.

RR1

Looking at *RR1*, most stations in the South East Asian region show an increase in the number of wet days (Figure 21). There are some localized regions on Java where there is a decrease. But in general the east coast of Australia and the islands Sumatra and Java in Indonesia are influenced the most. A particular increase can be observed in December, where the majority of the stations show a strong increase in wet days (Figure 22). Especially for Java *RR1* has a positive correlation with DENV transmission, this might hint that a an increase in dengue cases could be expected. Note that some stations give a change that is unrealistic (of up to 30 days). This is caused by a lack of homogeneity in the data for specific stations.

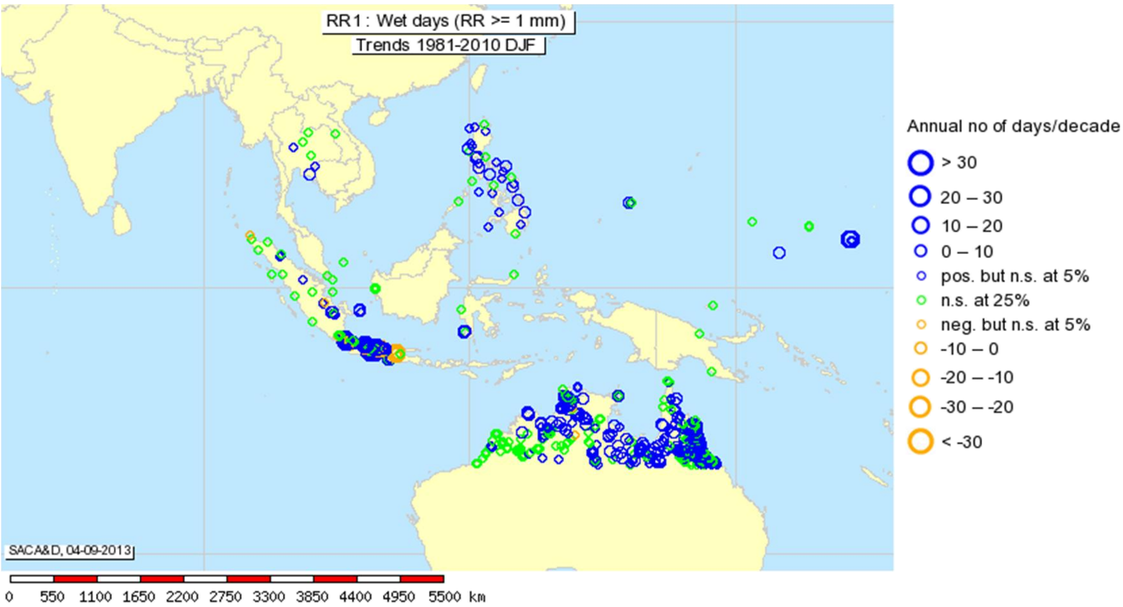


Figure 21: Trends over 1981 to 2010 for the months December, January and February for *RR1*. The circles indicate per decade how much *RR1* has changed, related to the conditions in the previous decade. Blue stands for an increase in *RR1*, yellow for a decrease. There is an increase of up to 30 rainy days per decade for those three months.

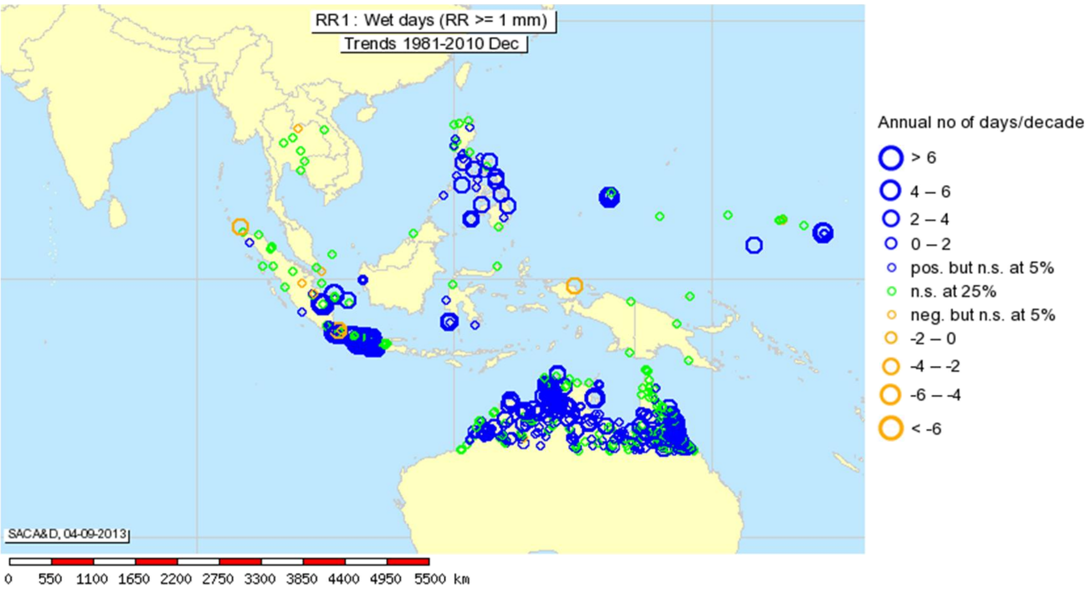


Figure 22: Trend of the amount of wet days in December over the period of 1981 to 2010. The circles indicate per decade how much *RR1* has changed, related to the conditions in the previous decade. Blue stands for an increase in *RR1*, yellow for a decrease.

t_n

t_n shows a small increase for all separate months and for December, January and February together of up to 1.5 °C for most of the region (Figure 23). Only in Australia there is no change visible. The correlation between dengue incidence and t_n is positive, thus this also points to a possible increase to vulnerability for dengue transmission in the Southeast Asian region.

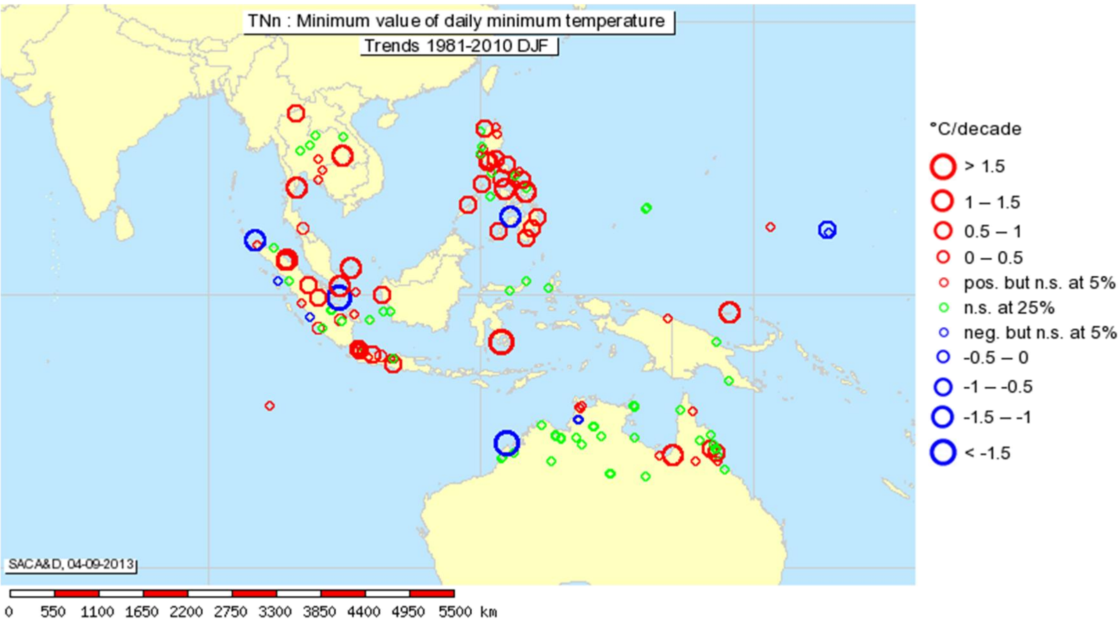


Figure 23: Trends over 1981 to 2010 for the months December, January and February for tn. The circles indicate per decade how much t_n has changed, related to the conditions in the previous decade. Red stands for an increase in t_n, blue for a decrease. There is an increase of 0.5 to 1 °C per decade in the Bandung region.

Z(T)

Although it is not fully completed yet, the dynamical model introduced in paragraph 3.4 has been inserted into the SACA&D database. Figure 24 shows the trend for Z(T) over the period 1981 to 2010. As the model is not yet optimal, we cannot draw any conclusions from these results. However, it is interesting to see how it looks when an index for dengue would be implemented in the SACA&D database. In the present state, a larger blue circle indicates stronger suitability for the transmission of DENV and thus an expected increase in dengue incidence.

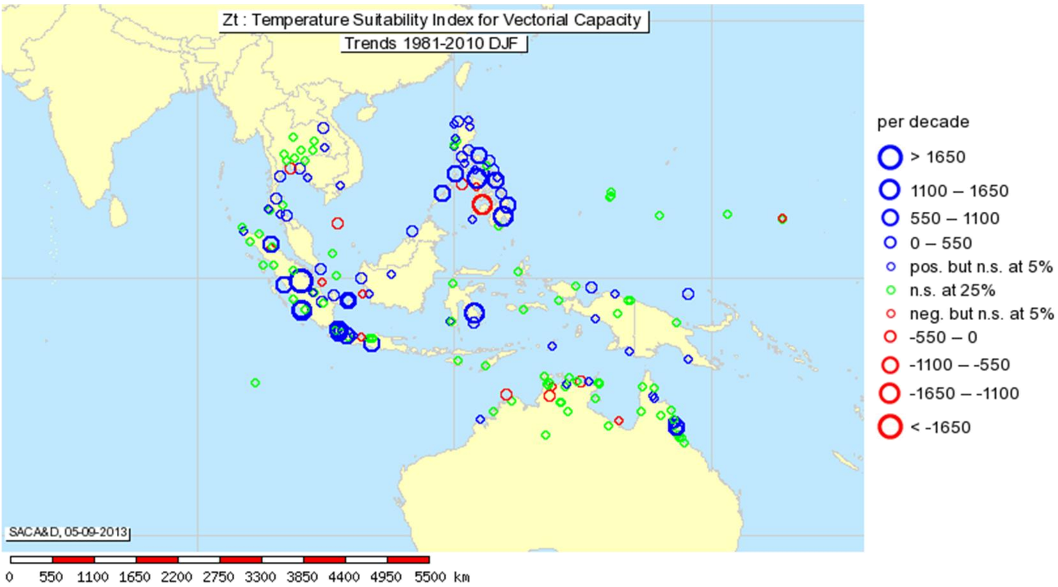


Figure 24: Trend over 1981 to 2010 for the months December, January and February for Z(T). The circles indicate per decade how much Z(T) has changed, related to the conditions in the previous decade. Blue stands for an increase in Z(T), red for a decrease.

5. Discussion

1. Do the data support the hypotheses?

In paragraph 1.2 four hypotheses and research goals have been presented. In this section the results are interpreted to determine whether they confirm the hypotheses.

1.1 Can a climate signal be distinguished in DENV transmission for Bandung, Indonesia?

During the analysis correlations with the health data were found for several climate indices. It is shown that there is a seasonal cycle in DENV transmission, which coincides with the climatological seasonal patterns. Thus, after it has already been confirmed for other areas that climate has an influence on DENV transmission [15, 29], our statistical analysis shows the expected correlation between climate and DENV transmission in Bandung, Indonesia.

1.2 Identification of relevant climate parameters for DENV transmission

Of the climate indices introduced in chapter 3, the results of the analysis point out that DTR, *RR1* and t_n have the biggest influence on DENV transmission in Bandung. This can be supported well with several other studies that found similar results.

1.2.1 RR1

The wet season in Bandung (December until April) is generally associated with higher dengue incidence, which is supported with the strong correlation found between dengue fever incidence and *RR1*. The weaker correlation with *RR* suggests that the *Ae. aegypti* needs rainfall on a regular basis rather than that there is a threshold for the required amount of rain over a specific period. The eggs of the mosquito only hatch when they are in water. A regular resupply of rain makes sure that the eggs stay wet, which might explain this preference. This requirement of rain to hatch for the eggs can also explain why there is a lag between climate and dengue incidence. In paragraph 4.3.1 it can be seen that the correlation for *RR1* is highest when a time lag of two months is included. This may be attributed to the development duration of egg to infective mosquito.

1.2.2 t_n

It has been found in some studies that the daily minimum temperature (t_n) is the most important factor for determining dengue transmission [34, 46]. It is suggested that a higher t_n causes an increase of the extrinsic incubation period of the virus. In this study strong correlations are found for both the temporal data analysis (R = 0.48, two months lag time) and for the data from which the seasonal cycle has been removed (R = 0.29, two months lag time). We consider this last test with correction for seasonality a very strong test. Therefore, this is a positive outcome which points to t_n being a specific climate index for DENV transmission. Other studies have also reported positive correlations between t_n and DENV transmission, when t_n is lagged by one or two months [16, 28, 34, 47-49].

1.2.3 DTR

A high correlation is found for DTR with a lag time of two months (φ = -0,56) (Figure 14). This is in coherence with the finding that Aedes mosquitoes prefer a low DTR [39, 50]. Lambrechts et al. state that an increasing DTR has a negative impact on survival rate of the *Ae. aegypti*, and that EIP increases with DTR, which would explain this correlation [39].

Although a positive correlation exists between RR1 and dengue incidence, the correlation between DTR and dengue incidence is higher. Also in other literature it is observed that rainfall has a lower correlation with dengue incidence than temperature. The general consensus in Indonesia is that dengue incidence increases during the wet season. This observation on itself seems correct. However, it must be regarded that this could also solely be caused by temperature variations, through small values of DTR or high values of t_n, since DTR is lowest during the wet season.

1.2.4 Comparison between empirical and dynamical models

During the analysis we found no notable correlation between DENV transmission and the empirical CAMA model, whereas in the original study a correlation of R = 0.90 was found [31]. The CAMA model for the Hong Kong region, China, apparently doesn't work for the situation of Bandung, Indonesia. It is clear that climate and the geographical situation of the two are very different. Apparently, this difference in conditions is decisive in the suitability of the model for a specific location. This is in range with the general consensus found in literature that most (empiric based) climate variability models can describe DENV transmission in specific locations and much less on a general scale [51]. In this light the goal to develop an overall climate index that can estimate dengue appearance at any location seems very ambitious.

However, when on the other hand we take a look at dynamical models and how they are constructed it seems a lot more likely that it is possible to create a general model, as long as the dynamics of DENV transmission are well enough characterized. Therefore, for our goal it seems that further investigation of dynamical models for DENV transmission is preferable.

The dynamical model used in this study is not complete in its development. It has not been adapted fully to match biological parameters of dengue virus and there is still some doubt about the mathematics used in its development. Instead the parameters of the flavivirus responsible for

Malaria have been used. The results for the dynamical model, expressed as Z(T), as they have been presented now are however showing some promise. For dataset 1 Spearman showed a decent correlation (φ = 0.43 with one month lag). Given that the model is not yet complete, it seems likely that improvement of the model might lead to a higher correlation. The lag time of just one month can also not be fully explained, a lag time of two months is what would be expected because of the period of development of the mosquito, in the next paragraph this is further elaborated.

1.2.5 Lag times

For t_n, DTR and *RR1* the correlations were highest when dengue incidence data was lagged two months behind the climate data. The several processes before dengue is diagnosed in a health centre include the period of embryonic development of the mosquito, hatching time, the adult and sexual development period of the mosquito, the time before the first blood meal in which the mosquito passes the infectious virus and the time before the appearance of clinical manifestations of dengue fever [43]. These factors together add up to a lag time of one to two months.

1.3 Trends for relevant climate parameters in the Southeast Asia region

Correlation analysis (paragraph 4.3.1) indicated that t_n, DTR and *RR1* all have a statistical relation with DENV transmission. An analysis of the trends of these climate indices gives us insight in how climate variability and possibly climate change can decrease or increase the risk of dengue fever in Southeast Asia, when one would assume that t_n, DTR and *RR1* affect DENV transmission in other areas similarly to Bandung, Indonesia.

1.3.1 Anomalies

t_n has unusually high values in the period leading to the dengue outbreaks of 2004 and 2007. Given the strong positive correlation with dengue incidence, this fuels the suggestion that t_n may have been instrumental in these outbreaks. DTR did not show any abnormal values during both outbreaks. For *RR1* this was only the case for the outbreak of 2004. As only two outbreaks are considered, these outcomes cannot be used to put the hypothesis about the use of these three climate indices for describing DENV transmission variability on a firmer footage. Analysis of the anomalies during outbreaks is however a useful tool for further research on climate and dengue, when more outbreaks can be analysed.

1.3.2. Trends

Southeast Asia is considered as an area which is extremely vulnerable to climate change [52]. The results from paragraph 4.6 show that the trends point to a small decrease in DTR and moderate increases in both t_n and *RR1*. All these effects have a positive influence on DENV transmission.

Climate change in South-East Asia can thus possibly attribute to an increase of DENV transmission in that region.

1.4 Creation of a climate index describing DENV transmission

We did not yet succeed in creating a climate index that can accurately describe DENV transmission. With the identification of t_n, DTR and *RR1* as major influences we have made an important step towards the development of such a climate index. Furthermore we conclude that dynamical models are better suitable than empirically derived models, as the empirical models seem to be only effective for specific regions. A third valid finding is that lag times of between one and two months must be included to increase the performance of this climate index.

A next step towards the development of a proper climate index with a high certainty of describing DENV transmission would be to further investigate how these climate variables influence the host-vector-parasite dynamics. Studies of Gething et al., Adams and Chen and Hsieh have already introduced some methods and models to describe these interactions [35, 53, 54]. They will need improvements, as in none of these models all three of the important climate variables have been included.

With the introduction of Z(T) in SACA&D, as displayed in figure 24 a first attempt has been made to produce a climate index. Even though the model behind Z(T) still has to be improved, it gives a first impression of the use of a dengue index in SACA&D.

2. Discussion of the research process

Looking back on this study, there are some shortcomings which have to be explained and some lessons to be learned for future applications.

2.1 Problems with data collections

The first task carried out for this study was the collection of dengue disease incidence data for the Upper Citarum Catchment area. It turned out that only useful data for the urban area Kota Bandung could be collected. Climate data was collected from BMKG, the meteorological institute of Indonesia. Both data collections contained some errors, the most important ones have already been described in paragraph 2.1. In the end we had to accept that the quality and accuracy of the collected health and climate data is lower than desired and that also therefore it was not possible to develop a climate index that is able to accurately describe DENV transmission.

2.2 Interpretation of the results

Some caution should be applied in the interpretation of the results.

2.2.1 Influence of climate variability on DENV transmission

Hay et al. [55] have conducted a research where they analysed meteorological and epidemiological data for DENV transmission in Bangkok. They found that dengue peaks every three years, even though there were no significant variations in temperature and rainfall besides what can be seen in the annual cycle. They suggest that this behaviour is not as much caused by climate, but that the oscillations in the diseases are natural intrinsic properties of the host-vector-parasite dynamics.

In our findings the Dengue virus is endemic throughout the year and over the twelve years of data analysed we can only identify two major outbreaks, namely in 2004 and 2007. Thus, we have not a clear pattern with outbreaks emerging every three years. The most obvious patterns really point more to an annual cycle. Although this behaviour can in theory as well be attributed to some natural intrinsic properties, the assumption that climate variability has at least partly an influence on DENV transmission is the more obvious explanation.

2.2.2 Negative effect of t_x on DENV transmission

Several studies found that dengue fever incidence is positively correlated with temperature as higher temperatures shorten the EIP and hence increase the infectious lifetime of *Ae. aegypti* [28, 56-59]. It is thus interesting to see that t_x has a negative correlation with the dengue incidence (paragraphs 4.3.2 and 4.4.1). It is observed that with temperatures rising to 30 °C the life span of the female mosquitoes increases, thereafter there is a decrease in survival time [3, 54] this would mean that up until 30 °C temperature should have a positive effect on DENV transmission. On the other hand it has been observed that around 26 °C there is a minimum in the time it takes for an adult female *Ae. aegypti* to start taking blood meals [50]. With higher temperature this time increases again, which can explain the negative correlation.

It can also be explained by the high, negative correlation between DTR and dengue incidence. DTR decreases with higher t_n and lower t_x which would mean that a lower t_x can actually increase DENV transmission. This can indicate that the negative impact of high t_x on DTR indirectly has a negative impact on DENV transmission, which is stronger than the consensus that high temperatures are positive for DENV transmission.

This is a very interesting finding. By far the most reviewed studies have looked only at the impact of temperature and not at the effect of DTR on dengue transmission, and as far as we know no study has been carried out to compare those effects. It would be interesting to study this specific finding. Because of time constraints a multi-variable analysis could not be carried out. In a future study this is useful to determine the correlations of multiple climate parameters with dengue incidence at the same time.

2.3 Analysis with Spearman Rank and Pearson correlation functions

The data is not normally distributed. The higher correlations for Spearman than for Pearson indicate that within the limits of this study the data seems to have a monotonic relationship, but not a linear relationship. This has also been determined by Descloux et al. and Earnest et al. [16, 29] say that an ordinary least squares linear regression model fails to account for the discontinuity in the relationship between DENV transmission and climate variability.

To deal with the discontinuity, Descloux et al. [16] have chosen to not look at dengue fever incidence rates, but purely at epidemic years. They formed a definition of epidemic years and made a yearly analysis purely on this definition (0 for non-epidemic years, 1 for epidemic years). This method can be interesting as a future approach.

A weak point of this study is that for the significance associated with the correlations no correction for autocorrelation has been made. This makes that the significance as found is overestimated.

3. Non-climatological influences on DENV transmission

DENV transmission patterns depend on more than on weather variables only. The disease is strongly influenced by economic, social, spatial, biological and technical factors as well.

3.1 Simplification of epidemiological dynamics

In this study some gross simplifications and generalizations have been made concerning the medical background of the dengue fever virus. First of all no distinguish has been made between different serotypes. Usually when there is an outbreak of dengue, one specific serotype is predominantly involved. People who got infected with a certain serotype develop immunity to this specific serotype, so during a next outbreak of the same serotype there will be less viable hosts available [60]. The World Health Organization has stated that introduction of new serotypes can result in explosive epidemics, this suggests that immunology is a factor in the occurrence of DENV outbreaks [61]. On the other hand people who have been infected with one serotype are known to be more perceptible to other serotypes of the dengue viruses, which can mean that they get more easily infected on the one hand and become much sicker on the other hand [6]. Also natural intrinsic properties and patterns of the pathogen are not included [55]. Overall, this extra medical dimension was too specific for the scope of this research and has therefore been left out. No attempts to relate climate to specific serotypes have been found.

3.2 Urban versus rural areas

Dickin et al. [62] stated that the influence of climate conditions on DENV transmission is bigger in urban areas than in rural regions. Urban areas are in general more receptive for DENV transmission, but this is dominantly due to non-climatic impacts. This can be an explanation for the generally weak correlations with climate variables found in this research, which took place in an urban area. During the data collection an attempt has been made to retrieve qualitative DENV transmission data for the more rural regions of the Citarum Catchment south of Bandung as well. This was however unsuccessful and thus eliminated the possibility of investigating the difference between rural and urban areas. Although it would be optimal to create a climate index for dengue variability that is universally applicable, it is imaginable that a set of indices is created that are specific for either, rural, sub-urban and urban regions. This option must be regarded during the development of this index.

3.3 Floods and droughts

Floods have a complex influence on dengue fever disease incidence dynamics. On the one hand heavy rainfall and floods can wash away breeding sites, repressing vector density [63, 64], but the remaining standing water afterwards provides excellent breeding places for *Aedes* mosquitoes on the other hand [65]. Besides a correlation with floods, there are also reasons to believe that there is an increase in transmission during extreme dry periods. This would be attributed to human behaviour, since in dry times people tend to store more water hence creating ideal breeding sites for the *Ae. aegypti*.

3.4 Socio-environmental factors

In general, research on the influence of climate variability on dengue transmission variability is considered very challenging since many other influences also play a role in this. Banu et al. [66] did a literature-review on studies that either include or exclude those. As non-climatic influences that can increase or decrease the risk at dengue infection they listed; facilities reducing contact with the vectors or the risk of transmitting DENV, differences in living standards and human behaviour, housing types, quality of garbage disposal, international trade and transport, public health interventions and vector eradication programs. This wide variety of possible influencing factors make that the accuracy of purely climatic based models will always be limited.

4. Future research

During this study many problems and frustrations have been faced especially regarding limited availability of data and the low quality of available data. In the research fields of DENV transmission and climate this is a general problem [62]. An easy conclusion is thus that in order for better results to be found, data should be available and it's quality should be high. However, a common problem is that better data is simply not available. And this strengthens the legitimacy of our goals, the development of a large scale climate based dengue index. At this moment it is still a major trend to model DENV transmission based on empirical findings [2, 15, 16, 31]. This makes models only applicable at the location for which it has been developed. For areas where not enough data is available to develop an empirical model we have to find alternatives. This study made an attempt to find a solution for this problem.

As the World Health Organization expects that the number of people at risk of getting infected with the dengue virus will increase in the next years (see paragraph 1.2) partly influenced by climate change, the topic assessed in this study will continue to be relevant. This study seems to be the first attempt to quantify the impact of climate on DENV transmission in Bandung. Therefore it can give some valuable input for assessing the influence of climate change on dengue in Bandung. Dickin et al. [62] have attempted to model the vulnerability for dengue in the whole of Malaysia with the Water-associated Disease Index (WADI). They mention that using more local meteorological records would likely improve the quality of the presented model. With SACA&D and the definition of a specific dengue climate index such a more general model could be improved as well.

6. Conclusion

1. Impact of climate variability on DENV transmission variability

The dengue fever incidence dynamics between 2001 and 2012 are influenced by climate variability in Bandung. January, February and March have been identified as the most vulnerable months for high DENV transmission. This falls together with peaks in the minimum daily temperature (t_n), the monthly rain days (*RR1)* and low values for the average diurnal temperature range (DTR).

2. How can the impact of climate variability be quantified based on specific climate variables

t_n, DTR and *RR1* display significant correlations with dengue fever incidence. Based on the results the expectation is that they are necessary components of a "climate based dengue index" for Bandung.

3. Upward trend in DENV susceptibility

The trends of t_n, DTR and *RR1* of show that between 1981 and 2010 they have developed in a way changed that conditions for dengue transmission seem to have improved. Although this study provides no conclusive basis, it indicates that studies to gain more insight on DENV transmission dynamics are very necessary and should be a high priority to reduce the increasing burden of this emerging disease for the population of Southeast Asia.

4. Creation of a "climate based dengue index"

It was not possible to create a working index within the limited available time. However a basis is created on which one could continue to build towards the creation of this index. In this process two remarks are of major importance:

- The tested empirical models turned out to be inapplicable for Bandung, Indonesia. This kind of models are specific for one region and often don't make sense for other regions. When one wants to create a universal "climate based dengue index" it seems more viable to create a dynamical model.

- In this study t_n, DTR and *RR1* are found to be the most interesting climate variables that influence DENV transmission, with the inclusion of a lag time of two months. It is necessary to specifically determine their role in the host-vector-pathogen dynamics, so that they can be implemented in a dynamical model.

5 Future perspective

The intentional goal of this study has been the creation of on universal "*climate based dengue index*" which can accurately describe dengue variability when a combination of certain climate parameters is known. This soon turned out to be too ambitious as the relationship between climate and DENV transmission is a tricky and complex one. This led to a downscaling of the expectations and goals, which nonetheless have been fulfilled and also fuel expectations for further elaboration on this topic. Limitations in the availability of data is still a constraint in assessing the vulnerability of remote areas for dengue. If a generally applicable climate index can be introduced into SACA&D, this would make it possible to also study areas for which no data is available. With the developments generated in this study a solid basis is established for a continuation towards the intentional goal; the creation of a climate index for DENV transmission.

7. References

1. Scott, T.W., et al., *Detection of multiple blood feeding in Aedes aegypti (Diptera: Culicidae) during a single gonotrophic cycle using a histologic technique.* J Med Entomol, 1993. **30**(1): p. 94-9.
2. Hales, S., et al., *Potential effect of population and climate changes on global distribution of dengue fever: an empirical model.* Lancet, 2002. **360**(9336): p. 830-4.
3. Tun-Lin, W., T.R. Burkot, and B.H. Kay, *Effects of temperature and larval diet on development rates and survival of the dengue vector Aedes aegypti in north Queensland, Australia.* Med Vet Entomol, 2000. **14**(1): p. 31-7.
4. Focks, D.A., et al., *Dynamic life table model for Aedes aegypti (Diptera: Culicidae): analysis of the literature and model development.* J Med Entomol, 1993. **30**(6): p. 1003-17.
5. Gubler, D.J. and G. Kuno, *Dengue and dengue hemorrhagic fever*, ed. C.I. Michigan. 1997.
6. Guzman, M.G., et al., *Dengue: a continuing global threat.* Nat Rev Microbiol, 2010. **8**(12 Suppl): p. S7-16.
7. Organization, W.H., *Denge and severe dengue Fact sheet N°117 Updated September 2013.* 2013.
8. Confalonieri, U., et al., *Human health. Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change.* Cambridge University Press, 2007: p. 41.
9. Organization, W.H. *WHO Dengue guidelines for diagnosis, treatment, prevention and control.* . 2009 [accessed 2013 20-08]; Available from: http://whqlibdoc.who.int/publications/2009/9789241547871_eng.pdf.
10. Gubler, D.J., *Dengue/dengue haemorrhagic fever: history and current status.* Novartis Found Symp, 2006. **277**: p. 3-16; discussion 16-22, 71-3, 251-3.
11. Rogers, D.J., et al., *The global distribution of yellow fever and dengue.* Adv Parasitol, 2006. **62**: p. 181-220.
12. Bhatt, S., et al., *The global distribution and burden of dengue.* Nature, 2013. **496**(7446): p. 504-7.
13. van Kleef, E., H. Bambrick, and S. Hales, *The geographic distribution of dengue fever and the potential influence of global climate change.* TropIKAnet, 2010.
14. Hii, Y.L., et al., *Climate variability and increase in intensity and magnitude of dengue incidence in Singapore.* Glob Health Action, 2009. **2**.
15. Johansson, M.A., D.A. Cummings, and G.E. Glass, *Multiyear climate variability and dengue--El Nino southern oscillation, weather, and dengue incidence in Puerto Rico, Mexico, and Thailand: a longitudinal data analysis.* PLoS Med, 2009. **6**(11): p. e1000168.
16. Descloux, E., et al., *Climate-based models for understanding and forecasting dengue epidemics.* PLoS Negl Trop Dis, 2012. **6**(2): p. e1470.
17. Arunachalam, N., et al., *Eco-bio-social determinants of dengue vector breeding: a multicountry study in urban and periurban Asia.* Bull World Health Organ, 2010. **88**(3): p. 173-84.
18. Indonesia, M.o.H., *Republic of Indonesia Directorate General of Disease Control & Environmental Health 2013.* 2013.
19. Soedarmo, S.P., *The Epidemiology, Control and Prevention of Dengue Hemorrhagic Fever (DHF) in Indonesia.* Trop Med Int Health, 1993. **35**(4): p. 12.
20. (BPS), P.S.K.B.
21. Suptriatna, A.K., *Estimating the basic reproduction number of dengue transmission during 2002-2007 outbreaks in Bandung, Indonesia.* Dengue Bulletin, 2009(33): p. 12.

22. Porter, K.R., et al., *Epidemiology of dengue and dengue hemorrhagic fever in a cohort of adults living in Bandung, West Java, Indonesia.* Am J Trop Med Hyg, 2005. **72**(1): p. 60-6.
23. SACA&D. [accessed 2013 20 July]; Available from: http://saca-bmkg.knmi.nl/rcc
24. Liebmann, B., et al., *Onset and end of the rainy season in South America in observations and the ECHAM 4.5 atmostpheric General Circulation Model.* J. Climate, 2007. **20**: p. 2037-2050.
25. Undurraga, E.A., Y.A. Halasa, and D.S. Shepard, *Use of expansion factors to estimate the burden of dengue in Southeast Asia: a systematic analysis.* PLoS Negl Trop Dis, 2013. **7**(2): p. e2056.
26. Guzman, M.G. and G. Kouri, *Dengue: an update.* Lancet Infect Dis, 2002. **2**(1): p. 33-42.
27. team, E.D.P., *European Climate assessment and dataset algorithm theoretical Basin Document (ATBD).* de Bilt, The Netherlands, 2012.
28. Lu, L., et al., *Time series analysis of dengue fever and weather in Guangzhou, China.* BMC Public Health, 2009. **9**: p. 395.
29. Earnest, A., S.B. Tan, and A. Wilder-Smith, *Meteorological factors and El Nino Southern Oscillation are independently associated with dengue infections.* Epidemiol Infect, 2012. **140**(7): p. 1244-51.
30. SACA&D. [accessed 2013 17 August]; Available from: Http://saca-bmkg.knmi.nl/rcc/indicesextremes/index.php.
31. Wong, M.C., et al., *A climate model for predicting the abundance of Aedes mosquitoes in Hong Kong.* Meteorological Applications, 2011. **18**(1): p. 105-110.
32. Martens, W.J.M., *Health impacts of climate change and ozone depletion: An ecoepidemiologic modeling approach.* Environmental Health Perspectives, 1998. **106**: p. 241-251.
33. Mellor, P.S. and C.J. Leake, *Climatic and geographic influences on arboviral infections and vectors.* Revue Scientifique Et Technique De L Office International Des Epizooties, 2000. **19**(1): p. 41-54.
34. Gomes, A.F., A.A. Nobre, and O.G. Cruz, *Temporal analysis of the relationship between dengue and meteorological variables in the city of Rio de Janeiro, Brazil, 2001-2009.* Cad Saude Publica, 2012. **28**(11): p. 2189-97.
35. Gething, P.W., et al., *Modelling the global constraints of temperature on transmission of Plasmodium falciparum and P. vivax.* Parasit Vectors, 2011. **4**: p. 92.
36. Focks, D.A., et al., *Dynamic life table model for Aedes aegypti (diptera: Culicidae): simulation results and validation.* J Med Entomol, 1993. **30**(6): p. 1018-28.
37. Garrett-Jones, C., *Prognosis for Interruption of Malaria Transmission through Assessment of the Mosquito's Vectorial Capacity.* Nature, 1964. **204**: p. 1173-5.
38. Kramer, L.D. and G.D. Ebel, *Dynamics of flavivirus infection in mosquitoes.* Adv Virus Res, 2003. **60**: p. 187-232.
39. Lambrechts, L., et al., *Impact of daily temperature fluctuations on dengue virus transmission by Aedes aegypti.* Proc Natl Acad Sci U S A, 2011. **108**(18): p. 7460-5.
40. Chan, M. and M.A. Johansson, *The incubation periods of Dengue viruses.* PLoS One, 2012. **7**(11): p. e50972.
41. Bayoh, M.N. and S.W. Lindsay, *Effect of temperature on the development of the aquatic stages of Anopheles gambiae sensu stricto (Diptera: Culicidae).* Bull Entomol Res, 2003. **93**(5): p. 375-81.
42. California, U.o. *About degree-days*. 2003; [accessed 2013 21 July]; Available from: http://www.ipm.ucdavis.edu/WEATHER/ddconcepts.html.
43. Depradine, C. and E. Lovell, *Climatological variables and the incidence of Dengue fever in Barbados.* Int J Environ Health Res, 2004. **14**(6): p. 429-41.
44. Hii, Y.L., et al., *Optimal lead time for dengue forecast.* PLoS Negl Trop Dis, 2012. **6**(10): p. e1848.

45. Focks, D.A. and R. Barrera. *Dengue Transmission Dynamics: Assessment and Implications for control*. 2006 [accessed 2013 22 August]; Available from: http://www.who.int/tdr/publications/publications/swg_dengue_2.htm.
46. Focks, D.A., et al., *A simulation model of the epidemiology of urban dengue fever: literature analysis, model development, preliminary validation, and samples of simulation results.* Am J Trop Med Hyg, 1995. **53**(5): p. 489-506.
47. Hurtado-Diaz, M., et al., *Short communication: impact of climate variability on the incidence of dengue in Mexico.* Trop Med Int Health, 2007. **12**(11): p. 1327-37.
48. Wu, P.C., et al., *Weather as an effective predictor for occurrence of dengue fever in Taiwan.* Acta Trop, 2007. **103**(1): p. 50-7.
49. Yasuno, M. and R.J. Tonn, *A study of biting habits of Aedes aegypti in Bangkok, Thailand.* Bull World Health Organ, 1970. **43**(2): p. 319-25.
50. Carrington, L.B., et al., *Reduction of Aedes aegypti vector competence for dengue virus under large temperature fluctuations.* Am J Trop Med Hyg, 2013. **88**(4): p. 689-97.
51. Arcari, P., N. Tapper, and S. Pfueller, *Regional variability in relationships between climate and dengue/DHF in Indonesia.* Singapore Journal of Tropical Geography, 2007. **28**(3): p. 251-272.
52. Yusuf, A.A. and H. Fransisco, *Climate Change vulnerability Mapping for South East Asia.* 2009.
53. Adams, B. and M. Boots, *How important is vertical transmission in mosquitoes for the persistence of dengue? Insights from a mathematical model.* Epidemics, 2010. **2**(1): p. 1-10.
54. Chen, S.C. and M.H. Hsieh, *Modeling the transmission dynamics of dengue fever: implications of temperature effects.* Sci Total Environ, 2012. **431**: p. 385-91.
55. Hay, S.I., et al., *Etiology of interepidemic periods of mosquito-borne disease.* Proc Natl Acad Sci U S A, 2000. **97**(16): p. 9335-9.
56. Halstead, S.B., *Dengue virus-mosquito interactions.* Annu Rev Entomol, 2008. **53**: p. 273-91.
57. Pant, C.P., S. Jatanasen, and M. Yasuno, *Prevalence of Aedes aegypti and Aedes albopictus and observations on the ecology of dengue haemorrhagic fever in several areas of Thailand.* Southeast Asian J Trop Med Public Health, 1973. **4**(1): p. 113-21.
58. Reiter, P., *[Dengue in the Americas].* Bull Soc Pathol Exot, 1996. **89**(2): p. 95-6; discussion 97.
59. Watts, D.M., et al., *Effect of temperature on the vector efficiency of Aedes aegypti for dengue 2 virus.* Am J Trop Med Hyg, 1987. **36**(1): p. 143-52.
60. Halstead, S.B., *Dengue.* Lancet, 2007. **370**(9599): p. 1644-52.
61. Organization, W.H., *Dengue haemorrhagic fever: Diagnosis, treatment, prevention and control. 2nd edition Genova.* 1997.
62. Dickin, S.K., C.J. Schuster-Wallace, and S.J. Elliott, *Developing a vulnerability mapping methodology: applying the water-associated disease index to dengue in malaysia.* PLoS One, 2013. **8**(5): p. e63584.
63. Ivers, L.C. and E.T. Ryan, *Infectious diseases of severe weather-related and flood-related natural disasters.* Curr Opin Infect Dis, 2006. **19**(5): p. 408-14.
64. Watson, J.T., M. Gayer, and M.A. Connolly, *Epidemics after Natural Disasters.* Emerging Infectious Diseases, CDC, 2007. **13**(1): p. 1-5.
65. Pradutkanchana, J., et al., *The etiology of acute pyrexia of unknown origin in children after a flood.* Southeast Asian J Trop Med Public Health, 2003. **34**(1): p. 175-8.
66. Banu, S., et al., *Dengue transmission in the Asia-Pacific region: impact of climate change and socio-environmental factors.* Trop Med Int Health, 2011. **16**(5): p. 598-607.

8. Appendices

1. APPENDIX A: Population of Bandung 2001-2012

2001	2.146.360
2002	2.142.914
2003	2.228.260
2004	2.232.624
2005	2.270.970
2006	2.296.848
2007	2.329.928
2008	2.374.198
2009	2.417.288
2010	2.394.873
2011	2.424.957
2012	2.455.517

Appendices table 1: Yearly population of Regency Kota Bandung from 2001 to 2012 [20]

2. APPENDIX B: Overview of Climate indices

1.	**Diurnal temperature range (DTR)**	**The difference of the minimum and maximum temperature in one day (calculated as $t_x - t_n$) in degrees Celsius.**
2.	*Precipitation sum (RR)*	The daily precipitation in mm/day.
3.	*Wet days (RR1)*	The number of days with RR> 1 mm in a given period. In this report the RR1 for a single month
4.	*Very heavy precipitation days (R20mm)*	The number of days with *RR*>20 mm in a given period. In this report the R20mm for a single month.
5.	*Highest 1-day precipitation amount (RX1day)*	The precipitation in mm for the day with the highest RR in a given period. In this report the RX1day of a single month.
6.	*Tg22d*	The average t_g of the previous 22 days
7.	*Tx22d*	The average t_x of the previous 22 days
8.	*Tn22d*	The average t_n of the previous 22 days
9.	*DTR22d*	The average DTR of the previous 22 days
10.	*RR15d*	The total RR over the previous 15 days
11.	*Hum15d*	The average humidity over the previous 15 days
12.	*CAMA*	The Climate *Aedes* Mosquito Abundance model expressed by formula *(1)* with *Tg*22d and RR15d filled in
13.	*tg<22*	The number of days in a month that tg lies below 22 °C
14.	*22tg26*	The number of days in a month that tg lies between 22 and 26 °C
15.	*tg>26*	the number of days that tg lies higher than 26 °C
16.	*Z(t)*	Temperature suitability index
17.	$P_i(t)$	The infection probability; probability that the Ae. mosquito obtains the dengue virus when feeding on an infected host
18.	$P_t(t)$	The transmission probability; probability that during a blood meal the Ae. Mosquito transmits the dengue virus

Appendices table 2: Climate indices introduced in Chapter 2

3. APPENDIX C: Results of real-time-data correlation tests

Dataset 1 Spearman Rank:

Correlation test:		**Spearman Rank**								
Significance test:		**F-Test**								
	0monthlag		*1monthlag*		*2monthslag*		*3monthslag*		*4monthslag*	
Index	r	p	r	p	r	p	r	p	r	p
tg	-0,08	0,30	0,00	0,64	0,04	0,95	0,14	0,25	0,25	0,00
tg<22	0,24	0,43	0,23	0,34	0,14	0,09	0,15	0,04	0,08	0,02
22tg26	0,16	0,11	0,27	0,00	0,27	0,00	0,11	0,14	0,10	0,48
tg>26	-0,01	0,01	0,01	0,01	0,07	0,03	0,22	0,62	0,28	0,68
Pt(31/07/13)	-0,15	0,15	-0,14	0,16	-0,17	0,11	-0,08	0,41	0,08	0,41
Z(T)(31/07/13)	0,29	0,00	0,43	0,00	0,52	0,00	0,40	0,00	0,22	0,18
P*Z	0,00	0,85	0,10	0,39	0,10	0,31	0,10	0,35	0,19	0,08
tn	0,16	0,11	0,31	0,00	0,48	0,00	0,48	0,00	0,36	0,00
tx	-0,27	0,01	-0,39	0,00	-0,49	0,22	-0,37	0,00	-0,18	0,34
tx<22	0,46	0,82	0,48	0,65	0,50	0,22	0,51	0,07	0,51	0,08
DTR	-0,24	0,01	-0,41	0,00	-0,56	0,00	-0,49	0,00	-0,30	0,01
RR	0,08	0,75	0,21	0,09	0,36	0,00	0,33	0,01	0,25	0,05
RR20	0,00	0,88	0,10	0,32	0,23	0,04	0,19	0,10	0,13	0,18
RR1	0,16	0,11	0,31	0,00	0,48	0,00	0,44	0,00	0,32	0,00
RR0	-0,16	0,11	-0,31	0,00	-0,48	0,00	-0,44	0,00	-0,31	0,00
Hum	0,62	0,00	0,62	0,00	0,60	0,00	0,50	0,00	0,43	0,00

Appendices table 3: Results of real-time Spearman rank analysis of dataset 1

Dataset 1 Pearson:

Correlation test:		**Pearson**								
Significance test:		**2sided t-test**								
	0monthlag		*1monthlag*		*2monthslag*		*3monthslag*		*4monthslag*	
Index	r	p	r	p	r	p	r	p	r	p
tg	-0,04	0,70	-0,04	0,67	0,05	0,63	0,12	0,26	0,32	0,00
tg<22	0,00	1,00	-0,03	0,74	-0,13	0,21	-0,06	0,56	-0,18	0,08
22tg26	0,15	0,16	0,17	0,10	0,14	0,18	-0,01	0,91	-0,07	0,49
tg>26	-0,14	0,16	-0,16	0,12	-0,08	0,44	0,04	0,67	0,17	0,11
Pt(31/07/13)	-0,11	0,27	-0,14	0,19	-0,08	0,46	-0,06	0,58	0,22	0,03
Z(T)(31/07/13)	0,27	0,01	0,32	0,00	0,31	0,00	0,15	0,15	-0,10	0,34
P*Z	0,02	0,82	0,03	0,77	0,10	0,32	0,00	0,98	0,20	0,05
tn	0,20	0,05	0,28	0,01	0,37	0,00	0,33	0,00	0,22	0,03
tx	-0,23	0,03	-0,30	0,00	-0,28	0,01	-0,18	0,08	0,13	0,19
tx<22	-0,02	0,84	0,01	0,96	0,05	0,62	0,41	0,00	0,12	0,24
DTR	-0,26	0,01	-0,34	0,00	-0,39	0,00	-0,30	0,00	-0,04	0,69
RR	0,10	0,32	0,18	0,08	0,27	0,01	0,22	0,03	0,07	0,48
RR20	0,07	0,47	0,15	0,15	0,22	0,03	0,17	0,10	0,04	0,73
RR1	0,20	0,05	0,27	0,01	0,39	0,00	0,32	0,00	0,15	0,15
RR0	-0,20	0,06	-0,27	0,01	-0,39	0,00	-0,32	0,00	-0,15	0,15
Hum	0,31	0,00	0,33	0,00	0,35	0,00	0,34	0,00	-0,02	0,88

Appendices table 4: Results of real-time Pearson analysis of dataset 1

Dataset 2 Spearman Rank:

Correlation test:		**Spearman Rank**										
Significance test:		**F-Test**										
	0dayslag		*10dayslag*		*20dayslag*		*30dayslag*		*40dayslag*		*50dayslag*	
index	r	p	r	p	r	p	r	p	r	p	r	p
tg	-0,13	0,00	-0,10	0,00	-0,10	0,00	-0,09	0,00	0,03	0,98	0,07	0,17
22dtg	-0,13	0,00	-0,09	0,00	-0,09	0,00	-0,09	0,00	0,07	0,19	0,09	0,09
tg<22	0,51	0,00	0,49	0,00	0,49	0,00	0,49	0,00	0,44	0,01	0,42	0,69
22tg26	0,25	0,27	0,28	0,97	0,28	0,97	0,28	0,97	0,31	0,01	0,34	0,00
tg>26	0,41	0,08	0,39	0,01	0,39	0,01	0,39	0,01	0,37	0,00	0,34	0,00
Pi*Pt(31/07/13)	-0,13	0,00	-0,08	0,00	-0,08	0,00	-0,07	0,00	0,02	0,84	0,07	0,05
CAMA	-0,05	0,14	0,04	0,12	0,04	0,13	0,04	0,12	-0,07	0,01	-0,03	0,52
Z(T)(31/07/13)	0,07	0,00	0,05	0,01	0,05	0,01	0,05	0,01	0,05	0,01	0,01	0,25
tn	-0,05	0,33	-0,08	0,20	-0,07	0,22	-0,07	0,22	0,06	0,02	0,03	0,02
22dtn	-0,06	0,67	-0,05	0,32	-0,05	0,32	-0,05	0,33	0,03	0,00	0,02	0,01
tx	-0,10	0,00	-0,04	0,00	-0,05	0,00	-0,04	0,00	-0,03	0,07	0,00	0,79
22dtx	-0,10	0,00	-0,09	0,00	-0,09	0,00	-0,09	0,00	-0,01	0,35	0,02	0,79
tx<22	0,50	0,00	0,48	0,42	0,48	0,42	0,48	0,42	0,48	0,08	0,46	0,00
DTR	-0,07	0,02	-0,01	0,14	-0,01	0,13	-0,01	0,14	-0,05	0,01	-0,03	0,12
22dDTR	-0,07	0,00	-0,07	0,00	-0,07	0,00	-0,07	0,00	-0,05	0,02	-0,03	0,08
RR	-0,05	0,35	0,00	0,78	0,00	0,68	0,00	0,75	-0,16	0,00	-0,08	0,03
15dRR	-0,04	0,38	0,05	0,05	0,05	0,05	0,05	0,04	-0,07	0,00	-0,02	0,63
RR20	-0,01	0,92	0,08	0,06	0,09	0,04	0,08	0,05	-0,08	0,00	0,03	0,29
RR1	0,05	0,08	-0,04	0,18	-0,04	0,22	-0,04	0,19	-0,13	0,00	-0,11	0,00
RR0	-0,04	0,08	0,05	0,18	0,05	0,22	0,05	0,19	0,15	0,00	0,13	0,00
Hum	-0,01	0,00	-0,05	0,00	-0,05	0,00	-0,06	0,00	-0,06	0,00	-0,01	0,00
15dHum	0,08	0,00	-0,07	0,00	-0,07	0,00	-0,07	0,00	-0,04	0,00	-0,01	0,02

Appendices table 5: Results of real-time Spearman rank analysis of dataset 2

Dataset 2 Pearson:

Correlation test:	Pearson											
Significance test:	2sided t-test											
	0dayslag		*10dayslag*		*20dayslag*		*30dayslag*		*40dayslag*		*50dayslag*	
index	r	p	r	p	r	p	r	p	r	p	r	p
tg	-0,07	0,02	-0,01	0,64	-0,02	0,50	0,05	0,12	0,00	0,93	0,01	0,65
22dtg	-0,04	0,22	0,00	0,99	0,03	0,32	0,02	0,61	0,05	0,09	0,15	0,00
tg<22	0,17	0,00	0,15	0,00	0,17	0,00	0,09	0,00	0,03	0,41	0,00	0,99
22tg26	-0,06	0,05	-0,07	0,04	-0,08	0,01	-0,04	0,16	0,10	0,00	0,12	0,00
tg>26	-0,01	0,71	0,00	0,93	0,01	0,81	0,01	0,87	-0,11	0,00	-0,13	0,00
Pi*Pt(31/07/13)	-0,11	0,00	-0,05	0,10	-0,08	0,01	0,01	0,87	-0,01	0,82	0,02	0,52
CAMA	0,03	0,32	0,03	0,29	0,04	0,27	0,03	0,41	0,20	0,00	0,30	0,00
Z(T)(31/07/13)	0,12	0,00	0,07	0,04	0,10	0,00	0,05	0,09	0,13	0,00	0,10	0,00
tn	0,08	0,01	0,07	0,02	0,14	0,00	0,14	0,00	0,14	0,00	0,14	0,00
22dtn	0,10	0,00	0,14	0,00	0,16	0,00	0,16	0,00	0,15	0,00	0,14	0,00
tx	-0,14	0,00	-0,07	0,02	-0,13	0,00	-0,05	0,10	-0,10	0,00	-0,08	0,01
22dtx	-0,13	0,00	-0,12	0,00	-0,10	0,00	-0,11	0,00	-0,05	0,11	0,06	0,04
tx<22	0,06	0,05	-0,03	0,35	0,07	0,02	-0,05	0,08	-0,05	0,13	-0,08	0,01
DTR	-0,14	0,00	-0,10	0,00	-0,17	0,00	-0,11	0,00	-0,15	0,00	-0,14	0,00
22dDTR	-0,14	0,00	-0,16	0,00	-0,16	0,00	-0,17	0,00	-0,12	0,00	-0,03	0,35
RR	0,07	0,03	0,02	0,53	0,04	0,24	0,05	0,13	0,03	0,42	0,24	0,00
15dRR	0,04	0,19	0,04	0,20	0,05	0,10	0,04	0,18	0,21	0,00	0,30	0,00
RR20	0,14	0,00	0,11	0,00	0,06	0,05	0,10	0,00	0,08	0,01	0,27	0,00
RR1	0,13	0,00	-0,01	0,74	0,00	0,93	0,07	0,03	0,02	0,54	0,16	0,00
RR0	-0,13	0,00	0,01	0,74	0,00	0,93	-0,07	0,03	-0,02	0,54	-0,16	0,00
Hum	0,16	0,00	0,04	0,26	-0,01	0,77	0,02	0,44	0,06	0,08	0,15	0,00
15dHum	0,08	0,01	0,00	0,90	0,01	0,70	0,05	0,10	0,13	0,00	0,15	0,00

Appendices table 6: Results of real-time Pearson analysis of dataset 2

Dataset 2 Season corrected Spearman:

Correlation test:		**Spearman Rank**								
Significance test:		**F-Test**								
	0 months lag		*1month lag*		*2 months lag*		*3 months lag*		*4 months lag*	
Index	r	p	r	p	r	p	r	p	r	p
tg	-0,08	0,30	0,00	0,64	0,04	0,95	0,14	0,25	0,25	0,00
tg<22	0,24	0,43	0,23	0,34	0,14	0,09	0,15	0,04	0,08	0,02
22tg26	0,16	0,11	0,27	0,00	0,27	0,00	0,11	0,14	0,10	0,48
tg>26	-0,01	0,01	0,01	0,01	0,07	0,03	0,22	0,62	0,28	0,68
Pt(31/07/13)	-0,15	0,15	-0,14	0,16	-0,17	0,11	-0,08	0,41	0,08	0,41
Z(T)(31/07/13)	0,29	0,00	0,43	0,00	0,52	0,00	0,40	0,00	0,22	0,18
P*Z	0,00	0,85	0,10	0,39	0,10	0,31	0,10	0,35	0,19	0,08
tn	0,16	0,11	0,31	0,00	0,48	0,00	0,48	0,00	0,36	0,00
tx	-0,27	0,01	-0,39	0,00	-0,49	0,22	-0,37	0,00	-0,18	0,34
tx<22	0,46	0,82	0,48	0,65	0,50	0,22	0,51	0,07	0,51	0,08
DTR	-0,24	0,01	-0,41	0,00	-0,56	0,00	-0,49	0,00	-0,30	0,01
RR	0,08	0,75	0,21	0,09	0,36	0,00	0,33	0,01	0,25	0,05
RR20	0,00	0,88	0,10	0,32	0,23	0,04	0,19	0,10	0,13	0,18
RR1	0,16	0,11	0,31	0,00	0,48	0,00	0,44	0,00	0,32	0,00
RR0	-0,16	0,11	-0,31	0,00	-0,48	0,00	-0,44	0,00	-0,31	0,00
Hum	0,62	0,00	0,62	0,00	0,60	0,00	0,50	0,00	0,43	0,00

Appendices table 7: Results of real-time Spearman rank analysis of dataset 1 after season correction

Dataset 2 Season corrected, Pearson:

Correlation test:		**Pearson**										
Significance test:		**2sided t-test**										
	0 months lag		*1month lag*		*2 months lag*		*3 months lag*		*4 months lag*		*5 months lag*	
Index	r	p	r	p	r	p	r	p	r	p	r	p
tg	0,00	0,99	0,05	0,65	0,09	0,37	0,05	0,66	0,16	0,12	-0,03	0,80
tg<22	0,05	0,62	-0,02	0,86	-0,04	0,71	-0,06	0,56	-0,04	0,67	0,03	0,74
22tg26	0,01	0,96	0,07	0,49	-0,03	0,81	-0,02	0,81	0,04	0,69	0,01	0,89
tg>26	-0,07	0,53	-0,02	0,83	0,04	0,67	0,06	0,56	-0,02	0,83	-0,07	0,49
Pt(31/07/13)	-0,05	0,65	0,04	0,71	0,04	0,67	-0,02	0,81	0,18	0,09	0,05	0,62
Z(T)(31/07/13)	0,14	0,18	0,09	0,40	0,13	0,20	0,03	0,74	-0,09	0,40	0,01	0,91
P*Z	0,02	0,86	0,11	0,27	0,13	0,21	-0,03	0,78	0,16	0,12	0,07	0,51
tn	0,13	0,21	0,15	0,15	0,25	0,01	0,15	0,15	0,04	0,69	-0,08	0,46
tx	-0,10	0,31	-0,06	0,55	-0,08	0,44	-0,05	0,60	0,15	0,15	0,03	0,78
tx<22	-0,01	0,93	0,06	0,58	0,06	0,54	0,00	0,98	-0,04	0,67	0,03	0,78
DTR	-0,14	0,16	-0,12	0,23	-0,19	0,06	-0,12	0,25	0,09	0,40	0,06	0,56
RR	0,03	0,81	0,01	0,90	0,04	0,70	-0,03	0,79	-0,08	0,42	0,04	0,71
RR20	0,00	0,99	0,04	0,67	0,07	0,52	0,02	0,82	-0,03	0,77	-0,01	0,93
RR1	0,00	0,99	0,04	0,71	0,06	0,56	0,03	0,74	0,00	0,97	-0,02	0,86
RR0	0,03	0,74	0,05	0,62	0,03	0,80	-0,01	0,95	-0,02	0,85	-0,01	0,92
Hum	0,49	0,00	0,47	0,00	0,48	0,00	0,36	0,00	0,35	0,00	0,38	0,00
30dDTR	-0,02	0,83	-0,04	0,71	-0,03	0,77	-0,01	0,94	0,00	0,97	-0,01	0,95
45dDTR	-0,02	0,86	-0,05	0,60	-0,09	0,41	-0,04	0,72	0,02	0,84	0,03	0,80
30dRR1	-0,01	0,92	0,04	0,69	0,06	0,54	0,03	0,78	-0,01	0,90	-0,02	0,87
30dZ(T)	0,01	0,95	0,06	0,54	0,09	0,36	0,04	0,70	-0,04	0,67	-0,04	0,69
60dDTR	-0,01	0,94	0,01	0,91	0,03	0,79	0,00	0,99	-0,01	0,95	0,01	0,95
RR10	0,03	0,80	0,05	0,62	0,05	0,65	-0,01	0,89	-0,02	0,81	0,00	0,98

Appendices table 7: Results of real-time Pearson analysis of dataset 1 after season correction

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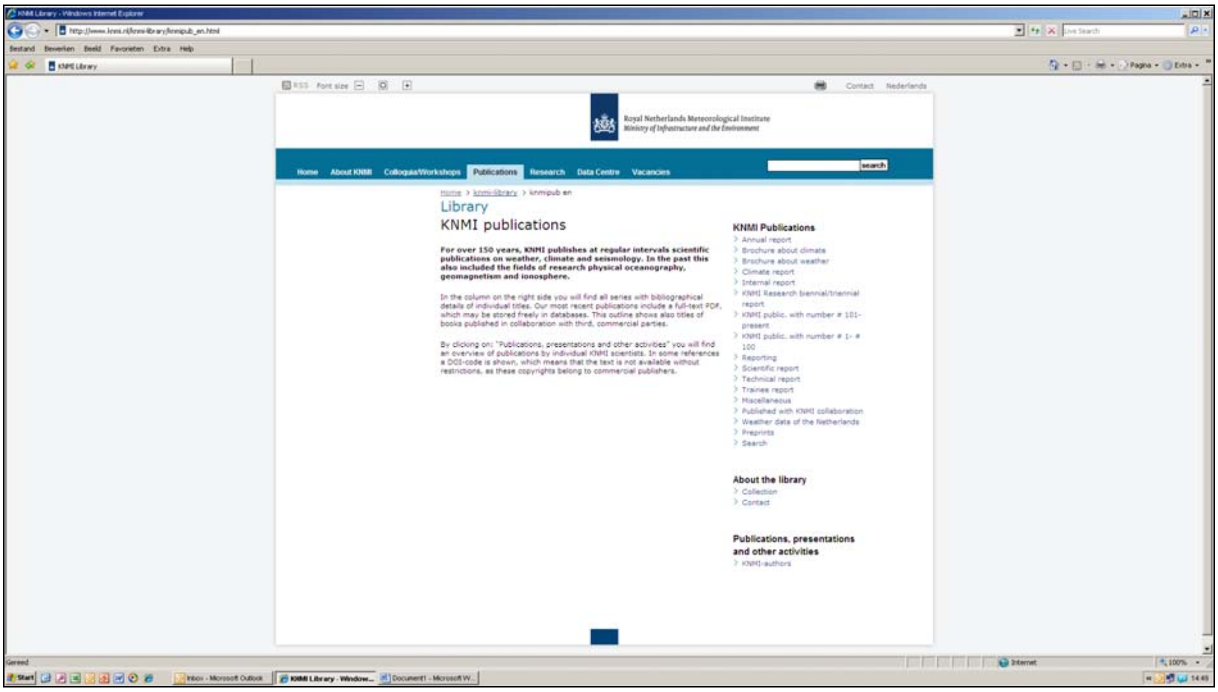

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