BURDEN OF DISEASES OF MALARIA UNDER CLIMATE CHANGE SCENARIOS IN THAILAND

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2013**

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Thesis
entitled

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BURDEN OF DISEASES OF MALARIA UNDER CLIMATE CHANGE SCENARIOS IN THAILAND

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ABSTRACT

Malaria is an extremely climate-sensitive tropical disease and can pose a threat to population health. The objective of this study was to estimate the avoidable burden of malaria in Thailand under different climate conditions. The study was based on two different climate projections: regional economic development (A2) and local environmental sustainability (B2). 20 years of climate data, including maximum temperatures, minimum temperatures, precipitation, humidity, and average wind speeds were used to create a nonlinear mixed regression model to determine the association between malaria incidences and the climate model. The avoidable burdens of disease were estimated based on the comparative risk assessment method from WHO Environmental Burden of Disease climate change guidance.

The results showed that the best fitting model is model 2, which has the adjusted R-Square = 0.818 and RMSE = 763.27. Scenario B2 had the least burden of malaria which decreased 21% from baseline, 15.7% in 2005, 8.9% in 2008, 29.8% in 2010, and there was also found an increase of 4.05% from baseline in 2003, 7.05% in 2006, 9.05% in 2007, 0.24% in 2009, and 1.74% in 2011. The average disease incidence of B2 = 26,869 persons/year, baseline = 28,521 persons/year, and A2 = 30,734 persons/year. These burdens converted to DALYs for international comparison as follows, baseline = 1,391 DALYs per year A2 = 1,500 DALYs per year, and B2 = 1,301 DALYs per year.

The model was compared with actual climate data to predict the incidence of malaria from 2012 to 2020. Malaria incidence increased with a trend line equation of $Y = 312.55X + 2480.1$, $R^2 = 0.74$, average incidences 79,703 persons/year or 4,042.9 DALYs/year. Scenario B2 showed decreased incidence of malaria with a trend line equation of $Y = 20.223X^3 – 363X^2 + 1801.4 X – 19.483$, $R^2 = 0.57$, average incidence of 40,407 persons/year, or 2,042.8 DALYs/years. Scenario B2 shows less incidence than A2 = 1,119.5 DALYs/years or 49.3%.

KEY WORDS: MALARIA/ NONLINEAR MIXED REGRESSION/AVOIDABLE BURDEN OF DISEASES/CLIMATE CHANGE/DALYs

90 pages

ภาระโรคของมาลาเรียในประเทศไทยภายใต้สภาวะภูมิอากาศเปลี่ยนแปลง

BURDEN OF DISEASES OF MALARIA UNDER CLIMATE CHANGE SCENARIOS IN THAILAND

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บทคัดย่อ

การศึกษาครั้งนี้มีวัตถุประสงค์เพื่อคาดการณ์ภาระโรคที่สามารถหลีกเลี่ยงได้ (Avoidable burden of diseases) ของโรคมาลาเรีย ภายใต้สภาวะภูมิอากาศในอนาคต โดยนำข้อมูลของสภาพภูมิอากาศของประเทศไทย 1991-2011 มาคาดการณ์ภายใต้สถานการณ์การเปลี่ยนแปลงสภาพภูมิอากาศ A2 และ B2 ในประเทศไทยของศูนย์เครือข่ายงานวิเคราะห์วิจัยและการฝึกอบรมการเปลี่ยนแปลงของโลก แห่งภูมิภาคเอเชียตะวันออกเฉียงใต้ (SEA START RC)

การสร้างแบบจำลองถดถอยแบบไม่เป็นเส้นตรง (Nonlinear regression modeling) ได้ใช้การนำเข้าข้อมูลสภาพภูมิอากาศของประเทศไทยในปี ค.ศ.1991-2011 ของกรมอุตุนิยมวิทยาจำนวน 5 ตัวแปรได้แก่ เดือน อุณหภูมิสูงสุด อุณหภูมิต่ำสุด ค่าความชื้นสัมพันธ์ ความเร็วลมเฉลี่ย และ ปริมาณน้ำฝน พบว่าแบบจำลองที่ให้ค่า ความแม่นยำ สูงสุดคือแบบจำลองที่ 2 โดยมีค่า adjusted R-Square 0.818 ด้วยค่า RMSE 763.27 และนำแบบจำลองมาทำการคาดการณ์ภาระโรคที่จะเกิดขึ้นในแต่ละสถานการณ์การเปลี่ยนแปลงสภาพภูมิอากาศโดยทำการเปรียบเทียบกับข้อมูลสภาพภูมิอากาศจริงในปี 2003-2011 และทำนายอุบัติการณ์เกิดโรคมาลาเรียอนาคตหรือปี 2012-2020

ผลการศึกษาพบว่าสถานการณ์เปลี่ยนแปลงสภาพภูมิอากาศ B2 เป็นสถานการณ์ที่มีอุบัติการเกิดโรคมาลาเรียน้อยที่สุดโดยอุบัติการณ์โรคมาลาเรียของปี 2004 ลดลงจาก baseline 21% 2005 15.7% 2008 8.9% 2010 29.8% และเพิ่มขึ้นจาก baselineในปี 2003 4.05% 2006 7.05% 2007 9.05% 2009 0.24% 0.2011 1.74% และมีอุบัติการณ์เกิดโรคโดยเฉลี่ย 2003-2011 เท่ากับ 26,869 คนต่อปี สำหรับสถานการณ์ A2 อยู่ที่ 30,734 คนต่อปี และ baseline 28,521 ต่อปี โดยแปลงเป็นดัชนีวัดภาระโรค (DALYs) สำหรับ baseline = 1,444.95 DALYs ต่อปี A2 = 1,560.77 DALYs ต่อปี และ B2 = 1,353.61 DALYs ต่อปี ตามลำดับ อย่างไรก็ตามพบว่าแบบจำลองมีความคาดเคลื่อนอยู่ระหว่าง 2.88-30.1%

นำแบบจำลองที่ได้ทำการเปรียบเทียบกับข้อมูลสภาพภูมิอากาศจริงเพื่อทำนายอุบัติการณ์เกิดโรคมาลาเรียที่อาจเกิดขึ้นในปี 2012-2020 พบว่า สถานกาณ์ A2 ทำให้อุบัติการณ์เกิดโรคมาลาเรียมีแนวโน้มเพิ่มสูงขึ้นโดยช่วงอุบัติการณ์เกิดโรคสูงสุดในแต่ละปีมีแนวโน้มสูงขึ้นทุกปีโดยมีสมการแนวโน้ม $Y = 312.55X + 2480.1$ ค่า $R^2 = 0.74$ โดยมีค่าเฉลี่ยอุบัติการณ์เกิดโรคต่อปีอยู่ที่ 79,703 คนต่อปี หรือ 4,042.9 DALYs ต่อปี สำหรับสถานการณ์ B2 อุบัติการณ์เกิดโรคมาลาเรียจะมีแนวโน้มลดลงโดยมีสมการแนวโน้ม $Y = 20.223X^3 – 363X^2 + 1801.4 X – 19.483$ ค่า $R^2 = 0.57$ โดยมีค่าอุบัติการณ์เกิดโรคอยู่ที่ 40,407 คนต่อปี หรือ 2,042.8 DALYs ต่อปี โดย B2 มีภาระโรคที่สามารถหลีกเลี่ยงได้จาก A2 = 1,119.5 DALYs ต่อปี หรือคิดเป็น 38.3% ต่อปี

90 หน้า

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CHAPTER I
INTRODUCTION

1.1 Introduction & Problem statement

Climate change is an emerging risk factor for human health. There is now widespread consensus among the scientific community that the earth is warming, that this is mainly due to human activities, and that this will continue for at least the next several decades (IPCC, 2001b). It is also clear that weather and climate exert a major influence on human health, both through direct effects of extreme events such as heat waves, floods and storms, and more indirect influences on the distribution and transmission intensity of infectious diseases, and on the availability of freshwater and food.

The children in sub-Saharan Africa between 700,000 and 2.7 million die each year by malaria cause. The factor include by climate and land-use change, drug resistance, ineffective control efforts, and various socio–demographic factors. Malaria is an extremely climate-sensitive tropical disease, making the assessment of the potential change in malarial risk, caused by past or projected global warming, one of the most important topics in the field of climate change and health (Patz et al., 2005). The incidence of malaria varies seasonally in highly endemic areas, and malaria transmission has been associated with temperature anomalies in some African highlands (Zhou et al., 2005). In addition, the climate change and global warming to affect human health either directly, such as wave thermal radiation of the storm and flood and drought frequency to be more indirect, such as the propagation of mosquitoes at large. Global warming would increase heat-related health problems, which mostly affect people with pre-established cardiovascular and respiratory disorders. On the other hand, global warming would reduce cold-related health problems, again most prevalent in people with cardiovascular disorders. Global climate change will affect disease vectors, which in turn may alter the current patterns.

The most common vectors, arthropods, are coldblooded, meaning that their internal temperature is greatly affected by the temperature of their environment. The incidence of arthropod-borne diseases will depend on both vector and host factors. Climate change would affect the range and abundance of species carrying diseases, and would affect the pathogens as well. Malaria, in particular, is generally thought to increase because of climate change. Other vector borne diseases may increase or decrease, but currently make much less victims than does malaria. Climate change would affect food- and waterborne diseases too, with cholera and diarrhoea being potentially most problematic (McMichael et al., 2001).

Thailand has study health index burden of diseases (Disability - Adjusted Life Years: DALYs) to measure the health status of the population. Measurement conditions, sum of loss health by a number of years lost due to death (Year of Life Lost: YLL) and years of living with disability (Year of Life Lost. due to Disability: YLD) in 1999 and 2004. Thailand’s first development of disease and injury was in 1999, the results showed that the population of Thailand is the loss of health, disease and injury burden estimated 9.5 million healthy years (DALYs) of this group of diseases, injuries and health problems as cancer are the top 3 of the Thai population (International Health Policy Program, Thailand, 2011).

The burden of disease of the Thai population in 2004, a national study found that the loss of healthy years is 9.8 million DALYs were lost as a result of the male population than female population and about 1.4 times. About 67 percent of health lost all (DALYs) are lost to premature death (YLLs) and rates of loss in the male population of one billion people, equal to 183 DALYs and 130 DALYs per one thousand women population (International Health Policy Program, Thailand, 2011).

Globally, an estimated 24% of the disease burden (healthy life years lost) and an estimated 23% of all deaths (premature mortality) was attributable to environmental factors. Diseases with the largest absolute burden attributable to modifiable environmental factors included: diarrhea, lower respiratory infections, 'other' unintentional injuries and malaria. The proportion of malaria attributable to modifiable environmental factors (42%) is associated with policies and practices regarding land use, deforestation, water resource management, settlement and modified house design, e.g. improved drainage.(WHO,2011)

The WHO has estimate the global burden of disease (GBD) that could be due to climate change in terms of disability adjusted life years (DALYS). This measure makes it possible to take into account impacts that do not necessarily lead to death but cause disability. Climate scenarios are derived from the output of global climate models that are, in turn, driven by scenarios of future greenhouse gas emissions (Figure 1-1). The attributable burden of climate change was estimated in relation to future climate scenarios relative to the baseline climate representing little or no anthropogenic climate change. Epidemiological models were used to estimate the degree to which these climatic changes are likely to affect a limited series of health outcomes (malaria, diarrhoeal disease, malnutrition, flood deaths, direct effects of heat and cold). These measures of proportional change can be applied to projections of the burden of each of these diseases in the future, to calculate the possible impacts of climate change on the overall disease burden (Haines A, 2006).

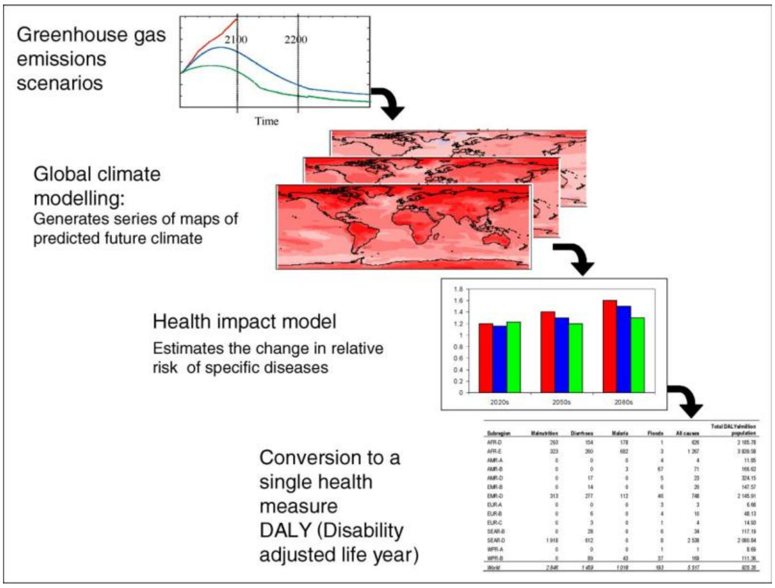

Figure 1-1 Comparative risk assessment process for climate change and health

Malaria has the highest possible change of distribution of climate change in the world (Table 1-1). In past 10 years of Thailand found the incidences of malaria was decrease in 2000-2003, the highest incidence in 2000 was 83.94 per hundred thousand populations. The lowest incidences in 2003 was 31.63 and the infection rate slightly during the period 2003 -2007, then decrease in 2008 -2009, equal to 45.72 and 36.61 per hundred thousand population, respectively (Figure 1-2).

Table 1-1 Global status of major vector-borne diseases (WHO, 1990)

No.	Disease	Pop at risk (million) (1)	Prevalence of infection (millions)	Possible change of distrubution as a result of climate change (2)
1	Malaria	2100	270	***
2	Lymphatic filariases	900	90.2	*
3	Onchocerciasis	90	17.8	*
4	Schistosomiasis	600	200	**
5	African trypanosomiasis	50	(25,000 new cases/year	*
6	Leishmaniases	350	12	?

(1) Bases on a world population estimated at 4.8 billion (1989).

(2) ? = not known; * = likely; ** = very likely; *** = highest likely

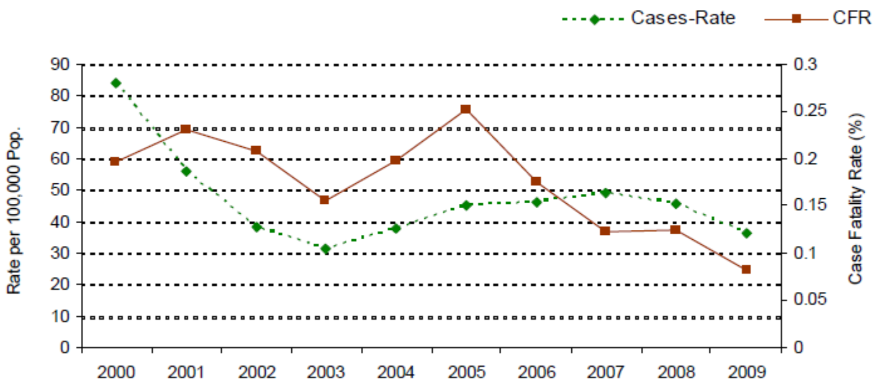

Figure 1-2 Reported Cases of Malaria per 100,000 Population, and Case fatality Rate, by Tear, Thailand, 2000 -2009

Malaria incidence is characterized by the seasonal pattern. It was found peak during may-june which is the rainy season. The reported found the highest incidences in 2006 was June and May on 2009. However malaria has top 5 large burdens of diseases in the world (Prüss-Üstün, 2006).

South region of Thailand in 2005-2008, the incidences rate has the highest in 2005 (Bureau of Epidemiology, 2010). By the way north region showed the highest infection rate. The infection rate was 88.82 per hundred thousand population, Followed by the South (68.37) Central (23.36) and Northeast (8.06), North region has been increase every year since 2007 (Figure 1.3).

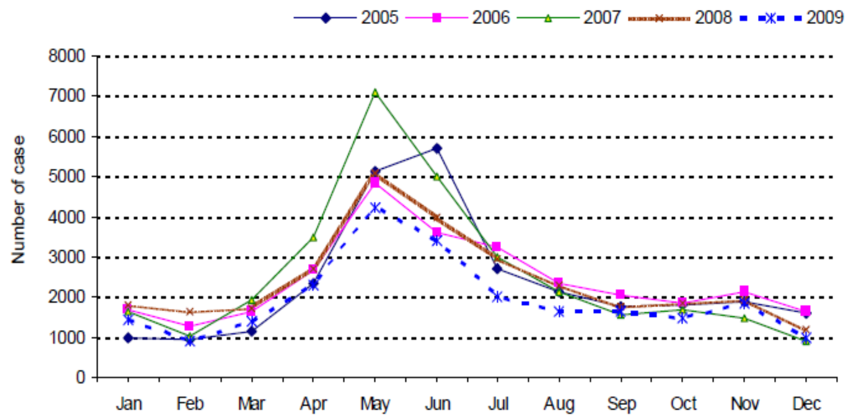

Figure 1-3 Reported Cases of Malaria by Month, Thailand, 2005 – 2009

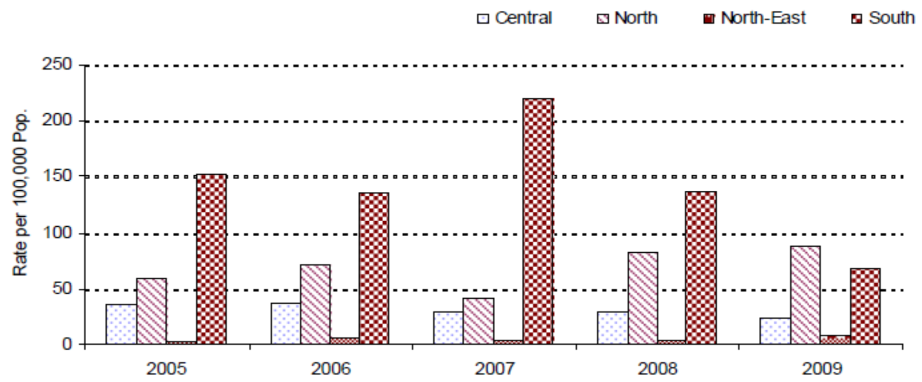

Figure 1-4 Reported Cases of Malaria per 100,000 Population, by Region, Thailand, 2005 – 2009

The patients according to occupation is farmers 7,882 (33.93%), followed by workers 5,225 patients (23.78%) does not know 4939 (21.26%) and students, 3,442 patients (14.82%). All of the patients reported 23,229 cases of malaria were reported Plasmodium vivax infection were 44.1% P.falciparum were 40.92% P.malariae 0.59 % and others 14.17% (Bureau of Epidemiology, 2010).

Although the incidence of the disease in the country is likely to decrease, however in the North of Thailand is likely increase the incidence of malaria has been attributed to climate change play an important role today, The World Health Organization has developed standardized comparative risk assessment methods for estimating aggregate disease burdens attributable to different risk factors. These have been applied to existing and new models for a range of climate-sensitive diseases in order to estimate the effect of global climate change on current disease burdens and likely proportional changes in the future. With the above the study of Avoidable burden of diseases under climate change is important to study.

1.2 Conceptual Framework

This conceptual of study is to find the burden of malaria that can be avoid in the future by use the statistical analyze associate with incidences and climate variables. The first step has been collected the climate parameters from Thai meteorological department considered such as maximum temperature, minimum temperature, precipitation, humidity and wind speed to find the statistic relationship between malaria incidences and climate variables, then use nonlinear regression technique to prediction the malaria incidence under climate change scenarios of SEA START RC. The study to know the change of burden of diseases that can be avoided in each scenario because of increasing greenhouse gases emission.

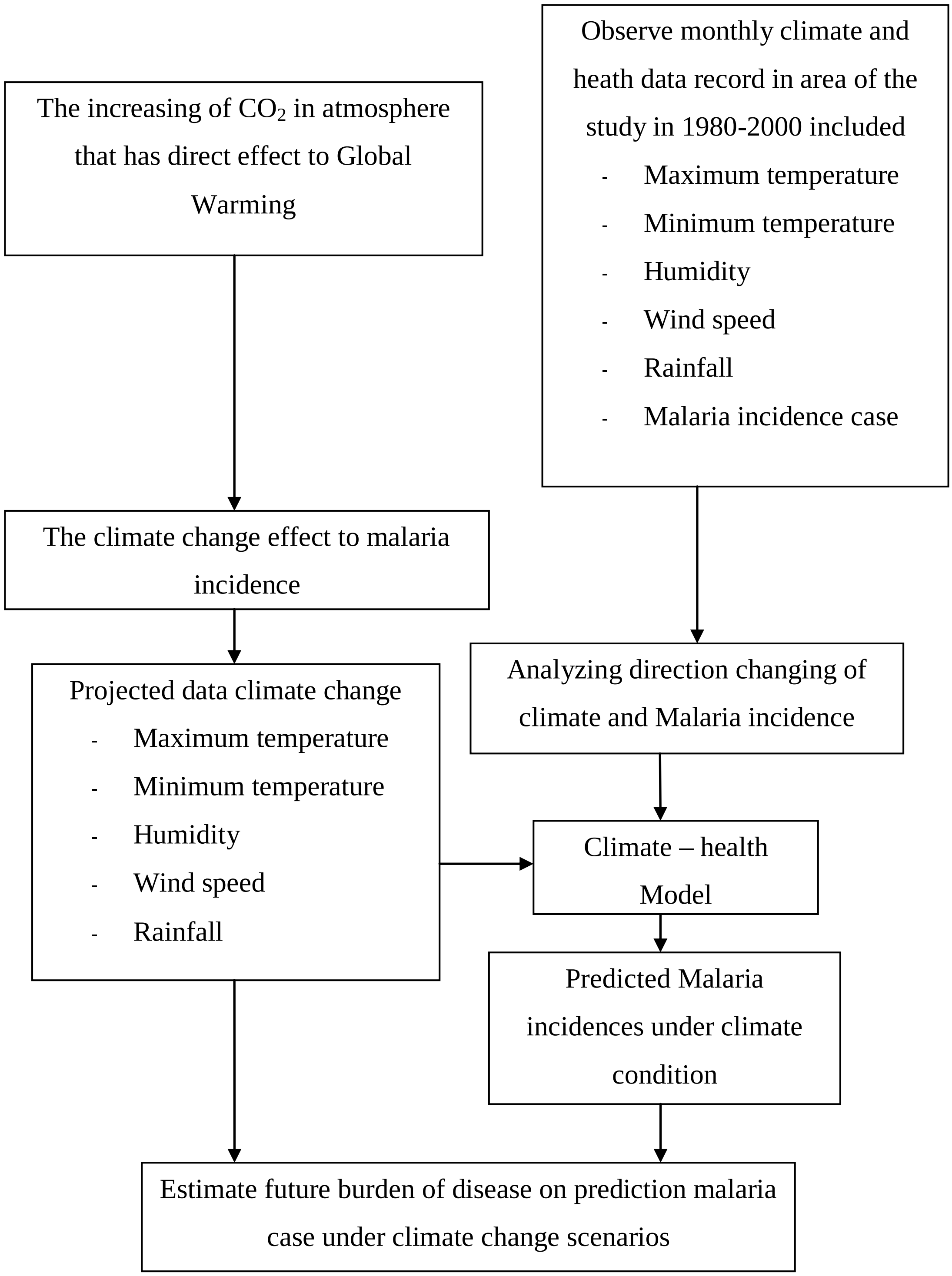

Figure 1.5 Conceptual framework

1.3 The purpose of the study

1. To study the incidences of malaria in Thailand 1991-2011.

2. To study the relationship between temperature, rainfall, humidity and wind speed of Malaria in Thailand in the past 20 years (1991-2011).

3. To study the statistical model to evaluate climate change human health impact on malaria in Thailand.

4. To study the avoidable burden of diseases under climate change scenarios in Thailand.

1.4 Scope of study

1. Areas of study were Thailand.

2. This research based on the comparative risk assessments on climate change impact on malaria in Thailand.

3. This study used secondary data.

1.5 Research hypothesis

1. The number of malaria cases was correlated with temperature.
2. The number of malaria cases was correlated with humidity.
3. The number of malaria cases was correlated with rainfall.
4. The number of malaria cases was correlated with wind speed.

1.6 Definition

1. Climate change is a significant and lasting change in the statistical distribution of weather patterns over periods ranging from decades to millions of years. It may be a change in average weather conditions or the distribution of events around that average (e.g., more or fewer extreme weather events).

2. Global warming is the increase in the average temperature near the earth's surface and oceans since the second half of the 20th century and has been estimated that the average temperature will increase continuously

1.7 Expected results

1. To evaluate the impact climate change on malaria diseases.
2. To be informed and aware of the adaptation under changing climate conditions.
3. Prediction avoidable diseases (DALYs).
4. Estimation disease burden from climatic factors of malaria and others mosquito-borne diseases.

1.8 Limitation of the study

Climate change is just only factor malaria but other factors such as migration and land-use changes not evaluate on this study. This research studied the relationship of climate change on malaria by SEA START RC prediction climate data that can be modified to apply to the entire country only seven variables included, maximum temperature, minimum temperature, precipitation, solar radiation, wind speed, wind direction, relative humidity. Unknown or unrecorded data in some station and some of non- climatic factors which were available in Thailand from annual reports but due to its incomplete it was not included in regression analysis such as migration and deforestation, Malaria incidences data used on this study are reported to the surveillance system, the participation of the provincial public hospitals and health facilities (hospitals, government facilities. Private hospitals are not covered). Surveillance report 506 data are known or suspected to be under-reported.

CHAPTER II
LITERATURES REVIEWS

2.1 Mosquito Borne Diseases

Mosquitoes are estimated to transmit disease to more than 700 million people annually in Africa, South America, Central America, Mexico and much of Asia with millions of resulting deaths. In Europe, Russia, Greenland, Canada, USA, Australia, New Zealand, Japan and other temperate and developed countries, mosquito bites are now mostly an irritating nuisance; but still cause some deaths each year(Mark S. Fradin,2006). Historically, Mosquitoes cause more human suffering than any other organism over one million people worldwide die from mosquito-borne diseases every year. Not only can mosquitoes carry diseases that afflict humans, they also transmit several diseases and parasites that dogs and horses are very susceptible to. These include dog heartworm, West Nile virus (WNV) and Eastern equine encephalitis (EEE). In addition, mosquito bites can cause severe skin irritation through an allergic reaction to the mosquito's saliva this is what causes the red bump and itching. Mosquito vectored diseases include protozoan diseases, i.e., malaria, filarial diseases such as dog heartworm, and viruses such as dengue, encephalitis and yellow fever. (AMCA, 1935)

2.2 Malaria

Malaria is one of the major causes of global mortality and morbidity. With an unknown number of 1 - 2.7 million patients dying annually and hundreds of millions afflicted, the need for containment and for reduction of the health burden is obvious. But due to the scarcity of resources, and the lack of a clear policy of their distribution, this control is not attained (Ross 1911).

Malaria is an infectious disease caused by the parasite genus *Plasmodium*.There are four identified species of this parasite causing human malaria, namely,*Plasmodium vivax*, *Plasmodium falciparum*, *Plasmodium ovale* and *Plasmodiummalariae*. *Plasmodium falciparum* is the commonest species spreading on the tropic and subtropics such as Africa, South America and Asia. *Plasmodium vivax* is found in the widest area. It can found in many temperature zones, subtropics and tropic such as China, Turkey, Latin America and Asia. *Plasmodium malariae* is found in the same breadth as *Plasmodium falciparum* but is much less common in areas such as Central America. *Plasmodium ovale* is found predominantly in tropic Africa, but many occur in the West Pacific . (Mashaal H, 1986)

Malaria is transmitted by the female anopheles mosquito. The *Plasmodium* genus of protozoa parasites has a life cycle which is split between a vertebrate host and an insect vector. The Plasmodium species, with the exception of *Plasmodium malariae* (which may affect the higher primates) are exclusively parasites of man. The basic life cycle of the parasite is shown in figure (2.5). The sporozoites from the mosquito salivary gland are injected into the human as the mosquito must infect anticoagulant saliva to ensure an even flowing meal. Once in the human bloodstream, the sporozoites arrive in the liver and penetrate hepatocytes, where they remain for 9-16 days, multiplying within the cells. On release, they return to the blood and penetrate red blood cells in which they produce either merozoites or micro and macrogametocytes, which have no further activity within the human host. Another mosquito arriving to feed on the blood may suck up these gametocytes into its gut, where exflagellation of microgametocytes occurs, and the macrogametocytes are fertilized. The resulting ookinete penetrates the wall of a cell in the midgut, where it develops into an oocyst. Sporogeny within the oocyst produces many sporozoites and, when the oocyst ruptures, the sporozoites migrate to the salivary gland, for injection into another host (Kreier JP, 1980).

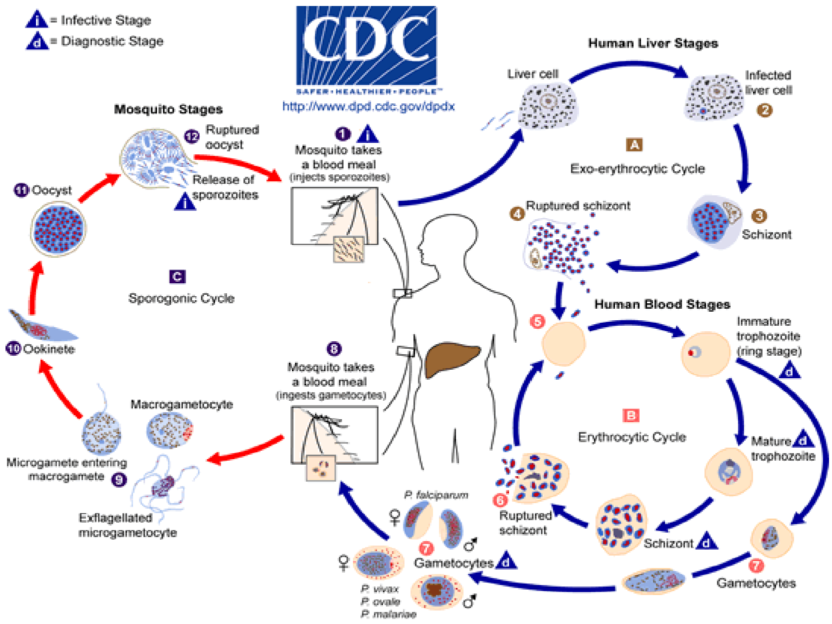

Figure 2-1 the malaria parasite life cycle

2.3 Climate change impact

The links between climate change and health have been reported in the 4th Assessment report by the Intergovernmental Panel on Climate Change (IPCC) which states that climate change is already contributing to the global burden of disease and premature death and that these effects are likely to increase in all countries (IPCC, 2007).

In the early 20th century, control of infectious diseases generally. But the disease has taken a new post. In many parts of the world food poisoning increases reflect the global situation. Never before has a number of factors such as population growth, rapid settlement. The density along the edge of the forest, the greater the discomfort. The trading range for the use of pesticides. And drug abuse Social and political issues and climate variability at the regional level**.**

There are many processes and living things. Associated with the disease was spread over a wide area. Furthermore The influence of the uncertainty of the climate and temperature, precipitation and humidity of the other as part of normal climate variability. It is clear that the disease is seasonal, so if there are changes in regional climate is expected to cause the formation of infectious diseases and food poisoning. Shifted to a wide area, such as global warming that is distributed according to geographical area (Both the height and latitude), which carries the disease has the potential to spread more widely. In addition, climate change can also change the range of motion of the conductor and the disease germs that may make the disease spread more effective (Atul A, 2005)

The spread of the disease do not need a conductor sometimes affected by climate change as well as diseases of Food Poisoning (Food borne disease) and infectious diseases are spread directly from one person to another person, The infection diseases that are dependent on several factors, but the factor of temperature and humidity are extremely important and the climate can affect human behavior and social impact on the spread of infectious diseases as well, so even a small amount of climate change on human tolerance levels can have a direct impact on human health immediately (McMichael, 2001).

2.3.1 Climatic factors have a direct influence on the organism that carries pathogens.

Weather conditions such as temperature, precipitation, relative humidity and wind can greatly affect the abundance, ecology and behaviour of mosquitoes and blackflies (Service, 1978)

- **Temperature**

Distribution of mosquito species can be limited by temperatures and thus tropical vectors could be expected to move further into currently cooler areas "provided appropriate habitat is present when climate change brings a general increase in ambient temperature. Mosquitoes respond to local temperature increases in various ways within limits higher temperatures mean more rapid development for larval populations and shorter times between bloodmeals quicker incubation times for virus infections and shorter life spans for adults although the latter is dependent on humidity.(Richard C. Russell, 1998)

- Rainfall

Rainfall has 2 principal influences on the mosquito life cycle.

1) The increased near-surface humidity associated with rainfall enhances mosquito flight activity and hostseeking behavior

2) Rainfall can alter the abundance and type of aquatic habitats available to the mosquito for oviposition. The first influence can increase mosquito abundance by accelerating the reproductive cycle, which requires mating, host-seeking, and blood-feeding flights. The second influence, however, has less certain consequences. Rainfall increases the wetness of soil near the surface and can expand saturated lowland areas. As a result, the moist, humid habitats preferred by many mosquito species for oviposition, such as swamps and floodwaters (e.g., puddles, water-filled divots), may increase in abundance. This change may favor an increase of mosquito species abundance in these habitats. Such changes in mosquito species composition, abundance, and age structure may then lead to an increase in local disease transmission. (Shaman, 2002)

- Relative humidity (RH)

Rainfall also helps increase relative humidity (RH) and modifies temperature, which affects the longevity of mosquitoes, and thus transmission of disease. If RH is below 60%, the life of mosquitoes is shortened which in turn reduces disease transmission. RH between 60%- 80% is considered to be optimum for effective transmission of malaria.

- Wind

Wind usually inhibits flight it appears that newly emerged adults of some mosquito species are specially adapted to take-off and flight in windy weather, thus promoting dispersal and colonization of new areas. Air turbulence and convection are usually greatest during the day,simuliids and day-flying mosquitoes are more likely to be swept into the upper air and carried long distances than mosquito species that are active at night. In central Alaska Gjullin et al. (1961) t'ound that winds of more than 3km/h considerably reduced mosquito flights, and when they reached 8 km/h flying ceased,but in marked contrast arctic species breeding in tundra localities were not appreciably affected by winds of up to 8 km/h, the critical threshold appeared to be about 11 km/h.Similarly, in Wisconsin Grimstad and DeFoliart (1974) found that mosquito flight was inhibited by winds of about 8 km/h, whereas in subarctic Canada Haufe reported that only speeds of about 29km/h or more reduced mosquito flight.(Service,1980)

Table 2.1 Effect of global warming on infection diseases

Emerging and forecasted effects of climate change/global warming on infectious diseases and other human health conditions in the world
Direct effect on other health conditions -Heat waves: Short-term increase in mortality, especially among those with cardiovascular and/or respiratory diseases, and increase in heat shock patients - Co-effect with air pollution: Increase in asthma and allergy patients Storms and floods: Increase in morbidity and accidental death
Indirect effect on infectious diseases - Expansion of mosquito- and tick-infested areas, and increase in mosquito activity: Increase in the number of patients with mosquito-borne infectious diseases (i.e. dengue and malaria) and expansion of epidemic areas. - Contamination of water and foods with bacteria: Increase in the number of patients with water- and foodborne infectious diseases - Deterioration of environmental and social conditions: Increased risk of infectious diseases

Table 2.2 Known effects of weather to health outcomes (Kovats , 2005)

Health Outcomes	Known Effects of Weather
Heat stress	• Deaths from cardiopulmonary disease increase with high and low temperatures • Heat-related illness and death increase during heat waves
Air-pollution-related mortality and morbidity	• Weather affects air pollutant concentrations • Weather affects distribution, seasonality, and production of aeroallergens
Health impacts of weather disasters	• Floods, landslides, and windstorms cause direct effects (deaths and injuries) and indirect effects (infectious disease, long-term psychological morbidity) • Droughts are associated with increased risk of disease and malnutrition
Mosquito-borne diseases, tick-borne diseases (e.g., malaria, dengue)	• Higher temperatures shorten the development time of pathogen in vectors and increase potential transmission to humans • Vector species have specific climate conditions (temperature, humidity) necessary to be sufficiently abundant to maintain transmission
Undernutrition	• Climate change may decrease food supplies (crop yields, fish stocks) or access to food supplies
Water-/food-borne diseases	• Survival of important bacterial pathogens is related to temperature • Water-borne diseases are most likely to occur in communities with poor water supply and sanitation • Increases in drought conditions may affect water availability • Extreme rainfall can affect transport of disease organisms into water supply

Global climate change would affect the health of human populations via diverse pathways.These would vary in their complexity, scale and directness. The timing of the various impactswould also differ some would occur soon; others would be deferred. There would be bothpositive and negative impacts, although expert scientific reviews (IPCC, 2001a) assess that the latter would clearly predominate. This mainly negative impact reflects the fact that climatic change would alter many natural ecological and physical systems that are integral to Earth's life-support systems.

Figure 2.1 shows the main pathways and categories of health impact of climate change. The more direct impacts on health include those caused by changes in exposure to weather extremes (heatwaves, winter cold), those due to increases in other extreme weather events (floods, cyclones, storm-surges, droughts), and those due to a rise in production of certain air pollutants and aeroallergens (spores and moulds). In some countries, decreases in winter mortality due to milder winters may compensate for increases in summer mortality due to the increased frequency of heatwaves

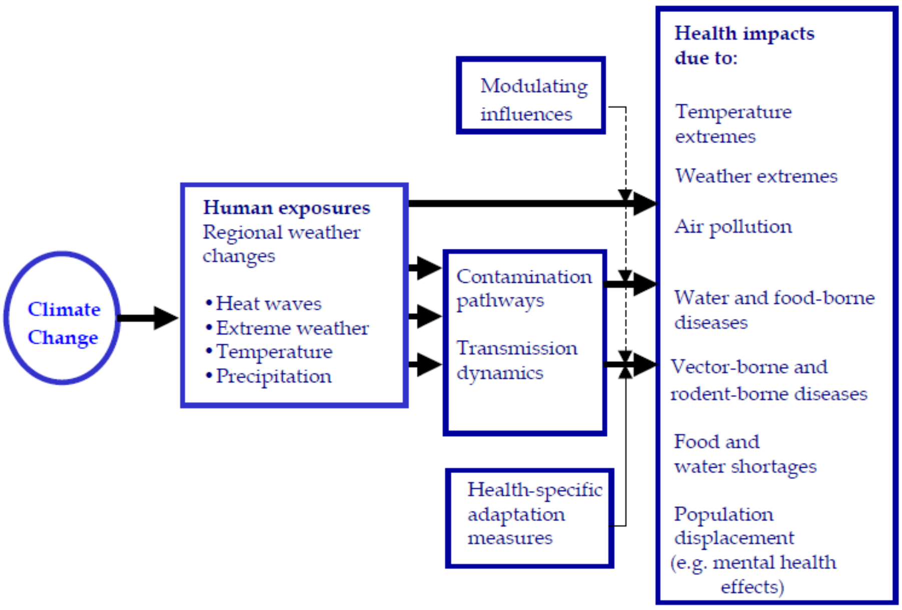

Figure 2-2 Pathways by which climate change affects human health (McMichael, 2003)

Figure 2.1 shows the main pathways and categories of health impact of climate change. The more direct impacts on health include those caused by changes in exposure to weather extremes (heatwaves, winter cold), those due to increases in other

extreme weather events (floods, cyclones, storm-surges, droughts), and those due to a rise in production of certain air pollutants and aeroallergens (spores and moulds). In some countries, decreases in winter mortality due to milder winters may compensate for increases in summer mortality due to the increased frequency of heatwaves (McMichael, 2003)

Research on the health impacts of climate change addresses three main topics (Fig. 2.2) current associations between climate and disease; the effect of recent changes in climate; and the evidence base for projecting the future impacts of climate change on health.(McMichael, 2003)

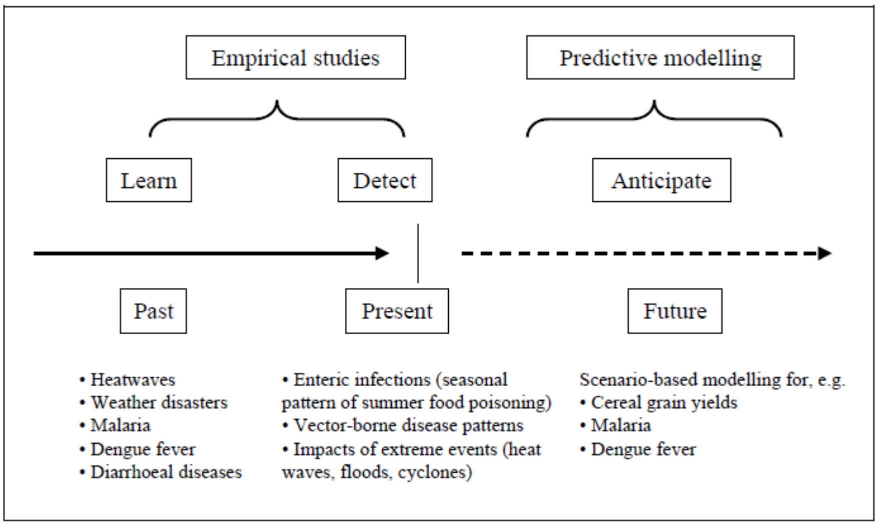

Figure 2-3 Three important research paths

2.3.2 Climate change scenarios

In the next 100 years, or since the 21's of the world will change in a way that is hard to guess. Thus, researchers have developed storylines differ in increasingly irreversible ways. Together they describe divergent futures that encompass a significant portion of the underlying uncertainties in the main driving forces. Which included driving force of greenhouse gas trajectories will continue to be demographic change, social and. economic development, and the rate and direction of technological change. Described as follows, (IPCC, 2000)

1. The A1 storyline and scenario family describes a future world of very rapid economic growth, low population growth, and the rapid introduction of new and

more efficient technologies. Major underlying themes are convergence among regions, capacity building, and increased cultural and social interactions, with a substantial reduction in regional differences in per capita income. The A1 scenario family develops into four groups that describe alternative directions of technological change in the energy system.

2. The A2 storyline and scenario family describes a very heterogeneous world. The underlying theme is self-reliance and preservation of local identities. Fertility patterns across regions converge very slowly, which results in high population growth. Economic development is primarily regionally oriented and per capita economic growth and technological change are more fragmented and slower than in other storylines.

3. The B1 storyline and scenario family describes a convergent world with the same low population growth as in the A1 storyline, but with rapid changes in economic structures toward a service and information economy, with reductions in material intensity, and the introduction of clean and resource-efficient technologies. The emphasis is on global solutions to economic, social, and environmental sustainability, including improved equity, but without additional climate initiatives.

4. The B2 storyline and scenario family describes a world in which the emphasis is on local solutions to economic, social, and environmental sustainability. It is a world with moderate population growth, intermediate levels of economic development, and less rapid and more diverse technological change than in the B1 and A1 storylines. While the scenario is also oriented toward environmental protection and social equity, it focuses on local and regional levels.

Table 2.3 The four SRES scenario families of the Fourth Assessment Report

balisation (homogeneous world)	A1 rapid economic growth 1.4 - 6.4 °C	B1 global environmental sustainability 1.1 - 2.9 °C
Regionalisation (heterogeneous world)	A2 regionally oriented economic development 2.0 - 5.4 °C	B2 local environmental sustainability 1.4 - 3.8 °C

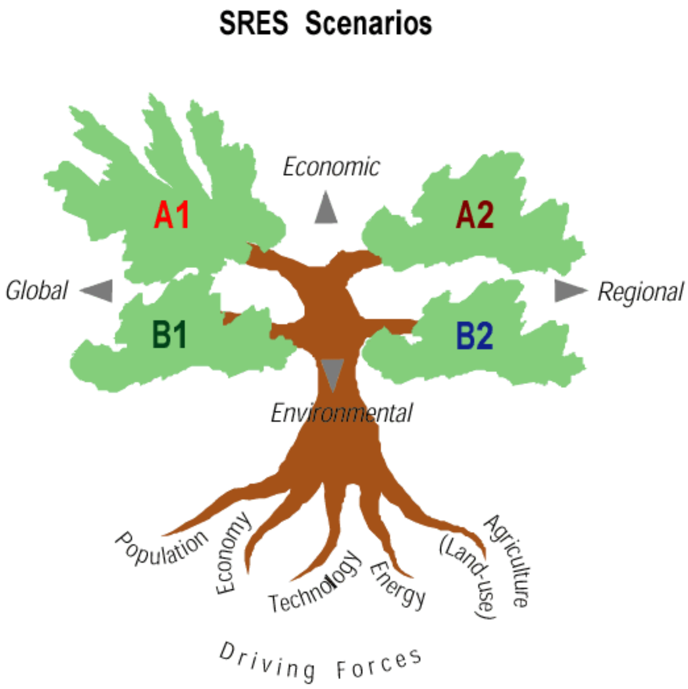

Figure 2-4 Schematic illustration of SRES scenarios (IPCC, 2001a)

2.4 History of diseases burden

Burden of diseases is the impact of a health problem in an area measured by financial cost, mortality, morbidity, or other indicators. It is often quantified in terms of quality-adjusted life years (QALYs) or disability-adjusted life years (DALYs), which combine the burden due to both death and morbidity into one index. One DALY can be thought of as one lost year of healthy life, and the burden of disease can be thought of as a measure of the gap between current health status and an ideal situation where the individual lives into old age free from disease and disability.(Prüss,2006)

The First global burden of disease (GBD) study in 1990 quantified the health effects of more than 100 diseases and injuries for eight regions of the world. It generated comprehensive and internally consistent estimates of morbidity and mortality by age, sex and region. It also introduced a new metric – the Disability-Adjusted Life Year (DALY) – to quantify the burden of diseases, injuries and risk factors. The DALY is based on years of life lost from premature death and years of life lived in less than full health.

Murray and Lopez used DALYs in their extensive Global Burden of Disease study to introduce morbidity into the predominantly mortality-based health discussions. Then the World Health Organization (WHO) endorsed the DALY approach which used in various studies on global, national and regional levels. In the year 2000-2002 the (GBD 1990 study) was updated and included a more extensive analysis of the mortality and burden of disease attributable to 26 global risk factors using a consistent analytic framework known as Comparative Risk Factor Assessment (CRA).

2.4.1 Disability-Adjusted Life Year

The DALY index calculates the years lost from an individual's ideal lifespan due to morbidity or premature mortality. The philosophy is to reflect egalitarian principles; e.g., only age and sex of the individual affected by a health outcome should be considered (Murray, 1994). The DALY is calculated as the sum of years of life lost to premature death and years lived with a disability, weighted by severity and duration (Pruess, 2000). Murray & Lopez 1996, has developed the index DALYs for a disease or health condition are calculated as the sum of the Years of Life Lost (YLL) due to premature mortality in the population and the Years Lost due to Disability (YLD) for incident cases of the health condition:

$$DALY = YLL + YLD$$

The YLL basically correspond to the number of deaths multiplied by the standard life expectancy at the age at which death occurs. The basic formula for YLL (without yet including other social preferences discussed below), is the following for a given cause, age and sex:

$$YLL = N \times L$$

where

N = number of deaths

L = standard life expectancy at age of death in years

Because YLL measure the incident stream of lost years of life due to deaths, an incidence perspective is also taken for the calculation of YLD. To estimate YLD for a particular cause in a particular time period, the number of incident cases in that period is multiplied by the average duration of the disease and a weight factor that reflects the severity of the disease on a scale from 0 (perfect health) to 1 (dead). The basic formula for YLD is the following (again, without applying social preferences):

$$YLD = I \times DW \times L$$

where

I = number of incident cases

DW = disability weight

L = average duration of the case until remission or death (years)

2.4.2 Environmental burden of diseases (EBD)

Early estimates of the global disease burden attributable to the environment, derived partly on the basis of expert opinion, were in general agreement (WHO, 1997: 23%; Smith, Corvalàn and Kjellström, 1999: 25—33%). A third major study of OECD countries, however, yielded significantly different results, concluding that only 2.1%-5.0% of the overall disease burden was attributable to the environment (Melse, 2001).

Even more recently, WHO developed a framework for a much more rigorous approach to burden of disease estimations. This project, known as the Comparative Risk Assessment (CRA), considered 6 environmental and occupational risk factors among a set of 26 environmental, occupational, social and behavioural risk factors having a major impact on population health (WHO, 2002). The total disease burden attributable to these risk factors was estimated across all 14 WHO subregions, 8 age groups, and by gender. The six environmental and occupational risk factors considered in the CRA were factors for which there was clear causal evidence that could be applied globally; for which global estimates of exposure could be obtained; and which had large impacts on people's health. However, this assessment remained limited in terms of the range of environmental risks assessed, and with respect to quantification of impacts in terms of specific health conditions. The present analysis goes a step further, providing timely new estimates of burden of disease from a much broader range of environmental risk factors, and in terms of the categories of diseases and health conditions affected. The analysis makes use of the results from the CRA, complemented by extensive literature reviews and standardized surveys of expert opinions, in an approach that aims to improve scientific rigour and transparency. Focusing on modifiable environmental risks, the current assessment examines "how much" such factors affect various diseases and injuries – both in terms of premature mortality and in terms of overall disease burden as measured by DALY's (disability adjusted life years), a weighted measure of death and disability.

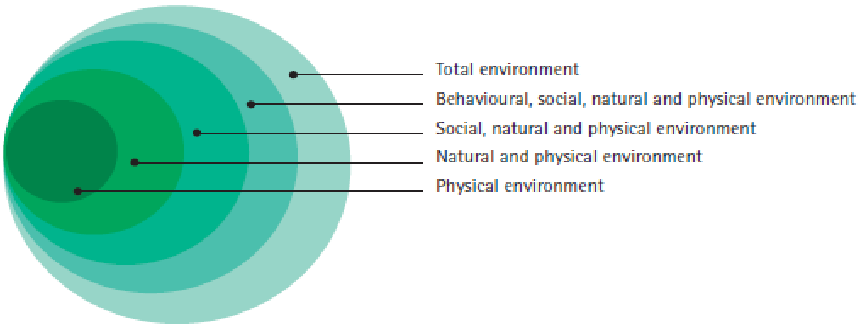

Figure 2-5 Environment definition (Smith, 1999).

WHO Focusing on modifiable environmental risks, the current assessment examines "how much" such factors affect various diseases and injuries – both in terms of premature mortality and in terms of overall disease burden as measured by DALY's (disability adjusted life years), a weighted measure of death and disability. The definition of "modifiable" environmental risk factors include those reasonably amenable to management or change. Factors not readily modifiable were not considered here (Prüss-Üstün, 2006). Environmental factors are the modifiable parts (or impacts) included;

- Pollution of air, water, or soil with chemical or biological agents;
- UV and ionizing radiation• noise, electromagnetic fields
- Occupational risks

- Built environments, including housing, land use patterns, roads
- Agricultural methods, irrigation schemes
- Man-made climate change, ecosystem change
- Behavior related to the availability of safe water and sanitation facilities, such as washing hands, and contaminating food with unsafe water or unclean hands.

Excluded environmental factors are:

- Alcohol and tobacco consumption, drug abuse;
- Diet (although it could be argued that food availability influences diet);
- The natural environments of vectors that cannot reasonably be modified (e.g. in rivers, lakes, wetlands);
- Impregnated bed nets (for this study they are considered to be non environmental interventions);
- Unemployment (provided that it is not related to environmental degradation, occupational disease, etc.);
- Natural biological agents, such as pollen in the outdoor environment;
- Person-to-person transmission that cannot reasonably be prevented through environmental interventions such as improving housing, introducing sanitary hygiene, or making improvements in the occupational environment.

2.4.3 Comparative Risk Assessment

Comparative Risk Assessment is defined as the systematic evaluation of the changes in population health which result from modifying the population distribution of exposure to a risk factor or a group of risk factors. World Health Organization study estimated the burden of two types. (Ministry of public health,2004)

1. Attributable burden of disease and Injury

The estimate current burden of disease and injury in the world's population resulting from exposure to risks in 2000. The burden of disease risk factors in the current year, a comparison of risk factors mentioned in the Theoretical minimum. (zero for risk factors for which zero exposure could be defined and reflected minimum risk, such as no smoking.)

2. **Avoidable burden of disease and Injury** in years 2000,2005,2010,2020 and 2030

For changes in the level of the risk factors that occurred in 2000 is expected to estimate the burden of disease will occur in the future by the terms of the risk factors in a way that is possible on multiple levels. (Alternative distribution of risk factor).

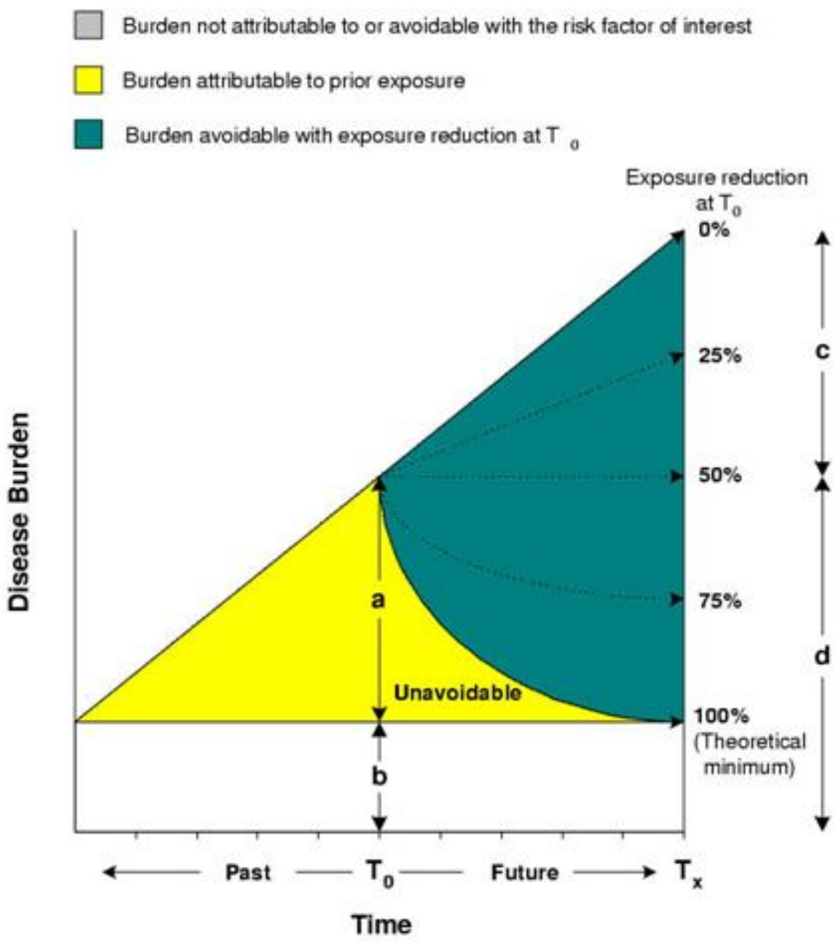

Figure 2-6 Attributable and avoidable burden of diseases

Where

a = disease at T_0 attributable to prior exposure

b = disease at T_0 not attributable to the risk factor (caused by other factors)

c = avoidable disease at T_x with a 50% exposure reduction at T0

d = disease at T_x after a 50% reduction in risk factor

Attributable fraction at T_0 due to prior exposure = a / (a + b)

Avoidable fraction at T_x due to 50% exposure reduction at T_0 = c / (c + d)

In general avoidable burden at T_y due to exposure reduction at T_0 is given by the ratio of the green area to total burden at T_y. Dashed arrows represent the path of burden after a reduction at T_0. Policy choices for feasible, plausible, and cost-effective exposure reductions can be chosen from the range of distributional transitions. Note that the burden attributable to other risk factors (grey area) may be decreasing, constant, or increasing over time. (Ezzati, 2000)

2.4.4 The Estimate of Attributable and Avoidable burden

A comparative study of disease burden, risk factors, WHO guidelines and the following four steps. (Fig 2.4)

1.) The selection and definition of risk factors.

2.) Risk Factor levels or scenarios

3.) Selective and estimation of the Current, Alternative and future distribution

4.) Estimate Risk factor-disease relationships

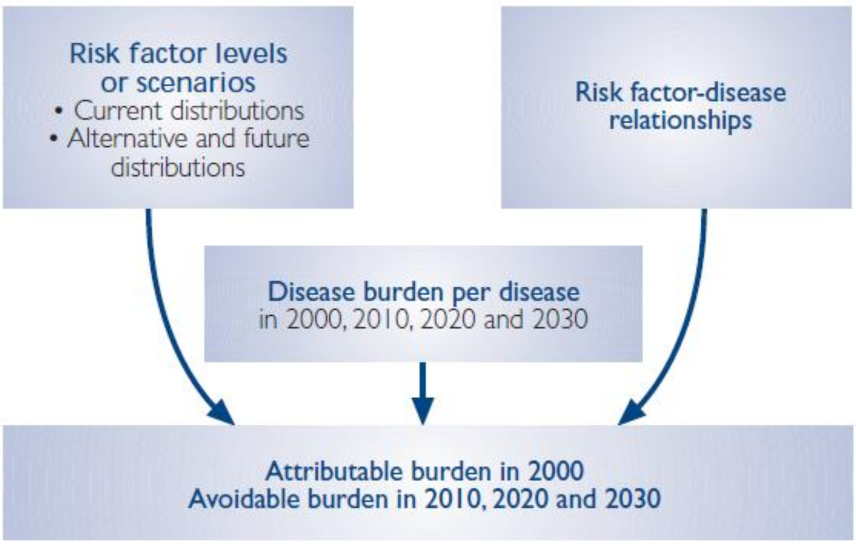

Figure 2-7 The Comparative risk assessment

2.5 Multiple regression analysis

Multiple regression is a general statistical technique used to analyze the relationship between a single dependent variable with normally distributed and several continuous independent variables. The general form of multiple regression model for p independent variables is given by (Hair, et al., 1998):

$$y = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + ... + \beta_p x_{ip} + \varepsilon_i$$

Where n is the number of observations

p is the number of parameter / regression coefficients

y_i is the value of dependent variable for the i^{th} observation

β_0 is y-intercept of the regression line

β_j is the partial regression coefficients for the independent variable

x_{ij} is the value of j^{th} the independent variable for the i^{th} observation

ε_i is the residual term for the observation

2.6 Statistical association between climate variability and malaria incidence

Zhou 2003 used nonlinear mixed-regression model to investigate the association between autoregression (number of malaria outpatients during the previous time period), seasonality and climate variability, and the number of monthly malaria outpatients of the past 10–20 years in seven highland sites in East Africa. The nonlinear mixed-regression models are as follows;

$$N_t = f(N_{i<t}, t) + g\big(T_{min}(t), T_{max}(t), Rain(t)\big) + e_t$$

where;

$$f(N_{i<t}, t) = \alpha + \sum_{i=1}^{d} \beta_i N_{t-i} + b_1 cos\left(\frac{2\pi}{12}t\right) + b_2 sin\left(\frac{2\pi}{12}t\right)$$

$$g = r_1 \sum_{i=\tau 1}^{\tau min} T_{\min (i)} + r_2 \sum_{i=\tau 2}^{\tau max} T_{\max (i)} + r_3 \sum_{i=\tau 3}^{\tau_R} Rain + r_{1-n} \sum_{i=\tau n}^{\tau max} interaction\ between\ all\ climate\ variables\ (i)$$

$f(N_{i<t}\ ,\ t)$ is a higher-order autoregressive model that test the effect of autoregression and was used sine and cosine function as seasonal function on this model.

$g\big(T_{min}(t), T_{max}(t), Rain(t), RH(t), Wind(t)\big)$ represents the effects of climate variability on malaria incidence.

α is the deterministic drift

β_i measures the lagged effect (autoregression)

d is the maximum number of lagged months is determined by the lagged autoregression analysis between monthly malaria incidences.

r_i is the regression coefficient.

Tmin = Monthly Minimum temperatures

Tmax = Monthly Maximum temperatures

Rain = Monthly total rainfall

2.7 Literatures reviews

The precise relationship between malaria transmission and the environmental parameters, however, is complex. For example, while precipitation creates potential larval habitats, too much precipitation in too short a period may wash larvae away. Likewise, droughts do away withlarval habitats, but may also weaken or reduce the predator populations and result in more intense malaria transmission later on. Coupled with the influences from other environmental and contextual determinants, malaria transmission is a nonlinear phenomenon but may still be approximated with regressions using linear predictors. Previously, the neural network method, a non-linear technique, has been used to model the malaria transmission in Thailand. (Kiang, 2006)

David R. Boyd, 2008 estimate the environmental burden of disease (EBD) in Canada for respiratory disease, cardiovascular disease, cancer, and congenital affliction. Quantifying the contribution of environmental exposures to the overall burden of disease could play an important role in shaping public health and environmental policy priorities. Using a combination of comparative risk assessment data and expert judgment to develop environmentally attributable fractions (EAFs) of mortality and morbidity for 85 categories of disease. They use the EAFs developed by the WHO, EAFs developed by other researchers, and data from Canadian public health institutions to provide an initial estimate of the environmental burden of disease in Canada for four major categories of disease. The results indicate that: 10,000-25,000 deaths; 78,000-194,000 hospitalizations; 600,000-1.5 million days spent in hospital; 1.1 million-1.8 million restricted activity days for asthma sufferers; 8000-24,000 new cases of cancer; 500-2500 low birth weight babies; and between $3.6 billion and $9.1 billion in costs occur in Canada each year due to respiratory disease, cardiovascular illness, cancer, and congenital affliction associated with adverse environmental exposures.

Promprou S. 2005 investigated climatic factors associated with Dengue Haemorrhagic Fever (DHF) incidence in southern Thailand, and compared the differential effects of climatic factors on the incidence of DHF in the areas bordering on the Andaman Sea and those on the Gulf of Thailand side of the peninsula. Climatic factors comprised rainfall, rainy days, relative humidity, maximum, minimum, and mean temperatures. The result indicated that the mean temperature, rainfall, and relative humidity were associated with DHF incidence in the areas bordering the Andaman Sea. Minimum temperature, rainy days, and relative humidity were associated with DHF incidence on the side of the southern peninsula Gulf of Thailand.

Hales 2002 modeled the reported global distribution of dengue fever on the basis of vapour pressure, which is a measure of humidity. They assessed changes in the geographical limits of dengue fever transmission, and in the number of people at risk of dengue by incorporating future climate change and human population projections into their model.The results are showed that the current geographical limits of dengue fever transmission can be modelled with 89% accuracy on the basis of long-term average vapour pressure. In 1990, almost 30% of the world population, 1·5 billionpeople, lived in regions where the estimated risk of dengue transmission was greater than 50%. With population and climate change projections for 2085, they estimate that about 5–6 billion people (50–60% of the projected global population) would be at risk of dengue transmission, compared with 3·5 billion people, or 35% of the population, if climate change did not happen.

Abeku T 2002 study Forecasting malaria incidence from historical morbidity patterns in Ethiopia. The aim of this study was to assess the accuracy of different methods of forecasting malaria incidence from historical morbidity patterns in areas with unstable transmission. They tested five methods using incidence data reported from health facilities in 20 areas in central and north-western Ethiopia. The accuracy of each method was determined by calculating errors resulting from the difference between observed incidence and corresponding forecasts obtained for prediction intervals of up to 12 months. Simple seasonal adjustment methods outperformed a statistically more advanced autoregressive integrated moving average method. In particular, a seasonal adjustment method that uses mean deviation of the last three observations from expected seasonal values consistently produced the best forecasts. Using 3 years' observation to generate forecasts with this method gave lower errors than shorter or longer periods. Incidence during the rainy months of June–August was the most predictable with this method. Forecasts for the normally dry months, particularly December–February, were less accurate. The study shows the limitations of forecasting incidence from historical morbidity patterns alone, and indicates the need for improved epidemic early warning by incorporating external predictors such as meteorological factors.

Zhou ,2003 has estimate Association between climate variability and malaria epidemics in the East African highlands, assessing the impact of climate in malaria resurgence is difficult due to high spatial and temporal climate variability and the lack of long-term data series on malaria cases from different sites. They used nonlinear mixed-regression model to investigate the association between autoregression (number of malaria outpatients during the previous time period), seasonality and climate variability, and the number of monthly malaria outpatients of the past 10–20 years in seven highland sites in East Africa. The model explained 65–81% of the variance in the number of monthly malaria outpatients. Nonlinear and synergistic effects of temperature and rainfall on the number of malaria outpatients were found in all seven sites. The net variance in the number of monthly malaria outpatients caused by autoregression and seasonality varied among sites and ranged from 18 to 63% (mean = 38.6%), whereas 12–63% (mean = 36.1%) of variance is attributed to climate variability.

Adami F. 2010 use remote sensing to predict malaria risk in Afghanistan by Provincial malaria epidemiological data (2004-2007) collected by the health posts in 23 provinces were used in conjunction with space-borne observations from NASA satellites. Specifically, the environmental variables, including precipitation, temperature and vegetation index measured by the Tropical Rainfall Measuring Mission and the Moderate Resolution Imaging Spectoradiometer, were used. Regression techniques were employed to model malaria cases as a function of environmental predictors. The resulting model was used for predicting malaria risks in Afghanistan. The entire time series except the last 6 months is used for training, and the last 6 month data is used for prediction and validation.The results is Surface temperature is the second strongest predictor. Precipitation is not shown as a significant predictor, as it may not directly lead to higher larval population. Autoregressiveness of the malaria epidemiological data is apparent from the analysis. The malaria time series are modelled well, with provincial average R^2 of 0.845. Although the R2 for prediction has larger variation, the total 6-month cases prediction is only 8.9% higher than the actual cases.

Patz, J.A. 2002 Disease outbreaks are known to be often influenced by local weather, but how changes in disease trends might be affected by long-term global warming is more difficult to establish. In a study of malaria in the African highlands, Hay *et al*. found no significant change in long-term climate at four locations where malaria incidence has been increasing since 1976. They contend, however, that their conclusions are likely to be flawed by their inappropriate use of a global climate data set. Moreover, the absence of a historical climate signal allows no inference to be drawn about the impact of future climate change on malaria in the region.

Martens, P. et al.1999 estimates of the potential impact of climate change on malaria transmission were calculated based on future climate scenarios produced by the HadCM2 and the more recent HadCM3 global climate models developed by the UK Hadley Centre. This assessment uses an improved version of the MIASMA malaria model, which incorporates knowledge about the current distributions and characteristics of the main mosquito species of malaria. The greatest proportional changes in potential transmission are forecast to occur in temperate zones, in areas where vectors are present but it is currently too cold for transmission. Within the current vector distribution limits, only a limited expansion of areas suitable for malaria transmission is forecast, such areas include: central Asia, North America and northern Europe. On a global level,the numbers of additional people at risk of malaria in 2080 due to climate change is estimated to be 300 and 150 million for *P. falciparum* and *P. vivax* types of malaria, respectively, under the HadCM3 climate change scenario. Under the HadCM2 ensemble projections, estimates of additional people at risk in 2080 range from 260 to 320 million for *P. falciparum* and from 100 to 200 million for *P. vivax*.

Tanser, F.C.2003 produced a spatiotemporally validated (against 3791 parasite surveys) model of *Plasmodium falciparum* malaria transmission in Africa. Using different climate scenarios from the Hadley Centre global climate model (HADCM3) climate experiments and showed sensitivity and specificity of 63% and 96%, respectively (within 1 month temporal accuracy),when compared with the parasite surveys. They estimate that on average there are 3·1 billion person-months of exposure (445 million people exposed) in Africa per year. The projected scenarios would estimate a 5–7% potential increase (mainly altitudinal) in malaria distribution with surprisingly little increase in the latitudinal extents of the disease by 2100. Of the overall potential increase (although transmission will decrease in some countries) of 16–28% in person-months of exposure (assuming a constant population), a large proportion will be seen in areas of existing transmission.

Teklehaimanot HD, 2004 used Poisson regression with lagged weather factors in a 4th-degree polynomial distributed lag model. For each week, the numbers of malaria cases were predicted using coefficients obtained using all years except that for which the prediction was being made. The effectiveness of alerts generated by the prediction system was compared against that of alerts based on observed cases. The usefulness of the prediction system was evaluated in cold and hot districts. The results are system predicts the overall pattern of cases well, yet underestimates the height of the largest peaks. Relative to alerts triggered by observed cases, the alerts triggered by the predicted number of cases performed slightly worse, within 5% of the detection system. The prediction-based alerts were able to prevent 10–25% more cases at a given sensitivity in cold districts than in hot ones.

CHAPTER III
METHODOLOGY

3.1 The research

This research is descriptive research

3.2 Equipments and material

1. SPSS statistical analyze software
2. Microsoft office 2007
3. WHO DALY calculation worksheet

3.3 Population in the study

The population of Thailand’s patients with malaria last 20 years (1991 - 2011) using data from National Disease Surveillance (Surveillance Report 506) of the Bureau of Epidemiology, Disease Control Department, Ministry of Public Health Thailand.

3.4 Methodological Framework

In this research using method from WHO Environmental Burden of Disease Series, No. 14: This will include main step, Selecting the scenarios and time period, Climate change modeling, Health impact model, and Conversion to a single health measure DALY (Disability adjusted life year). This research has made to the guidelines of the WHO to the study's purpose was to create a statistical climate health model of Thailand to predict and compare incidence under climate scenarios projected with the actual incidence of the disease under real climate condition and improve the results by converted to DALYs for more international comparison.

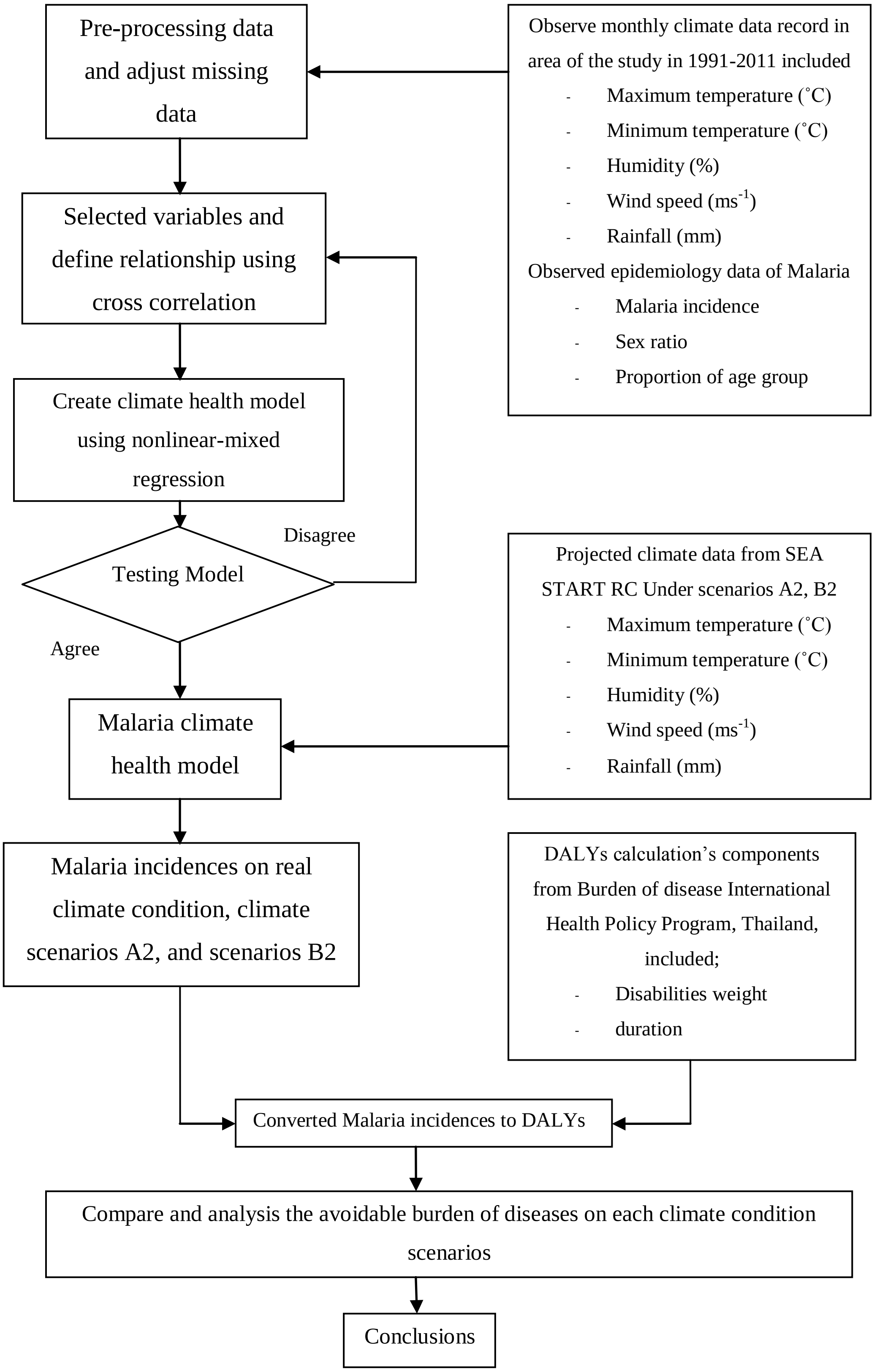

Figure 3-1: Methodological Framework

3.5 Comparative risk assessment

Comparative Risk Assessment is defined as the systematic evaluation of the changes in population health which result from modifying the population distribution of exposure to a risk factor or a group of risk factors. The application of the Comparative Risk Assessment adapted on Climate change study (Campbell-Lendrum D, 2006), concepts of avoidable, attributable disease burdens under alternative climate change scenarios are illustrated graphically in Figure 3-1.

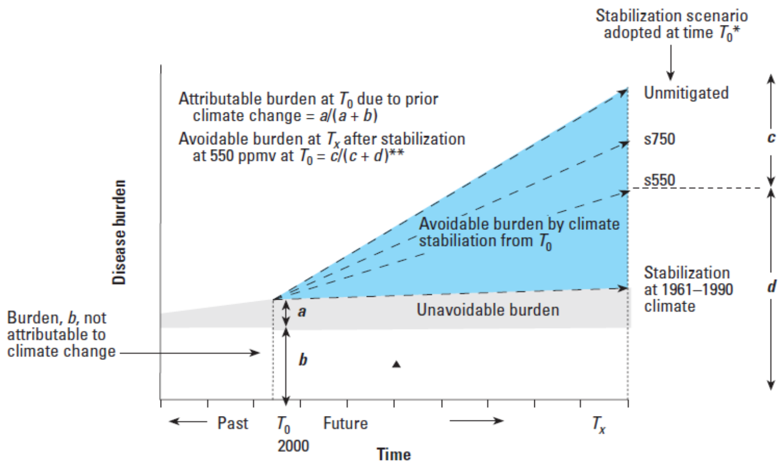

Figure 3-1 Comparative risk assessment definitions of attributable and avoidable disease burden, in the context of climate change (Campbell-Lendrum D, 2006)

Where

a = amount of disease at T_0 attributable to prior anthropogenic climate change

b = amount of disease at T_0 not attributable to prior anthropogenic climate change

c = amount of disease avoidable at T_x with GHG stabilization at 550 ppmv at T_0

d = amount of disease predicted at T_x despite GHG stabilization at 550 ppmv at T_0

*Dashed arrows represent total of burden after a given shift in risk distributions at T_0.

**Avoidable burden by T_x would be given by ratio of different shaded areas.

3.6 Select the scenarios and time period for assessment

To calculate attributable and avoidable future burdens and the population at risk, the first step is to select plausible scenarios of the future, including changes in emissions of greenhouse gases which are the main determinants of global climate change. This research will use climate scenarios from SEA START RC and time period between years 2003-2011. The steps are as follows,

3.6.1. Data Collection

1. Climate data using 20 years (1991-2011) contains the rainfall (Rainfall Intensity), the average monthly temperature (Average Ambient Temperature) The average maximum temperature (Maximum Temperature), RH (Relative Humidity), wind speed, time (month) of the Department of Meteorology.

2. Data collection and reporting of malaria incidences in Thailand in the past 20 years (1991-2011) of the Bureau of Epidemiology.

3. The exposure is the output of global climate models that predict the effect of future emissions scenarios on climate properties. The Predicted climate data using dataset from Southeast Asia START Regional Center (SEA START RC) projected. These data are the daily climate data (transform to monthly data) under three different GHG scenarios conditions included, Scenarios A2 and Scenarios B2. The two different GHG Scenarios will be referred in Figure 3-1.

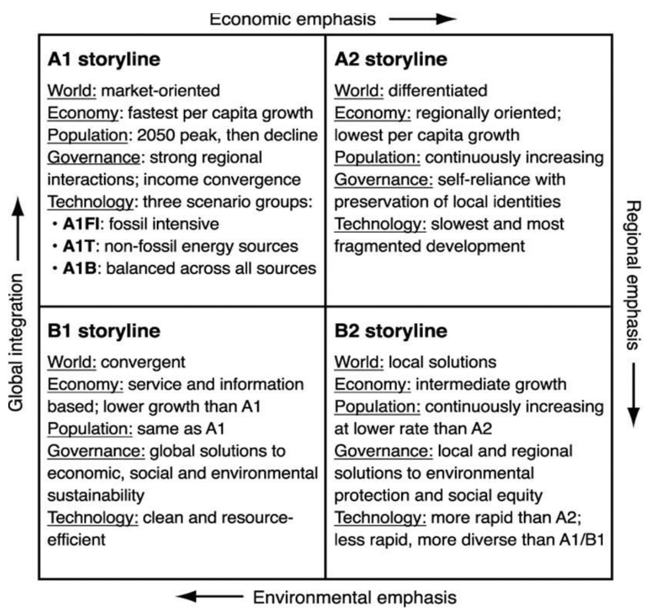

Figure 3-2 Climate change scenarios

3.7 Quantify the relationship between climate and each health outcome

This involves a statistical analysis of the effect of past variations in climate on disease either in time. The appropriate methods in this study for assessing quantitative relationships between climate and health are statistic correlation and non-linear regression technique. The steps are as follows,

3.7.1. Data analysis

1.Use descriptive statistics, mean, maximum and minimum number of reports of rainfall (Rainfall Intensity) the highest average monthly temperature (Maximum Temperature) RH (Relative Humidity) and wind speed .

2. Analysis of the correlation coefficients of independent variables, including rainfall (Rainfall Intensity), the highest average monthly temperature (Maximum Temperature), RH (Relative Humidity), and wind speed. Following the steps belows:

$$r = \frac{\sum_{i=1}^{n}\left(\left(x_i - \bar{x}\right)\left(y_i - \bar{y}\right)\right)}{\sqrt{\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2 \sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2}}$$

Where;	r	=	correlation coefficient
	X and Y	=	variables data
	$\bar{X}$ and $\bar{Y}$	=	average of variables data

3. The results of the analysis the incidence rate per hundred thousand populations. The incidence of malaria by using a monthly rate of incidence of the year 1991 to 2011 with graph.

4. Analysis of the incidence of diseases associated with climate change with Coefficient Correlation of the data. Number of cases reported in the epidemiological report using three independent variables, climate variables, including rainfall, the highest average monthly temperature and relative humidity. The results are reported as incidence rate.

5. Create equation for the relationship to predict the incidence of malaria in the model scenarios of climate change SEA START RC in 2003-2011 comparing with real climate data.

6. The annual incidence rate used to calculate the avoid disease burden that occur in the future.

3.8 Statistical association between climate variability and malaria incidence

In this step using the adapted nonlinear mixed- regression technique from Zhou, 2003 (refer to chapter 2) because of classification on the function type in model such as, autocorrelation, climate variability function also included seasonal function which should be applied in a regression for studying with seasonal patterns (Stolwijk, 1999), monthly data input (this study used monthly data) and Zhou used model application in East African (tropical zone) similar with Thailand. The expected case numbers for a given month were modeled using a regression with lagged weather factors. Linear regression is used to model the dependency of the malaria cases on the environmental parameters. The number of malaria outpatients, N_t, at a given time is likely to be affected by the previous number of malaria outpatients (autoregression), seasonality, and climate variability. Thus, the dynamics of the number of monthly malaria outpatients can be modeled as

$$N_t = f(N_{i<t}, t) + g\big(T_{min}(t), T_{max}(t), Rain(t), RH(t), Wind(t)\big) + e_t$$

, Where

$$f(N_{i<t}, t) = \alpha + \sum_{i=1}^{d} \beta_i N_{t-i} + b_1 cos\left(\frac{2\pi}{12} t\right) + b_2 sin\left(\frac{2\pi}{12} t\right)$$

$$g = r_1 \sum_{i=\tau 1}^{\tau min} T_{\min{(i)}} + r_2 \sum_{i=\tau 2}^{\tau max} T_{\max{(i)}} + r_3 \sum_{i=\tau 3}^{\tau_R} Rain\ (i) + r_4 \sum_{i=\tau 4}^{\tau_R} RH\ (i)$$
$$+ r_5 \sum_{i=\tau 5}^{\tau_R} Wind\ (i)$$
$$+ r_{1-n} \sum_{i=\tau n}^{\tau max} interaction\ between\ all\ climate\ variables\ (i)$$

$f\ (N_{i<t}\ ,\ t)$ is a higher-order autoregressive model that test the effect of autoregression and use sin cos function as seasonal function on this model.

$g\big(T_{min}\,(t), T_{max}\,(t), Rain(t), RH(t), Wind(t)\big)$ represents the effects of climate variability on malaria incidence. Parameter α is the deterministic drift, and β_i measures the lagged effect (autoregression), *d is* the maximum number of lagged months is determined by the lagged autoregression analysis between monthly malaria incidences. r_i is the regression coefficient.

Tmin	=	Monthly Minimum temperatures
Tmax	=	Monthly Maximum temperatures
Rain	=	Monthly total rainfall
RH	=	Monthly humidity
Wind	=	Monthly wind speed

3.9 Stepwise Nonlinear mixed-regression model

A multiple regression analysis to examine the relationship of the dependent variable Y and X are the independent variables were the number of cases of malaria. The dependent variable Y as well as meteorological data from meteorological station indicated that the air pressure (atmospheric pressure) of rainfall (precipitation) relative humidity (relative humidity), temperature (temperature), wind direction (wind direction) and wind speed (wind speed) is. The independent variable X is used in the model is obtained by selecting the appropriate settings as described in the next section.

Stepwise is method to choose the independent variables in the model by selecting a variable for each independent variable in the model are that it will be cut off later. There is a need to test whether the independent variable on the model then helped to explain the variability of the dependent variable Y as independent variables in the model, they will be test and selected highest Multiple Coefficient of Determination, The explanatory power of the regression is summarized by its "R-squared" value, computed from the sums-of-squares terms as,

$$R^2 = \frac{SSR}{SST} = 1 - \frac{SSE}{SST}$$

Where R^2 = Coefficient of Determination

SSR = the sum of squared deviations of predicted values (predicted using regression) from the mean value.

SSE = the sum of squared deviations of actual values from predicted values.

SST = the sum of squared deviations of individual measurements from the mean. The total sum of squares is a sum of 2 portions.

R^2 also called the coefficient of determination, is often described as the proportion of variance "accounted for", "explained", or "described" by regression. It is important to keep in mind that a high R^2 does not imply causation. The relative sizes of the sums-of-squares terms indicate how "good" the regression is in terms of fitting the calibration data. If the regression is "perfect", all residuals are zero, SSE is zero, and R^2 is 1. If the regression is a total failure, the sum-of-squares of residuals equals the total sum-of-squares, **no** variance is accounted for by regression, and R^2 is zero.(Notes,2009)

Adjusted R^2**.** The R^2 value for a regression can be made arbitrarily high simply by including more and more predictors in the model. The adjusted $R^2$is one of several statistics that attempts to compensate for this artificial increase in accuracy. The adjusted R^2 is given by

$$\bar{R}^2 = 1 - \frac{\text{MSE}}{\text{MST}}$$

Where MSE and MST are the mean squared terms previously defined in the ANOVA table. Referring to the ANOVA table shows that ratio of mean squared terms is related to the ratio of sum-of-squares terms by

$$\frac{\text{MSE}}{\text{MST}} = \frac{(n-1)\text{SSE}}{(n-K-1)\text{SST}}$$

Where n = number of observations

K = number of predictors

Equations used to predict the effect of the error of the most accurate predictions by choosing the appropriate equation with minimum RMSE (Root mean squared error) which has the following equation,

$$\text{RMSE} = \sqrt{\frac{\sum(\text{A}_{\text{t}-}\ \text{F}_{\text{t}})^2}{\text{n}}}$$

Where;

At = Actual or observed data

Ft = Prediction or mode

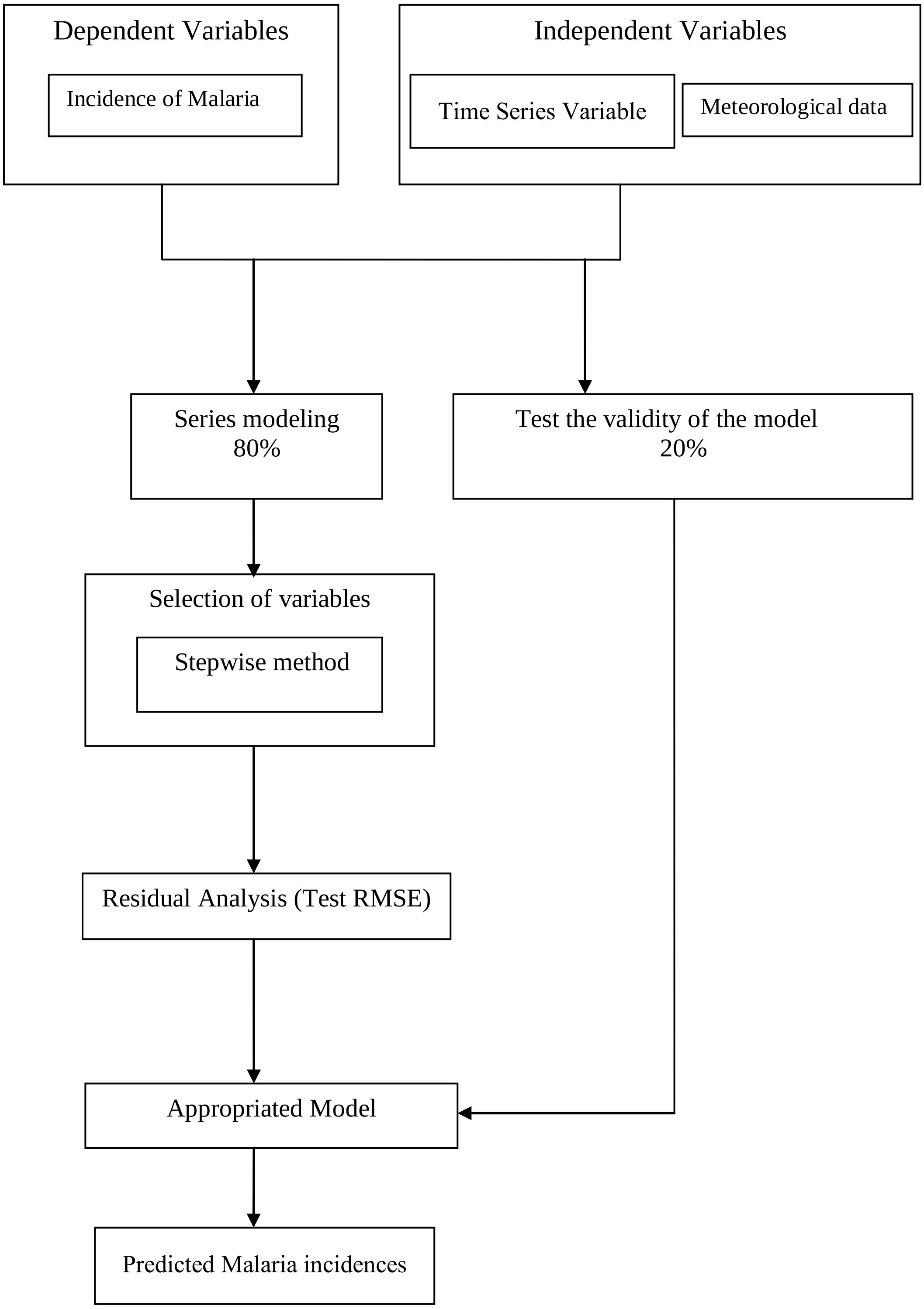

Figure 3.3 Step of The multiple regression models to predicted malaria incidences

3.10 Global Burden of disease

- Global Burden of disease calculation

DALYs for a disease or health condition are calculated as the sum of the Years of Life Lost (YLL) due to premature mortality in the population and the Years Lost due to Disability (YLD) for incident cases of the health condition (Murray & Lopez ,1996). Calculation is

$$\text{DALY} = \text{YLL} + \text{YLD}$$

The YLL basically correspond to the number of deaths multiplied by the standard life expectancy at the age at which death occurs. The basic formula for YLL (without yet including other social preferences discussed below), is the following for a given cause, age and sex:

$$\text{YLL} = N \times L$$

Where:

N = number of deaths

L = standard life expectancy at age of death in years

Because YLL measure the incident stream of lost years of life due to deaths, an incidence perspective is also taken for the calculation of YLD. To estimate YLD for a particular cause in a particular time period, the number of incident cases in that period is multiplied by the average duration of the disease and a weight factor that reflects the severity of the disease on a scale from 0 (perfect health) to 1 (dead). The basic formula for YLD is the following

$$\text{YLD} = I \times DW \times L$$

Where:

I = number of incidence cases

DW = disability weight

L = average duration of the case until remission or death (years)

CHAPTER IV
RESULTS AND DISCUSSION

4.1 Data analysis

This chapter present the result and discussion experiment which include three sections are data collection and analysis, create model, prediction and estimation.

Observed climate data were collected in the years 1991-2011 data from monitoring stations in each year climate data from some stations during 1991-2000 are missing. Therefore, it is necessary to have an analysis by adjust missing data and cut missing data from all observer data before find analyze data based on using moving average method and trend estimation. Analysis found that the maximum temperature, minimum temperature and relative humidity shown increasing but the wind speed in the year 2011 is likely to decrease over the year 1991, however wind speed showed a continuous increase from 1999.

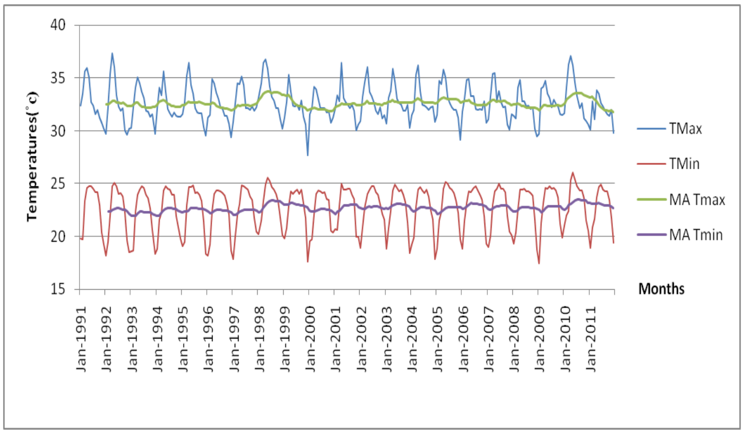

Figure 4-1 Maximum and Minimum temperature in Thailand 1991-2011

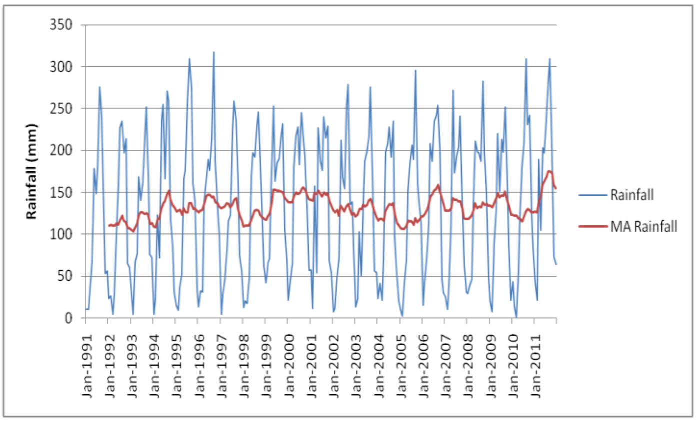

Figure 4-2 Total Rainfall in Thailand 1991-2011

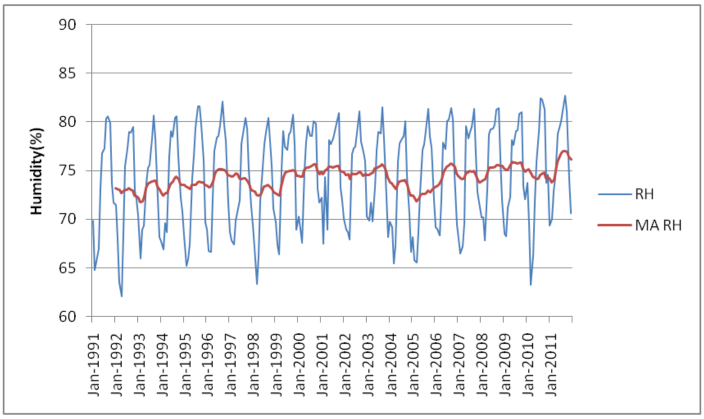

Figure 4-3 Average Humidity in Thailand 1991-2011

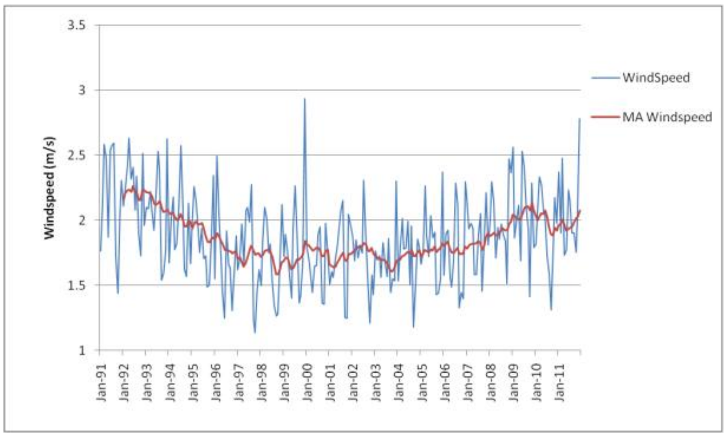

Figure 4-4 Maximum Wind speed in Thailand 1991-2011

The analysis of the relationship between climate factors and the incidence of malaria will be tested by correlation of each factor will be time lag period of climatic factors on the incidence of disease. In this study, showed that wind speed has maximum lag period = 5 months with correlation = 0.282 and humidity and rainfall have has maximum lag period = 0 months with correlation = 0.297 and 0.241 respectively. The Association between climate variables and Malaria incidence data included time lag period shown in Table 4-1.

Table 4-1 Correlation between variables with malaria incidences

Variable	**Lag period, τ (Months)**	**Correlation**	**Sig**
Case	1	0.842	0.000 **
Maximum temperatures	0	0.046	0.469
Maximum temperatures	1	0.288	0.000**
Maximum temperatures	2	0.427	0.000**
Minimum temperatures	0	0.250	0.000**
Minimum temperatures	1	0.297	0.000**
Rainfall	0	0.241	0.000**
RH	0	0.171	0.007**
Wind speed	0	0.073	0.245
Wind speed	1	0.061	0.337
Wind speed	2	0.161	0.011*
Wind speed	3	0.251	0.000**
Wind speed	4	0.258	0.000**
Wind speed	5	0.282	0.000**

** Correlation is significant at the 0.01 level (2-tailed).

* Correlation is significant at the 0.05 level (2-tailed).

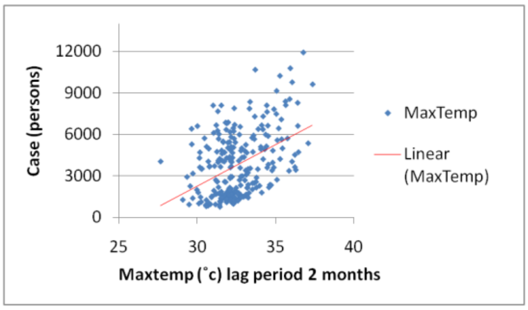

Figure 4-5 Association between maximum temperature and cases

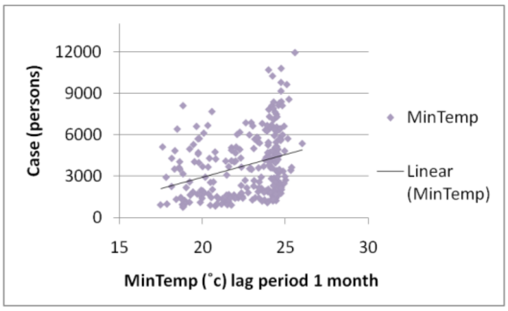

Figure 4-6 Association between minimum temperatures and cases

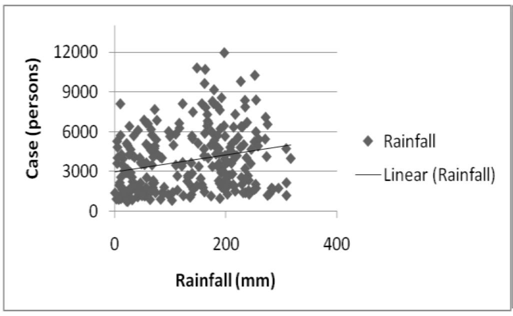

Figure 4-7 Association between rainfall humidity and malaria incidences

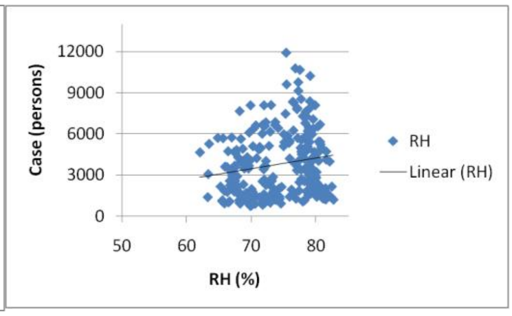

Figure 4-8 Association between and malaria incidences

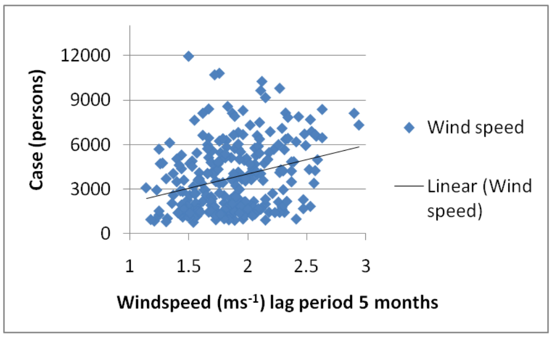

Figure 4-9 Association between wind speed and malaria incidences

4.2 Climate–health model

Selecting variables and test time lag period climate variable associate with malaria incidence. The next step regression analysis by stepwise method by statistic software SPSS, The statistical models using adapted nonlinear mixed regression model from Zhou, 2003 is given by,

$$N_t = f(N_{i<t}, t) + g\big(T_{min}(t), T_{max}(t), Rain(t), RH(t), Wind(t)\big) + e_t$$

Where

$$f(N_{i<t}, t) = \alpha + \sum_{i=1}^{d} \beta_i N_{t-i} + b_1 cos\left(\frac{2\pi}{12}t\right) + b_2 sin\left(\frac{2\pi}{12}t\right)$$

$$g = r_1 \sum_{i=\tau 1}^{\tau min} T_{\min(i)} + r_2 \sum_{i=\tau 2}^{\tau max} T_{\max(i)} + r_3 \sum_{i=\tau 3}^{\tau_R} Rain\,(i) + r_4 \sum_{i=\tau 4}^{\tau_R} RH\,(i)$$
$$+ r_5 \sum_{i=\tau 5}^{\tau_R} Wind\,(i)$$
$$+ r_{1-n} \sum_{i=\tau n}^{\tau max} interaction\ between\ all\ climate\ variables\,(i)$$

$f(N_{i<t}\ , t)$ is a higher-order autoregressive model that test the effect of autoregression and was used sine and cosine function as seasonal function on this model.

$g\big(T_{min}(t), T_{max}(t), Rain(t), RH(t), Wind(t)\big)$ represents the effects of climate variability on malaria incidence.

α is the deterministic drift

β_i measures the lagged effect (autoregression)

d is the maximum number of lagged months is determined by the lagged autoregression analysis between monthly malaria incidences.

r_i is the regression coefficient.

Tmin	=	Monthly Minimum temperatures
Tmax	=	Monthly Maximum temperatures
Rain	=	Monthly total rainfall
RH	=	Monthly average humidity
Wind	=	Monthly average wind speed

The model will be tested in three types which given by;

- Model No EV which assume the environment factors do not affect the number of patients (g (x) = 0).
- Model 1 which assume the environmental factors influence the number of patients assume g (x) ≠ 0 and assume the interaction between all climate variables = 0 due to no interaction with the environment.
- Model 2 which assume the environmental factors influence the number of patients assume g (x) ≠ 0 and assume the interaction between all climate variables ≠ 0 due to environmental factors are related. The results are shown in Table 4-2 – 4-4.

Table4-2 Nonlinear mixed regression analysis between time series data with malaria incidence

Model	**Method**	**R**	**R square**	**Adjusted R Square**	**Sig**
No EV	Stepwise	0.842	0.710	0.708	0.000**
1	Stepwise	0.908	0.825	0.821	0.000**
2	Stepwise	0.907	0.823	0.818	0.000**

** Correlation is significant at the 0.01 level (2-tailed).

* Correlation is significant at the 0.05 level (2-tailed).

Table 4-2 shows the best adjusted R square value those using variables that have been selected by testing correlation and lag effect to create the best model in 3 types of this study which show in Table 4-3.

Table 4-3 Model fitting results and effects of autocorrelation and seasonality ($f(N_{i<t}, t)$)

Model Type	α	***d***	β	***b1***	***b2***
No EV	596.37	1	0.84	-	-
1	- 25,790.64	1	0.90	2,218.16	1,158.79
2	- 25,404.83	1	0.91	1,421.37	1,497.25

In Table 4-4 shows the fitting results and effect of climate variables include parameter and significant value of model 1 and model 2.

Table 4-4 Model fitting results and effect of climate variables (*g(x)*)

Parameter	Model 1	Sig.	Model 2	Sig.
Tmin (τ = 1)	511.411	0.000**	-	-
Tmax (τ = 2)	201.81	0.004**	-	-
RH (τ = 0)	107.39	0.000**	-	-
Wind speed (τ = 5)	-	0.000**	-	-
Rainfall (τ = 0)	-	-	-	-
SumTmax × RH	-	-	3.331	0.000**
SumTmin × Wind speed	-	-	22.629	0.000**
SumTmin × Wind speed × RH	-	-	-0.263	0.000**

** Correlation is significant at the 0.01 level (2-tailed).

* Correlation is significant at the 0.05 level (2-tailed).

4.3 Residual analysis

Residual analyze in this study was used by Root Mean Sqaure Error (RMSE), to compare actual data sets (Years 1991-2011) with generated data sets from model to select the best model with minimum RMSE. The results will be show on Table 4-5, Table 4-6.

$$\mathrm{RMSE} = \sqrt{\frac{\sum(A_{t-} F_t)^2}{n}}$$

At = Actual

Ft = Prediction

Table 4-5 Residual analysis

Model Type	RMSE
No EV	1,258.14
1	767.24
2	763.27

Table 4-6 Comparison of malaria incidences between models and actual (year 2003-2011)

Years	Actual (current)	Model 1	Percent over estimate	Model 2	Percent over estimate
2003	19,910	23,830	16.45	21,252	6.32
2004	23,656	22,993	-2.88	21,890	-8.07
2005	28,131	30,357	7.33	29,908	5.94
2006	28,962	32,084	9.73	31,038	6.69
2007	30,889	32,199	4.07	32,454	4.82
2008	28,902	32,040	9.79	31,376	7.88
2009	23,229	26,330	11.78	29,311	20.75
2010	25,639	34,139	24.90	36,676	30.09
2011	20,835	24,541	15.10	22,778	8.53
Average	25,573	28,724	-	28,520	-
Total	230,153	258,514	-	256,684	-

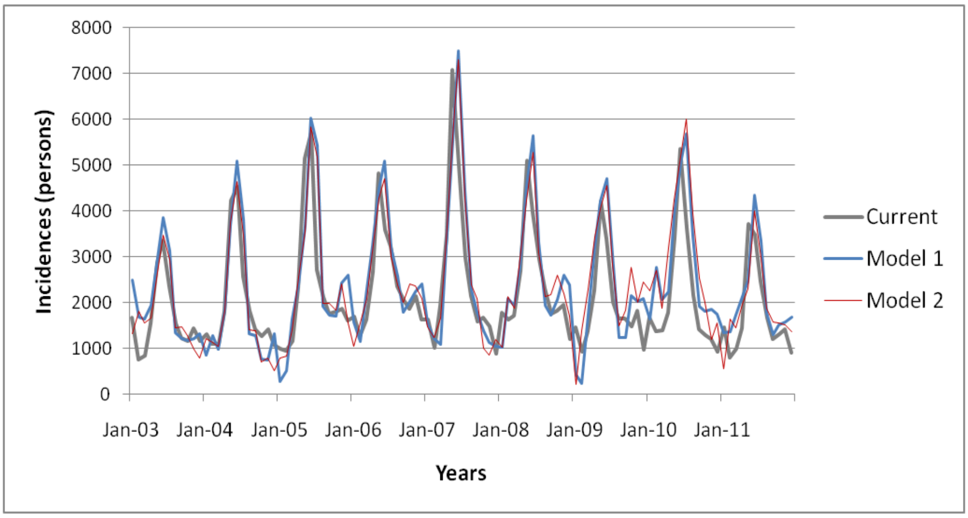

Figure 4-10 Comparison of malaria incidence in model 1, 2 and actual incidence (monthly)

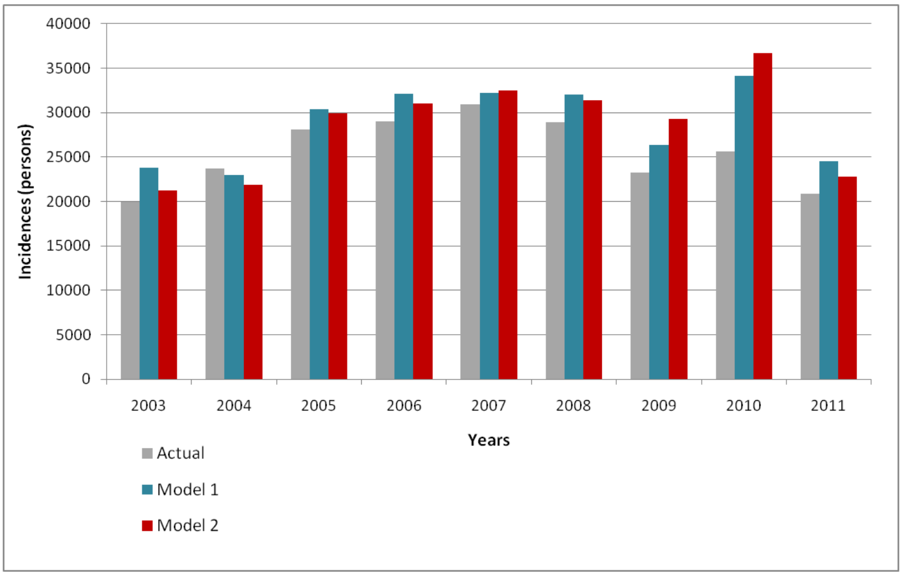

Figure 4-11 Comparison of malaria incidence in model 1, 2 and actual incidence

The results showed that the RMSE of model 2 is less than model 1, so the prediction process using model 2. Both models are adapted by non linear mixed-regression technique but model 2 using interaction of climate variables meanwhile model 1 only use climate variables at max lag period (τ_{max}). As a result the model 2 shows potential better prediction than model 1.

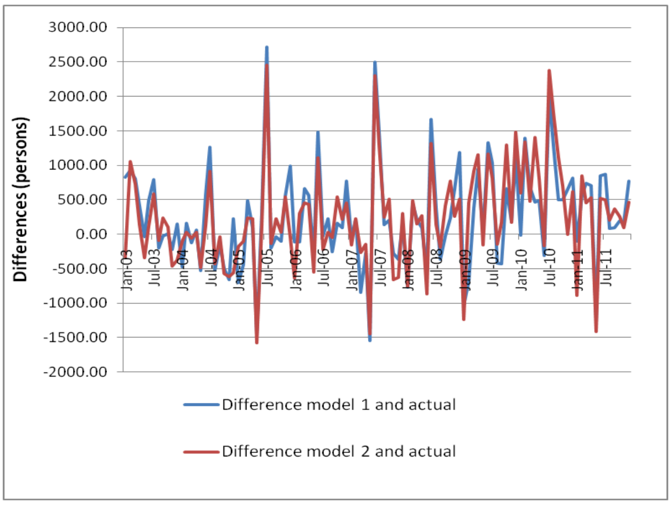

Figure 4-12 Difference of model and actual malaria incidence

Figure 4-12 shows the differences of each model were compared with monthly actual data and found similar trends of a difference. However, the results show the average difference on model 1 and model 2 is equal to 267 and 246. Results will show at appendix.

4.4 Prediction climate change impact process

4.4.1 Compare prediction under climate conditions

In the selection of model to predict in this study, we choose the model with the least RMSE. Next step is compare prediction under climate conditions with the climate baseline (actual data). The results has been shown in Table 4-7.

Table 4-7 Results estimate malaria incidence and percent difference from climate scenario A2 and B2 compare with climate baseline (years 2003-2011)

Years	**Climate baseline (Current)**	**A2**	**B2**	**Difference A2 to baseline (%)**	**Difference B2 to baseline (%)**
2003	21,252.13	27,019.07	22,113.70	27.14	4.05
2004	21,890.49	27,737.81	17,307.79	26.71	-20.93
2005	29,908.37	36,403.02	27,769.28	21.72	-7.15
2006	31,037.78	33,026.89	33,357.58	6.41	7.47
2007	32,454.48	35,923.62	34,346.45	10.69	5.83
2008	31,375.61	33,790.66	28,597.62	7.70	-8.85
2009	29,310.87	28,808.53	29,380.21	-1.71	0.24
2010	36,675.74	27,467.70	25,772.39	-25.11	-29.73
2011	22,778.46	26,426.57	23,174.28	16.02	1.74
Average	28,520.44	30,733.76	26,868.81	9.95	-5.26
Total	256,683.93	276,603.90	241,819.30	7.76	-5.79

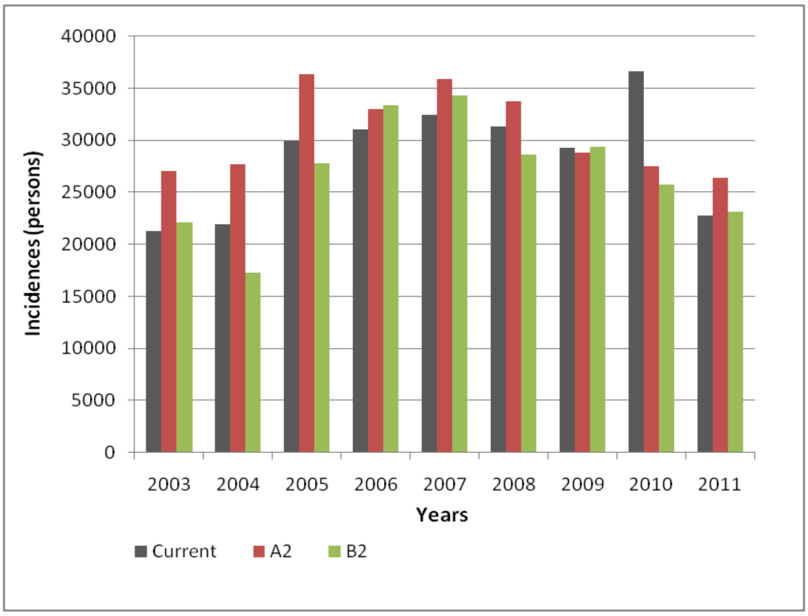

Figure 4-13 Results estimate of malaria incidences under climate scenarios

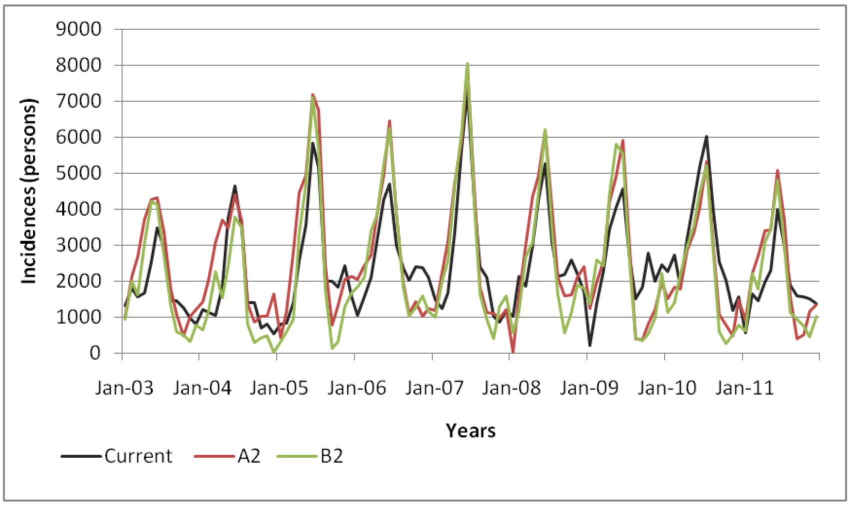

Figure 4-14 Results estimate of malaria incidences under climate scenarios (monthly)

4.4.2 Future prediction

The next step after comparing malaria model under climate conditions is future prediction process to estimate malaria burden under climate change scenarios, by input projection data A2, B2 from SEA START RC in 2012-2020 to nonlinear mixed regression model. The results show in table 4-8.

Table 4-8 Results estimate future (2012-2020) malaria incidence (persons) and percent difference from baseline

Years	Baseline	A2	B2	A2 Difference	Difference (%)	B2 Difference	Difference (%)
2012	42,410.22	38,180.50	31,272.98	4229.72	-9.97	11137.24	-26.26
2013	55,190.06	65,404.59	44,187.03	-10214.53	18.51	11003.04	-19.94
2014	58,817.35	74,793.90	47,402.54	-15976.55	27.16	11414.81	-19.41
2015	59,971.73	89,754.60	50,973.88	-29782.86	49.66	8997.85	-15.00
2016	60,339.11	80,159.58	65,530.60	-19820.46	32.85	-5191.49	8.60
2017	60,456.03	76,061.89	32,037.19	-15605.86	25.81	28418.84	-47.01
2018	60,493.24	94,065.30	25,208.01	-33572.06	55.50	35285.22	-58.33
2019	60,505.08	101,834.38	38,689.14	-41329.30	68.31	21815.94	-36.06
2020	60,508.85	97,072.39	28,361.26	-36563.55	60.43	32147.59	-53.13
Average	57,632.41	79,703.01	40,406.96	-22070.61	38.30	17225.45	-29.89
Total	518,691.68	717,327.13	363,662.64	-198635.45	38.30	155029.04	-29.89

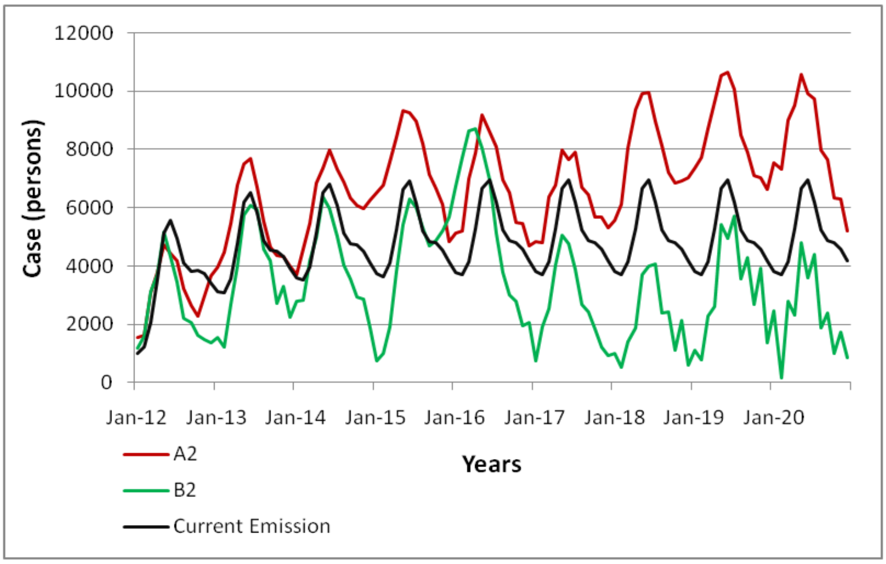

Figure 4-15 Results future prediction estimate of malaria incidences (monthly).

The results were found the average incidence of malaria 40,407 persons/year under climate scenario B2 and the average incidence of malaria 79,703 persons/year under climate change scenario A2. In addition the incidence of diseases under climate scenario B2 less than the climate change scenario A2 39,296 people per year, or 49.3% per year, for the reason that the incidence of the disease because predicts the future impact of climate change in different routine cause deviate from the actual data which mean reduce the accuracy of prediction process. Next, the study showed current emission has average incidence 57,632 person/year, which higher than

B2 scenarios 29.9% and less than A2 38.3%. However compare model with actual data showed over estimate from actual around -2.88% - 24.9%.

4.5 Convert climate change impact to DALYs score process

DALYs is a measure of overall disease burden, expressed as the number of years lost due to ill-health, disability or early death, which are calculated as the sum of the Years of Life Lost (YLL) due to premature mortality in the population and the Years Lost due to Disability (YLD) for incident cases of the health condition, with the following formula.

$$YLL = N \times Le$$

Where

N = number of deaths

Le = standard life expectancy at age of death in years

$$YLD = I \times DW \times L$$

Where

I = number of incident cases

DW = disability weight

L = average duration of the case until remission or death (years)

The necessary components to convert the incidence of malaria in WHO DALYs calculation template is the sex ratio which were collected from Annual Epidemiological Surveillance Report Bureau of Epidemiology Disease Control (Table 4-10) and Thailand population at midyear (1^{st} July) from the Office for National Statistics and life expectancy table West level 26 (Table 4-8) from WHO.

Table 4-9 Life-expectancy on this study

AGE GROUP	AVERAGE AGE AT DEATH	SEX	
		MALES	FEMALES
0	0.1	79.94	82.43
1-4	2.6	77.77	80.28
5-9	7.5	73.10	75.47
10-14	12.5	67.47	70.51
15-19	17.5	62.38	65.55
20-24	22.5	57.91	60.63
25-29	27.5	53.00	55.72
30-34	32.5	47.97	50.83
35-39	37.5	43.08	45.96
40-44	42.5	38.10	41.13
45-49	47.5	33.21	36.36
50-54	52.5	28.53	31.68
55-59	57.5	23.94	27.10
60-64	62.5	19.51	22.64
65-69	67.5	15.40	18.32
70-74	72.5	11.83	14.24
75-79	77.5	8.83	10.59
80-84	82.5	6.37	7.56
85+	90.0	3.88	4.25

Identification of malaria will be divided into three types: Episodes, Anaemia and Neurological sequelae. Using Burden of disease International Health Policy Program, Thailand DALYs components including, disability weight, duration and proportion of episodes according to Table 4-9.

Table 4-10 Proportion of malaria**,** disability weight and duration in each Malaria Type (WHO, 2000)

Malaria type	Proportion of episodes	Duration (years)	Disability weight	Age group(years)
Episodes	-	0.01	0.211 0.195 0.172	0-4 5-14 15+
Neurological sequelae (treated) in 0-4 years old	0.00134	55.3 (Male) 63.9 (Female)	0.436	0-4
Anaemia	0.12048	0.167	0.012	All age

Table 4-11 Malaria incidences sex ratio and proportions of deaths from incidences (National surveillance reports, 2003-2001)

Years	Malaria incidences sex ratio (Male: Female)	Proportions of deaths from incidences
2003	2.1:1	0.001557
2004	1.9:1	0.001987
2005	1.78:1	0.002524
2006	2.05:1	0.001761
2007	1.9:1	0.001230
2008	1.9:1	0.001246
2009	1.98:1	0.000818
2010	1.9:1	0.001326
2011	1.9:1	0.000521
Average	1.934:1	0.001441

Table 4-10 was used for classification to identify the incidence by sex. Example is shown below,

<u>Example</u>

In 2003 has total malaria incidences 21,252.13 persons, then from Table 4-8 has sex ratio Male: Female = 2.1:1, so we can find incidences male and female by below method.

Female

= 21,252.13 persons / 3.1 (from ratio 2.1:1)

= 6,856 persons

Male

= 2.1 × 6,856 persons

= 14,397 persons

Complete results are shown in Table 4-11 and 4-12.

Table 4-12 The number of incidences (males) under climate condition

Years	Climate baseline (Current)	A2	B2
2003	14,397	18,303	14,980
2004	14,342	18,173	11,340
2005	19,150	23,308	17,780
2006	20,861	22,198	22,421
2007	21,263	23,536	22,503
2008	20,556	22,139	18,736
2009	19,475	19,141	19,521
2010	24,029	17,996	16,885
2011	14,924	17,314	15,183
Average	**18,778**	**20,234**	**17,706**

Table 4-13 The number of incidences (females) under climate condition

Years	Climate baseline (Current)	A2	B2
2003	6,856	8,716	7,133
2004	7,548	9,565	5,968
2005	10,758	13,095	9,989
2006	10,176	10,828	10,937
2007	11,191	12,387	11,844
2008	10,819	11,652	9,861
2009	9,836	9,667	9,859
2010	12,647	9,472	8,887
2011	7,855	9,113	7,991
Average	**9,743**	**10,499**	**9,163**

The number of deaths assuming sex ratio equal to incidences (Table 4-10) (refer to limitation of study) results are shown in Table 4-12, 4-13.

Table 4-14 The number of male deaths under climate condition (persons)

Years	Climate baseline (Current)	A2	B2
2003	22	28	23
2004	28	36	23
2005	48	59	45
2006	37	39	39
2007	26	29	28
2008	26	28	23
2009	16	16	16
2010	32	24	22
2011	8	9	8
Average	**27**	**30**	**25**

Table 4-15 The number of female deaths under climate condition (persons)

Years	Climate baseline (Current)	A2	B2
2003	11	14	11
2004	15	19	12
2005	27	33	25
2006	18	19	19
2007	14	15	15
2008	13	15	12
2009	8	8	8
2010	17	13	12
2011	4	5	4
Average	**14**	**16**	**13**

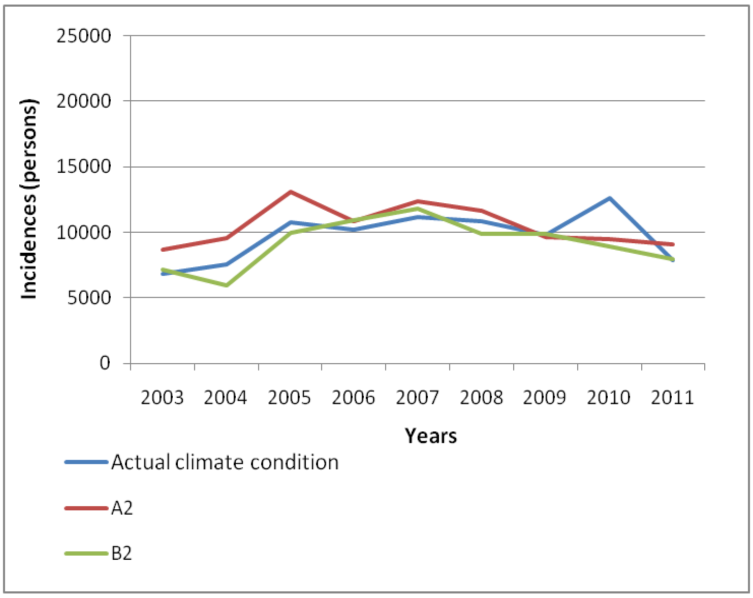

Figure 4-16 Comparison of malaria incidence under climate scenarios (females)

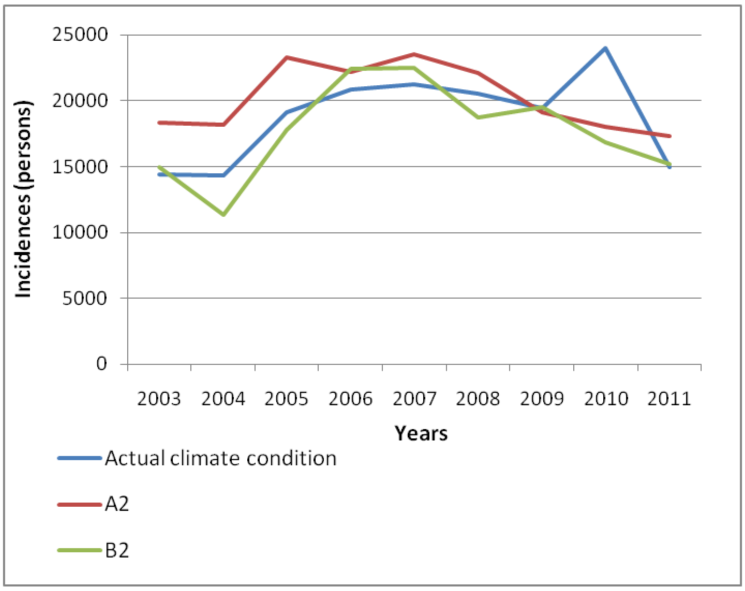

Figure 4-17 Comparison of malaria incidence under climate scenarios (males)

The results were shown with the number of cases and deaths by sex, then next step is to identify the incidences were divided according to the three types of malaria type Episodes, Neurological sequelae in 0-4 years old and Anaemia by use ratio from Table 4-11

Example

Incidence of males under climate baseline 2003 is 14,397 persons. Therefore, from Table 4-9 proportions of episodes in a number of cases of each type are as follows.

Episodes

= 14,397 persons

Neurological sequelae (treated) in 0-4 years old

= 0.00134 × Episodes

= 0.00134 × 14,397 persons

= 19 persons

Anaemia

= 0.12048 × 14,397

= 1,735 persons

The results of classification of malaria incidences are shown in Table 4-14 and 4-15. The table shows the incidences numbers each under climate conditions.

Table 4-16 Classification of malaria incidences 2003-2011 (males)

Years	Episodes			Anaemia			Neurological sequelae		
	Climate baseline	A2	B2	Climate baseline	A2	B2	Climate baseline	A2	B2
2003	14,397	18,303	14,980	1,735	2,205	1,805	19	25	20
2004	14,342	18,173	11,340	1,728	2,189	1,366	19	24	15
2005	19,150	23,308	17,780	2,307	2,808	2,142	26	31	24
2006	20,861	22,198	22,421	2,513	2,674	2,701	28	30	30
2007	21,263	23,536	22,503	2,562	2,836	2,711	28	32	30
2008	20,556	22,139	18,736	2,477	2,667	2,257	28	30	25
2009	19,475	19,141	19,521	2,346	2,306	2,352	26	26	26
2010	24,029	17,996	16,885	2,895	2,168	2,034	32	24	23
2011	14,924	17,314	15,183	1,798	2,086	1,829	20	23	20
Average	18,778	20,234	17,706	2,262	2,438	2,133	25	27	24

Table 4-17 Classification of malaria incidences 2003-2011 (females)

Years	Episodes			Anaemia			Neurological sequelae		
	Climate baseline	A2	B2	Climate baseline	A2	B2	Climate baseline	A2	B2
2003	6,856	8,716	7,133	826	1,050	859	9	12	10
2004	7,548	9,565	5,968	909	1,152	719	10	13	8
2005	10,758	13,095	9,989	1,296	1,578	1,203	14	18	13
2006	10,176	10,828	10,937	1,226	1,305	1,318	14	15	15
2007	11,191	12,387	11,844	1,348	1,492	1,427	15	17	16
2008	10,819	11,652	9,861	1,303	1,404	1,188	14	16	13
2009	9,836	9,667	9,859	1,185	1,165	1,188	13	13	13
2010	12,647	9,472	8,887	1,524	1,141	1,071	17	13	12
2011	7,855	9,113	7,991	946	1,098	963	11	12	11
Average	9,743	10,499	9,163	1,174	1,265	1,104	13	14	12

The classification malaria incidences has been identified, Next step is to find the proportion of incidences with both male and female in each age specific by collecting data from the National surveillance reports, Thailand, and transformed into age-specific WHO calculation format. This is shown in Table 4-12 and 4-13 (WHO age group format).

Table 4-18 Proportion of malaria incidences in each age (WHO format)

Year	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**Average**
Age	Proportion	Proportion	Proportion	Proportion	Proportion	Proportion	Proportion	Proportion	Proportion	Proportion
0-4	0.05	0.06	0.07	0.07	0.06	0.07	0.07	0.07	0.08	0.067
5-14	0.19	0.20	0.22	0.20	0.21	0.22	0.23	0.23	0.25	0.218
15-29	0.31	0.31	0.31	0.31	0.31	0.31	0.30	0.29	0.29	0.303
30-44	0.27	0.24	0.23	0.25	0.24	0.23	0.23	0.22	0.21	0.236
45-59	0.12	0.11	0.10	0.11	0.11	0.11	0.11	0.12	0.11	0.112
60-69	0.04	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.04	0.046
70-79	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.009
80+	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.009
Total	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**

Table 4-19 Proportion of deaths in each age (WHO format)

Years	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**Average**
Age	Proportion	Proportion	Proportion	Proportion	Proportion	Proportion	Proportion	Proportion	Proportion	Proportion
0	0.03	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.008
1-4	0.00	0.04	0.06	0.06	0.00	0.03	0.00	0.03	0.00	0.024
5-9	0.10	0.04	0.06	0.00	0.05	0.03	0.05	0.00	0.09	0.047
10-14	0.03	0.04	0.06	0.08	0.03	0.06	0.00	0.06	0.00	0.039
15-19	0.15	0.11	0.07	0.10	0.11	0.07	0.21	0.07	0.05	0.103
20-24	0.15	0.11	0.07	0.10	0.11	0.07	0.21	0.07	0.05	0.103
25-29	0.08	0.10	0.07	0.06	0.04	0.07	0.00	0.04	0.05	0.056
30-34	0.08	0.10	0.07	0.06	0.04	0.07	0.00	0.04	0.05	0.056
35-39	0.05	0.11	0.10	0.11	0.12	0.13	0.08	0.07	0.09	0.094
40-44	0.05	0.11	0.10	0.11	0.12	0.13	0.08	0.07	0.09	0.094
45-49	0.06	0.03	0.05	0.08	0.09	0.08	0.11	0.16	0.14	0.089
50-54	0.06	0.03	0.05	0.08	0.09	0.08	0.11	0.16	0.14	0.089
55-59	0.03	0.04	0.03	0.04	0.04	0.03	0.05	0.04	0.09	0.044
60-64	0.03	0.04	0.03	0.04	0.04	0.03	0.05	0.04	0.09	0.044
65-69	0.02	0.02	0.04	0.02	0.03	0.03	0.01	0.02	0.02	0.022
70-74	0.02	0.02	0.04	0.02	0.03	0.03	0.01	0.02	0.02	0.022

75-79	0.02	0.02	0.04	0.02	0.03	0.03	0.01	0.02	0.02	0.022
80-84	0.02	0.02	0.04	0.02	0.03	0.03	0.01	0.02	0.02	0.022
85+	0.02	0.02	0.04	0.02	0.03	0.03	0.01	0.02	0.02	0.022
Total	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**

The study was found an age group 15-29 years has the highest proportion of patients (31%) then the next step is to calculate burden of diseases (DALYs) under climate scenarios, by input data from classification of malaria incidences (refer to Table 4-15, 4-16) and transform to the age groups by proportion (refer to Table 4-17, 4-18) and DALYs calculation components (refer to Table 4-9) input on WHO DALYs calculation worksheet (Refer to WHO DALYs worksheet). The results are shown in Table 4-19.

Table 4-20 Results of converted DALYs under climate scenarios

Years	Real Climate	A2	B2	A2-real climate model (%)	B2-Real climate model (%)
2003	1,175.65	1,279.83	1,191.22	8.86	1.32
2004	1,433.71	1,816.68	1,133.57	26.71	-20.93
2005	2,197.45	2,701.15	2,060.51	22.92	-6.23
2006	1,820.49	1,937.15	1,956.55	6.41	7.47
2007	1,468.39	1,625.35	1,553.99	10.69	5.83
2008	1,435.96	1,546.49	1,308.82	7.70	-8.85
2009	1,095.24	1,086.15	1,097.83	-0.83	0.24
2010	1,712.81	1,282.78	1,203.61	-25.11	-29.73
2011	664.87	771.36	676.43	16.02	1.74
AVERAGE	**1,444.95**	**1,560.77**	**1,353.61**	**8.02**	**-6.32**
TOTAL	**13,004.57**	**14,046.94**	**12,182.52**	**8.02**	**-6.32**

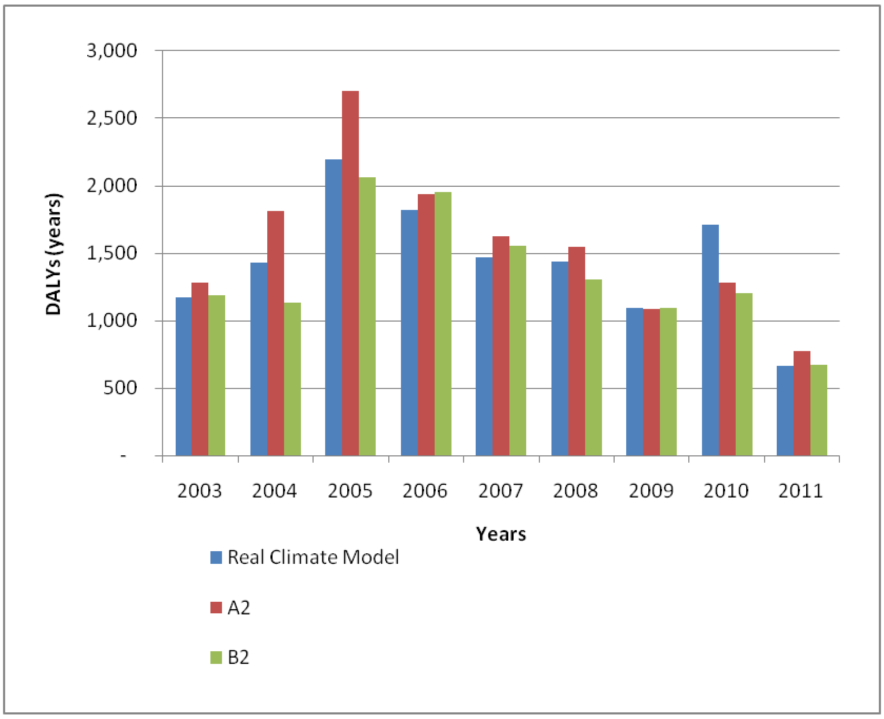

Figure 4-18 DALYs of Malaria in Thailand (2003-2011)

The study was found average impact of baseline 2003-2011 = 1,444.95 DALYs/year, A2 = 1,560.77 DALYs/year and B2 = 1,353.61 DALYs/year, therefore the results were concluded that A2 has increased 8.02% from baseline, and B2 can avoid burden 6.32% from baseline

4.6 Predict climate change impact in 2012-2020

The prediction 2012 - 2020 due to unknown proportion of future, the research was used the average malaria proportion of males to females (refer to Table 4-10), which collected data from the Bureau of Epidemiology in Thailand, assuming no change or proportion of the incidence and mortality rate = 1, because limitation of study in this research.

Table 4-21 Results of future prediction (2012-2020) converted DALYs under climate scenarios

Years	Current Emission	A2	B2	A2 difference	% difference	B2 difference	% difference
2012	2151.2	1936.7	1524.9	214.6	10.0	626.4	29.1
2013	2799.5	3317.6	2241.4	-518.1	-18.5	558.1	19.9
2014	2983.5	3793.9	2404.5	-810.4	-27.2	579.0	19.4
2015	3042.0	4552.8	2585.6	-1510.7	-49.7	456.4	15.0
2016	3060.7	4066.0	3324.0	-1005.4	-32.8	-263.3	-8.6
2017	3066.6	3858.2	1625.1	-791.6	-25.8	1441.5	47.0
2018	3068.5	4771.4	1278.7	-1702.9	-55.5	1789.8	58.3
2019	3069.1	5165.5	1962.5	-2096.4	-68.3	1106.6	36.1
2020	3069.3	4923.9	1438.6	-1854.7	-60.4	1630.7	53.1
AVERAGE	2923.4	4042.9	2042.8	-1119.5	-38.3	880.6	30.1
TOTAL	26310.3	36386.0	18385.1	-10075.7	-38.3	7925.2	30.1

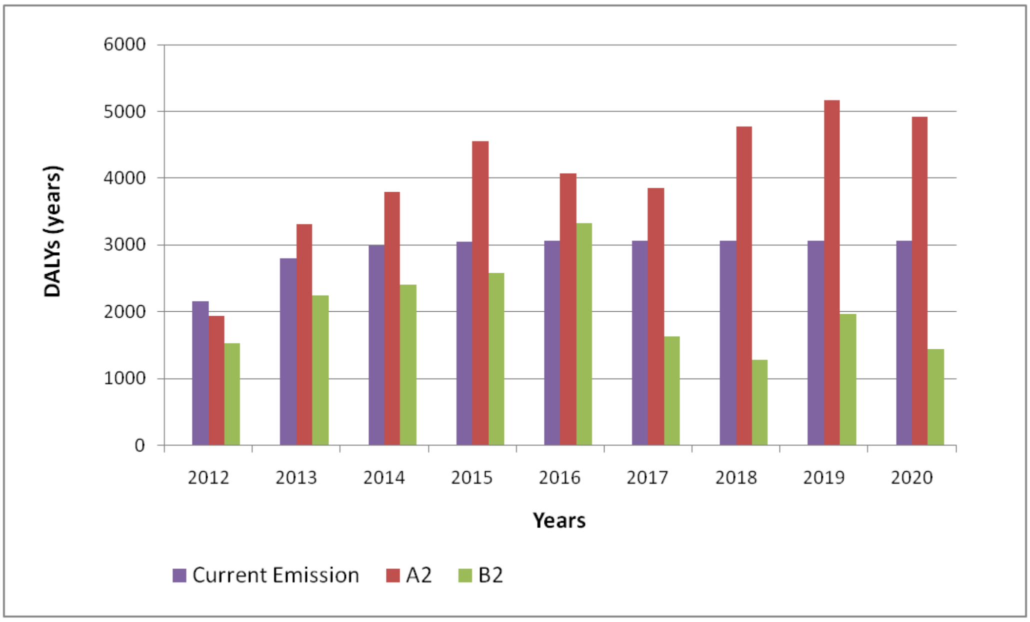

Figure 4-19 DALYs of Malaria in Thailand 2012-2020

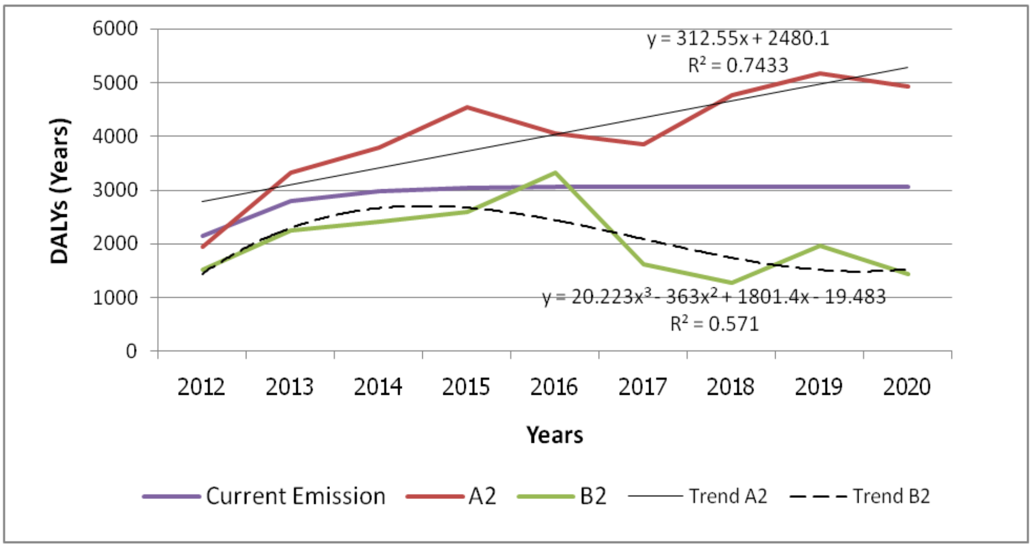

Figure 4-20 DALYs of Malaria in Thailand (2) 2012-2020

The study found that the burden of diseases was highest in climate change scenario A2 2019 equal to 4,965.42 DALYs. The lowest DALY was found in climate change scenario B2 2018 equal to 1,229.14 DALY. The climate change scenario A2 had increasing continuous trend with trend line equation Y = 312.55X + 2480.1, R^2 = 0.74., The climate change scenarios B2 had a decreasing trend with trend line equation Y = $20.223X^3 - 363X^2 + 1801.4$ X – 19.483, R^2 = 0.57. However the average avoidable burden of diseases from climate change scenario B2 equal to 1,916.07 DALYs per year (A2 = 3,886.30 DALYs per year, B2 = 1970.23 DALYs per year).

The climate change scenarios B2 has avoidable burden of climate change scenario A2 up to 49.3%. The environmental policy is important to reduce the possible impact of climate change, although climate factors would affect the incidence of malaria disease entirely however malaria caused by many factors, factor of population migration, water management in the watershed area, typical of tropical rain forest, knowledge of climate change on infectious diseases affecting people in the area.

The study found climate change scenarios B2, A scenario family describes a world in which the emphasis is on local solutions to economic, social, and environmental sustainability can avoid burden of climate change scenario A2 which in high population growth up and technological change are more fragmented and slower than in other storylines to 49.3%. However, malaria is a disease that is caused by many factors not only climate factor (Zhou, 2003). There is also a factor in the migration, water management in the watershed area, knowledge of climate change impact. Appropriate policy environment for reduced greenhouse gases emission close to environmental sustainability is essential to reduce the burden of the country.

CHAPTER V
CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

The objectives of study are estimate the avoidable burden of diseases of malaria by using a nonlinear regression technique to estimate the incidence under climate change scenarios, the study found that climate change is related to the incidences that forecasts of malaria by study of the factors Time lag period or $\tau > 0$ the factors as follows: T max, T min and Wind speed have lag period (Months) equal to 2 (R = 0.427), 1 (R. = 0.297) and 5 (R = 0.282) months.

The study shows Model 2 is the best fitting result with adjusted R-Square 0.818 minimum RMSE = 763.27 and model 1 with adjusted R-Square 0.821 and RMSE = 767.24. Both models are adapted by non linear mixed-regression technique, only model 2 used interactions of climate variables meanwhile model 1 only use climate variables at max lag period (τ_{max}). As a result the model 2 shows potential better prediction than model 1. Model 2 show decreasing incidence under climate scenarios B2. Incidences of 2004 decreased 21% 2005 15.7% 2008 8.9% Year 2010 29.8% decreasing and increasing in 2003 to 4.05%. 2006 07.05% 2007 09.05% 2009 0.24% 2011 1.74%, and for some year the number is increasing because there are no input other factors involved with the topography, habitats, social factors and deforestation.

In 2003 under climate scenarios A2 the regionally economic development. The incidence of the disease increased by 01.27% 2004 26.71% 2005 21.72% 2006 6.41% 2007 10.69% 2008 07.07%. 2011, 16.2%, and the number decreased in 2009 and 2011, 1.71% and 25.1%, respectively. The study found that up to 7 years from 9 years have an increasing the number of patients. Only 2009-2010 incidence were decreased because in the incidence of malaria is due to other factors like topography and social factors that are not taken into the study. However as the years 2003-2011 malaria incidence under climate scenarios A2 Climate baseline increases were 7.8% and a higher than climate scenarios B2 the local environmental sustainability 13.6%.

The test model used to forecast 20120 2020 was found climate scenario A2 cause increasing malaria incidence trends from 2012 to 2020, with the increasing rate steadily 2012 to 2020, the average equal to 79,703 person/year and climate scenario B2 will cause a decrease in malaria incidence rates of A2 2012-2020 40,407 person/year (decrease 49.3% per year from A2)

The converted incidence to DALYs process from WHO Environmental Burden of Disease Series, No. 14 for international comparison. DALYs provide by the climate data condition in each type the climate Scenarios A2 cause disease burden of malaria years 2003-2011 increasing of 8% or 981 DALYs increasing of real climate data. Climate Scenarios B2 and the burden of malaria disease in 2003-2011 decreasing 6.5% or 815 DALYs from actual climate which reduced significantly. Prediction in the future was found highest DALY score is equal to 4,965.42 DALY under climate change scenario A2 in 2019 and climate scenario B2 has the lowest DALY is equal to 1,229.14 DALY in 2018. The scenario A2 had increasing continuous trend with trend line equation $Y = 312.55X + 2480.1$, $R^2 = 0.74$., the climate change scenarios B2 had a decreasing trend with trend line equation $Y = 20.223X^3 – 363X^2 + 1801.4 X – 19.483$, $R^2 = 0.57$.

5.2 Recommendations

1. The climate and malaria incidence data are not enough to analyze the long-term. The statistical model was limitation.

2. Climate - health model for malaria in this study is statistical model which is statistically correlated. The future research should using biological model by laboratory data to define the relationship between meteorological factors for diverse result (Kearney, 2009).

3. Analysis or prediction by using spatial modeling using GIS (Geographic Information System) took the ability to analyze the terrain and malaria distribution.

4. Climate change may affect health through a range of pathways not only changes in Malaria diseases but also other vector-borne diseases, flooding and drought, heat waves may affect.

6. Addition or appropriated climate scenarios in Thailand are required for analysis for more diverse results.

7. The other factor such as average temperatures, migration, population density should be used in future research.

8. The lag period in this study, using monthly data. Next research should be used daily lag period in the analysis for more diverse results.

9. Malaria incidences data used on this study are reported to the surveillance system, the participation of the provincial public hospitals and health facilities (hospitals, government facilities. Private hospitals are not covered). Surveillance report 506 data are known or suspected to be under-reported.

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APPENDICES

APPENDIX A

SPSS

Prepare data and analyses

20 years malaria Complete lag.sav [DataSet2] - SPSS Data Editor

File Edit View Data Transform Analyze Graphs Utilities Window Help

1 : Years 1991

	MinTlag1	MintLag2	MintLag3	Mintlag4	Rain	Rainlag1	Rainlag2	Rainlag3	RainLag4	RH	RH1	RH2
1	18.85	21.51	23.28	23.90	10.00	24.57	95.86	241.01	234.32	69.87	71.00	75.53
2	19.83	18.85	21.51	23.28	10.31	10.00	24.57	95.86	241.01	64.82	69.87	71.00
3	19.75	19.83	18.85	21.51	34.12	10.31	10.00	24.57	95.86	65.63	64.82	69.87
4	23.36	19.75	19.83	18.85	66.91	34.12	10.31	10.00	24.57	66.97	65.63	64.82
5	24.60	23.36	19.75	19.83	178.16	66.91	34.12	10.31	10.00	73.05	66.97	65.63
6	24.76	24.60	23.36	19.75	148.16	178.16	66.91	34.12	10.31	76.79	73.05	66.97
7	24.75	24.76	24.60	23.36	178.92	148.16	178.16	66.91	34.12	77.27	76.79	73.05
8	24.49	24.75	24.76	24.60	275.53	178.92	148.16	178.16	66.91	80.28	77.27	76.79
9	24.18	24.49	24.75	24.76	238.59	275.53	178.92	148.16	178.16	80.60	80.28	77.27
10	24.20	24.18	24.49	24.75	157.03	238.59	275.53	178.92	148.16	79.86	80.60	80.28
11	22.96	24.20	24.18	24.49	52.81	157.03	238.59	275.53	178.92	73.69	79.86	80.60
12	20.34	22.96	24.20	24.18	56.30	52.81	157.03	238.59	275.53	71.72	73.69	79.86
13	19.25	20.34	22.96	24.20	23.28	56.30	52.81	157.03	238.59	71.43	71.72	73.69
14	18.17	19.25	20.34	22.96	26.07	23.28	56.30	52.81	157.03	67.97	71.43	71.72
15	19.48	18.17	19.25	20.34	4.16	26.07	23.28	56.30	52.81	63.48	67.97	71.43
16	22.01	19.48	18.17	19.25	28.36	4.16	26.07	23.28	56.30	62.07	63.48	67.97
17	24.74	22.01	19.48	18.17	99.48	28.36	4.16	26.07	23.28	68.39	62.07	63.48
18	25.10	24.74	22.01	19.48	161.95	99.48	28.36	4.16	26.07	75.44	68.39	62.07
19	24.75	25.10	24.74	22.01	227.20	161.95	99.48	28.36	4.16	77.25	75.44	68.39
20	24.06	24.75	25.10	24.74	235.14	227.20	161.95	99.48	28.36	78.97	77.25	75.44
21	24.07	24.06	24.75	25.10	197.00	235.14	227.20	161.95	99.48	78.87	78.97	77.25
22	23.81	24.07	24.06	24.75	214.24	197.00	235.14	227.20	161.95	79.49	78.87	78.97
23	22.27	23.81	24.07	24.06	65.25	214.24	197.00	235.14	227.20	72.91	79.49	78.87
24	19.66	22.27	23.81	24.07	59.98	65.25	214.24	197.00	235.14	72.08	72.91	79.49
25	18.50	19.66	22.27	23.81	26.19	59.98	65.25	214.24	197.00	70.38	72.08	72.91
26	18.61	18.50	19.66	22.27	4.17	26.19	59.98	65.25	214.24	65.94	70.38	72.08

*20 years malaria Complete lag.sav [DataSet2] - SPSS Data Editor

File Edit View Data Transform Analyze Graphs Utilities Window Help

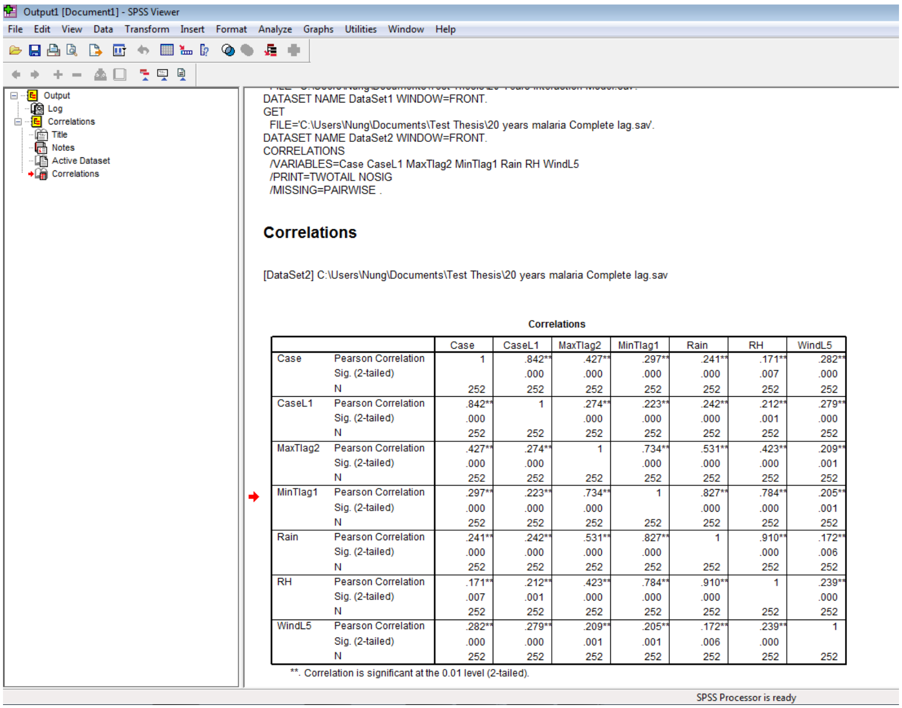
18 : WindL8 1.438356164 Visible: 69 of 69 Variables

	RH1	RH2	RH3	RH4	Wind	WindL1	WindL2	WindL3	WindL4	WindL5	WindL6	WindL7	WindL8	WindL9	WindL10	Case	CaseL1	CaseL2	CaseL3
1	71.00	75.53	79.79	79.49	1.76164	2.3247	2.0589	1.9219	1.8932	2.90	2.52	2.85	2.05	2.60	2.47	8102	9264.00	8541.00	7522.00
2	69.87	71.00	75.53	79.79	2.14932	1.7616	2.3247	2.0589	1.9219	1.89	2.90	2.52	2.85	2.05	2.60	5722	8102.00	9264.00	8541.00
3	64.82	69.87	71.00	75.53	2.58219	2.1493	1.7616	2.3247	2.0589	1.92	1.89	2.90	2.52	2.85	2.05	5700	5722.00	8102.00	9264.00
4	65.63	64.82	69.87	71.00	2.47808	2.5822	2.1493	1.7616	2.3247	2.06	1.92	1.89	2.90	2.52	2.85	5758	5700.00	5722.00	8102.00
5	66.97	65.63	64.82	69.87	1.86986	2.4781	2.5822	2.1493	1.7616	2.32	2.06	1.92	1.89	2.90	2.52	8120	5758.00	5700.00	5722.00
6	73.05	66.97	65.63	64.82	2.53562	1.8699	2.4781	2.5822	2.1493	1.76	2.32	2.06	1.92	1.89	2.90	10798	8120.00	5758.00	5700.00
7	76.79	73.05	66.97	65.63	2.57260	2.5356	1.8699	2.4781	2.5822	2.15	1.76	2.32	2.06	1.92	1.89	9157	10798.00	8120.00	5758.00
8	77.27	76.79	73.05	66.97	2.59452	2.5726	2.5356	1.8699	2.4781	2.58	2.15	1.76	2.32	2.06	1.92	6558	9157.00	10798.00	8120.00
9	80.28	77.27	76.79	73.05	1.72055	2.5945	2.5726	2.5356	1.8699	2.48	2.58	2.15	1.76	2.32	2.06	6701	6558.00	9157.00	10798.00
10	80.60	80.28	77.27	76.79	1.43836	1.7205	2.5945	2.5726	2.5356	1.87	2.48	2.58	2.15	1.76	2.32	8107	6701.00	6558.00	9157.00
11	79.86	80.60	80.28	77.27	2.06164	1.4384	1.7205	2.5945	2.5726	2.54	1.87	2.48	2.58	2.15	1.76	6876	8107.00	6701.00	6558.00
12	73.69	79.86	80.60	80.28	2.30548	2.0616	1.4384	1.7205	2.5945	2.57	2.54	1.87	2.48	2.58	2.15	6668	6876.00	8107.00	6701.00
13	71.72	73.69	79.86	80.60	2.11233	2.3055	2.0616	1.4384	1.7205	2.59	2.57	2.54	1.87	2.48	2.58	4968	6668.00	6876.00	8107.00
14	71.43	71.72	73.69	79.86	2.26575	2.1123	2.3055	2.0616	1.4384	1.72	2.59	2.57	2.54	1.87	2.48	4291	4968.00	6668.00	6876.00
15	67.97	71.43	71.72	73.69	2.43288	2.2658	2.1123	2.3055	2.0616	1.44	1.72	2.59	2.57	2.54	1.87	5287	4291.00	4968.00	6668.00
16	63.48	67.97	71.43	71.72	2.63151	2.4329	2.2658	2.1123	2.3055	2.06	1.44	1.72	2.59	2.57	2.54	4668	5287.00	4291.00	4968.00
17	62.07	63.48	67.97	71.43	2.31507	2.6315	2.4329	2.2658	2.1123	2.31	2.06	1.44	1.72	2.59	2.57	5649	4668.00	5287.00	4291.00
18	68.39	62.07	63.48	67.97	2.40959	2.3151	2.6315	2.4329	2.2658	2.11	2.31	2.06	1.44	1.72	2.59	9632	5649.00	4668.00	5287.00
19	75.44	68.39	62.07	63.48	2.07534	2.4096	2.3151	2.6315	2.4329	2.27	2.11	2.31	2.06	1.44	1.72	9784	9632.00	5649.00	4668.00
20	77.25	75.44	68.39	62.07	2.33836	2.0753	2.4096	2.3151	2.6315	2.43	2.27	2.11	2.31	2.06	1.44	7869	9784.00	9632.00	5649.00
21	78.97	77.25	75.44	68.39	1.89315	2.3384	2.0753	2.4096	2.3151	2.63	2.43	2.27	2.11	2.31	2.06	6453	7869.00	9784.00	9632.00
22	78.87	78.97	77.25	75.44	1.72740	1.8932	2.3384	2.0753	2.4096	2.32	2.63	2.43	2.27	2.11	2.31	6348	6453.00	7869.00	9784.00
23	79.49	78.87	78.97	77.25	2.51644	1.7274	1.8932	2.3384	2.0753	2.41	2.32	2.63	2.43	2.27	2.11	6177	6348.00	6453.00	7869.00
24	72.91	79.49	78.87	78.97	1.96301	2.5164	1.7274	1.8932	2.3384	2.08	2.41	2.32	2.63	2.43	2.27	6601	6177.00	6348.00	6453.00
25	72.08	72.91	79.49	78.87	2.10137	1.9630	2.5164	1.7274	1.8932	2.34	2.08	2.41	2.32	2.63	2.43	6407	6601.00	6177.00	6348.00
26	70.38	72.08	72.91	79.49	2.08904	2.1014	1.9630	2.5164	1.7274	1.89	2.34	2.08	2.41	2.32	2.63	3621	6407.00	6601.00	6177.00
27	65.94	70.38	72.08	72.91	2.22055	2.0890	2.1014	1.9630	2.5164	1.73	1.89	2.34	2.08	2.41	2.32	3504	3621.00	6407.00	6601.00
28	68.91	65.94	70.38	72.08	2.07397	2.2205	2.0890	2.1014	1.9630	2.52	1.73	1.89	2.34	2.08	2.41	4311	3504.00	3621.00	6407.00
29	69.37	68.91	65.94	70.38	1.92192	2.0740	2.2205	2.0890	2.1014	1.96	2.52	1.73	1.89	2.34	2.08	6665	4311.00	3504.00	3621.00
30	73.66	69.37	68.91	65.94	2.19041	1.9219	2.0740	2.2205	2.0890	2.10	1.96	2.52	1.73	1.89	2.34	7483	6665.00	4311.00	3504.00
31	75.27	73.66	69.37	68.91	2.53151	2.1904	1.9219	2.0740	2.2205	2.09	2.10	1.96	2.52	1.73	1.89	5881	7483.00	6665.00	4311.00
32	75.61	75.27	73.66	69.37	2.39315	2.5315	2.1904	1.9219	2.0740	2.22	2.09	2.10	1.96	2.52	1.73	5665	5881.00	7483.00	6665.00
33	78.33	75.61	75.27	73.66	1.53973	2.3932	2.5315	2.1904	1.9219	2.07	2.22	2.09	2.10	1.96	2.52	5248	5665.00	5881.00	7483.00
34	80.67	78.33	75.61	75.27	1.59315	1.5397	2.3932	2.5315	2.1904	1.92	2.07	2.22	2.09	2.10	1.96	6808	5248.00	5665.00	5881.00
35	78.32	80.67	78.33	75.61	1.76986	1.5932	1.5397	2.3932	2.5315	2.19	1.92	2.07	2.22	2.09	2.10	6860	6808.00	5248.00	5665.00
36	72.23	78.32	80.67	78.33	2.62740	1.7699	1.5932	1.5397	2.3932	2.53	2.19	1.92	2.07	2.22	2.09	7675	6860.00	6808.00	5248.00
37	68.20	72.23	78.32	80.67	1.67397	2.6274	1.7699	1.5932	1.5397	2.39	2.53	2.19	1.92	2.07	2.22	4838	7675.00	6860.00	6808.00

Data View Variable View

SPSS Processor is ready

Correlation analyses



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DATASET NAME DataSet1 WINDOW=FRONT.
GET
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DATASET NAME DataSet2 WINDOW=FRONT.
CORRELATIONS
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  /PRINT=TWOTAIL NOSIG
  /MISSING=PAIRWISE .
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Correlations

[DataSet2] C:\Users\Nung\Documents\Test Thesis\20 years malaria Complete lag.sav

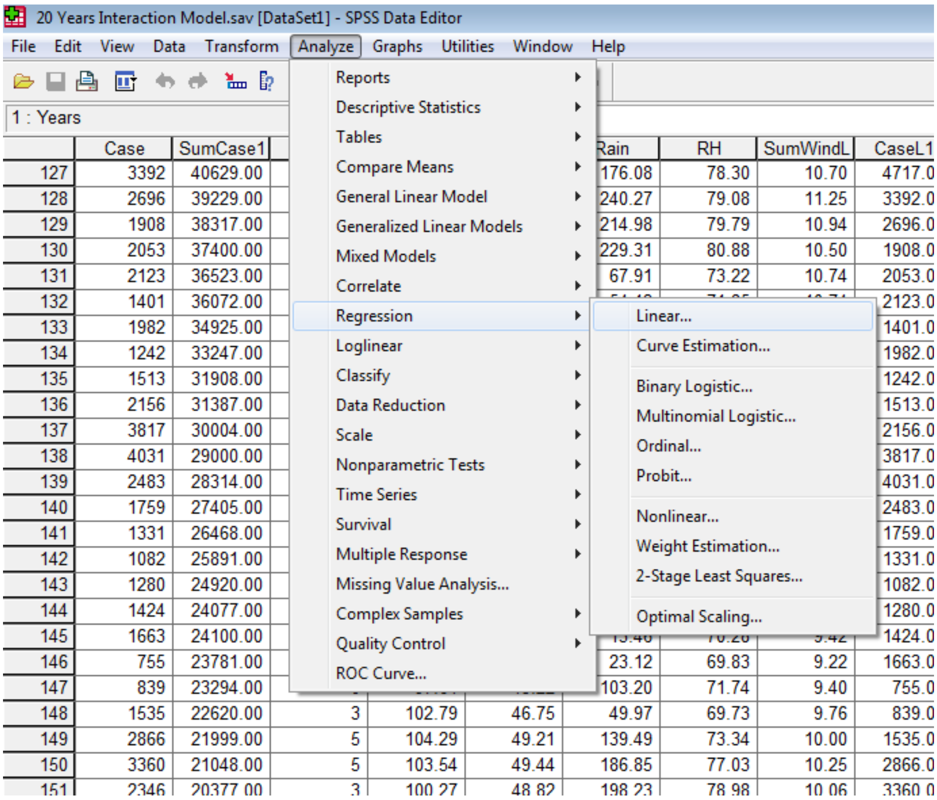
Correlations

		Case	CaseL1	MaxTlag2	MinTlag1	Rain	RH	WindL5
Case	Pearson Correlation	1	.842**	.427**	.297**	.241**	.171**	.282**
	Sig. (2-tailed)		.000	.000	.000	.000	.007	.000
	N	252	252	252	252	252	252	252
CaseL1	Pearson Correlation	.842**	1	.274**	.223**	.242**	.212**	.279**
	Sig. (2-tailed)	.000		.000	.000	.000	.001	.000
	N	252	252	252	252	252	252	252
MaxTlag2	Pearson Correlation	.427**	.274**	1	.734**	.531**	.423**	.209**
	Sig. (2-tailed)	.000	.000		.000	.000	.000	.001
	N	252	252	252	252	252	252	252
MinTlag1	Pearson Correlation	.297**	.223**	.734**	1	.827**	.784**	.205**
	Sig. (2-tailed)	.000	.000	.000		.000	.000	.001
	N	252	252	252	252	252	252	252
Rain	Pearson Correlation	.241**	.242**	.531**	.827**	1	.910**	.172**
	Sig. (2-tailed)	.000	.000	.000	.000		.000	.006
	N	252	252	252	252	252	252	252
RH	Pearson Correlation	.171**	.212**	.423**	.784**	.910**	1	.239**
	Sig. (2-tailed)	.007	.001	.000	.000	.000		.000
	N	252	252	252	252	252	252	252
WindL5	Pearson Correlation	.282**	.279**	.209**	.205**	.172**	.239**	1
	Sig. (2-tailed)	.000	.000	.001	.001	.006	.000	
	N	252	252	252	252	252	252	252

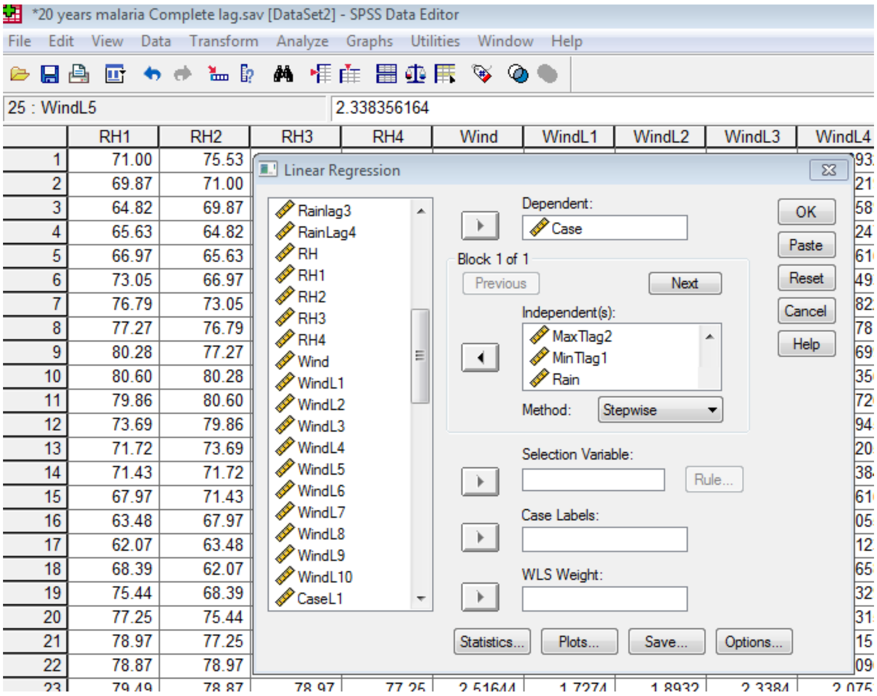
**. Correlation is significant at the 0.01 level (2-tailed).

Create model

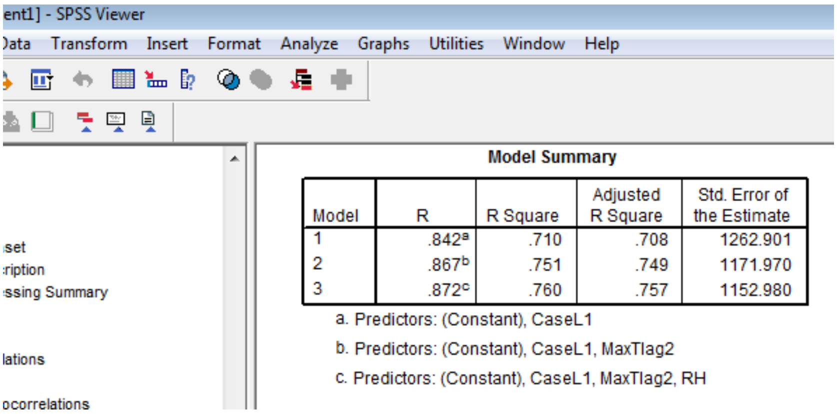
- Regression analyses



- Selected variables



Sample model output


Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.842a	.710	.708	1262.901
2	.867b	.751	.749	1171.970
3	.872c	.760	.757	1152.980

a. Predictors: (Constant), CaseL1

b. Predictors: (Constant), CaseL1, MaxTlag2

c. Predictors: (Constant), CaseL1, MaxTlag2, RH

APPENDIX B
MODELS OUTPUT

Comparison of model and actual incidences (monthly)

Month/Year	Actual incidence	Model A	Model B	Difference Model A-Actual	Difference Model B-Actual
Jan-03	1,663	2,485.67	1,327.34	822.67	-335.66
Feb-03	755	1,680.92	1,814.13	925.92	1,059.13
Mar-03	839	1,642.17	1,564.16	803.17	725.16
Apr-03	1,535	1,943.80	1,671.70	408.80	136.70
May-03	2,866	2,826.32	2,526.75	-39.68	-339.25
Jun-03	3,360	3,848.52	3,471.19	488.52	111.19
Jul-03	2,346	3,136.37	2,933.14	790.37	587.14
Aug-03	1,541	1,344.37	1,444.04	-196.63	-96.96
Sep-03	1,227	1,205.38	1,463.18	-21.62	236.18
Oct-03	1,168	1,177.10	1,269.28	9.10	101.28
Nov-03	1,438	1,213.76	971.24	-224.24	-466.76
Dec-03	1,172	1,325.81	795.97	153.81	-376.03
Jan-04	1,319	846.66	1,220.53	-472.34	-98.47
Feb-04	1,108	1,268.72	1,136.85	160.72	28.85
Mar-04	1,102	982.04	1,041.64	-119.96	-60.36
Apr-04	1,806	1,863.52	1,837.19	57.52	31.19
May-04	4,219	3,689.55	3,739.16	-529.45	-479.84
Jun-04	4,521	5,091.93	4,643.50	570.93	122.50
Jul-04	2,563	3,822.88	3,474.60	1,259.88	911.60
Aug-04	1,831	1,314.75	1,401.81	-516.25	-429.19
Sep-04	1,420	1,276.37	1,385.91	-143.63	-34.09
Oct-04	1,273	777.59	697.01	-495.41	-575.99
Nov-04	1,410	745.56	790.57	-664.44	-619.43
Dec-04	1,084	1,313.79	521.71	229.79	-562.29

Month/Year	Actual incidence	Model A	Model B	Difference Model A-Actual	Difference Model B-Actual
Jan-05	981	282.38	798.12	-698.62	-182.88
Feb-05	941	503.60	835.71	-437.40	-105.29
Mar-05	1,164	1,649.07	1,397.31	485.07	233.31
Apr-05	2,326	2,415.71	2,556.70	89.71	230.70
May-05	5,137	3,682.83	3,554.93	-1,454.17	-1,582.07
Jun-05	5,713	6,016.97	5,835.32	303.97	122.32
Jul-05	2,717	5,438.17	5,166.97	2,721.17	2,449.97
Aug-05	2,118	1,919.35	1,978.86	-198.65	-139.14
Sep-05	1,754	1,716.85	1,980.28	-37.15	226.28
Oct-05	1,802	1,704.15	1,825.62	-97.85	23.62
Nov-05	1,870	2,426.72	2,417.58	556.72	547.58
Dec-05	1,608	2,600.98	1,560.96	992.98	-47.04
Jan-06	1,695	1,577.76	1,051.58	-117.24	-643.42
Feb-06	1,261	1,142.27	1,563.96	-118.73	302.96
Mar-06	1,629	2,291.71	2,088.63	662.71	459.63
Apr-06	2,677	3,240.64	3,110.71	563.64	433.71
May-06	4,827	4,496.58	4,271.31	-330.42	-555.69
Jun-06	3,599	5,083.47	4,709.17	1,484.47	1,110.17
Jul-06	3,226	3,205.26	2,997.94	-20.74	-228.06
Aug-06	2,353	2,573.26	2,379.25	220.26	26.25
Sep-06	2,049	1,794.21	2,005.69	-254.79	-43.31
Oct-06	1,863	2,021.81	2,402.25	158.81	539.25
Nov-06	2,144	2,243.17	2,362.18	99.17	218.18
Dec-06	1,639	2,413.96	2,095.12	774.96	456.12
Jan-07	1,636	1,565.62	1,477.98	-70.38	-158.02
Feb-07	1,014	1,225.06	1,234.18	211.06	220.18
Mar-07	1,927	1,077.79	1,657.33	-849.21	-269.67
Apr-07	3,487	3,207.89	3,341.13	-279.11	-145.87
May-07	7,087	5,542.68	5,644.60	-1,544.32	-1,442.40
Jun-07	4,993	7,494.91	7,299.06	2,501.91	2,306.06

Month/Year	Actual incidence	Model A	Model B	Difference Model A-Actual	Difference Model B-Actual
Jul-07	2,975	4,457.26	4,257.86	1,482.26	1,282.86
Aug-07	2,144	2,279.07	2,389.69	135.07	245.69
Sep-07	1,579	1,779.82	2,092.96	200.82	513.96
Oct-07	1,669	1,391.65	1,008.53	-277.35	-660.47
Nov-07	1,490	1,127.83	862.33	-362.17	-627.67
Dec-07	888	1,049.66	1,188.85	161.66	300.85
Jan-08	1,788	1,019.42	1,025.75	-768.58	-762.25
Feb-08	1,638	2,078.55	2,122.65	440.55	484.65
Mar-08	1,723	1,932.72	1,868.70	209.72	145.70
Apr-08	2,698	2,791.24	2,962.29	93.24	264.29
May-08	5,101	4,542.25	4,237.03	-558.75	-863.97
Jun-08	3,962	5,633.78	5,276.80	1,671.78	1,314.80
Jul-08	2,950	3,327.03	3,086.27	377.03	136.27
Aug-08	2,314	1,945.54	2,124.88	-368.46	-189.12
Sep-08	1,761	1,734.31	2,172.28	-26.69	411.28
Oct-08	1,827	2,062.33	2,595.55	235.33	768.55
Nov-08	1,944	2,591.13	2,196.85	647.13	252.85
Dec-08	1,196	2,381.33	1,706.56	1,185.33	510.56
Jan-09	1,454	422.78	213.16	-1,031.22	-1,240.84
Feb-09	921	241.46	1,378.39	-679.54	457.39
Mar-09	1,377	1,757.03	2,292.95	380.03	915.95
Apr-09	2,278	3,220.47	3,428.64	942.47	1,150.64
May-09	4,208	4,215.34	4,051.59	7.34	-156.41
Jun-09	3,388	4,715.20	4,548.63	1,327.20	1,160.63
Jul-09	2,019	3,054.23	2,831.80	1,035.23	812.80
Aug-09	1,643	1,227.10	1,499.45	-415.90	-143.55
Sep-09	1,660	1,227.15	1,831.11	-432.85	171.11
Oct-09	1,479	2,144.02	2,777.57	665.02	1,298.57
Nov-09	1,828	2,014.60	1,998.52	186.60	170.52
Dec-09	974	2,090.68	2,459.07	1,116.68	1,485.07

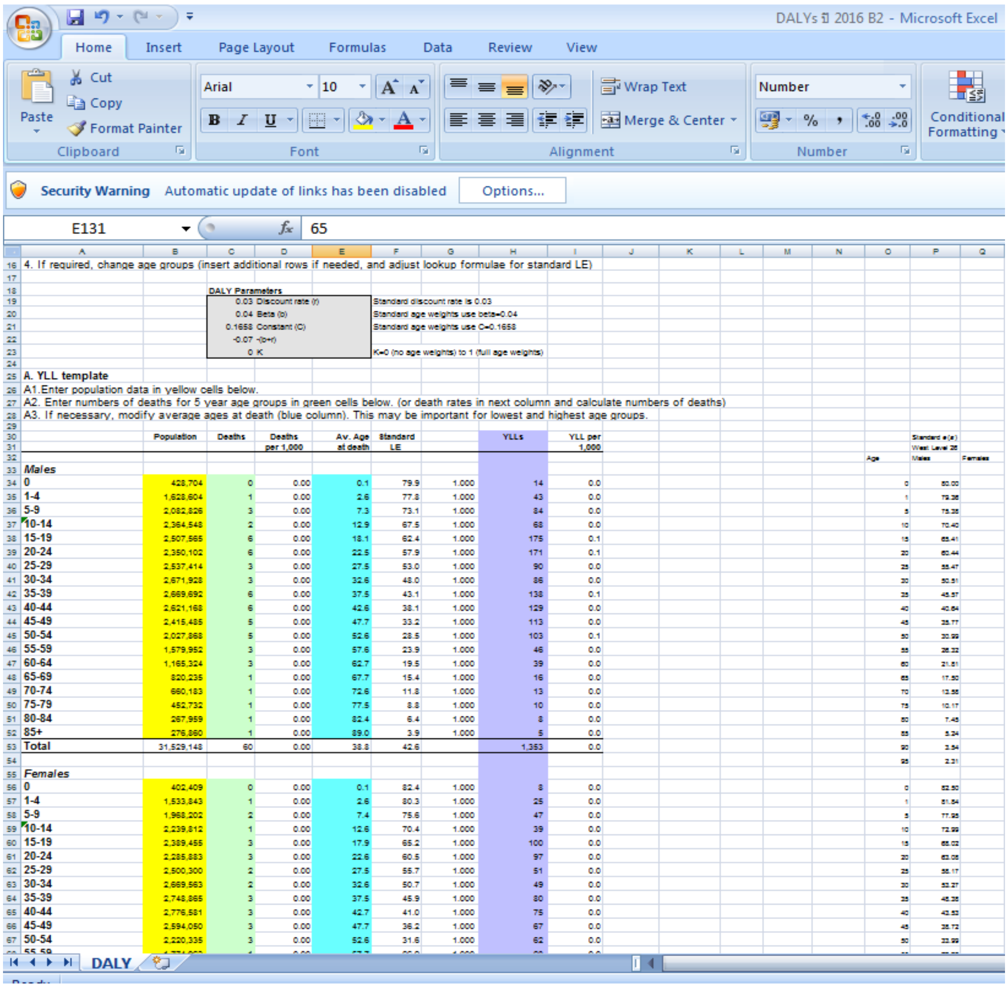
Month/Year	Actual incidence	Model A	Model B	Difference Model A-Actual	Difference Model B-Actual
Jan-10	1,667	1,647.49	2,259.02	-19.51	592.02
Feb-10	1,371	2,761.78	2,714.68	1,390.78	1,343.68
Mar-10	1,395	2,076.12	1,867.14	681.12	472.14
Apr-10	1,783	2,245.28	3,187.38	462.28	1,404.38
May-10	3,425	3,914.68	4,229.66	489.68	804.66
Jun-10	5,359	5,053.21	5,194.63	-305.79	-164.37
Jul-10	3,632	5,679.41	6,014.15	2,047.41	2,382.15
Aug-10	2,165	3,451.65	3,931.19	1,286.65	1,766.19
Sep-10	1,420	1,921.46	2,531.33	501.46	1,111.33
Oct-10	1,300	1,800.94	2,008.22	500.94	708.22
Nov-10	1,195	1,843.67	1,188.65	648.67	-6.35
Dec-10	927	1,743.57	1,549.69	816.57	622.69
Jan-11	1,450	1,349.38	557.24	-100.62	-892.76
Feb-11	792	1,356.65	1,640.69	564.65	848.69
Mar-11	990	1,730.03	1,449.24	740.03	459.24
Apr-11	1,434	2,139.20	1,960.43	705.20	526.43
May-11	3,709	2,463.15	2,296.00	-1,245.85	-1,413.00
Jun-11	3,483	4,336.15	4,000.46	853.15	517.46
Jul-11	2,469	3,336.93	2,972.26	867.93	503.26
Aug-11	1,674	1,760.67	1,880.65	86.67	206.65
Sep-11	1,210	1,299.60	1,581.26	89.60	371.26
Oct-11	1,305	1,503.12	1,563.97	198.12	258.97
Nov-11	1,412	1,583.54	1,505.77	171.54	93.77
Dec-11	907	1,682.49	1,370.49	775.49	463.49
AVERAGE	2,131.05	2,393.64	2,376.70	262.60	245.66

APPENDIX C

DALYs

Input Incidences data to WHO Calculation worksheet format

- Deaths



Input malaria incidences on each types

- Episodes
- Anaemia
- Neurological sequelae

Episodes	Population	Incidence	Incidence per 1,000	Age at onset	Duration (years)	Disability Weight	YLDs	YLD per 1,000
Males								
0-4	2,057,308	2915	0	2.5	0.0	0.211	6	0.0
5-14	4,447,374	9428	0	10.0	0.0	0.195	18	0.0
15-29	7,395,081	13086	0	22.5	0.0	0.172	23	0.0
30-44	7,962,788	10181	0	37.5	0.0	0.172	18	0.0
45-59	6,023,305	4823	0	52.5	0.0	0.172	8	0.0
60-69	1,985,559	1978	2	65.0	0.0	0.172	3	0.0
70-79	1,112,915	394	10	75.0	0.0	0.172	1	0.0
80+	544,819	394	30	85.0	0.0	0.172	1	0.0
Total	31,529,148	43,199	1.4	28.3	0.0	0.18	78	0.0
Females								
0-4	1,936,252	1507	0	2.5	0.0	0.211	3	0.0
5-14	4,208,014	4874	0	10.0	0.0	0.195	10	0.0
15-29	7,175,638	6765	0	22.5	0.0	0.172	12	0.0
30-44	8,195,009	5263	0	37.5	0.0	0.172	9	0.0
45-59	6,588,448	2493	0	52.5	0.0	0.172	4	0.0
60-69	2,286,452	1022	3	65.0	0.0	0.172	2	0.0
70-79	1,429,752	204	15	75.0	0.0	0.172	0	0.0
80+	727,320	204	40	85.0	0.0	0.172	0	0.0
Total	32,546,885	22,332	0.7	28.3	0.0	0.18	40	0.0

Anaemia	Population	Incidence	Incidence per 1,000	Age at onset	Duration (years)	Disability Weight	YLDs	YLD per 1,000
Males								
0-4	2,057,308	351	0	2.5	0.2	0.012	1	0.0
5-14	4,447,374	1136	0	10.0	0.2	0.012	2	0.0

DALYs outputs in each year

C. Total DALYS = YLL+YLD	*Males*			*Females*			*Persons*		
	Population	DALYs	DALYs per 1,000	Population	DALYs	DALYs per 1,000	Population	DALYs	DALYs per 1,000
Age									
0-4	2,057,308	745	0.4	1,936,252	407	0.2	3,993,560	1,152	0.3
5-14	4,447,374	172	0.0	4,208,014	97	0.0	8,655,388	269	0.0
15-29	7,395,081	461	0.1	7,175,638	262	0.0	14,570,719	723	0.0
30-44	7,962,788	373	0.0	8,195,009	215	0.0	16,157,797	588	0.0
45-59	6,023,305	272	0.0	6,588,448	161	0.0	12,611,753	433	0.0
60-69	1,985,559	60	0.0	2,286,452	37	0.0	4,272,011	97	0.0
70-79	1,112,915	24	0.0	1,429,752	16	0.0	2,542,667	40	0.0
80+	544,819	13	0.0	727,320	8	0.0	1,272,139	22	0.0
Total	31,529,148	2,122	0.1	32,546,885	1,202	0.0	64,076,033	3,324	0.1

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