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MALARIA EPIDEMICS UNDER CLIMATE CHANGE SCENARIOS IN THAILAND
โรคระบาดของมาลาเรียภายใต้สภาวะภูมิอากาศเปลี่ยนแปลงในประเทศไทย

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Abstract

The objective of this study was to estimate avoidable burden on disease of malaria in Thailand under climate conditions in the future. The study was based on climate projection under 2 different situations which included the regionally economic development (A2) and the local environmental sustainability (B2). 1991-2011 climate data collection was used to create nonlinear mixed regression model. The variables in monthly time step, which included maximum temperature, minimum temperature, precipitation, humidity, average wind speed.

The results were found the best fitting model, model 2, which adjusted R-Square = 0.818 and RMSE = 763.27. The average disease incidence in the year of 2003-2011 on B2 = 26,869 persons/yr, baseline = 28,521 persons/yr, and A2 = 30,734 persons/yr. These burdens converted to DALYs for international comparison which were, baseline = 1,391 DALYs/yr, A2 = 1,500 DALYs/yr, and B2 = 1,301 DALYs/yr. The compared model with actual climate data to predict the incidence of malaria in 2012-2020 found malaria incidence has increased the incidence with trend line equation $Y = 312.55X + 2480.1$, $R^2 = 0.74$ average incidences 79,703 persons/yr or 4,042.9 DALYs/yr. The scenario B2 has been decreased incidence of malaria with trend line equation $Y = 20.223X^3 - 363X^2 + 1801.4X - 19.483$, $R^2 = 0.57$, Average incidence 40,407 persons/ yr, or 2,042.8 DALYs/yrs. Scenarios B2 could have been avoided by A2 = 1,119.5 DALYs/yrs or 49.3 %.

Keyword: Malaria, nonlinear mixed regression, climate change projection data, DALYs

บทคัดย่อ

การศึกษานี้มีวัตถุประสงค์เพื่อคาดการณ์ภาระโรคที่สามารถหลีกเลี่ยงได้ (Avoidable burden of diseases) ของโรคมาลาเรีย ภายใต้สภาวะภูมิอากาศในอนาคต โดยนำข้อมูลของสภาพภูมิอากาศของประเทศไทย

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พ.ศ.2534-2554 มาคาดการณ์ภายใต้สถานการณ์การเปลี่ยนแปลงสภาพภูมิอากาศ (A2) และ (B2) ในประเทศไทยของศูนย์เครือข่ายงานวิเคราะห์วิจัยและการฝึกอบรมการเปลี่ยนแปลงของโลก แห่งภูมิภาคเอเชียตะวันออกเฉียงใต้ (SEA START RC)ได้ใช้การนำเข้าข้อมูลสภาพภูมิอากาศของประเทศไทยในปี พ.ศ.2534-2554 ของกรมอุตุนิยมวิทยาจำนวน 5 ตัวแปรได้แก่ เดือน อุณหภูมิสูงสุด อุณหภูมิต่ำสุด ค่าความชื้นสัมพันธ์ ความเร็วลมเฉลี่ย และ ปริมาณน้ำฝน เพื่อสร้างแบบจำลองถดถอยไม่เป็นเส้นตรงแบบผสมพบว่าแบบจำลองที่ให้ค่า ความแม่นยำสูงสุดคือแบบจำลองที่ 2 โดยมีค่า adjusted R-Square 0.818 ด้วยค่า RMSE 763.27

การศึกษาในปี พ.ศ.2546-2554 พบว่าสถานการณ์เปลี่ยนแปลงสภาพภูมิอากาศ B2 เป็นสถานการณ์ที่มีอุบัติการณ์เกิดโรคมาลาเรียน้อยที่สุดกล่าวคือมีอุบัติการณ์เกิดขึ้น 26,869 คนต่อปี หรือคิดเป็น 1,301 DALYS ต่อปี A2 = 30,734 คนต่อปี หรือคิดเป็น 1,500 DALYS ต่อปี เมื่อนำแบบจำลองถดถอยไม่เป็นเส้นตรงแบบผสมไปทำนายอุบัติการณ์เกิดโรคที่จะเกิดขึ้นในอนาคต ปี พ.ศ. 2555-2563 พบว่าอุบัติการณ์มาลาเรียในแบบจำลอง A2 มีแนวโน้มที่สูงขึ้นด้วยสมการแนวโน้มคือ $Y = 312.55X + 2480.1$, $R^2 = 0.74$ มีอุบัติการณ์เฉลี่ย 79,703 คนต่อปี หรือคิดเป็น 4,042.9 DALYS ต่อปี ในขณะที่แบบจำลอง B2 ส่งผลให้อุบัติการณ์ของมาลาเรียมีแนวโน้มที่เพิ่มขึ้นจากนั้นจึงลดลงอย่างต่อเนื่อง ด้วยรูปแบบชองสมการกำลังสามคือ $Y = 20.223X^3 - 363X^2 + 1801.4X - 19.483$, $R^2 = 0.57$ โดยมีอุบัติการณ์ 40,407 คนต่อปี หรือคิดเป็น 2,042.8 DALYS ต่อปีซึ่งน้อยกว่า แบบจำลอง A2 อยู่ 1,119.5 DALYS ต่อปี หรือคิดเป็น 49.3%

คำสำคัญ: มาลาเรีย, การถดถอยไม่เป็นเส้นตรงแบบผสม, ข้อมูลคาดการณ์การเปลี่ยนแปลงภูมิอากาศ, DALYS

Introduction

Climate change is an emerging risk factor for human health. It is now clear the global climate has been changed in worldwide today. Climate changes in our region are important impact on human health [(1)]. Especially, malaria, an infection disease that is sensitive to the climate. 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 a minimal climate change impact on human tolerance levels can have a direct impact on human health immediately [(2)].

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 [(3)]. The incidence of malaria varies seasonally in highly endemic areas, and malaria transmission has been associated with temperature anomalies in some African highlands [(4)].

The WHO has estimated 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 and epidemiological models. These scenarios were used to estimate the degree to which these climatic changes are likely to affect a limited series of health outcomes (malaria, diarrheal 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 [5].

Prediction malaria incidence facilitates early public health responses to minimize morbidity and mortality. Climate variables such as temperature, precipitation, relative humidity and wind [6] are potential predictors of malaria incidence have been examined in time series studies. In this study, we used adapted nonlinear time series analysis [7] to determine the association between climatic variability and the number of monthly malaria outpatients over the past 20 years and predicted the next 10 years burden in Thailand.

Methodology

In this research, we used WHO Environmental Burden of Disease Series, climate change guidance, estimating attributable and avoidable burdens of disease method [8, 9]: The main step includes as following.

1. Selecting the scenarios and time period
2. Climate change modeling
3. Health impact model
4. Conversion to a single health measure DALY (Disability adjusted life year)

This research follows guidelines of the WHO and set the study's purpose to create a Statistical Climate health model of Thailand to predict and compare incidences under climate scenarios projected with the actual incidence of the disease under real climate conditions and improve the results by convert to DALYs to enable international comparison possible.

Data Collection

1. Climate data during 1991-2011 from the Department of Meteorology were used including rainfall (Rainfall Intensity), average monthly temperature (Average Ambient Temperature), average maximum temperature (Maximum Temperature), RH (Relative Humidity), wind speed and time (month).

2. Reports of malaria incidences in Thailand during 1991-2011 were collected from the Bureau of Epidemiology.

3. The predicted climate data used dataset from Southeast Asia START Regional Center (SEA START RC) projected. These data are daily climate data (transform to

monthly data) under two different GHG emission scenarios; scenarios A2 (regionally economic development) and scenarios B2 (local environmental sustainability). Our goal is to find the malaria burden difference between the environmental focus (B2) and the economic focus (A2) in the heterogeneous world (regional development)[1].

Statistical association between climate variability and malaria incidence

In this step, the adapted nonlinear mixed- regression technique from Zhou [6] was used. This is due to the existence of classification on the function type such as, autocorrelation, climate variability function, and seasonal function [10].

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 (N_t) can be modeled as in Equation (1).

$$N_t = f(N_{i<t}, t) + g\big(T_{min}(t), T_{max}(t), Rain(t), RH(t), Wind(t)\big) \tag{1}$$

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

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

$f(N_{i<t}, t)$ is a higher-order autoregressive model used to test the effect of autoregression by using 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.

α is the deterministic drift

β_i measures the lagged effect (autoregression)

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

r_i is the regression coefficient.

Tmin = Minimum temperatures

Tmax = Maximum temperatures

Rain = Total rainfall

RH = Relative humidity

Wind = Wind speed

And the model evaluation method used the Root Mean Square Error (RMSE) (also called the root mean square deviation, RMSD) is a frequently used measure of the difference between values predicted by a model and the values actually observed from the environment that is being modelled.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_{obs,i} - X_{model,i})^2}{n}}$$

Where X_{obs} is observed values and X_{model} is modelled values at time/place i.

Estimate burden of disease

Disability-Adjusted Life Year (DALYs) 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 incidences cases of the health condition [11]. Calculation is

DALY = YLL + YLD

The number of years lost due to premature (Year of Life Lost - YLL) or premature death is a component of the disease burden and mortality indicators. The measurement is based on the time of the death of the life lost prematurely. The basic formula for YLL (without including other social preferences), is the following for a given cause, age and sex:

YLL = N x L

Where;

N = number of deaths

L = standard life expectancy at age of death in years

YLD = I x DW x L

Where;

I = number of incidence cases

DW = disability weight

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

Results and discussion

Correlation between variables with malaria incidences

The study showed that wind speed has maximum lag period of 5 months with correlation of 0.282 while humidity and rainfall have maximum lag period of 0 month with correlations of 0.297 and 0.241 respectively.

Table 1 Correlation between variables with malaria incidences

Variable	Lag period, τ (Months)	Correlation	Significance
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 0.05 level (2-tailed).

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

Although spatial incidences data in Thailand were not used, significant relationship is found conforming to the results of Zhou [7], as well as some climate variables such as; RH and Rainfall are no lagged period (Table 1). However, these data are surveillance and spatial analysis was not used.

Nonlinear mixed regression analysis

Variables were selected and tested with time lag period climate variable associated with malaria incidence. The next step is regression analysis by stepwise method. The model was tested in three assumptions as following.

- Model No EV assuming the environment factors having no affect to the number of patients; ($g(x) = 0$).

- Model 1 assuming the environmental factors having an influence on the number of patients given $g(x) \neq 0$ and assuming the interaction between all climate variables = 0 due to no interaction with the environment.

- Model 2 assuming the environmental factors having an influence on the number of patients given $g(x) \neq 0$ and assuming the interaction between all climate variables $\neq 0$ due to environmental factors related.

The results are shown in Tables 2-4 below.

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

Model	Method	R	R square	Adjusted R Square	Significance
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**

Table 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

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

Parameter	Model 1	Significance	Model 2	Significance
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 0.05 level (2-tailed).

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

Table 4 shows the fitting results and effect on climate variables including parameter and significant value of Model 1 and Model 2. Significance on interaction effect between maximum or minimum monthly temperature, RH and wind speed with the number of malaria incidences are concluded.

The results show that Model 2 has the best accuracy, therefore the prediction process model 2 is used. Both models are adapted by non linear mixed-regression technique; Model 2 used interaction of climate variables, Model 1 only use climate variables at max lag period (τ_{max}). As a result, Model 2 which combined the interaction between climate variables shows potential better prediction than Model 1. In fact, the regression model in this study can represent and predict malaria burden with reasonable accuracy when there is sufficient malaria epidemiological data (non under reported province data) available for input to the model. In the prediction period, although there may be some over estimated between the actual incidences and predicted, The RMSE (Table 5) is relatively small when compared with overall malaria burden (Figure 1).

Table 5 Residual analysis

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

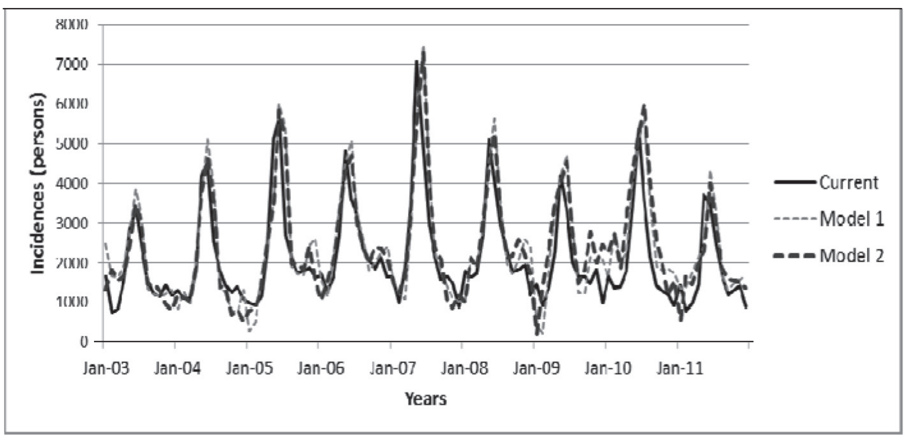

Figure 1 Comparison models 1, 2 with actual incidence

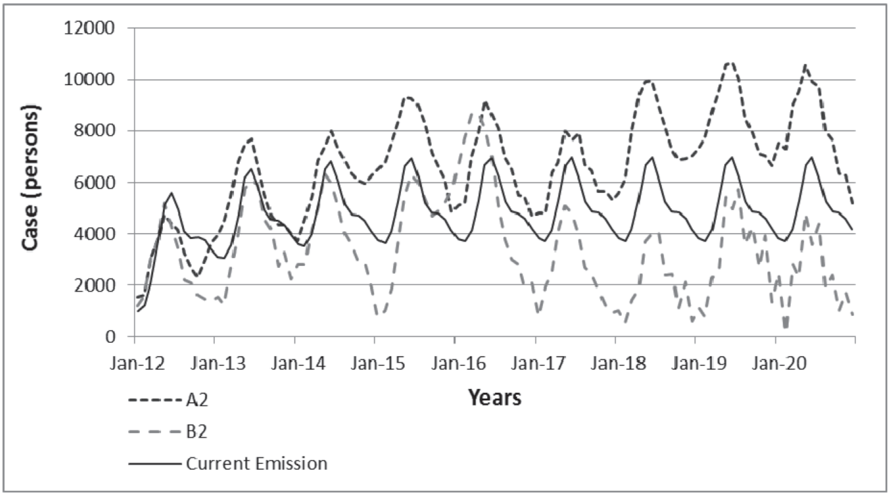

Figure 2 Results estimate of malaria incidences under climate scenarios (monthly)

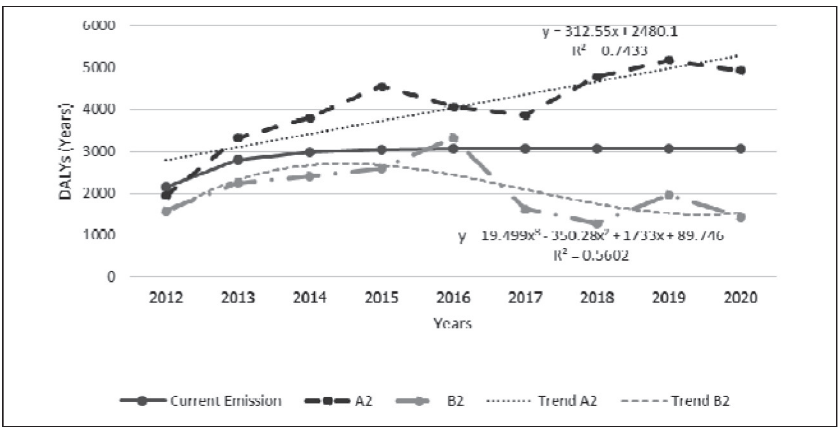

Figure 3 DALYs of Malaria in Thailand (2) 2012-2020

The compared models with actual climate data to predict the incidence of malaria in 2012-2020 found malaria incidences would increase with trend line, Equation Y = 312.55X + 2480.1 R^2 = 0.74, average incidences 79,703 persons/ yr or 4,042.9 DALYs/ yr. The scenario B2 predicted would decrease incidence of malaria with trend line, Equation $Y = 20.223X^3 – 363X^2 + 1801.4 X – 19.483$ R^2 = 0.57, average incidence 40,407 persons/ yr, or 2,042.8 DALYs/ yr.

Conclusions

Climatic factor and seasonal pattern are the most direct affect on malaria transmission in Thailand. However, other factors are also influencing malaria epidemiology. For example, socioeconomic condition, public health service, military conflict, migration and water resources management may all modulate the suitability for malaria transmission. The changes in extreme climate such as extreme rainfall, an average temperature increase of result in a greater incidence of malaria. Each factor could vary with lagged period while rainfall causing a direct effect on the incidence of malaria has lagged period = 0 month. Therefore, quoted in the research[2] "a minimal climate change impact on human tolerance levels can have a direct impact on human health immediately" is reliable.

In fact, the national monthly malaria cases can be modelled and predicted using nonlinear mixed regression. Our results showed the global climate change B2, The local environmental sustainability scenarios can prevent disease burden around 49.3% from global climate change as Model A2 in 2012-2020. However, reducing greenhouse gases emission by international agreement or national policy can reduce or minimize amount of diseases. There are the possibilities that those others mosquito-borne diseases such as dengue fever diseases and other climate-health impact [3] would be reduced as well.

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