論文の内容の要旨

Improvement of Malaria Transmission Model by Calibration of Surface Water Formation Parameter and Future Projection over Africa

(地表水面形成パラメータの較正によるマラリア伝染モデルの改良及びアフリカにおける将来予測)

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Malaria has been a major public health and endemic disease in some countries over the world. There were estimated 429,000 malaria deaths globally and mostly in African region. Due to its burden, World Health Organization (WHO) designates malaria as one of Sustainable Development Goals' No.3 target 3.3 which states that "By 2030, end the epidemics of AIDS, tuberculosis, malaria and neglected tropical disease. Several attempts have been conducted to reduce malaria cases, such as using some treatments and protections. However, these efforts still could not eradicate malaria disease. Some researchers have conducted observation field studies by mosquito catchment, examination of sporozoite rate and human bite rate to derive Entomological Inoculation Rate (EIR) which represent probability of a person got infected from malaria disease. Unfortunately, these EIR numbers are limited in some observation sites and sparse. Therefore, malaria transmission model is utilized to describe malaria transmission risk.

Parasite, mosquito, and human are three main factors driver on malaria. Climatic factors affect development of mosquito and parasite. Availability of water is diagnosed become one of factor influencing the spread of malaria. The representation of surface water formation parameter in current malaria model assume constant and not realistic due to the availability of observation dataset. This study aims to determine highly influential climatic factor on malaria disease, determine an optimize pond growth rate optimized parameter and analyze the impact of climate change in the future projection.

Vector borne infectious disease model (VECTRI) developed by International Center for Theoretical Physics (ICTP) is used in this study. We implement VECTRI on Africa region with latitude -38^0 S – 38^0 N and longitude -20^0 W – 55^0 E due to high risk of malaria disease in this tropical region from year to year. This model is used as the basis for validation in historical period, parameterization of surface water formation parameter and projection simulation in future period. We select this model due to its dynamic, incorporation with climatic (precipitation and temperature) and non-climatic (population density) factor. Chapter 2 describe definition of malaria disease, malaria model development, climatic and non-climatic factors drivers on malaria and the detail of VECTRI model mechanism.

In Chapter 3, we explained the methodology, forcing datasets, and simulation scenario used in this study. We conducted three experiments on historical period and one experiment on projection period under three RCPs emission scenarios. Three experiments on historical period is used for validation of model result on historical period and calibration of water fraction against pond growth rate to optimize surface water formation parameter. Existing available observation data (EIR) is explained in this chapter. This study uses EIR annual number which is located in 12 countries in Africa, i.e. Senegal, Republic of Congo, Burundi, Gambia, Democratic Republic of Congo, Gabon, Cameroon, Eritrea, Uganda, Zambia, Tanzania and Kenya.

Validation of simulation results and parameterization of surface water on historical period are discussed in Chapter 4. Parameterization of pond growth rate (K_w) is conducted within two steps. First, by adjusting K_w parameter against EIR observation (K_{we}) on historical period (1983 - 2006) until EIR simulation is closest to EIR observation site studies. The results show that EIR overestimate or underestimate in existing EIR observation sites. Therefore, we do tuning this parameter by increasing (decreasing) K_w, to decrease (increase) EIR model result until the results improve and close to EIR observation result. The results reveal that K_{we} parameter is not constant in existing observation sites. Second, by tuning K_w parameter against water fraction. We utilize satellite observation water fraction, GSMaWS (Global Satellite Mapping of Wet Surface) for calibration of water fraction for period 2014 – 2018. Spatial distribution of pond growth rate against water fraction (K_{wg}) is derived by minimization of Root Mean Square Deviation (RMSD) between water fraction observation and water fraction from model calculation. From K_{we} and K_{wg}, a topographical parameter and a scaling factor is needed to refine the parameter. Then, by multiplication of scaling factor, pond growth rate optimized (by adjusting K_w from K_{we} and K_{wg}) and topography, we interpolate a scaling factor using simple inverse distance weighting. After multiplication of scaling factor, topography and optimized of K_w from HIST-1 and HIST-2&3, we derive a spatial distribution of optimized K_w to be used in projection simulation. K_w gives impact to the formation of water fraction changes. Water fraction give impact to the availability of surface water for malaria breeding places which will influence to the number of survival larva. The survival larva will affect to the number of larva which will hatch into adult mosquito. Then, the number of mosquito will determine percentage of parasite inside mosquito's body (Circumsporozoite Protein Rate or CSPR). If CSPR is multiplied with human bite rate (hbr), we derive EIR number. Therefore, K_w can control EIR number.

Climate change can alter the distribution of vector borne disease, increasing flood and drought, risk of disasters and malnutrition effects (Haines *et al*., 2006). It takes more effort and challenge to predict distribution of malaria in future period compare to historical period due to uncertainties, limited data, climate data variability and the complex physical, social and economic interactions (Semakula *et al.*, 2017). Malaria is sensitive to climate change in vector spreading and parasite development that cause malaria disease (Ngarakana-Gwasira *et al.*, 2016), the impact of climate change on future projection is still being examined. Impact of climate change on projection simulation period is discussed in chapter 5. We utilized CMIP6 (Coupled Model Intercomparison Project Phase 6) under three Representative Concentration Pathways (RCPs) scenarios (RCP 2.6, RCP 7.0 and RCP 8.5) for precipitation and temperature from MIROC model as climate forcing. We use SEDAC (Socioeconomic Data and Applications Center) for population density forcing datasets under three Shared Socioeconomic Pathways (SSPs) scenarios. Comparing to observed historical datasets, output from climate models are mostly bias (Muerth *et al.*, 2013). A bias correction is implemented to correct precipitation and temperature datasets for projection period. A scaling factor is determined to calculate difference between historical observation and projection observation dataset. Then, this scaling factor is multiplied with daily projection datasets to correct predicted datasets on future period (Lafon *et al.*, 2013). A spatial distribution of optimized pond growth rate from Chapter 4 is applied to improve surface water formation parameter. Precipitation will increase or decrease regarding the emission scenario and location in projection simulation. Meanwhile, temperature is increasing in projection period. For projection simulation, west, central and southeast part of Africa are more favorable conditions for malaria transmission under three RCPs scenario. Inter annual variability of EIR annual projection is determined by calculating coefficient variation of EIR annual number. Coefficient variation is determined from standard deviation of EIR annual mean divided by average of EIR annual. Coefficient variation average for EIR annual projection under RCP 2.6 is 0.079, under RCP 7.0 is 0.087, and under RCP 8.5 is 0.087. From this number it shows that EIR annual projection under RCP 8.5 has higher variability compare to other two RCPs scenario.

Precipitation and temperature give impact to EIR number. In projection simulation, we divided the analysis of each scenario into two regions i.e. west part of Africa (latitude: $0^0 – 25^0$ N, longitude: -20^0W – 12^0 E) and central-south part of Africa (latitude: $25^0 – 38^0$ S, longitude: 12^0E – 55^0 E). In west part of Africa, the risk of malaria in projection period compare to historical period are -23.14% under RCP 2.6, -39.51% under RCP 7.0, and -19.22% under RCP 8.5. Therefore, the worst scenario is RCP 8.5 and the better scenario is RCP 7.0 for west part of Africa. In central-south part of Africa, the risk of malaria in projection period compare to historical period are 40.48% under RCP 2.6, 45.23% under RCP 7.0, and 100.78% under RCP 8.5. For central-south part of Africa, the worst scenario is RCP 8.5 and the better scenario is RCP 2.6.

Population density gives proportional impact to control EIR. Precipitation characteristic (monthly average precipitation, standard deviation of monthly average precipitation, and Consecutive Wet Days (CWD)) affect EIR changes from projection period compare to historical period. Monthly average of precipitation and standard deviation of monthly average precipitation have relative contribution to EIR in west part of Africa, meanwhile CWD give more impact to EIR in central and southeast part of Africa. Correlation coefficient of precipitation and standard deviation is higher in western, central and eastern part of Africa, CWD's correlation coefficient is higher near equator line from west to eastern part of Africa and temperature's correlation coefficient from central part to southern part of Africa.

Due to uncertainties on projection period, we add ensemble members of each RCPs scenario. We conducted simulations for three ensemble member of each RCPs scenario. By considering each value of correlation coefficient of each variable divided by value of total correlation coefficient of all variables, contribution of each variable related EIR changes from projection period compared to historical period for spatial mean of African region in west part of Africa is 21.68% for precipitation, 35.32% for standard deviation of precipitation, -6.71% for CWD and 49.72% for temperature. Meanwhile, in central – south part of Africa, the contribution of each variables is 0.85% for precipitation, 41.01% for standard deviation of precipitation, -18.95% for CWD and 77.09% for temperature.

Chapter 6 conclude and discussed recommendation for further study improvement. This study utilizes Entomological Inoculation Rate (EIR) annual number for validation of model simulation in historical period. The result shows that by tuning pond growth rate parameter against EIR, the model result can be improved to EIR observation. Further, utilizing other validation datasets such as number of malaria cases in each observation site in Africa could improve the model result. Besides that, this study utilizes highly resolution of water fraction observation dataset around 0.1 degree resolution (~11 km). Higher resolution surface water with pond scale (< 10 m) daily datasets are needed to improve the model performance and make the model more realistic. An economic growth for projection simulation and other social factors need to be implemented to make the simulation more realistic.