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Heatstroke risk projection in Japan under current and near future climates

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Abstract

This study assesses heatstroke risk in the near future (2031-2050) under RCP8.5 scenario. The developed model is based on a generalized linear model with the number of ambulance transport due to heatstroke (hereafter the patients with heatstroke) as the explained variable and the daily maximum temperature or Wet-Bulb Globe Temperature (WBGT) as the explanatory variable. With the model based on the daily maximum temperature, we performed the projection of the patients with heatstroke in case of considering only climate change (Case 1), climate change and population dynamics (Case 2), and climate change, population dynamics, and long-term heat acclimatization (Case 3). In Case 2, the number of patients with heatstroke in the near future will be 2.3 times higher than that in the baseline period (1981-2000) on average nationwide. The number of future patients with heatstroke in Case 2 is about 10% larger than that in Case 1 on average nationwide despite of population decline. This is due to the increase in the number of elderly people from the baseline period to the near future. However, there were 21 prefectures where the number of patients in Case 2 is smaller compared to Case 1. Comparing the results from Cases 1 and 3 reveals that the number of patients with heatstroke could be reduced by about 60% nationwide by acquiring heat tolerance and changing lifestyles. Notably, given the lifestyle changes represented by the widespread use of air conditioners, the number of patients with heatstroke in the near future was lower than that of the baseline period in some areas. In other words, lifestyle changes can be an important adaptation to the risk of heatstroke emergency. All of the above results were also confirmed in the prediction model with WBGT as the explanatory variable. (291 words, Word limit is less than 300)

Keywords: Number of patients with heatstroke, Near future projection, Heat acclimatization, Climate change adaptation, Generalized linear model (less than 5)

1. Introduction

In recent years, the incidence of heatstroke in Japan has increased due to climate change, and this is becoming a major social issue (e.g., Ando et al., 2004; Fujibe 2013). For example, from May to September 2018, which was abnormal hot summer across the country, the number of emergency patients with heatstroke was 95,137 nationwide, of which 32,496 were hospitalized and 160 died (Fire and Disaster Management Agency, 2019, https://www.fdma.go.jp/disaster/heatstroke/item/heatstroke003_houdou01.pdf). The number of deaths due to heatstroke in 2018 was 1,581. This number of deaths is far greater than the number of deaths caused by other weather-related disasters, such as floods and landslides (the number of deaths from the 2018 Japan floods, which were one of the most torrential in decades, was 225). Residents are concerned that heatstroke will become increasingly serious as climate change progresses. It is therefore important to assess all of the risks associated with heatstroke in a future climate.

Extensive studies on the increase in heat-related excess mortality or deaths associated with future climate change have been conducted mainly in Europe, the United States, Japan, and China (e.g., Hayhoe et al., 2004; Knowlton et al., 2007; Doyon et al., 2008; Gosling et al., 2009; Jackson et al. 2010; Li et al., 2013, Honda et al., 2014). Li et al. (2013) predicted that future heat-related excess deaths in New York, USA, under the Special Report on Emissions Scenarios (SRES) A2 scenario would increase by +22.2% (2020s), +49.4% (2050s), and +91.0% (2080s), compared to levels in the 1980s. Doyon et al. (2008) predicted a 10% increase in summer heat-related mortality in Montreal, Canada, in 2080 compared to that in 1981-1999 under the SRES A2 scenario. Similar studies have continued to be conducted after the release of the future climate projection datasets for the Representative Concentration Pathway (RCP) scenarios (Chen et al., 2017; Huber et al., 2020). In recent years, projections have also been conducted in developing countries, including those in

Southeast Asia. For example, Gasparrini et al. (2017) projected heat-related excess mortality rates of more than 5% in Southeast Asia, central and southern Europe, and Latin America in the 2090s under the RCP8.5 scenario. Guo et al. (2018) predicted that heat-related deaths would increase by more than 700% in some countries of Southeast Asia and South America during the period of 2031-2080 under the RCP8.5 scenario compared to the 1971-2020 period. Thus, future projections of heatstroke risk have been dominated by studies that use heat-related excess mortality or deaths as indicators. In these studies, it is necessary to consider not only climate change but also social change. Social changes include demographic changes and long-term heat acclimatization over a span of several decades due to lifestyle changes. Among the previous studies, those that consider demographic changes are Gosling et al. (2009); Jackson et al. (2010); Honda et al. (2014); Chen et al. (2017); Guo et al. (2018). Studies considering long-term heat acclimation are Hayhoe et al. (2004); Knowlton et al. (2007); Gosling et al. (2009); Li et al. (2013); Guo et al. (2018).

Therefore, the main purpose of this study is to develop a statistical model and predict heatstroke risk (the number of ambulance transport due to heatstroke) in the near future (2031-2050) under RCP2.6 and RCP8.5 scenarios all over Japan by prefecture. This statistical model is based on the generalized linear model which uses maximum temperature or WBGT as explanatory variable and daily number of ambulance transport due to heatstroke as a predictor variable. When predicting the number of ambulance transport due to heatstroke by statistical model, it is known that there is a problem of underestimation in early summer and overestimation in late summer (Fuse et al., 2014; Sato et al., 2020; Ikeda and Kusaka, 2021). This error is due to short-term heat acclimatization (Ono, 2013; Fujibe et al., 2018b). Therefore, our model takes this effect into account. The near future heatstroke risk is determined by three types of experiments. (i) Future projection considering only climate change. (ii) Future projection considering climate change and population. (iii) Future projection considering climate change, population and long-term acclimatization. The detail information of experiments is described in section 3.

2. Data

2.1 Number of heatstroke emergency patients

In this study, we used a dataset on the number of ambulance transport due to heatstroke for 2010 - 2018 published by the Fire and Disaster Management Agency of the Ministry of Internal Affairs and Communications, Japan.

The definition of heat stroke is "a general term for any disorder that results from an imbalance of water and salt (e.g. sodium) in the body due to a breakdown in the body's ability to regulate the temperature in a high-temperature environment" and includes sunstroke, heat cramps, heat exhaustion and heat stroke (Fire and Disaster Management Agency 2021)". Based on the above definition, the medical doctor determines whether the patient brought to the emergency room has a heatstroke. The data on the number of emergency patients with heatstroke by that medical doctor's initial diagnosis is used in this study. There are three types of age-related data in this dataset: the number of heatstroke emergency patients per day by prefecture in all age groups, aged 65 years and older, and under 64 years old (newborn babies, infants, juveniles, and adults combined). The number of ambulance transport due to heatstroke is simply called "the number of patients with heatstroke" and used as an indicator of heatstroke risk in this study.

2.2. Current climate data

The temperature data were taken from hourly observations made by the Automated Meteorological Data Acquisition System (AMeDAS) operated by the Japan Meteorological Agency. AMeDAS stations are located at a density of approximately 20 km. We used the spatial average of all stations' values within a prefecture to improve the spatial representativeness of the temperature value used for each prefecture. However, because the climate of Tokyo differs markedly between the mainland and the islands, spatial averages of Tokyo are calculated by excluding data from observation stations on the islands (these islands have 0.2% of the total population of Tokyo). The daily maximum temperatures were determined from the hourly temperature values obtained from these averages.

WBGT was calculated using the formula of Yaglou and Minard (1957). The black globe temperatures there are not measured by JMA were estimated by the method of Okada and Kusaka, 2013. The daily maximum WBGT was calculated from the hourly values of WBGT. Detailed methods for estimating the WBGT are described in the Supplement 1.

2.3 Climate scenario data

As the climate scenario data, we used the 1-km mesh statistical downscaling (DS) dataset provided by Institute for Agro-Environmental Sciences, National Agriculture and Food Research Organization (NARO) (Nishimori et al., 2019). This DS dataset were created from four GCMs outputs, MIROC5, MRI-CGCM3, GFDL-CM3, and HadGEM2-ES. These GCMs were carefully selected by SI-CAT, project for climate change adaptation in Japan. For the period of climate scenarios used in this study, the baseline period is set to 1981-2000 and the near future is set to 2031-2050.

Unfortunately, the NARO dataset stores only data for daily (mean, maximum, minimum) and monthly mean values, not store hourly values. Due to this limitation, it is impossible to calculate the daily maximum WBGT with only this dataset. In addition, it should be noted that the reliability of each meteorological variable differs. To be honest, it is reported that the reliability of air temperature and solar radiation is relatively high, while that of humidity and wind speed is relatively low (Nishimori et al., 2019).

A similar idea as the pseudo-global warming approach (Kimura and Kitoh 2007, Sato et al 2007) was applied to estimate the future WBGT to overcome these problems in this study. First, a time series of daily maximum temperature from June 1 to September 30 is generated using the baseline period data from NARO's dataset. Second, this time series is averaged over 15 days and then averaged over 10 years. Third, similar time series data is generated using the future climate scenario data of NARO's dataset. From the difference between these two-time series, we obtain the climate change component data (ΔT). This ΔT is daily data of the amount of temperature increase from the present to the future, which contains a gentle seasonal change. The pseudo future dry-bulb temperature is estimated from the actual temperature of the present climate T plus future temperature increase ΔT. The pseudo future WBGT is estimated using pseudo future dry-bulb temperature ($T+\Delta T$), wet-bulb temperature (Tw) and globe temperature (Tg). Here, the future Tw should be calculated from the future relative humidity and the pseudo future temperature ($T+\Delta T$). However, in this study, pseudo future Tw is calculated from the current relative humidity and the pseudo future temperature, considering the result of the previous study that the relative humidity does not change significantly in Japan in the near future (Byrne and O'Gorman 2016). Similarly, the pseudo future Tg is calculated from the current solar radiation, wind speed and the pseudo future temperature.

2.4 Population data

As the current (baseline) population data by prefecture, we used the data from the 1990 Population Census. As the future population data by prefecture, we used the "Future Population Estimates by Region for Japan" provided by the National Institute of Population and Social Security Research (National Institute of Population and Social Security Research 2018). This dataset is a statistical future projection of the population by prefecture and municipality. This data is suitable for the purpose of this study because it is estimated by age group (0-14 years, 15-64 years, 65 years and older, and 75 years and older).

The population data here is the nighttime population for both base and near-future values. If the population of a prefecture is expressed using nighttime population, there will be an error in the risk of heatstroke if a person suffers from heatstroke during the daytime in a prefecture other than his or her home. However, this error is expected to have only a little effect on the predictions of this study for the following two reasons. The first reason is that the difference between the daytime and nighttime populations is small except in a few prefectures. According to the 2005 census, the difference between the daytime and nighttime population is about 20% even in Tokyo, where the daytime population is much larger than the nighttime population, and about 12% even in Saitama, where the daytime population is much smaller than the nighttime population. In other prefectures, the difference between the daytime and nighttime populations was less than 10%. Another reason is that most of the people suffering from heatstroke are young children and the elderly. Since the difference between the daytime and nighttime populations occurs mainly in the age group that commutes to work or school, these are different age groups from the young children and elderly.

3. Method

3.1 Model overview

In this study, the six models shown in Table 1 were created and compared for accuracy. The characteristics of the proposed models for the number of patients with heatstroke prediction are as follows:

(i) The model is based on generalized linear models (GLM, Nelder and Wedderburn, 1972).

(ii) The predictor variable is the number of heatstroke emergency patients.

(iii) The default explanatory variable is the daily maximum temperature. (but, we can also use WBGT instead).

(iv) Differences in regional, seasonal (short-term heat acclimatization), and age of heatstroke risk were considered when identifying the model parameters.

Regarding (i), GLM equation is expressed as follows.

$$log\,(y) \;= \alpha + \beta x \qquad (1)$$

Here, x is the explanatory variable, y is the objective variable, and α and β are partial regression coefficients (parameters). Each parameter was identified by the maximum likelihood method, which assumes a Poisson distribution. First, as a default model, we created a model with the estimated parameters using data from Tokyo and adapted the model to the entire country.

Regarding (ii), the results of this model will provide useful information for examining the requirements of the emergency medical system in consideration of the increase in the number of patients with heatstroke due to future climate change.

Regarding (iii), it is expected that the use of the daily maximum temperature leads to a high practicality in making future predictions. This is because the humidity, wind speed and solar radiation used in the WBGT estimation have tendency with lower availability and robustness of future climate scenario data, compared with temperature. On the other hand, WBGT is possibly more suitable for explanatory variables under current climate than temperature. These pros/cons are trade-off relationship for future projection; thus, we compare the accuracies between the two models; the one uses the temperature as the explanatory variable and the other uses the WBGT. And then, we individually predict future heatstroke risk using the two models. The comparison of such models might be important attempt to understand the uncertainty among prediction models.

Regarding (iv), it is expected that the proposed model will improve the accuracy of the future projection of the number of emergency transport due to heatstroke by considering the factors not limited to the meteorological field. We will describe these factors in the subsection 3.2 – 3.4 in detail.

3.2. Consideration of regional dependency in the model

The degree of heat tolerance of people is known to vary among regions (Keatinge et al., 2000; Curriero, 2002; Gosling et al., 2007; Fujibe et al., 2018a). For example, when exposed to the same temperature, people in the cooler regions of northern Japan have a higher risk of heatstroke that people in warmer regions (Fujibe et al., 2018a). To account for these regional differences in heat tolerance, we performed parameter estimation for each prefecture individually.

3.3 Consideration of short-term heat acclimatization in the model

The predictions calculated from equation (1) are problematic in that they underestimate the predictions in the early summer and overestimate the predictions in the late summer. This is because the effect of short-term acclimatization is not included when using a single equation as described before. Like Ikeda and Kusaka (2021), using an actual number of patients with heatstroke one day before and the cumulative days from the start of summer season as explanatory variables is an example of ways to consider the short-term acclimatization effect. However, the actual number of patients with heatstroke is not able to use under the future climate projection. Cumulative days might be useful idea in the future projection because it indicates the number of hot days experienced in one summer. However, it cannot be applied to the model in this study because the timing of mid-summer may change in the long term, and in that case, simple cumulative days may not be able to represent this change.

In this study, we propose the method to divide the predicted period from June to September into three sub-periods: early summer, mid-summer, and late summer, based on the time series of daily maximum temperature (Fig. 1). The equations are respectively constructed for early summer and late summer using data in these sub-periods (equation 2 and 3) to consider the effect of short-term acclimatization. These equations are respectively used in early summer and late summer instead of equation (1).

$$log\left(y_{p1}\right) = \alpha_{p1} + \beta_{p1}x \quad (2)$$

$$log\left(y_{p3}\right) = \alpha_{p3} + \beta_{p3}x \quad (3)$$

As mentioned above, if equation (1) is used for the entire summer, it will underestimate the number of emergency cases in early-summer and overestimate the number of emergency cases in late-summer. In this study, in order to mitigate these errors, we divided the period into three parts, focusing on the temperature increase from early-summer to mid-summer and the temperature decrease from mid-summer to late-summer. The period division was carried out using the values of [posterior five-day mean minus previous five-day mean] (hereafter referred to as the “five-day mean difference”). This five-day mean difference represents the trend of temperature change in about 10 days. When temperature rises over a span of about 10days, five-day mean difference shows positive value. The method of period division is as follows. The example of this method is shown in Figure 1.

- Start date of the early-summer period: June 1
- End date of the early-summer period: 7 days after the last day when the value of the five-day mean difference exceeded the threshold. This end date is picked from the period from June 1 to August 9. The thresholds are 50th to 95th percentile of the five-day mean difference and set by prefectures. For example, at Fukuoka in 2018, the end date of the early-summer period is set to August 9 (the end of the period shown in orange in Fig.1). If the date selected is on or after August 10, the end date of the early-summer period is uniformly set to August 9. This is because the tendency to underestimate the prediction values generally finishes by early August in any year.
- Start date of the late-summer period: The date when the value of five-day mean difference falls below the threshold for the first time during the period August 10 – September 30. The thresholds are fifth to 50th percentile of the five-day mean difference and set by prefectures. For example, at Fukuoka in 2018, the start date of the late-summer period is set to August 14th (the start of the period shown in blue in Fig. 1).
- End date of the late-summer period: September 30
- Mid-summer period: From the day after the end of the early summer period to the day before the start of the late summer period (the period shown in green in Fig. 1). In mid-summer period, the error in the predictions based on the non-division model is enough small and there is no need to revise them.

3.4. Consideration of differences in patient's age in the model

It is well known that the risk of heatstroke is higher in the elderly than in the young (Nakai et al., 1999; Smoyer et al., 2000; McGeehin and Mirabelli, 2001; Basu and Samet, 2002;

Flynn et al., 2005; Hajat et al., 2007; Anderson and Bell, 2009). Therefore, to account for these differences in heatstroke risk by age, we separately predicted the number of patients with heatstroke 65 and older and under 64 years of age (Figure 2).

3.5. Factors not considered in the model

The following factors related to the heatstroke risk are not used in the prediction model. (i)sex (Semenza et al., 1996; Whitman et al., 1997; Havenith, 2005; Vaidyanathan et al., 2020), (ii) use of air conditioners or air conditioner penetration rate (Semenza et al., 1996; Basu and Samet, 2002; Anderson and Bell, 2009), and (iii) socioeconomic status (Anderson and Bell, 2009; Hondula et al., 2015; Fujibe et al., 2020), (iv) whether they are living in a nursing home or not (Kovats and Hajat 2008), (v) clinical or pathophysiological factors, (vi) urban heat islands (Kovats and Hajat 2008), and (vii) air pollution levels (Piver et al. 1999).

(i) Sex could not be considered in this study because the dataset on the number of heatstroke emergency patients used in this study did not distinguish between men and women.

(ii) The penetration rate of air conditioners is around 90% in most prefectures, except in a few areas. The presence or absence of air conditioner use may have something to do with the presence or absence of heatstroke occurrence, but it is difficult to obtain such data at the national level. For this reason, this factor is not used in the prediction model.

As for (iii) and (iv), in Japan there is almost no gap between the rich and the poor, and social security and medical insurance are almost well provided for all citizens. This leads that air conditioners are considered to be sufficiently widespread for nursing care facilities. Regarding (v), predicting what will happen to the number of people with diseases related to heat stroke risk in the future (whether it will increase or decrease) is highly uncertain and unrealistic. Regarding (vi), Japan's cities are already mature, and it is unlikely that further urbanization will enhance the heat island effect (Adachi et al. 2012, Kusaka et al. 2016). Regarding (iiv), the effect of air pollutants on heatstroke is smaller than the effect of temperature (e.g., Shumway et al., 1988, Smoyer et al., 2000, Rainham and Smoyer-Tomic 2003). The impact of air pollutants on heatstroke in Toronto 1980-1996 was small (Rainham and Smoyer-Tomic 2003). During that period, the NO2 concentration in Toronto was 0.0238 ppm, while the NO2 concentration in Tokyo in 2018 was 0.015 ppm, which is lower than that in Toronto. In addition, air pollutants in Tokyo have been decreasing in recent years and are expected to continue to do so in the future (Morikawa et al., 2021). Therefore, air pollutants are not considered in this study.

In addition, this study did not consider the geospatial population density pattern within a prefecture. However, if it is considered, the risk of heatstroke can be assessed in more spatial detail. This will be useful information for the optimal allocation of medical facilities.

3.6. Changing explanatory variables in the model

The thermal indices, WBGT (Yaglou and Minard, 1957), and Universal Thermal Climate Index (UTCI; Fiala et al., 2012), are widely used to measure heatstroke risk in the world. In Japan, WBGT are the most widely used and also recognized as an effective guideline for work and exercise environments. Moreover, WBGT has been standardized internationally by the International Organization for Standardization. The UTCI is often used worldwide, but its application to Japanese people is considered questionable as it is based on the physiological responses of Caucasian human models. In this study, we used the daily maximum WBGT as explanatory variable as well as daily maximum temperature, and investigated the effect of different explanatory variables on the prediction accuracy.

3.7. Verification of model accuracy

Cross-validation was performed with any one year of data from 2010-2018 as test data and the remaining eight years as training data. The predictive accuracy of the models was assessed by mean absolute error (MAE) and root mean squared error (RMSE), and models with small values of each of these parameters was considered to have higher predictive accuracy.

3.8. Design of Baseline and near-future projection

First, we will estimate the number of patients with heatstroke in Baseline period (1981-2000) using statistical models developed in chapter 3 by prefecture. Second, we will perform the future projection of heatstroke risk in Japan by prefecture. The heatstroke risk in this study means the number of patients with heatstroke, as described in Section 1. We use Model 6 in table 1 for future projection of the number of patients with heatstroke. We perform two sensitivity experiments (Cases 2 and 3) in addition to control experiment (Case 1) to discuss the uncertainty of future projection results. The future projection experiments are summarized in Table 2.

- Case 1: Future projection considering neither near future demographics nor long-term acclimatization into account.
- Case 2: Future prediction considering only the near future demography.
- Case 3: Future prediction considering both near future demography and long-term acclimatization.

Case 1 is an experiment to evaluate the increase in the risk of heatstroke due solely to the increase in temperature caused by climate change. In this experiment, the number of patients with heatstroke in the entire region is used as the risk indicator, but it is assumed that the demographics will not change between now and the future. In other words, the increase in risk in this experiment is the same as the increase in the risk of heat stroke for each individual resident.

Case 2 is an experiment to evaluate the variation in the risk of heatstroke by considering the temperature increase due to climate change and demographic change from the baseline period to the near future. In this experiment, we can obtain the projected number of patients with heatstroke for the entire region at each time point in the baseline period and near future. Thus, this future projection is able to assess the risks related to the burden on the emergency medical system associated with an increase in the number of patients with heatstroke. The burden on the emergency medical system refers specifically to the shortage of emergency transport systems and inpatient beds, as indicated in Chapter 1. Therefore, it is expected that the results of this future projection will be very useful information for the government to formulate adaptation measures to climate change.

It is known that heat acclimatization can occur over a long period of time, apart from short-term acclimatization throughout the single summer. Petkova et al. (2014) noted that the excess mortality observed between 1973 and 2006 was much lower than that observed between 1900 and 1948, indicating that people have become acclimatized to the heat during this period. They concluded that this acclimatization is due to the improvement of the living environment and the widespread use of air conditioners. Therefore, in this study, the following experiments (a) and (b) are conducted to evaluate long-term heat acclimatization from the baseline to the near future. In both Case 3a and Case 3b were considered population dynamics.

(a) An experiment in which individuals are assumed to have heat tolerance equivalent to late summer throughout one summer season (Case 3a).

(b) An experiment using a climate analogue to account for lifestyle changes in a cold region with particularly low air conditioning penetration (Case 3b).

In the prediction experiment of Case 3a, we particularly examine the effect of long-term acclimatization due to the acquisition of heat tolerance. Equation (3) for late summer, described in 3.3, is used to predict the number of patients with heatstroke in near future over the entire summer period, including early and mid-summer. This is based on the assumption that the government and individuals will have heat tolerance equivalent to that of late summer throughout the entire summer period by taking all kinds of heat countermeasures.

In the prediction experiment of Case 3b, we examined the effects of long-term acclimatization due to the acquisition of heat tolerance and lifestyle changes. In this experiment, targeting the areas are Hokkaido, Aomori, Iwate, Miyagi, Akita, Yamagata, Fukushima, Nagano, and Yamanashi. These areas have low percentages of households with air conditioning during the baseline period. We first looked for the three prefectures of that the current daily maximum temperature is the close to the near future daily maximum temperature of a target prefecture. And then, using the prediction models of the selected three prefectures, the near-future projections were made for the target prefecture. This procedure was finally conducted for nine target prefectures with low air conditioner penetration rate today. This method is a kind of the climate analog approach (e.g., Ishizaki et al. 2012). This near-future prediction is based on the assumption that the inhabitants of the regions with low air-conditioner penetration rates in the baseline period will acquire the same heat tolerance or change their lifestyles as those of other regions with similar climates in the near future.

The targeting nine prefectures (Hokkaido, Aomori, Iwate, Miyagi, Akita, Yamagata, Fukushima, Nagano, and Yamanashi) had particularly low air conditioner penetration rates in 1999 (specifically, 9.3% in Hokkaido, 30.2% in Aomori, 35.6% in Iwate, 59.1% in Miyagi, 56.7% in Akita, 67.8% in Yamagata, 58.4% in Fukushima, 44.8% in Nagano, and 72.0% in Yamanashi). The air conditioner penetration rates in the other prefectures are all above 80%

(based on the 1999 National Survey of Actual Consumption, https://www.e-stat.go.jp/dbview?sid=0000111013).

The future projections are carried out using daily maximum WBGT instead of daily maximum temperature as an explanatory variable. The method of calculating the daily maximum WBGT in baseline and near-future is described in Section 2.3 and Supplement 1.

4. Accuracy of the proposed statistical models under the current climate

4.1 *Improvement in model accuracy by considering regional and short-term heat acclimatization and age*

First, we developed a model to predict the number of heatstroke emergency patients using the daily maximum temperature data for Tokyo and conducted prediction experiments and accuracy verification (cross-validation) for each prefecture (Model 1). The prediction errors of the Model 1 were 5.5 (MAE) and 10.6 (RMSE), on average, across the country.

Second, we performed prediction with Model 3 and compared the results between Models 1 and 3. As a result, it was confirmed that the MAE could be reduced by about -19% (-46% to -3% in each prefecture) and the RMSE by about -25% (-48% to -0% in each prefecture) on average, across the country by taking into account regional characteristics (Figure 3).

As the third experiment, we performed prediction with Model 5 and compared the results between Models 3 and 5. We found that, from the results, considering the short-term heat acclimatization (i.e., effect of Model 5) reduced the MAE by about 12% (-22% to -3% in each prefecture) and the RMSE by about 12% (-20% to -4% in each prefecture) on average, across the country.

Last, we compared errors between the odd-numbered model group (Models 1, 3, 5) with the even-numbered model group (Models 2, 4, 6), indicating that the prediction accuracy on average, across the country remained almost unchanged when differences in risk by age were considered.

We explicitly show the effect of improving the accuracy due to considering the period division (i.e., Model 5 effect) using data for 2018 Fukuoka Prefecture (one of the major prefectures in Japan) as an example from the cross-validation results. In 2018, a severe heat wave was experienced across Japan. Thus, predicting the number of patients with heatstroke in 2018 using climate data from 2010-2017 is a good example for a prediction experiment for a warmer future using standard summer data. The results showed that the early summer period is characterized by having a relatively high number of patients with heatstroke and the late summer period is characterized as having relatively fewer patients (Figure 4). Note that it was also confirmed in many prefectures other than Fukuoka. Figure 4 shows the time series of daytime predictions obtained from the model with and without period division and benchmark model (i.e., Models 1, 3, vs 5). It can be seen that the model without period division (Model 3) significantly underestimates the peak in the number of patients from early July to early August. It also tends to overestimate the peak in mid to late August. On the other hand, these tendencies of underestimation and overestimation are greatly improved in the model with period division (Model 5) (32% reduction in MAE and 29% reduction in RMSE).

4.2 *Effect of different explanatory variables on prediction accuracy*

The explanatory variables with the highest prediction accuracy for each region were investigated for the predictions obtained using Model 6. From the perspective of MAE (Figure 5), the daily maximum WBGT would be selected as the best explanatory variable in 27 of the 46 regions. From the perspective of RMSE (Figure 6), the daily maximum WBGT would be selected as the best explanatory variable in 31 of the 46 regions. These results suggest that WBGT is better explanatory variable than daily maximum temperature for predicting the number of patients with heatstroke. This is consistent with studies that have shown that humidity is an important explanatory variable for heatstroke risk (Zhang et al, 2014; Sherwood, 2018). However, in the majority of prefectures, the difference in the error between the temperature models and WBGT models was less than 10%, with a maximum of 20% (MAE) and 25% (RMSE).

5. Future projection of the number of patients with heatstroke

5.1 Baseline

The estimated total number of patients with heatstroke per summer (averaged for 20 years x 4 GCMs) for the Baseline period is shown in Figure 7. This figure shows that the average total number of patients with heatstroke in all prefectures is 3.8/10,000 per summer, with a spread from a maximum of 6.3/10,000 (Kagoshima) to a minimum of 1.6/10,000 (Hokkaido) by prefecture. This spread reflects the regionality of both the temperature spread and tolerance to the heat.

5.2 Result of near future projection only effect of climate change: Case 1

Figure 8(a) shows a map of future changes in the risk of heatstroke (for Case 1). This figure indicates that the average total number of patients with heatstroke in all prefectures is 8.9/10,000 per summer, with a large spread from the maximum value of 18.6/10,000 (Kagoshima) to the minimum value of 5.2/10,000 (Tokyo) by prefecture.

Figure 9 shows the rate of increase in the number of patients with heatstroke from the baseline period (1981-2000) to the near future (for Case 1) on the averaged nationwide. This figure indicates that the number of patients with heatstroke in the near future will be 1.2-2.9 times (2.1 times in the ensemble average of 4 GCMs) in the case of RCP2.6 scenario and 1.4-3.3 times (2.2 times in the ensemble average of 4 GCMs) in the case of RCP8.5 compared to the baseline period. This range of values is due to the uncertainty of the GCMs; since there is no significant difference in the prediction results between the RCP2.6 and RCP8.5 scenarios because of near future projection, we will only discuss the prediction results for RCP8.5 from now on. The regions with the highest increase in the heat stroke risk from the baseline period to the near future are found to be Hokkaido, northern Tohoku, southern Kanto, Tokai, and Kyushu (Fig. 10a) (see Fig.A1 in Supplement 2 for the names of Japanese prefectures and regional categories). The prefecture with the highest rate of increase was Hokkaido, with 313.6%. One of the reasons for this may be that Hokkaido has experienced a larger increase in temperature due to climate change (about 2.2°C increase) than other regions (see Fig.A2(a) in Supplement 3).

5.3 Result of future projection with population dynamics: Case 2

The risk map of patients with heatstroke in the near future (2031-2050) obtained from the future prediction experiment of Case 2 is shown in Figure 8(b). This figure indicates that the total number of patients with heatstroke nationwide is 9.6/10,000 per summer, with a large spread from a maximum of 20.4/10,000 (Kagoshima) to a minimum of 5.7/10,000 (Tokyo) by prefecture.

A map of the increase rate in the number of patients with heatstroke from baseline to the near future (under RCP8.5 scenario) for each prefecture of Case 2 is shown in Fig. 10 (b). The increase rate on the average nationwide in the number of patients with heatstroke from baseline period to the near future on the average nationwide obtained from Case 2 is 234.4% in the ensemble mean of four GCMs. This increase rate on the average nationwide is about 10% larger than that in Case 1. The reason must come from the differences between Cases 1 and 2, that is (i) the increase in total population from the baseline to the near future, (ii) the increase in the elderly population, or (iii) both. Let us now consider which of these three factors was dominant. The population of Japan in the baseline (1990) is about 120 million, while the population in the near future (2040) will be about 110 million. Therefore, if the experiment only considers the increase or decrease in population, the number of patients with heatstroke in Case 2 should be smaller than in Case 1. This means that the reason for the increase the number of patients with heatstroke is the increase in the elderly population. In fact, the proportion of elderly people in the total population has almost tripled from 12.0% to 35.3% from baseline to near future. In all prefectures, the increase rate was higher than 100%. We can see that the increase rate is high in the prefectures with large population that include the Tokyo metropolitan area and other major urban areas. Among these prefectures, the difference in the prediction between Case 1 and Case 2 is the largest in Tokyo. In Tokyo, the rate of future increase is 360.0% in Case 2, but 239.3% in Case 1. The population of Tokyo as a whole increase by 16.6% from baseline to the near future, and the aging rate also increases by 18.6% from baseline to the near future. In other words, in Tokyo, the risk of heatstroke in Case 2 was particularly high compared to Case 1 due to two effects; total population increase and increase in the aging rate from the baseline period to the near future, in addition to climate change.

The demographic changes from the baseline to the near future can be classified into the following four patterns for each prefecture.

(1) The population of the prefecture increases, and the proportion of elderly people in the total population also increases. (Tokyo type)

(2) The population of the prefecture increases, but the proportion of elderly people in the total population decreases.

(3) The population of the prefecture decreases, but the proportion of elderly people in the total population increases.

(4) The population of the prefecture decreases, and the proportion of elderly people in the total population decreases.

In type (1), the number of patients with heatstroke is definitely higher in Case 2 than Case 1 where only the temperature increase due to climate change is considered. However, in the case of type (3), the results of future projections will depend on whether the decline in population or the increase in the aging rate is dominant. There were no prefectures that corresponded to type (2) and (4) (i.e., prefectures where the population aging rate decreases from baseline to the near future).

As a result of comparing Case 2 and Case 1, we found that there were 26 prefectures out of 46 prefectures where the number of patients with heatstroke was higher in Case 2. Of the 26 prefectures, 6 prefectures including Tokyo were classified as type 1 (Tokyo-type). In these prefectures, the number of patients with heatstroke will increase due to the following three factors: (1) climate change, (2) population growth, and (3) increase in the aging population. The remaining 20 prefectures were classified as type 3. In these prefectures, the number of patients with heatstroke will increase due to climate change and an increase in the aging population. Among these 20 prefectures, Fukuoka will have the highest increase rate. In Fukuoka Prefecture, the increase in the number of patients with heatstroke from baseline to the near future in Case 2 was estimated 289.8% (compared to 236.5% in Case 1).

In contrast to the prefectures belonging to the type 1 or type3 (e.g., Tokyo and Fukuoka), 21 of the 46 prefectures had a lower number of patients with heatstroke in Case 2 than in Case 1. The largest difference in the prediction between Cases 1 and 2 was observed in Akita Prefecture, where the increase in Case 2 was only 174.8%, but 235.9% in Case 1. In other words, the risk in Case 2 is 61.1% lower than in Case 1. Focus on demographic changes in Akita, the total population will decrease by 45.2% from the baseline period to the near future, while the population aging rate will increase by 31.9%. This situation has both a restraining effect on the number of patients with heatstroke (population decline) and an increasing effect on the number of patients with heatstroke (aging of the population). In the case of Akita, this restraining effect was dominant, which may have resulted in a lower number of patients with heatstroke in Case 2 than in Case 1. Thus, demographic changes have the effect of increasing or decreasing the number of patients with heatstroke, which is an important consideration for future projections (Table 3).

5.4 Result of near future projection with consideration of long-term acclimatization: Case 3

The map of the near-future projection for Case 3a is shown in Figure 8(c). This figure shows that the average total number of patients with heatstroke for all prefectures is 7.3 per summer, with a wide range from a maximum of 14.7 per 10,000 people (Kagoshima) to a minimum of 3.9 per 10,000 people (Tokyo) by prefecture.

Figure 10(c) shows a map of the average increase rate in the number of patients with heatstroke in each prefecture in Case 3a. The average increase rate on average nationwide is 164.5 %. This is about 60% smaller than Case 1, where only the effect of temperature increase due to climate change is considered. In Hokkaido, where the increase in the number of patients with heatstroke from baseline to the near future was the highest in Case 1, the value in Case 3a was reduced by about 100% compared to Case 1.

The map of the near-future projection for Case 3b is shown in Figure 8(d). This figure shows that the average total number of patients with heatstroke in the nine prefectures is 5.3 people per summer, with a spread from a maximum of 10.1 people/10,000 people (Yamanashi) to a minimum of 1.4 people/10,000 people (Hokkaido) by prefecture. Figure 10(d) shows a map of the increase rate in the number of patients with heatstroke from the baseline period to the near future for Case 3b. The average value for the nine prefectures is 119.7%. In four of the nine prefectures, the number of emergency heatstroke cases decreased compared to the current climate (Hokkaido: 66.0%, Miyagi: 85.3%, Yamagata: 77.0%, and Fukushima: 92.6%, assuming the value of baseline to be 100%).

5.5 Near future projections with explanatory variables changed to daily maximum WBGT (with population dynamics)

Fig. 11 shows the map of number of patients with heatstroke when the same assumptions as in Case 1, Case 2, Case 3a, and Case 3b are made and the explanatory variable is changed to the daily maximum WBGT to predict the number of patients with heatstroke in near future. Taking Case 2 (experiment considering demographics) as an example, the total number of patients with heatstroke is 10.4/10,000 per summer nationwide, with a large spread from the maximum value of 18.2/10,000 (Saga) to the minimum value of 5.1/10,000 (Hokkaido). The difference in the prediction between the model with daily maximum WBGT and the model with daily maximum temperature is only about 9%. This result suggests that there is no significant difference in the prediction results of the two models when we focus on the number of patients with heatstroke nationwide. However, looking at each prefecture, there are some prefectures where the results of near-future prediction between the daily maximum temperature model and the daily maximum WBGT model is largely different (Tables A1(a), A1(b) in Supplement 4).

6. Conclusions

The main aim of this study was to estimate the number of ambulance transport due to heat stroke under the current and near future climates with a newly developed statistical model. The model proposed in this study has the following three characteristics:

1) The dependent variable (predictor) was set as the number of heatstroke emergency patients. Directly predicting the number of emergency patients allows us to assess, not only the risk of heatstroke incidence among people, but also the burden on the emergency medical system.
2) The daily maximum temperature, which is readily available from future climate prediction datasets, was selected as an explanatory variable.
3) The seasonality of heatstroke risk (short-term heat acclimatization) was considered by dividing the summer period into three sub-periods: early summer, mid-summer, and late summer, with parameter identification appropriate for each period.

The proposed model considers not only temperature but also three main factors —region, short-term heat acclimatization, and age— that are considered to affect the prediction accuracy. The results of cross-validation showed that the prediction error was reduced by about 22% and 12% respectively due to considering regional characteristics and short-term heat acclimatization. On the other hand, it was found that the age did not much contribute to the model accuracy.

In order to confirm the practicality and validity of the proposed model, we compared its accuracy with models in which the explanatory variables were changed from the maximum temperature to WBGT. The model with WBGT was the most accurate in the majority of prefectures. However, the difference in the prediction error between the model with temperature and the model with WBGT was less than 10% in the majority of prefectures.

We therefore conclude that models using maximum temperatures instead of the WBGT as the explanatory variable can be used in practical situations by considering regional differences and short-term heat acclimatization.

With the statistical model developed, three near-future projections of the heatstroke risk were made: one considering only temperature increase due to climate change (Case 1), one considering temperature increase due to climate change and demographic change (Case 2), and one considering temperature increase due to climate change, demographic change, lifestyle change, and long-term heat acclimatization (Case 3a, b). In Case 1, the risk of heatstroke from the perspective of residents increases by about 2.2 times from baseline to the near future on the average nationwide (the ensemble means of 4 GCMs under the RCP8.5 scenario). The increase in risk was particularly pronounced in Hokkaido, where the risk of heatstroke increase was greater than three times. The risk of heatstroke from the perspective of the government in Case 2 increased by a factor of 2.3 from baseline to the near future on the average nationwide. This result suggests that the burden of heatstroke emergency cases on the emergency medical system in the near future cannot be ignored. The heatstroke risk in the near future in Case 2 is greater than that in Case 1 on the average nationwide. However, there were some prefectures such as in Akita that the effect of population decline on risk reduction is more dominant than the climate change on risk increase. Whether demographic change increases or decreases risk is not uniquely determined. From the prediction of Case 3a, it is found that the risk of emergency heatstroke can be reduced by about 30% on average nationwide by acquiring heat tolerance and changing lifestyles.

Lifestyle changes mean various changes for the adaptation to the worse thermal environment, as represented by the widespread use of air conditioners. See Section 3.8 for details. Case 3b shows that the risk of emergency heatstroke in the near future is lower than that in the baseline in some regions, such as Hokkaido. In other words, the results suggest that there is much room for risk control in cold regions by promoting the acquisition of heat tolerance and lifestyle changes.

Finally, in order to confirm the uncertainty of the explanatory variables, a comparison experiment was conducted using the daily maximum WBGT as an explanatory variable. As a result, the difference between the prediction result of the number of patients with heatstroke by the daily maximum temperature model and that by the daily maximum temperature WBGT model was about 9% on average nationwide.

Data Availability Statement

- The number of ambulance transport datasets analyzed in this study are available at [https://www.fdma.go.jp/disaster/heatstroke/post3.html].
- The current climate data (AMeDAS) analyzed in this study are available at [https://www.data.jma.go.jp/gmd/risk/obsdl].
- The statistical downscaling datasets (Nishimori et al., 2019) analyzed in this study are available at [doi:10.20783/DIAS.568].
- The population datasets analyzed in this study are available at [Baseline (1990); https://www.e-stat.go.jp/dbview?sid=0000031399] and [Near future (2040); https://www.ipss.go.jp/pp-shicyoson/j/shicyoson18/t-page.asp].
- The datasets generated and analyzed in this study (TableA1) are available at [https://doi.org/10.2151/jmsj.2022-030.].

Supplement

Supplement 1: How to calculate the maximum daily WBGT

In this study, the following equation was used to calculate WBGT (Yaglou and Minard, 1957). Day and night were discriminated based on the value of horizontal-plane insolation; a positive horizontal-plane insolation value was judged to be daytime and zero was judged to be nighttime.

$$WBGT = 0.7T_w + 0.2T_g + 0.1T_d \quad \text{(daytime)}$$

$$WBGT = 0.7T_w + 0.3T_d \quad \text{(nighttime)}$$

The dry-bulb and wet-bulb temperatures were based on the aforementioned values. The black-bulb temperature (*Tg*) was estimated using the equation by Okada and Kusaka (2013). When using this equation, the values of wind speed and solar radiation are also required. The wind speed was the spatial average of AMeDAS observations, as well as the temperature. Solar radiation was measured by the meteorological observatory. However, some meteorological observatories do not observe insolation. In such cases, the values were estimated from the time series of sunshine duration using the equation by Kondo (1994) and Kondo and Xu (1997). The daily maximum WBGT was obtained from the hourly values of WBGT obtained using this method.

Supplement 2: Regional Classification of Japan

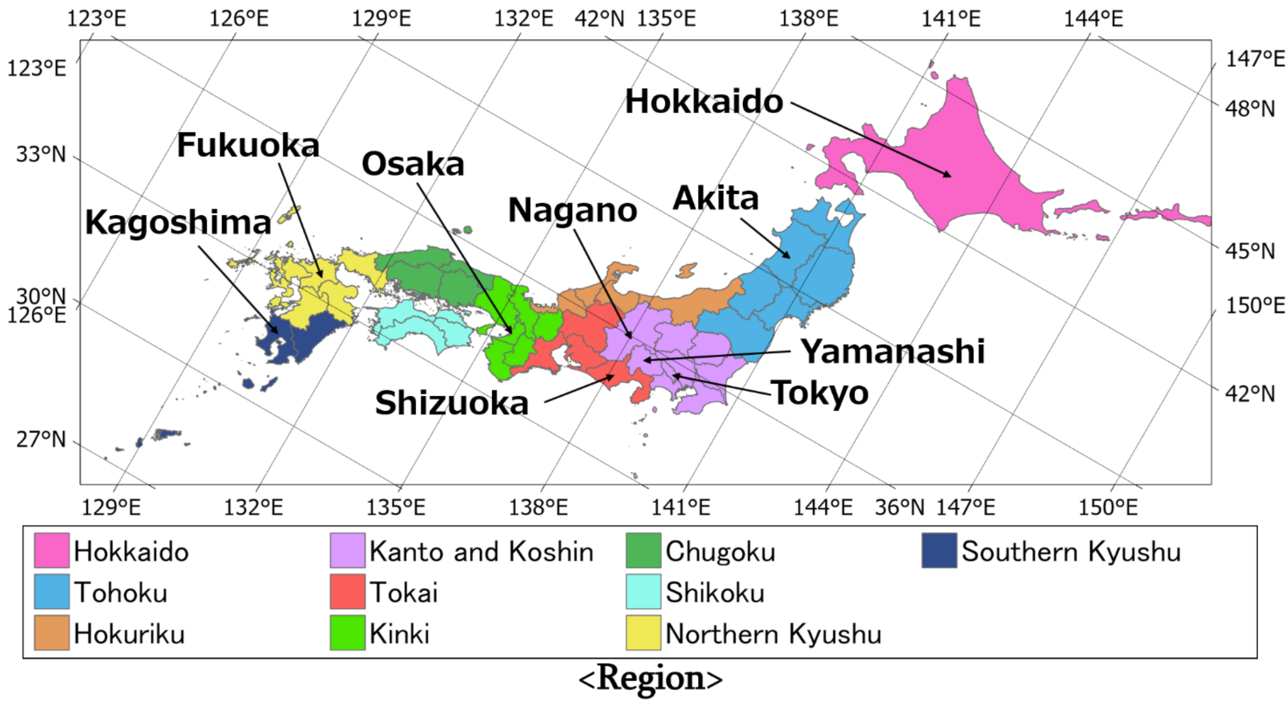
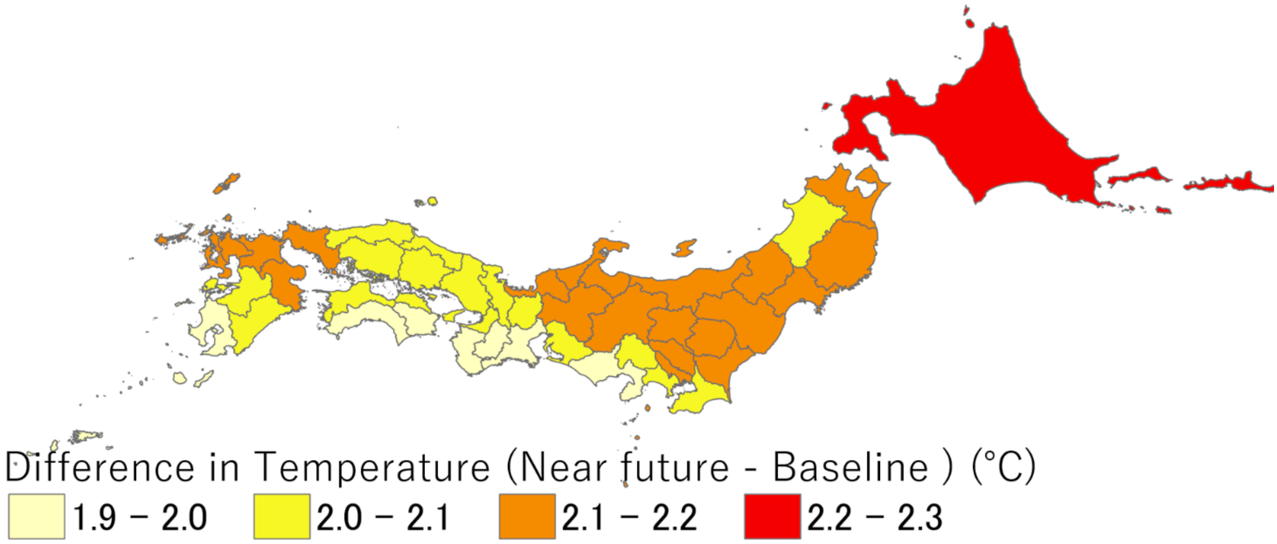
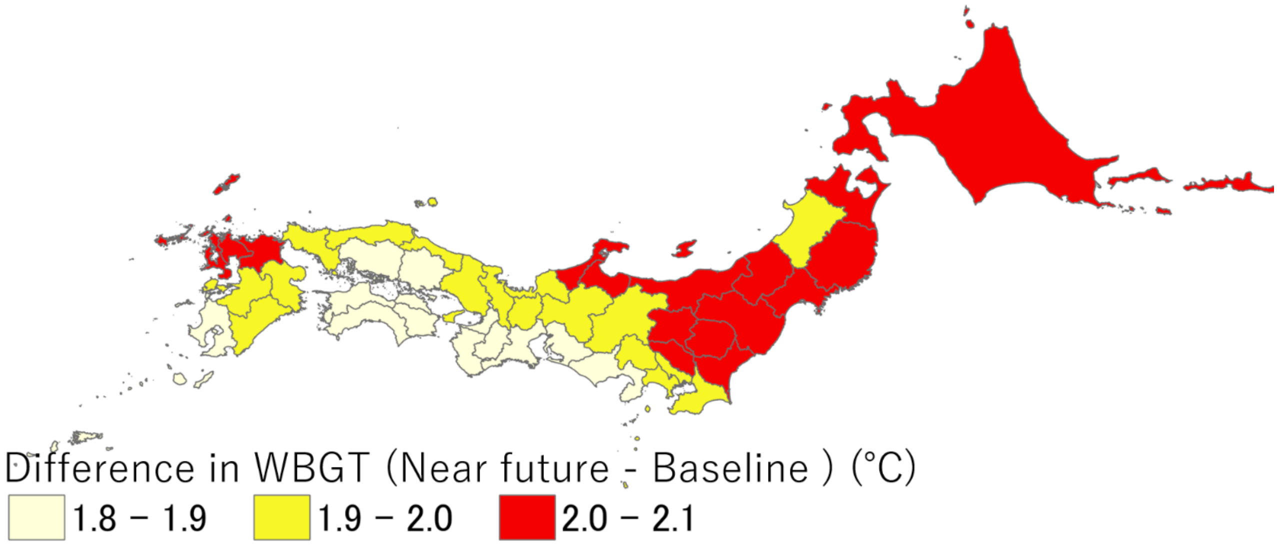


Fig. A1: Regional classifications and names of major prefectures in Japan. Based on the forecast categories used in the JMA's regional seasonal forecasts. Note that this classification is slightly different from the standard classification by the government.

Supplement 3: Increase in daily maximum temperature and daily maximum WBGT from the baseline period to the near future period



(a)



(b)

Fig. A2: Increase in (a) daily minimum temperature and (b) daily maximum WBGT (°C) from the baseline period to the near future period for each prefecture. Daily maximum temperature and daily maximum WBGT were ensemble averages from four GCMs, GFDL-CM3, HadGEM2-ES, MIROC5, and MRI-CGCM3 (RCP8.5).

Supplement 4: The number of people transported to emergency rooms for heat stroke in each experiment (Beseline, Case1, Case2, Case3a and Case3b) and the days with high risk of heat stroke.

Table A1: The number of heatstroke emergency patients in summer and days with high risk of heat stroke in each prefecture predicted in this study. (a) explanatory variable is daily maximum temperature, (b) daily maximum temperature is daily maximum WBGT. The days with high risk of heat stroke are (a) extremely hot days (daily maximum temperature ≧ 35℃) and (b) dangerous days (daily maximum WBGT ≧ 31℃).

(a)

Pref.	Number of extremely hot days Beseline	Number of extremely hot days Near future	Number of patients with heatstroke Baseline	Number of patients with heatstroke Near future (Case 1)	Number of patients with heatstroke Near future (Case 2)	Number of patients with heatstroke Near future (Case 3a)	Number of patients with heatstroke Near future (Case 3b)
Hokkaido	0.0	0.6	914.9	3018.1	3385.5	914.9	603.5
Aomori	0.1	1.7	381.3	888.1	1108.3	381.3	493.3
Iwate	0.3	2.6	433.9	907.4	1099.2	433.9	595.9
Miyagi	0.3	2.1	590.6	1483.2	1603.9	590.6	504.1
Akita	0.5	5.1	432.8	756.5	1026.5	432.8	607.7
Yamagata	0.6	5.8	373.1	715.9	873.5	373.1	287.3
Fukushima	0.2	3.9	832.4	1654.7	1924.8	832.4	770.9
Ibaraki	1.2	10.5	922.6	2117.5	2368.9	922.6	―
Tochigi	0.1	3.4	566.9	1389.8	1523.9	566.9	―
Gunma	1.0	9.6	833.6	1901.2	2095.3	833.6	―
Saitama	11.0	33.9	1865.9	5624.3	5515.4	1865.9	―

Chiba	0.7	10.1	1620.3	5109.1	5225.9	1620.3	—
Tokyo	2.8	17.0	2161.1	7778.3	7058.8	2161.1	—
Kanagawa	0.5	9.8	1587.4	5777.3	5652.2	1587.4	—
Niigata	0.6	8.4	954.2	1892.4	2222.5	954.2	—
Toyama	1.2	14.2	272.2	567.0	646.5	272.2	—
Ishikawa	0.6	9.7	399.6	951.5	1025.2	399.6	—
Fukui	1.7	18.0	257.2	539.4	605.5	257.2	—
Yamanashi	1.8	14.5	281.1	597.1	689.8	281.1	653.9
Nagano	0.0	1.9	594.3	1328.1	1482.3	594.3	690.4
Gifu	0.9	12.6	729.0	1559.9	1773.2	729.0	—
Shizuoka	0.5	7.1	2039.9	5479.4	6064.3	2039.9	—
Aichi	2.8	23.3	2326.4	7074.3	6831.0	2326.4	—
Mie	1.9	16.8	731.1	1748.5	1950.8	731.1	—
Shiga	0.8	12.0	361.2	1081.2	1070.5	361.2	—
Kyoto	4.8	29.4	1096.2	2686.3	2836.2	1096.2	—
Osaka	3.2	27.1	2899.6	7405.1	7854.7	2899.6	—
Hyogo	1.2	16.3	2194.9	5853.7	6099.3	2194.9	—
Nara	2.1	15.4	571.6	1126.4	1317.7	571.6	—
Wakayama	0.2	4.7	600.4	1052.8	1294.9	600.4	—
Tottori	1.2	11.1	290.7	547.6	620.4	290.7	—
Shimane	0.6	7.4	339.1	607.1	716.3	339.1	—
Okayama	1.9	15.9	1024.9	2244.6	2403.7	1024.9	—

Hiroshima	0.7	8.1	1079.9	2508.1	2630.9	1079.9	–
Yamaguchi	0.8	10.1	594.8	1161.8	1423.0	594.8	–
Tokushima	0.4	7.4	330.6	623.8	748.6	330.6	–
Kagawa	3.6	27.5	504.0	1123.1	1247.9	504.0	–
Ehime	0.4	8.6	706.1	1398.7	1641.3	706.1	–
Kochi	0.1	3.2	426.1	802.7	1013.2	426.1	–
Fukuoka	2.1	21.4	1555.5	4508.4	4535.8	1555.5	–
Saga	4.0	26.6	456.4	941.9	1062.3	456.4	–
Nagasaki	0.0	2.7	705.7	1485.0	1763.3	705.7	–
Kumamoto	1.1	17.9	955.9	2115.4	2333.3	955.9	–
Oita	0.6	9.5	511.1	1068.7	1210.6	511.1	–
Miyazaki	0.8	10.9	620.5	1316.0	1533.3	620.5	–
Kagoshima	0.1	3.2	1126.5	2622.2	3066.6	1126.5	–

(b)

Pref.	Number of dangerous days Beseline	Number of dangerous days Near future	Number of patients with heatstroke Baseline	Number of patients with heatstroke Near future (Case 1)	Number of patients with heatstroke Near future (Case 2)	Number of patients with heatstroke Near future (Case 3a)	Number of patients with heatstroke Near future (Case 3b)
Hokkaido	0.0	0.1	753.0	2047.3	2169.6	1463.9	532.9
Aomori	0.2	2.2	300.5	763.2	679.0	499.6	760.4
Iwate	0.0	2.1	350.3	888.3	818.5	567.7	964.5
Miyagi	0.2	5.5	579.9	1507.2	1746.5	1208.7	1317.7
Akita	0.3	5.3	353.7	891.8	669.6	603.8	983.2
Yamagata	0.0	4.1	362.1	910.9	802.5	583.6	773.4
Fukushima	0.0	1.4	692.2	1692.2	1619.2	1156.0	1035.1
Ibaraki	3.1	18.7	1052.6	2708.6	2885.0	2324.7	—
Tochigi	0.0	4.2	521.7	1340.6	1482.1	1214.6	—
Gunma	0.2	5.3	792.6	1999.4	2126.4	1625.8	—
Saitama	4.4	23.9	2149.4	5376.9	7803.5	5795.4	—
Chiba	1.5	18.5	1770.2	4624.7	6051.3	5148.1	—
Tokyo	0.0	6.2	2382.9	7860.8	12166.3	7247.1	—
Kanagawa	0.5	13.0	1557.1	4639.6	6581.0	4792.1	—
Niigata	1.0	12.7	852.0	2112.8	1970.5	1623.1	—
Toyama	0.6	15.0	243.8	611.5	622.3	474.0	—
Ishikawa	0.4	10.2	418.1	1108.9	1216.8	1044.5	—
Fukui	0.0	10.2	211.0	571.3	580.1	452.5	—
Yamanashi	0.0	5.7	305.4	750.3	767.7	557.1	912.5

Nagano	0.0	0.7	430.6	992.1	1,030	800.1	894.0
Gifu	0.1	7.3	866.8	2103.3	2135.1	1587.0	—
Shizuoka	0.1	6.3	1031.0	2538.5	2771.2	2356.6	—
Aichi	0.4	13.7	2342.4	6075.4	8717.1	6534.6	—
Mie	3.2	21.2	785.8	2009.3	2094.4	1526.7	—
Shiga	2.8	19.6	349.0	814.9	1106.3	828.2	—
Kyoto	0.1	12.6	1006.6	2341.9	2783.6	2077.8	—
Osaka	0.3	10.7	2329.8	6048.6	7166.3	5834.3	—
Hyogo	1.2	16.5	1787.2	4162.9	5088.0	4088.8	—
Nara	0.4	14.9	587.9	1341.2	1331.5	1076.8	—
Wakayama	0.2	8.6	511.4	1119.4	950.2	676.4	—
Tottori	0.0	5.8	263.9	697.2	661.8	541.5	—
Shimane	0.1	11.2	312.5	755.8	668.9	527.1	—
Okayama	0.4	9.1	925.7	2168.4	2400.3	1919.7	—
Hiroshima	0.6	14.2	1353.9	3061.8	3456.4	2112.2	—
Yamaguchi	4.1	25.4	514.4	1321.1	1096.8	822.5	—
Tokushima	2.4	20.3	347.5	784.5	719.3	578.7	—
Kagawa	2.2	25.7	492.2	1200.9	1241.2	875.8	—
Ehime	0.4	14.1	678.6	1604.7	1480.7	1192.3	—
Kochi	0.9	12.3	317.4	762.0	634.0	468.5	—
Fukuoka	4.3	28.3	1352.9	3613.8	4513.7	3612.8	—
Saga	4.5	30.6	533.8	1364.0	1264.9	909.5	—

Nagasaki	0.3	13.8	599.1	1537.8	1366.3	1179.6	—
Kumamoto	0.6	20.4	844.3	2263.9	2293.8	1882.5	—
Oita	2.0	23.6	531.6	1297.2	1317.9	957.3	—
Miyazaki	3.2	26.6	479.7	1161.5	1104.8	904.3	—
Kagoshima	0.6	19.8	842.6	2089.3	1911.8	1530.9	—

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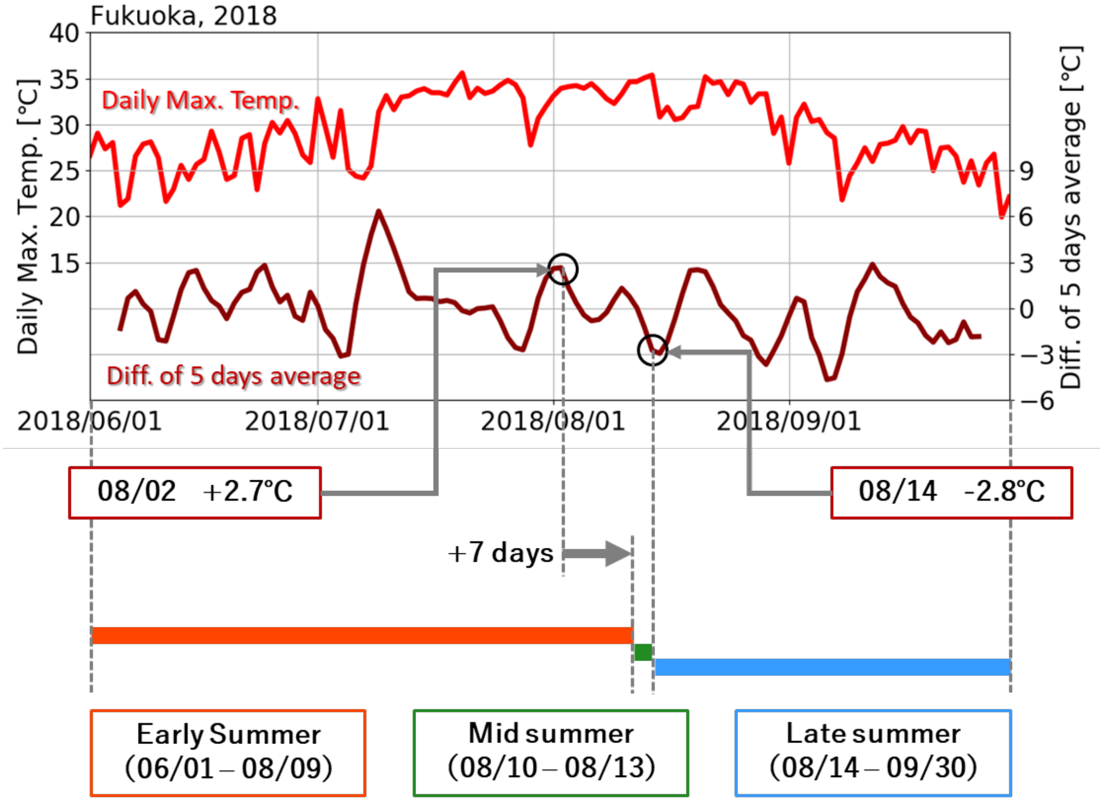

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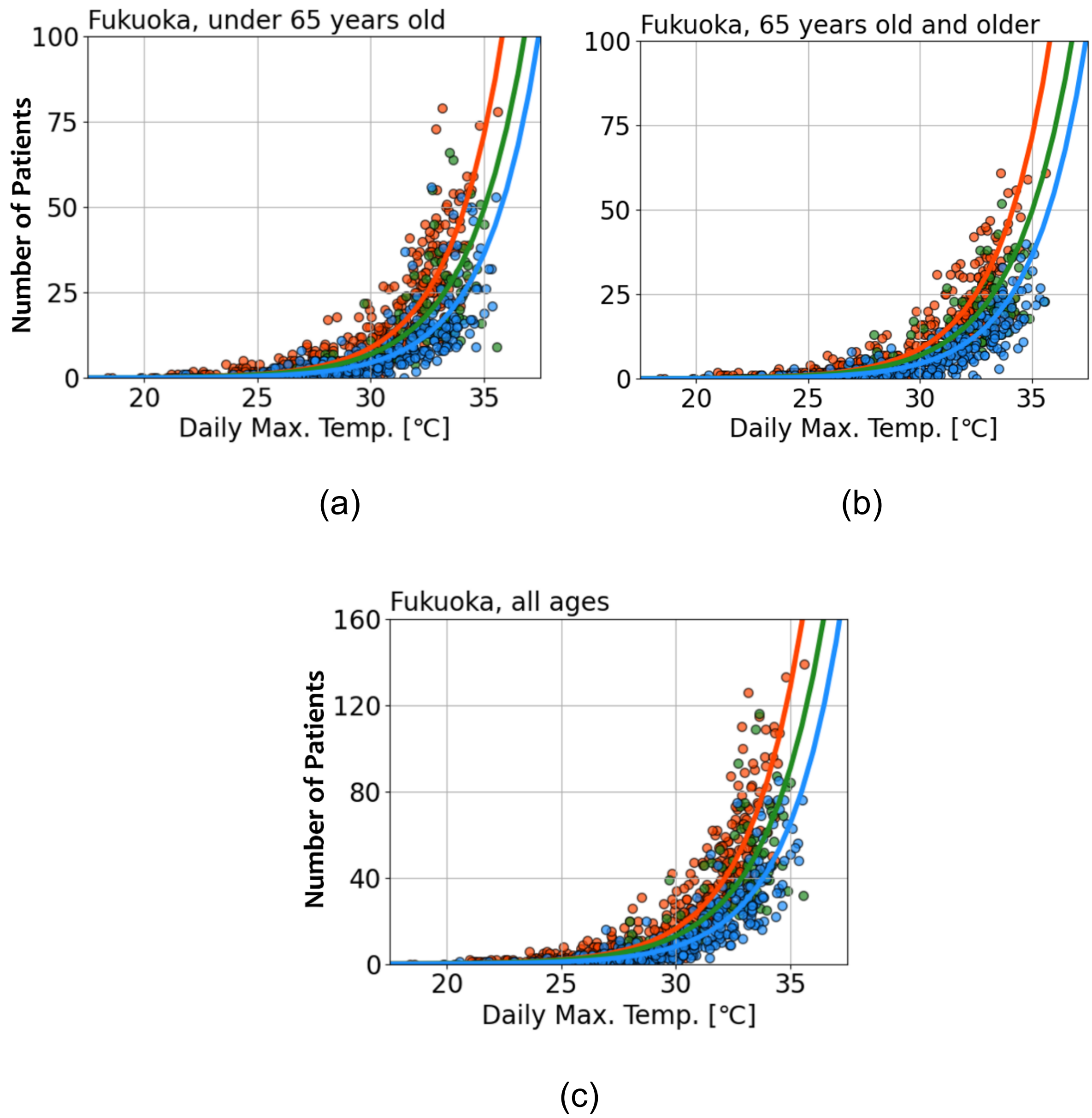

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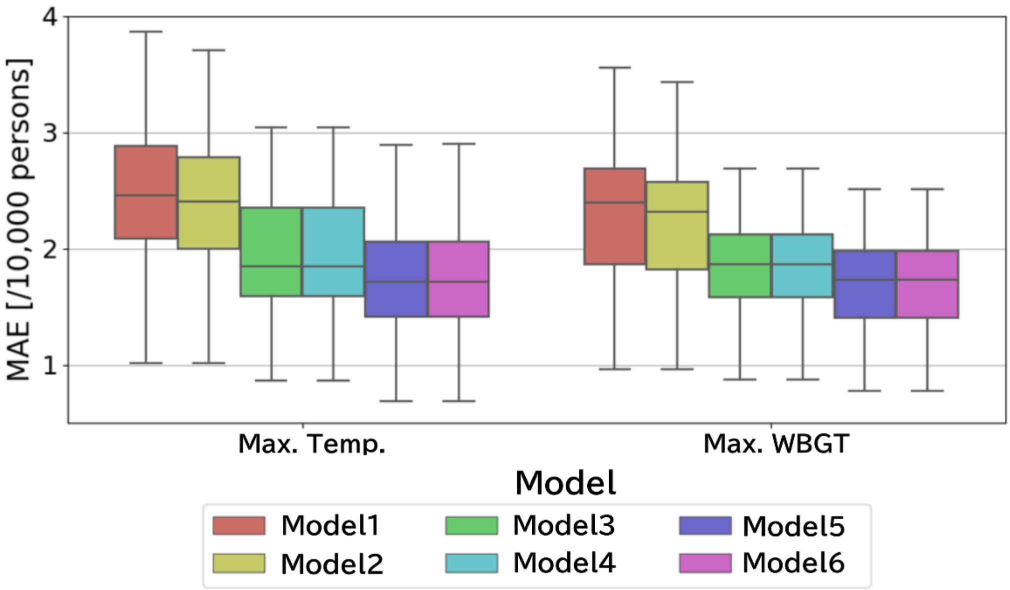

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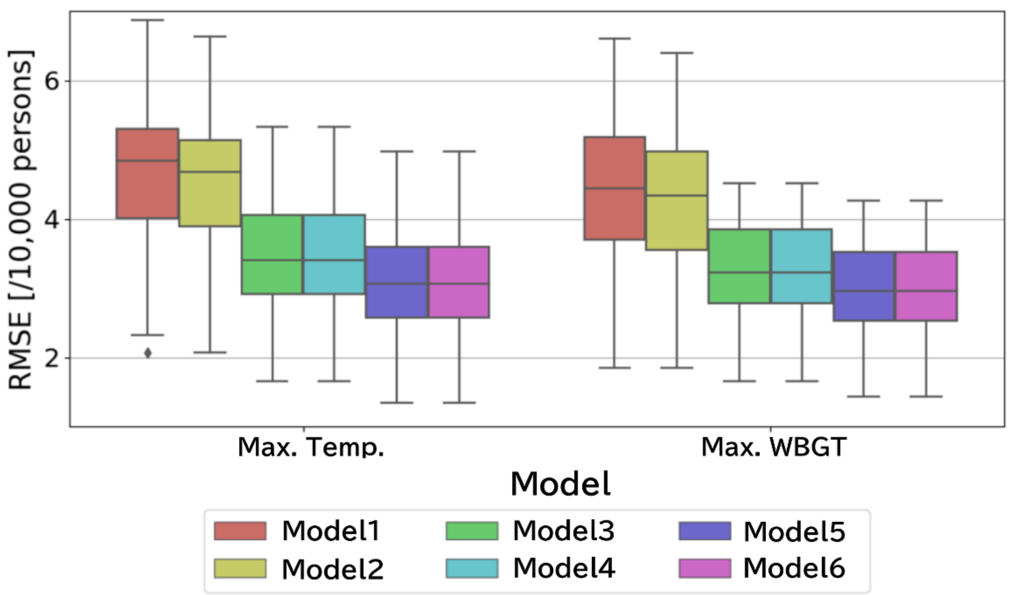

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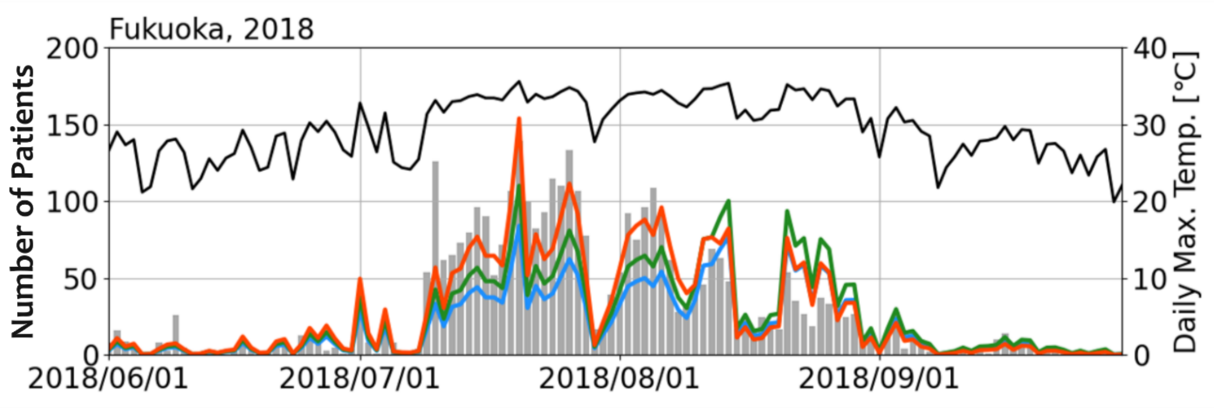

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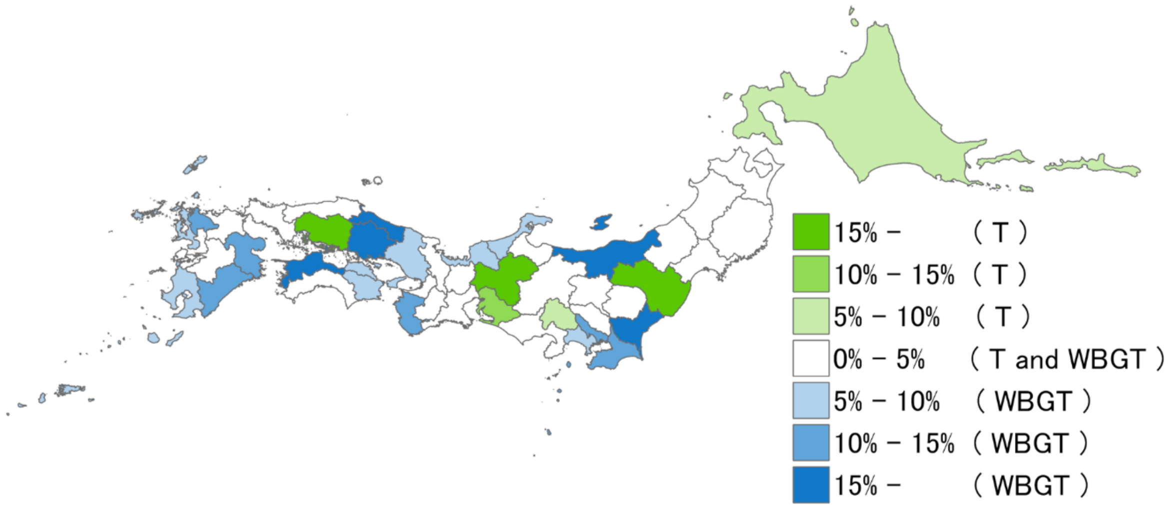

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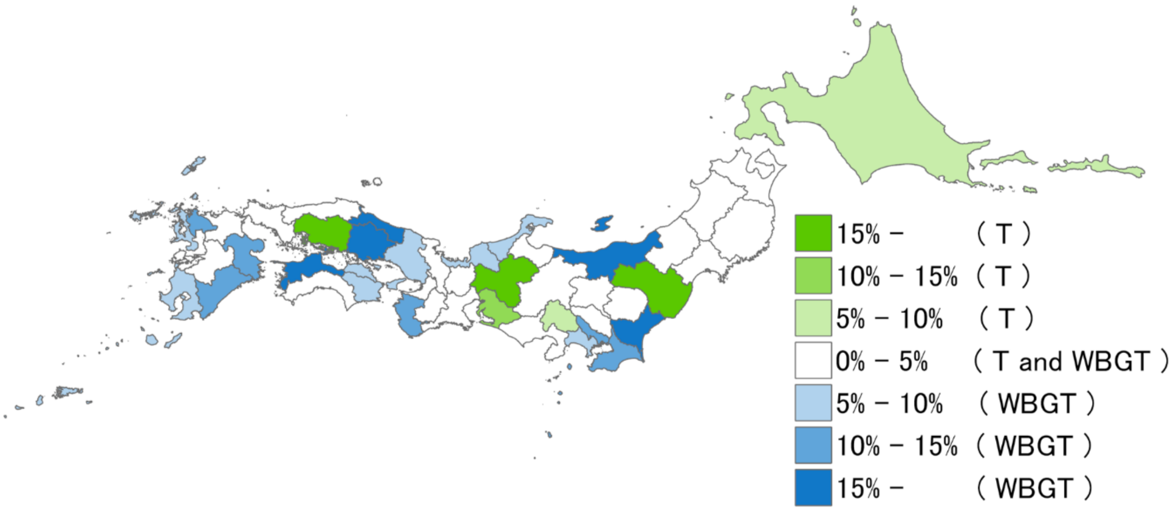

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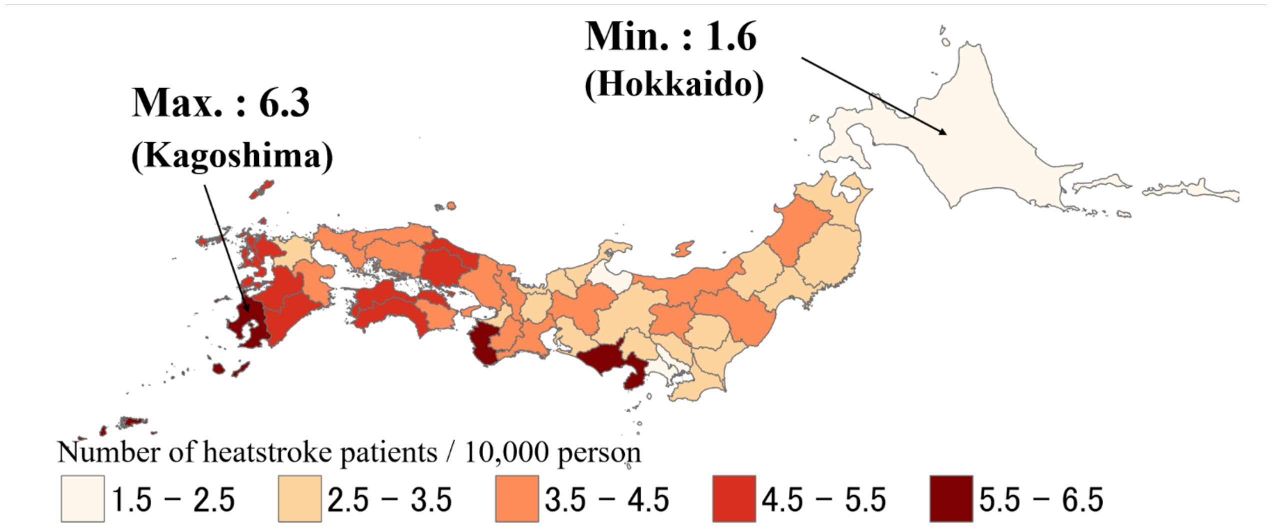

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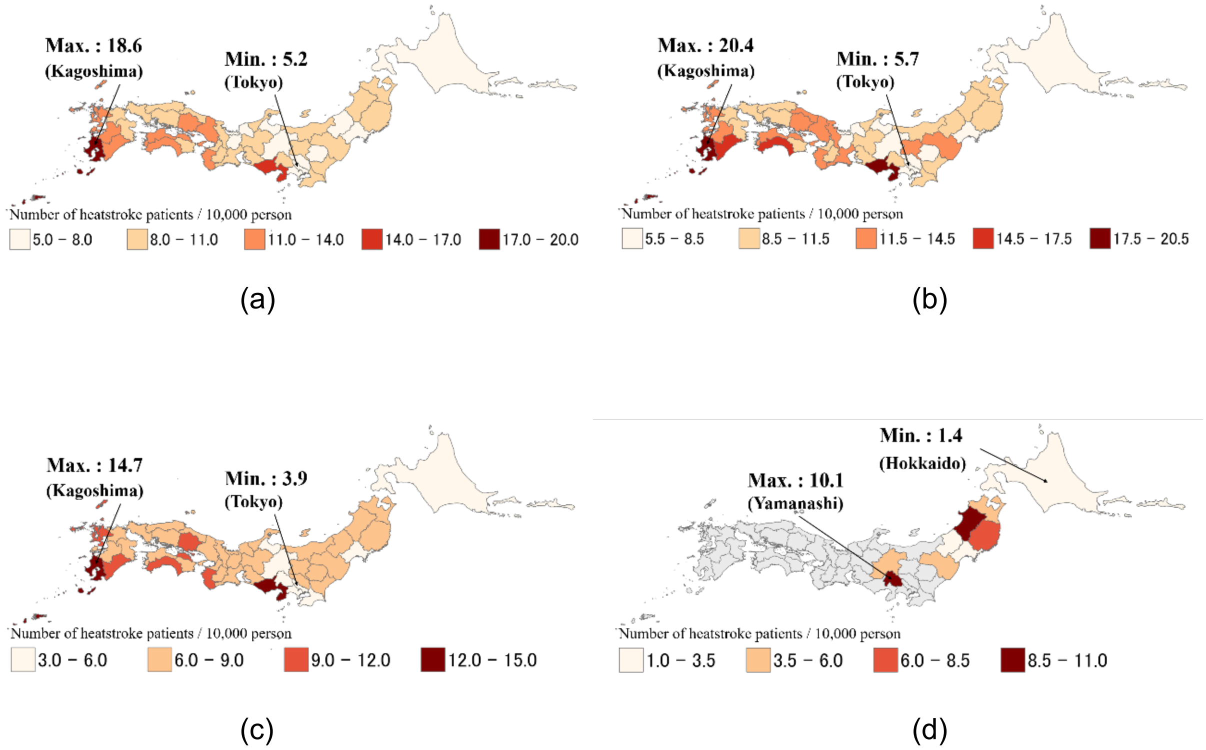

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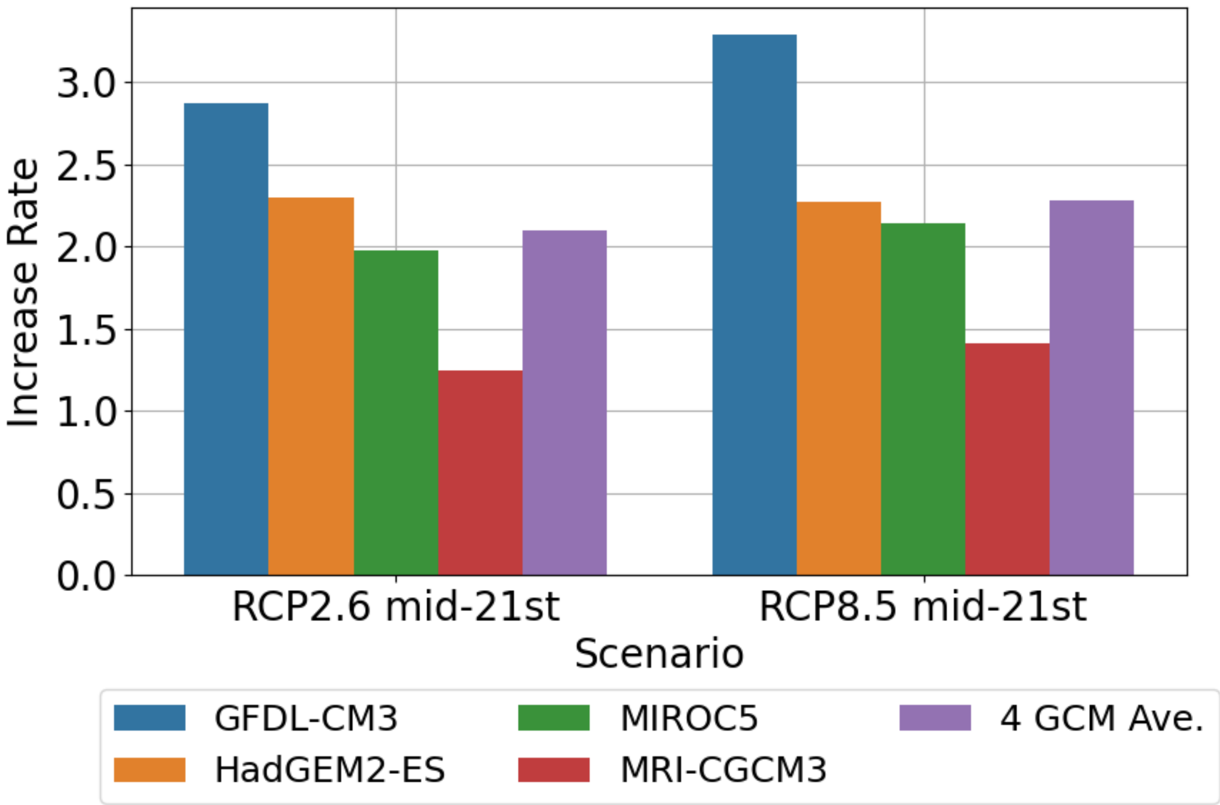

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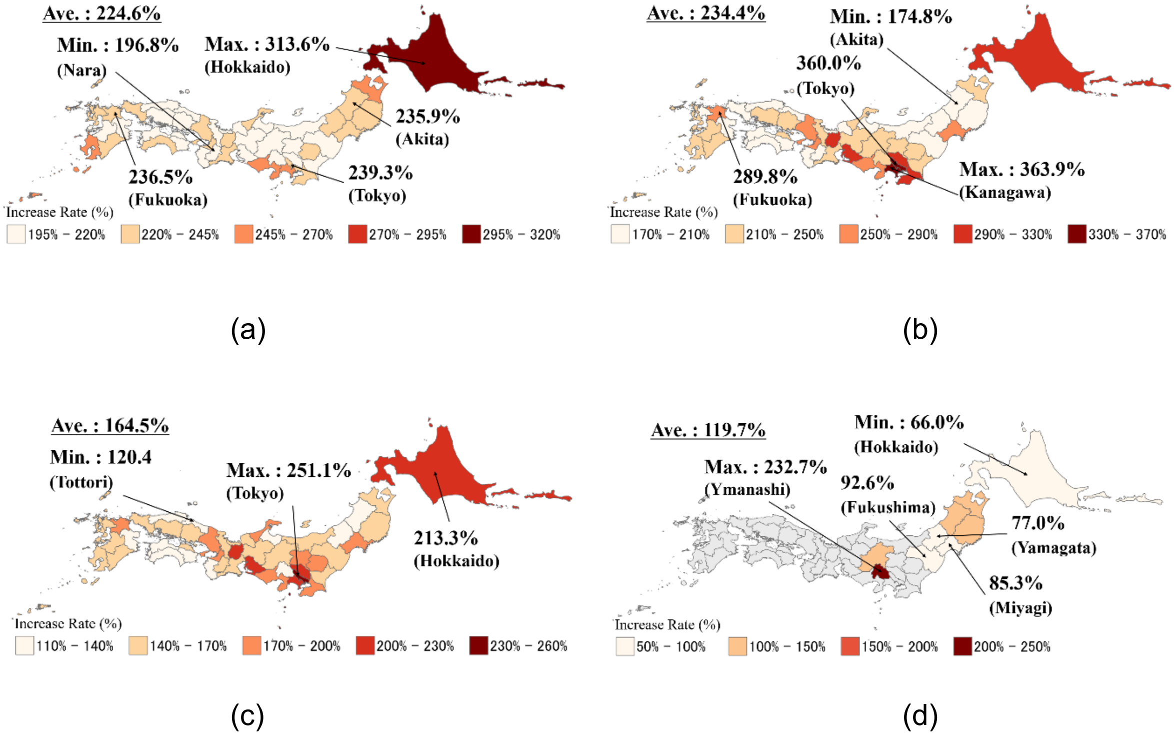

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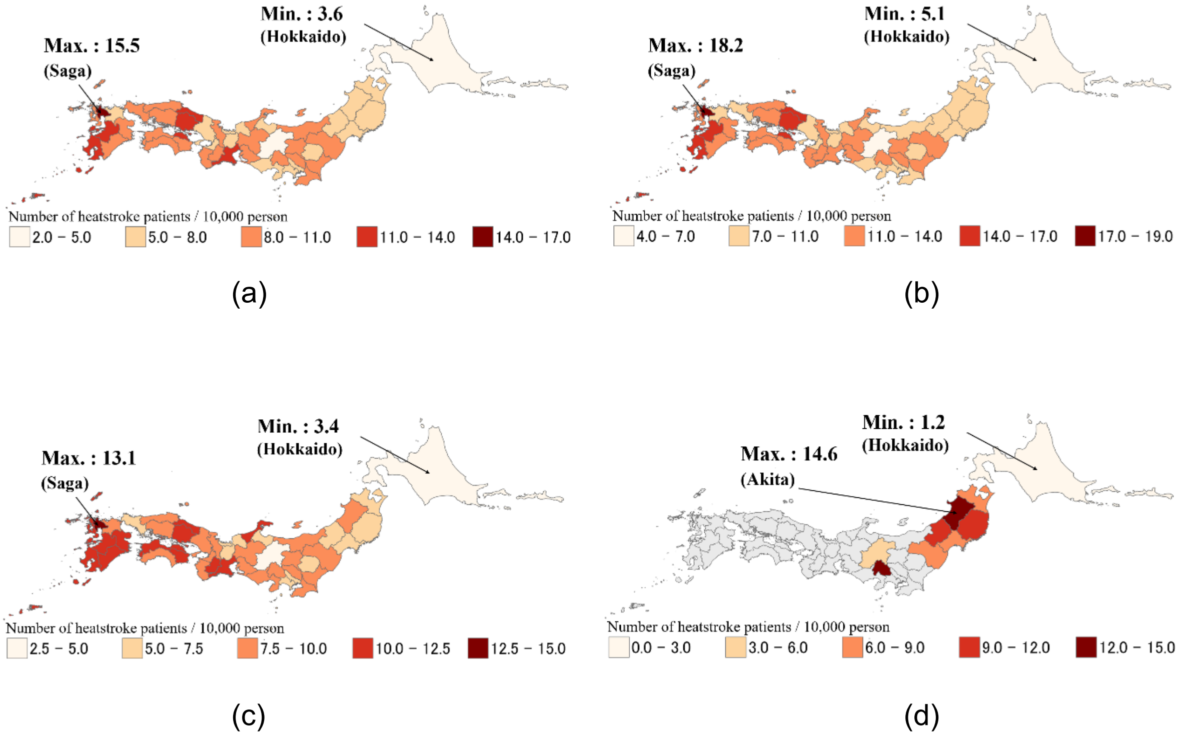

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Table 1 List of models that were compared for accuracy.

	Fitted Data			
	Tokyo	Each Prefecture	Period Division	Age Group
Model 1	○			
Model 2	○			○
Model 3		○		
Model 4		○		○
Model 5		○	○	
Model 6		○	○	○

Table 2 List of future projection experiments and featured factor.

	Climate Change Scenarios	Population	Long-term Acclimatization
Case 1	RCP 8.5	1990	—
Case 2	RCP 8.5	2040	—
Case 3a	RCP 8.5	2040	Late summer equation
Case 3b	RCP 8.5	2040	Climate analog

Table 3 Patterns of change in population and increase/decrease in risk of heatstroke emergencies from baseline period to near future.

		The proportion of elderly people in the total population	
		Increase	Decrease
Population	Increase	Prefectures at increased risk：6	—
	Decrease	Prefectures at increased risk：20 Prefectures at decreased risk：20	—