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Review of future weather data for building simulations available in Japan and confirmation of its characteristics

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Abstract. Buildings use a large amount of energy, depending on the climate. To design buildings with high energy and thermal performance in the future, it is necessary to use weather data that reflect future climatic information. Some future weather files for building simulations have been developed. However, these datasets are based on different predictions, and each future weather file has a different creation process. Such methodological differences may lead to differences in predicting the energy and thermal performance of buildings. Understanding the characteristics of each data type is necessary for its appropriate use. However, limited information is available for properly utilizing future weather data for building simulations. This study aims to provide information on the characteristics of future weather data for better utilization. After thoroughly reviewing the existing data and creation methods, we propose a framework for understanding future weather data based on their creative process. We collected five types of future weather datasets available in Japan and compared their characteristics. One of these datasets is the future weather dataset based on climate information provided by the National Institute for Environmental Studies (NIES). We confirmed the degree of variation in each weather element and predicted cooling/heating demand using future weather data available in Japan.

1 Introduction

Climate change is progressing as a result of CO_2 emissions by humans. Buildings have generally been used for decades, and building longevity is critical to reducing CO_2 emissions over their life cycle. Therefore, considering climate change is essential for adequately assessing thermal comfort in buildings and implementing a climate-adaptive design in a changing climate. Various future weather files have been developed for building simulations that reflect climate change to properly consider climate change in the building design process.

In Japan, Soga [1] developed future reference weather years for building simulation. Expanded AMeDAS Reference Weather Year (EA-RWY) -based future weather files were published in Japan. Various global attempts have been detailed in a review by Nielsen and Kolarik [2]. For globally available data, CCWorldWeatherGen, developed by the University of Southampton in the UK, can generate future weather data from the current reference year weather data at every place in the world [3]. Moreover, METEONORM version 8 software allows users to generate future weather files for any location [4]. WeatherShift, developed by Arup and Argos Analytics, can generate future weather files for building simulations for any country in the world [5]. Various organizations and researchers are developing future weather data for building simulations. It is important to note that future weather files employ different future climate information and creation methodologies. Therefore, future weather data for building simulations contain uncertainties owing to their creation process in addition to the uncertainties contained in climate change predictions. To use future weather data appropriately, it is essential to elucidate the uncertainties and their characteristics, depending on the applied methods. However, there is insufficient information to understand the characteristics and uncertainties of future weather data. Each future weather file is used ambiguously for impact assessment.

There is no unified framework for understanding methodologies for generating future weather files. Some of the proposed frameworks for understanding the methodologies for future weather data are as follows. Ramon [6] identified three methods: (1) dynamical downscaling, (2) stochastic weather generators, and (3) morphing. Nielsen and Kolarik [2] stated that there are two methods for increasing the temporal and spatial resolution required for building simulations: (1) dynamical downscaling and (2) statistical downscaling. They classified the method of morphing as a type of statistical downscaling. While these frameworks have some common points, some confusion can be observed. This confusion can be clarified by asking the following questions: In the above frameworks, dynamical downscaling is usually classified as a method different

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from morphing. However, if we use dynamically downscaled Global Climate Models (GCMs) data as future climate information in the morphing method, which method should we consider was used to generate future weather data? This question has no clear answer based on the framework described above.

This paper presents a framework for organizing future weather data by reviewing existing weather files and the methodologies used to create them. It appears that the aforementioned confusion is due to the confusion in positioning the "downscaling" process. Based on the proposed framework, we will attempt to organize future weather data available in Japan systematically. In this arrangement, we included future weather data developed by the Takenaka Corporation based on the climate information provided by the National Institute for Environmental Studies (NIES) [7]. Furthermore, we analyzed the meteorological elements of future weather files to understand the characteristics and uncertainties of the currently available weather data. Finally, simulations for estimating the heat load were conducted for a Japanese standard housing with each future weather dataset. Based on the simulation results, we confirmed the combined characteristics and variabilities of future weather files.

2 Review of future weather data for building simulations

2.1 Process of developing future weather files

Various organizations have developed future weather data, and various methods have been used to create them. As mentioned above, there is no comprehensive framework for understanding creation methodologies. However, there are three common processes for generating future weather data can be used in building simulations: future climate prediction by GCMs, downscaling of GCM outputs, and generation of hourly time-series values of future weather conditions. Understanding the characteristics of future weather data from these processes is crucial because the differences in each process result in differences in the characteristics of future weather data. Figure 1 shows the generation processes for future weather data. The process is described as follows.

2.2 Future climate information

Regardless of the methodology, future climate information is necessary to generate weather data for building simulations. The future climate is predicted by GCMs with CO_2 emission scenarios, and the future information to be adopted will largely determine the characteristics of future weather data. Future weather data that reflect a single GCM prediction and scenario, such as CCWorldWeatherGen, have the advantage that the nature of the generated data is clear. However, because of the uncertainty associated with GCM predictions, it is preferable to consider climate information from multiple GCMs. Such a strategy is applied in WeatherShift and METEONORM 8.

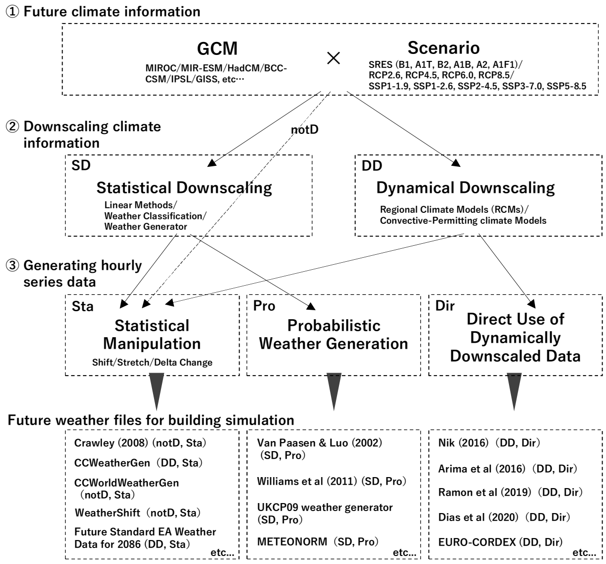


Fig. 1. Steps for generating future weather files

2.3 Downscaling climate information

GCMs have a coarse spatial resolution of approximately 100 km per mesh. Using downscaled GCM data with finer spatial and temporal resolutions is preferred for creating future weather data for building simulations. Downscaling methods can be broadly classified into statistical and dynamic methods. Statistical downscaling methods derive relationships between observation points based on historical data. The GCM information is downscaled based on statistical relationships. Statistical downscaling methods are reliable because they are based on actual observations; however, it is uncertain whether the statistical relationships from the past to the present are applicable in the future. Dynamic downscaling is conducted with the regional climate model (RCM), which uses GCM climate projections as boundary conditions to produce more detailed data with high spatial and temporal resolution.

Morphing is generally considered a downscaling method in architectural research. This is because Belcher [8] described morphing as a downscaling method. However, in climate research, statistical downscaling does not include morphing. The original purpose of downscaling was to add locality information to the GCM. However, the morphing procedure does not add any information to the climate information itself. Whether the morphing method is considered a downscaling method is a matter of personal preference, but the authors think it is more reasonable to understand the morphing method as a method for generating hourly time-series data sets, as described below.

2.4 Generating hourly time-series data

Building simulations such as heat load estimations require annual meteorological data for hourly time-series values. However, because most GCM outputs are often published as daily values, a method for generating hourly time-series data is required to develop future weather data. Methods for generating time-series meteorological data sets can be broadly classified into three categories: (1) statistical manipulation, (2) probabilistic weather generation, and (3) direct use of dynamically downscaled outputs (Figure 1).

"Statistical manipulation" is the most widely adopted method, in which current typical weather year data is statistically manipulated using future climate information to generate future weather data. Morphing is the most widely used method for this purpose [2]. In this method, the climate change values are calculated between the present and future climate data predicted by GCMs, and by adding or multiplying these values to the current weather data, future weather files are generated. Future weather data based on this method are reliable because their basic characteristics are based on current base weather data. However, it only considers the statistical values of climate change and ignores the relationship between the meteorological components in creation. Given these characteristics, morphing is the best method for generating future climate data for assessing average future conditions or changes. More sophisticated statistical manipulation methods, such as the "delta change," which allows for a range of climate change values, have also been proposed in recent years. The future EA-RWY has applied this new statistical manipulation method.

The "probabilistic weather generation" is a method for creating future weather data by directly using an output-stochastic weather generator. Because stochastic weather generation is generally positioned as a statistical downscaling method, future weather data based on this method must include the process of statistical downscaling. Future weather data generated by this method are expected to reproduce various conditions in a probabilistic manner. METEONORM 8 uses this method. Future reference weather years based on the UKCP09 weather generator [9] have been published in the UK.

Finally, there is a "direct use of dynamically downscaled outputs" method. This method has the advantage of considering the climate information added by the RCM. It has not been widely used because of its high computational cost and the difficulty of multi-ensemble modeling. However, in the UK, as dynamical downscaling data have been published in the European Coordinated Regional Downscaling Experiment (EURO-CORDEX) [10], future weather data based on this method will increase. As discussed by Nik [11], this method is useful for assessing extreme weather conditions. However, Tootkaboni et al. [12] reported that future weather data generated by this dynamic method tend to show different future trends than other future weather data, suggesting that the climate information added by the RCM should be treated with caution. Furthermore, the RCM output often includes systematic bias; thus, Arima et al. [13] recommended the implementation of bias correction in this method.

The three processes presented in this study for creating future weather data determine its characteristics. All future weather data can be comprehensively understood and organized in terms of these processes (see Figure 1).

3 Future weather data available in Japan and its characteristics

3.1 Future weather data available in Japan

While various types of future weather data have been developed around the world, this study focuses on five types of future weather data available in Japan: Expanded AMeDAS Future Reference Weather Year, CCWorldWeahterGen, WeatherShift, METEONORM 8, and NIES-based future weather data. The last dataset is not publicly available, but NIES data are publicly available. The NIES data were statistical downscaled to GCM outputs, and we used predictions by MIROC6h and MRI-ESM2-0. We conducted a statistical manipulation similar to morphing to generate an hourly series of NIES-based future weather data.

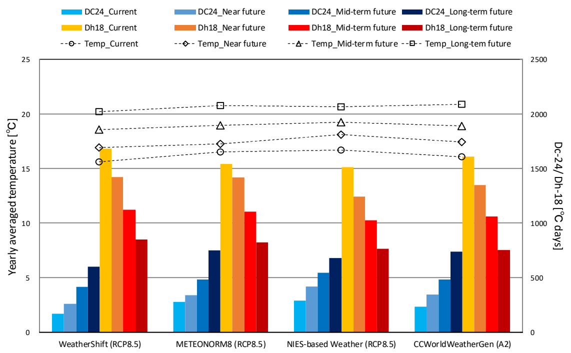
The following sections present the statistical characteristics of each meteorological element for each future weather dataset. Of the available future weather files, this study employed data based on the scenarios of RCP 8.5 and SRES A2 as high-emission scenarios and RCP 4.5 and SRES A1B as medium-emission scenarios. We classified the 2020s/2030s as the near future, 2050s/2060s as the mid-term future, and the 2080s/2090s as the long-term future, and compared the characteristics of the data for the relevant periods.

3.2 Temperature characteristics

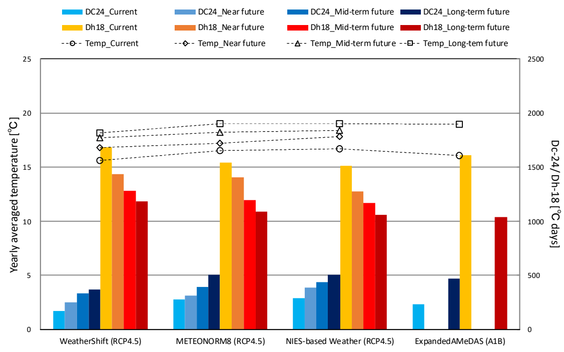
Figure 2 shows the annual average temperature and cooling/heating degree days for each future weather data set for Tokyo. Figure 1 (a) shows the results for the high-emission scenarios, and Figure 1 (b) shows the results for the medium-emission scenarios. The cooling degree days (Dc24) and heating degree days (Dh18) were calculated with set temperatures of 24 °C and 18 °C, respectively. The temperature-related absolute values of each future weather dataset were similar, and the expected balance between Dc24 and Dh18 was not significantly different. Currently, Dc24 is smaller than Dh18 in Tokyo. However, the balance changes gradually, and at the end of the 21st century, Dc24 and Dh18 will be balanced in the high-emission scenario (Figure 1a); however, Dh18 will still be more significant in the medium-emission scenario (Figure 1b). Figure 2 depicts the annual average temperature and degree days change values from the current period. This figure also shows no significant differences in the temperature characteristics among future weather data. In Tokyo, the high-emission scenario showed an increase of approximately 4 °C (Figure 2a). In comparison, the medium-emission scenario showed an increase of approximately 2 °C (Figure 2b).

3.3 Locality of temperature increase

Figure 4 shows the long-term future annual mean temperature and cooling and heating degree days (Dc24 and Dh18) at eight locations in Japan. In all locations, the annual mean temperatures of future weather data are similar, and the balance between cooling and heating degree days is expected to be similar. In the long-term future, based on the high-emission scenario, Dc24 and Dh18 are balanced in all regions except Sapporo and Sendai, which are located in high-latitude areas. In contrast, in the medium-emission scenario, Dh18 is still larger than Dc24 in regions other than Kagoshima at low latitudes. Figure 5 shows the future long-term changes in the annual mean temperature, and cooling and heating degree days. Among future weather data, a gap in the annual mean temperature increase of approximately 1 °C for the high-emissions scenario and 0.5 °C for the medium-emissions scenario exists. Both future weather datasets include similar regional trends, with higher temperature increases projected at higher latitudes.

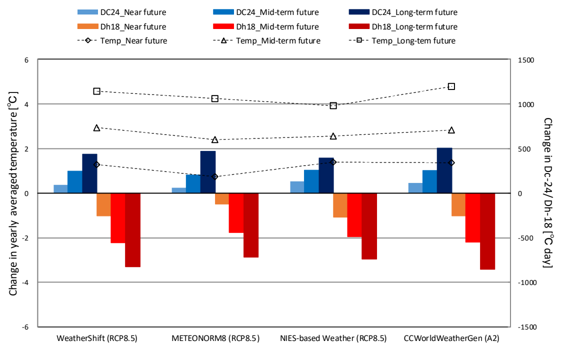


(a) High-emission scenarios (RCP8.5, SRES A2)

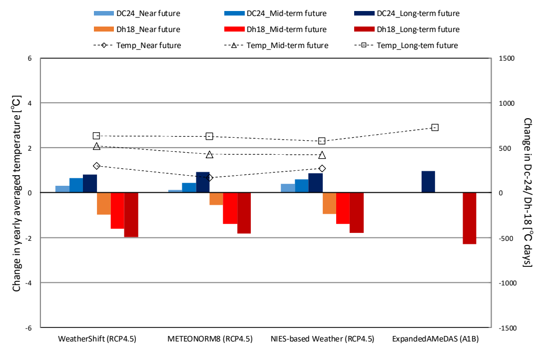


(b) Medium-emission scenarios (RCP4.5, SRES A1B)

Fig. 2. Yearly average temperature and cooling/heating degree days (Dc24, Dh18) at Tokyo

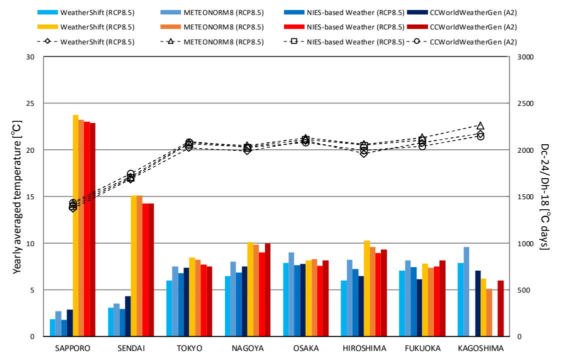


(a) High-emission scenarios (RCP8.5, SRES A2)

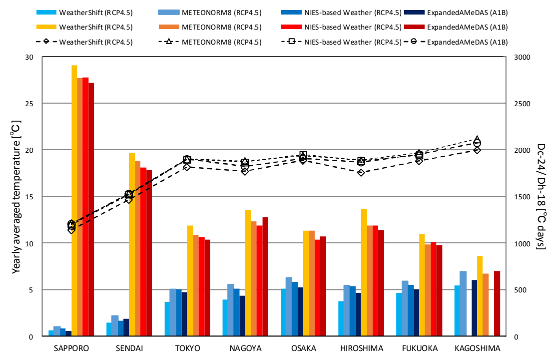


(b) Medium-emission scenarios (RCP4.5, SRES A1B)

Fig. 3. Future increase/decrease in yearly average temperature and cooling/heating degree days (Dc24, Dh18) at Tokyo

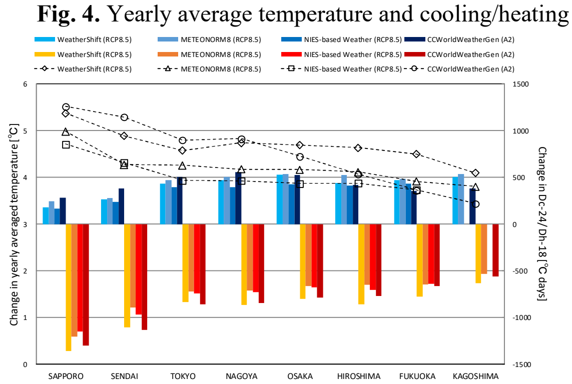


(a) High-emission scenarios (RCP8.5, SRES A2)

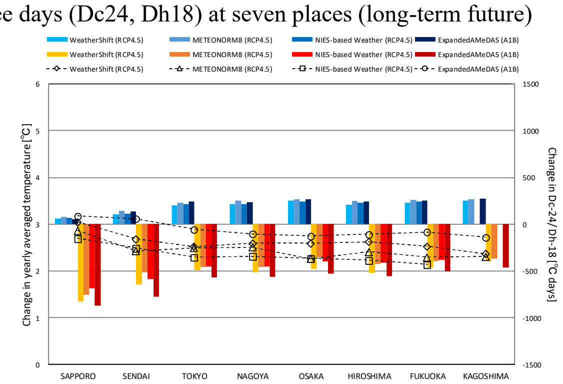


(b) Medium-emission scenarios (RCP4.5, SRES A1B)

Fig. 4. Yearly average temperature and cooling/heating degree days (Dc24, Dh18) at seven places (long-term future)



(a) High-emission scenarios (RCP8.5, SRES A2)



(b) Medium-emission scenarios (RCP4.5, SRES A1B)

Fig. 5. Future increase/decrease in yearly average temperature and cooling/heating degree days (Dc24, Dh18) at seven places (long-term future)

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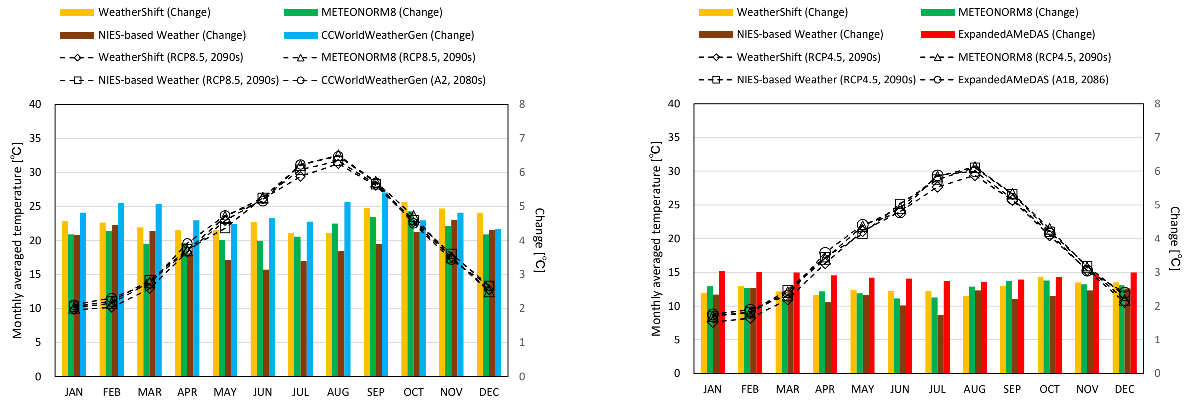
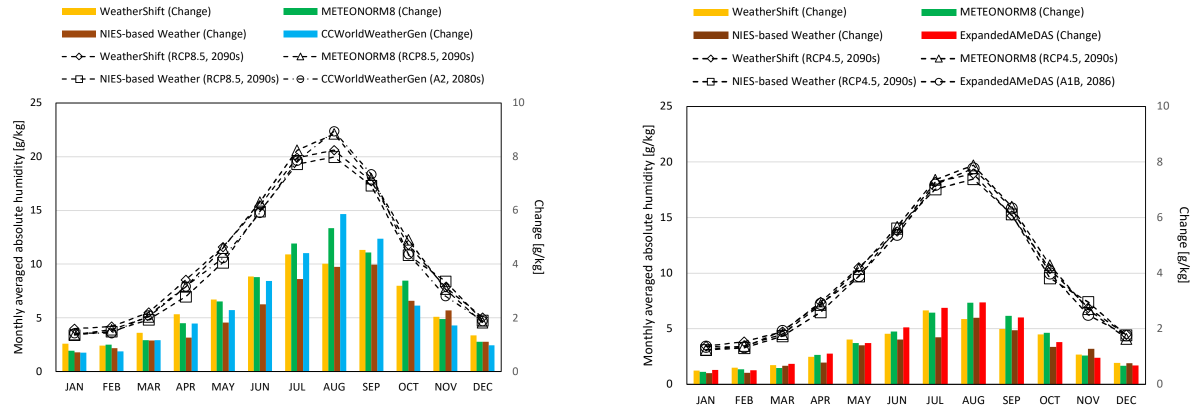


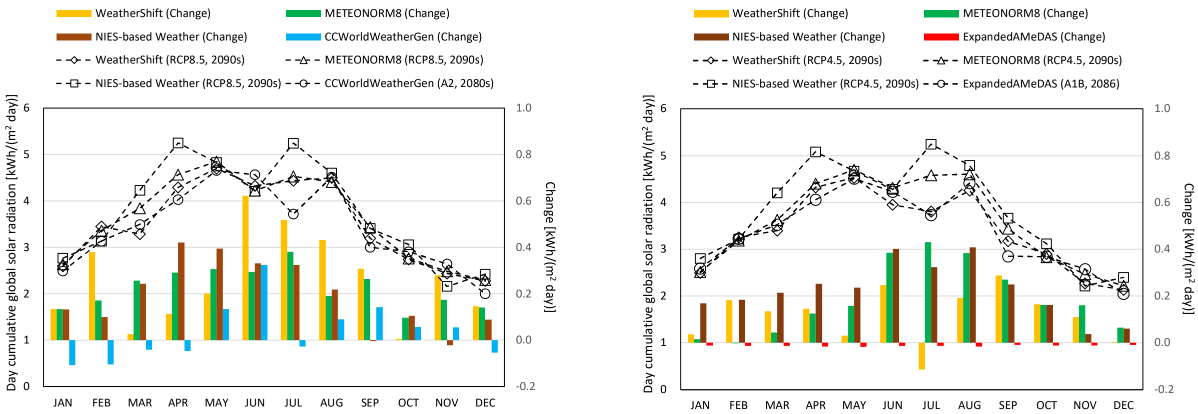
(a) High-emission scenarios (RCP8.5, SRES A2) Medium-emission scenarios (RCP4.5, SRES A1B)

Fig. 6. Monthly average temperature and its change at Tokyo in long-term future



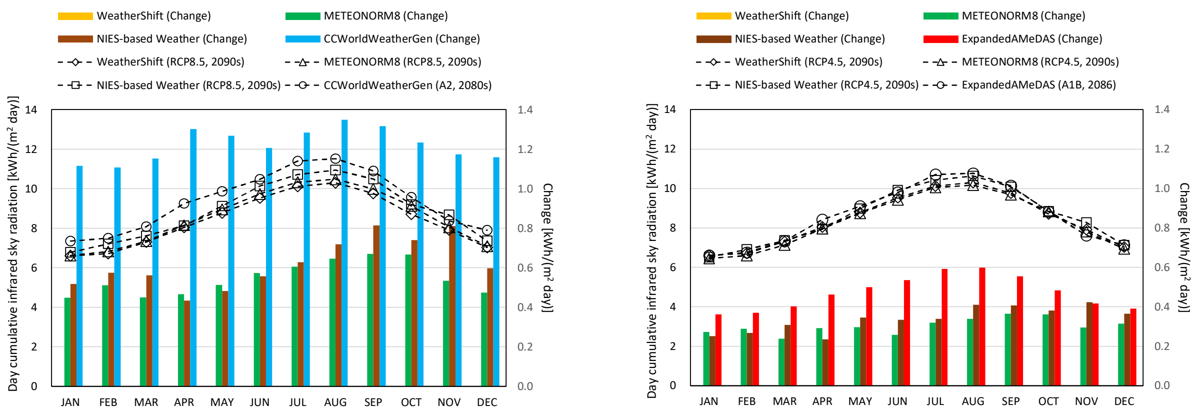
(a) High-emission scenarios (RCP8.5, SRES A2) (b) Medium-emission scenarios (RCP4.5, SRES A1B)

Fig. 7. Monthly average absolute humidity and its change at Tokyo in long-term future



(a) High-emission scenarios (RCP8.5, SRES A2) (b) Medium-emission scenarios (RCP4.5, SRES A1B)

Fig. 8. Monthly averaged daily-cumulative global solar radiation and its change at Tokyo in long-term future



(a) High-emission scenarios (RCP8.5, SRES A2) (b) Medium-emission scenarios (RCP4.5, SRES A1B)

Fig. 9. Monthly averaged daily-cumulative infrared sky radiation and its change at Tokyo in long-term future

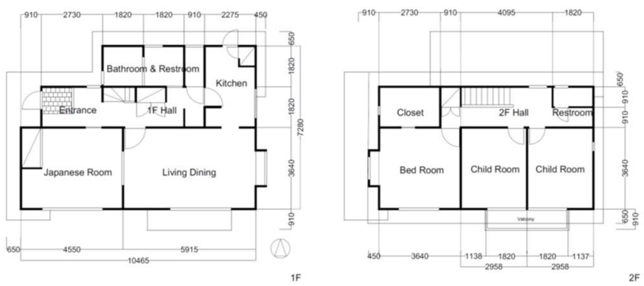
CCWorldWeatherGen reflects significant regional differences compared to other future weather data, with a rise of 5.5 °C in Sapporo and 3.4 °C in Kagoshima in high-emission scenarios. However, CCWorldWeatherGen does not employ downscaled climate information, so the predicted regional differences should be handled cautiously.

3.4 Characteristics of other weather elements

Figures 6–9 depict the monthly average of each weather element and its change in the long-term future in Tokyo. For temperature in Figure 6, there was no significant seasonality in temperature change; however, for absolute humidity in Figure 7, a higher increase was predicted for the summer season. While there are no significant differences in absolute values or changes in temperature and absolute humidity among future weather data, significant differences can be observed in global solar radiation and atmospheric radiation. For example, in Figure 8 (a), CCWorldWeatherGen shows a decreasing trend in global solar radiation. In contrast, the other future weather data show an increasing trend. For the medium-emission scenario in Figure 8 (b), the Expanded AMeDAS future weather data predict little change. In Figure 9, CCWorldWeatherGen predicts the greatest increase in atmospheric radiation for high-emissions scenarios, with an annual average increase of 1.2kWh/(m^{2}day), while WeatherShift considers no change. For the medium-emissions scenario in Figure 9 (b), Expanded AMeDAS considers the most substantial change. Because atmospheric radiation is an essential mechanism of global warming, the amount of change is not expected to be significantly small in some future weather data. These differences in the treatment of climate change among the future weather data are likely to affect the predicted heat load.

4 Future prediction of thermal heat load for standard housing in Japan

Cooling and heating load calculations were performed by targeting a standard Japanese house model in Tokyo (lat. 35.69°, lon. 139.76°) using five types of future weather data available in Japan. By confirming the differences in the predicted heat load, we can confirm the combined characteristics of the future weather data.



(a) first floor plan (area 65.4 m^2, volume 163 m^3) (b) second floor plan (area 52.1 m^2, volume 125 m^3)

Fig. 10. The floor plans of standard housing model
(Each of the 12 rooms has each air-node and is subject to air conditioning.)

4.1 Simulation conditions

4.1.1 Software for thermal heat load simulation

The thermal environment of residential building for heat and mass transfer (THERB for HAM) [14] predicts current and future cooling and heating loads in a typical Japanese house.

4.1.2 Future weather files

Five types of future weather files were used in these simulations: CCWorldWeahterGen, WeatherShift, METEONORM 8, Extended AMeDAS (EA) Future Weather Data 2086, and NIES-based future weather data. Similar to the previous section, this section uses data based on RCP8.5 and SRES A1 as high-emission scenarios and RCP4.5 and SRES A1B as medium-emission scenarios. EA-RWY (1995) and EA-RWY (2010) were used as base-current weather year data for the CCWorldWeatherGen and NIES-based future weather data, respectively. JGMY was used as the base current weather data for WeatherShift. As WeatherShift has a selectable climate change risk rate for users, we used the one created with a 50% risk.

4.1.3 Building model

Simulations were conducted targeting a typical wooden house in Japan, as defined by the Institute for Built Environment and Carbon Neutral for SDGs (IBECs). The family consisted of a couple and two children. The floor plan of the building model is shown in Figure 10. The total floor area of the model was 117.5 m^2, and the ratio of openings to the area was 10 %. Table 1 presents the thermal properties of each part of the model. The average thermal transmittance of the building envelope was 0.87 W/(m^{2}K), and the building envelope performance met the current energy conservation standards under the Japanese energy conservation law. Humidity was considered in terms of the outside air and internal load without considering the absorption and emission in the building frames. Air conditioning was set at 27 °C for cooling, with dehumidification at 60% from May to September, and 20 °C for heating during the other seasons. Air conditioning and ventilation settings are listed in Table 2. Internal heat generation was given on schedule, and the human body load was considered 64 W and 59 g/h per person.

Table 1. Thermal properties of a model house

Heat transmission coefficient [W/(m^{2}K)]	Exterior wall	0.65
	Window	3.67
	Floor	0.71
	Ceiling (attic floor)	0.53
	Roof (first floor)	0.53
Solar absorptance [-]	Outdoor surface	0.70
Solar transmittance [-]	Window	0.82

Table 2. Air conditioning and ventilation settings

Content	Room	Setting
Cooling	All rooms	27 ˚C/ 60 % for 24 hours
Heating	All rooms	20 ˚C for 24 hours
Ventilation	All rooms	0.56 times/hour for 24 hours
	Under floor/ attic space	20 times/hour for 24 hours
	Bath & Restroom, Kitchen	Local ventilatin on a schecule

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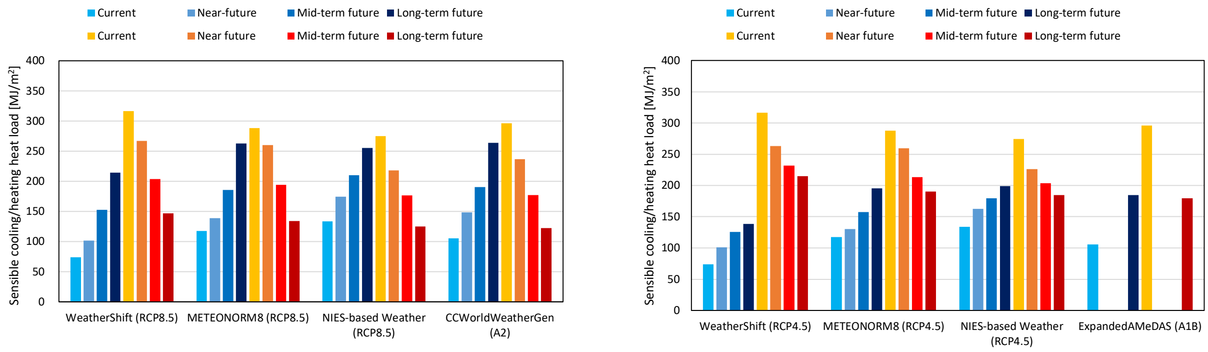
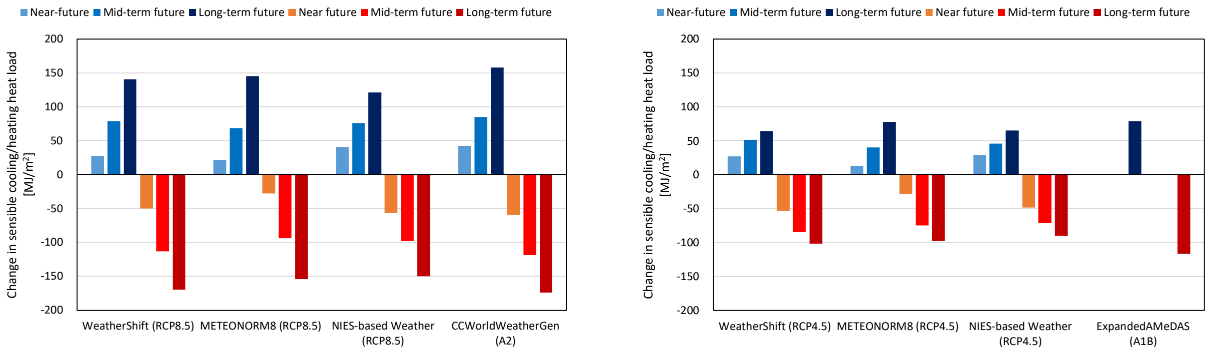


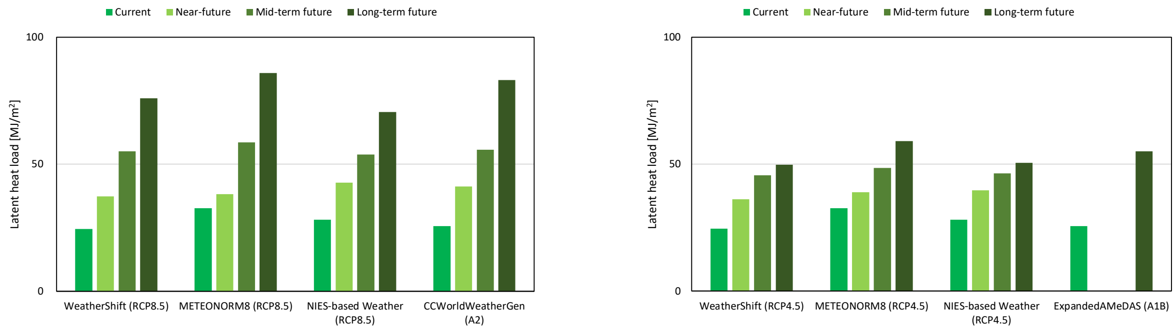
(a) High-emission scenarios (RCP8.5, SRES A2) (b) Medium-emission scenarios (RCP4.5, SRES A1B)

Fig. 11. Sensible cooling/heating load per year at Tokyo



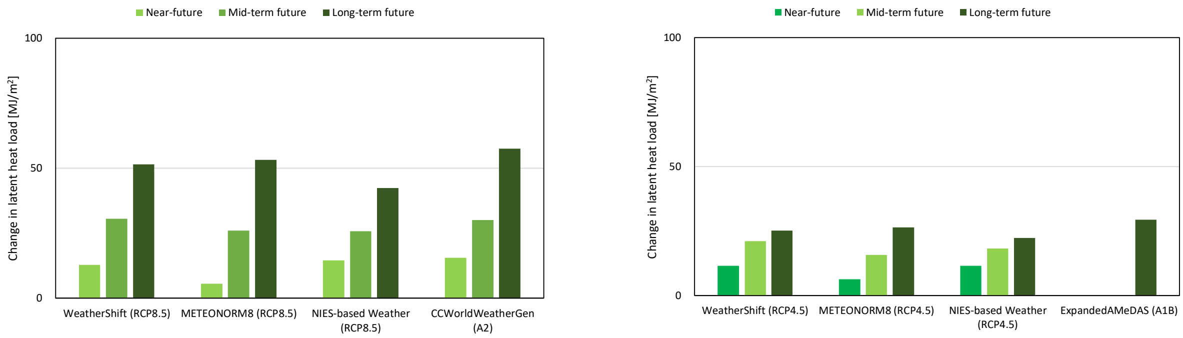
(a) High-emission scenarios (RCP8.5, SRES A2) (b) Medium-emission scenarios (RCP4.5, SRES A1B)

Fig. 12. Future increase/decrease in sensible cooling/heating load per year at Tokyo



(a) High-emission scenarios (RCP8.5, SRES A2) (b) Medium-emission scenarios (RCP4.5, SRES A1B)

Fig. 13. Latent cooling load per year at Tokyo



(a) High-emission scenarios (RCP8.5, SRES A2) (b) Medium-emission scenarios (RCP4.5, SRES A1B)

Fig. 14. Future increase in latent cooling load per year at Tokyo

4.2 Future heat load of a standard house in Japan

Figure 11 shows the sensible cooling and heating loads predicted using the present and future weather data. The predicted balance between cooling and heating loads was relatively similar among the weather data when comparing the same periods. While the sensible heating load is higher than the sensible cooling load in the current period, based on the high-emission scenario, the sensible cooling load is predicted to be higher than the sensible heating load in the future. The absolute magnitude of the final sensible heating/cooling load varies by approximately 50 MJ/m^2 in the future weather data. These differences in the absolute heat load are caused by differences in the characteristics of the base current weather data or how future climate information is treated. Figure 12 shows the future changes in sensible heating and cooling loads. Under the high-emissions scenario, the largest change was predicted by CCWorldWeatherGen. Part of this higher increase was presumably because CCWorldWeatherGen data reflected the strongest increase in atmospheric radiation. However, the changes in sensible heating and cooling loads show generally similar trends (Figure 12), indicating that many of the absolute values in future weather data are derived from the difference in and selection of base current weather data.

Figure 13 shows the latent cooling (dehumidification) load predicted by the current and future weather data, and Figure 14 shows the amount of change. Similar trends in the latent cooling load can be observed in absolute values and the amount of change predicted among future weather data. This trend difference can be interpreted from the characteristics of the absolute humidity in Figure 7. For example, CCWorldWeatherGen predicted the strongest increase in latent heat load (Figure 13a). Future weather data showed the largest change in absolute humidity in the high-emission scenario (Figure 7a). Conversely, the NIES-based future weather data in Figure 13 (b) predicted the lowest latent heat load increase. This weather data had a slightly smaller increase in absolute humidity than the other future weather data (Figure 7b).

5 Conclusion

This study examined future weather data and proposed a framework for understanding it based on how it is generated. Future weather data can be systematically understood in terms of the applied GCMs and scenarios, downscaling of GCM outputs, and methods for generating hourly time-series data. Furthermore, we analyzed the meteorological elements and conducted heat load simulations to confirm the characteristics and uncertainty of future weather data available in Japan. While temperature and absolute humidity showed similar increasing trends, there were different global solar radiation and atmospheric radiation trends. Consequently, differences appear in the predicted heat loads among the future weather data. Nevertheless, similar trends in changes in heating and cooling loads were predicted for all future weather data. There were differences in the absolute predicted values of heat load; hence, attention should be paid to the characteristics of the base-current weather data to justify these differences.

Future climate information is publicly available in many countries, and climate data from the NIES is available in Japan. With the development of future weather data, it is necessary to improve our understanding of their characteristics, and we hope that our study will contribute to this endeavor.

Acknowledgment

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