STUDY OF FUTURE WEATHER DATA CONSIDERING GLOBAL AND LOCAL CLIMATE CHANGE FOR BUILDING ENERGY SIMULATION

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ABSTRACT

Climate change phenomena such as global warming and urban heat island effects cause serious problems for the development of building technology. Therefore, it is imperative that architects and designers consider the effects of climate change on long-term building performance. At present, energy simulations are often used to evaluate the indoor thermal environment and energy consumption of buildings. In these simulations, it is common to use regional weather data that are usually based on current or past weather conditions. However, most buildings have a lifespan of several decades, during which climate can gradually change. Therefore, the design of energy conservation systems such as ventilative cooling strategies and energy simulations should incorporate climate change predictions in order to ensure that buildings are adaptable to future climatic conditions. As a result, future weather scenarios are very important for simulating building performance.

The purpose of this study is to construct future standard weather data using numerical meteorological models, for use in architectural designs. At present, the climatic data used for this purpose are obtained from a Global Climate Model (GCM). Although a GCM can predict long-term global warming, its coarse grid resolution (~100 km) cannot describe the details of local phenomena. Therefore, we employ a downscaling method. We input GCM data into a Regional Climate Model (RCM) as initial and boundary conditions, and physically downscale the data using the RCM. RCM uses nested regional climate modeling and can analyze the local climate at fine grid resolutions (~1 km). The climatic scenarios obtained via this method are expected to accurately predict local phenomena such as the urban heat island effect.

The results confirm that the weather data generated via the dynamical downscaling method can predict local climate. We subsequently constructed a prototype of the future standard weather data based on the Model for Interdisciplinary Research On Climate (MIROC) and the Weather Research and Forecasting (WRF) Model, and simulated building energy consumption using regional climate data. By comparing present and future energy simulations, we estimated the impact of climate change on the energy performance of a building.

KEYWORDS

Climate change / Future Standard Weather Data / Building Energy Simulation / Dynamical Downscaling

1 INTRODUCTION

In building energy simulations, it is common to use regional weather data that are usually based on current or past weather conditions. However, most buildings have a lifespan of several decades, during which climate can gradually change. Therefore, energy simulations should incorporate climate change predictions in order to ensure that buildings are adaptable to future climatic conditions. The purpose of this study is to make future standard weather data for building energy simulation. This study employs a dynamical downscaling method to derive future standard weather data at a local scale, which are used to simulate the energy performance of buildings under future climate change scenarios. We first review the literature on standard weather data and dynamical downscaling.

1.1 Standard Weather Data

Standard weather data are useful in a wide range of applications. Generally, standard weather data are obtained by combining monthly weather data representing average monthly weather over several years. In Japan, expanded AMeDAS (Automated Meteorological Data Acquisition System) weather data are published and used as standard data. AMeDAS uses regional climate information that is collected across the country at intervals of about 16 km [Akasaka et al., 2004]. The standard weather data set requires 8 weather components: temperature, humidity, solar radiation, sky radiation, wind velocity and wind speed, precipitation, sunshine hours. However, most AMeDAS stations observe only temperature, wind direction and wind velocity, precipitation, sunshine hours, and include some missing data due to automated observation. It is therefore necessary to interpolate the required regional climate information omitted by AMeDAS. As a result, standard weather data will include uncertainness associated with estimation and interpolation. Alternatively, the use of a dynamical downscaling method can provide all of the components needed for a standard weather data set. In addition, regional climate information can be calculated for any location without being restricted to observation stations.

1.2 Dynamical Downscaling

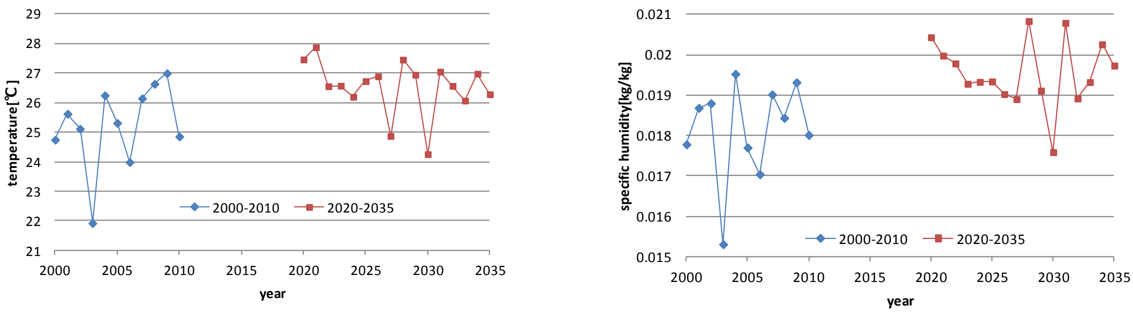
There is a climate data predicted by a Global Climate Model (GCM). GCM is a mathematical model of the general circulation of the planetary atmosphere and ocean. Although a GCM can predict long-term climatic trends, but its coarse grid resolution (~100 km) cannot describe the details of local phenomena. The use of GCM data is problematic in applications that need more detailed regional climate information. The objective of downscaling is to bridge the spatial gaps in data sets between the climate information predicted by GCM and the regional climate information needed for other applications. Downscaling uses two methods: statistical downscaling (SD) or dynamical downscaling (DD). In SD, statistical relationships derived from regional data are used to downscale large-scale climate data, so this method requires regional observations. When using this method in predicting future regional climate, an important question is whether the relationship derived from current data can apply to future conditions influenced by global warming. In order to resolve this problem, we use a dynamical downscaling method. In DD, GCM data are input as initial- and boundary conditions to a Regional Climate Model (RCM); the RCM analysis is then used to physically downscale the GCM data. RCM uses nested regional climate modeling, and can analyze the local climate at high resolutions (~1 km). Previous studies have successfully reproduced regional climate from GCM data [Yuqing et al., 2004]. Using dynamical downscaling, we can obtain all of the detailed spatial–temporal information required for a standard weather data model.

2 DETAILS OF DYNAMICAL DOWNSCALING METHOD

The process of dynamical downscaling to produce future standard weather data utilizes a GCM and RCM. In this study, we use the MIROC4h (Model for Interdisciplinary Research On Climate version4) as GCM and WRF (Weather Research and Forecasting) as RCM.

2.1 MIROC

This study uses MIROC4h developed by the Center for Climate System Research (CCSR), the National Institute for Environmental Studies (NIES), the Frontier Research Center for Global Change (FRCGC), as GCM. MIROC4h reproduces global warming at a horizontal scale of approximately 60 km [Nozawa, 2007]. Fig. 1 shows that monthly mean temperature and annual specific humidity change at surface 2 m in August in Otemachi in Tokyo, Japan. In this study, we use present weather data for the period 2006 to 2010, and use future weather data for from 2031 to 2035. In Otemachi, the monthly average surface temperature in August increases by 0.87℃ between the present (2006–2010) and the future (2031–2035) study periods, and specific humidity increases by 0.00144 [kg/kg].



a) Temperature b) Specific humidity

Fig. 1 Trend in monthly average surface temperature and humidity in August in Tokyo predicted by MIROC.

2.2 Description of WRF Model

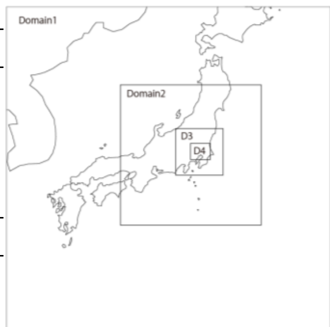
We use the weather research and forecasting model (WRF, version 3.4) as the RCM [William, C. S., et al., 2008]. The WRF model was mainly developed by the National Center for Atmospheric Research (NCAR), and is commonly used for local climate studies.

2.3 Analysis

We use USGS (U.S. Geological Survey) 24-category land use data. Fig. 2 and Table 1 show the nesting regions of the WRF. The target areas in this study are the Kanto region in Japan, and Tokyo and its surrounding area. We use four levels of nested regional climate modeling, where the first and fourth levels have horizontal spatial resolutions of 54 km and 2 km respectively. We use the Noah land surface model (Noah LSM) as a land physics scheme. Noah LSM requires soil temperature and humidity which are not predicted by MIROC, so we also use National Centers for Environmental Prediction (NCEP) Final Operational Global Analysis (FNL) data for soil temperature and humidity. Table 2 shows the weather component list of MIROC and FNL data, and Table 3 shows the applied physics scheme. We simulated from 1 July to 31 August, and the target analysis term is the period 1–30 August in each year.

Table 1 Nesting region in WRF simulation

Items	Content
Map projection system	Lambert conformal conic projection
Horizontal grid dimensions and grid spacing	Domain 1: 38×38 (horizontal scale 54 [km]) Domain 1: 49×49 (horizontal scale 18 [km]) Domain 1: 49×49 (horizontal scale 6 [km]) Domain 1: 61×52 (horizontal scale 2 [km])
Vertical levels	28 (from surface to the 50 hPa level)



Time step	Domain 1: 180 sec; Domain 2: 60 sec; Domain 3: 20 sec; Domain 4: 20/3 sec.
Nesting	Two-way nesting

Fig. 2 The nesting region

Table 2 Weather component used as initial and boundary conditions in WRF simulation

a) MIROC4h

Longitude, Latitude	0.5625º
Time	6 hour
Geopotential height	17 layers□
Temperature	17 layers□
Specific humidity	17 layers□
Wind velocity	17 layers□
Sea surface pressure	Surface
Surface temperature	Surface
Sea surface temperature	Surface

※17 layers (1000, 950, 900, 850, 700, 500, 400, 300, 250, 200, 150, 100, 70, 50, 30, 20, 10 [hPa])

b) FNLº

Longitude, Latitude	1
Time	6 hour
Soil temperature	4 layers※
Soil water	4 layers※

※4 layers (0–10, 10–40, 40–100, 100–200 [cm])

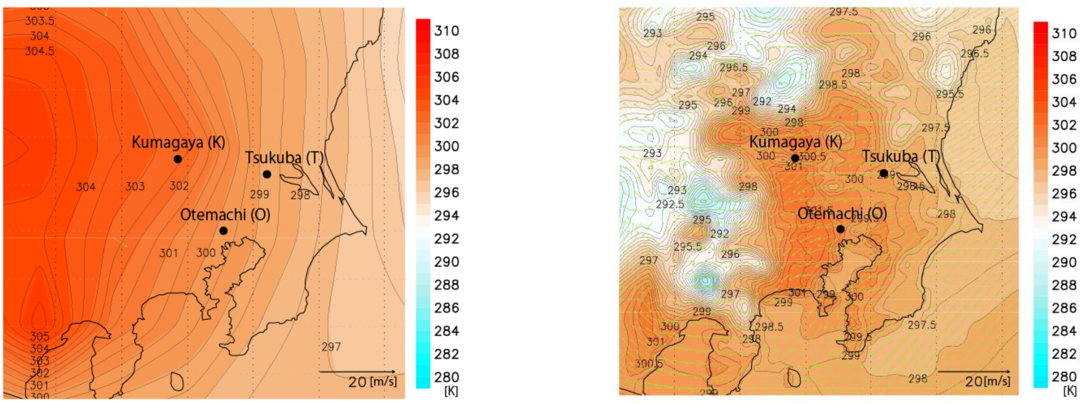
Table 3 WRF physics scheme

Cumulus parameterization	Domains 1&2: Grell 3D scheme; Domains 3&4: none
Microphysics	WRF Single-moment 6-class scheme
Planetary boundary layer	Yonsei University scheme
Longwave radiation	RRTM scheme
Shortwave radiation	Dudhia scheme
Land surface	Noah Land Surface Model (Noah LSM)

3 DYNAMICAL DOWNSCALING USING MIROC AND WRF

3.1 Locality Reproduced by Dynamical Downscaling

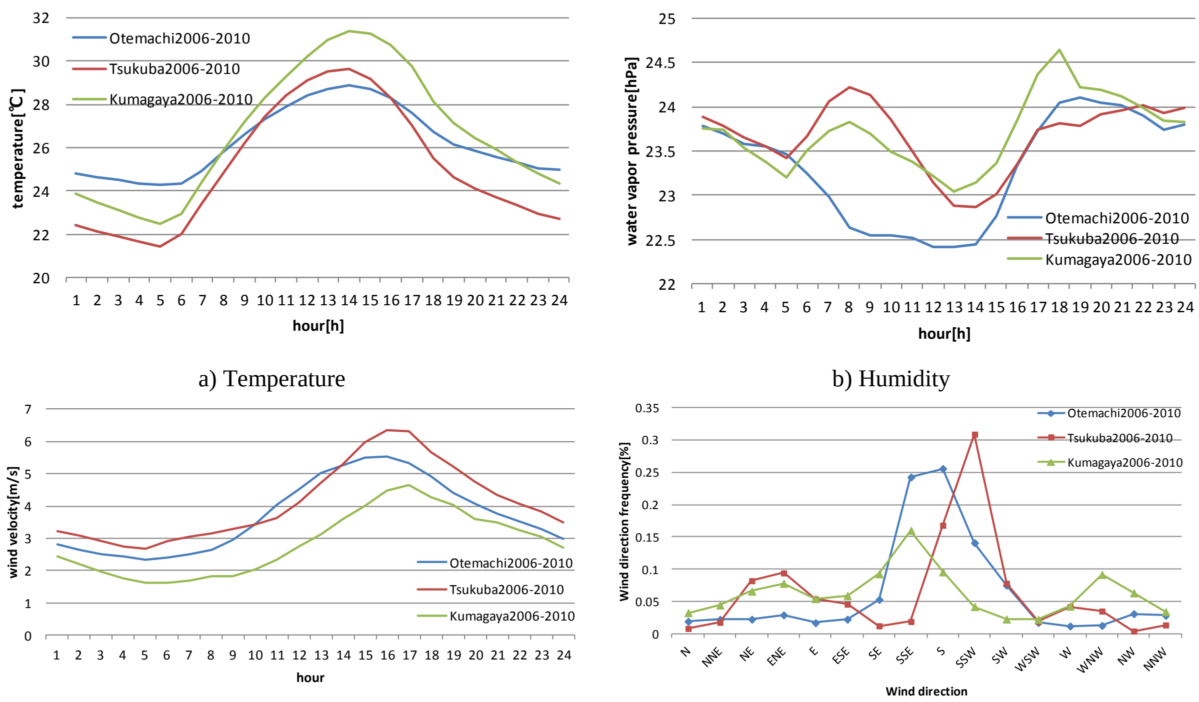
Fig. 3 shows surface temperature at 2 m and wind field at 10 m above the surface, as predicted by MIROC and WRF at 21:00 hr on 16 August 2006. The 60-km horizontal grid scale of MIROC is too coarse to represent local climate information. On the other hand, the high resolution of WRF can reproduce the locality considering the regional topographic effects.



a) MIROC b) WRF

Fig. 3 Temperature at 2 m and wind field at 10 m predicted by MIROC and WRF at 21:00 hr on 16 August 2006

Fig. 4 represents the mean daily changes in weather components and the mean wind direction (according to frequency of direction) from August 2006–August 2010 for each of the three study locations: Otemachi (lat 35.9, long 39.76), Tsukuba (lat 36.65, long 40.12), and Kumagaya (lat 36.15, long 39.38). As shown in Fig. 4 a), the night-time temperature in Otemachi is higher than that in Tsukuba and Kumagaya due to urban heat retention. It is noticeable that the maximum daytime temperature in Kumagaya is attributed to heat generated in urban areas south of Kumagaya, which is transported by the south sea breeze from Tokyo Bay. Fig 4 b) show that humidity increases during the morning in Tsukuba and Kumagaya, but not in Otemachi. Wind velocity is low at Kumagaya due to its inland location (Fig.4 c)) and wind direction is different among 3 cities (FIg.4 d)). Thus, we can derive local climate information from a GCM via dynamical downscaling, by employing land use data in the WRF.



a) Temperature

b) Humidity

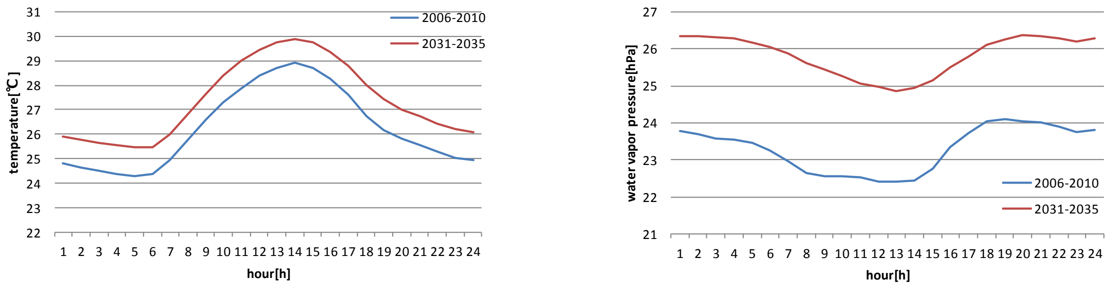
c) Wind velocity

d) Wind direction

Fig. 4 Daily changes five-year (August 2006–August 2010) mean weather component and wind direction distribution for each of the three cities, predicted by WRF

3.2 Changes in Weather Components between Present and Future

Fig. 5 shows the mean daily weather components for August 2006–August 2010 in Otemachi compared with the changes predicted for 2031–2035. The data predict future increases in both temperature and humidity. We can see the increases in other cities, and Table 4 shows the present and future five-year mean temperature and humidity, and the temperature and humidity increase reproduced by WRF and MIROC. From the WRF result, it is evident that the maximum temperature change is at Tsukuba, (1.27°C), and the minimum temperature change is at Kumagaya; and that the maximum change in specific humidity is at Tsukuba, (0.00173 [kg/kg]), and the minimum change at Kumagaya (0.00111 [kg/kg]). However, in the MIROC result, the predicted temperature and humidity changes at Otemachi and Tsukuba are smaller than those predicted by WRF; in contrast, WRF predicts smaller changes at Kumagaya. Based on the results, it is evident that local climate change can be reproduced using a dynamical downscaling method.



a) Temperature b) Humidity

Fig. 5 Five-year mean temperature and humidity daily change in August in Otemachi predicted by WRF comparing the present and future

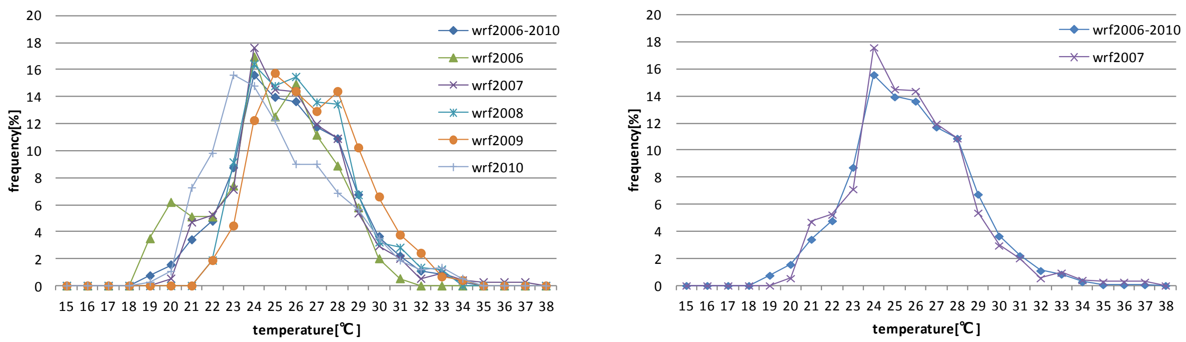
Table 4 Present and future 5-year mean temperature and humidity in August reproduced by MIROC and WRF

	Temperature [°C]		Specific humidity [kg/kg]		Temperature Increase [°C]		Specific humidity Increase [kg/kg]	
	MIROC	WRF	MIROC	WRF	MIROC	WRF	MIROC	WRF
Otemachi 2006–2010	25.72	26.24	0.0187	0.0147	0.86	1.12	0.00144	0.0016
Otemachi 2031–2035	26.59	27.36	0.0198	0.0163				
Tsukuba 2006–2010	26.27	25.06	0.0187	0.0149	0.92	1.27	0.0015	0.00173
Tsukuba 2031–2035	27.19	26.33	0.0202	0.0166				
Kumagaya 2006–2010	24.89	26.67	0.0181	0.0150	0.81	0.50	0.00144	0.00111
Kumagaya 2031–2035	25.70	27.17	0.0196	0.0161				

4 APPLICATON OF WEATHER DATA TO ENERGY SIMULATION

4.1 Selecting Standard Weather Data

Generally, when standard weather data are estimated, data from the same month are selected over a period of several years, and then these standard months are combined to produce standard weather data for one year. Fig. 6 a) shows frequency distribution for temperature in August 2006–2010, and Fig. 7 a) shows the same for August 2031–2035 in Tokyo. Here, we selected the standard month that represents average temperature for the present (2006–2010) using temperature frequency deviation from 5-year (August 2006–2010) average temperature frequency V_y defined by formula (1). Here, $F_{y,i}$ is the frequency of temperature i in year y, and F_i is the average frequency of temperature i over 5 years (2006–2010). Table 5 shows deviation V_y from the mean in each of the present five years (2006–2010). As shown in Table 5, the smallest deviation during the present period (2006–2010) is during 2007. We therefore select weather data from 2007 as standard weather data for the present five-year period; similarly, the period 2031–2035 is represented by data for 2034. Fig. 6 b) and Fig. 7 b) show good agreement in the temperature frequency of the standard year and the five-year mean.



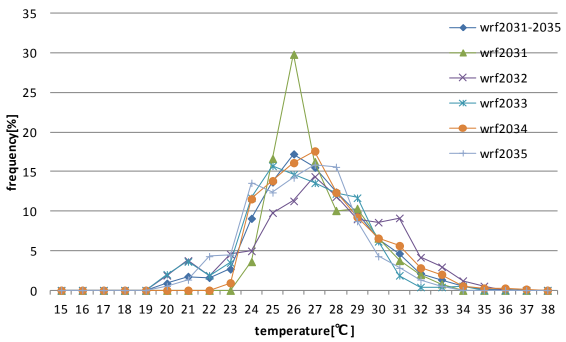
a) 5 yr in August in the present and 5-year mean b) August 2007 and 5-year mean

Fig. 6 Temperature frequency distributions predicted by dynamic downscaling in present

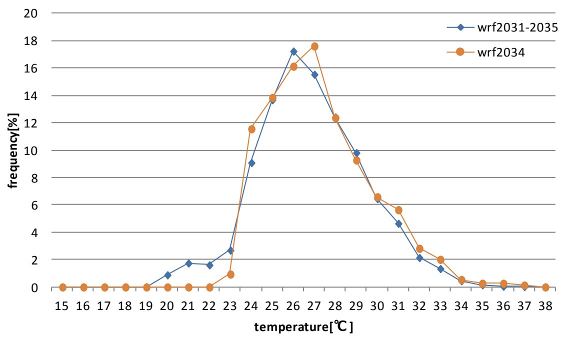
$$V_y = \quad F_{y,i} - F_i \quad {}^{2}\,{}^{1/2} \qquad (1)$$

Table 5 Standard deviation of temperature frequency from 5 years mean distribution

Year	2006	2007	2008	2009	2010
V_y	7.2	3.7	19.4	9.7	11.7



a) for 5 yr in August in the 2030s and 5-year mean



b) August in 2034 and 5-year mean

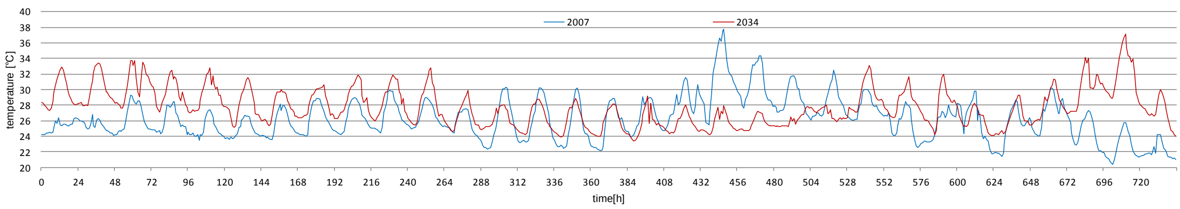
Fig. 7 Future temperature frequency distributions predicted by dynamic downscaling

Table 6 Standard deviation of annual temperature frequency from 5-year mean (2031–2035)

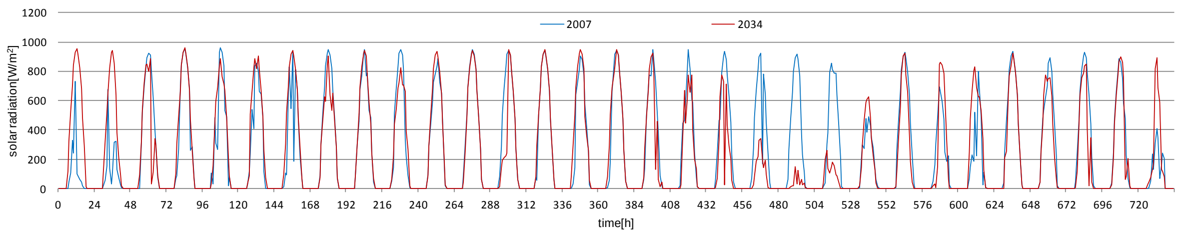
Year	2031	2032	2033	2034	2035
V_y	14.8	10.5	6.5	4.8	7.9

4.2 Sample Standard Weather Data

The WRF results show an average temperature of 26.23°C in August 2007, which increases by 1.52°C to 27.75°C in August 2034. Fig. 8 compares daily temperature and solar radiation between August 2007 and August 2034. These hourly weather data for a month generated by dynamical downscaling are used to simulate the energy consumption of buildings.



a) Surface 2 m temperature

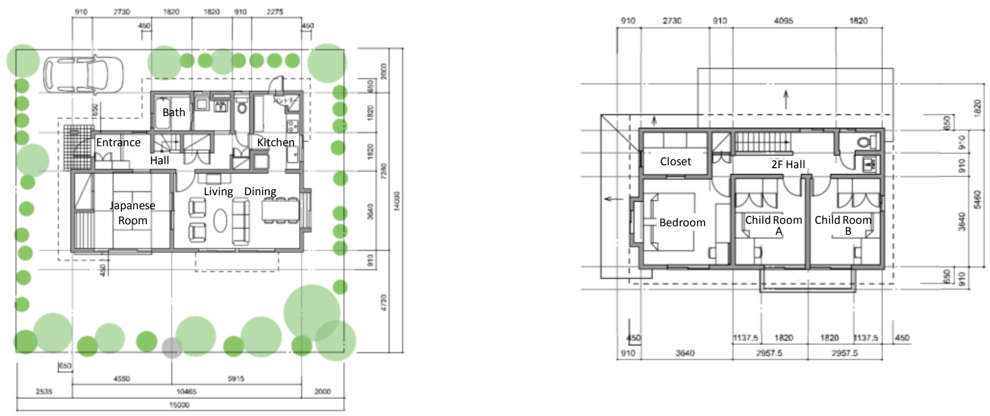


b) Solar radiation

Fig. 8 Temporal variation in surface temperature and solar radiation in Tokyo during August (2007 and 2034) generated by WRF

4.3 Building Energy Simulation Conditions

We used energy simulation to analyze the impact of climate change on the energy consumption [Urano, 2009] of a standard detached house located in Tokyo. Fig. 9 illustrates plans for a typical house used for environmental studies of architecture in Japan. TRNSYS software (University of Wisconsin, USA) was used for the energy simulations. The weather data generated by WRF were used to analyze the energy consumption of the house during August under present (2007) and future (2034) climate scenarios. We assumed a cooling system with units located in the combined living and dining room with a kitchen (termed LDK), a bedroom, and a child's room (A); these rooms had areas of 29.8 m^2, 13.3 m^2, and 10.8 m^2, respectively. The cooling equipment was assumed to be activated when the air temperature in these rooms exceeded 26°C in accordance with the time schedule shown in Table 8. The thermal properties of the house are illustrated in Table 9. The simulation term is for one month, from 1–31 August of each year.



a) First floor b) Second floor

Fig. 9 Plans for a model house (the standard house model in Japan) used in the building energy simulation

Table 8 Air conditioning setting

ROOM	Preset Temperature [°C]	Schedule of air conditioning
LDK	26	6:00–10:00, 12:00–14:00, 16:00–24:00
BEDROOM	26	21:00–23:00
CHILD ROOM (A)	26	20:00–21:00, 22:00–24:00

Table 7 Thermal property of a model house

ROOM	Heat transmission coefficient [W/m^2K]	Solar absorptance [-]	Convective heat transfer coefficient [W/m^2K]
External wall	1.671	0.8	3.05 (indoor), 17.7 (outdoor)
Roof	2.591	0.8	3.05 (indoor), 17.7 (outdoor)

4.4 Building Energy Simulation Result

Fig. 10 presents times series of the variation in sensible heat load in the LDK area. Small and large of heat load of each cases differ from day to day. For example, on 20 August, the sensible heat load in 2007 is greater than that for 2034, because the outdoor temperature in 2007 is higher than that predicted in 2034 (Fig. 10). Fig. 11 show mean daily sensible heat load in the LDK and bedroom. The mean daily sensible heat load in future is higher than that at present. Table 9 show the total sensible heat load for the month of August in Otemachi. In August 2007, total sensible heat load is 2.35×10^6 [MJ/month], compared with 2.70×10^6 in August 2034. The sensible heat load is predicted to increase by 15% between the two study periods, which is considerable for simulation of a building's thermal performance.

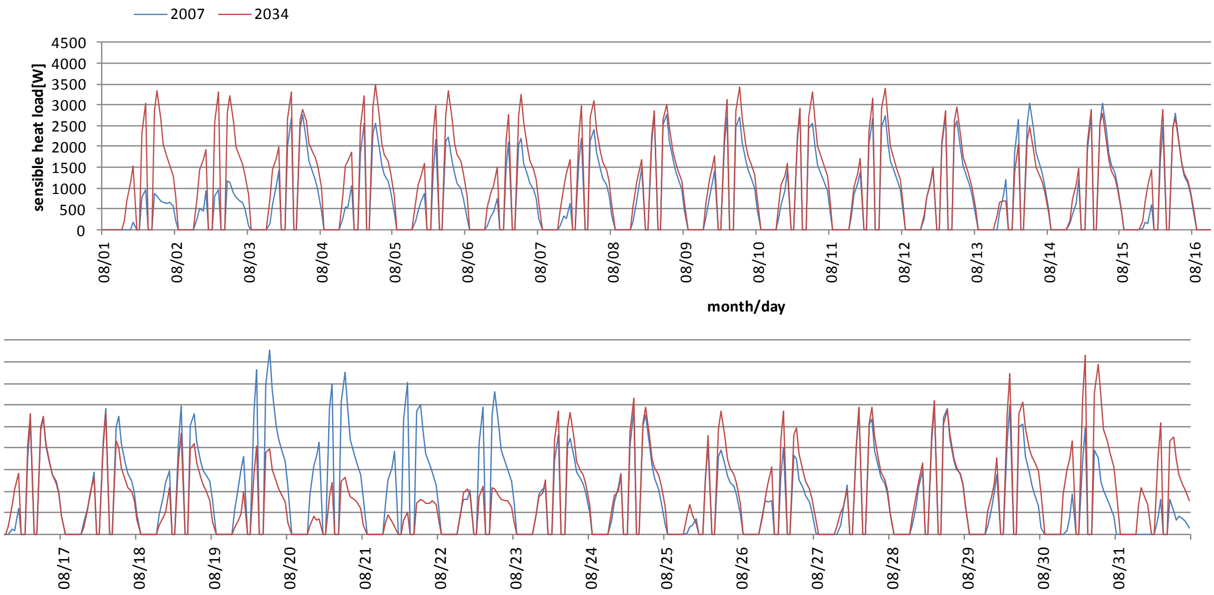
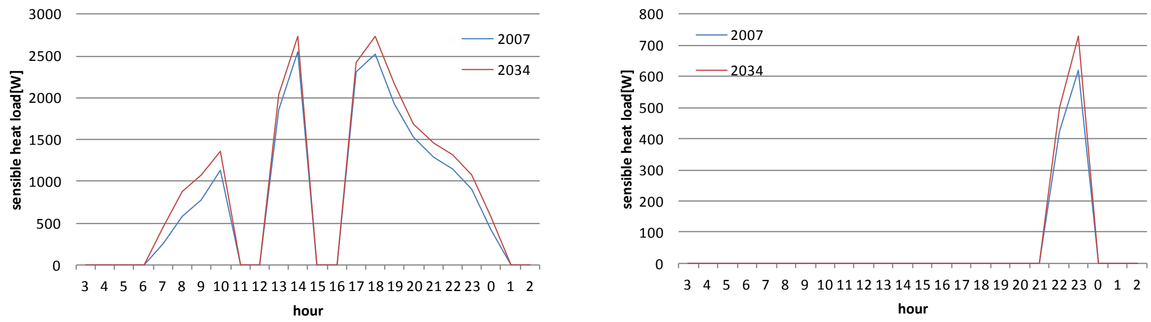


Fig. 10 Change in sensible heat load in LDK area during August. Simulated by TRNSYS using standard weather data generated by WRF



a) LDK b) Bedroom

Fig. 11 Change in mean daily sensible heat load in LDK area and bedroom between August 2007 and 2034

Table 9 Total sensible heat load of model house during August: 2007 and 2034

Case	Sensible heat load for one month [MJ/month]
2007	2.35×10^6
2034	2.70×10^6

5 CONCLUSIONS

Using a dynamical downscaling method with the WRF model, we can obtain regional climate information and local climate changes. In other existing methods, climate change is predicted by GCM and added to current weather data in order to predict future local weather data, but the effect of local climate change is not considered. To create future standard weather data, which requires high-resolution climate information at scales of a few km, this dynamical downscaling method is a useful way to consider regional characteristics and regional climate change. Future weather data derived from dynamical downscaling are expected to represent both global climate change and local climate phenomena, and by using this method, designers can take future local climatic conditions into consideration.

We assessed the impact of climate change from the present to the 2030s in terms of the energy consumption of a detached house in Tokyo, Japan. We simulated climate using the downscaling technique with global and regional climate models to derive regional weather data for August for the present (2006–2010) and during the 2030s (2031–2035). Standard weather data predict that outdoor temperature will increase by 1.52°C (from 26.23°C to 27.75°C) from the present (2007) to the future (2034). As a result, the sensible heat load for the house was predicted to increase by 15% under the study conditions.

6 ACKNOWLEDGEMENTS

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