Near Future Weather Data for Building Energy Simulation in Summer/Winter Seasons in Tokyo Developed by Dynamical Downscaling Method

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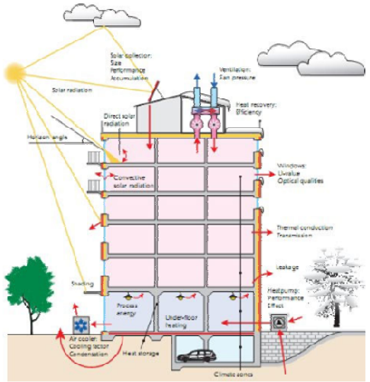
1. Background & Purpose



■Background of this research

Building energy simulation is conducted to design energy-saving building using weather data

There are some problems

- Climate change such as Global Warming is in progress
- Weather Conditions effect building performance

global warming

heat island

Buildings are used for several decades where the climate change is proceeding and the changing weather effect building energy simulation

We need future weather data for building energy simulation to design low-energy buildings adopting to future climatic conditions

1. Background & Purpose

■Purpose of This Study

- Making the future weather data for building energy simulations

What is the future weather data for building energy simulation ?

- The hourly one-year data set of each weather components, such as temperature, humidity, solar radiation, wind velocity and wind direction, etc.
- The weather data must represent local weather conditions
- The future weather data need climate change information

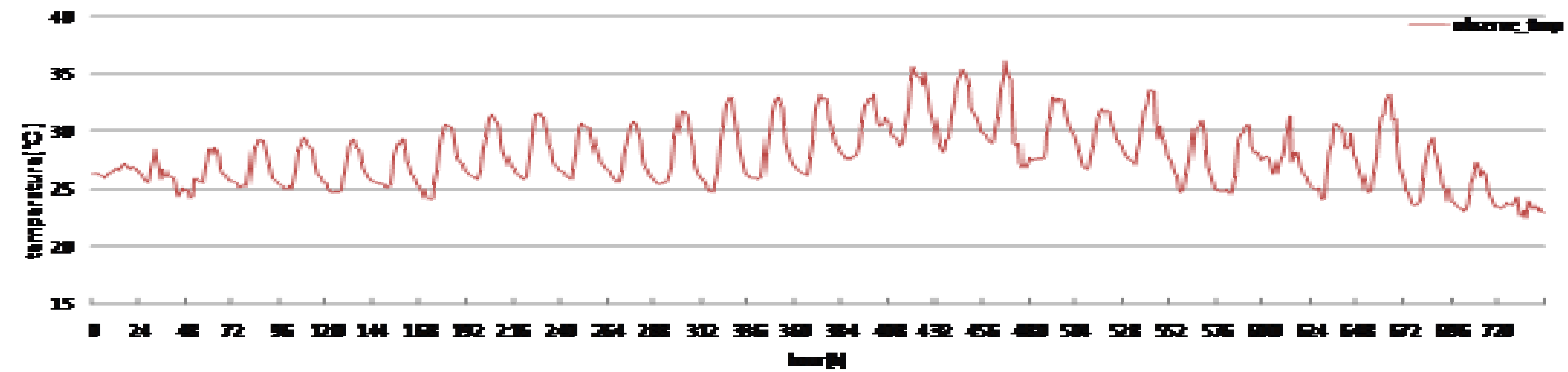
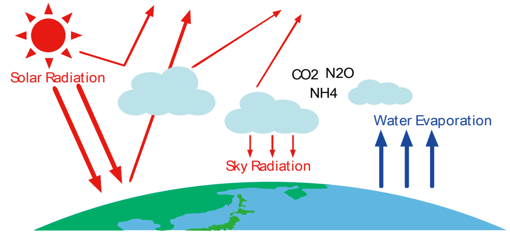


Fig. Temperature temporal changes in August

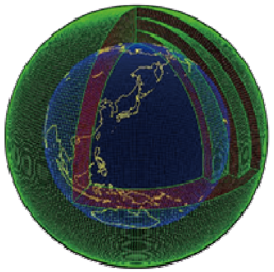
2. Methodology of Dynamical Downscaling

We apply two climate models to make future weather data for building energy simulation



global scale climate

■Global Climate Model (GCM)

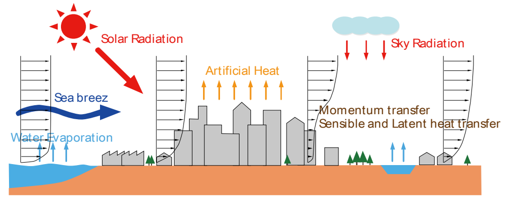


The analysis region of GCMs is the whole earth

Feature：Predicting global scale (hundreds km) climate such as global warming

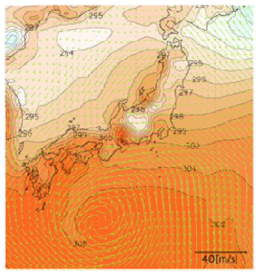
Problems：Grid scale is too course to predict the mesoscale (a few km) climate

Building energy simulation requires more spatial detailed weather information



mesoscale meteorology

■Regional Climate Model (RCM)



The analysis region of RCMs is frexible

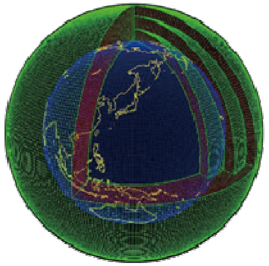
Feature : Predincting local weather (a few km)

Problems：RCM can’t predict global scale climate by itself because of restriction of its analysis region. This model need initial and boundary conditions.

We use these two climate models to make the future weather data which have locality and global climate change information

2. Methodology of Dynamical Downscaling

■Flow of making future weather data



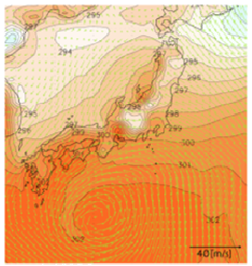
Future weather data predicted by GCM

Model for Interdisciplinary Research On Climate (**MIROC4h**)

Presented by Kimoto lab.(Atmosphere and Ocean Research Institute, The Tokyo Univ.)

RCP4.5, which was adopted by IPCC the 5th Reports is used (Medium-low scenario)

Input the GCM data as initial and boundary condition for RCM

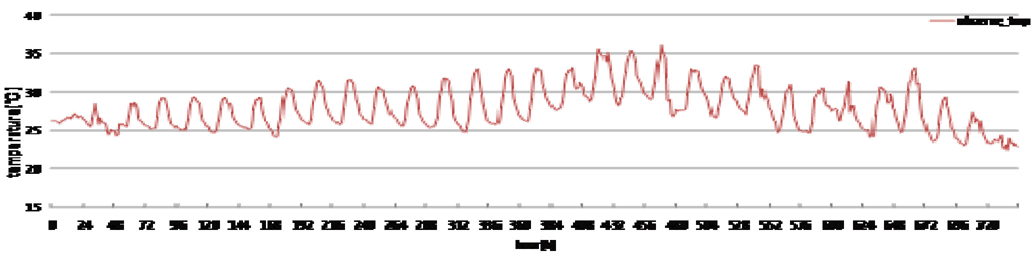


RCM can derive the local weather information from GCM

(This process is called Dynamical Downscaling)

Weather Research and Forecasting Model (**WRF**)

Dynamical Downscaling the GCM data with RCM



The Future Weather Data

- climate change information
- local climate phenomena

Purpose of This Presentation

①Suggesting the new method of making future weather data for building energy simulation

To Confirm the Following

②How accurately the current weather data obtained based MIROC4h can reproduce the current climate conditions

③The reproducibility of the climate change of the downscaled weather data

Making a prototype of future weather data

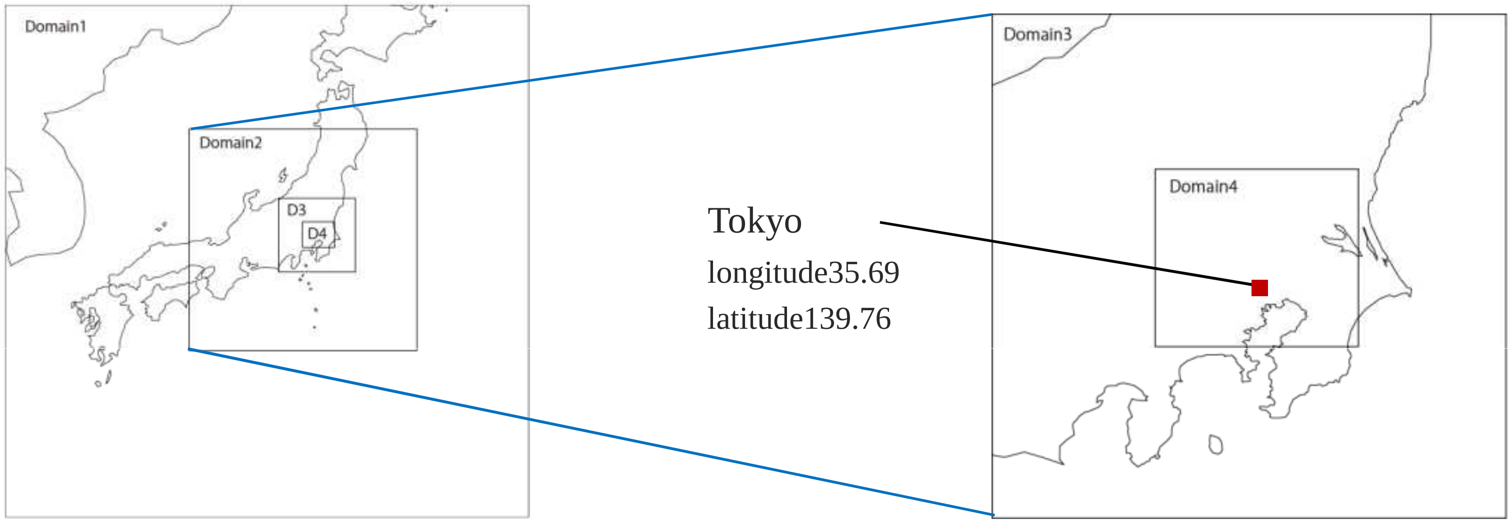
④Trying to make a prototype of future weather data

⑤by conducting building energy simulation using the prototype, we estimate the impact of climate change on building energy consumption

2. Analysis Conditions of Dynamical Downscaling

■Analysis Region

The biggest domain covers whole Japan, and the main target is Tokyo



- Smallest horizontal gird scale is 2km
- Vertical gird is 35 divided from surface to the 50hPa

■Time Period

- Current 2001~2010
- Future 2026~2035

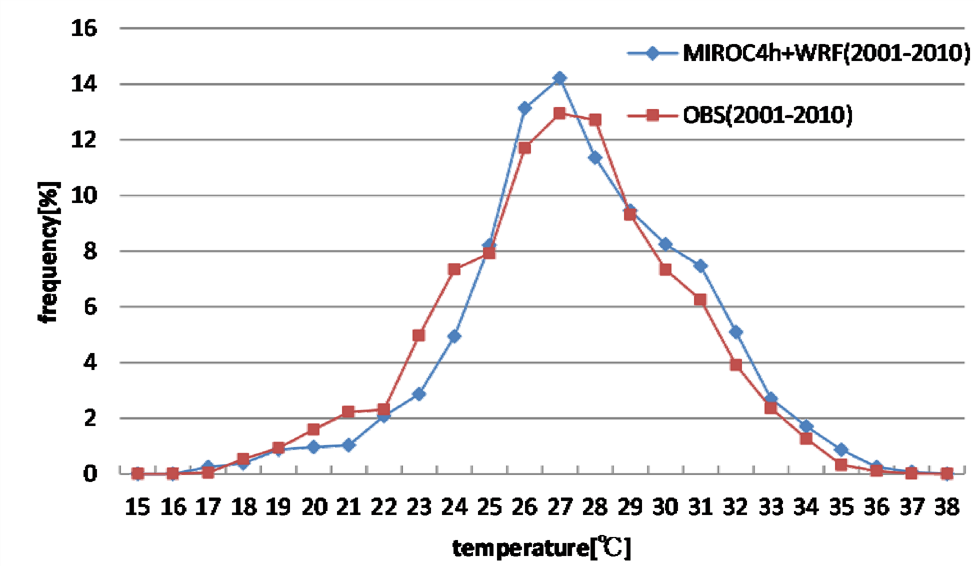
Target Season is August and January

OUTLINE

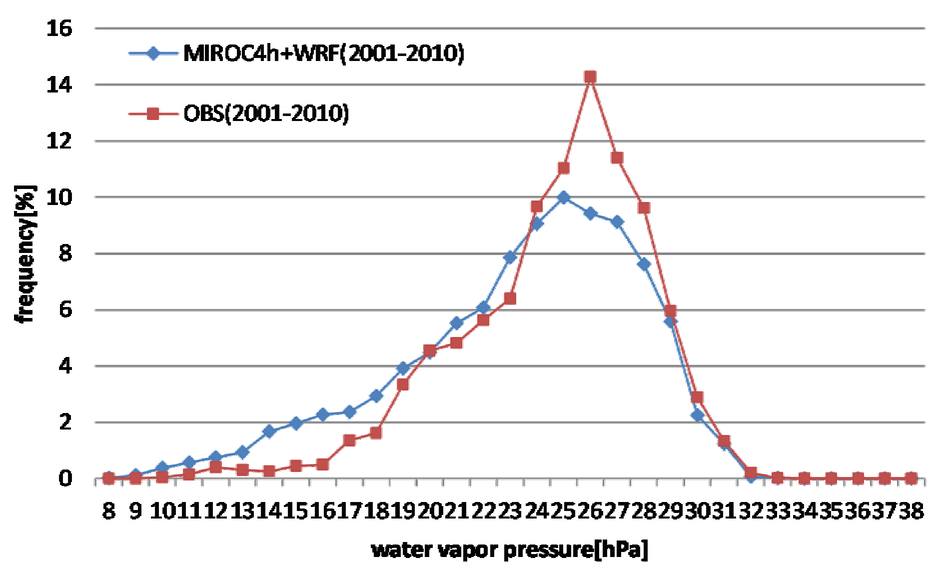
1. Background & Purpose
2. Methodology of Dynamical Downscaling
3. Results of Dynamical Downscaling
4. Constructing Prototype of Future Weather Data
5. Building Energy Simulation for Near-Future Data
6. Conclusions

3. Results of Dynamical Downscaling

■Reproducibility of Current Climate Conditions



a) temperature



b) water vapor pressure

Fig. Frequency of temperature and water vapor pressure in August 2001-2010 at Tokyo

(Observation , Simulation(MIROC4h+WRF))

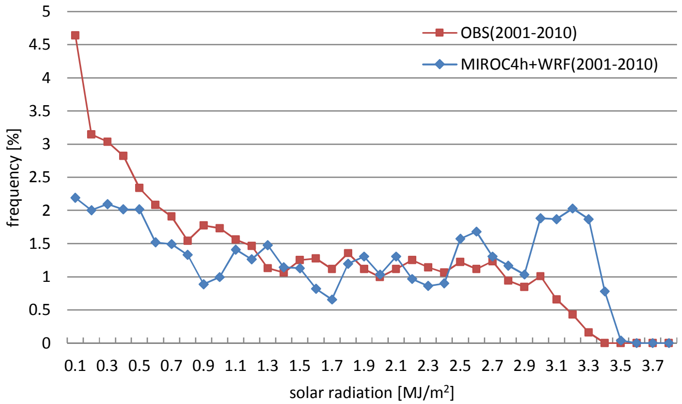
The frequency of each weather temperature and water vapor pressure have good agreement with observation

However, the climate model output have systematic error, called bias

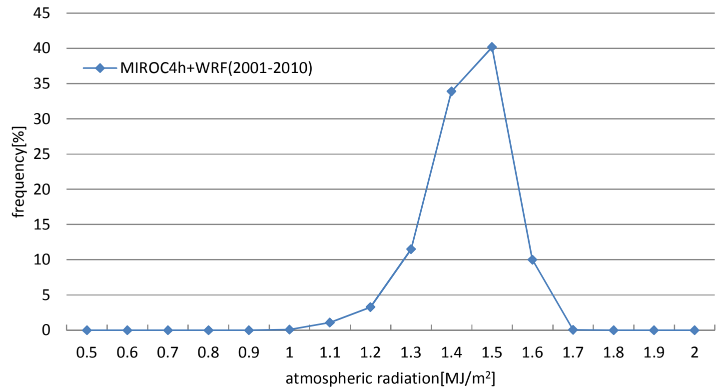
In August,
The temperature differences (at 2m) between MIROC+WRF and OBS were 0.54℃
The water vapor pressure differences (at 2m) between MIROC+WRF and OBS were 1.19hPa

3. Results of Dynamical Downscaling MIROC4h

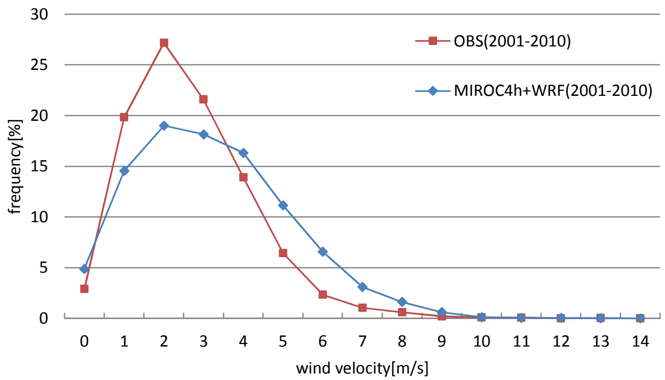
■Reproducibility of Current Climate Conditions



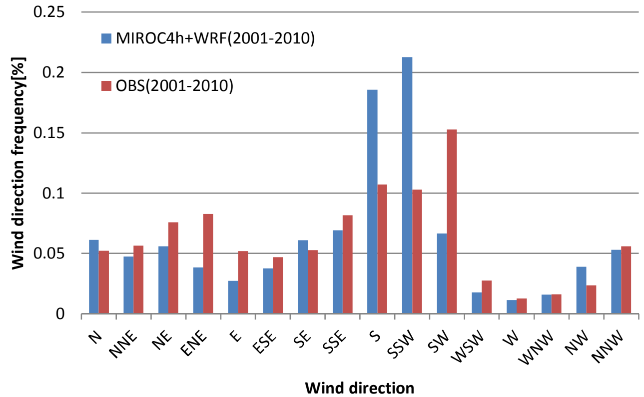
a) solar radiation



b) atmospheric radiation



c) wind velocity



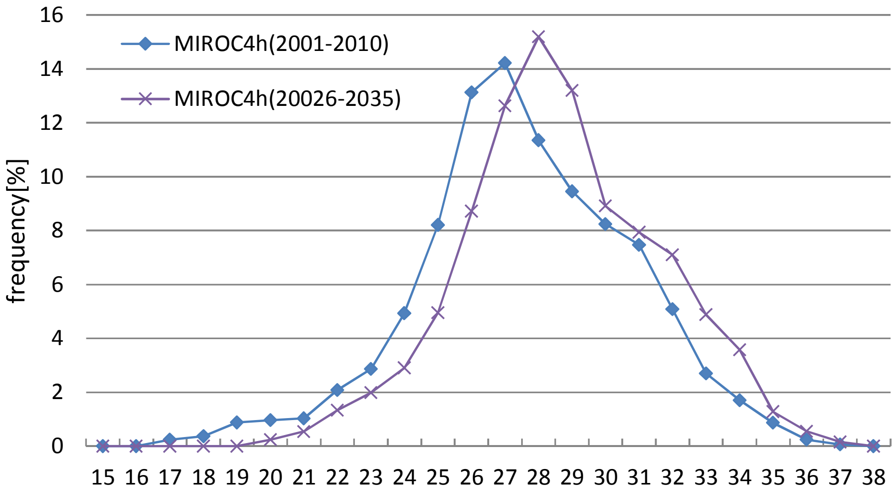
d) wind direction

Fig. Frequency of each weather component in August 2001-2010 at Tokyo
(Observation , Simulation(MIROC4h+WRF))

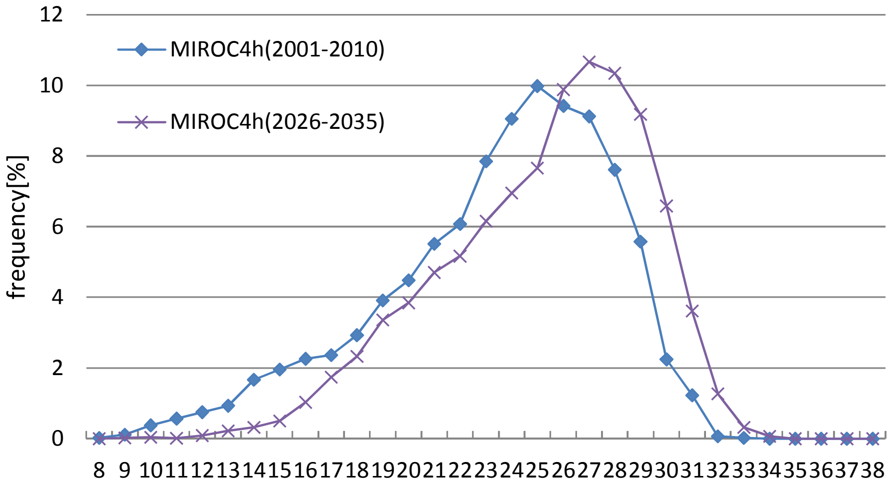
We can get all weather components needed for building energy simulation by dynamical downscaling GCM

3. Results of Dynamical Downscaling MIROC4h

■Future simulation in summer 2026-2035



a) Temperature at 2m



b) water vapor pressure at 2m

Fig. Frequency of weather components in August 2026-2035 at Tokyo
(Current Simulation(2001-2010) , Future Simulation(2026-2035))

In August,

Temperature increases by 1.11℃ from current to future

Water vapor pressure increases by 1.81hPa from current to future

Future weather data by this method represent climate change

3. Results of Dynamical Downscaling MIROC4h

■Future simulation in summer 2026-2035

Table. Monthly average for the 10-year mean of each weather component in Tokyo in August and January
(Horizontal solar radiation and atmospheric radiation are monthly mean sun integrated value)

	Temperature[℃]	Water vapor pressure [hPa]	Horizontal solar radiation [MJ/m^2]	Atmospheric radiation [MJ/m^2]	Wind velocity [m/s]
OBS (Aug)	27.5	25.1	15.5	-	3.13
CASE1(Aug)	28.1 (0.54)	23.9 (-1.19)	19.5 (3.96)	35.8	3.72 (0.60)
CASE2 (Aug)	29.2 (+1.11)	25.7 (+1.81)	19.5 (-0.05)	36.6 (+0.94)	3.76 (+0.03)
OBS (Jan)	6.26	4.33	9.31	-	3.28
CASE1 (Jan)	8.10 (1.84)	4.69 (0.37)	10.6 (1.32)	22.4	3.90 (0.62)
CASE2 (Jan)	8.70 (+0.60)	4.89 (+0.20)	10.6 (-0.02)	22.6 (+0.17)	3.79 (-0.11)

(Observation(2001-2010), Current Simulation(2001-2010) , Future Simulation(2026-2035))

The range of bias and climate change differ depending on months

Regarding bias,
the temperature differences (at 2m) were 0.54℃ in August and 1.84℃ in January.

Regarding climate change from current to future,
temperature increase by 1.11℃ in August and 0.60℃ in January.

4. Constructing Prototype of Future Weather Data

■Climate Model Bias

As we showed, weather model output include bias because of some reasons

① the course of grid resolution
② inaccuracy of parameterization
③ inaccuracy of land use data etc....

▼ A bias modification is needed to directly use the climate model output for building energy simulation

■Bias Modification

Using 10-year average and standard deviation of the current simulation and observation, following modification is adapted to the model output of temperature, humidity, solar radiation

$$X_{c,modi} = \overline{X_{obs}} + \frac{\sigma_{obs}}{\sigma_c}(X_c - \overline{X_c}) \quad (1)$$

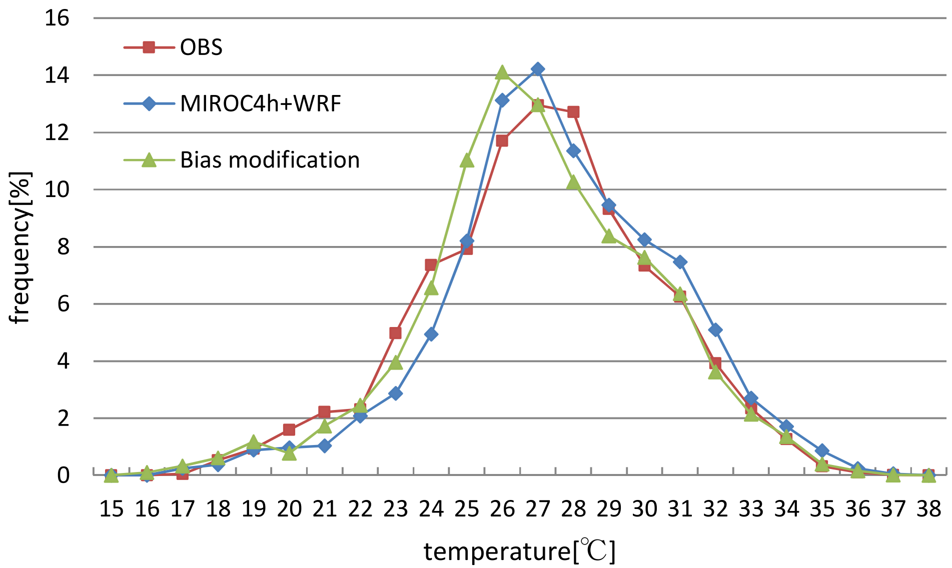
$$X_{f,modi} = \overline{X_{obs}} + (\overline{X_f} - \overline{X_c}) + \frac{\sigma_{obs}}{\sigma_c}(X_f - \overline{X_f}) \quad (2)$$

$X_{c,modi}$:Modified weather data
X_c :Model output
$\overline{X_{obs}}$:Average of observation data
$\overline{X_c}$:Average of output data
$\frac{\sigma_{obs}}{\sigma_c}$:ratio of standard deviation

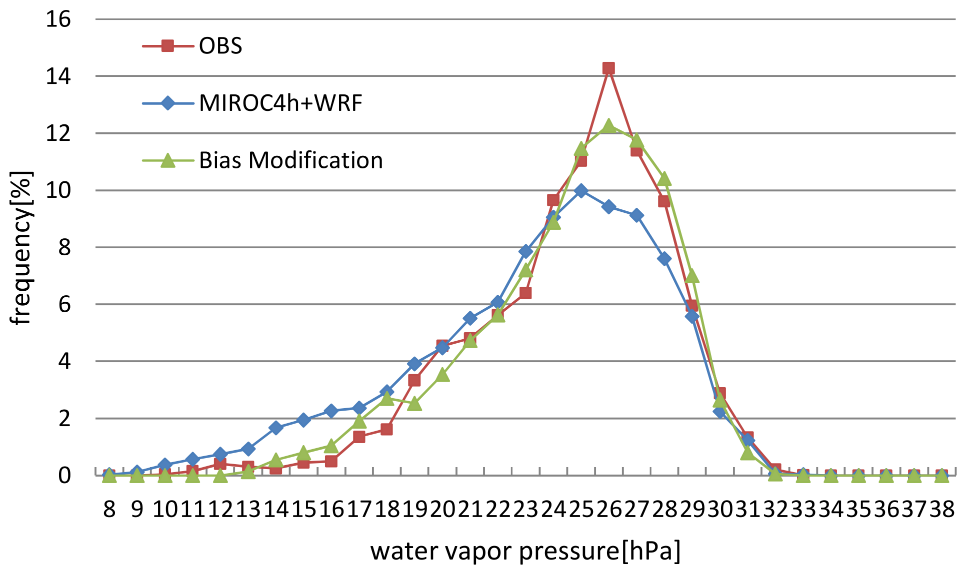
After modification, the average and standard deviation of the current weather data accord with that of observation

4. Constructing Prototype of Future Weather Data

■The results of Bias modification



a) temperature



b) water vapor pressure

Fig. Frequency of weather components in August 2001-2010 at Tokyo

(Observation , MIROC4h+WRF (raw output) , Bias Modification (bias-corrected output))

Before bias modification, the frequency of water vapor pressure don’t agree with observation well
However, after bias modification, the results show more agreement with that of observation

We use this bias corrected data as the weather data for building energy simulation

OUTLINE

1. Background & Purpose
2. Methodology of Dynamical Downscaling
3. Results of Dynamical Downscaling
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5. Building Energy Simulation for Near-Future Data
6. Conclusions

5. Building Energy Simulation for Near-Future Data

■Analysis Conditions of Energy Simulation

Building Energy Simulation Software:TRNSYS17

Input Weather Data: Current(2001-2010) and Future(2026-2035) Weather Data in August and January (temperature, relative humidity, solar radiation)

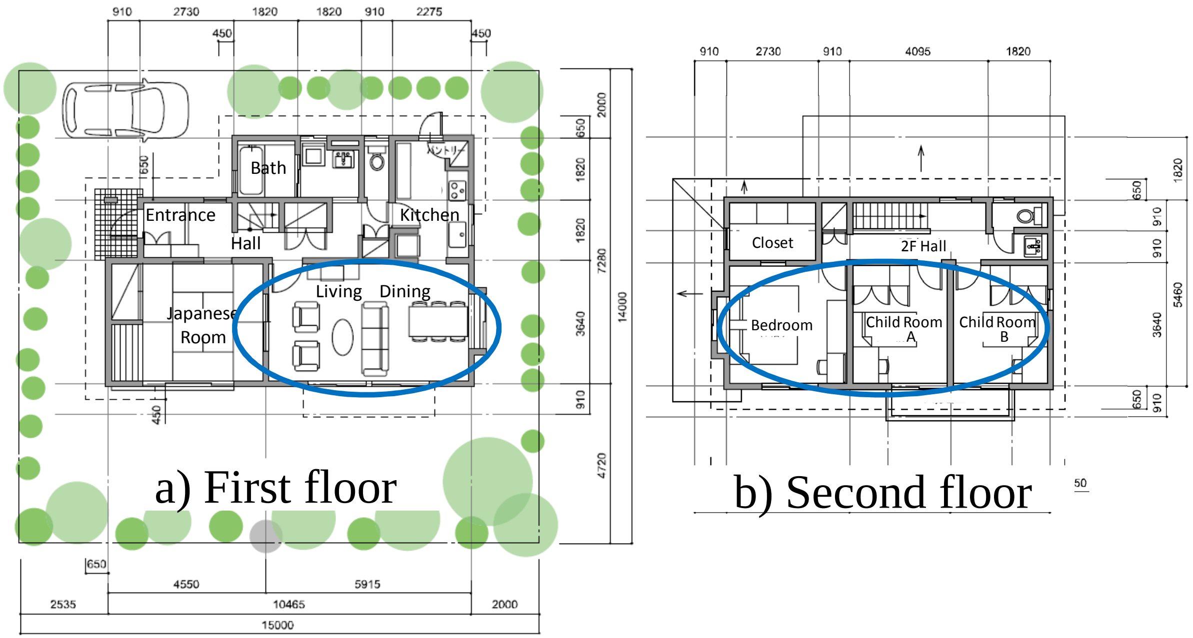


Fig. Target model house (at Tokyo)

(A two-story detached house, which floor space is 120m^2, where a four person family live)

Table. Thermal Property of the model

Component	Heat transmission coefficient [W/m^{2}K]
External wall	0.385
Roof	0.294
Window	5.72

Component	Solar absorptance [-]
External wall	0.8
Roof	0.8
Window	0.875 (Solar heat gain coefficient)

Component	Convective heat transfer coefficient [W/m^{2}K]
All	3.05 (indoor), 17.7 (outdoor)

The rooms for Air conditioning is LDK, bedroom, and child rooms

Air conditioning setting: Temp.27°C, Relative Humid. 60% in Aug. / Temp.20°C in Jan.

Air change rate is 0.5/h for all rooms

5. Building Energy Simulation for Near-Future Data

■Estimation of the Impact of Climate Change on the Monthly Heat Load

Table. Monthly heat load at all rooms in August and January for the ten-year mean

a) Summer

Input Weather Data	Sensible Heat Load [MJ/month]	Latent Heat Load [MJ/month]	Total Heat Load [MJ/month]
WD_Aug (2001-2010)	2.55×10^3	6.87×10^2	3.23×10^3
WD_Aug (2026-2035)	2.88×10^3 (113%)	8.18×10^2 (119%)	3.70×10^3 (114%)

b) Winter

Input Weather Data	Sensible Heat Load [MJ/month]
WD_Jan (2001-2010)	1.25×10^3
WD_Jan (2026-2035)	1.14×10^3 (91%)

In August, sensible heat load increases by 13%, latent heat load increases by 19%, and total heat load (sensible and latent heat load) increases by 14%

In January, sensible heat load decreases by 9%

The sum of the total heat load in August and January increases 8% from current to future simulations.

5. Building Energy Simulation for Near-Future Data

■Estimation of the Impact of Climate Change on Maximum Heat Load

Table. Maximum heat load in August and January for 10 years

a) Summer

Input Weather Data	Sensible Heat Load [kW]	Latent Heat Load [kW]	Total Heat Load [kW]
WD_Aug (2001-2010)	3.35	1.12	3.79
WD_Aug (2026-2035)	3.42 (102%)	1.24 (109%)	4.14 (102%)

b) Winter

Input Weather Data	Sensible Heat Load [kW]
WD_Jan (2001-2010)	2.61
WD_Jan (2026-2035)	2.46 (94%)

(The maximum heat loads is defined as the topmost 0.5% among the heat loads for 10 years)

In August,
maximum sensible heat load increases by 2%, and maximum latent heat load increases by 9%

In January,
maximum sensible heat load decreases by 6%

In August, the impact of climate change on the maximum heat load (2% ↑) is smaller than that of the mean monthly heat load (14%↑).
The future weather data by dynamical downscaling method hold the future weather disturbance predicted by GCM

Summary and Challenges for the Future

Summary

- Suggesting a new method of making future weather data by dynamical downscaling
- Confirming the GCM and RCM bias through dynamical downscaling
- Bias corrected weather data show good agreement with observation
- Using the weather data made by suggested method, we estimated the impact of climate change on building energy simulation.
  The impact of climate change on maximum heat load (2%) is smaller than that of monthly heat load(14%).

Challenges for the future

- By using some GCM results, enhancing the prediction accuracy and suggesting the prediction range
- Attempting to create future weather data considering urban change, which effect on energy consumption.

2. Analysis Conditions of Dynamical Downscaling

■Initial and Boundary Conditions

MIROC4h

Temperature, Humidity, Wind velocity and direction, Geopotential height (6hourly)

Sea surface pressure and Sea surface temperature(24hourly)

Scenario

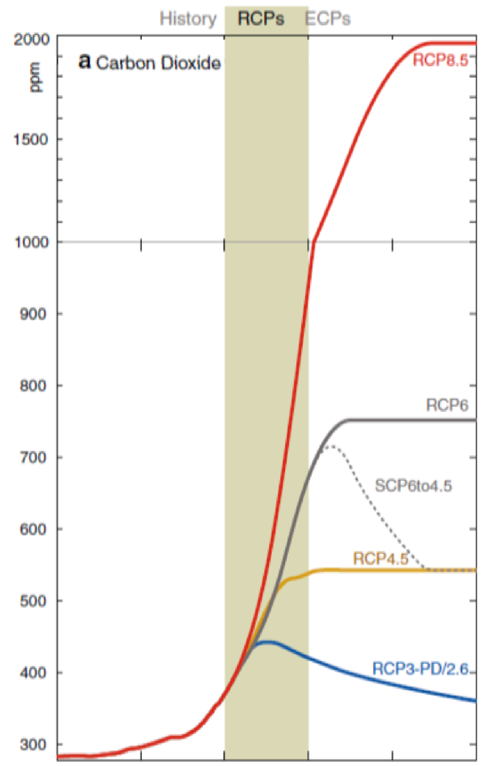
・ RCP4.5, which was adopted by IPCC the 5th Reports (Medium-low scenario)

Model Descriptions

・ MIROC4h is composed 5 components (Atmosphere, Land, River, Sea, Ice)

・ Horizontal resolution of atmosphere model is 60km

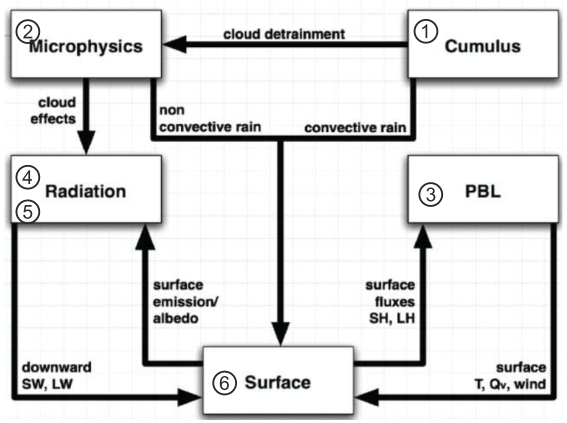
・ The number of the vertical grids is 56 and the top level is 40km



Concentration of CO_2 in the atmosphere

3. Analysis Conditions of Dynamical Downscaling

■Physics Scheme



①Cumulus parameterization	(1,2Dom.)Kain-Fritsch, (3,4Dom.)None
②Microphysics	WRF Single-Moment 6-class scheme
③Planetary boundary layer	Yonsei University Scheme
④Longwave radiation	RRTM
⑤Shortwave radiation	Dudhia
⑥Land surface	Noah Land Surface Model

■Region of the analysis

Map projection system	Lambert conformal conic projection
Horizontal grid dimensions and grid spacing	Domain 1: 38×38 (horizontal scale 54 [km])
	Domain 2: 49×49 (horizontal scale 18 [km]))
	Domain 3: 49×49 (horizontal scale 6 [km])
	Domain 4: 61×52 (horizontal scale 2 [km])
Vertical levels	35 (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	One-way nesting

■MIROC4h

Data interval	Longitude, Latitude	0.5625°
	Time	6hour
Weather Components	Geopotential height	17layer※
	Temperature	17layer※
	Specific humidity	17layer※
	Wind velocity	17layer※
	Sea surface pressure	Surface(24h)
	Surface temperature	Surface(24h)
	Sea surface temperature	Surface(24h)

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

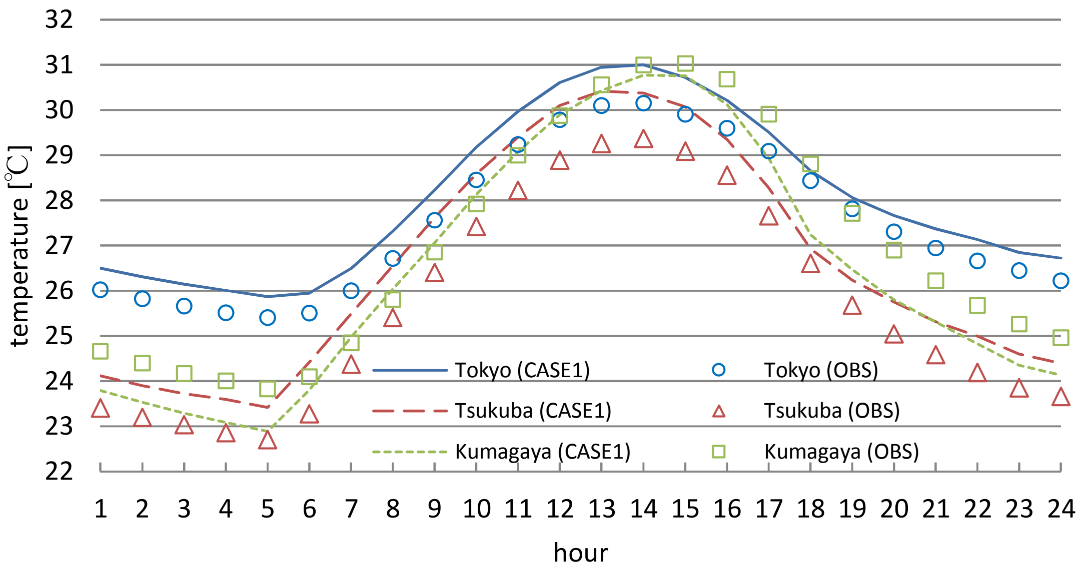
■Land Use data

Domain 1,2,3:
USGS

Domain 4:
National Land Numerical Information

3. Results of Dynamical Downscaling

■Reproducibility of Current Climate Conditions



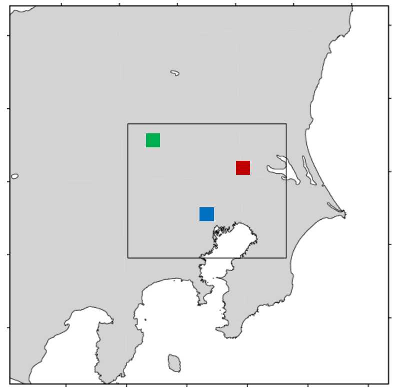


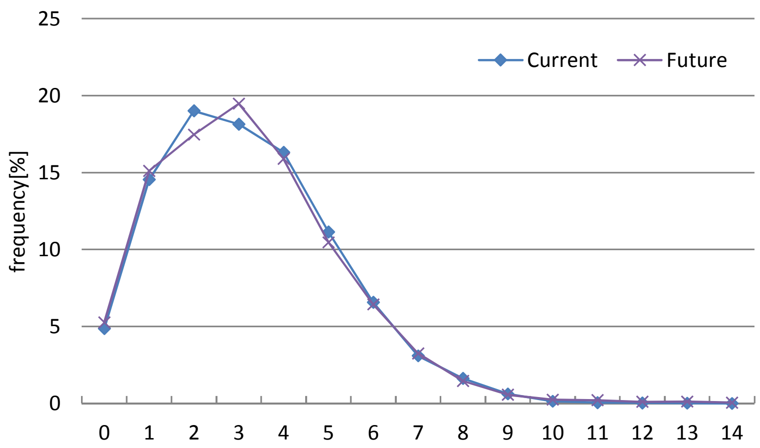
Fig. Ten years averaged temperature at 2m daily change at Tokyo, Tsukuba, and Kumagaya for current climate conditions (2001-2010)

The largest amount of diurnal temperature range was in Kumagaya, followed by Tsukuba and Tokyo.

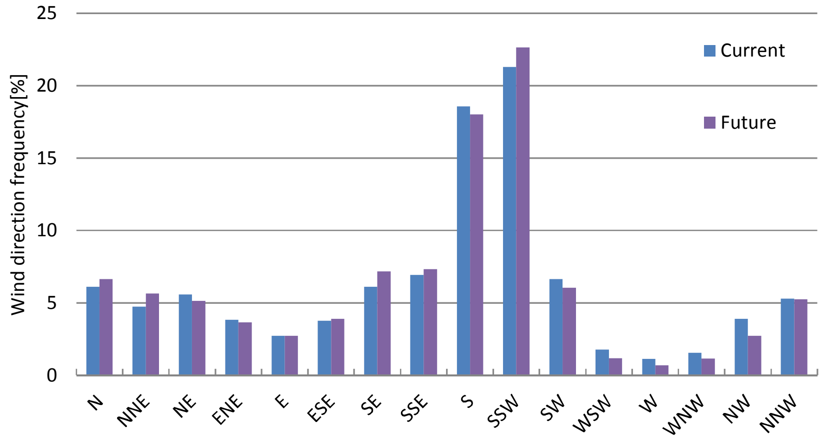
The reproducibility of the regional characteristics by dynamical downscaling was confirmed

4. Results of Dynamical Downscaling MIROC4h

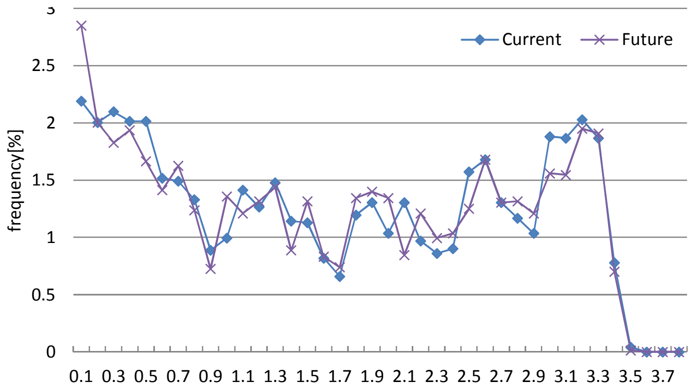
■Other weather components results in summer 2026-2035



c) wind velocity



d) wind direction



e) solar radiation

Fig. Frequency of each weather component at Tokyo

(Current Simulation(2001-2010) , Future Simulation(2026-2035))

Wind and solar radiation won't change much from current to future

5. Constructing Prototype of Future Weather Data

■Standard Weather Data

There are some kind of Weather data for building energy simulations
Most useful one is the one-year data set which represent the average weather conditions for several decades, called standard weather data here

■The methods of making standard weather data

There are some methods of making standard weather data

- Typical Meteorological Year(TMY)
- Expanded AMeDAS Reference Weather Year(EA-RWY)
- SHASE Reference Weather Year(EA-RWY)

We use this method in this paper

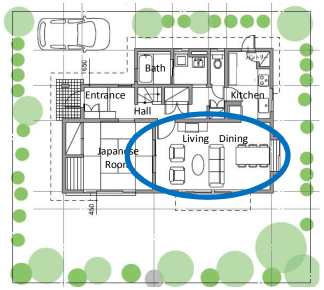
■SHASE Method

SHASE method is the easy method using average of temperature, humidity, and solar radiation

①The monthly weather data which represent the most average weather conditions among several decades is selected for each months

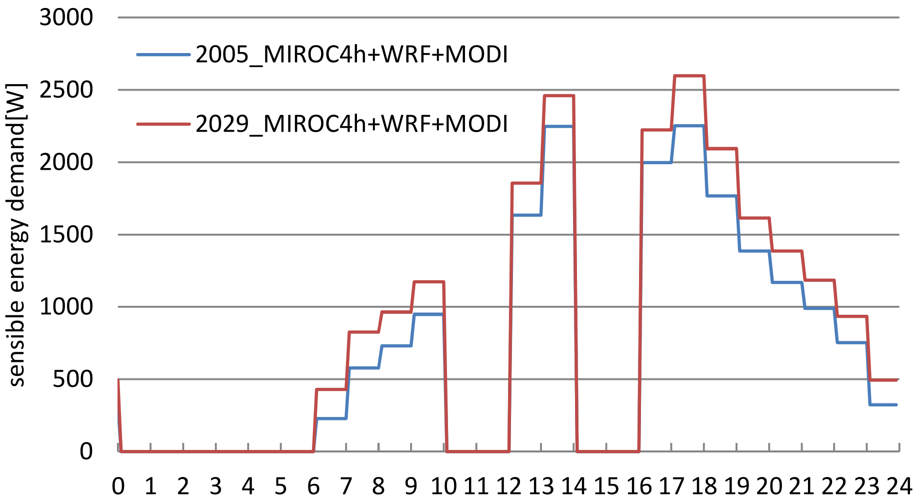
②Each month weather data is combined to complete one year standard weather data

6. Building Energy Simulation Using Future Weather Data

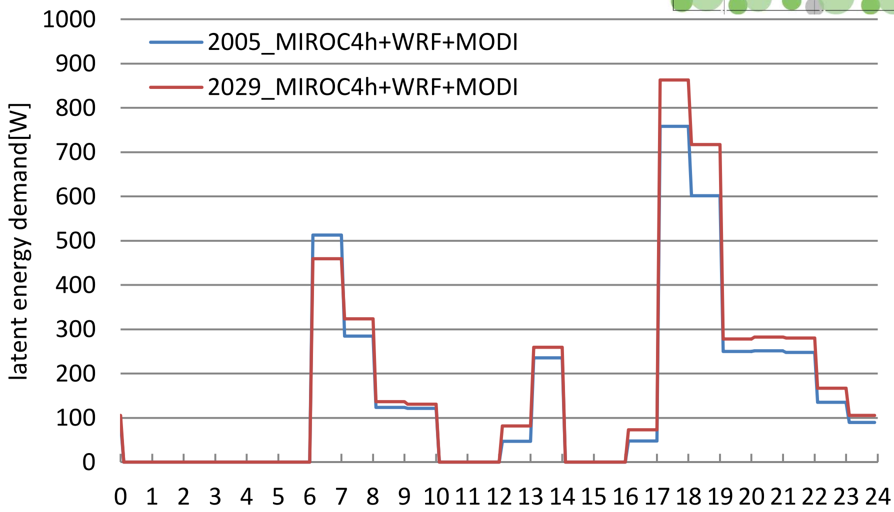


■The results of energy simulation

Using future standard weather data,
we estimate the effect of climate change on energy simulation



a) sensible heat load



b) latent heat load

Fig. Monthly averaged Daily change of heat load in August at Tokyo
(Current Standard Weather Data, Future Standard Weather Data)

Sensible heat load increase 26% and latent heat load increase 10% from current(2010s) to future(2030s)

Using standard weather data made by our method, we could estimate building energy load considering climate change

３．近未来標準気象データの試作 (気候モデルのバイアス補正)

■系統誤差(バイアス)

気象・気候モデルはバイアスを有する
①格子解像度の粗さ
②パラメタリゼーションの不正確さ
③土地利用データの不正確さ

GCMの力学的ダウンスケーリング(RCMを使用)の結果はGCMとRCMの両バイアスを含む

▼ **建築熱負荷計算の気象データとして活用する際には何らかのバイアス補正が必要**

■バイアス補正

気温、湿度、日射量に対して平均値(10年間)と標準偏差(10年間)を用いた以下の補正手法を実施

気温、湿度

$$X_{c,modi} = \overline{X_{obs}} + \frac{\sigma_{obs}}{\sigma_c}\left(X_c - \overline{X_c}\right)$$

$$X_{f,modi} = \overline{X_{obs}} + \left(\overline{X_f} - \overline{X_c}\right) + \frac{\sigma_{obs}}{\sigma_c}\left(X_f - \overline{X_f}\right)$$

日射量

$$X_{c,modi} = \frac{\overline{X_{obs}}}{\overline{X_c}} X_c$$

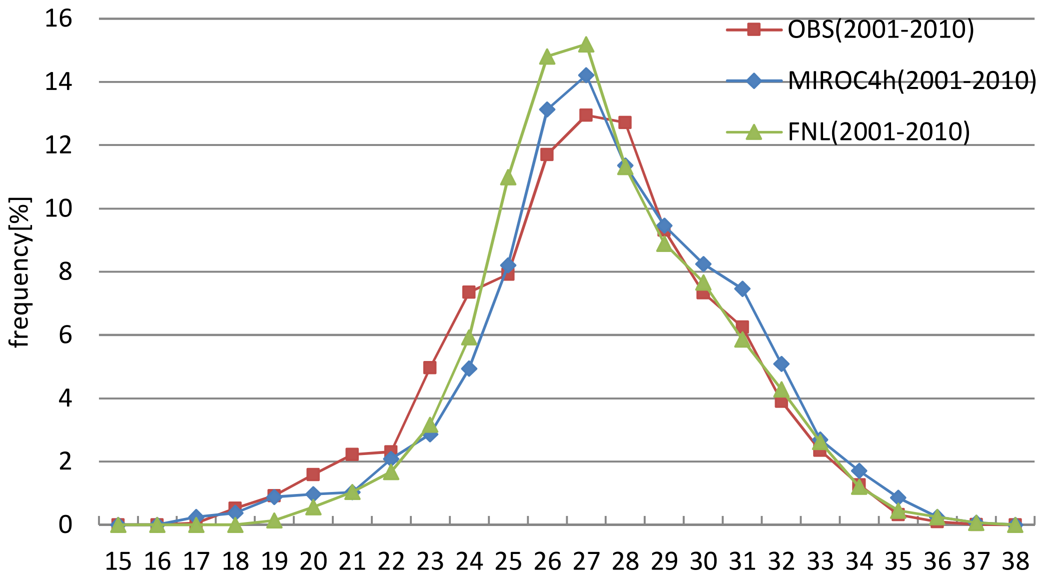
$$X_{f,modi} = \frac{\overline{X_{obs}}}{\overline{X_c}} X_f$$

$X_{c,modi}$：補正後の解析値(1時間間隔)
X_c：補正前の解析値(1時間間隔)
$\overline{X_{obs}}$：解析値の平均値
$\overline{X_c}$：解析値の平均値
σ_{obs}/σ_c：10年間の標準偏差の比
$\overline{X_{obs}}/\overline{X_c}$：10年間の平均値の比

補正後の現在(2001-2010)のWRF解析値の平均値と標準偏差が現在(2001-2010)の観測値の平均値と標準偏差と一致する補正

4. Results of Dynamical Downscaling MIROC4h

■Reproducibility of Current Climate Conditions (Temperature)



a)temperature

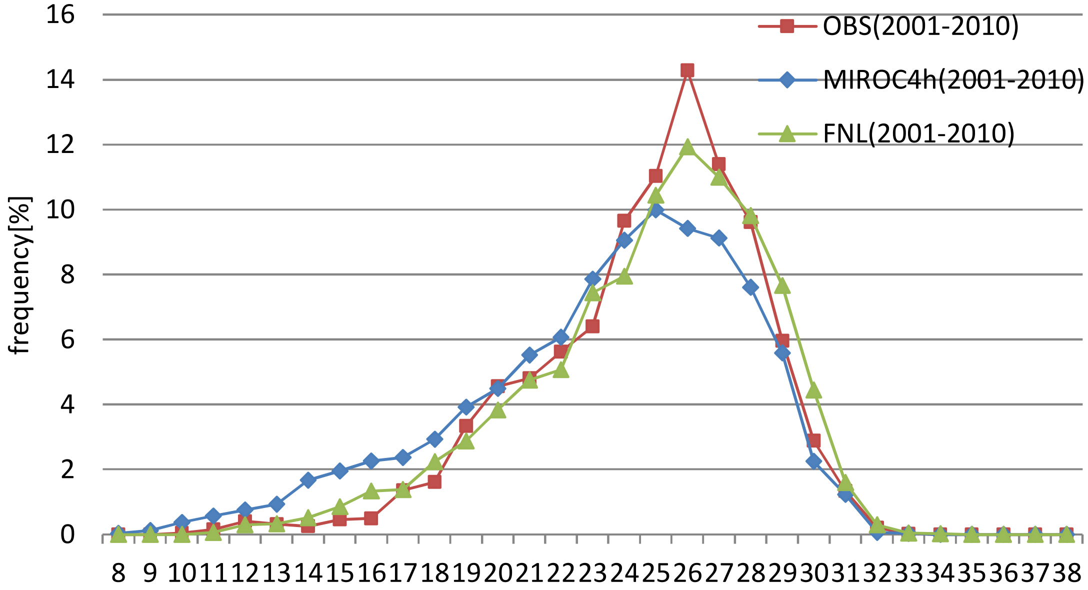
Fig. Frequency of temperature in August 2001-2010 at Tokyo
(Observation , Simulation(MIROC4h+WRF) , Simulation(FNL+WRF))

The Results of dynamical downscaling would include both of GCM and RCM bias
In the result of temperature,
the results of both simulations show good agreement with observation

GCM and RCM don’t have bias about temperature in summer simulation

4. Results of Dynamical Downscaling MIROC4h

■Water vapor pressure in summer 2001-2010



b)water vapor pressure

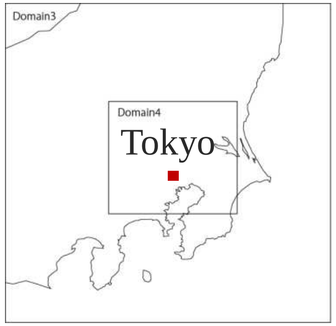


Fig. Frequency of water vapor pressure in August 2001-2010 at Tokyo
(Observation , Simulation(MIROC4h+WRF) , Simulation(FNL+WRF))

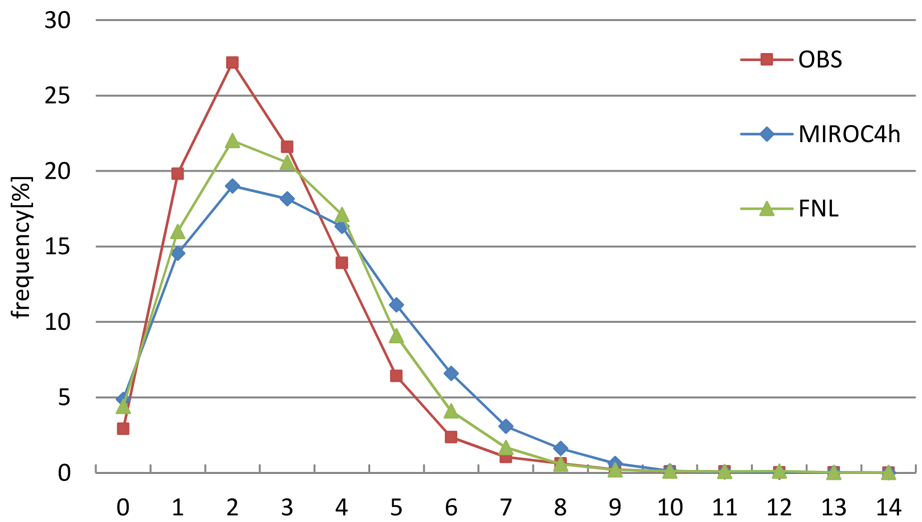
In the result of water vapor pressure,
The Simulation(FNL+WRF) show good agreement with Observation

On the other hand,
The Simulation(MIROC4h+WRF) doesn't show agreement with Observation

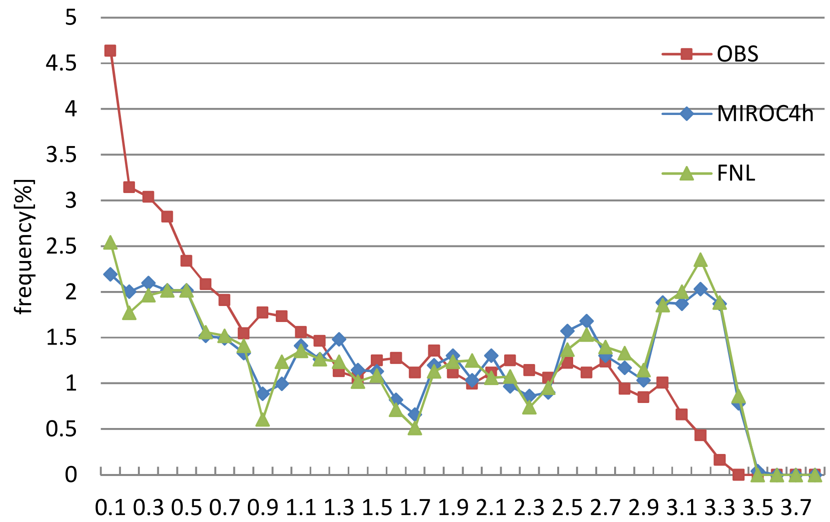
GCM have bias of water vapor pressure in summer simulation

4. Results of Dynamical Downscaling MIROC4h

■Other weather components results in summer 2001-2010



c)wind velocity



e)solar radiation

Fig. Frequency of each weather components in August 2001-2010 at Tokyo

(Observation , Simulation(MIROC4h+WRF) , Simulation(FNL+WRF))

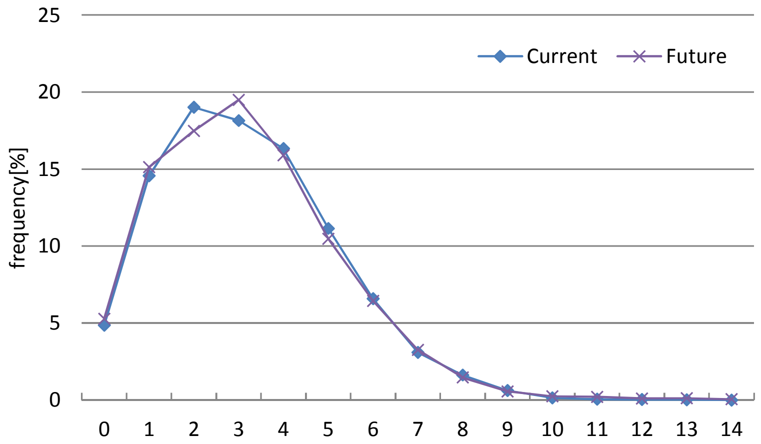
In wind velocity simulation, The difference from observation is more bigger in Simulation(MIROC4h+WRF) than in Simulation(FNL+WRF)

In solar radiation, both of Simulation(MIROC4h+WRF) and (FNL+WRF) differ from Observation, so RCM have bias.

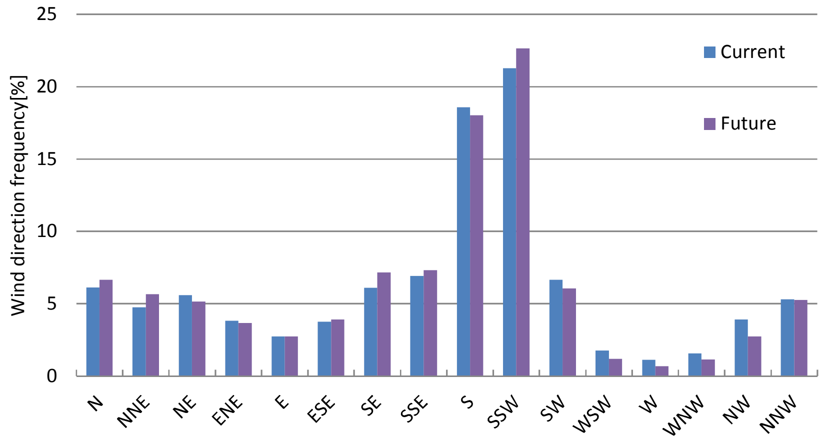
Each weather components have each bias

4. Results of Dynamical Downscaling MIROC4h

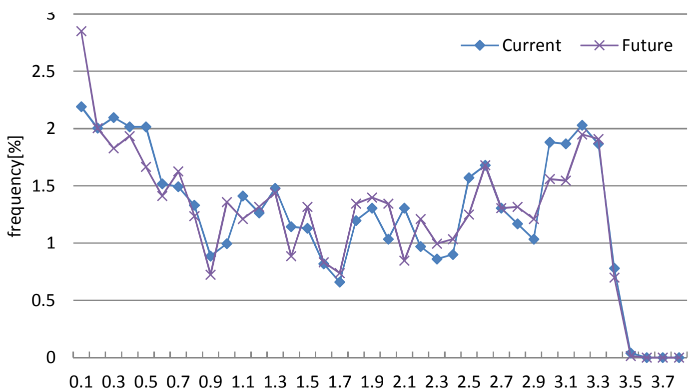
■Other weather components results in summer 2026-2035



c)wind velocity



d)wind direction



e)solar radiation

Fig. Frequency of each weather components at Tokyo

(Current Simulation(2001-2010) , Future Simulation(2026-2035))

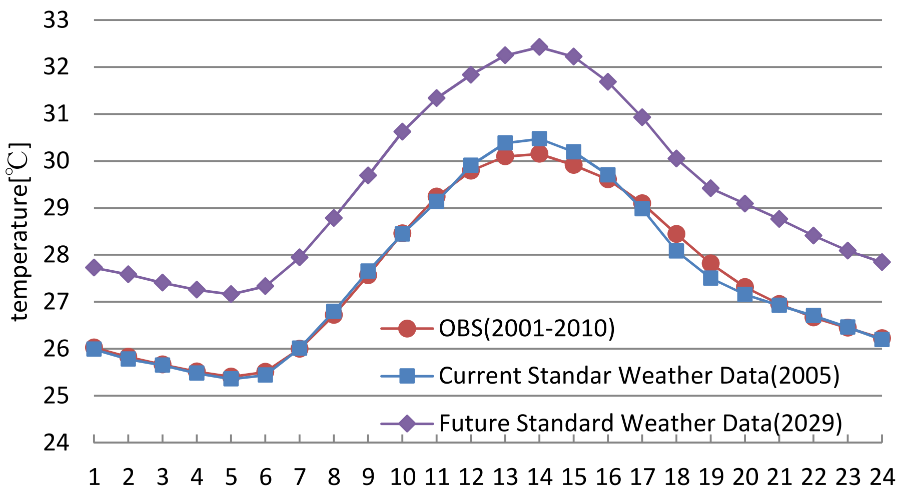
Wind and solar radiation won’t change from current to future

5. Constructing Prototype of Future Standard Weather Data

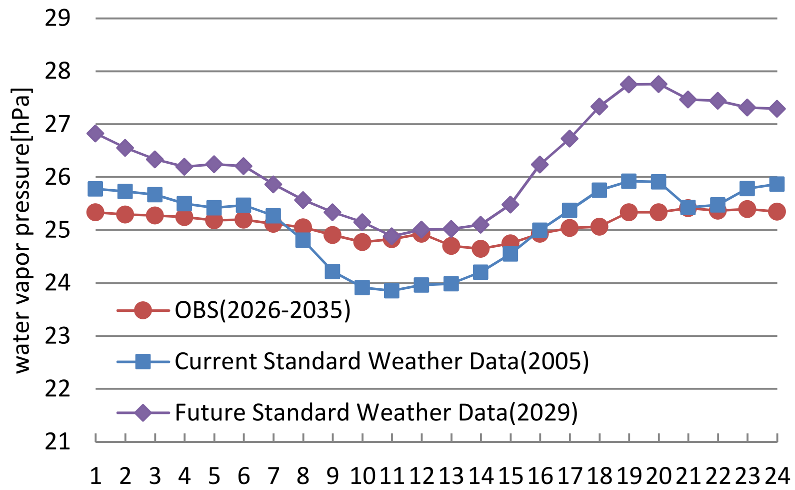
■The standard weather data selected by SHASE method

by using SHASE method for selecting standard weather data in August

2005 year data is selected for August current(2001 2010) standard weather data
2029 year data is selected for August future(2026 2035) standard weather data



a)temperature



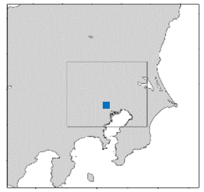
b)water vapor pressure

Fig. Daily change of Standard Weather Data

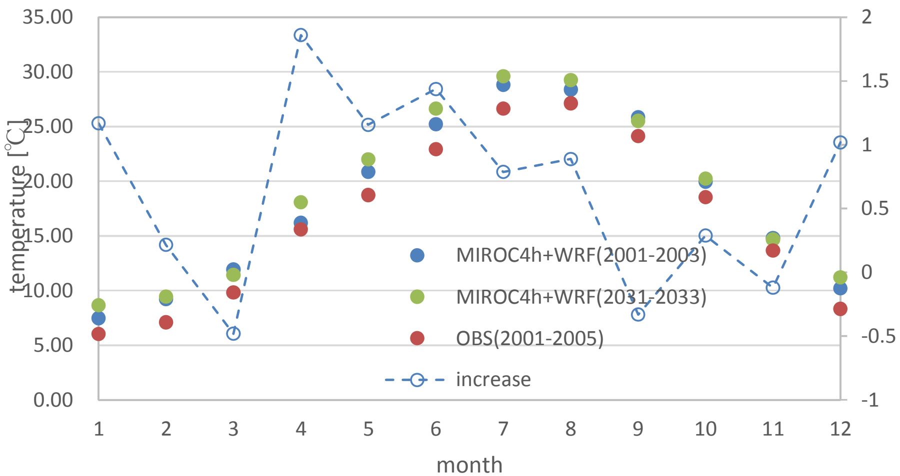
(Observation, Current Standard Weather Data, Future Standard Weather Data)

- Current Standard Weather Data show good agreement with observation
- Future Standard Weather Data represent climate change

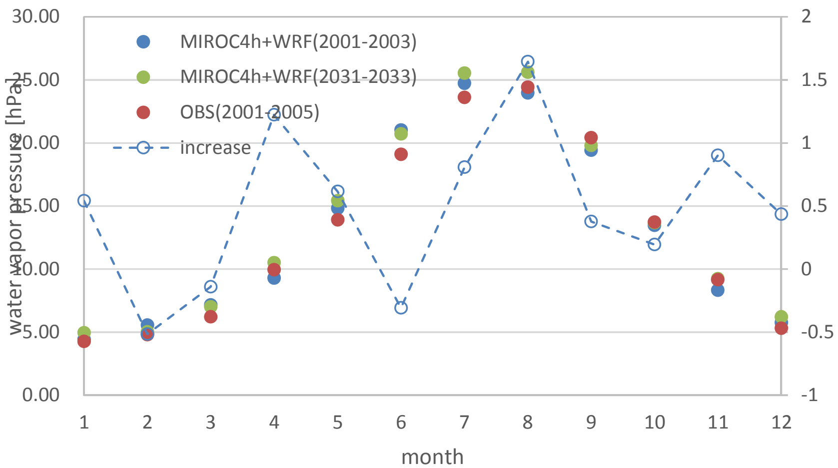
. GCMの力学的ダウンスケーリング



■近未来の解析に る気候 の (年間)



気温



気

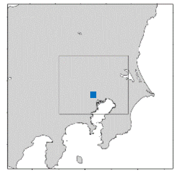
現在(200 -200)と近未来(2031-2033)の の 気象要 の平均値(手)

(O Sが観測値、MIROC4h WRF(現在)、 MIROC4h WRF(未来))

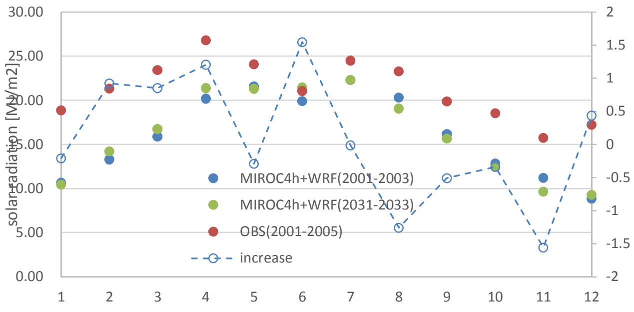
気温は4 が 1. 、3 は -0.4 、年間 0.

気 は が 1. 4hPa、2 が -0. 2hPa、年間 0.4 hPa

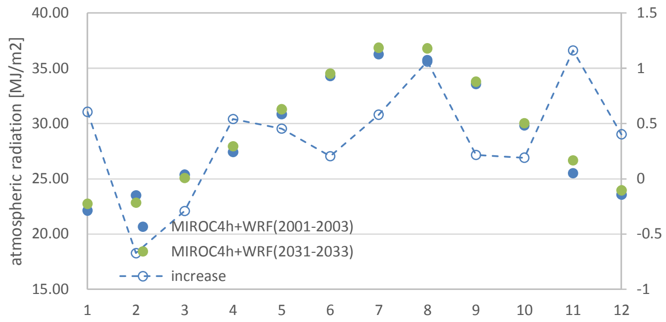
気候 の さは る

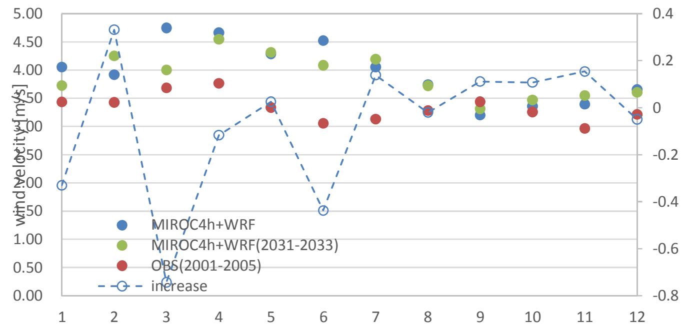


■近未来の解析に る気候 の (年間)



日射量





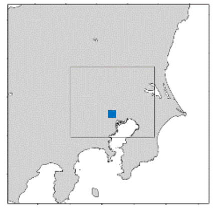
気 射量

現在(200 -200)と近未来(2031-2033)の の 気象要 の平均値(手)

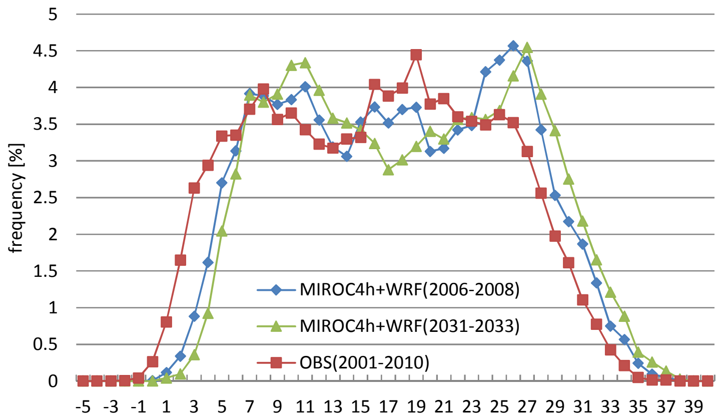
(O Sが観測値、MIROC4h WRF(現在)、 MIROC4h WRF(未来))

	気温	気	日射量	気 射量	
年平均の差	0.	0.4 2hPa	0.0 M m2	0.3 1M m2	-0.0 m s
差 現在	0.03	0.03	0.004	0.013	0.01

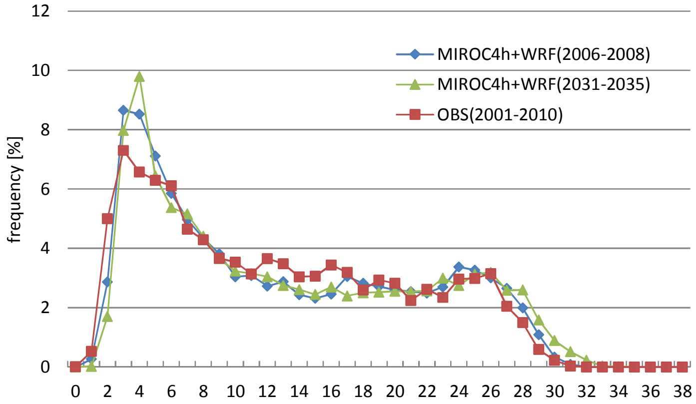
解析 は、気候 に 年平均値は 以 の気象要 、
気候 の は気温、 気 、 日射量 は さい



■近未来の解析に　る気候　　の　　(気温、湿度)



気温



気

現在(200　-200　)と近未来(2031-2033)の　気象要　の　度　　(　手　)

(O　Sが観測値、MIROC4h　WRF(現在)、 MIROC4h　WRF(未来))

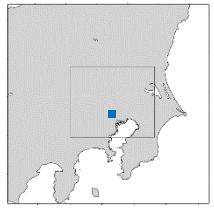
	2006-2008	2031-2033	未来/現在
平均値	1　.2	1　.	1.04
0.　(131　)	34.	3　.	1.03
0.2　(　3　)	3　.　1	3　.　1	1.03
0.1　(2　)	3　.　1	3　.3	1.02
値	3　.　0	3　.	1.00

	2006-2008	2031-2033	未来/現在
平均値	13.21	13.　1	1.04
0.　(131　)	2　.　0	31.4	1.0
0.2　(　3　)	30.3	32.1	1.0
0.1　(2　)	30.	32.44	1.0
値	31.　1	34.4	1.0

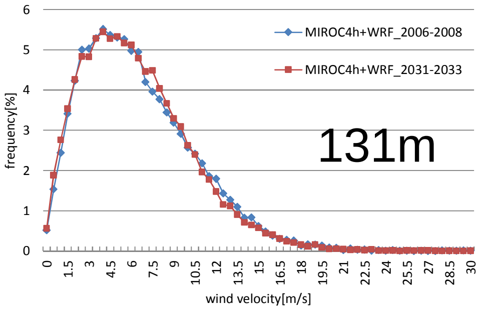
気温の平均値は4%、　　値　近の値は2%　3%　度　　、　　値の　　は　と　　　い

気　の平均値は4%、　　値　近の値は5%　度　　、　　値は8%　　　する

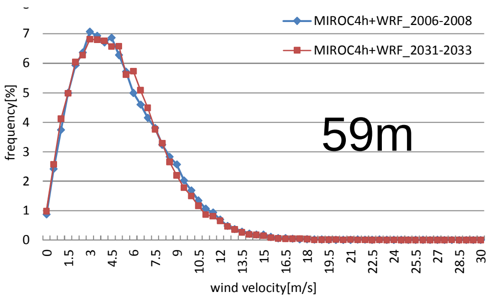
. GCMの力学的ダウンスケーリング



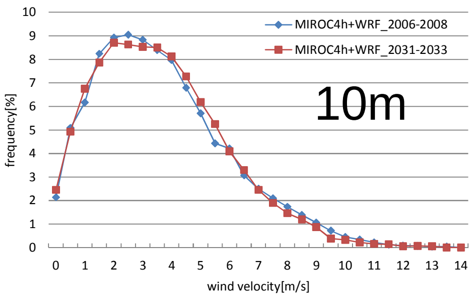
■近未来の解析に る気候 の ( )



	2006-2008		2031-2033	未来/現在
平均値	6.77	平均値	6.62	0.98
0.5%(131)	19.90	0.5%(131)	19.47	0.98
0.2%(53)	22.32	0.2%(53)	22.05	0.99
0.1%(26)	24.83	0.1%(26)	23.53	0.95
値	35.27	値	37.56	1.06



	2006-2008		2031-2033	未来/現在
平均値	5.34	平均値	5.24	0.98
0.5%(131)	15.38	0.5%(131)	15.07	0.98
0.2%(53)	17.27	0.2%(53)	17.03	0.99
0.1%(26)	19.12	0.1%(26)	18.27	0.96
値	27.35	値	28.50	1.04



	2006-2008		2031-2033	未来/現在
平均値	3.96	平均値	3.89	0.98
0.5%(131)	11.31	0.5%(131)	11.16	0.99
0.2%(53)	12.69	0.2%(53)	12.54	0.99
0.1%(26)	14.04	0.1%(26)	13.41	0.95
値	19.99	値	21.07	1.05

現在(200 -200)と近未来(2031-2033)の 度の の 度 (手)

平均値は2%、 近の は2% 5% し、 は 5% する とが 測
測 度の は るが、GCMとRCMに 未来に る 値の 測が

OUTLINE

1. Background & Purpose
2. Methodology of Dynamical Downscaling
3. Results of Dynamical Downscaling
4. Constructing Prototype of Future Weather Data
5. Building Energy Simulation for Near-Future Data
6. Conclusions