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

Yusuke ARIMA\textsuperscript{a}, Ryozo OOKA\textsuperscript{b}, Hideki KIKUMOTO\textsuperscript{b}, Toru YAMANAKA\textsuperscript{c}

\textsuperscript{a}UTOKYO, \textsuperscript{b}UTOKYO, IIS, \textsuperscript{c}KAJIMA CO.
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

  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 component, 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 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 coarse to predict the mesoscale (a few km) climate.

  Building energy simulation requires more spatial detailed weather information.

- **Regional Climate Model (RCM)**
  - The analysis region of RCMs is flexible.
  - Feature: Predicting local weather (a few km).
  - Problems: RCM can’t predict global scale climate by itself because of restriction of its analysis region. This model needs 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

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

To Confirm the Following

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

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

Making a prototype of future weather data

④ Trying to make a prototype of future weather data

⑤ by 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

  ![Domain Map](image)

  - Smallest horizontal grid scale is 2km
  - Vertical grid 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

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°C
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

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

Fig. Frequency of weather components in August 2026-2035 at Tokyo

(a) Temperature at 2m

(b) Water vapor pressure at 2m

In August,

Temperature increases by 1.11°C from current to future

Water vapor pressure increases by 1.81 hPa 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)

<table>
<thead>
<tr>
<th></th>
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<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>OBS (Aug)</td>
<td>27.5</td>
<td>25.1</td>
<td>15.5</td>
<td>-</td>
<td>3.13</td>
</tr>
<tr>
<td>CASE1(Aug)</td>
<td>28.1 (0.54)</td>
<td>23.9 (-1.19)</td>
<td>19.5 (3.96)</td>
<td>35.8</td>
<td>3.72 (0.60)</td>
</tr>
<tr>
<td>CASE2 (Aug)</td>
<td>29.2 (+1.11)</td>
<td>25.7 (+1.81)</td>
<td>19.5 (-0.05)</td>
<td>36.6 (+0.94)</td>
<td>3.76 (+0.03)</td>
</tr>
<tr>
<td>OBS (Jan)</td>
<td>6.26</td>
<td>4.33</td>
<td>9.31</td>
<td>-</td>
<td>3.28</td>
</tr>
<tr>
<td>CASE1 (Jan)</td>
<td>8.10 (1.84)</td>
<td>4.69 (0.37)</td>
<td>10.6 (1.32)</td>
<td>22.4</td>
<td>3.90 (0.62)</td>
</tr>
<tr>
<td>CASE2 (Jan)</td>
<td>8.70 (+0.60)</td>
<td>4.89 (+0.20)</td>
<td>10.6 (-0.02)</td>
<td>22.6 (+0.17)</td>
<td>3.79 (-0.11)</td>
</tr>
</tbody>
</table>

( 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

\[
X_{c,\text{modi}} = \overline{X_{\text{obs}}} + \frac{\sigma_{\text{obs}}}{\sigma_c} (X_c - \overline{X_c}) \quad (1)
\]
\[
X_{f,\text{modi}} = \overline{X_{\text{obs}}} + (\overline{X_f} - \overline{X_c}) + \frac{\sigma_{\text{obs}}}{\sigma_c} (X_f - \overline{X_f}) \quad (2)
\]

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

- \(X_{c,\text{modi}}\): Modified weather data
- \(X_c\): Model output
- \(\overline{X_{\text{obs}}}\): Average of observation data
- \(\overline{X_c}\): Average of output data
- \(\frac{\sigma_{\text{obs}}}{\sigma_c}\): Ratio of standard deviation
- \(\frac{\sigma_{\text{obs}}}{\sigma_c}\): Ratio of standard deviation
4. Constructing Prototype of Future Weather Data

The results of Bias modification

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

4. Constructing Prototype of Future Weather Data

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)

Table. Thermal Property of the model

<table>
<thead>
<tr>
<th>Component</th>
<th>Heat transmission coefficient [W/m²K]</th>
</tr>
</thead>
<tbody>
<tr>
<td>External wall</td>
<td>0.385</td>
</tr>
<tr>
<td>Roof</td>
<td>0.294</td>
</tr>
<tr>
<td>Window</td>
<td>5.72</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Component</th>
<th>Solar absorptance [-]</th>
</tr>
</thead>
<tbody>
<tr>
<td>External wall</td>
<td>0.8</td>
</tr>
<tr>
<td>Roof</td>
<td>0.8</td>
</tr>
<tr>
<td>Window</td>
<td>0.875 (Solar heat gain coefficient)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Component</th>
<th>Convective heat transfer coefficient [W/m²K]</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>3.05 (indoor), 17.7 (outdoor)</td>
</tr>
</tbody>
</table>

Fig. Target model house (at Tokyo)
(A two-story detached house, which floor space is 120m², where a four person family live)

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

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>WD_Aug (2001-2010)</td>
<td>2.55×10^3</td>
<td>6.87×10^2</td>
<td>3.23×10^3</td>
</tr>
<tr>
<td>WD_Aug (2026-2035)</td>
<td>2.88×10^3 (113%)</td>
<td>8.18×10^2 (119%)</td>
<td>3.70×10^3 (114%)</td>
</tr>
</tbody>
</table>

b) Winter

<table>
<thead>
<tr>
<th>Input Weather Data</th>
<th>Sensible Heat Load [MJ/month]</th>
</tr>
</thead>
<tbody>
<tr>
<td>WD_Jan (2001-2010)</td>
<td>1.25×10^3</td>
</tr>
<tr>
<td>WD_Jan (2026-2035)</td>
<td>1.14×10^3 (91%)</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th></th>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>WD_Aug (2001-2010)</td>
<td>3.35</td>
<td>1.12</td>
<td>3.79</td>
</tr>
<tr>
<td>WD_Aug (2026-2035)</td>
<td>3.42 (102%)</td>
<td>1.24 (109%)</td>
<td>4.14 (102%)</td>
</tr>
</tbody>
</table>

b) Winter

<table>
<thead>
<tr>
<th>Input Weather Data</th>
<th>Sensible Heat Load [kW]</th>
</tr>
</thead>
<tbody>
<tr>
<td>WD_Jan (2001-2010)</td>
<td>2.61</td>
</tr>
<tr>
<td>WD_Jan (2026-2035)</td>
<td>2.46 (94%)</td>
</tr>
</tbody>
</table>

(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
3. Analysis Conditions of Dynamical Downscaling

**Physics Scheme**

<table>
<thead>
<tr>
<th>Cumulus parameterization</th>
<th>(1,2Dom.)Kain-Fritsch, (3,4Dom.)None</th>
</tr>
</thead>
<tbody>
<tr>
<td>Microphysics</td>
<td>WRF Single-Moment 6-class scheme</td>
</tr>
<tr>
<td>Planetary boundary layer</td>
<td>Yonsei University Scheme</td>
</tr>
<tr>
<td>Longwave radiation</td>
<td>RRTM</td>
</tr>
<tr>
<td>Shortwave radiation</td>
<td>Dudhia</td>
</tr>
<tr>
<td>Land surface</td>
<td>Noah Land Surface Model</td>
</tr>
</tbody>
</table>

**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 6-hour
- **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)

**Land Use data**

- Domain 1,2,3: USGS
- Domain 4: National Land Numerical Information

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

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 Method**
    SHASE method is the easy method using average of temperature, humidity, and solar radiation.
    ① The monthly weather data which represent the most average weather conditions among several decades is selected for each months.
    ② Each month weather data is combined to complete one year standard weather data.

  We use this method in this paper.
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.

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

\[
\begin{align*}
X_{c,modi} &= \bar{X}_{obs} + \frac{\sigma_{obs}}{\sigma_c} (X_c - \bar{X}_c) \\
X_{f,modi} &= \bar{X}_{obs} + (X_f - \bar{X}_c) + \frac{\sigma_{obs}}{\sigma_c} (X_f - \bar{X}_f) \\
X_{c,modi} &= \frac{\bar{X}_{obs}}{\bar{X}_c} X_c \\
X_{f,modi} &= \frac{\bar{X}_{obs}}{\bar{X}_c} X_f
\end{align*}
\]

\(X_{c,modi}\)：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）
\(\bar{X}_{obs}\)：解析値の平均値
\(\bar{X}_c\)：解析値の平均値
\(\frac{\sigma_{obs}}{\sigma_c}\)：10年間の標準偏差の比
\(\frac{\bar{X}_{obs}}{\bar{X}_c}\)：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)

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

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

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.

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
近未来の解析における気候の動向

現在(2001-2005)と近未来(2031-2033)の気象要因の平均値（年間）

気温は4.4が1.1、3は-0.3が1.4、年間は0.
気は、4が4hPa、2が-0.2hPa、年間は0.4hPa

気候のさはる
GCMの力学的ダウンスケーリング

近未来の解析における気候の年間の気象要因の平均値（年間）

現在（2001-2003）と近未来（2031-2033）の気候の気象要因の平均値（手）

(OBSが観測値、MIROC4h WRF(現在)、MIROC4h WRF(未来))

<table>
<thead>
<tr>
<th>気温</th>
<th>気压</th>
<th>日射量</th>
<th>気射量</th>
</tr>
</thead>
<tbody>
<tr>
<td>年平均の差</td>
<td>0.03</td>
<td>0.42hPa</td>
<td>0.00Mm2</td>
</tr>
<tr>
<td>増加現在</td>
<td>0.00</td>
<td>0.03</td>
<td>0.004</td>
</tr>
</tbody>
</table>

解析は、気候の気温、気压、日射量は高い、年平均値は以上の気象要因、気候の気温、気压、日射量は高い。
近未来の解析に る気候 の (気温、湿度)

現在(200-200)と近未来(2031-2033)の気象要の度 (手)
(OBSが観測値、MIROC4h WRF(現在)、MIROC4h WRF(未来))

2006-2008 2031-2033 未来/現在

<table>
<thead>
<tr>
<th></th>
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</thead>
<tbody>
<tr>
<td>気温</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>平均値</td>
<td>1.2</td>
<td>1.04</td>
<td></td>
</tr>
<tr>
<td>値</td>
<td>0. (131) 34. 3 . 1.03</td>
<td>0.2 (3) 3 . 1 3 . 1.03</td>
<td>0.1 (2) 3 . 1 . 1.02</td>
</tr>
</tbody>
</table>
| 気候の平均値は4%、値近の値は2% 3%の度、値は8%する
近未来の解析における気候の力学的ダウンスケーリング

<table>
<thead>
<tr>
<th></th>
<th>周年期</th>
<th>2006-2008</th>
<th>2031-2033</th>
<th>未来/現在</th>
</tr>
</thead>
<tbody>
<tr>
<td>平均値</td>
<td></td>
<td>6.77</td>
<td>6.62</td>
<td>0.98</td>
</tr>
<tr>
<td>0.5%(131)</td>
<td></td>
<td>19.90</td>
<td>19.47</td>
<td>0.98</td>
</tr>
<tr>
<td>0.2%(53)</td>
<td></td>
<td>22.32</td>
<td>22.05</td>
<td>0.99</td>
</tr>
<tr>
<td>0.1%(26)</td>
<td></td>
<td>24.83</td>
<td>23.53</td>
<td>0.95</td>
</tr>
<tr>
<td>値</td>
<td></td>
<td>35.27</td>
<td>37.56</td>
<td>1.06</td>
</tr>
</tbody>
</table>

現在(200-200)と近未来(2031-2033)の度の度の度(手

|               |        | 5.34       | 5.24       | 0.98      |
| 0.5%(131)     |        | 15.38      | 15.07      | 0.98      |
| 0.2%(53)      |        | 17.27      | 17.03      | 0.99      |
| 0.1%(26)      |        | 19.12      | 18.27      | 0.96      |
| 値            |        | 27.35      | 28.50      | 1.04      |

|               |        | 3.96       | 3.89       | 0.98      |
| 0.5%(131)     |        | 11.31      | 11.16      | 0.99      |
| 0.2%(53)      |        | 12.69      | 12.54      | 0.99      |
| 0.1%(26)      |        | 14.04      | 13.41      | 0.95      |
| 値            |        | 19.99      | 21.07      | 1.05      |

現在(200-200)と近未来(2031-2033)の度の度の度(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に未来にする値の測が
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