Selecting CMIP6-Based Future Climate Scenarios for Impact and Adaptation Studies

Hideo Shioyama1,2, Noriko N. Ishizaki3, Naota Hanasaki1, Kiyoshi Takahashi1, Seita Emori1, Rui Ito5, Toshiyuki Nakaegawa4, Izuru Takayabu4, Yasuaki Hijjoka1, Yukari N. Takayabu2, and Ryosuke Shibuya2

1National Institute for Environmental Studies, Tsukuba, Japan
2Atmosphere and Ocean Research Institute, University of Tokyo, Kashiwa, Japan
3Japan Meteorological Business Support Center, Tsukuba, Japan
4Meteorological Research Institute, Japan Meteorological Agency, Tsukuba, Japan

Abstract

Climate change impact assessment studies often use future projections of only a few global climate models (GCMs) due to limited research resources. Here we develop a novel method to select a small subset of GCMs that widely capture the uncertainty range of large ensemble. By applying this method, we select a subset of five GCM projections from the Coupled Model Intercomparison Project Phase 6 (CMIP6) ensemble for impact and adaptation studies in Japan. At first, we omit GCMs whose global warming projections have been evaluated to be overestimated in the recent literature. Then, we select a subset of five GCMs that widely capture the uncertainty ranges for 8 climate variables and have good performances in present-climate simulations. These selected GCM simulations will be used to provide better climate scenarios for impact and adaptation studies than those in the previous impact assessment project.

(Citation: Shioyama, H., N. N. Ishizaki, N. Hanasaki, K. Takahashi, S. Emori, R. Ito, T. Nakaegawa, I. Takayabu, Y. Hijjoka, Y. N. Takayabu, and R. Shibuya, 2021: Selecting CMIP6-based future climate scenarios for impact and adaptation studies. SOLA, 17, 57–62, doi:10.2151/sola.2021-009.)

1. Introduction

Climate change projections based on global climate models (GCMs) are essential for impact assessments and planning adaptation strategies. Because there are intrinsic uncertainties in climate change projections, it is necessary to investigate the ranges of GCM simulations. However, policy makers often prefer to use a small set of climate scenarios as representative climate futures (Whetton et al. 2012) or storylines (Shepherd 2019) rather than the full GCM ensemble. Limited research resources also cause many impact assessment researchers to use outputs of only a few GCMs out of the many ones that contributed to the Coupled Model Intercomparison Project Phase 5 (CMIP5) or 6 (CMIP6). For example, a global-scale multi-sector impact assessment project, phase 2b of the Intersectoral Impact Model Intercomparison Project (ISIMIP2b; https://www.isimip.org), used only four GCMs from CMIP5 (Frieler et al. 2017). It has been suggested that the ISIMIP2b GCM subset does not broadly represent the CMIP5 uncertainty ranges of future projections (McSweeney and Jones 2016; Ito et al. 2020). Another coordinated multi-sector impact assessment project in Japan called S-8 also used only four CMIP5 GCMs (Hanasaki et al. 2014; Ishizaki et al. 2020). Shioyama et al. (2020, hereafter Shi2020) suggested that the selected GCMs of S-8 do not cover the CMIP5 range of shortwave radiation changes in Japan. Shi2020 also developed a method to select a better subset of GCMs that are more widely distributed and are not biased regarding shortwave radiation.

For the successor impact assessment project of S-8, called S-18 (2020-2024, https://s-18ccap.jp/en/), and the Climate Change Adaptation Research Program (CCARP) of National Institute for Environmental Studies (https://ccca.nies.go.jp/en/program/index.html), we will produce a CMIP6-based (Eyring et al. 2016; O’Neill et al. 2016) dataset of bias-corrected climate scenarios in Japan in a future study. This dataset should meet the following conditions:

• The national (Japanese) GCMs MRI-ESM2.0 and MIROC6 should be involved because support from national modelling centres is useful for impact researchers.
• The dataset includes 8 climate variables (see the next section) that are widely used in impact model research.
• The performance of the present climate simulations of the selected GCMs should be good.
• The selected GCM subset covers the CMIP6 distributions of future changes in the 8 variables well.
• All the selected GCMs have the output data of three shared socioeconomic pathways (SSPs): SSP1-2.6, SSP2-4.5 and SSP5-8.5 (O’Neill et al. 2016).
• The issue of overestimated future warming in CMIP6 (see Section 2) should be addressed.

Although several methods of model selection have been developed (McSweeney et al. 2012; Cannon 2015; Mendlik and Gobiet 2016; Shi2020), no methods meet the above conditions. For example, Shi2020’s method is adaptive for only one variable. Shi2020 and Cannon (2015) selected GCMs to maximize the distance between GCMs for future climate change projections. The method of Mendlik and Gobiet (2016) is based on a combination of principal component analysis and clustering of future climate change projections. Those methods do not take into account the performance of the present climate simulations. McSweeney et al. (2012) eliminated GCMs that perform particularly poorly in the present climate simulations of the major features of Southeast Asian climate (specifically, the Asian summer monsoon), and then selected from those remaining a subset that captures a broad range of future changes in temperature, monsoon characteristics and precipitation. Their method is difficult to extend to 8 variables. The aim of this paper is to develop a novel method to select a small subset of GCMs that meets the above conditions.

2. The CMIP6 simulations and pre-filtering

We investigate changes in the 8 variables from the 1995–2014 mean to the 2080–2099 mean: the daily mean surface air temperature (tas), daily maximum surface air temperature (tasmax), daily minimum surface air temperature (tasmin), precipitation (pr), surface downward shortwave radiation (rswd), surface downward longwave radiation (rlsw), surface relative humidity (hurs) and surface wind speed (sfcWind). Although the observed statistics of those variables are slightly compared to the other variables, we have decided to include it because of its demands in climate change impact studies. We analyse the seasonal mean values (Dec.–Feb. (DJF),
Shiogama et al., Selecting CMIP6-Based Future Projections for Impact Assessments

Mar.–May (MAM), June–Aug. (JJA) and Sept.–Nov. (SON) of the above anomalies and annual averaged global mean temperature changes.

We collect the outputs of 21 GCMs from the CMIP6 ensemble that provide the monthly mean data of the 8 variables for all the historical, SSP1-2.6, SSP2-4.5 and SSP5-8.5 runs (Eyring et al. 2016; O’Neill et al. 2016) (Table 1). Because, in a future study, we would like to capture the bias-corrected data of a single ensemble member for each selected GCM, only one ensemble member for each GCM is examined here. Please note that most of our analyses are based on the monthly mean variables, although daily data are necessary for the bias correction process. In a future study, we will consider the availability of daily data in our model selection process in Section 3.

First, FGOALS-g3 is omitted because of very large biases in the Japan area (e.g., a warm bias of 10°C relative to the NCEP Climate Forecast System Reanalysis (Saha et al. 2014)).

Several GCMs of CMIP6 have equilibrium climate sensitivities higher than the upper bound of the likely range in the IPCC 5th Assessment Report (i.e., 4.5°C) (Collins et al. 2013; Zelinka et al. 2020). Recent studies have suggested that some of these high-sensitivity GCMs have overestimated the global mean surface air temperature trends in recent decades compared to the observations, and the reliabilities of their future warming projections are low (Tokarska et al. 2020; Liang et al. 2020; Nijsse et al. 2020). Observationally constrained CMIP6 warming is consistent with the CMIP5 range (Tokarska et al. 2020). Therefore, based on the study by Tokarska et al. (2020), we exclude 5 GCMs with large warming trends in recent decades: CanESM5, EC-Earth3, EC-Earth3-Veg, HadGEM3-GC31-LL and UKESM1-0-LL. ACCESS-CM2 (the 1981–2017 global mean tas trend (2015–2017 is under SSP2-8.5) is 0.25°C/decade), ACCESS-ESM1-5 (0.34°C/decade), CanESM5-CanOE (0.35°C/decade) and MPI-ESM1-2-LR (0.18°C/decade) were not analysed by Tokarska et al. (2020).

We omit ACCESS-ESM1-5 and CanESM5-CanOE due to the large recent warming trends. To the best of our knowledge, this is the first study that incorporates the observational constraints of future warming trends in the CMIP6 ensemble into the model selection process. Hereafter, we call the remaining 13 GCMs CMIP6* (Table 1). We will select a GCM subset that well covers the uncertainty ranges of the CMIP6* ensemble instead of the original CMIP6 ensemble. These pre-filtering processes reduce the maximum values of future global mean surface air temperature changes (2080–2099 minus 1995–2014) from 2.0°C, 3.3°C and 5.7°C to 1.9°C, 2.8°C and 4.9°C for SSP1-2.6, SSP2-4.5 and SSP5-8.5, respectively.

### Table 1. The analysed CMIP6 models, ensemble members and priorities.

| Model name       | Ensemble member | Selected (Tiers) | Omitted |
|------------------|-----------------|------------------|---------|
| MRI-ESM2-0       | r1i1p1f1        | 1                |         |
| MIROC6           | r1i1p1f1        | 1                |         |
| ACCESS-CM2       | r1i1p1f1        | 2                |         |
| ACCESS-ESM1-5    | r1i1p1f1        |                  |         |
| CanESM5          | r1i1p1f1        |                  |         |
| CanESM5-CanOE    | r1i1p2f1        |                  |         |
| CNRM-CM6-1       | r1i1p1f2        |                  |         |
| CNRM-CM6-1-HR    | r1i1p1f2        |                  |         |
| CNRM-ESM2-1      | r1i1p1f2        |                  |         |
| EC-Earth3        | r1i1p1f1        |                  |         |
| EC-Earth3-Veg    | r1i1p1f1        |                  |         |
| FGOALS-g3        | r1i1p1f1        |                  | ✓       |
| GFED-ESM4        | r1i1p1f1        |                  |         |
| HadGEM3-GC31-LL  | r1i1p1f3        |                  |         |
| INM-CM4-8        | r1i1p1f1        |                  |         |
| INM-CM5-0        | r1i1p1f1        |                  |         |
| IPSL-CM6A-LR     | r1i1p1f1        | 2                |         |
| MIROC-ES2L       | r1i1p1f2        |                  |         |
| MPI-ESM1-2-HR    | r1i1p1f2        | 2                |         |
| MPI-ESM1-2-LR    | r1i1p1f1        |                  |         |
| UKESM1-0-LL      | r1i1p1f2        |                  |         |

3. Selection methods and results

#### 3.1 Selection methods

We will select a subsample of GCMs that are distributed to widely capture the CMIP6* uncertainty ranges of all 8 variables. Additionally, we will consider the performances of the present-climate simulations in the model selection process.

We define $N$ as the total number of CMIP6* GCMs (13 here). Let $R(i,v)$ be the spatiotemporal root mean square error (RMSE) over the $15^\circ$N–$55^\circ$N, $120^\circ$E–$157.5^\circ$E region (including land and ocean area) across the four seasons for the $v$-th variable of the $i$-th GCM. The NCEP Climate Forecast System Reanalysis (Saha et al. 2014) data during the 1995–2014 period are used as the reference. All the data have been interpolated to a $1^\circ \times 1^\circ$ grid. We divide $R(i,v)$ by the median across the GCMs to compute the normalized RMSE, $\bar{R}(i,v)$. We also compute the weighted averages of $\bar{R}(i,v)$ across the variables:

$$
\bar{R}(i) = \frac{\sum w(v)\bar{R}(i,v)}{\sum w(v)},
$$

where $w(v)$ is the weight of the $v$-th variable. We can take into account the priorities of variables for targeted impact assessment studies by changing $w(v)$ for each variable. For example, if impact researchers are interested in $pr$ rather than the other variables, it is possible to set $w(pr) = 2$ and set the weights to 1 for the other variables. Because S-18 and CCARP cover a wide area of impact research and important variables are different between research topics, we set $w(v) = 1$ for all the variables. Figure 1 shows $\bar{R}(i,v)$ and $\bar{R}(i)$. MRI-ESM2.0 has good performance for the present-climate simulations for all the variables. MIROC6 has better skills for tasmin, $pr$ and hrs than the median of CMIP6* but does not have good skills for tasmax, rlds and sfcWind. We use $\bar{R}(i)$ in part of the model selection process, as mentioned below. When we computed $\bar{R}(i,v)$ and $\bar{R}(i)$ using data in a longer period (1980–2014), there is little changes in biases (not shown) and the selected GCMs are not different from those mentioned later.

The area-averaged anomalies (2080–2099 minus 1995–2014) for the west and east Japan (Fig. 2, land area only) are calculated for each variable, because these two areas have different climatology. Let $X(i,s,a,e,v)$ be a value of the $v$-th variable for the $i$-th GCM, $s$-th season, $a$-th SSP and $e$-th region. The number of GCMs that can be selected is denoted by $M$. The GCM subsample from the CMIP6* ensemble is selected based on the following method.
(i) For each season \((s)\), region \((a)\), SSP \((e)\) and variable \((v)\), we divide the max-min ranges of \(\{X(i,s,a,e,v), i = 1, \ldots, N\}\) into \(M\) equal-length bins (Fig. 3a).

(ii) We randomly sample \(X(i,s,a,e,v)\) of the \(M\) GCMs \(R\) times, which are denoted by \(Y(j,r,s,a,e,v), j = 1, \ldots, M\) and \(r = 1, \ldots, R\). Here, \(R = 10,000\).

(iii) For each \(r, s, a, e\) and \(v\), we define \(\{Z(m,r,s,a,e,v), m = 1, \ldots, M\}\) as the numbers of \(\{Y(j,r,s,a,e,v), j = 1, \ldots, M\}\) that fall into the \(m\)-th bin of (i) (Fig. 3a).

(iv) For each \(r\) and \(v\), we define the unevenness, \(U(r,v)\), as the variance of \(\{Z(m,r,s,a,e,v), m = 1, \ldots, M\} s = 1, \ldots, 4, a = 1, 2, e = 1, \ldots, 3\}. Smaller \(U(r,v)\) values indicate that the subset of GCMs has a less biased distribution.

(v) The mean unevenness \(\bar{U}(r)\) is defined as

\[
\bar{U}(r) = \frac{\sum_{v} w(v) U(r,v)}{\sum_{v} w(v)},
\]

where \(w(v) = 1\) for all the variables as mentioned above. The black solid lines of Fig. 3b show the maximum and minimum values of the 10,000 \(U(r)\) values as a function of the selected number of models \(M\). As \(M\) increases, the max-min range of \(\bar{U}(r)\) shrinks.

(vi) We search subsets of the \(M\) GCMs whose \(U(r)\) value is less than or equal to the 10th percentile values of the 10,000 randomly generated GCM subsets (the black dashed line of Fig. 3b) and that include both MRI-ESM2.0 and MIROC6. Because some daily variables are missing for CNRM-CM6-1-HR, we omit the subset that includes CNRM-CM6-1-HR. If \(M = 5\), 97 candidates of subsets pass these criteria.

Fig. 2. The locations of the areas in west and east Japan analysed in this study. We focus on the land area where observed data are available for bias correction processes to produce climate scenarios (Ishizaki et al. 2020). We computed the area averages over these regions.

Fig. 3. (a) Schematic diagram of the model selection process (iii) in the case of \(M = 5\). (b) The horizontal axis is the number of selected GCMs. The vertical axis indicates the mean unevenness. The solid black lines are the maximum and minimum values of the 10,000 randomly selected subsets. The dashed line is the 10th percentile value. The orange line shows the selected subsets. (c) The unevenness value for each variable and their average for the selected GCMs where \(M = 5\). (d) The FRC (%) for each variable and their averages for \(M = 4\) (blue), 5 (red), 6 (light blue) and 7 (green).
(vii) For each candidate of the GCM subsets that pass criterion (vi), we compute the maximum value of \( R(i) \) across the M GCMs, \( \max(R(i)) \). The subsets having the lowest value of \( \max(R(i)) \) are selected.

(viii) Finally, from the candidates of GCM subsets that pass criterion (vii), we select a subset whose M-GCM-total-value of \( R(i) \) is the lowest.

The orange line of Fig. 3b indicates \( U(r) \) for the selected GCM subsets as a function of M. Figure 3c shows the unevenness for each variable for the selected GCMs with \( M = 5 \). The unevenness value of hrs is greater than those of the other variables.

For the selected GCM subsets, we investigate the fraction of the range captured (FRC) (McSweeney et al. 2016) for each variable: (a) we compute the ratio between the max-min range of the M selected GCMs and the max-min range of all the CMIP6* GCMs; (b) the ratios of (a) are averaged across all the combinations of region, season and SSPs. When \( M = 4 \), the FRC values of tas, tasmax and tasmin are larger than those of the other variables (Fig. 3d). The FRC values generally increase as the number of selected models increases. For \( M \geq 5 \), the FRC values exceed 72% except for pr (67%) and hrs (60%).

### 3.2 Spreads of the selected subset of GCMs

Although \( M = 6 \) has a better FRC than \( M = 5 \), by consulting with the members of S-18 and CCARP, we determine that \( M = 5 \) due to limited research resources of impact assessments. Because it highly depends on the impact researchers how many GCMs they can use, we also determine the two priorities of GCMs to be used in S-18 and CCARP: Tier 1 is composed of MRI-ESM2.0 and MIROC6; Tier 2 is composed of ACCESS-CM2, IPSL-CM6A-LR and MPI-ESM1-2-HR (Table 1). Impact researchers can choose the tiers of simulations to be performed for themselves. Coincidently, MRI-ESM2.0, MIROC6, IPSL-CM6A-LR and MPI-ESM1-2-HR are the 10 GCMs used in the 3rd phase of the ISIMIP (ISIMIP3b) (Lange 2020) (MIROC6 is Tier 2 of ISIMIP3b and the other are 4 of 10 GCMs used in the 3rd phase of the ISIMIP (ISIMIP3b)). Impact researchers can choose Japanese impact assessments in S-18/CCARP and world-scale impact assessments in ISIMIP3b for these GCMs. Because tas, tasmin and tasmax are temperature variables, we test whether the selected GCMs can change if \( w = 1/3 \) for these 3 variables and \( w = 1 \) for the other variables. In that case, ACCESS-CM2, INM-CM5-0 and MPI-ESM1-2-HR are selected as the Tier 2 GCMs.

Figure 4a shows the global mean air temperature changes for SSP1-2.6 and SSP5-8.5. Although the global mean air temperature changes are not used for the model selection process, the 5 selected GCMs cover the distributions of CMIP6* well. Figures 4b–e indicate the four examples of climate changes averaged over west and east Japan (see Supplementary Figs. S1–S8 for the changes in all the variables). It is confirmed that the 5 selected GCMs are widely distributed and are not biased in most cases.

Figures 5, 6 and S9–S11 compare the maximum, median and minimum values and \( 2\times \) the standard deviation (2\( \sigma \)) at each grid between all the CMIP6* GCMs and the selected 5 GCMs for changes in some variables in SSP5-8.5 for example for DJF (Fig. 5), pr for JJA (Fig. 6), rds for DJF (Fig. S9), hrs for JJA (Fig. S10) and sfcWind for DJF (Fig. S11). The 5 selected GCMs reasonably represent the maximum, median and minimum change patterns and \( 2\sigma \) of these variables. Although the amplitudes of the negative pr anomalies over the ocean region south of Japan are different between Figs. 6c and 6g (the minimum change patterns of pr), these differences may not influence impact assessment studies of the land area.

### 4. Summary and discussion

We develop a novel method of selecting GCMs based on the CMIP6 ensemble as representative climate future scenarios (Whetton et al. 2012). This new method can be used for GCM selection processes for impact assessments in any countries and regions. Here we apply it for impact and adaptation studies of Japan. We first consider the recent literature on the overestimated warming issue of the CMIP6 ensemble (Tokarska et al. 2020; Liang et al. 2020; Nijssse et al. 2020) in the model selection process. ISIMIP3 could not take into account this issue in its model selection process (Lange 2020). We selected a subset of 5 GCMs that widely captures the uncertainty ranges for the 8 variables, while the S-8 dataset considered only the spreads of tas and pr (Hanasaki et al. 2014). We also take into account the performances of the present-climate simulations, while Shi2020 did not.

Shi2020 and Cannon (2015) selected GCM subsets with the maximum distance between the GCMs. If there is a single outlier GCM, the GCMs at the other end tend to be frequently selected in the maximum distance methods. To avoid such biased distributions of the selected GCMs, we apply the equal-length binning.

While McSweeney et al. (2012) and Mendlik and Gobiet (2016) considered the spatial patterns of climate change in their model selections, we do not. Instead, we will investigate and report spatial patterns of climate change and atmospheric circulation changes in each selected GCM in future studies.
Changes in tasmax, DJF, SSP5-8.5 (°C)

Fig. 5. Changes in tasmax for DJF of SSP5-8.5 (°C). The top panels indicate the (a) maximum, (b) median, (c) minimum and (d) 2σ of the CMIP6* ensemble for each grid point. The bottom panels show the (e) maximum, (f) median, (g) minimum and (h) 2σ of the 5 selected GCMs for each grid point.

Changes in pr, JJA, SSP5-8.5 (mm/day)

Fig. 6. Changes in pr for JJA of SSP5-8.5 (mm day⁻¹). The top panels indicate the (a) maximum, (b) median, (c) minimum and (d) 2σ of the CMIP6* ensemble for each grid point. The bottom panels show the (e) maximum, (f) median, (g) minimum and (h) 2σ of the 5 selected GCMs for each grid point.
Acknowledgements

This research was supported by the Environment Research and Technology Development Fund (JPMEEF20192004) of the Environmental Restoration and Conservation Agency of Japan, the Integrated Research Program for Advancing Climate Models (JPMXD0717935457 and JPMXD0717935561) (MEXT, Japan) and the Climate Change Adaptation Research Program of NIES.

Edited by: Y. Kosaka

References

Cannon, A. L., 2015: Selecting GCM scenarios that span the range of changes in a multimodel ensemble: Application to CMIP5 climate extremes indices. *J. Climate*, 28, 1260–1267.

Frieler, K., S. Lange, F. Piontek, C. P. O. Reyner, J. Schewe, L. Warszawski, F. Zhao, L. Chini, S. Denvil, K. Emanuel, T. Geiger, K. Halladay, G. Hutt, M. Mengel, D. Murakami, S. Ostberg, A. Popp, R. Riva, M. Stevanovic, T. Suzuki, J. Volkholz, E. Burke, P. Ciais, K. Ebi, T. D. Eddy, J. Elliott, E. Galbraith, S. N. Gosling, F. Hattermann, T. Hickler, J. Hinkel, C. Hof, V. Huber, J. Jägermeyr, V. Krysanova, R. Marcé, H. Müller Schmied, I. Mouratiadou, D. P. Tittensor, R. Vautard, M. van Vliet, M. F. Biber, R. A. Betts, B. Li Bodirsky, D. Derings, S. Froliking, C. D. Jones, H. K. Lotze, H. Lotze-Campen, R. Sahajpal, K. Thonicke, H. Tian, and Y. Yamagata, 2017: Assessing the impacts of 1.5°C global warming – simulation protocol of the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP2b). *Geosci. Model Dev.*, 10, 4321–4345, doi:10.5194/gmd-10-4321-2017.

Hanasaki, N., K. Takahashi, Y. Hijioka, H. Kusaka, T. Iizumi, T. Ariga, K. Matsuhashi, and N. Mimura, 2014: Climate, population, and land use scenarios for climate change impacts and adaptation polices assessments in Japan (second edition). *Environ. Sci.*, 27, 362–373, doi:10.11353/ensej.27.362. (in Japanese)

Ishizaki, N. N., M. Nishimori, T. Iizumi, H. Shiogama, N. Hanasaki, and K. Takahashi, 2020: Evaluation of two bias-correction methods for gridded climate scenarios over Japan. *SOLA*, 16, 80–85.

Ito, R., H. Shiogama, T. Nakaegawa, and I. Takayabu, 2020: Uncertainties in climate change projections covered by the ISIMIP and CORDEX model subsets from CMIP5. *Geosci. Model Dev.*, 13, 859–872, doi:10.5194/gmd-13-859-2020.

Lange, S., 2020: ISIMIP3b bias adjustment fact sheet (Available online at: https://www.isimip.org/gettingstarted/isimip3b-bias-correction/, accessed 5 August 2020).

Liang, Y., N. P. Gillett, and A. H. Monahan, 2020: Climate model projections of 21st century global warming constrained using the observed warming trend. *Geophys. Res. Lett.*, 47, e2019GL086757, doi:10.1029/2019GL086757.

McSweeney, C. F., and R. G. Jones, 2016: How representative is the spread of climate projections from the 5 CMIP5 GCMs used in ISI-MIP? *Clim. Serv.*, 1, 24–29, doi:10.1016/J.CLISER.2016.02.001.

McSweeney, C. F., R. G. Jones, and B. B. B. Booth, 2012: Selecting ensemble members to provide regional climate change information. *J. Climate*, 25, 7100–7121.

Mendlik, T., and A. Gobiet, 2016: Selecting climate simulations for impact studies based on multivariate patterns of climate change. *Climatic Change*, 135, 381–393.

Nijssse, F. J. M. M., P. M. Cox, and M. S. Williamson, 2020: Emergent constraints on transient climate response (TCR) and equilibrium climate sensitivity (ECS) from simulated historical warming in CMIP5 and CMIP6 models. *Earth Syst. Dynam.*, 11, 737–750.

O’Neill, B. C., C. Tebaldi, D. P. van Vuuren, V. Eyring, P. Friedlingstein, G. Hutt, R. Knutti, E. Kriegler, J.-F. Lamarque, J. Lowe, G. A. Meehl, R. Moss, K. Riahi, and B. M. Sanderson, 2016: The Scenario Model Intercomparison Project (ScenarioMIP) for CMIP6. *Geosci. Model Dev.*, 9, 3461–3482, doi:10.5194/gmd-9-3461-2016.

Saha, S., and co-authors, 2014: The NCEP climate forecast system version 2. *J. Climate*, 27, 2185–2208, doi:10.1175/JCLI-D-12-00823.1.

Shepherd, T. G., 2019: Storyline approach to the construction of regional climate change information. *Proc. Roy. Soc. A.*, 475, 20190013.

Shiogama, H., R. Ito, Y. Imada, T. Nakaegawa, N. Hirota, N. N. Ishizaki, K. Takahashi, I. Takayabu, and S. Emori, 2020: Selecting future climate projections of surface solar radiation in Japan. *SOLA*, 16, 75–79, doi:10.2151/sola.2020-013.

Taylor, K. E., R. J. Stouffer, and G. A. Meehl, 2012: An overview of CMIP5 and experimental design. *Bull. Amer. Meteor. Soc.*, 93, 485–498.

Tokarska, K. B., M. B. Stolpe, S. Sippel, E. M. Fischer, C. J. Smith, F. Lehner, and R. Knutti, 2020: Past warming trend constrains future warming in CMIP6 models. *Sci. Adv.*, 6, doi:10.1126/sciadv.aaa9549.

United Nations Framework Convention on Climate Change. 2015: Adoption of the Paris Agreement. *FCCC/CP/2015/L.9/Rev.1.*

Whetton, P., K. Hennessy, J. Clarke, K. McInnes, and D. Kent, 2012: Use of representative climate futures in impact and adaptation assessment. *Climatic Change*, 115, 433–442.

Zelinka, M. D., T. A. Myers, D. T. McCoy, S. Po-Chedley, P. M. Caldwell, P. Ceppi, and co-authors, 2020: Causes of higher climate sensitivity in CMIP6 models. *Geophys. Res. Lett.*, 47, e2019GL085782, doi:10.1029/2019GL085782.

Manuscript received 21 November 2020, accepted 26 January 2021

SOLA: https://www.jstage.jst.go.jp/browse/sola/