Selecting Future Climate Projections of Surface Solar Radiation in Japan

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Abstract
The ensemble average projections of the Coupled Model Inter-comparison Project Phase 5 (CMIP5) ensemble show future increases in shortwave radiation at the surface (SW) in Japan. We reveal that the Arctic Oscillation-like atmospheric circulation trends cause cloud cover decreases around Japan, leading to increases in the SW.

In many cases, impact assessment studies use the outputs of only a few models due to limited research resources. We find that the four climate models used in the Japanese multisector impact assessment project, S-8, do not sufficiently capture the uncertainty ranges of the CMIP5 ensemble regarding the SW projections. Therefore, the impact assessments using the SW of these four models can be biased. We develop a novel method to select a better subset of models that are more widely distributed and are not biased, unlike the S-8 models.

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1. Introduction

Future projections of downward shortwave radiation (sunlight) on the Earth’s surface (SW) are essential inputs for a wide range of impact assessment studies of anthropogenic climate change, e.g., agriculture, ecosystem, human health and photovoltaic systems. However, while analyses of temperature and precipitation changes in Japan are abundant (e.g., Ogata et al. 2014; Ishizaki et al. 2017; Nayak et al. 2017; Suzuki-Parker et al. 2018; Yokoyama et al. 2019), studies on the future projections of the SW in Japan are limited. Wild et al. (2015) examined the global-scale future projections of the SW of the Coupled Model Inter-comparison Project Phase 5 (CMIP5, Taylor et al. 2012) ensemble up to the year 2049 under representative concentration pathway 8.5 (RCP8.5, van Vuuren et al. 2011). Figure 2 of Wild et al. (2015) shows that the SW increases due to decreases in cloud cover in Japan in the median projections of the CMIP5 ensemble; however, the reason for the cloud cover change is unclear. Therefore, it is worthwhile to investigate the reason causing the future SW increases in Japan.

It should be noted that many impact assessment studies use outputs of only a few global climate models (GCMs) out of many CMIP5 GCMs due to limited research resources and data availability. Furthermore, policy makers are willing to consider a small set of climate scenarios as representative climate futures (Whetton et al. 2012) or storylines (Shepherd 2019) rather than the full GCM ensemble for their planning of adaptation strategies. For example, phase 2b of the Intersectoral Impact Model Inter-comparison Project (ISIMIP2b; https://www.isimip.org), a global scale multisector impact assessment project, uses only four GCMs of CMIP5 (Frieler et al. 2017). However, McSweeney and Jones (2016) and Ito et al. (2019) noted that the selected subset of ISIMIP2b are not ideal because the subset does not broadly represent the uncertainty ranges of the CMIP5 ensemble, regarding future changes in temperature and precipitation. Although the CMIP5 ensemble does not necessarily represent the full uncertainty in the climate projections (Knutti 2010), it is better to capture the model spread. A coordinated multisector impact assessment project in Japan, “Comprehensive Study on Impact Assessment and Adaptation for Climate Change” (called S-8, http://www.nies.go.jp/s8/index.html), also used only four GCMs: MRI-CGCM3.0, MIROC5, GFDL CM3, and HadGEM2-ES (Hanasaki et al. 2014). The results of multisector impact assessments in S-8 are widely used in climate change adaptation planning in Japanese national and local governments (http://www.env.go.jp/en/cc/adaptation/mat02.pdf). However, no one knows whether this subset adequately captures the uncertainty ranges of CMIP5 or has a biased distribution.

The aims of the present study are to (1) investigate changes in the SW in Japan, (b) examine whether the four GCMs used by S-8 have a biased distribution, and (c) develop a method to select a better subset. Although we focus on the SW, some impact assessment models use multiple climate variables, including the SW (e.g., temperature and precipitation). Therefore, the development of model selection methods considering multiple climate variables is important. In the summary and discussion section, we briefly explain how our method could be expanded to consider multiple variables.

2. Data

We analyze 25 GCMs from the CMIP5 ensemble (Table 1). S-8 uses four GCMs (GFDL-CM3, HadGEM2-ES, MIROC5 and MRI-CGCM3) from the CMIP5 ensemble as the common climate scenarios for multisector impact assessments in Japan. The initial-condition-ensemble average of the historical, RCP2.6 and RCP8.5 runs are calculated for each GCM. We examine changes from the 1986–2005 mean to the 2076–2095 mean.

The analyzed variables include the seasonal mean downward shortwave radiation at the surface (SW), cloud cover, and sea level pressure (SLP). Here, winter, spring, summer and autumn are defined as December-February (DJF), March-May (MAM), June-August (JJA) and September-November (SON), respectively. We also compute 8-day high-passed filtered air temperature and meridional wind at the 850-hPa level and examine their multiplication, i.e., the meridional heat transport as the indicator of storm track activity at the low level (vT850). We exclude CESM1-CAM5, GISS-E2-H, GISS-E2-R, HadGEM2-AO, HadGEM2-ES, NorESM1-ME and NorESM1-M of CMIP5 from the analyses using vT850 due to their limited data availability.

In Figs. 1 and 2, we focus on RCP8.5 because of the better signal-to-noise ratio than that of RCP2.6. Changes in the above-mentioned variables of RCP8.5 are divided by the global mean temperature change (ΔT). When we compare RCP8.5 and RCP2.6 in Figs. 3 and 5, we do not divide the variables by ΔT because the low signal-to-noise ratio of ΔT in RCP2.6 adds noise to the results.
3. Results

Figure 1 shows the ensemble mean changes in the SW/ΔT, (cloud cover)/ΔT and vT850/ΔT around Japan for each season using RCP8.5. The ensemble average projections show increases in the SW over Japan in all seasons except Hokkaido (the northern island of Japan) in DJF (the top panels of Fig. 1). The increases in the SW are caused by decreases in cloud cover (the middle panels of Fig. 1). The decreases in cloud cover relate to the weakening of storm track activities around Japan (the bottom panels of Fig. 1). Analyses of the clear-sky SW changes indicate that changes in aerosol emissions are important for the SW changes in China but not for those in Japan (not shown).

To investigate the reason for the ensemble mean climate change patterns around Japan, we extend the analyses from Japan to the Northern Hemisphere. We find Arctic Oscillation-like patterns of SLP trends (the bottom panels of Fig. 2), i.e., negative SLP trends in the high-latitude region surrounded by positive SLP trends in the middle-latitude regions of the Pacific and Atlantic oceans (Thompson and Wallace 2000; Collins et al. 2013). These Arctic Oscillation-like patterns accompany poleward shifts of the jet stream (contours of Fig. 2) (Collins et al. 2013), weakening the westerly wind and storm track activities around Japan (the middle panels of Fig. 2). Weakened storm track activities increase the SW in Japan (top panels of Fig. 2).

The above analyses are based on the RCP8.5 scenario. To inform adaptation policies, it is necessary to investigate climate scenarios meeting the 2°C goal of the Paris Agreement (United

| Model name       | Ensemble size (RCP2.6, 8.5) |
|------------------|-----------------------------|
| MRI-CGM3         | 1,1                         |
| MIROC5           | 3,3                         |
| bcc-csm1-1       | 1,1                         |
| bcc-csm1-1-m     | 1,1                         |
| BNU-ESM          | 1,1                         |
| CanESM2          | 5,3                         |
| CCSM4            | 6,6                         |
| CESM1-CAM5       | 3,3                         |
| CNRM-CM5         | 1,1                         |
| CSIRO-Mk3-6-0    | 10,10                       |
| GFDL-CM3         | 1,1                         |
| GFDL-ESM2G       | 1,1                         |
| GFDL-ESM2M       | 1,1                         |
| GISS-E2-H        | 3,3                         |
| GISS-E2-R        | 3,3                         |
| HadGEM2-AO       | 1,1                         |
| HadGEM2-ES       | 2,2                         |
| IPSL-CM5A-LR     | 4,4                         |
| IPSL-CM5A-MR     | 1,1                         |
| MIROC-ESM        | 1,1                         |
| MIROC-ESM-CHEM   | 1,1                         |
| MPI-ESM-LR       | 3,3                         |
| MPI-ESM-MR       | 1,1                         |
| NorESM1-M        | 1,1                         |
| NorESM1-ME       | 1,1                         |

Fig. 1. Ensemble mean changes in climate variables around Japan. (top) shortwave (W m⁻² °C⁻¹), (middle) cloud cover (% °C⁻¹) and (bottom) vT850 (m s⁻¹ °C⁻¹) for DJF, MAM, JJA and SON using RCP8.5. These changes are divided by the global mean temperature changes. Gray shading indicates grids under the ground.
Figure 3 shows the scatter plots of the SW averaged over the Japan area (125°E−155°E, 25°N−47.5°N) between RCP8.5 and RCP2.6. There are large positive correlations. Therefore, we confirm that we can use the information obtained from the high radiative forcing scenario (RCP8.5) in the low radiative forcing scenario (RCP2.6). The four S-8 GCMs are not ideally distributed, at least in terms of the solar irradiance changes. The four S-8 GCMs do not cover the upper half of the uncertainty ranges of the SW in MAM. By contrast, the four GCMs are located within the upper half of the range of the SW in JJA and SON.

Furthermore, we develop a method to select a subsample of GCMs that are distributed to widely capture the uncertainty ranges of the CMIP5 ensembles. We define $N$ as the total number of GCMs (25 here). Let $X(i,s,e)$ be the SW of the $i$-th GCM for the $s$-th season of the $e$-th RCP. $Y(i,s,e)$ is the rank of $X(i,s,e)$, i.e., the $i$-th GCM has the largest SW for the $s$-th season of the $e$-th RCP if $Y(i,s,e)=N$. We refer to $M$ as the number of subsamples of GCMs that can be selected. We randomly sample $R$-times $Y(i,s,e)$ of $M$ GCMs, which are denoted by $Z(j,r,s,e)$ ($j=1,...,M; r=1,...,R$). Here, $R$ is 10,000. We compute the mean distance ($D(M,r)$) of the subsamples as follows:

$$D(M,r) = \frac{1}{8} \sum_i \sum_s \sum_e \frac{2}{M(M-1)} \sum_{k=1}^{M} \sum_{j=1}^{M} (Z(k,r,s,e) - Z(j,r,s,e))^2.$$

(Eq. 1)
By using the rank \( r(i, s, e) \) instead of \( X(i, s, e) \), our method is insensitive to the existence of outlier GCMs. Larger \( D(M, r) \) values indicate a wider and more unbiased distribution of subsamples in the rank space.

Figure 4 shows the mean distance of the SW as a function of the selected model numbers, \( M \). Black solid, dotted and dashed lines indicate the maximum, 50% and minimum values of the 10,000 random samples, respectively. As the selected model number \( M \) increases, the min-max range shrinks. The red cross denotes the mean distance of the four GCMs used in S-8. The mean distance of S-8 is lower than the 50% value of \( D(4, r) \), suggesting that the S-8 subsample is not an ideal choice, at least for the SW scenarios in Japan.

It is a usual practice for national research projects related to impact assessments and adaptation strategies to use climate scenarios including those from national GCMs, because technical support is available from national modeling centers. In Japan, MRI-CGCM3 and MIROC5 are the national GCMs in the CMIP5 generations and are involved in the S-8 subset. Using our method, we can also select the maximum distance subsample including MRI-CGCM3 and MIROC5 (blue line of Fig. 4).

The diamonds of Fig. 5 show the SW changes in the maximum distance subsample, including MRI-CGCM3 and MIROC5, in a scenario in which we can select eight GCMs. The selected models are MRI-CGCM3, MIROC5, GFDL-CM3, IPSL-CM5A-LR, BNU-ESM, HadGEM2-AO, GISS-E2-R and CCSM4. The selected GCMs (Fig. 5) are widely distributed and are not biased, unlike the S-8 subset shown in Fig. 5, at least in relation to the SW scenarios of Japan.

4. Summary and discussion

We characterize the future projections of solar radiation changes in the CMIP5 ensemble in Japan. The Arctic Oscillation-like pattern of the SLP trends causes a weakening of westerly wind and storm-track activity, decreasing cloud cover, and increasing SW. The changes in SW would lead to increases in the photovoltaic energy potential. However, the increases in photovoltaic energy potential could be canceled by decreases in wind energy potential due to weakening of wind (Ohba 2019) (Fig. 2). It is worth assessing climate change effects on the combined potential of photovoltaic and wind energies in Japan.

We examine whether the four GCMs used in the Japanese multisector impact assessment project, S-8, sufficiently capture the uncertainty ranges of the CMIP5 ensemble. The four GCMs do not capture the ranges of the CMIP5 ensemble and are biased: the four S-8 GCMs are biased lower for MAM and higher for JJA and SON. Therefore, impact assessments using the solar radiation scenarios of these four GCMs may be biased.

We also develop the method to select a better subset of GCMs. The selected GCMs are widely distributed and are not biased, unlike the S-8 subset. Our method is somewhat similar to that of Cannon (2015), who successively selected a GCM with the maximum distance from previously selected GCMs, whereas we select the maximum distance subset from the randomly resampled GCMs. Although we use only the SW as the indicator to select the GCMs in this study, we can easily extend our method to include other indicators (e.g., temperature and precipitation changes). By computing the ranks of GCMs for each indicator, we can combine multiple indicators without considering their units. Previous studies (McSweeney et al. 2012; Cannon 2015; Mendlik and Gobiet 2016) also used multiple variables to select GCMs. McSweeney et al. (2012) and Mendlik and Gobiet (2016) considered the spatial patterns of changes in variables in their model selection processes. It may be better to consider changes in, for example, Asian monsoon and Arctic Oscillation to select models for impact assessments in Japan as well as changes in regional mean variables. We do not consider the performance in the historical simulations of each GCM projection in the current method.

For a next project of impact and adaptation studies in Japan, we are developing an extended method considering many variables, the performances of the present climate simulations and the spread of the future projections. We will represent those results in a future paper.

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