NOTES AND CORRESPONDENCE

Climate Downscaling as a Source of Uncertainty in Projecting Local Climate Change Impacts

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Abstract

This study assessed the sensitivity of the simulated future impact on forage yield over Japan to the precipitation change in growing season derived from the multiple downscaling models, taking the regional climate projection ensemble dataset for Japan as an example. Three regional climate models (RCMs: NHRCM, NRAMS, and TWRF), and one statistical model (CDFDM) provided the fine-resolution (20-km) climate data over Japan from the climate projection performed by a global climate model (GCM: MIROCHI) under A1B scenario. With the common boundaries for the RCMs (and predictor for the statistical model), there is a consistency for the increased summer precipitation. However, discrepancies were found for the degree of precipitation increase and change in the mean summer maximum number of consecutive dry days. These discrepancies caused the spread of the simulated future change in forage yield over Japan by 3.3–11.4% (2081–2100), relative to the present-day one (1981–2000). These results showed that the direction (increase or decrease) and amplitude of the simulated future impact differ between the climate scenarios from the downscaling models and those from the parent GCM, indicating that climate downscaling is a source of uncertainty in simulating future impact.

1. Introduction

Uncertainty in projecting future impacts hinders at developing local climate adaptation strategies. Among various sources of uncertainty, it has been intensively studied for emission scenarios, GCMs, and in part impact models if we took agricul-

tural impacts as examples (e.g., Tebaldi and Lobell 2008, Challinor et al. 2009). However, few studies are available for the uncertainty of impacts associated with climate downscaling (notable exceptions are Mearns et al. (2001) and Tsvetsinskaya et al. (2003)), while climate downscaling (both dynamical and statistical) is a key for regional climate projection.

Recently, multi-downscaling model ensembles, including RCMs and statistical models, are available via climate downscaling intercomparison

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projects (see Arritt and Rummukainen (2011) for overview). A Japanese project, The Multi-model Ensemble and Downscaling Methods for Assessment of Climate Change Impact (called S-5-3), has provided an ensemble dataset for Japan (Ishizaki et al. in this issue). This offers a good test bed to examine the uncertainty of impacts due to climate downscaling.

The purpose of this study is to assess the sensitivity of simulated impacts to the spread of regional climate scenarios from the multiple downscaling models, using the S-5-3 ensemble dataset as an example. The central focus of this study was precipitation as this climatic variable is characterized by a large spatiotemporal variability. The sensitivity analysis of simulated impact to precipitation may provide useful information to infer the uncertainty of impact due to climate downscaling. We used a forage growth model for alfalfa (called SIMFOY) as an example of impact model, which is simple enough in modeling to analyze relationships between simulated impact on forage yield and given precipitation scenario.

2. Data and methods

2.1 Downscaled climate data

Daily climate data from MIROCHI GCM (K-1 model developers 2004) and three nonhydrostatic RCMs (NHRCM, NRAMS, and TWRf) were used (Table 1). The RCMs covered the whole of Japan with a common grid interval of 20 km and a nearly common center pole position of the domain, while the domain sizes were slightly different. The initial and lateral boundary conditions, including sea surface temperature, were commonly given from MIROCHI outputs for the periods 1981–2000 and 2081–2100 (A1B).

The settings of spin-up and integration differed by the RCMs. Only NRAMS sequentially inte-

grated throughout each 20-year period. Other two performed the downscaling experiments in a manner of time-slice with a 2-month spin-up period. However, such differences are generally insignificant for long-term downscaling experiments as RCMs depend more on lateral boundary conditions than on initial one (Castro et al. 2005). All RCMs used the cumulus parameterization scheme of Kain and Fritsch (1993) (K-F), whereas, for other parameterizations, e.g., microphysics, radiation, planetary boundary layer, the scheme differed by the RCMs (see Iizumi et al. (2011) for more details).

For statistical model, we used the cumulative distribution function-based downscaling method (CDFDM; Iizumi et al. 2010, 2011). The CDFDM uses daily GCM precipitation as a predictor of local precipitation at a site. The GCM error in daily precipitation was defined for each percentile of empirical cumulative distribution functions (CDFs) provided from daily GCM and observations for the training period 1981–2000. We gathered daily data for each of warm season (May–October) and cold season (November–April) to separately provide empirical CDFs. The defined GCM error is then removed from the empirical CDF of daily GCM data for the downscaling period 2081–2100 (and 1981–2000). The CDFDM was applied to each 139 surface observatories maintained by the Japan Meteorological Agency (Fig. 1). Then we spatially interpolated the downscaled daily GCM data, using the inverse-distance weighting average method for the consistent comparison with the RCMs (the improvement to statistical climate downscaling achieved by the use of more sophisticated interpolation methods is presented in Iizumi and Nishimori (2012)).

Compared to quantile-based mapping (Wood et al. 2004), which is a CDF-based statistical bias correction method, CDFDM can incorporate

Table 1. List of acronyms, types, and institutes for downscaling models used in this study (more detailed list can be seen in Iizumi et al. (2011)).

Acronym	Type	Model and institutes
NHRCM	Dynamical	Operational nonhydrostatic mesoscale model developed by the Japan Meteorological Agency with the Meteorological Research Institute
NRAMS	Dynamical	Regional Atmospheric Modeling System version 4.3 modified by the National Research Institute for Earth Science and Disaster Prevention
TWRf	Dynamical	Weather Research and Forecasting model version 3 set up by the Center for Computational Sciences, University of Tsukuba
CDFDM	Statistical	Cumulative distribution function-based downscaling method developed by the National Institute for Agro-Environmental Sciences

Fig. 1. Surface observatories where CDFDM were applied (red). Contours indicate altitude above sea level for every 500 m. Colors indicate the areas of Japan: NJ, Northern/Japan Sea side; NP, Northern/Pacific side; EJ, Eastern/Japan Sea side; EP, Eastern/Pacific side; WJ, Western/Japan Sea side; and WP, Western/Pacific side.

changes in maximum values of a climatic variable on the basis of GCM projections as shown in Fig. 2. In contrast, the maximum values of a climatic variable derived from quantile-based mapping are constrained to be equal to those of existing observations even in future climate conditions.

2.2 Forage growth model

We used a simple forage growth model, SIM-FOY (Selirio and Brown 1979). Daily data for mean surface air temperature, precipitation, solar radiation, relative humidity, and wind speed were required for model inputs. In this model, the potential biomass at given day is calculated from the potential cumulative growth curve (represented by a logistic function). The crop development time is calculated from the growing degree-day above 5°C. Alfalfa flowers appear at approximately 550°C day and this corresponds to the harvesting time. The potential daily growth increment is calculated taking water stress into account.

Soil moisture in root zone was calculated by a one-layer “bucket” water balance model with 150-mm bucket depth. In the simulations, the soil moisture at 1-day before germination was reset to be a climatological value for 1981–2000. Emergence time was fixed 1st May for both the present-day and future. Daily potential evapotranspiration is calculated by the method of Priestley and Taylor (1972). Daily simulated actual evapotranspiration corresponds to the potential one if the existing soil moisture meets the potential one, while actual

Fig. 2. Mean probability density function of summer (June–July–August) daily precipitation (≥ 1 mm/day) averaged over the terrestrial grids of Japan for CDFDM and observation.

JJA MEA

Fig. 3. Geographical pattern of projected mean summer precipitation change (upper panel) and corresponding value for each area (lower panel) in the future (2081–2100), relative to the present-day (1981–2000), for the downscaling models (NHRCM, NRAMS, TWRF, and CDFDM) and parent GCM (MIROCHI). In the lower panel, a large symbol is presented only when the projected change is statistically significant at 1% confidence level.

evapotranspiration is reduced if no enough soil moisture existed.

3. Results and discussion

3.1 Projected change in summer precipitation

All downscaling models (NHRCM, NRAMS, TWRF, and CDFDM) and GCM simulated the increased mean summer precipitation in the whole

of Japan in the end of the 21st century (2081–2100) under A1B scenario, relative to the present-day (1981–2000) (Fig. 3). The RCMs added more detailed information on the geographical pattern of the precipitation change, while the statistical model (CDFDM) showed the almost similar pattern with that of the GCM. The increased precipitation is a consistent tendency among the downscaling mod-

JJA CDD

Fig. 4. Same as Fig. 2 but for the mean summer maximum number of consecutive dry days.

els, while the amplitude of the precipitation increase varied one RCM to another (for instance, 30–51% for WJ (27% for the GCM)). By contrast, for all areas, the increased precipitation from the statistical model (20–41% among the six areas) is in almost the same level with that from the GCM (the corresponding values are 22–39%).

We calculated the mean summer maximum number of consecutive dry days (CDD) and illustrated Fig. 4. A large discrepancy emerged. The NHRCM projected the increased CDD in all areas except

for WJ (i.e., higher drought risk). In contrast, the decreased CDD was projected by NRAMS. TWRF fell into the middle of these two. The GCM projection showed the small change in CDD and CDFDM followed the GCM in many cases.

The increased mean summer precipitation over Japan is likely linked to the increased activity of East Asian monsoonal rain band in that season associated with the strengthening of anticyclonic cells (Kimoto et al., 2005). This signal is so strong that all downscaling models are qualitatively consistent

for the increased precipitation in summer. Meanwhile, the discrepancy in the CDD change among the downscaling models might be attributed to the fact that no clear signal is shown for the CDD by the parent GCM.

One possible reason for the discrepancies is the cumulus parameterization because NHRCM used the modified version of the K-F scheme, whereas other RCMs commonly used its original version. However, this is not the only reason as the settings of other physical parameterization schemes (e.g., the microphysics), size and location of domain, nudging schemes, and time integration interval are different by the RCMs.

3.2 Discrepancy in the simulated future impacts

For simplicity, in this study, we considered only the precipitation change, while simulated climate impacts on forage yield are affected by various climatic variables. For climatic variables other than precipitation (e.g., temperature), we commonly used NHRCM outputs in all impact model simulations as NHRCM in general shows higher skill in reproducing the present-day climate (Yoshida et al. in this issue). We simulated the forage growth and yield year by year for each of the present-day and future climate conditions (only the precipitation was altered) and computed the difference in the simulated yield between the two as the climate impact (Fig. 5).

Despite of the differently sourced precipitation, there is a consistency for the increased yield in NP and NJ. However, a discrepancy was seen in EP and WP among the downscaling models. NHRCM, TWRF, and CDFDM showed the decreased yield in a part of EP, WJ, and WP with the different degree of yield decrease (on area average, -1 to 2%), while NRAMS and GCM showed the slight increase in yield in these areas (1 – 4%).

A linear relationship between the simulated impact and June precipitation change, both averaged over the six areas, emerged with some sort of areas differences (Fig. 6), suggesting that major portion of the discrepancy could be attributed to the June precipitation. The most rapid modeled forage growth appeared in June, indicating that the growth rate is heavily relies on the soil moisture condition during this period. The decreased June precipitation from NHRCM and TWRF stressed the forage growth and decreased yield. In contrast, the decreased yield in WP was shown from CDFDM in spite of the increased June precipita-

Fig. 5. Geographical pattern of the simulated changes in forage yield (Δ Yield) and June precipitation (Δ Prec06) in the future (2081–2100), relative to the present-day (1981–2000), for the downscaling models and parent GCM.

Fig. 6. Scatter plot between the June precipitation change (ΔPrec06) and simulated changes in forage yield (ΔYield), both averaged over the six areas of Japan for the downscaling models and parent GCM. Error bar in x- and y-axis indicates the maximum-minimum range of ΔPrec06 and ΔYield that represents area differences, respectively.

tion. This is in part attributed to that the simulated soil moisture from CDFDM was drier than that from the RCMs (except for NHRCM) in most months even in the future wetter condition as CDFDM adjusted the absolute value of precipitation through its algorithm (Fig. 7).

Similar results were observed for the June–July–August precipitation, but the precipitation–yield linkage clearly emerged in June due to the appearance of the most rapid growth rate and the largest precipitation increase during the period compared to other months in summer. This strong linkage between the simulated impact and June precipitation change would be informative when one sought to weight each downscaling model according to their skill to reduce the uncertainty of the simulated impact.

4. Conclusions

Climate downscaling is a promising technique to added spatially detailed information on GCM outputs. At the same time, nevertheless, climate downscaling is a source of uncertainty in projecting future impacts on a local scale. The results indicate

Fig. 7. Time series of the simulated soil moisture in root zone in the present-day and future climate conditions for the downscaling models and parent GCM. Data were averaged over the terrestrial grids of Japan and 20-year period (1981–2000 or 2081–2100).

that the simulated climate impact on forage yield in Japan is sensitive to climate downscaling, i.e., the direction (increase or decrease) and amplitude of the simulated impact could vary between the climate scenarios from the downscaling models and those from the parent GCM. This finding suggests that one should not place too much trust in one downscaling model regardless of methodological type (dynamical or statistical) and the consistency

(e.g., the increased yield in NJ and NP) increases the credence of the simulated impact. A use of multi-downscaling models ensemble, hopefully, which provided in conjunction with multi-GCM and multi-methodological type, is strongly recommended for impact assessment and following adaptation strategy development.

Issues not explored here is to compare the degree of uncertainty in simulated future impacts between multi-GCM and multi-downscaling model conditioned on a single GCM. Efforts of downscaling model intercomparison would stimulate the better understanding on which source of uncertainty is more dominant for simulated local impact.

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