Sampling Downscaling in Summertime Precipitation over Hokkaido

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(Manuscript received 11 November 2014, in final form 8 April 2015)

Abstract

The sampling downscaling (SmDS) in which a regional atmospheric model is integrated for sampled periods was performed for summertime Hokkaido. Selected are top two and bottom two years of the general circulation model projection onto the first singular value decomposition mode where heavy precipitation in southern Hokkaido is correlated with the moisture flux convergence in the synoptic field. The SmDS result integrated for the four years successfully reproduces the dynamical downscaling for 30 years, in terms of climatological precipitation and the 99-percentile value of daily precipitation. This indicates that SmDS can be applied to the environment where local precipitation is mostly controlled by synoptic climate patterns. A further statistical consideration in this study supports the notion. It is also demonstrated that SmDS selects a group of years where extreme events likely occur another group of years where they rarely occur.

Keywords dynamical downscaling; extreme events; regional climate

1. Introduction

The dynamical downscaling (DDS) is a widely-used technique to estimate high-resolution data that are physically consistent with prescribed low-resolution data such as reanalysis data and general circulation model (GCM) outputs, by using a regional atmospheric model (RAM) for a limited domain. In the DDS, a RAM is integrated typically with $O(10)$ km horizontal resolution nested into a GCM with $O(100)$ km horizontal resolution and can considerably resolve the geographical features such as mountains and coastlines. Hence, by using the RAM, one can realistically simulate local phenomena such as orographic rainfall (Frei et al. 2003) and snow-albedo
feedback (Leung et al. 2004), and estimate a regional climate change including a land effect characterized locally (Sato and Kimura 2005). However, a RAM integration in DDS mostly has much computational costs in order to satisfy the Courant–Friedrichs–Lewy condition. Moreover, if the DDS result largely depends on the GCM imposed as the RAM boundary condition (Plummer et al. 2006; Fowler et al. 2007; Piani et al. 2010), we would spend still more costs for multi-GCM experiments in order to evaluate uncertainty in a local climate change.

Conversely, the statistical downscaling (SDS) is another downscaling method, based on an observed statistical relationship between a regional variable and a global circulation pattern (e.g., von Storch 1995; Hay et al. 2002; Imada et al. 2012). The SDS may evaluate a regional climate depending on the observation density, and it takes a little computations. However, because the empirical relationship in the present climate is not always applied to the future climate, the reliability of SDS results strongly depends on the stability of statistics (Wilby et al. 2004).

Recently, Kuno and Inatsu (2014) proposed the sampling downscaling (SmDS), in which the DDS is performed for a few years based on the statistical relation between a synoptic climate pattern and a local precipitation amount. On the basis of a robust observed linkage between winter Asian monsoon and regional snowfall in Hokkaido, they showed that SmDS actually provided a similar result to conventional DDS. The SmDS is one of the techniques with mixing DDS with SDS, extending previous works; Frey–Buness et al. (1995) obtained a regional climate feature based on DDS for a few large-scale weather types that were a priori classified. Pinto et al. (2014) attempted to select the representative days for DDS based on the probability density function (PDF) of 2 m air temperatures; Yamada et al. (2014) established a statistical equation which approximately follows the Clausius–Clapeyron relationship equation between 99-percentile value of sub-hourly precipitation and near surface temperature. Using the near surface temperature given by DDS, they successfully estimated the 99-percentile value of sub-hourly precipitation in Sapporo for future climate. However, in order to demonstrate the relevance of the DDS–SDS mixture, we need statistical consideration as well as a pile of case studies in which a particular DDS–SDS mixture method is applied to different domains and seasons. For example summertime rainfall in Hokkaido is possibly related to local-scale phenomena such as topographic rainfall, cumulus cloud convection, and small-scale rainband. Hence, a study extending Kuno and Inatsu (2014) to boreal summer deserves our attention to ascertain the applicability of SmDS.

The purpose of this study is (1) to apply SmDS to summertime precipitation over Hokkaido as another case study from Kuno and Inatsu (2014) and (2) to estimate the error in SmDS with statistical consideration. For the first purpose, we compare SmDS for four years with DDS for 30 years (hereafter full DDS) in terms of the daily-mean precipitation, the standard deviation of June–July–August (JJA) mean precipitation, and the 99-percentile value of daily precipitation. The 99-percentile value of daily precipitation is calculated during the JJA days for all years used. For the second purpose, we theoretically consider the error of the mean and the 99-percentile value estimated in SmDS.

This paper is organized as follows. Datasets and models we used are described in Section 2. A general overview of SmDS with error estimation consideration is stated in Section 3. In Section 4, the result of SmDS for four selected years is compared with the result of DDS for 30 years, in terms of the climatological precipitation and the 99-percentile value of daily precipitation in Hokkaido in summer. Section 5 summarizes this paper.

2. Data and models

2.1 Observed data

We used a set of observed datasets for SmDS. Precipitation dataset is APHRO_JP V1207 (Yatagai et al. 2012). The horizontal resolution is 0.05° × 0.05°. We used a 6-hourly reanalysis dataset, JRA-25/JCDAS (Onogi et al. 2007), for the moisture flux convergence vertically integrated from surface pressure to 100 hPa. The horizontal resolution of the reanalysis data is 1.25° × 1.25°. The analysis period is JJA from 1981 to 2010.

2.2 GCMs

We performed DDS experiments with multiple atmosphere-ocean GCMs in Coupled Model Inter-comparison Project phase 3 (CMIP3) as the boundary condition. GCMs we used are the Model for Interdisciplinary Research on Climate version 3.2 (hereafter MIROC) developed by the University of Tokyo (Hasumi and Emori 2004); the fifth generation atmospheric GCM in Max Plank Institute for meteorology (hereafter MPI; Roeckner et al. 2003); and Community Climate System Model version 3 in the National Center for Atmospheric Research (hereafter...
NCAR; Collins et al. 2006). These three GCMs can reproduce the present climate over Japan in summer (Inatsu et al. 2015). Following Kuno and Inatsu (2014), we selected the last decade of the 20th century experiment called 20C3M in CMIP3 as the current climate.

2.3 RAM

The RAM that we used is the Japan Meteorological Agency/Meteorological Research Institute non-hydrostatic model (JMA/MRI-NHM) [see Saito et al. (2006) for more details]. The model domain covers 132°E–152°E and 38°N–50°N (Fig. 1) of which center is Hokkaido Island (Fig. 2). The horizontal resolution is 10 km with grid number 161 × 133 and there are 40 vertical levels. The inner dotted line is the domain used in singular value decomposition (SVD) analysis.

3. General concept of SmDS

3.1 Procedure

We will give the procedure of SmDS in a nutshell (Fig. 3). See Kuno and Inatsu (2014) for more details. First, we took the singular value decomposition (SVD) analysis between moisture flux convergence around Hokkaido (120°E–160°E by 30°N–60°N) and precipitation over Hokkaido (139°E–146°E by 41°N–46°N; Fig. 1) based on JJA-mean data from 1981 to 2010. Since the SVD analysis provides the highly-co-variate spatial patterns between the two, we obtained a heterogeneous spatial pattern for the first mode of moisture flux convergence around Japan referred to as $g_1(x)$, where $x$ is the position vector.

Next, we projected GCM’s moisture flux convergence anomaly, $G(\tilde{t})$, onto the first SVD mode, $g_1(x)$, where $\tilde{t}$ denotes a sequential union of the GCM periods. The projected time-series $s(\tilde{t})$ was used as an index to select years for SmDS. Finally, we conducted the DDS for years with top two and bottom two of $s(\tilde{t})$. In this paper, as has already mentioned above, we conducted the DDS for 30 years in total and then the statistics for all years were compared with the statistics for selected years.

Fig. 1. The surface height (m) from the sea level as the bottom boundary condition for the regional atmospheric model (RAM). The shading level is shown in the reference in the right. The outer solid line indicates the lateral boundary of the RAM. The horizontal resolution is 10 km with grid number 161 × 133 and there are 40 vertical levels. The inner dotted line is the domain used in singular value decomposition (SVD) analysis.

Fig. 2. Fourteen subprefectures in Hokkaido with their names shown in the color reference. (b) The surface height (m) in Hokkaido as the bottom boundary condition for the RAM. The shading level is shown in the reference in the right. The dashed line shows the location of Hidaka Mountains.
3.2 Error estimation theory

We here consider the error in SmDS estimates of statistical precipitation amount. First, though the sample number is practically finite, we regard it as population $\Omega$ with $N$ samples as

$$\Omega = \bigcup_{k=1}^{N} \omega_k,$$

(1)

where a sample $\omega_j$ is the $j$-th year with the amount of daily data being $n$ as

$$\omega_j = \{P_{j,1}, P_{j,2}, \ldots, P_{j,n}\},$$

(2)

where $n$ is the number of days in a single sample. Regional variable $P$ and global variable $Q$ are set as probabilistic variables on the population $\Omega$. A set of the sample mean of $P$ expressed as

$$\Sigma_P = \{\bar{P}_1, \bar{P}_2, \ldots, \bar{P}_N\},$$

(3)

is assumed to follow the normal distribution with its mean $\mu_P$ and its variance $\sigma_P^2$, where the overbar means the average over a sample. It is remarked that the central limit theorem warrants Gaussianity of sample-mean distribution even if the original data does not follow the normal distribution. A set of the sample mean of $Q$ similarly expressed as

$$\Sigma_Q = \{\bar{Q}_1, \bar{Q}_2, \ldots, \bar{Q}_N\},$$

(4)

is assumed to follow the standard normal distribution. Unless $\Sigma_Q$ is standardized, the $Z$ transformation is to be taken. Further, given that the linear regression equation between $\Sigma_Q$ and $\Sigma_P$, the residual variance $E^2$ is calculated as $E^2 = (1 - r^2)\sigma_P^2$, where $r$ is a correlation coefficient between global and regional variables. Selecting $2M$ samples from $\Sigma_Q$, the estimation error variance is given as

$$E^2 = \frac{(1 - r^2)\sigma_P^2}{2M}$$

(5)

This is the estimation error of mean in SmDS. The estimation error variance is a function of the number of selecting years, correlation coefficient between $\Sigma_Q$ and $\Sigma_P$, and the inter-sample variance $\sigma_P^2$. Therefore, more selecting years and higher correlation between global and regional variables make the smaller estimation error variance in SmDS. Even if the samples are randomly selected, its estimation error follows Eq. (5). However, as mentioned below, if we selected the samples such that the mean of $\Sigma_Q$ is zero, the bias of the mean would be zero.

Next, we will consider the bias of both mean and 99-percentile value in SmDS. In SmDS, we select top $M$ and bottom $M$ years in the statistical estimation for the regional variable. Now we renumber the element of $\Sigma_Q$ in its decreasing order as

$$\Sigma_Q = \{\bar{Q}_{(1)}, \bar{Q}_{(2)}, \ldots, \bar{Q}_{(N)}\},$$

(6)

where

$$\begin{pmatrix} 1 & 2 & \cdots & N \\ I(1) & I(2) & \cdots & I(N) \end{pmatrix},$$

(7)

is an element of $n$-dimensional symmetric group. Following this permutation rule, the element of $\Sigma_P$ is renumbered as

$$\Sigma_P = \{\bar{P}_{(1)}, \bar{P}_{(2)}, \ldots, \bar{P}_{(N)}\}.$$  

(8)

We define two sample groups as

$$\Omega_+ = \bigcup_{k=1}^{M} \omega_{(1)(k)}, \text{ and } \Omega_- = \bigcup_{k=N-M+1}^{N} \omega_{(1)(k)},$$

(9)

corresponding to selecting top $M$ and bottom $M$ years.
from $\Sigma_0$ in SmDS. The mean of $P$ over $\Omega_+$ and $\Omega_-$ are respectively expressed as

$$\mu_p \pm \alpha \sigma_p,$$  \hspace{1cm} (10)

where $\alpha$ is the mean of the upper $M/N$ of the normal distribution expressed as

$$\alpha = \frac{\int_{-\infty}^{\infty} xN(0,1)(x)dx}{\int_{-\infty}^{\infty} N(0,1)(x)dx} = \frac{N}{\sqrt{2\pi M}} \exp\left(-\frac{\beta^2}{2}\right),$$  \hspace{1cm} (11)

noting that

$$\int_{-\infty}^{\infty} N(0,1)(x)dx = \frac{M}{N}.$$  \hspace{1cm} (12)

Hence, the expected value of sample group $\bar{\Omega} = \Omega_+ \cup \Omega_-$ is $\mu_p$, so that the mean of SmDS estimates is unbiased.

We next assume that the daily precipitation for the $j$-th sample follows log-normal distribution of

$$f_j(x; A_j, B_j) = \frac{1}{\sqrt{2\pi B_jx}} \exp\left[-\frac{(\ln x - A_j)^2}{2B_j^2}\right].$$  \hspace{1cm} (13)

Moreover if the (square root of) intra-sample variance, $\sigma_{0,j}$, is proportional to the $j$-th mean as

$$\sigma_{0,j} = \nu \overline{P}_j,$$  \hspace{1cm} (14)

then the parameters of $A_j$ and $B_j$ in Eq. (13) are estimated as

$$A_j = \ln \frac{\overline{P}_j}{\sqrt{v^2 + 1}} \text{ and } B_j = \sqrt{\ln (v^2 + 1)}.$$  \hspace{1cm} (15)

Here $\nu$ is a proportional coefficient that is assumed to be constant. In the full DDS estimation, the $\varepsilon$-percentile value of $X_\varepsilon$ is to be found such that

$$\varepsilon \left/ 100 \right. = \frac{1}{2N} \sum_{j=1}^{N} \text{erfc}\left[-\frac{\ln \frac{\overline{X}_\varepsilon \sqrt{v^2 + 1}}{\overline{P}_j}}{\sqrt{2\ln (v^2 + 1)}}\right].$$  \hspace{1cm} (16)

A Monte-Carlo simulation for sampling from the normal distribution of $\overline{P}_j$ with the inter-sample mean of $\mu_p$ and the inter-sample standard deviation of $\sigma_p$ at a fixed $v$ provides the $\varepsilon$-percentile value $X_\varepsilon$ from Eq. (16). The parameter $v$ is approximately equal to 2 in daily precipitation in Hokkaido (not shown). Figure 4a shows the 99-percentile estimation value in the $(\mu_p, \sigma_p)$ space. The 99-percentile value is smaller for smaller mean and standard deviation. In the realistic range for daily precipitation in Hokkaido (the PDF shown in Fig. 4b), the 99-percentile value ranges between 20 and 100 mm day$^{-1}$.

Conversely, in the SmDS estimation, the $\varepsilon$-percentile value is $X_\varepsilon$ is such that

$$\frac{\varepsilon}{100} = \frac{1}{4M} \sum_{j=1}^{M} \text{erfc}\left[-\frac{\ln \frac{\overline{X}_\varepsilon \sqrt{v^2 + 1}}{\overline{P}_j}}{\sqrt{2\ln (v^2 + 1)}}\right]$$  \hspace{1cm} (17)

Similarly in Fig. 4a, a Monte-Carlo simulation for the selected samples satisfied with $|\overline{P}_j - \mu_p| > \beta \sigma_p$ provides the estimation of $\varepsilon$-percentile value in SmDS by Eq. (17). Figure 4b shows the ratio of SmDS to full DDS estimations for 99-percentile value for the given parameter of $2M/N = 2/15$. In the domain where the inter-sample standard deviation is smaller than the average, the SmDS can estimate the 99-percentile value correctly. Elsewhere, the SmDS tends to overestimate the 99-percentile value compared with the full DDS estimation. Thinking of the realistic $(\mu_p, \sigma_p)$ in daily precipitation in Hokkaido, the difference of the 99-percentile estimation by SmDS and full DDS is quite small.

A Monte-Carlo simulation for the selected samples satisfied with $\overline{P}_j > \mu_p + \beta \sigma_p$ or $\overline{P}_j < \mu_p - \beta \sigma_p$ provides the first or last term of right-hand-side of Eq. (17) (Fig. 4c). The first-term estimates the 99-percentile value almost twice larger than the SmDS. The 99-percentile value with only the last-term in Eq. (17) is near zero in the domain where the inter-sample standard deviation is smaller than the average; elsewhere it is larger for the large mean value. This encourages that the technique of SmDS originally proposed in Kuno and Inatsu (2014) can select two important groups with a few years where heavy precipitation frequently occurs and with another few years where heavy precipitation rarely occurs.
4. Results

4.1 SmDS setup

Figure 5a shows the observed daily-mean precipitation over Hokkaido in JJA. The precipitation amount is ~6 mm day$^{-1}$ in Hidaka and Iburi subprefectures and is less than 4 mm day$^{-1}$ in northern Hokkaido (See also Fig. 2a). This contrast is caused by mountain ranges in central Hokkaido called Hidaka Mountains (Fig. 2b) that blocks a warm, moist air mass from the southwest due to the summertime Asian monsoon (cf. Inatsu et al. 2015). The standard deviation of JJA-mean precipitation shows less than 2 mm day$^{-1}$ in almost all Hokkaido except for the part of the Hidaka and Iburi subprefectures (Fig. 5b). The 99-percentile value of daily precipitation (Fig. 5c) shows more than 80 mm day$^{-1}$ in Hidaka and Iburi subprefectures and less than 40 mm day$^{-1}$ in Abashiri subprefecture. A large amount of monthly precipitation is attributed to daily heavy precipitation, which is consistent with the assumption that the daily precipitation roughly follows the log-normal distribution (Section 3.2).

Following the instruction of SmDS illustrated in
Fig. 3, we performed the SVD analysis for an inter-annual variation of precipitation over Hokkaido and that of moisture flux convergence around Japan. We then obtained a set of heterogeneous maps for the first SVD mode with the squared covariance fraction being 68.7%. This mode means that an anomalously large precipitation in southern Hokkaido is related to anomalously large moisture flux convergence around northern Japan (Figs. 6a, b). The correlation coefficient between their time-series is 0.87 (Fig. 6c) and the first mode explains 43.8% of variance in local precipitation fluctuation over Hokkaido (Fig. 6a). This is the evidence that moisture transported toward Hokkaido strongly controls precipitation in southern Hokkaido.

As the next step of SmDS (Fig. 3), we calculated the sampling index [denoted by $s(t)$ in Section 3.1], by projecting GCMs’ moisture flux convergence anomaly onto the first SVD mode (Fig. 7). It is noted that the projection has a non-zero average for each model, because the GCM anomaly is defined as the departure from the observed daily-mean precipitation (Fig. 5a). Based on the projection, we picked up 1991 and 1992 in MPI as top two, and 1995 and 1996 in MIROC as bottom two.

4.2 Comparison with conventional DDS
Following Kuno and Inatsu (2014), we compared the SmDS result for four sampled summers with the full DDS result for 30 summers. The daily-mean precipitation in both results is quite similar (Figs. 8a, b); it is more than 12 mm day$^{-1}$ in Hidaka and Kami-kawa subprefectures and less than 4 mm day$^{-1}$ in Abashiri subprefecture. The spatial correlation coefficient between SmDS and full DDS is 0.96, while the precipitation amount is reduced by 10% uniformly over Hokkaido. The standard deviation of JJA-mean precipitation for full DDS shows more than 4 mm day$^{-1}$ in Hidaka subprefecture and less than 4 mm day$^{-1}$ in northeastern Hokkaido (Fig. 8c). The SmDS result of standard deviation of JJA-mean precipitation is underestimated in Hidaka subprefecture (Figs. 8c, d). The 99-percentile value of daily precipitation in both results is also similar (Figs. 8e, f); it is more than 80 mm day$^{-1}$ in Hidaka subprefecture and less than 60 mm day$^{-1}$ in northeastern Hokkaido. The spatial correlation coefficient is 0.85, while the 99-percentile value is a bit smaller around Hidaka subprefecture.
and is a bit larger in Abashiri subprefecture in SmDS. Hence, SmDS can also reproduce the precipitation pattern and its characteristics of the extreme events over Hokkaido in summer, which is consistent with Kuno and Inatsu (2014) for wintertime Hokkaido. Our analysis for summertime Hokkaido thus supports the notion that SmDS can be applicable to the situation that a synoptic-scale pattern mostly controls local precipitation.

4.3 Interpretation of results

Recalling a statistical consideration in Section 3.2, the mean estimate of SmDS is unbiased with an estimation error of

$$
\sqrt{\frac{(1-r^2)}{2M} \sigma_p^2},
$$

where the sample number $2M = 4$ in this paper. The inter-sample variance $\sigma_p^2$ gives a similar spatial pattern to the intra-sample variance $\sigma_0^2$ (Figures not shown) but the amount of $\sigma_p^2$ is much less than $\sigma_0^2$. Figure 9a shows the correlation coefficient between statistical and DDS estimations for precipitation over Hokkaido, noting that the statistical estimation here means the projection of GCM time-series onto the first SVD mode (Fig. 6b). The correlation coefficient is more than 0.6 in Oshima and Ishikari subprefec-

Fig. 6. Heterogeneous regression maps of (a) precipitation and (b) vertically integrated moisture flux convergence for the first SVD mode based on the interannual variability in JJAs from 1981 to 2010. The precipitation is based on AHORO_JP V1207, and the moisture flux convergence is based on JRA-25/JCDAS. The contour interval is 0.3 mm day$^{-1}$ with the shading denoted to the right of each panel. (c) The time-series of (solid) precipitation and (dashed) moisture flux convergence for the first SVD mode.
and central mountains in Hokkaido, and it is less than 0.4 in Hidaka and Shiribeshi subprefectures and northern Hokkaido. A low correlation means a weak control by a synoptic situation at least represented by the first SVD mode.

Figure 9b shows the estimation error given by Eq. (18). It shows more than 6 mm day$^{-1}$ in Hidaka subprefecture and less than 2 mm day$^{-1}$ northeastern Hokkaido. The spatial distribution mostly depends on the inter-sample standard deviation $\sigma_p$ (Fig. 8c). Figure 9c shows the relative error of daily-mean precipitation (%) calculated by

$$\frac{\text{SmDS} - \text{full DDS}}{\text{full DDS}} \times 100.$$ \hfill (19)

The relative error falls within $\pm 10 \%$ in Oshima and Ishikari subprefectures and eastern Hokkaido. However, the SmDS result underestimates the precipitation for full DDS more than 30 % in Hidaka subprefecture. This might be possibly attributed to the difficulty of reproducing the stratiform type of rain that was prominently observed in the western side of Hidaka mountain range (Sugimoto et al. 2013). The spatial pattern of relative error is consistent to the spatial pattern of the estimation error (Figs. 9b, c).

Figure 10a shows the ratio of SmDS to full DDS for the 99-percentile value of daily precipitation. The error range of the ratio ranges within $\pm 20 \%$ except for Hidaka, Oshima and Abashiri subprefectures and the central mountains in Hokkaido. Although Section 3.2 suggested that SmDS tends to overestimate the 99-percentile value by 10 % – 40 % (Fig. 4b), the SmDS underestimates the 99-percentile value more than 20 % in Hidaka subprefecture. It is probably because the daily-mean precipitation in SmDS underestimates the daily-mean precipitation in full DDS more than 30 % (Figs. 8a, b). Figures 10b, c show the 99-percentile value for top two and bottom two years of SmDS respectively. In almost all areas the 99-percentile value for top two years of SmDS shows much larger than that for bottom two years of SmDS. The 99-percentile value ranges showed in both maps are consistent to the ranges estimated in the error theory (Fig. 4c). In this study we can conclude that SmDS extracts a set of optimal years where the heavy precipitation likely occurs and another set of years where the heavy precipitation rarely occurs.

5. Conclusions and discussions

We have applied SmDS developed by Kuno and Inatsu (2014) to summertime precipitation over Hokkaido. By using the SVD analysis, we extracted a spatial pattern of a global variable, which mostly
controls the precipitation over southern Hokkaido. Both of the spatial distributions for the mean and 99-percentile value in SmDS were similar to those of the DDS for 30 years. This indicates that SmDS can be applied to the place where the synoptic field strongly controls the local precipitation.

The error theory for the mean and 99-percentile value in SmDS was established in this study. In SmDS estimation, the mean should be unbiased and the 99-percentile value tends to be overestimated compared with that in full DDS. Moreover, it turned out that the estimation error of the mean in SmDS depended on the correlation coefficient between global and regional variables, the number of samples, and the standard deviation of JJA-mean precipitation. Since the standard deviation of JJA-mean precipitation strongly contributes to the estimation error, the estimation error is large even if the correlation between the global and regional climate field is high. This adds a new sight for a necessary condition for the
original discussion by Kuno and Inatsu (2014).

Basically, since the SmDS method is based on a statistical method, it is quite difficult to specify the reason for the difference from the full DDS statistics in a particular season in a physical sense. The SmDS only shows possible error range at the significant level of $2\alpha$ within

$$\pm t_{\alpha}(2M) \sqrt{\frac{(1-r^2)}{2M}} \sigma_p,$$

(20)

from Eq.(18), where $t_{\alpha}(2M)$ is a student’s $t$-value with the degree of freedom of $2M$. In the case of $\alpha=0.025$, the difference between full DDS and SmDS for daily-mean precipitation falls within this range in all areas in Hokkaido for both summer and winter cases (See also Kuno and Inatsu 2014).

As mentioned in Section 1 and Inatsu et al. (2015), the DDS result is strongly influenced by the GCM boundary condition. Compared to the DDS result with the observed data, we found that the model climatology overestimated both the daily-mean precipitation and 99-percentile value (Figs. 5, 8). It is likely that this overestimation is because of the bias of GCM. In climate modeling community, the ensemble mean is often used for DDS experiment (e.g., Kendon et al. 2010; Donat et al. 2011; Inatsu et al. 2015) because the ensemble mean possibly provides the most optimal estimation than any other individual model mean (Pierce et al. 2009). However the DDS experiment using multi-GCM requires much more computational costs. The important thing in this problem is how to select a few subsets of GCM-RAM pairs and climate scenarios. Some studies have recently attempted to establish the method which reduces the ensemble members (e.g., Pennell and Reichler 2011; Evans et al. 2013). There is a possibility that the criterion of GCM selection can be established by using the SmDS method. For instance, Kuno and Inatsu (2014) discussed that the average of the projection in each model discrete year, $\bar{s}(i)$, is regarded as the GCM bias. If we selected a set of GCMs so that $\bar{s}(i)$ is zero, we could reduce the GCM bias in terms of the SVD mode. Since there is a room for discussing about this, we will report it elsewhere.
Acknowledgments

We would like to thank two anonymous reviewers to help us improve the manuscript; and thank Prof. S. Minobe, Dr. Y. N. Sasaki, Dr. H. Na, Dr. C. H. O’Reilly, Dr. T. J. Yamada, and Dr. T. Sato for giving us insightful comments. This study is supported by the Research Program on Climate Change Adaptation and Grant-in-Aid for Scientific Research on Innovative Areas 22106008, 25800259, and 26310201, all funded by Ministry of Education, Sports, Culture, Science and Technology, Japan. The JMA/MRI-NHM and JRA-25/JCDAS reanalysis data were used with a permission of the JMA. The dynamical downscaling was performed by using the Hokkaido University High Performance Computing System. Figures were drawn using Grid Analysis and Display System.

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