Incremental dynamical downscaling for probabilistic analysis based on multiple GCM projections

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Abstract A dynamical downscaling method for probabilistic regional-scale climate change projections was developed to cover the inherent uncertainty associated with multiple general circulation model (GCM) climate simulations. The climatological increments estimated by GCM results were statistically analyzed using the singular vector decomposition. Both positive and negative perturbations from the ensemble mean with the magnitudes of their standard deviations were extracted and added to the ensemble mean of the climatological increments. The analyzed multiple modal increments were utilized to create multiple modal lateral boundary conditions for the future climate regional climate model (RCM) simulations by adding them to reanalysis data. The incremental handling of GCM simulations realized approximated probabilistic climate change projections with the smaller number of RCM simulations. For the probabilistic analysis, three values of a climatological variable simulated by RCMs for a mode were analyzed under an assumption of linear response to the multiple modal perturbations.

1. Introduction

Global climate model (GCM) simulations as reported by the Intergovernmental Panel for Climate Change [Intergovernmental Panel on Climate Change, 2013] show a wide range of climate change projections for a given Representative Concentration Pathway (RCP). The output of GCM’s is often used to drive regional climate model (RCM) simulations due to improved description of regional atmospheric circulations largely as a result of improved topographic forcing [Means et al., 2003]. To capture the uncertainty associated with GCM simulations more accurately for a given region, every GCM run should have an associated RCM run and the range of projected future climate reported. However, the high computational costs of high-resolution RCM simulations make such an endeavor difficult. In addition, large biases in GCMs reduce the quality of regional climate projections since regional biases of RCMs are not necessarily lower than those of the driving GCMs. [Means et al., 2003].

One way to reduce the GCM bias problem called “anomaly nesting” was proposed by Misra and Kanamitsu [2004]. The lateral boundary conditions (LBCs) of RCM simulations are created from a GCM current and future result; however, the LBCs are modified such that climatological mean values of the current result are equal to those of reanalysis data. Another way is to add a climate perturbation mean monthly signal between current and future GCM simulations to the reanalyses to produce future boundary conditions used to perform an RCM projection. This type of approach was used by Schar et al. [1996], Kimura and Kitoh [2007], and Sato et al. [2006] and called the pseudo–global warming (PGW) method by Sato et al. [2006]. The technique is presented in detail in section 2.

Regional-scale probabilistic climate change projections are often studied using a Bayesian approach using the output of multiple GCM and/or RCM simulations under the same emission scenario [e.g., Tebaldi et al., 2004; Greene et al., 2006; Furrer et al., 2007; Manning et al., 2009]. In this study a new approach is proposed for probabilistic future projection based on the PGW method by statistically analyzing multiple GCM climate projections under an incremental field. A key feature of the current methodology is the significant reduction in the computer time needed.

2. PGW Method

The PGW method is used to perform time-sliced downscaling of climate changes projected by GCMs. Two climatological downscaling experiments are performed in the time-slice method: present and future climate...
simulations. For the present climate simulation, reanalysis data are used as six hourly LBCs for an RCM simulation, while GCM results are directly used in general downscaling. Thus, the influences of GCM biases are much reduced in the PGW method. For the future climate simulations, a climatological increment (future minus present climate states) for each month estimated by the GCM simulations is added to the reanalysis data, and the newly created data are used as LBCs of an RCM simulation. The climatological increment of the spatial distribution is calculated by yearly averaging of monthly mean data within the target years. In the PGW method, only a monthly mean climatological increment field is assumed to be reliable. Variables for climatological increments are skin surface temperature and the three-dimensional geopotential height, air temperature, humidity, and wind velocity. In this study the given land surface temperature is used only for the initial condition, and a land surface scheme calculates the land surface condition. The handling of climate changes in humidity is difficult because supersaturated conditions often occur in the conventional statistical controls. Two approaches are available: (1) relative humidity is assumed to be unchanged [Hara et al., 2008; Wakazuki et al., 2015] and (2) climate changes in the modified relative humidity (MRH) proposed by Wakazuki [2013] are estimated. The MRH is applied for the following experiments. A limitation of the PGW is that this method assumes that year-to-year and short-term variations in the present climate are the same in the future.

For multiple GCM downscaling in the PGW method, various RCM simulations are performed with various GCMs for the future climate, while a single RCM simulation is performed for the present climate. This feature makes the probabilistic estimation of the future climate statistically easier to handle because the diversity of reproducibility in the present climate simulation does not need to be considered. An additional advantage of the PGW method is that a downscaling simulation for the future climate can be carried out with a climatological increment of a specific statistic value estimated by multiple GCM simulation results, such as an ensemble mean (EM). For example, Kawase et al. [2009] pointed out that a result of an RCM climate projection with a climatological increment estimated by the EM of multiple GCM simulations showed a characteristic feature of rainfall similar to that of the EM of RCM results that were individually simulated with a climatological increment of each GCM simulation. This result suggests that using the EM with the PGW approach can provide the most reliable estimation of the regional climate change signal produced when running many RCMs with multiple GCMs. On the other hand, the information about the quantitative uncertainty due to the diversity of the GCM results is currently estimated through an RCM simulation for each GCM run. For large numbers of GCMs, this task can be unwieldy due to the large amounts of computer time required. Instead of running one RCM for each GCM run, this paper presents a method to estimate uncertainty around the mean climate estimate with the smaller number of PGW simulations.

3. Statistical Analysis for Downscaling of Multiple GCMs

$X$ is a vector of the monthly mean grid point data averaged for the extracted GCM years with $P$ columns. $P$ is equal to the degrees of freedom (the number of spatial grids times the number of elements times 12 (months)). Climatological increments from the present to the future climates with multiple GCMs ($\Delta X^g$) are expressed as follows:

$$\Delta X^g = \begin{pmatrix} X^{(1)}_p - X^{(1)}_f \\ X^{(2)}_p - X^{(2)}_f \\ \vdots \\ X^{(N)}_p - X^{(N)}_f \end{pmatrix}.$$ 

The upper superscripts in parentheses are the labels of GCMs. $N$ is equal to the number of GCM simulations. The subscripts $p$ and $f$ are the labels of the present and future climates, respectively. $\Delta X$ is a matrix with $N$ rows and $P$ columns ($N \times P$). The superscript $g$ means that the variables are under the multiple GCM space. For multiple GCM downscaling, the number of RCM simulations for the future climate is $N$. In the case that $N$ is very large, the computational costs of the RCM simulations is very high. To reduce the number of RCM runs, a statistical analysis is performed for $\Delta X^g$. 

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ΔX^g is divided into an EM (ΔX) and perturbations from the EM. The perturbations are standardized by using Σ to identify ΔX^g:

\[ \Delta X^g = \Delta X + \Delta X^g \Sigma. \]  (1)

Σ is a diagonal P × P matrix with standard deviation values, which are constant within a p level plane of an element, on the diagonal elements. The ΔX^g is analyzed using the Singular Vector Decomposition (SVD):

\[ \Delta X^g = u s V^T. \]

The u, s, and V provide a real-valued matrix factorization of ΔX^g. The u is an N × M matrix with orthonormal columns, where M is the number of modes (N ≥ M). V is an orthonormal P × M matrix that shows independent spatial distribution patterns of ΔX^g and is called the singular vector. The s is an M × M diagonal matrix, with the nonnegative singular values, s1, s2, ..., sm, on the diagonal. The square of each singular value is proportional to the variance explained by each singular vector. Thus, S is newly defined by the modification from s as an M × M diagonal matrix, with the standard deviations of the singular vectors, σ1, σ2, ..., σm, on the diagonal.

By using the singular vectors (V) and the standard deviations (Σ), three types of statistically analyzed perturbations from the EM are constructed:

\[
\begin{align*}
\Delta X^{(0)} &= 0 \\
\Delta X^{(+)} &= s V^T \\
\Delta X^{(-)} &= -s V^T
\end{align*}
\]  (2)

where the superscripts (0), (+), and (−) correspond to nonperturbation (only the EM), positive perturbations (PPs) for multiple modal singular vectors, and negative perturbations (NPs), respectively. Therefore, the three constructed types of climatological increments statistically analyzed (ΔX^(0), ΔX^(+), and ΔX^(-)) are expressed by using equations (1) and (2):

\[
\begin{pmatrix}
\Delta X^{(0)} \\
\Delta X^{(+)} \\
\Delta X^{(-)}
\end{pmatrix} =
\begin{pmatrix}
\Delta X \\
\Delta X + s V^T \Sigma \\
\Delta X - s V^T \Sigma
\end{pmatrix}
\]  (3)

The PP, EM, and NP cover the diversity of increments of multiple GCMs within the standard deviation range for each mode. The numbers of increment patterns are 3, 5, 7, ..., 2 M + 1 ... for only the first mode, first and second modes, first to third modes, ..., first to Mth modes, respectively. The SVD is applied for all monthly data simultaneously: the length of the column of ΔX^g is 12 times that of the column in the case that the SVD is applied for each month. If the SVD is applied for each month, a seasonal continuity of ΔX^g is not realized.

Figure 1 shows the horizontal distributions of climatological increments estimated by multiple GCMs. Eighteen GCM simulations including BCCR-BCM2.0, CGCM3.1(T47), CGCM3.1(T63), CNRM-CM3, CSIRO-Mk3.0, CSIRO-Mk3.5, GFDL-CM2.0, GFDL-CM2.1, FGOALS-g1.0, INGV-SXG, NM-CM3.0, IPSL-CM4, MIROC3.2 (hires), MIROC3.2 (medres), ECHAM5_MPIOM, MRI-CGCM2.3.2, CCSM3, and UKMO-HadCM3 (special report on emissions scenarios A1B, phase three of coupled model intercomparison project [Meehl et al., 2007]) were used to estimate the climatological increments. Target periods for the present and future climates are 2000–2009 and 2090–2099, respectively. The SVD was applied within the domain shown around Japan. Nearly geostrophic winds are observed because the analyzed data are monthly means. A large (small) temperature increment is identified for the PP (NP) of the first mode (Figures 1c and 1d), while the temperature increment is medium for the EM and for the second and third mode perturbations. The circulation patterns among the first, second, and third modes are quite different. The result of the RCM simulation with the EM increment is the most likely future state because the LBC corresponds to the mean state of all GCM.

4. RCM Experiments

RCM simulations for present and future climates were performed. ERA-Interim [Dee et al., 2011] was used as the LBC for the present climate. On the other hand, the LBCs, which were created by adding the statistically analyzed increments described in section 3 to the reanalysis data, were used for the future climate simulations. Ten 14 month simulations that started on 1 September were calculated in parallel (from
1999–2000 to 2008–2009) for both the present and future climates. Data from the first two months were considered to be spin-up periods. The Weather Research and Forecasting (WRF) model [Skamarock et al., 2008] version 3.3.1 was used as the RCM. Physical schemes are double-moment 6-class scheme cloud microphysics [Lim and Hong, 2010], Kain-Fritsch scheme [Kain, 2004] for cumulus parameterization, and Noah land surface model [Chen and Dudhia, 2001] for land surface process. The grid size was 24 km. The numbers of grids were 112 × 91 horizontally with 35 levels in the vertical. Figure 2 shows regionally averaged results of the present and future climate simulations averaged in June, July, and August (JJA). The domain shown around Japan is the simulation area except for lateral damping spaces. In June and July, a monsoon circulation impacts the climate in Japan, and a large amount of rainfall is brought by a rainband called the Baiu front. Convective rainfalls are frequently observed in August. Rainfall in excess of 1000 mm was observed over the islands of Japan (Figure 2a). The rainfall is projected to increase in the EM future climate due to global warming (Figure 2b). Significant variations in rainfall distribution are simulated with the PP and NP from the EM for the first, second, and third modes (Figures 2c–2h). For temperature distributions, the magnitudes of perturbations are large only for the first mode, with almost symmetric patterns for PP and NP (not shown). However, for rainfall distribution, the magnitudes of the perturbations are large for all modes up to the third mode. The symmetry of the pattern is not clear at the local scale, although symmetric patterns are roughly observed.

Figure 1. Horizontal distributions of climatological variables at 700 hPa in March. Variables are temperature (shaded), geopotential height (contours), and wind velocity (arrows). Shown are (a) the present climate estimated by ERA-Interim and (b–h) climatological fields estimated by multiple GCMs, including (Figure 1b) the EM and (Figures 1c, 1e, and 1g) NP and (Figures 1d, 1f, and 1h) PP of (Figures 1c and 1d) first, (Figures 1e and 1f) second, and (Figures 1g and 1h) third modes. The left and right sides of each panel for (Figures 1c–1h) are the climatological increments and the departure from the EM, respectively.

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5. Probabilistic Analysis

RCM simulation results with multimodal increments are statistically analyzed to obtain probabilistic climate change projection information for the future climate. Figure 3 provides schematics of the statistical analysis. For example, three simulations are performed for the first mode perturbation including the EM simulation. Three cumulative distribution functions (CDFs) of a meteorological variable, such as regionally averaged 2 m
air temperature (T2), are shown as three curves in Figure 3a. Then three climatological variables are obtained with a specified value of CDF. The values of the probabilistic density function (PDF) for the three extracted values of the climatological variable are estimated simply when the diversity of is assumed to be normally distributed. Here the Gaussianity of RCM-simulated climatological variables for a diversity of seems to be reasonable except for the extremes, since the Gaussianity has been assumed for variables of . Namely, the three PDF values with increments of the EM, PP, and NP for the first mode are estimated by applying the standard normal distribution to be

\[
\frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}.
\]

The M-modal PDF is as follows:

\[
f(x_1, x_2, \ldots, x_M) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}.
\]

where \(x_i\) is the \(i\)th mode perturbation with the unit magnitude of \(\sigma_i\). The distribution of PDFs under dual modal space is shown by gray shades in Figure 3b. Five values are distributed around the center, corresponding to the EM. An axis for the first mode results is assumed to be orthogonal to an axis of the second mode results, as they are simulated with the independent increment patterns. In the space of the multidimensional PDF, the contours of climatological variables, such as an annual mean T2, are drawn as shown in Figure 3b. The contours can be estimated by the multiple regression analysis (MRA):

\[
y = a_0 + \sum_{i=1}^{M} a_i x_i,
\]

where \(y\) is a climatological variable and \(a_0\) and \(a_i\) are regression coefficients. By using the MRA result, the multidimensional PDF can be converted to a one-dimensional PDF of \(y (f(y))\) by equations (4) and (5). Consequently, the estimated PDF curve shows the probability of the climatological variable in the future climate, which covers a range of uncertainties associated with GCM future projections.

The contours of the climatological variables (Figure 3b) are indicated by straight lines as an example. The linearity corresponds to the fact that the change in the climatological variable estimated by RCM simulations shows a linear response to a climatological increment pattern estimated by multiple GCMs. However, some regional features may bring nonlinearity into the RCM simulations. Figure 4 shows regionally averaged climatological variables obtained by RCM simulation results with the first mode perturbations, including T2 and rainfall for regions A (wide area) and B (narrow area). Perturbations not only of the minus and plus \(\pm \sigma\) but also of \(\pm 1.5\), \(\pm 0.5\), and \(1.5-\sigma\) were calculated for the first mode perturbation. T2 shows an almost linear response for both wide and narrow area averages, as shown in Figures 4a and 4c because the T2 gradually increased with the large perturbation. The rainfall in the wide area also shows an almost linear response (Figure 4b). Rainfall increases much more with a higher temperature increase in the wide area.
Figure 4. Regionally averaged (a, c) T2 and (b, d) rainfall averaged within domains (Figures 4a and 4b) A and (Figures 4c and 4d) B estimated by RCM simulations in JJA for the present climate and the future climates. The perturbations for the future climate simulations are $-1.5\sigma$, $-1.0\sigma$, $-0.5\sigma$, the EM, $0.5\sigma$, $1.0\sigma$, and $1.5\sigma$ of the first mode, where $\sigma$ is the standard deviation of perturbations.

Figure 5. PDF results for the future climate estimated using the first, first to second, first to third, first to fourth, and first to fifth modes in (a–d) JJA and (e–h) September within the spin-up periods. Results include (Figures 5a, 5b, 5e, and 5f) T2 and (Figures 5c, 5d, 5g, and 5h) rainfall averaged within domains (Figures 5a, 5c, 5e, and 5g) A and (Figures 5b, 5d, 5f, and 5h) B. Closed triangles are results of the present climate RCM simulation. PDF values (closed squares), averages (AVE), and standard deviations (STD) estimated by 18 RCM results calculated individually with each GCM increment by the PGW method are also shown (Figures 5e–5h).
The fact seems to be associated with the Clausius-Clapeyron effect. On the other hand, the rainfall in the narrow area shows a nonlinear response with multiple peaks (Figure 4d). This feature is associated with a more complicated response in the regional-scale circulation. The multiple peaks make the MRA identify contours of the climatological variable inapplicable for nonlinearity. Therefore, linearity is assumed in the MRA. If nonlinearity is considered for the function fitting, the reliability becomes low because the number of fitting samples is small: only three per mode.

The estimated final results of the PDF in the future climate are shown in Figures 5a–5d. This result is estimated by multiple modal perturbations of $-1\sigma$, the EM, and $1\sigma$. The PDF of T2 and rainfall show almost Gaussian shapes. The PDF of T2 is roughly determined only with the first mode for both wide and narrow area averages because the shapes of PDFs estimated with higher-order mode results are almost the same as that with only the first mode. The PDF of the rainfall is roughly determined within the second mode for wide-area averages. On the other hand, to determine the PDF of the rainfall for narrow-area averages, first to fourth mode simulations are required. For the narrow-area rainfall, the uncertainty is projected to be small by using only the first mode perturbation. However, the uncertainty is larger when using the higher-order mode perturbations. For example, a decrease of signal in Figure 2g and an increase in Figure 2c within domain B play a role in the expansion of uncertainty. This climatological feature suggests that various changes in circulation patterns result in the variation of rainfall patterns. In this case, nine simulations, which is half the number of GCM simulations, are needed for the fourth mode perturbations.

6. Conclusion and Discussion

A dynamical downscaling method for probabilistic regional-scale climate change projections was developed with multiple GCM climate simulations results. The climatological increments estimated by GCM simulations were statistically analyzed by using the SVD to create multiple modal LBCs for the future climate RCM simulations. The incremental handling for GCM simulations realized approximated probabilistic climate change projections with a smaller number of RCM simulations. For the probabilistic analysis, climatological variables are assumed to show a linear response to analyzed increments of GCMs, although nonlinearity was seen for local-scale rainfall. This probabilistic method is applicable to regional-scale climate change impact assessment. The merit of this method is that a small number of RCM simulations can be used to estimate the uncertainty of GCM climate change projections, avoiding the need to perform large numbers of simulations. The method is called the “incremental dynamical downscaling and analysis system (InDDAS)).”

Some problems remain to be solved in the future. First, further development of techniques to handle climate changes in for year-to-year and short-term variations is needed. Second, the handling of nonlinearity is an issue to be solved. Figures 5e–5h show that standard deviations of narrow range rainfall estimated by 18 RCM results calculated individually with each GCM by the PGW method (25.4 mm) were larger than those estimated by InDDAS (12.5 mm) due to the nonlinearity (Figure 5h), although averages and standard deviations of T2 were almost the same between two methods (Figures 5e and 5f). An inflation of uncertainty might be a practical solution for InDDAS. Third, the Gaussian assumption in the estimation of probability should be modified to treat extremes. Fourth, the similarity of GCM simulations should be reduced, as independence was not considered in this study. Fifth, some empirical and statistical bias correction methods using observation data must be applied for both the present and future climate RCM results to create the probabilistic information, as no bias corrections were applied in the current study.

References

Chen, F., and J. Dudhia (2001), Coupling an advanced land surface—hydrology model with the Penn State—NCAR MMS modeling system Part I: Model implementation and sensitivity, Mon. Weather Rev., 129, 569–585, doi:10.1175/1520-0493(2001)129<0569:caalsh>2.0.co;2.

Dee, D. P., et al. (2011), The ERA-Interim reanalysis: Configuration and performance of the data assimilation system, Q. J. R. Meteorol. Soc., 137(656), 553–597, doi:10.1002/qj.828.

Furrer, R., S. Sain, D. Nyckha, and G. Meehl (2007), Multivariate Bayesian analysis of atmosphere-ocean general circulation models, Environ. Ecol. Stat., 14(3), 249–266, doi:10.1007/s10651-007-0018-z.

Greene, A. L. Goddard, and U. Lall (2006), Probabilistic multimodel regional temperature change projections, J. Clim., 19, 4326–4343, doi:10.1175/JCLI3864.1.

Hara, M., T. Yoshikane, H. Kawase, and F. Kimura (2008), Estimation of the impact of global warming on snow depth in Japan by the pseudo-global-warming method, Hydrol. Res. Lett., 2, 61–64, doi:10.3178/HRL.2.61.
Intergovernmental Panel on Climate Change (2013), *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, edited by T. F. Stocker et al., 1535 pp., Cambridge Univ. Press, Cambridge, U.K., doi:10.1017/CBO9781107415324.

Kain, J. S. (2004), The Kain–Fritsch convective parameterization: An update, *J. Appl. Meteorol.*, 43, 170–181, doi:10.1175/1520-0450(2004)043<0170:TKCPAU>2.0.CO;2.

Kawase, H., T. Yoshikane, M. Hara, F. Kimura, T. Yasunari, B. Ailikun, H. Ueda, and T. Inoue (2009), Intermodel variability of future changes in the Baiu rainband estimated by the pseudo global warming downscaling method, *J. Geophys. Res.*, 114, D24110, doi:10.1029/2009JD011803.

Kimura, F., and A. Kitoh (2007),Downscaling by pseudo global warming method, in *The Final Report of the Research Project on the Impact of Climate Changes on Agricultural Production System in Arid Areas (ICCAP)*, pp. 43–46, Research Institute for Humanity and Nature, Kyoto.

Lim, K. S., and S. Hong (2010), Development of an effective double-moment cloud microphysics scheme with prognostic cloud condensation nuclei (CCN) for weather and climate models, *Mon. Weather Rev.*, 138, 1587–1612, doi:10.1175/2009MWR2968.1.

Manning, L. J., J. W. Hall, H. J. Fowler, C. G. Kilsby, and C. Tebaldi (2009), Using probabilistic climate change information from a multimodel ensemble for water resources assessment, *Water Resour. Res.*, 45, W11411, doi:10.1029/2007WR006674.

Mearns, L. O., F. Giorgi, P. Whetton, D. Pabon, M. Hulme, and M. Lal (2003), Guidelines for use of climate scenarios developed from regional climate model experiments TGCIA-IPCC Rep., 38 pp. [Available at http://www.ipcc-data.org/guidelines/dgm_no1_v1_10-2003.pdf.]

Meehl, G. A., C. Covey, T. Delworth, M. Latif, B. McAvaney, J. F. B. Mitchell, R. J. Stouffer, and K. E. Taylor (2007), The WCRP CMIP3 multi-model dataset: A new era in climate change research, *Bull. Am. Meteorol. Soc.*, 88, 1383–1394, doi:10.1175/bams-88-9-1383.

Misra, V., and M. Kanamitsu (2004),Anomaly nesting: A methodology to downscale seasonal climate simulations from AGCMs, *J. Clim.*, 17, 3249–3262, doi:10.1175/1520-0442(2004)017<3249:ANAMTD>2.0.CO;2.

Sato, T., F. Kimura, and A. Kitoh (2006), Projection of global warming onto regional precipitation over Mongolia using a regional climate model, *J. Hydrol.*, 333, 144–154, doi:10.1016/j.jhydrol.2006.07.023.

Schär, C., C. Frei, D. Lüthi, and H. C. Davies (1996), Surrogate climate-change scenarios for regional climate models, *Geophys. Res. Lett.*, 23, 669–672, doi:10.1029/96GL0265.

Skamarock, W. C., J. B. Klemp, J. Dudhia, D. O. Gill, D. M. Barker, M. G. Duda, X. Y. Huang, W. Wang, J. G. Powers (2008), A description of the advanced research WRF version 3, *NCAR Tech. Note*. 475, 113, doi: 10.5065/D68S4MVH.

Tebaldi, C., L. Mearns, D. Nychka, and R. Smith (2004), Regional probabilities of precipitation change: A Bayesian analysis of multimodel simulations, *Geophys. Res. Lett.*, 31, L24213, doi:10.1029/2004GL021276.

Wakazuki, Y. (2013), Modified relative humidity using the Johnson’s SB distribution function, *SOLA*, 9, 111–114, doi:10.2151/sola.2013-025.

Wakazuki, Y., M. Hara, M. Fujita, C. Suzuki, X. Ma, and F. Kimura (2015), Effect of climate change on the snow disappearance date in mountainous areas of central Japan, *Hydrol. Res. Lett.*, 9(2), 20–26, doi:10.3178/hrl9.20.