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Estimation of High-Resolution Precipitation Distributions in a River Basin from Outputs Simulated by a General Circulation Model

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Synopsis

We provided a downscaling technique which estimates sub-grid scale precipitation distribution from outputs simulated by a general circulation model, with a method classifying spatial distribution of sea level pressure around Japan. Downscaled precipitation distribution for the present-day climate show much better agreement with the observations than the raw model output, suggesting that our downscaling technique is reasonable. When the downscaled future and present-day precipitation distributions are putted into a basin model, it is estimated that discharge in the Tone River will decrease from spring to summer because the precipitation and snowmelt decreases due to the global warming.

Keywords: downscaling, pattern classification, Tone River

1. Introduction

Since the end of the 1980s', a lot of climate change studies using a coupled ocean-atmosphere general circulation model (CGCM) are being performed to investigate climatic impacts of the global warming (e.g., Intergovernmental Panel on Climate Change (IPCC), 2001). These studies show that, due to the global warming, the amount and the distribution of precipitation in the end of the 21st century will change all over the world, and this is also a big matter of concern for the water resource management.

In the recent global warming studies, because the computing power and resources are increasing, the spatial resolution of the CGCM is increasing; it has about 100km horizontal resolution in the atmosphere and about 20km in the ocean (Kimoto et al., 2005). However, this resolution is still too coarse to be used for the water resource management studies; important sub-grid scale processes as well as complex orography cannot be resolved. In other words, there is still a big gap between the resolution and performance of the CGCM and those required by the water resource management studies. For this reason, “Downscaling” techniques have been desired as a mean of bridging this gap.

As a technique of downscaling, there are some methods; dynamical, stochastic, and regression-based methods (Wilby and Dettinger, 2000). In this study, we provide a downscaling technique which spatially and temporally interpolates the precipitation distribution simulated by a CGCM, with an approach to the classification of the spatial distribution of the sea level pressure (SLP) focusing on the area of Japan. Relationships between the spatial distribution of the SLP

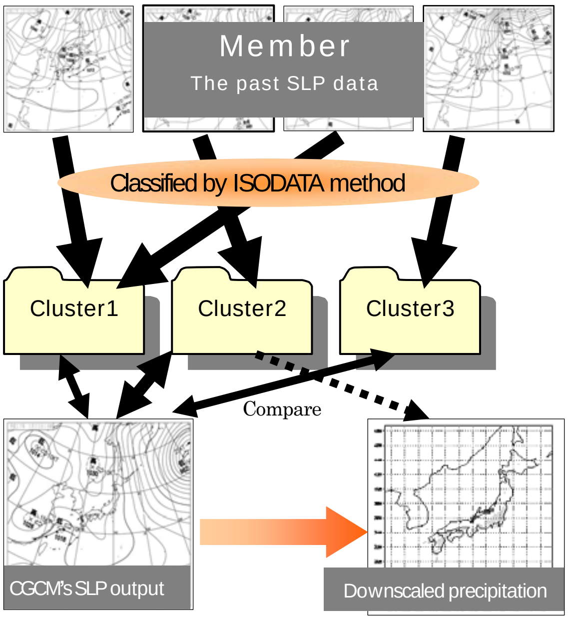

Fig. 1 The schematic of the downscaling technique presented here. See text for detail.

and that of the precipitation are empirically estimated with observations, because the precipitation distributions are expected to be strongly associated with the synoptic-scale disturbances around Japan. This method has the advantage that it does not require too much computational resources. Therefore, we can discuss changes in probability by performing downscaling and analysis many times. As an example of the application to the water resource management, future changes in hydrological indices of the Tone River basin are evaluated by putting the downscaled data into a distributed basin model.

2. The downscaling method and runoff model

In order to estimate the empirical relationships between the SLP and the precipitation, the pattern of the SLP is classified into some clusters by the pattern classification method. About the observations, we use the European Center for Medium range Weather Forecasting (ECMWF) re-analysis (ERA40; Uppala et al., 2005) dataset for the SLP, and the Automated Meteorological Data Acquisition System (AMeDAS) dataset for the precipitation for the past 25years from 1976 to 2000 around Japan (110-160E,15-60N). As a method of the pattern classification, the Iterative Self Organizing Data Analysis Techniques A (ISODATA) method (Ball and Hall, 1967) is used. In the ISODATA, (1) all members (ERA40 SLP value) are randomly classified into some clusters. (2) The cluster center is calculated as an average distribution of the cluster members. (3) The cluster is divided if the variance of distances is larger than a certain threshold value. (4) If the distance between any couple of

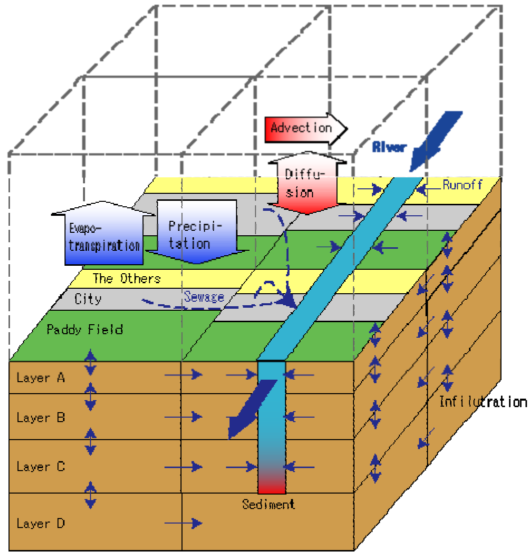

Fig. 2 The schematic of a kind of distributed runoff model generally known as Hydro-BEAM; The watershed is modeled as a uniform array of multi-layered mesh cells, each containing information regarding surface land use characteristics, ground surface slope and runoff direction, and the presence/absence of a channel.

cluster centers comes closer than a certain threshold

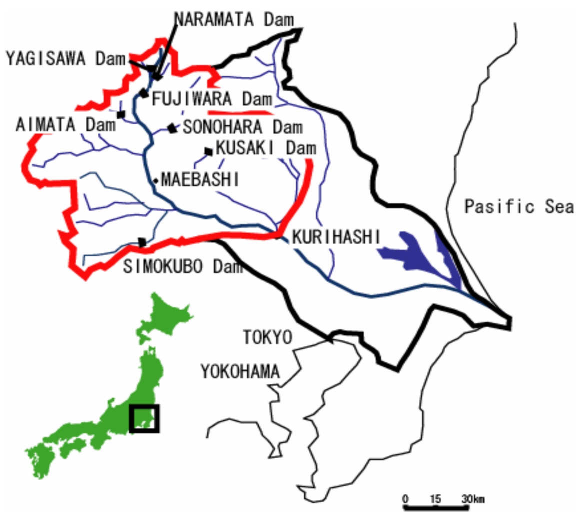

Fig. 3 Maps of the Tone River basin; Thick black line shows the catchments area and thick red line shows the simulated area.

value, corresponding two clusters are combined. (5) The cluster centers are calculated again. (6) All members are classified into the nearest clusters again by the calculation of distances to all cluster centers. These steps from (2) to (6) are repeated 20 times to stabilize the classification. After this, most suitable clusters and members are calculated by the ISODATA. Note that the distance between the cluster centers and a cluster, $OF_{i,j}$, is calculated as the summation of an root-mean-square difference at the grit points:

$$OF_{i,j} = \frac{1}{N_x N_y}\sqrt{\sum_{x}^{N_x}\sum_{y}^{N_y}\left(SLP_i(x,y) - CL_j(x,y)\right)^2} \quad (1)$$

where, $SLP_i(x,y)$ is the SLP at (longitude,latitude) = (x,y), $CL_j(x,y)$ j-th cluster center, and N_x and N_y the number of calculated grids in the longitude and the latitude, respectively. The distance between a pair of cluster centers is calculated as the same way:

$$OF_{i,j} = \frac{1}{N_x N_y}\sqrt{\sum_{x}^{N_x}\sum_{y}^{N_y}\left(CL_i(x,y) - CL_j(x,y)\right)^2} \quad (2)$$

For the optimization of some threshold values, Akaike Information Criterion (AIC; Akaike, 1973) is used.

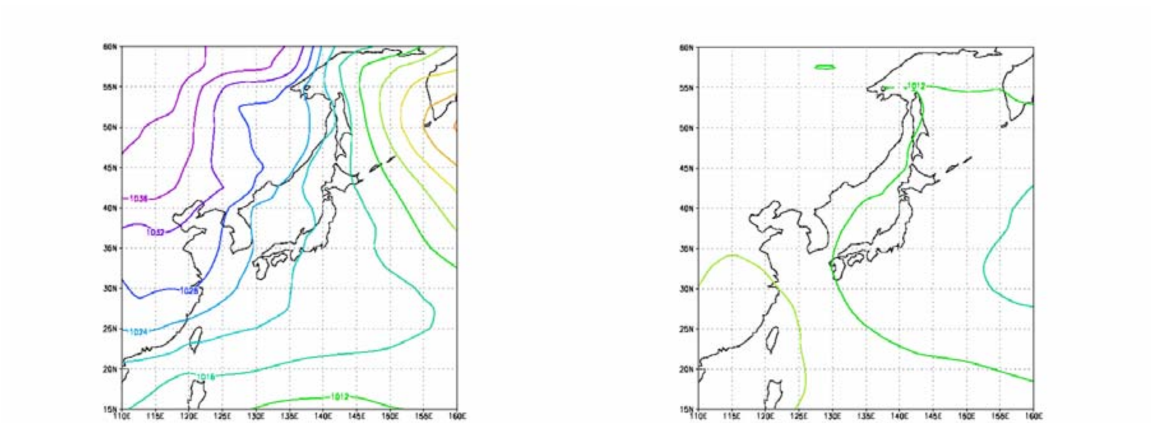

Fig. 4 SLP patterns of the clusters which have the largest number of members in January (left) and in August (right).

Table 1 Total members, number of clusters, maximum and minimum members in a cluster, and average members per a cluster for each month

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Total members	3100	2828	3100	3000	3100	3000	3100	3100	3000	3100	3000	3100
Number of clusters	251	261	200	194	182	157	153	151	225	237	248	248
Max. members in a cluster	56	44	44	46	80	62	51	87	65	46	45	39
Min. members in a cluster	2	1	3	4	4	4	6	4	2	2	2	1
Average members	12	11	16	15	17	19	20	21	13	13	12	13

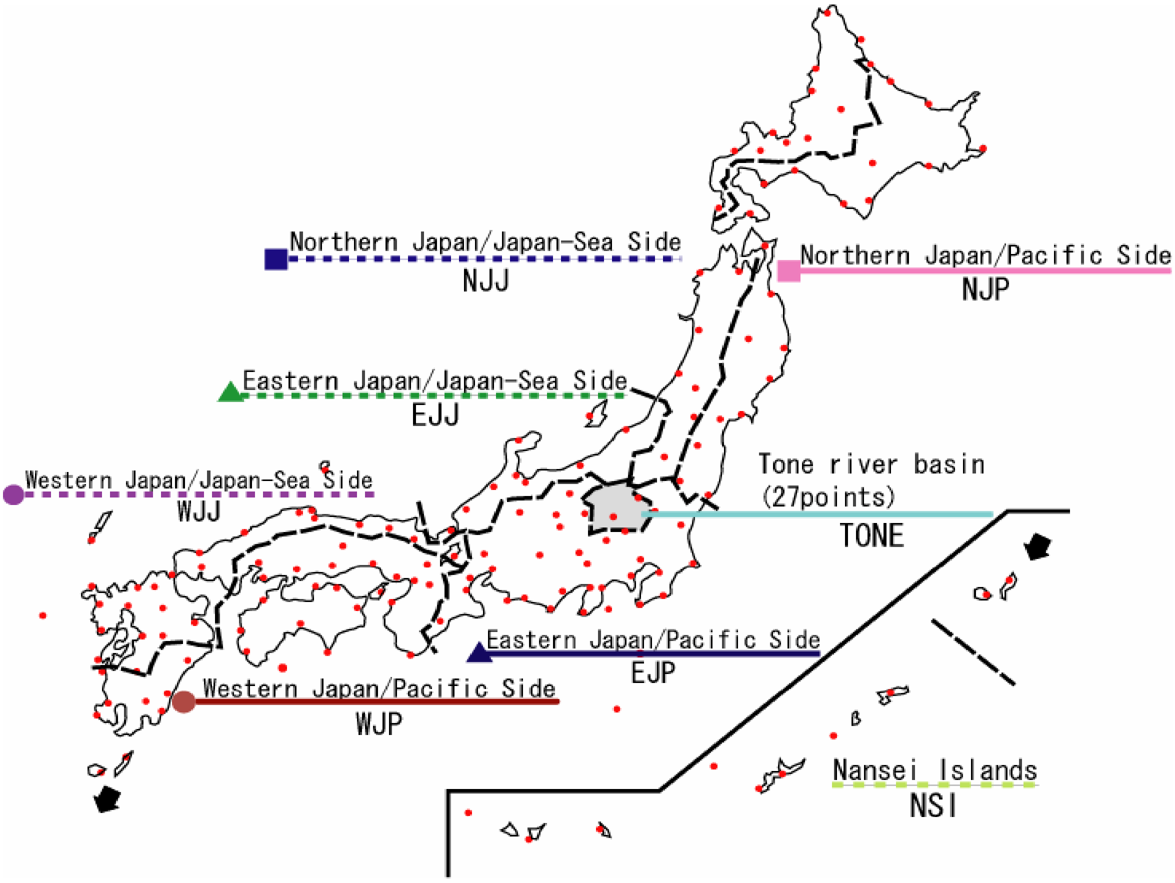

Fig.5 Maps of seven climatic areas and major observation points (filled small red circles). The area of the Tone river basin which has 27 observation points is also shown. The name of the area and its abbreviated name is indicated over and beneath of the line, respectively.

As for the CGCM data, we use the output from the CGCM developed cooperatively by the Center for Climate System Research of the University of Tokyo, the National Institute for Environmental Studies, and the Frontier Research Center for Global Change of the Japan Agency for Marine-Earth Science and Technology (Kimoto et al., 2005). For each simulated SLP, one cluster is selected which minimizes the difference between the simulated SLP and the cluster center as shown in Fig.1. Then, an AMeDAS observational precipitation data for 6hours which corresponds to the selected cluster is randomly sampled and regarded as the downscaled output. The downscaled precipitation has the temporal and spatial resolution of 1hour and about 17km respectively.

The downscaled output is inputted to a kind of distributed runoff model, called by Hydrological Basin Environment Assessment Model (Hydro-BEAM) (Kojiri et al., 1998). Figure 2 shows the schematic of this model. In the Hydro-BEAM, the watershed is modeled as a uniform array of multi-layered mesh cells, each containing information regarding surface land use characteristics, ground surface slope and runoff direction, and the presence/absence of a channel. The model uses four shallow subsurface layers. A finite difference approximation of kinematic wave model is used to model watershed runoff on surface. A linear storage model is used to the subsurface layers.

In this study, the upper basin of the Tone River (upper than KURIHASHI) is simulated. The Tone River is a river in the southeast region of Japan (Fig.3). It is 322 km in length and has a catchment area of 16,840 km² that is the largest in Japan. The Tone River is important because it supplies water for more than 30 million inhabitants of Tokyo metropolitan area. The mesh resolution which divides the river catchments area is 2km considering about the size of the basin area. The downscaled precipitation data is interpolated into the meshes by the Thiessen polygon. The evapotranspiration is calculated by the heat balance model in each mesh. The amount of snow cover and snowmelt are calculated by the model which considers the processes of snowfall, snowmelt and infiltration which refer the ground temperature (Kojiri et al., 1998). We use the CGCM-simulated temperature after linearly interpolating it about the time.

3. Results and discussions

3.1 Downscaling with pattern classification method

The SLP patterns of the clusters which have the largest number of members in January and August are shown in Fig.4. In January, the cluster represents an SLP pattern in which high pressure lies to the west and low

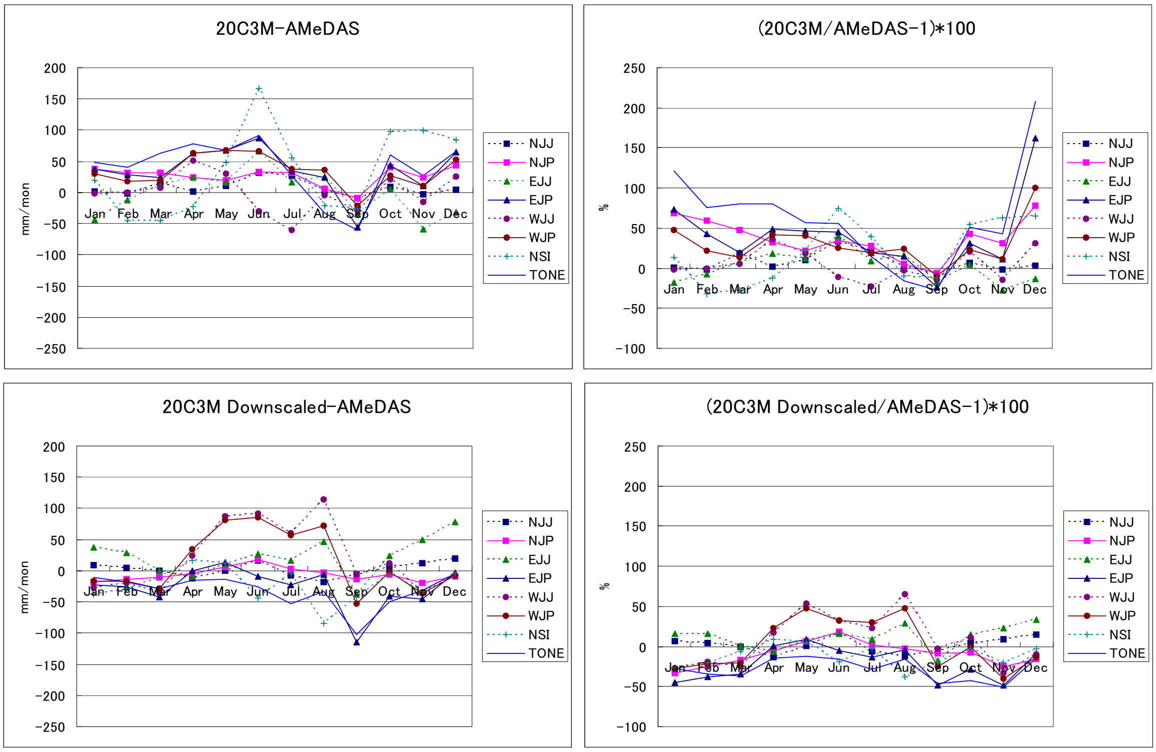

Fig.6 Errors in precipitation between the observations and the raw CGCM data (upper panels) and that between the observations and the downscaled results (lower panels). Left panels show raw differences (mm/mon) and right panels show ratios of difference (%). See Fig.5 for the line legends.

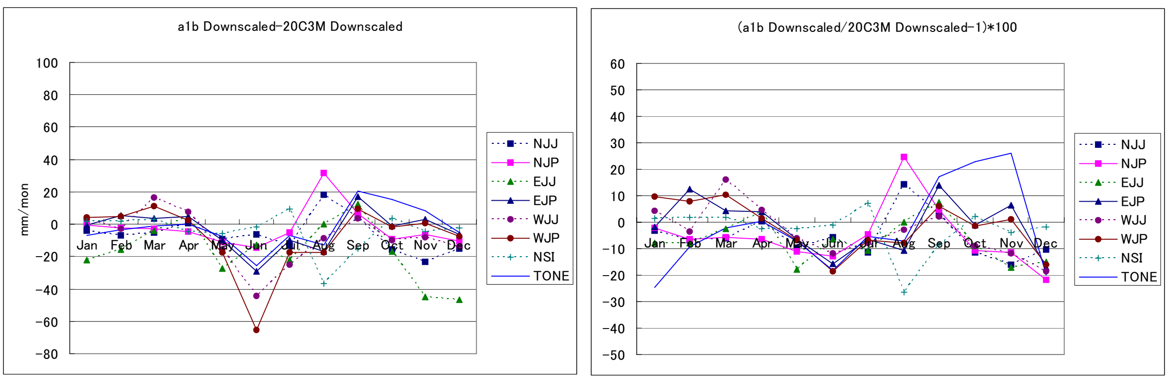

Fig.7 Same as Fig.6 but for differences between the downscaled result of the 20th century and the result of the 21st century; See Fig.5 for the line legends.

pressure to the east. In August, on the other hand, it represents the strong Pacific high. These two patterns are the typical pattern in the East-Asia in each month. In addition, the average numbers of cluster members are 10-20 and the largest number of members in a cluster is 87 (Table 1). This means that the specific clusters do not have too many members. Therefore, the classification method of the observed SLP patterns is reasonable.

The output of the 20th century climate change

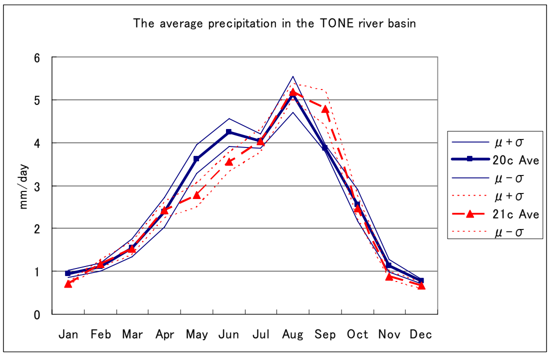

Fig. 8 The average precipitation in the Tone River basin; Solid blue and dashed red line shows the result of the 20th and the 21st century, respectively. Thin lines show the values added/subtracted one standard deviation to/from the average.

simulation (20C3M) with the CGCM is downscaled for 1976-2000. Figure 6 shows errors in precipitation between the observations and the raw CGCM data, and also the errors between the observations and the downscaled results (ensemble mean of five downscaled results) for seven climatic areas and the Tone River basin (see Fig.5 about the climatic areas and observation points). From winter to spring, the downscaled results have a comparatively good representation. On the other hand, the downscaled results still overestimate in summer over the western part of Japan, while they still underestimate in autumn almost all over the Japan. However, these errors are smaller than those between the raw CGCM data and the observations. Therefore, this method is meaningful.

Future SLP patterns projected by a CGCM based on the IPCC Special Report on Emissions Scenarios (SRES; IPCC, 2000) A1B scenario are downscaled for the years from 2076 to 2100. Figure 7 shows the difference in precipitation due to the global warming. The results suggest that the precipitation decrease in June all over Japan, and it also decrease in winter over the Eastern part of Japan and the areas along the Sea of Japan. It is also suggested that the precipitation increase in August over the Northern part of Japan.

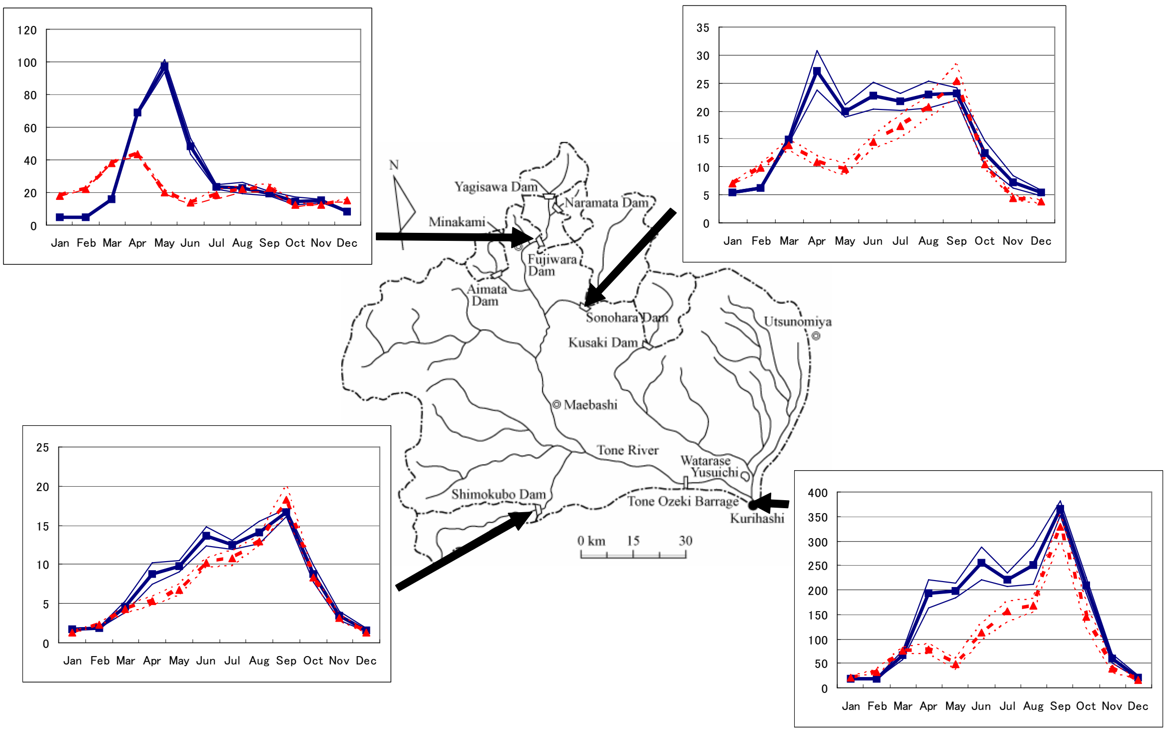

Fig. 9 The flow discharges at the Fijiwara Dam, Simokubo Dam, Sonohara Dam and Kurihashi. See Fig.8 for the line legends.

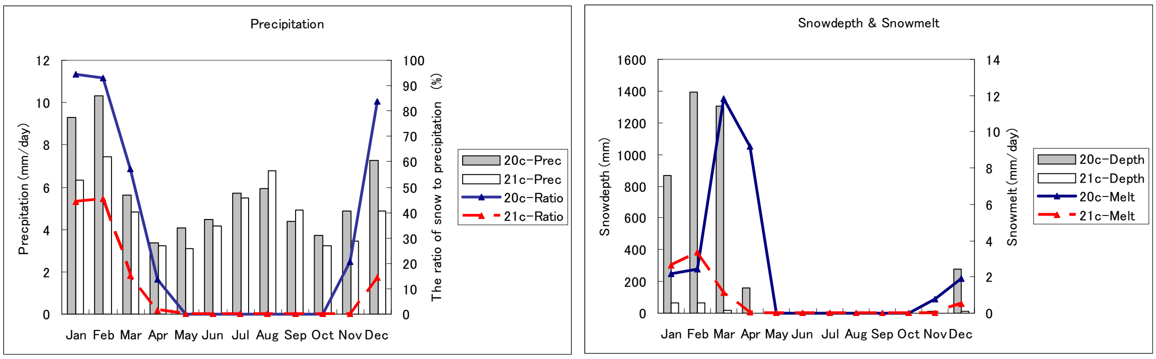

Fig10. Changes in the precipitation, the ratio of snow to precipitation, snowmelt and snow depth in the Fujiwara Dam. Left panel: Solid blue and dashed red line shows the downscaled precipitation in the 20th and the 21st century, respectively. Gray and white bar shows the ratio of snow to precipitation in the 20th and the 21st century, respectively. Right panel: Solid blue and dashed red line shows the snowmelt in the 20th and the 21st century, respectively. Gray and white bar shows the ratio of snow depth in the 20th and the 21st century, respectively.

3.2 The estimation of the future hydrological indices in the Tone River

The downscaled future precipitation datasets are inputted to the Hydro-BEAM, a kind of river runoff model, in order to investigate the changes in the future hydrological indices in the Tone River basin. The Hydro-BEAM requires a lot of computational resources, so it is calculated for the years 1991-2000 (present-day climate) and for the years 2091-2100 (future climate). Figure 8 shows the ensemble mean precipitation in the Tone River basin, and Fig.9 shows ensemble mean flow discharges in some important points. Figure 9 show that the flow discharge decreases in spring and summer while increases in winter due to the global warming. These changes are affected by the reduction of the precipitation in spring as shown in Fig.8. However, it seems that it is not enough to explain these changes in the flow discharge. Therefore, we investigate the changes at the Fujiwara Dam, the upper point of this basin. Figure 10 shows the changes of the precipitation, the ratio of snow to precipitation, snowmelt and snow depth in the Fujiwara Dam. In winter, the ratio of snowfall to precipitation decreases due to the global warming, in addition to a decrease in precipitation. Consistently, the snow depth largely decreases and the maximum snowmelt season becomes earlier. Therefore, the changes in flow discharge are affected by both the reduction of the precipitation in spring and the changes in snowfall and snowmelt. However, this result may be affected by the underestimation of the downscaled precipitation, thus it should be interrupted carefully.

4. Conclusion

We provide a downscaling technique with a pattern classification method, and also estimate the future hydrological indices of the Tone River basin using the downscaled precipitation data. Although the downscaled results for the present-day climate simulation have some errors in summer, these errors are smaller than the errors between the raw simulation data and the observations. Thus, the downscaling technique using a pattern classification of the SLP seems to be reasonable. The downscaled results based on the IPCC SRES A1B scenario simulation suggests that, due to the global warming, the precipitation decreases in June all over Japan and also decreases in winter over the Eastern part of Japan and the areas along the Sea of Japan. At the same time, it also suggests that the precipitation in the summer will increase in the future due to the warming. In the Tone River basin, with the reduction of the precipitation and snowfall and the earlier snowmelt, it is suggested that the flow discharge will increase in winter while it will decrease from spring to summer. Therefore, these results give warning about the water resources in spring.

On the other hand, there is some problem. The downscaling method proposed here is based on the assumption that the empirical relationship will not change and the extreme events that never happened in the 20th century will also never happen in the 21st century. In addition, there is some error between the observations and the downscaled output, thus it has better to include a kind of correction. Furthermore, the CGCM and the downscaled output underestimate the frequency of the extreme event like water flood and shortage. In order to reduce these problems, we have to improve the downscaling method. For example, the other meteorological variables might be used.

However, as we have shown here, the downscaling technique using a pattern classification is reasonable, easy to use, and need not so much computer resources. For this reason, we believe that this method is useful.

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数値気候モデル出力を用いた時空間高解像度降水分布の推定

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要旨

気圧パターン分類法を用いて，気候モデル出力から日本域の高解像度降水分布を推定するダウンスケーリング手法を開発した。現在条件で推定した降水分布は気候モデル出力よりも観測に近く，本手法が有効であることが示された。現在および将来条件下で推定した降水分布を入力した流域モデル結果から，利根川上流域では温暖化に伴い春～夏に降水量が減少し，また融雪期が早まりその量も減少するため，流量が減少することが示された。

キーワード:ダウンスケーリング，パターン分類法，利根川