ESTIMATION OF PROBABLE RAINFALL CONSIDERING UNCERTAINTY BASED ON MASSIVE ENSEMBLE CLIMATE PROJECTIONS IN THE TOKACHI RIVER BASIN

FUMIHIKO UEMURA
Docon Co., Ltd., River Environmental Dept., Sapporo, Hokkaido, Japan, fu1747@docon.jp

SHIGEKAZU MASUYA, TAKATOSHI YOSHIDA, NORIAKI OMURA
Docon Co., Ltd., River Planning Dept., Sapporo, Hokkaido, Japan

SHO TOMURA, MANABU CHIBA, TARO YAMAMOTO
River Center of Hokkaido, Sapporo, Hokkaido, Japan

ATSUSHI TAKEDA
Hokkaido Regional Development Bureau, Ministry of Land, Infrastructure, Transport and Tourism, Sapporo, Hokkaido, Japan

TSUYOSHI HOSHINO, TOMOHITO YAMADA
Hokkaido University, Graduate School, Faculty of Engineering, Sapporo, Hokkaido, Japan

ABSTRACT

The IPCC (Intergovernmental Panel on Climate Change) Fifth Assessment Report leaves no doubt that the climate system is warming, and extreme rainfall events might be more severe and more frequent in most mid-latitude land areas. A high likelihood is predicated for the above situation. In August 2016, three typhoons successively made landfall in Hokkaido, Japan, and heavy rains fell in various places. As a result, rivers flooded and sediment disasters occurred, mainly in eastern Hokkaido. Recently, there is the concern that the impact of such climate changes will become apparent. In light of this, flood control measures considering future climate change are required in Japan. Current flood control plans have safety levels that are based on limited observation data from the past several decades to a maximum of about 100 years. It is essential to utilize climate projections data to respond to events occurring under future climate change. In this study, we estimated the annual maximum average rainfall per basin from the output rainfall of a climate model using d4PDF, which is a massive ensemble of climate projections. Moreover, we proposed methods to evaluate the accuracy of this model and to calculate rainfall probability considering the range of uncertainty. The projection data of past climate were found to closely reproduce the observed values. In addition, 1/150 annual exceedance probability (AEP) rainfall has uncertainty: The range will be about 170mm/72hr under the current climate and about 260mm/72hr under the future climate. In the case of a GEV distribution, it became clear that the median of 1/150 AEP rainfall will be about 1.4 times the current rainfall in the future assuming the scenario of RCP8.5.

Keywords: climate change, extreme rainfall event, massive ensemble climate projections, annual exceedance probability, uncertainty

1. INTRODUCTION

In the Hokkaido Heavy Rainfall Disaster of August 2016, three typhoons made landfall in a week in Hokkaido, Japan. It was the first recorded occurrence of three typhoons in a single week there, and new rainfall records were set in many areas of Hokkaido. According to the IPCC Fifth Assessment Report (IPCC, 2014), extreme rainfall events are very likely to be more severe and more frequent in most mid-latitude land areas by the end of this century. In light of this, the Hokkaido Government and the Hokkaido Regional Development Bureau of the Ministry of Land, Infrastructure, Transport and Tourism (MLIT) of Japan established a committee on climate change that noted the need for scientific predictions of the future effects of climate change, and the planning of flood management policy to address such change.

Policy-makers have been setting the safety level of flood control based on probable rainfall calculated from past observation data. However, the utilization of climate projection data is indispensable for promoting flood control measures under the future climate. To estimate the probable rainfall for once in several hundred years, which is the target of flood control measures, large amounts of experimental data, including low-frequency and high-intensity rainfall cases, are required for the climate model. At present, the results of such a massive ensemble experiment were made open to the public as the “database for Policy Decision making for Future climate change (d4PDF)” by the Ministry of Education, Culture, Sports, Science and Technology’s Climate Change Risk

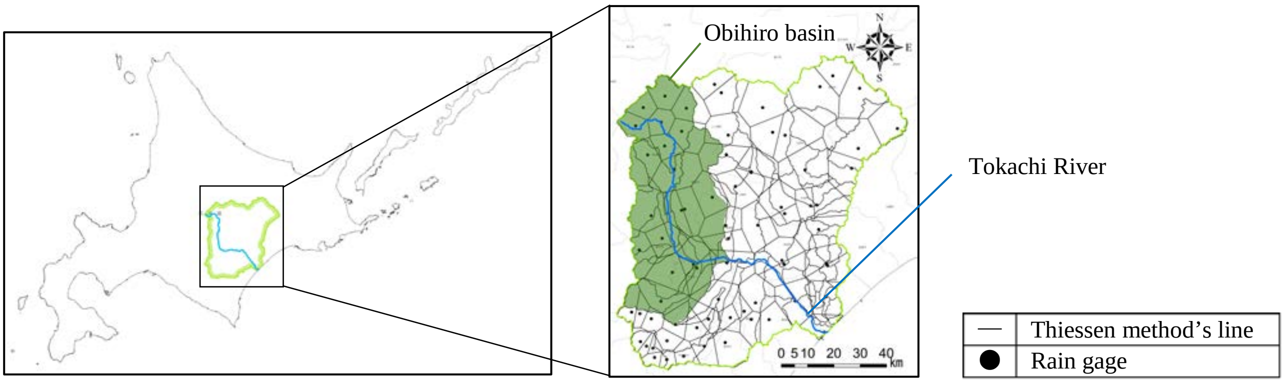

Figure 1. The overview of target basin

Information Creation Program, and it became possible to discuss the reproduction and change of extreme weather based on the probability density distribution (Mizuta et al., 2016).
Studies have been carried out to estimate the annual maximum rainfall from the d4PDF, and to estimate the probable rainfall under the future climate (Tanaka et al., 2017; Tachikawa et al., 2017). However, no bias correction method for the massive ensemble data has been established, and little confirmation has been made on how closely the estimated annual maximum rainfall reproduces the actual annual maximum rainfall. The d4PDF regional model has a horizontal resolution of 20km, but it has been pointed out that the reproducibility of high-intensity hourly rainfall differs depending on the model resolution (Sasaki et al., 2011). To estimate the probable rainfall on the scale of the river basin in Hokkaido region, verification with a higher-resolution climate model is necessary.

In addition, the rainfall output from climate models varies as a result of uncertainties due to boundary conditions, initial conditions, and nonlinearities inherent in the climate system, so it is necessary to consider the possible range of stochastic rainfall using large ensemble data. By using rainfall data from the d4PDF, the ranges of probable rainfall have been shown for the past climate and the future climate. Tachikawa et al. (2017) estimated the range based on the treatment of the past 3,000 years as one sample and the future 900 years for each of six sea surface temperature (SST) patterns as another sample. Tanaka et al. (2017) estimated the 95% confidence interval of the probable rainfall by a method using variance and the likelihood profile, based on each group of ensemble members (60 years) as 1 sample. Kitano et al. (2017) assumed that the distribution of the probable rainfall from each group of ensemble members of past experiments appears as that of the probable rainfall that actually occurred, and they showed the distribution in which the probable rainfall could be obtained by the gamma distribution. In contrast, from the viewpoint of flood control planning, the relationship between the range of model uncertainty and the probability of rainfall calculated from observation results has not been discussed.

In this study, toward applying climate projection data to flood control measures, we used massive ensemble climate projection data and 5km-mesh data to which it was downscaled to determine how well the climate model reproduces the observation data. Additionally, we estimated the uncertainty of probable rainfall by using a method that enables climate projection data to be compared to observation data. Finally, we discuss uncertainty with respect to the development of flood control measures that address climate change. This study was conducted and verified by the Technical Review Committee on Climate Change Projections (water field) in Hokkaido Region, which was established by the Hokkaido Regional Development Bureau of the MLIT (2018).

2. METHOD

2.1 Target area

The target area is the Tokachi river basin in eastern Hokkaido, Japan. This catchment measures 2,678km^2. This area suffered severe damage from the Hokkaido Heavy Rainfall Disaster of August 2016. The annual maximum rainfall was calculated from the depth of rainfall averaged over the watershed area whose downstream end includes the Obihiro observation site (Figure 1). This site is in the largest urban area of the eastern Hokkaido region. The rainfall duration was 72 hours in this watershed, which were set in consideration of the flood arrival time under the current flood control plan.

2.2 Rainfall data

2.2.1 Climate projection data

As rainfall data, we used the output values from the regional climate model (RCM20) provided by d4PDF. The grid size of RCM20 is 20km. We used the two datasets of the past and future massive ensemble projections provided by d4PDF. The past experiment is 60 years (1951–2010) × 50 ensemble members, so the total period of the climate simulation is 3,000 years. The future experiment is 60 years (equivalent to 2090 in the RCP 8.5

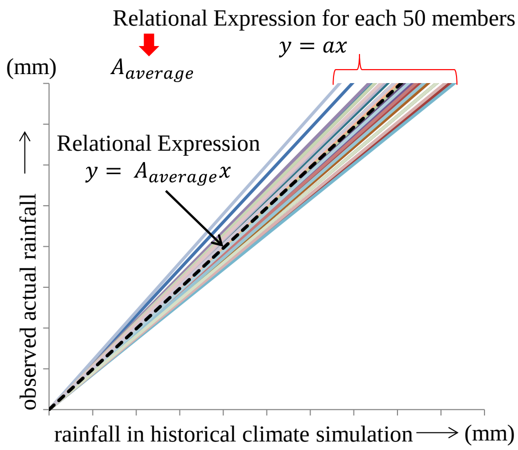

Figure 2. The method of bias correction

scenario) × 6 SST patterns × 15 ensemble members, so the total period of the climate simulation is 5,400 years. The RCP 8.5 scenario is the worst case of the four climate change scenarios presented in the IPCC Fifth Assessment Report: It assumes warming of 4℃ by 2090.

In addition, for rainfall data we also used the dynamical downscaling model (RCM5) (Yamada et al., 2018) from RCM20, in order to reproduce rainfall events for the target basin in more detail. The grid size of RCM5 is 5km. The simulation of the dynamical downscaling to RCM5 set the calculation area and period as follows, in order to efficiently extract the data of massive rainfall events.

1. The calculation area is the latitude and longitude range of 800km with 142.5E and 42.75N as a center. In consideration of the development of typhoons over the Pacific Ocean, it set more toward the area south of Hokkaido.
2. The calculation period was set as the 5 days before and after the rainfall event, with 5 days as the preconditioning term, making a total of 15 days. The date of the rainfall event was set from the occurrence time of the annual maximum rainfall event in the rainfall data in RCM20.

The estimation of probable rainfall requires annual maximum rainfall. Thus, the maximum of the accumulated rainfall within the duration of rainfall was estimated, and sample datasets of annual maximum rainfall were made for both models. The hourly rainfall of each case was weighted by the area of each mesh of the climate model as a share of the target basin. The date of occurrence of the annual maximum rainfall for RCM20 was utilized to set the calculation period for downscaling.

RCM5 was simulated using the Earth Simulator supercomputer of Japan Agency for Marine-Earth Science and Technology (JAMSTEC), Japan. This simulation was carried out with the help of “Assessment of changes in flood risk due to climate change in Hokkaido,” an earth simulator special promotion program from 2017 in Japan. Both models use the non-hydrostatic regional climate model (NHRCM), which is the latest climate model provided by the Meteorological Research Institute, and both are characterized by the use of MRI/JMA-SiB as the land surface model for long-time integration.

2.2.2 Observation data

The observation value for rainfall was calculated based on the hourly rainfall data of the ground station in the target basin. The duration of data collection was 60 years (1951–2010), it matches the duration of the past experiment on the climate model. The number of stations used varies from year to year with the establishment or closure of stations, but in 2010 there were 30 stations. From the hourly rainfall data of each station, the basin average hourly rainfall was calculated by the Thiessen method, and the annual maximum rainfall within the duration of rainfall was calculated.

2.3 Bias correction

The bias correction is based on Piani’s method (Piani et al., 2010) applied to rainfall data of NHRCM in Meteorological Research Institute Technical Report No.73 (2015). In this method, the bias is corrected by the linear equation of the relational expression y = ax + b, and the numerical value is easy to handle. The coefficients are calculated from the regression formula by the least squares method. The formula is made by sorting model values and observation values in ascending or descending order, and plotting the model values on the x axis and the observation values of corresponding ranks on the y axis (Figure 2).

In this study, to take into account the characteristics of the data, we revised Piani’s method as follows.

1. The corrected annual maximum value must be positive, so the regression formula was altered to y = ax (b = 0)
2. So that the massive ensemble data would correspond to the observation data, whose number of samples is limited, a regression formula was made for every 50 ensemble members from the past experiment. The

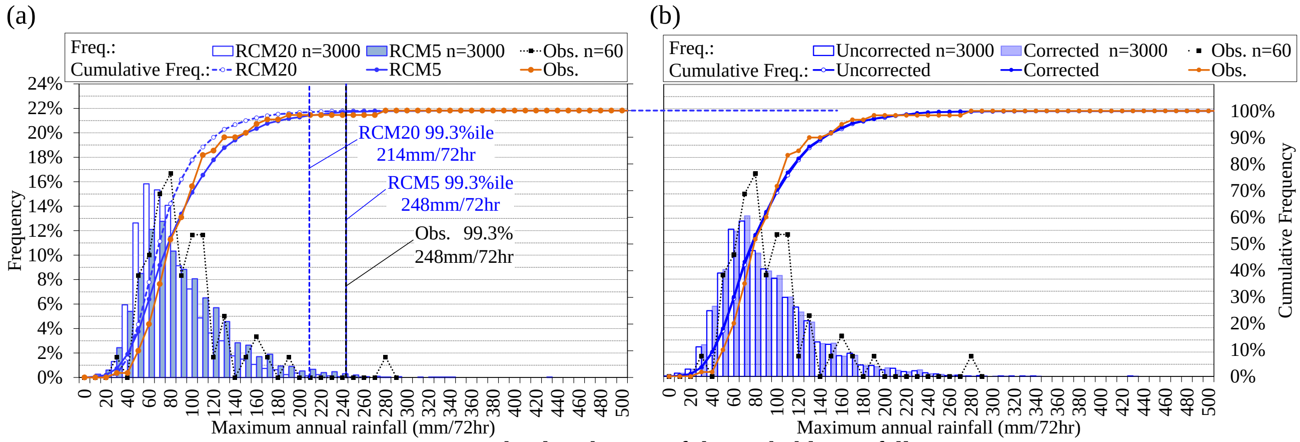

Figure 3. The distribution of the probable rainfall

(a: Left) A comparison of RCM20 and RCM5 uncorrected data. (b: Right) A comparison of corrected and uncorrected RCM5 data. (Freq.: Frequency, Obs.: Observation data)

Table 1. The distribution of probable rainfall

(a: left) A comparison of rainfall for RCM20 and RCM5 uncorrected data. (b: right) A comparison of the cumulative frequency for corrected and uncorrected of RCM5 data.

(a)

	Obs.	RCM20		RCM5	
Max	283.8	340.1	(56.3)	439.6	(155.8)
99.3%ile	248.1	214.1	(−34.0)	248.3	(0.2)
99%ile	230.3	203.0	(−27.3)	239.0	(8.7)
95%ile	167.4	150.9	(−16.5)	178.6	(11.2)
50%ile	88.2	79.3	(−8.9)	87.2	(−1.0)
Min	36.5	32.3	(−4.2)	5.0	(−31.5)

Obs.: Observation data

(b)

Rainfall	Cumulative Frequency (RCM5)				
(mm)	Obs.	Uncorrected		Corrected	
40	2%	3%	(1)	4%	(2)
50	2%	9%	(7)	9%	(7)
60	10%	17%	(7)	18%	(8)
70	20%	29%	(9)	30%	(10)
80	35%	42%	(7)	43%	(8)
90	52%	52%	(0)	53%	(1)
100	60%	61%	(1)	62%	(2)
110	72%	69%	(−3)	70%	(−2)
120	83%	76%	(−7)	77%	(−6)
130	85%	82%	(−3)	82%	(−3)
140	90%	86%	(−4)	87%	(−3)
Average			(1)		(2)

Obs.: Observation data

coefficient “a” in the regression formula for each member was averaged for use as the coefficient of the correction expression.

2.4 Estimation of probable rainfall

The probable rainfall was analyzed by using the extreme value statistics. For the distribution function, we used a Gumbel distribution and a GEV (generalized extreme value) distribution, because flood control plans in Japan often use these distributions. SLSC shows the goodness of fit of the distribution function to the sample group (Takara and Takasao, 1988). The model calculated that SLSCs above 0.04 are not good fits. In this study, the evaluation by SLSC excluded some cases in which the SLSC was above 0.04 from the estimation of the probable rainfall.

2.4.1 Resampling

In this study, we estimated the uncertainty of the rainfall by using a resampling method. It estimated the possible range of probable rainfall in the case of 60 years of rainfall data being available as the uncertainty of the rainfall.

1. Past experiments
   The sea surface temperatures of past experiments are the output values from the climate model using observation data as boundary conditions. Therefore, the method randomly sampled one case of the annual maximum rainfall from ensemble members of each year, and made sample rainfall that is the annual maximum rainfall of 60 years from 1952 to 2010. For example, the method first sampled one case from 50 ensemble members of 1951, then one case from 50 ensemble members of 1952, and repeated the sampling until 2010. This method made for 100,000 samples, and the probability evaluation was carried out for each sample.
2. 4°C warming experiments
   The SST in the 4 °C warming experiment has 6 patterns, therefore Tachikawa et al. (2017) considered the uncertainty of the rainfall for each SST pattern. In contrast, in this study, under the assumption that each SST has an equal probably of occurring, the resampling method randomly sampled 60 cases from the 5,400

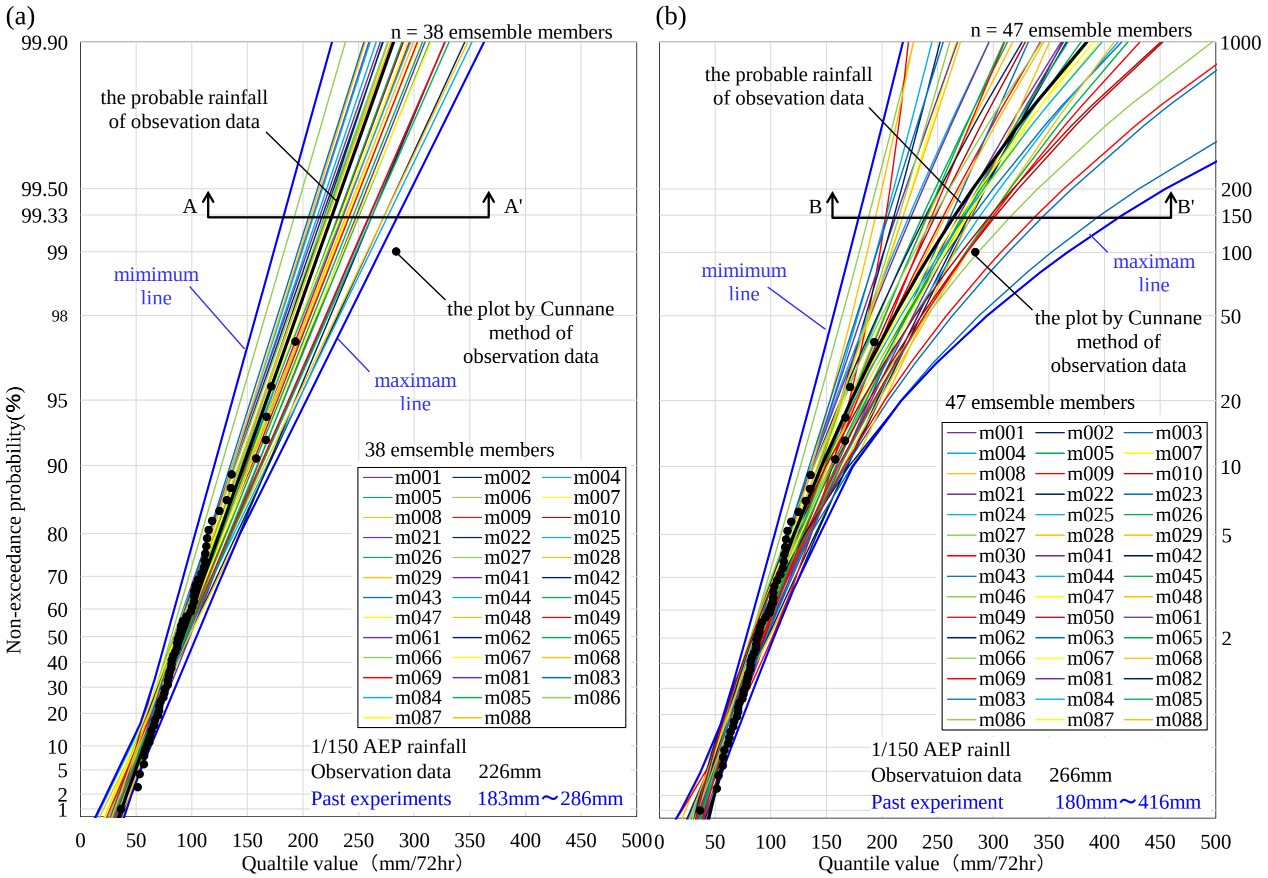

Figure 4. Estimation of probable rainfall in the case of the past experiment
(a: left) the Gumbel distribution, (b: right) the GEV distribution

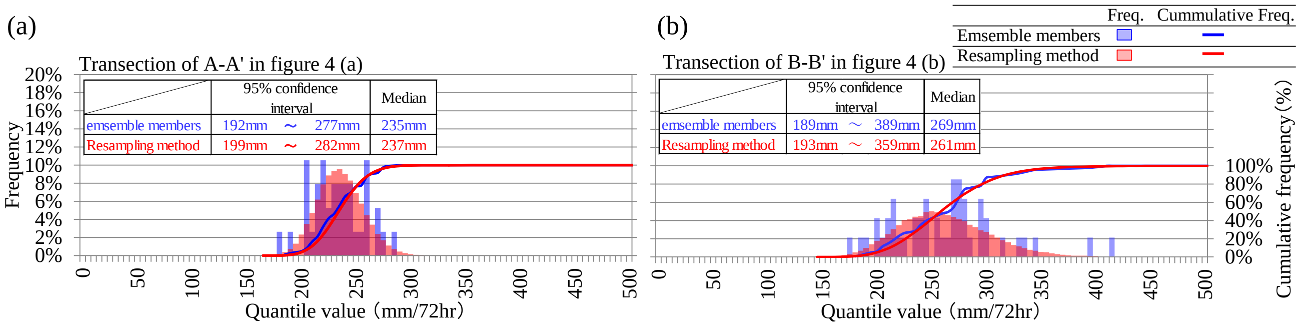

Figure 5. Frequency distribution of 1/150 AEP rainfall
(a: left) the Gumbel distribution, (b: right) the GEV distribution

cases of annual maximum rainfall regardless of the SST pattern or year. As in past experiments, we generated 100,000 samples by this method, and carried out the probability evaluation for each sample.

3. Results

3.1 Accuracy of the climate model

3.1.1 Horizontal resolution of climate models

Figure 3(a) show the relative frequency distribution of the annual maximum rainfall for the RCM20 and the RCM5. Table 1(a) shows the percentile value for each model and the difference from the actual rainfall. The absolute value of the difference from the actual rainfall is smaller in the RCM5 than in the RCM20. At the 99.3 percentile value (annual probability of exceeding 1/150), the change in resolution resulted in a decrease in actual rainfall from −34.0mm to 0.2mm/72hr. These results confirm that downscaling to the high-resolution model improved the reproducibility of the frequency distribution of actual rainfall.

From Table 1(a), the maximum values from the climate model were greater after downscaling, and these values included low-frequency and high-intensity rainfall events. These extreme values are important for greater accuracy in probability analysis. In contrast, the RCM5 data included some cases whose rainfall was several millimeters. The calculation period for each RCM5 dataset is 15 days set in the reference to the time when the annual maximum rainfall occurs in the RCM20 data. For this reason, it is assumed that, in some cases, rainfall does not occur within the calculation period in the target area due to the spatiotemporal variation of rainfall before and after the downscaling.

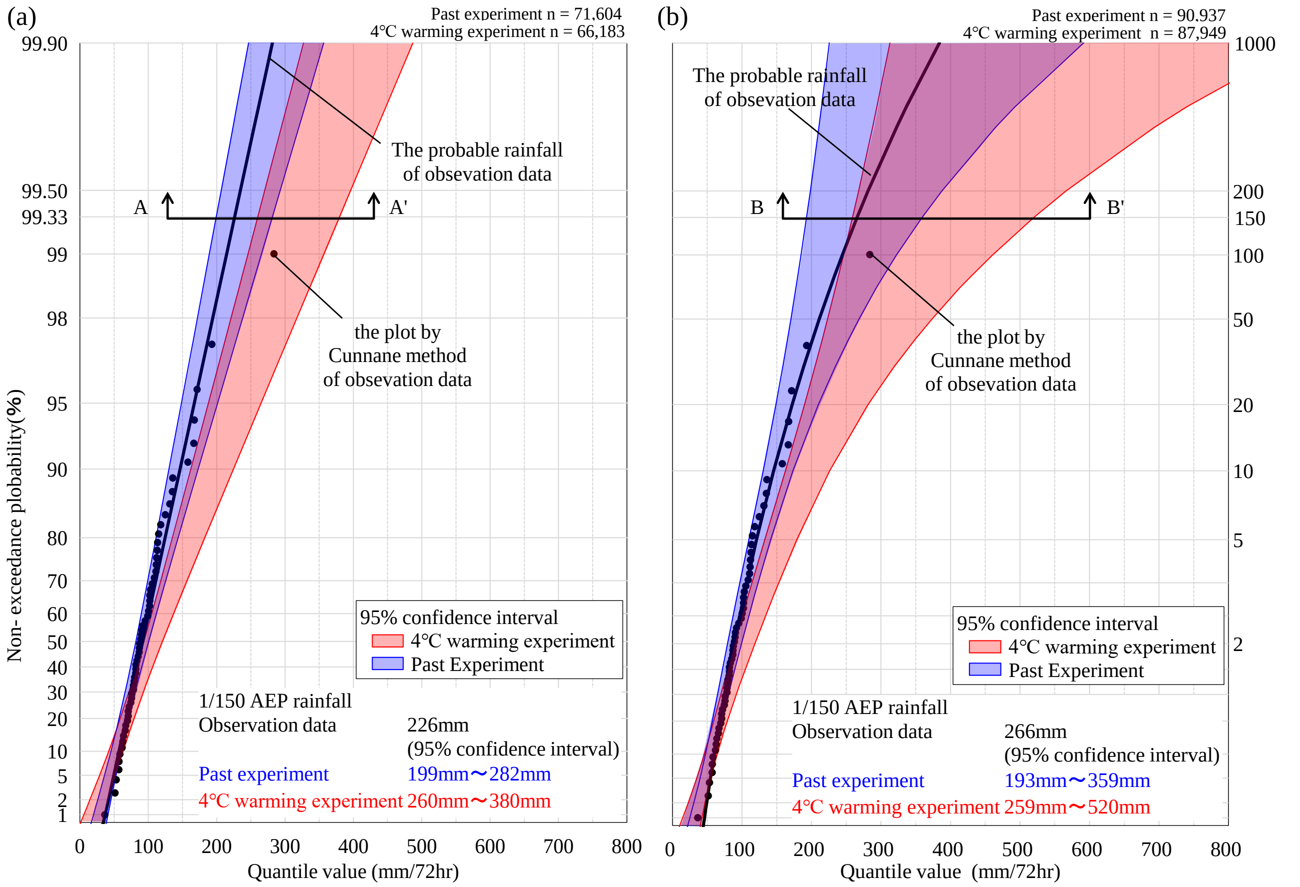

Figure 6. Estimation of probable rainfall in the case of the past and the future experiments by using a resampling method
(a: left) the Gumbel distribution, (b: right) the GEV distribution

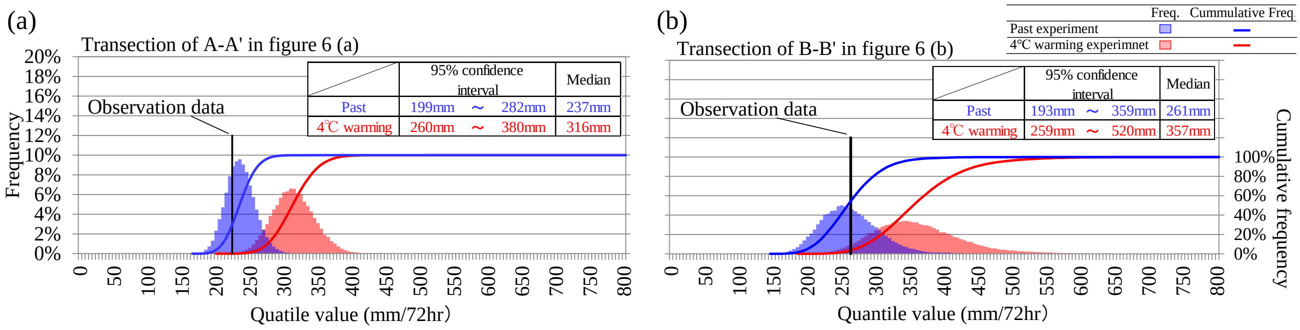

Figure 7. Frequency distribution of 1/150 AEP rainfall
(a: left) the Gumbel distribution, (b: right) the GEV distribution

3.1.2 Bias correction

Figure 3(b) show the relative frequency distribution of the annual maximum rainfall for the RCM5 data before and after bias correction. Table 1(b) shows the difference of the cumulative relative frequency from the actual rainfall before and after bias correction for each model. The cumulative relative frequency was calculated for each 10-mm class. The correction coefficient is close to 1.0 for both models in the target area. Specifically, the correction coefficients were a = 0.99 for the RCM5 data and a = 1.14 for the RCM20 data. This result showed that even the un-corrected data are able to closely reproduce the frequency distribution of the actual rainfall. In the RCM20 data, the difference of the cumulative relative frequency from the actual rainfall decreased from an average of 8 points to an average of 2 points after bias correction. These results confirmed that the bias correction improved the reproducibility of the frequency distribution for the actual rainfall.
In addition, this study applied a simple method in which the correction formula has one coefficient. Consequently, it is possible that some classes of rainfall were not corrected, because the coefficient a is uniformly multiplied by the model value. From the RCM5 data in Table 1(b), it was not confirmed that the correction formula removed the difference in cumulative relative frequency from the actual rainfall in some classes of rainfall. In cases when the frequency of actual rainfall deviates remarkably for a part of the class and the difference in cumulative relative frequency from the model value is large, correction of the relational formula in this study has a limit. Therefore, attention should be given to the application of this method, because a deviation of the frequency distribution is likely to occur in watersheds with limited observed rainfall datapoints.

3.2 Uncertainty of rainfall

3.2.1 *Case 1: 50 ensembles*

Figure 4 (a) and (b) shows the result of the case that estimated the probable rainfall each ensemble members at past experiments. The evaluation by SLSC excluded total 12 cases in the case of the Gumbel distribution, and total 3 cases in the case of the GEV distribution from 50 ensemble patterns. The SLSC of these cases were above 0.04. The range of the 1/150 annual exceedance probability (AEP) is between 183 and 286mm/72hr in the case of the Gumbel distribution and 180 and 416mm/72hr in the case of the GEV distribution. The 1/150 AEP of the observation rainfall is 226mm/72hr in the case of the Gumbel distribution and 266mm/72hr in the case of the GEV distribution.
Figure 5 (a) and (b) shows the distribution of 1/150 AEP from 50 ensemble patterns. In the estimation of the probable rainfall for each ensemble members, it confirmed the unevenness of the distribution.

3.2.2 *Case2: Resampling*

To make it easier to visually compare the range of probable rainfall in the past experiments to that in the 4 °C warming experiments, we calculated the frequency distribution of probable rainfall by using a resampling method. Figure 6 (a) and (b) show the results for the case in which the probable rainfall was estimated for each sample in the past climate and future climate experiments. The case in which the SLSC exceeded 0.04 in the probability evaluation for 100,000 samples was excluded in the preparation of probable rainfall distribution. The range of the 1/150 AEP is between 199 and 282mm/72hr in the case of the Gumbel distribution and between 193 and 359mm/72hr in the case of the GEV distribution. The 1/150 AEP of the observed rainfall is 226mm/72hr in the case of the Gumbel distribution and 266mm/72hr in the case of the GEV distribution. For both the Gumbel distribution and the GEV distribution, the range of the AEP from the climate model included the AEP from the observation data. The result shows that this climate model closely reproduces the observation data for the roughly 60 years of available data.
Regarding the median value and the 95% confidence interval, the distribution of probable rainfall from the probability evaluation of ensemble members and the distribution of the probable rainfall from samples prepared by using the resampling method roughly coincide with each other (Figure 5 (a), (b)). Therefore, in estimating the change of the probable rainfall in the 4°C warming experiments, we applied the resampling method.

3.3 Change of probable rainfall in future climate

For past experiments and 4 ° C warming experiments, the distribution of probable rainfall of 100,000 samples made by resampling was compared. The 95% confidence interval of the Gumbel distribution became 199–282mm per 72 hours in the past experiment and 260–380mm/72hr in the 4°C warming experiment, when 1/150 probable rainfall (Figure 6 (a), (b)) at the Obihiro observation site was observed. Median values of the past experiment and the 4°C warming experiment were 237mm/72hr and 316mm/72hr (Figure 7 (a), (b)), respectively, and the values for the 4°C warming experiment were about 1.33 times as great as those of the past experiment. In contrast, the 95% confidence interval of the GEV distribution was 193–359mm/72hr in the past experiment and 259–520mm/72hr in the 4°C warming experiment. Median values of the past experiment and the 4°C warming experiment were 261mm/72hr and 357mm/72hr, respectively, and the values in the 4°C warming experiment were about 1.37 times as large as those in the past experiment.

4. DISCUSSION

The range of probable rainfall as determined by the resampling method showed the difference from sample to sample. These differences occur as a result of initial conditions and boundary conditions such as SST. Thus it is possible to regard this range as the potential value of probable rainfall when weather periods of about 60 years were repeated many times. In this study, the range of the AEP from past experiment models included the AEP from the observation data. Not only does this result show that the climate model has good reproducibility, but it also shows that it is possible that the probable rainfall from observations has become large or small. We would like to emphasize that the past observations are just some of the many possibilities that could have occurred. Therefore, when flood control plans are developed in the future, we need to take into account the uncertainty of the observation data.
Gumbel and GEV differ in terms of the number of parameters. The Gumbel distribution has two parameters, whereas the GEV distribution has three parameters. Thus, in the GEV distribution, the extreme distribution model better fit the extreme values contained in the sample. For this reason, the 95% confidence interval of the GEV distribution is wider than that of the Gumbel distribution. This result indicates that the selection of the extreme distribution model makes a big difference in flood control planning.
When we compare the results of the past experiment to those of the 4 °C warming experiment, we find that the distribution of probability rainfall of the same scale overlaps in both probability distributions. It is indicated that rainfall events that are expected to occur in the future climate may well occur in the current climate. In addition,

when developing future flood control plans, there are various methods of setting the planned rainfall from the range of the probable rainfall. For instance, policy-makers consider the uncertainty as risk, and they can select the maximum or median, etc. within the range of the probable rainfall as the target. In this regard, our approach that indicate the width of probable rainfall will contribute to the development of flood control plans.

5. CONCLUSIONS

In this study, to assist in the development of flood control plans considering climate change, this paper presented an evaluation method for probable rainfall considering uncertainty based on massive ensemble climate projection data and used the method to determine the change of probable rainfall under the future climate.
The main results of this study are listed below.

1. It was confirmed that downscaling to RCM5 achieved greater reproducibility of the observation rainfall. In addition, it was confirmed that RCM5 after downscaling includes cases of low-frequency and high-intensity rainfall.
2. The range of the probable rainfall calculated from the past experiment model included the probable rainfall calculated from the observation rainfall.
3. The median value of 1/150 annual exceedance probability rainfall in the Obihiro-upper basin of the Tokachi River in the 4℃ warming experiment is about 1.33 times that of the past experiment in the Gumbel distribution and about 1.37 times that of the past experiment in the GEV distribution.
4. By showing the possible range of the probable rainfall, it becomes possible to select the target of rainfall considering both the current climate and the future climate after warming of 4℃.

ACKNOWLEDGMENTS

This study used the d4PDF provided by Ministry of Education, Culture, Sports, Science and Technology and the Climate Change Risk Information Creation Program. The annual maximum basin average rainfall used in the analysis was obtained by using the Earth Simulator in 2017 with the support of the Earth Simulator Special Promotion program and the SI-CAT (Social Implementation Program on Climate Change Adaptation Technology). Here we express our gratitude.

REFERENCES

IPCC (2014). Summary for Policymakers. *In Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge, UK, pp. 3–29.

Kitano, T., Takahashi, R. and Tanaka, S. (2017). Comprehensible estimation of return levels of extreme precipitation in utilizing numerous ensemble members produced by climate model. *Journal of JSCE. Ser. B1, Hydraulic engineering*, No. 73 (4), pp. I_1–I_6, in Japanese with English abstract.

Meteorological Research Institute (MRI). (2015). Projection of Future Climate Change around Japan by using MRI Non-hydrostatic Regional Climate Model. Technical reports of the MRI, No. 73, in Japanese with English abstract.

Mizuta, R., Murata, A., Ishii, M., Shiogama, H., Hibino, K., Mori, N., Arakawa, O., Imada, Y., Yoshida, K., Aoyagi, T., Kawase, H., Mori, M., Okada, Y., Shimura, T., Nagatomo, T., Ikeda, M., Endo, H., Nosaka, M., Arai, M., Takahashi, C., Tanaka, K., Takemi, T., Tachikawa, Y., Temur, K., Kamae, Y., Watanabe, M., Sasaki, H., Kitoh, A., Takayabu, I., Nakakita, E. and Kimoto. M. (2017). Over 5000 years of ensemble future climate simulations by 60 km global and 20 km regional atmospheric models. *American Meteorological Society*, pp. 1383–1398.

Piani, C., Haerter, J. O. and Coppola, E. (2010). Statistical bias correction for daily precipitation in regional climate models over Europe. Theoretical & Applied Climatology, vol.99, pp. 187–192.

Sasaki, H., Murata, A., Hanafusa, M., Oh'izumi, M. and Kurihara, K. (2011). Reproducibility of present climate in a non-hydrostatic regional climate model nested within an atmosphere general circulation model, *SOLA*, vol.7, pp. 173–176.

Tachikawa, Y., Miyawaki, K., Tanaka, T., Kazuaki, Y., Ichikawa, Y. and Kim, S. (2017). Analysis of annual maximum river discharge distribution under climate change using d4PDF. *Proceedings of the Annual Meeting of Japan Society of Hydrology and Water Resource*, No. 30, pp. 56–57, in Japanese.

Takara, K. and Takasao, T. (1988). Criteria for evaluating probability distribution models in hydrologic frequency analysis. Proceedings of JSCE, No. 393, II-9, pp. 151–60, in Japanese with English abstract.

Tanaka, S. (2017). Frequency analysis of extreme precipitation in the Tone river basin using "d4PDF". *DPRI Annual*, No. 60 B, pp. 757–764, in Japanese with English abstract.

The Hokkaido Government and the Hokkaido Regional Development Bureau of the MLIT. (2018). Summary of the committee. *The Technical Review Committee Report on Climate Change Projections (water field) in Hokkaido Region*, in Japanese. (https://www.hkd.mlit.go.jp/ky/kn/kawa_kei/splaat000000vdyw-att/splaat0000019r1f.pdf)

Yamada, T., Hoshino, T., Masuya, S., Uemura, F., Yoshida, T., Omura, N., Yamamoto, T., Chiba, M., Tomura, S., Tokioka, S., Sasaki, H., Hamada, Y. and Nakatsugawa, M. (2018). The influence of climate change on flood risk in Hokkaido. *Advances in river engineering*, Vol. 24, pp. 391–396, in Japanese with English abstract.