

Review:

# Assessing Climate Change Impact on Water Resources in the Tone River Basin, Japan, Using Super-High-Resolution Atmospheric Model Output

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[Received October 6, 2008; accepted January 5, 2009]

We examined the potential impact of climate change on Tokyo metropolitan water resources in the Tone River basin using output from a super-high-resolution global atmospheric general circulation model, AGCM20, having 20-km spatial resolution and 1-hour temporal resolution. AGCM20 is run on the Earth Simulator and being developed under the Japanese government's Kakushin21 program. AGCM20 has an advantage in simulating orographic rainfall and frontal rain bands, so we used its output to analyze Tone River basin water resources. The basin covers 16,840 km<sup>2</sup> and the main channel is 322 km long from its source to the Pacific Ocean. AGCM20 outputs hourly precipitation and daily variables such as snowfall, rainfall, snowmelt, evaporation, and transpiration for a present period, 1979-1998, and a projected period, 2075-2094. A comparison of these two periods showed that snow-related variables will decrease and all others will increase. Based on a comparison of ordered daily precipitation curves (ODPC) between AGCM20 and the Automated Meteorological Data Acquisition System (AMeDAS), a high-resolution Japan Meteorological Agency (JMA) surface observation network, we corrected AGCM20 precipitation data bias, and calculated the standardized precipitation index (SPI) drought indicator. The SPI for less than 6 months does not show noticeable variations under climate change, but the yearly SPI predicts more frequent dry conditions, indicating increased future vulnerability to subtle droughts.

**Keywords:** climate change, AGCM20, SPI, water resources, Tone River Basin

## 1. Introduction

Intergovernmental Panel on Climate Change (IPCC) Assessment Report 4 (AR4) states that globally averaged temperatures have apparently increased since the mid 20<sup>th</sup>

century [1], which is assumed due mainly to human activities such as fossil fuel burning and deforestation. Anthropogenic warming is thus believed to influence many of the Earth's physical and biological systems [2]. Unequivocal climate change thus brings us to a point where we must clarify its potential impact on society and nature.

Climate change is expected to strongly affect the hydrologic cycle in coming decades [3, 4]. Long-term changes in water resources depend mainly on the amount of precipitation and evapotranspiration (the sum of evaporation and plant transpiration from the earth's land surface into the atmosphere) [5]. Many researchers suggest that climate change accelerates water cycles with more precipitation and increased evapotranspiration, limiting freshwater resources less in the next century [6, 7], but increased precipitation does not necessarily mean sustainable water resources because less frequent but heavier precipitation may lead to extremely dry periods [8]. Under future climate conditions, the risk of water problems may remain or even increase due to variations in seasonal patterns and increased numbers of extreme events. In areas dominated by snow, seasonal variations in water resources due to climate change become more apparent [9]. A warmer world will mean less snowfall in winter and earlier snow melting in spring, shifting much surface runoff to earlier seasons [10, 11].

Future water supply conditions, especially for fresh water, are difficult to assess due to rapid and uncertain changes in society [12]. Domestic and industrial water demand is mainly determined by the population and its water use. As the urban population increases, fresh water must be drawn increasingly from distant watersheds as local surface and groundwater sources cease to meet water demand for water or become depleted or polluted. Obtaining additional water resources invariably requires time to prepare required equipment and facilities, and rapidly changing climatic and environmental conditions demand that urban and national water supply conditions be monitored regularly and comprehensively.

Heavily populated Tokyo is no exception. De-

spite Japan's abundant average annual precipitation of 1,690 mm/year, which is twice the global average of 807 mm/year, the water supply's seasonal nature – over 70% of rain falls from May to September, and Japan's high population density – 338 person/km<sup>2</sup> – prevent the water supply from being sustainable [13]. Water allocation in Japan is only about 3,230 m<sup>3</sup>/person/year – half of the world average of 8,559 m<sup>3</sup>/person/year. Given Tokyo's population density of 13,416 person/km<sup>2</sup>, the already critical nature of the area's water resources becomes apparent.

Over 75% of all Tokyo area water comes from the Tone River northeast of the city [14], with annual snowfall in the upper river basin one of the major sources at over half of annual precipitation. We studied the potential impact of climate change on the Tone River basin, particularly Tokyo's water resources, using the output from a super-high-resolution global atmospheric general circulation model, AGCM20. This paper is organized as follows: Section 2 outlines AGCM20 and the study area. Section 3 analyzes model output checked versus AMeDAS observation data. Section 4 assesses the water resource problem using a standardized precipitation drought index, and presents results and a brief discussion. Section 5 summarizes conclusions.

## 2. Data and Study Area

### 2.1. Super-High-Resolution Atmospheric Model

Climate condition projections use numerical models to simulate global atmospheric and oceanic circulation. The rapid evolution of these general circulation models (GCMs) in the last three decades was enabled by increased in computer capacity and a better understanding of natural phenomena correspondingly improving model complexity, e.g., spatial resolution in model operation. Climate models used in the First Assessment Reports (1990) of the Intergovernmental Panel on Climate Change (IPCC) [15] were run at a coarse resolution using a 500 km × 500 km grid for the most detailed horizontal resolution. Models in Assessment Report 4 (AR4) (2007) [1] were run at a 100 km × 100 km grid in the most detailed resolution.

Despite such improvements, the GCM spatial operating scale remains hydrologically coarse, and GCM output averaged for each grid cell makes it difficult to use GCM output, as is, in regionalized water resource problems. Expecting sophisticated terrain effects on hydrologic variables, such as precipitation and evapotranspiration, from such data is not always reasonable, either. To bridge the spatial resolution gap between GCMs and hydrologic use, hydrologists often physically or stochastically downscale GCM output.

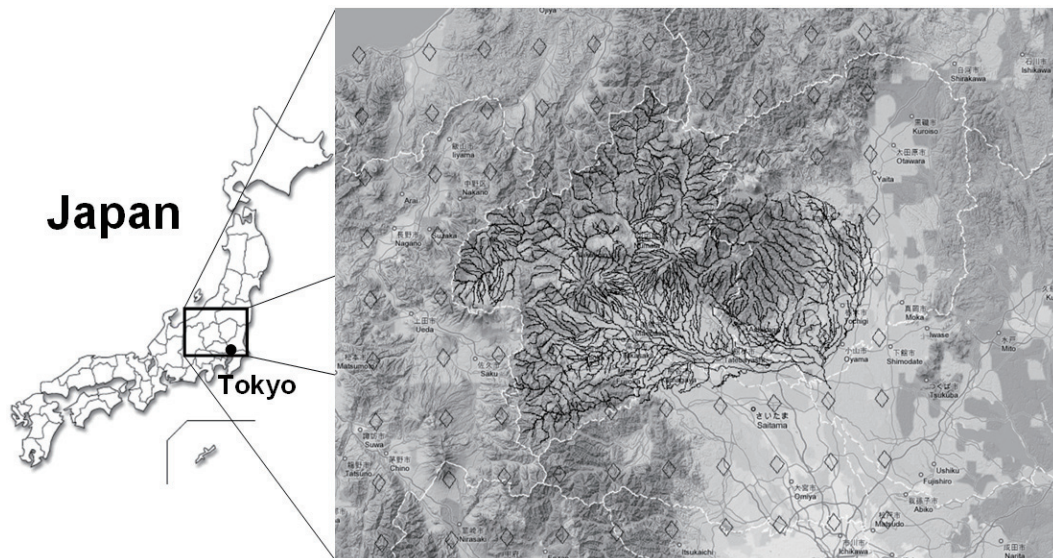
In 2007, Japan's Ministry of Education, Culture, Sports, Science, and Technology (MEXT) launched the Innovative Program of Climate Change Projection for the 21<sup>st</sup> Century (Kakushin21) to develop AGCM20, a very-

high-resolution atmospheric model having 20-km spatial and 1-hour temporal resolution. After several test simulations, AGCM20 showed advantages in simulating orographic rainfall and frontal rain bands [16]. Due to the spatial scale of frontal rain bands and the difficulty of simulating physical tropical cyclone behavior using conventional GCMs, a high-spatial-resolution model was required to simulate extreme precipitation more accurately and to project trends based on climate change. AGCM20 has the advantages of avoiding conventional problems on a spatial scale, not requiring further regional downscaling using a regional climate model or statistical downscaling. The 20-km spatial resolution was considered for investigating water resource problem in major Japanese river basins.

The hydrologic data we used is output by AGCM20, run on the Earth Simulator, a parallel-vector supercomputer. Working with the Meteorological Research Institute (MRI), Japan, the Japan Meteorological Agency (JMA) developed a next-generation global atmospheric model prototype for climate simulation and weather prediction [17]. The resulting model conducts simulation using triangular truncation at wave number 959 with a linear Gaussian grid (TL959) in the horizontal based on 1920 × 960 grid cells about 20 km in size and 60 levels in the vertical.

AGCM20 uses the HadISST1 dataset [18] as observed monthly mean climatologic sea surface temperature (SST) for a boundary condition of controlled simulation. HadISST1 provides global sea ice and sea surface temperature (GISST) datasets from 1871 uniquely combining monthly, globally complete fields of SST and sea ice concentration on a 1° latitude × 1° longitude grid [18]. SST projected for simulation was estimated from the ensemble mean of GCM simulation output under the A1B emission scenario [19] from the model output of the Coupled Model Intercomparison Project Phase 3 (CMIP3) [20]. According to the A1B scenario of the Special Report on Emissions Scenarios (SRES) [19], IPCC, the global average temperature is expected to increase 2.5°C and the CO<sub>2</sub> concentration to become 720 ppm by 2100. Under these conditions, the daily mean temperature average for Japan will increase up to +4.4°C by the end of this century. The ensemble mean of SST for AGCM20 projection simulation was additionally composed with an annual variation of the current HadISST1 SST to make the estimation more realistic.

AGCM20 output data is mainly related to hydrologic variables, such as rainfall, snowfall, evaporation, and transpiration. The model provides present output (1979-1998) and future output (2075-2094), which we analyzed for each term to determine any considerable change in or effect on water resource problems. The data is test-run output of AGCM20 provided in 2008. (Refer to Mizuta et al. (2006) [16] and Kitoh and Kusunoki (2007) [17] for details on AGCM20 and Kusunoki and Mizuta (2008) [21] for simulation environment details.)



**Fig. 1.** Tone River basin and Tokyo metropolis (left). Lines at right represent the channel network of the upper Kurihashi gauging station (8,772 km<sup>2</sup>). Diamonds represent corresponding AGCM20 output grid points.

**Table 1.** AGCM20 Hydrologic Variables.

Variable	Description	Time Resolution
<i>precipi</i>	Precipitation (rainfall and snowfall)	Hourly
<i>prcsn</i>	Snowfall from atmosphere	Daily
<i>prcsl</i>	Rainfall reaching soil layer (throughfall)	Daily
<i>sn2sl</i>	Snowmelt into soil layer	Daily
<i>evpsl</i>	Evaporation from soil layer	Daily
<i>trnsl</i>	Transpiration from soil root zone	Daily

## 2.2. Tone River Basin

The 16,840 km<sup>2</sup> Tone River basin northeast of Tokyo, Japan, [14] is the site of a 322 km river emptying into the Pacific Ocean. The basin population is about 12 million, and the basin itself covers half of Japan's capital, which has a population of about 24 million. About half of the basin is covered by forest (45.5%) and 30% of the land is used for farming (paddy field: 18.2%, cropland: 11.2%). Residential districts account for 6.4% of land use and city use for 3.7%.

Japan's rather high amount of annual precipitation averages 1,690 mm/yr, with 1,380 mm/yr in the Tone River basin [13]. Tokyo's high population density, however, has severely compromised regional water resources. According to the Tokyo Metropolitan Government, Tokyo's population was 12.36 million – 10% of the nation's population – in September 2003. With an area of 2,187 km<sup>2</sup>, the overall population density is 565 persons/km<sup>2</sup>, and even denser in the city's 23 central wards. This means that 8.34 million people occupied 621 km<sup>2</sup> as of September 2003, making a population density of 13,416 persons/km<sup>2</sup>.

Up to the 1950s, Tokyo depended on the Tama River basin for its water supply, but its dependence on the Tone River basin increased as the city grew larger and denser. Today, 75% of all water and 88% of the Tokyo metropolitan domestic water supply come from the Tone River and

its tributaries. Eight dams control the upper Tone River and water produced from them – 6.5 million m<sup>3</sup>/day [14] – is sent to Tokyo through the Musashi Canal in the river's middle reaches. Our study area (**Fig. 1**) is the 8,772 km<sup>2</sup> northern basin, which covers the starting point of the Musashi Canal.

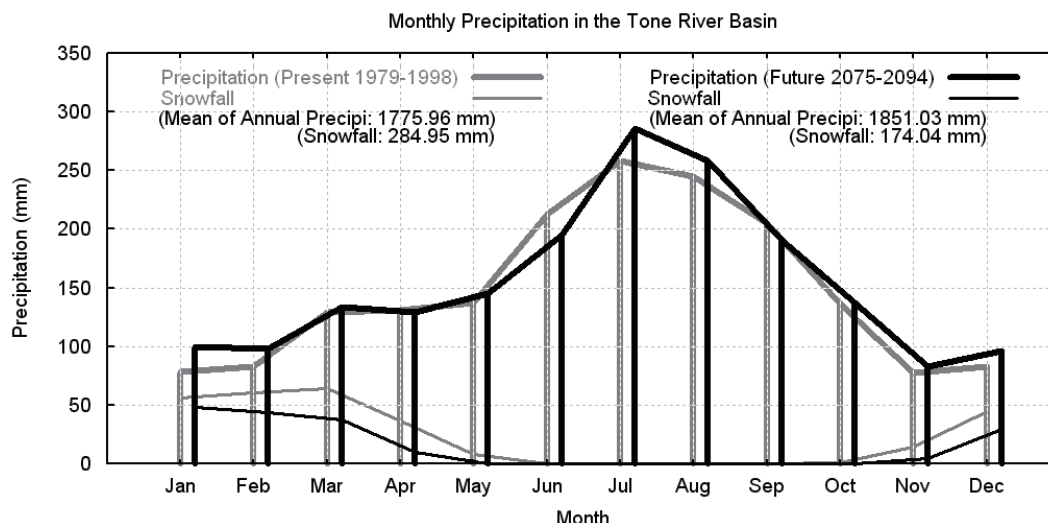
## 3. Atmospheric Model Output Analysis

### 3.1. Model Output Hydrologic Variables

AGCM20 hydrologic variables include precipitation data and other values related to soil moisture. Hourly precipitation data available from model output, together with daily snowfall data, is considered as pure rainfall and snowfall from the atmosphere (**Table 1**). Variable *prcsn* specifies rainfall reaching the soil (throughfall excluding other loss such as interception) and variable *sn2sl* snowmelt into the soil. Variable *evpsl* specifies evaporation and variable *trnsl* transpiration from the soil layer. (Evaporation and transpiration from the canopy are also considerable from AGCM20, but it is more straightforward to consider direct in- and outflow for the soil layer if water resources are the main concern.)

We compared *precipi* and *prcsn* for the present (1979-1998) and future (2075-2094) to determine the main effects of climate change. To compare these two sets of Tone River basin data, we prepared basin-averaged values by averaging 24 grids covering the entire basin (**Fig. 1**). Analyzed values are all basin-averaged.

Monthly variations in rainfall and snowfall precipitation were produced from a 20-year mean of individual months for the present and future (**Fig. 2**). According to AGCM20 simulation, future annual precipitation will increase slightly from 1,776 mm to 1,851 mm (4.2%), while snowfall will decrease significantly from 285 mm to 174 mm (38.9%). Climate change, which is mainly a temperature increase, appears to cause the decrease in



**Fig. 2.** Monthly rainfall and snowfall precipitation patterns in the Tone River basin, produced from the mean of 20 years for each present and future term.

**Table 2.** Changes in Tone River basin hydrologic variables (unit: mm/yr).

Variable	Present	Future	Change
1. <i>precipi</i>	1,776	1,851	+ 4.2 %
2. <i>prcsn</i>	285	174	- 38.9 %
3. <i>prcsl</i>	1,336	1,511	+ 13.1 %
4. <i>sn2sl</i>	269	168	- 37.8 %
5. <i>evpsl</i>	278	330	+ 18.9 %
6. <i>trnsl</i>	240	276	+ 14.8 %
Net <i>precipi</i> to soil (3+4-5-6)	1,087	1,073	- 1.3 %

snowfall. Winter rainfall, however, increases in the future, and total Tone River basin precipitation shows a slight increase.

Future increased annual precipitation and decreased winter snowfall are also shown by output from the regional climate model (RCM20) [22] of JMA and MRI. Fujihara et al. (2008) [23], in analyzing RCM20 output, showed that annual Tone River basin precipitation will increase about 200 mm at the end of this century. Wada et al. (2005) [24], also analyzing RCM20 output to assess nationwide flood and drought risk, showed that winter and spring precipitation will decrease in the future for most of Japan, while extreme daily precipitation will increase in some parts of northern Japan. RCM20 output is based on the IPCC SRES A2 scenario [22], which assumes a more apparent temperature increase by 2100 than the A1B scenario [19].

Other AGCM20 output variables (**Table 2**) indicated a dramatic increase in evaporation – 18.9% – and transpiration – 14.8% – and an approximate 100 mm/yr additional loss from available water resources. In effect, future net precipitation shows a 13.1% decrease in AGCM20 simulation.

Briefly, then, total present precipitation data has slightly larger values than historical observations in the Tone River basin. As stated, annual Tone River precipitation is 1,380 mm/yr – but shown by model output from

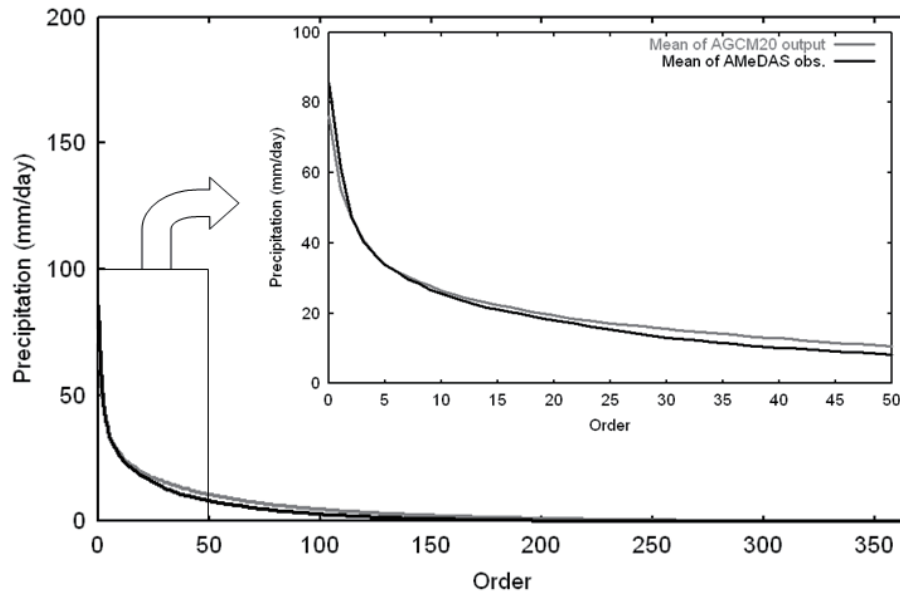
controlled simulation for the present to be 1,776 mm/yr, which is a considerable overestimation. It thus appears necessary to check controlled simulation reproducibility more carefully. Using AMeDAS observation data for the present (1979-1998), we compared AGCM20 output to observation, especially for precipitation, as detailed below.

### 3.2. Precipitation Data Reproducibility

Despite much improved technology and computerization, models still do not provide realistic simulation because resolving all-important spatial and time scales remains far beyond current capabilities. Given this, we verified AGCM20 controlled simulation reproducibility, which becomes acceptable if comparable to historical precipitation, snow, and evaporation observation. Any critical bias between AGCM20 output and historic observation requires correction or modification of original data to eliminate the bias both in controlled simulation output and in projection simulation output, also considered for further analysis and use.

Precipitation data for the present (1979-1998) comes from AMeDAS observations at over 30 stations around the Tone River basin. Since data is point-gauged, AMeDAS data must be converted to the same 20-km grid-based data format as AGCM20 output using an inverse-distance weighting factor. A comparison of AGCM20 precipitation output and grid-based converted AMeDAS precipitation data showed that AGCM20 output data has larger precipitation than that observed. Basin-averaged annual precipitation for the last two decades (1979-1998) shows a significant discrepancy of 1,776 mm from AGCM20 and 1,416 mm from AMeDAS observation – a 25.4% overestimation. Annual daily maximums from AGCM20 are, however, lower than maximum historical observations.

To understand this difference, we sorted daily precipitation for each year by amount and plotted it (**Fig. 3**). Ordered daily precipitation curves (ODPC) of AMeDAS



**Fig. 3.** Ordered daily precipitation curves (ODPC) from AMeDAS data and AGCM20 output. Black line: AMeDAS ODPC mean. Gray line: AGCM20 ODPC mean.

and AGCM20 output mostly overlap, but the mean of each order's daily precipitation shows a clear difference in the two datasets (bold solid lines; black: mean AMeDAS observation ODPC; gray: mean AGCM20 output ODPC).

AGCM20 simulation precipitation output has lower values for higher-level rainfall of over 40 mm/day and higher values for lower-level amounts of less than 40 mm/day compared to AMeDAS observation. The slight overestimation for lower-level AGCM20 rainfall results in the significantly overestimated annual precipitation. The considerable AGCM20 output bias must be corrected or decreased before data can be considered in further analysis, as detailed below.

### 3.3. AGCM20 Bias Correction

Bias correction of GCM output is subtle. Even though critical bias in model output must be corrected, this cannot be done arbitrarily as simulation output from a physically-based atmospheric model. Model output consists of results from dynamic reactions among many physically related state variables in a complex model, of which precipitation is just one state value among many.

We attempted to correct AGCM20 precipitation output bias by adjusting ranked daily precipitation amounts of model output to ranked historical values – so-called “daily scaling” – used in research such as the studies of Chiew (2003) [25], Harrold and Jones (2003) [26], and Kiem et al. (2008) [27]. This bias correction deals with daily variant scaling factors, or scaling ratios, based on ODPC information. Through this procedure, AGCM20 precipitation output for annual volume and daily maximum matched historic observation values. When we consider each order's precipitation values from both observation and model output, the procedure enables consideration of two sets of histograms from datasets, e.g., a pair

of histograms of the first annual maximum, second maximum, third, etc., of observation and output. Although the histograms would be shaped differently, we could correct the first and second moments of each dataset from model output to match the moments of the observation dataset.

Let  $x_1$  then be original AGCM20 output values having first and second moments as  $\mu_1$ ,  $\sigma_1$ , and  $x_2$  is the modified value, which has the first and second moments of AMeDAS observation,  $\mu_2$  and  $\sigma_2$ . Assuming that these two datasets are distributed normally, these values can be related by standardizing the distribution:

$$\frac{x_1 - \mu_1}{\sigma_1} = \frac{x_2 - \mu_2}{\sigma_2} \quad \dots \quad (1)$$

Eq. (1) is rewritten for  $x_2$ :

$$x_2 = \frac{\sigma_2}{\sigma_1} (x_1 - \mu_1) + \mu_2 \quad \dots \quad (2)$$

or

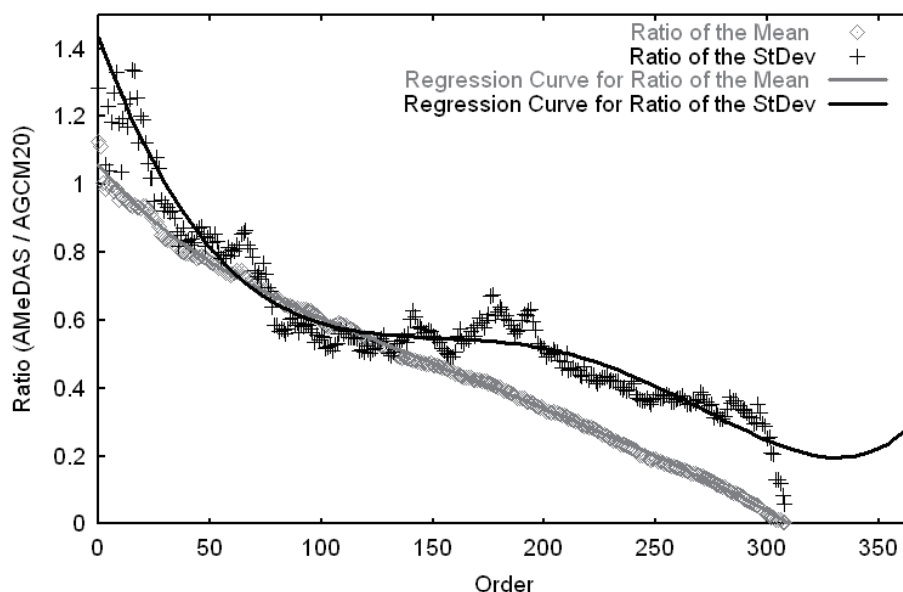
$$x_2 = r_\sigma (x_1 - \mu_1) + r_\mu \mu_1 \quad \dots \quad (3)$$

where  $r_\mu = \mu_2/\mu_1$  and  $r_\sigma = \sigma_2/\sigma_1$ .

Original value  $x_1$  can be AGCM20 output for the present and future. Ratios of first moment values,  $r_\mu$ , and second moment values,  $r_\sigma$ , are acceptable from AGCM20 output for the present and AMeDAS observation. This means that model output for the present is corrected to have the same values as the observation's first and second moments, and model output for the future is corrected with the same proportion of present term correction using ratios  $r_\mu$  and  $r_\sigma$ .

For the ratio of each order's first moment of observation to present output (diamonds) and the ratio of each order's second moment (crosses) (Fig. 4; gray line: ODPC mean regression curve; black: ODPC standard deviation), regression curve equations are calculated with a





**Fig. 4.** Ratio of ODPC mean (diamonds: mean of ordered daily precipitation curves) and ratio of ODPC standard deviation (crosses). Gray line: Regression curves of ODPC mean. Black line: Regression curves of ODPC standard deviation.

**Table 3.** Regression function constant values and root mean square error (RMSE).

Constant	$r_{\mu}$	$r_{\sigma}$
<i>A</i>	$-8.0065 \times 10^{-13}$	$9.7844 \times 10^{-13}$
<i>B</i>	$7.6117 \times 10^{-10}$	$-1.9023 \times 10^{-10}$
<i>C</i>	$-2.9278 \times 10^{-7}$	$-2.9095 \times 10^{-7}$
<i>D</i>	$5.5698 \times 10^{-5}$	$1.2427 \times 10^{-4}$
<i>E</i>	$-7.8169 \times 10^{-3}$	$-1.7841 \times 10^{-2}$
<i>F</i>	1.0564	1.4331
Regression RMSE	0.99999	0.98888

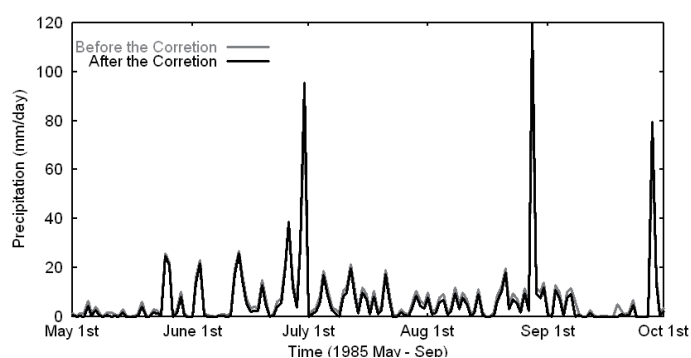
five-ordered polynomial:

$$f(r) = ax^5 + bx^4 + cx^3 + dx^2 + ex + f \dots (4)$$

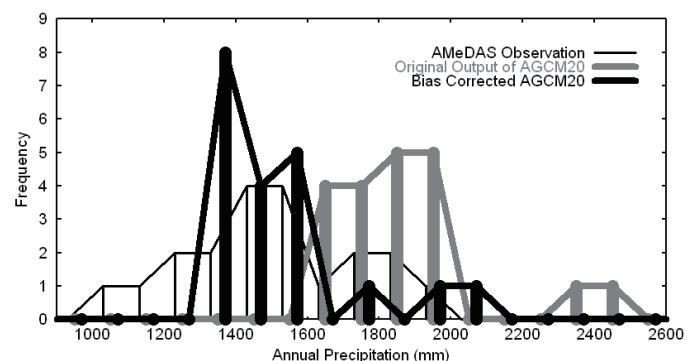
Constant values for the mean ratio and standard deviation ratio are shown in **Table 3** with regression root mean square error.

In one example of bias correction results (**Fig. 5**) for daily precipitation before and after bias correction from May to September 1985, the low amount of precipitation, which is less than 40 mm/day, shows a decreased amount after correction and a high amount of precipitation has a higher amount than original values. Bias correction using ordered daily precipitation values does not disturb the original time series of precipitation and provides a way to simultaneously modify annual precipitation and annual maximum values.

Histograms of annual precipitation produced by AMeDAS observation and AGCM20 output (**Fig. 6**) are distributed around 1,416 mm with a normal distribution pattern (black connected with thin lines). Before bias correction, annual AGCM20 output precipitation (gray) showed results significantly different from observation. After correction, considerable AGCM20 output bias was removed and the annual precipitation mean resembles that observed (black histogram, **Fig. 6**). The annual precipita-



**Fig. 5.** Results of bias correction from May to September 1985. Precipitation of  $\leq 40$  mm/hr decreased and precipitation  $> 40$  mm/hr increased.



**Fig. 6.** Histograms from AMeDAS observation (black), original AGCM20 output (dark gray), and bias-corrected AGCM20 output (dark black). After bias correction, AGCM20 output precipitation had the same annual mean as AMeDAS observation, 1,405 mm.

tion mean before correction was 1,776 mm and 1,405 mm after correction. The bias-corrected AGCM20 data histogram remains skewed and does not match the observation histogram exactly, which will require further consideration in future research.

## 4. Water Resources Condition Assessment by Drought Indicator

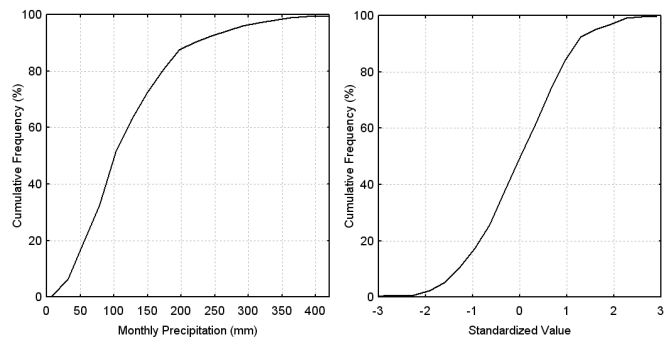
### 4.1. Standardized Precipitation Index

Most of the many indicators used to identify drought conditions, such as the Palmer drought severity index [28], crop moisture index [29], and surface water supply index [30], require multiple input data, including temperature, soil moisture, snow pack, and reservoir storage, in addition to precipitation data. McKee et al. (1993) [31] therefore introduced the standardized precipitation index (SPI) to assign a single numerical value to precipitation for assessing drought conditions. The SPI enables anomalously dry or wet periods to be determined on a particular time scale for any location having a precipitation record.

SPI calculation is based on the long-term precipitation record for a period, such as only for spring or a certain month, with calculation for multiple, mutually independent desired periods, freeing analysis from seasonal variation and/or characteristics of precipitation patterns for the particular location. For one-month time scale SPI analysis, for example, precipitation data for each month from January to December is pooled separately for 12 independent SPI calculations. The SPI is designed to quantify the precipitation deficit for multiple time scales, which reflect drought impact on different water resources. Soil moisture conditions respond to precipitation anomalies over a relatively short time (shorter than six months), whereas groundwater and reservoir storage reflect long precipitation anomalies (over six months). McKee et al. (1993) [31] calculated the SPI for 3-, 6-, 12-, 24-, and 48-month time scales.

Technically, the SPI is the number of standard deviations that the observed value would deviate from the long-term mean for a normally distributed random variable. Since precipitation is not normally distributed, the long-term record was first fitted to a probability distribution such as gamma distribution and then converted to a normal distribution so that the mean SPI for the location and desired period is zero [32]. Conversion is done by equiprobability transformation, which Panofsky and Brier (1958) [33] suggested was such that the probability of being less than a given value of the original distribution, e.g., gamma, would be the same as the probability of being less than the corresponding value of the converted distribution, e.g., standard normal. The cumulative monthly precipitation probability was converted to standard normal random variables with mean zero and a variance of one, which is the value of the SPI. Positive SPI values indicate greater than median precipitation, and negative less than median precipitation. Because the SPI is normalized, wetter and drier climates are represented the same way, and abnormal wet periods can also be monitored using the SPI.

Thanks to its simplicity and flexibility, SPI analysis has been widely accepted, e.g., Seiler et al., 2002 [34]; Min et al., 2003 [35]; Morid et al., 2006 [36]; and National Drought Mitigation Center, US [37]. Hayes et al. (1999) [38] showed how the SPI could be used for operational



**Fig. 7.** Cumulative frequency distribution curves with monthly precipitation data of present and future (left) and with standardized values for SPI analysis (right). Results are from one-month SPI.

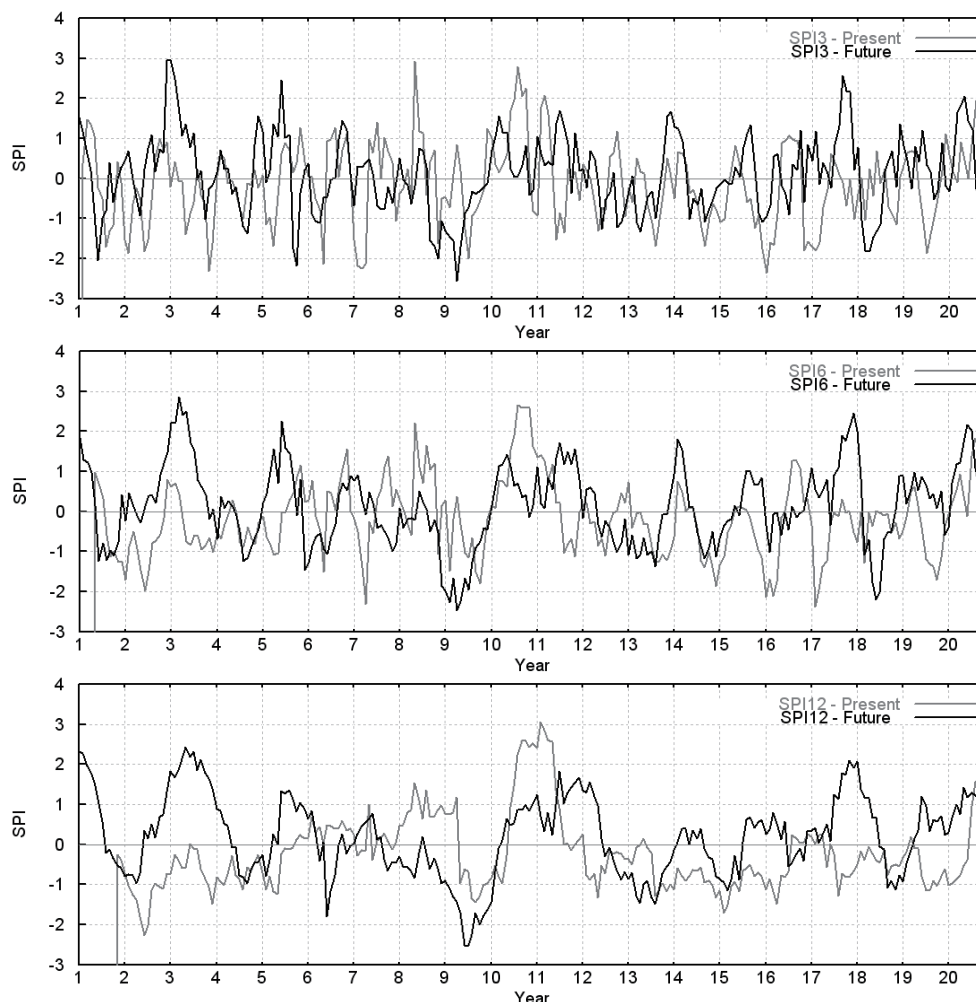
drought monitoring with varying time scales and it could identify drought in advance of other drought indexes. SPI analysis is thus useful both for checking drought conditions and for investigating abnormal wet conditions such as for flood risk monitoring [34].

### 4.2. SPI Analysis of AGCM20 Output

After bias correction for present and future AGCM20 output, we conducted more detailed analysis using the SPI to determine critical conditions through climate change in the future, first analyzing bias-corrected precipitation AGCM20 output, and then original AGCM20 output for the SPI. In both cases, AGCM20 output for present and future climate conditions was merged and regarded as one dataset both to investigate variability change in precipitation patterns under climate change and to observe overall pattern change. With 20 years of data for each present and future condition, the merged dataset covers 40 years of precipitation. McKee et al. (1993) [31] proposed over 30 years for SPI calculation, and Guttman (1994) [39] suggested 40-60 years for stable SPI parameter estimation. Since the SPI is probability-related, longer precipitation data records yield presumably more reliable results [40].

In converting SPI analysis with cumulative frequency distribution precipitation for present and future in cumulative frequency distribution curves, monthly Tone River basin precipitation is distributed from 0 to 400 mm and cumulative frequency for the median value, 200 mm, is 90% (**Fig. 7**). The example shows one-month precipitation data, but the same procedure can be applied to other time scales. Specifically, the SPI can be calculated for any month in the record or data for the previous  $n$  months, so the SPI for a certain month was calculated with an accumulated precipitation for the previous  $n$  months. To check water resource conditions for the Tone River basin, we calculated and analyzed the SPI for three (SPI-3), six (SPI-6), and 12 (SPI-12) months of the present (1979-1998) and future (2075-2094).

SPI-3, SPI-6, and SPI-12 results are about one century apart (**Fig. 8**). Even though annual future precipitation increases in rainfall compared to the present, the SPI of future data does not show wetter conditions. Positive SPI



**Fig. 8.** SPI analysis results with 3 months (top), 6 months (middle), and 12 months (bottom) of data for bias-corrected present and future AGCM20 output data.

**Table 4.** SPI and corresponding cumulative probability.

SPI	Cumulative Probability	SPI	Description
2.0	0.9772	$2.0 \leq$	Extremely Wet
1.5	0.9332	$1.5 \leq$	Very Wet
1.0	0.8413	$1.0 \leq$	Moderately Wet
0	0.500	$-1.0 \sim 1.0$	Normal
-1.0	0.1587	$\leq -1.0$	Moderately Dry
-1.5	0.0668	$\leq -1.5$	Very Dry
-2.0	0.0228	$\leq -2.0$	Extremely Dry

values indicate wet conditions and negative values indicate dry conditions, with larger magnitude proportional to the severity of the condition (Table 4). SPI values less than  $-1.5$  are regarded as severely dry and a value less than  $-2.0$  is extremely dry.

Table 5 shows the number of months exceeding severely wet ( $\geq 1.5$ ) and dry ( $\leq -1.5$ ) and extremely wet ( $\geq 2.0$ ) and dry ( $\leq -2.0$ ) conditions, calculated from modified AGCM20 output for the present and future. Short and intermediate SPI values show similar occurrence in the number of extreme conditions, but SPI12 values for assessing long-term water resource conditions show notable behavior. Even though future annual pre-

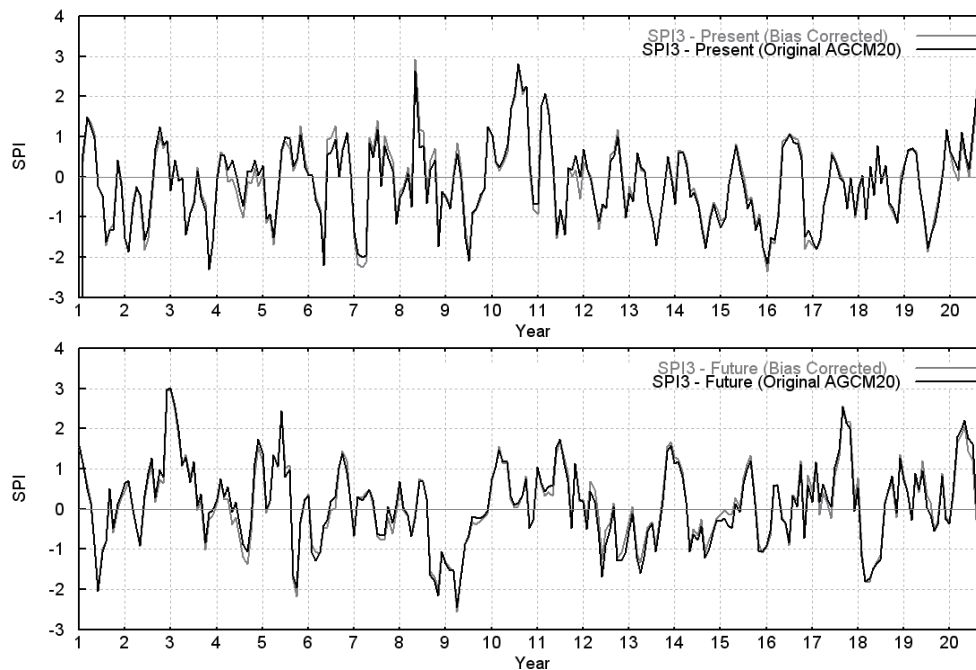
**Table 5.** Months exceeding severely (extremely) wet (dry) conditions.

Present		Wet	Future	
$2.0 \leq$	$1.5 \leq$		$1.5 \leq$	$2.0 \leq$
7	11	SPI-3	17	7
8	14	SPI-6	24	8
12	15	SPI-12	26	2
Present		Dry	Future	
$\leq -2.0$	$\leq -1.5$		$\leq -1.5$	$\leq -2.0$
5	28	SPI-3	11	4
6	13	SPI-6	11	3
2	4	SPI-12	9	5

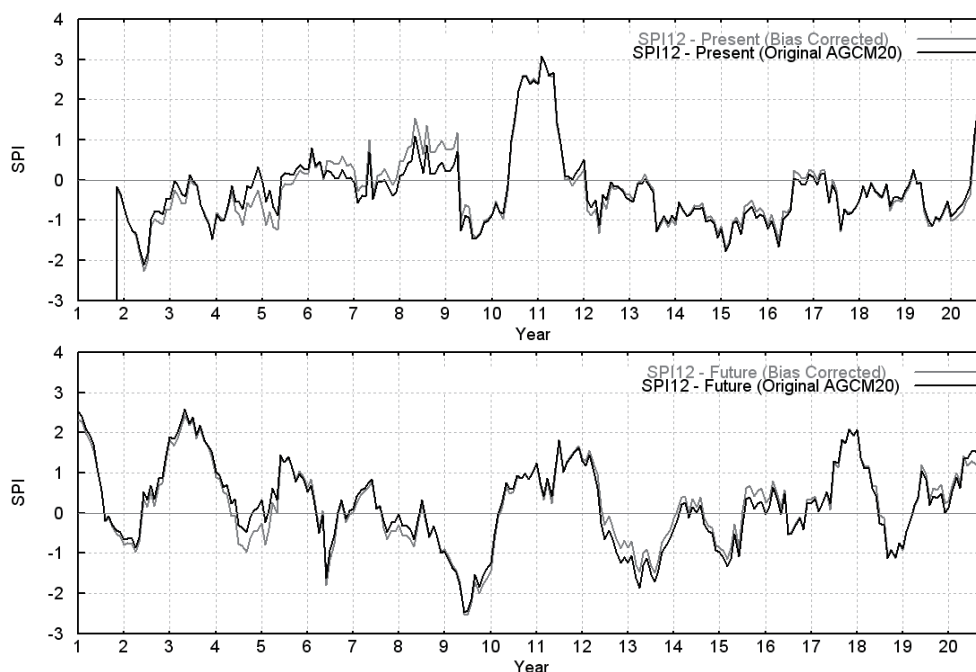
cipitation is increased compared to that for the present, SPI-12 shows more frequent dry conditions in the future. SPI analysis was done using precipitation data only, and does not consider other hydrologic variables related to water loss, evaporation, or transpiration. If these losses are considered in SPI analysis, results will be more apparent because net precipitation in the Tone River basin will decrease in the future according to AGCM20 output analysis.

To understand the effect of bias correction on AGCM20





**Fig. 9.** SPI analysis results for 3 months of present (up) and future (down) with bias-corrected and original AGCM20 output data.



**Fig. 10.** SPI analysis results for 12 months of present (up) and future (down) with bias-corrected and original AGCM20 output data.

precipitation output, we redid SPI analysis again with original AGCM20 precipitation output. Because bias correction is an additional modification to original model output, it is desirable that results from SPI analysis resemble original AGCM20 output (**Figs. 9** and **10**). As expected SPI-3 and SPI-12 results do not show significant differences before and after bias correction.

## 5. Conclusions

We have analyzed high-resolution atmospheric model AGCM20 output to determine potential water-related crises in the Tone River basin, the main domestic water source of metropolitan Tokyo, Japan. Some 75% of all water and 88% of Tokyo's water supply comes from this basin, which enjoys a rather high amount of annual precipitation. Tokyo's high population density, however, has

severely compromised its water resources.

We analyzed AGCM20 output for 1979-1998 and 2075-2094 to determine potential overall changes in the basin's water resources, finding that projected annual precipitation is expected to increase 4.2% together with a severely reduced 38.9% decrease in future snowfall. This decrease must be compensated for by increased rainfall season. AGCM20 simulation indicated that evaporation and transpiration would increase about 20% in the future.

AGCM20 precipitation output in controlled simulation showed some discrepancies from observed precipitation, such as a smaller daily maximum but a larger annual amount overestimated by 25.4%. Through bias correction using ODP, we removed the bias and corrected present and future AGCM20 output.

Based on corrected data, we conducted a more detailed analysis to determine potential changes in water resources using a drought indicator, the standardized precipitation index (SPI), calculated for a short term of three months (SPI-3), an intermediate term of six months (SPI-6), and a long term of 12 months (SPI-12). SPI-3 and SPI-6 showed a similar number of extreme conditions, but SPI-12 showed more frequent wet conditions for the present and more frequent dry conditions for the future – the opposite of behavior to the brief analysis with annual precipitation, since the future has more increased annual precipitation. Our SPI analysis used only precipitation data, without considering loss through evapotranspiration. Since net precipitation is predicted to decrease in the future, Tone River basin water resources should be more fully analyzed taking into account other hydrologic variables related to water resources.

## Acknowledgements

This work was done within the framework of the "Integrated assessment of climate change impact on watersheds in a disaster environment (PM: Prof. Eiichi Nakakita, DPRI, Kyoto University)" supported by the Kakushin Program of the Ministry of Education, Culture, Sports, Science and Technology of Japan (MEXT).

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