Assessment of the climate change risks for inflow into Sagami Dam reservoir using a hydrological model
Sho Momiyama, Masaki Sagehashi and Michihiro Akiba

ABSTRACT
Adverse effects of future climate change on water supply systems are of concern. High turbidity caused by abrupt flood, and drought caused by continuous dry days are the major risks. To assess such risks, a comprehensive method to simulate hydrology with high spatiotemporal resolution should be developed. In this study, a series of methods from parameter estimation to future simulation using the Soil and Water Assessment Tool (SWAT) was demonstrated for Sagami Dam reservoir, which is a typical water supply reservoir in Japan. A proposed parameter calibration method by optimizing percent bias followed by optimizing Nash–Sutcliffe efficiency gave good performance of model prediction of the daily average reservoir inflow in the past. Using this model, the changes in inflow under expected climate change were simulated. Three predicted daily climates by the Model for Interdisciplinary Research on Climate version 5 (MIROC5) under three representative concentration pathways, i.e., RCP 2.6, 4.5, and 8.5, in 2081–2100 were used for the simulation, whereas observed daily climate during 1981–2000 was used as the past reference. The risks were discussed by considering their seasonality, indicating increases in flood and drought in June and July, and in February and April, respectively.

Key words | climate change, flood and drought risk, Sagami Dam reservoir, SWAT model, water resource management

INTRODUCTION
The development of safe water supply systems has played an important role in the maintenance of public health all over the world. To continue this role, adequate long-term planning considering business continuity and rational countermeasures to maintain safety while taking environmental changes into consideration is essential. One of the most controversial topics discussed with regard to environmental change today is climate change, and the stress of climate change on the water supply is recognized in developed and developing countries (Sun et al. 2008).

Water Safety Plans (WSPs) (Davison et al. 2005) have been implemented worldwide to ensure safe drinking water through good water supply practices. The effects of climate change on WSPs have been discussed (GWP & UNICEF 2014; Staben et al. 2015). Along with Integrated Water Resource Management considered in the Sustainable Development Goals, the effects of climate change on water resources deserve careful attention.

Climate change is expected to have various impacts on the water supply. Among these changes, the adverse effects of extreme meteorological events, including increases in the concentrations of dissolved organic matter, micropollutants, and pathogens (Delpla et al. 2009), are a matter of some concern. On the other hand, although qualitative changes in boundary conditions due to climate change have become clear, their degree and impact on the water supply system are still unclear (Staben et al. 2015). Some limited effects, such as precipitation and temperature, on water quality
can be assessed by experiments. However, the complicated structure of the natural environment in a whole watershed makes it difficult to clarify the effects of climate change on raw water. Therefore, hydrological models should be employed to analyze the effects quantitatively.

The effects of climate change vary depending on the region as well as the structure of its water supply system. Fundamentally, the hydrological model should take into consideration the regional characteristics of water dynamics. Furthermore, the models should be designed to address issues required by researchers. Therefore, various modeling studies in various regions are required.

For maintenance of water quantity, many studies have been designed to predict the effects of climate change on the water supply, such as flooding and drought. Thomas et al. (2011) reported decreasing minimum flow during the summer months, especially in small catchments (less than 500 km²) that will be affected first by climate change. From the viewpoint of water supply business, drought is one of the phenomena of greatest concern, and some efforts have been implemented to reproduce low flow in hydrological models (Fujimura et al. 2014, 2015).

Hydrological events, such as flooding and drought, should be clarified locally for detailed analysis of the climate change adaptability of hydrological provisioning services, such as water supply. Detailed hydrological models that can simulate the effects of local meteorological events, such as heavy precipitation or continuous periods of no precipitation, predicted in the future should be used. In general, the prediction of future climate change is provided by General Climate Models or Global Circulation Models (GCMs). Mouri (2015) predicted the spatiotemporal variations of monthly fluvial wash-load sediment caused by climate change all over Japan divided into a 10-km mesh using four typical GCMs, i.e., the Model for Interdisciplinary Research on Climate (MIROC), the Meteorological Research Institute Atmospheric General Circulation Model (MRI-GCM), the Hadley Centre Global Environment Model (HadGEM), and the Geophysical Fluid Dynamics Laboratory (GFDL) climate model. Kotsuki et al. (2013) estimated the impact of climate change on water stress throughout Japan using a super high-resolution GCM (MRI-AGCM3.1S) by monthly-based calculation results. Sato et al. (2015) estimated the changes in monthly discharge of nine major rivers throughout Japan caused by climate change using a hydrological model (Hydro-BEAM) with reference to the output of MRI-AGCM3.2S.

Such GCM-based simulations are useful to assess the future risks of flooding and drought in water supply businesses. On the other hand, predictions with short time steps, such as daily prediction, are desirable to estimate high turbidity events caused by extreme floods, and extremely low water flow caused by continuous periods with little or no precipitation. Meanwhile, the changes in water availability, i.e., drought risk, should be discussed taking the season into consideration, because the total water demand usually changes significantly depending on the season. The predictive capability of the models should also be guaranteed not only for peak flows but also for base flow. Therefore, assessment of the effects of future climate change on water flow using GCM calculation results combined with a short time step distributed hydrological model is essential for water supply businesses. In other words, a systematic method to assess the drought and flood risk for water supply businesses using a hydrological model with high temporal resolution should be developed. Thus, throughout demonstration of the method, i.e., parameter calibration and validation of the hydrological model employed, the analysis of the model prediction uncertainty, simulation of future risk of drought and flood using future climate prediction as the input, and quantitative assessment of the risk, is described in this study. The target is the Sagami Dam reservoir watershed, which is a reservoir supplying raw water for water supply businesses in Kanagawa prefecture.

**STUDY AREA**

In this study, hydrological modeling of the Sagami Dam reservoir watershed (Figure 1) was implemented. This reservoir is located at the upper flow of the Sagami River, and was completed in the year 1947 to secure drinking, industrial, and agricultural water supplies, and power supply for Yokohama city, Kawasaki city, etc. Today, it stabilizes the river water flow, and contributes drinking water to more than eight million people (JWWA 2015) through Yokohama Waterworks and others.
METHODS

Hydrological model

The Soil Water Assessment Tool (SWAT) (Arnold et al. 2012) is one of the most widely used hydrological models in the world. SWAT is a semi-distributed parameter model that calculates the daily water discharge from a watershed. It was developed in the USA, where river flow is generally calm (Shimizu et al. 2012), and its adaptability should be confirmed by rational methods for its application to other countries. Many studies of climate effects on watershed hydrology using SWAT for Asian countries, including Japan, have been reported and some of them deal with the effects of climate variation. For example, Zang et al. (2015) reported the effect of climate variation on green and blue water provision at Heihe River Basin in China using SWAT over the past period. Fan & Shibata (2015) evaluated the effects of future climate change calculated by MIROC3.2-HI and land use changes predicted by the Conversion of Land Use and its Effect (CLUE) model on nitrogen and phosphorus wash-out in Teshio River. From the viewpoint of special attention for the quantification of flood and drought risks of the water supply business, Obonai et al. (2015) reported modeling of turbidity of river flow into the Kamafusa Dam reservoir under heavy precipitation using SWAT, and resultant changes in costs of a drinking water treatment process, which obtains raw water from the Kamafusa Dam reservoir. This simulation, however, only modified the intensity of heavy rain events observed in the past to calculate the effects, and did not employ the detailed prediction of future climate by GCM as an input.

Geographical data preparation

The altitude distribution of the watershed was calculated based on a 50-m resolution digital elevation model provided by the Geospatial Information Authority of Japan. Using this distribution, sub-watersheds in the Sagami Dam reservoir watershed were estimated by the river line production function of ArcSWAT (Figure 2).

The land use data for 2006 provided by MLIT (2016) was used for the land use distribution of the watershed (Figure 3) corresponding to the land use data of ArcSWAT (Table 1). Forests covered about 77% of the watershed. There is some controversy regarding the handling of paddy fields in SWAT (Xie 2015). Here, paddy fields were assumed simply as ‘water,’ as in our previous study (Obonai et al. 2015), considering the small fraction of the watershed (ca. 2%). With regard to the vicinity of the mountaintop of Mt. Fuji, the area classified as ‘wasteland’ by the land use data of MLIT was considered as ‘bare’ included in the database of MWSWAT (Texas A&M Agrilife Research et al. 2016),
which is another interface of SWAT. Another ‘wasteland’ area located at the foothills of Mt. Fuji by MLIT is classified as ‘slender wheatgrass’. Furthermore, ‘Other land’ is classified as residential-med/low density (Figure 3). No land use changes in the future were assumed in this study.

About 80% of the watershed is covered by brown forest soil (soil data provided by MLIT). Thus, the soil was assumed to be a monolithic soil, i.e., a single hydrological parameter set for the soil was assumed throughout the watershed. In addition, some of the parameters not affecting the water flow were set as the initial values of ArcSWAT.

Furthermore, the Doshi Daiichi Power Plant (Figure 1) obtains water from the outside of the watershed to the inside. The data of the water flow were obtained from Kanagawa Prefecture, the administrator of the power plant.

**Meteorological data preparation**

Climate data for precipitation, maximum and minimum temperatures, amount of solar radiation, wind speed, and relative humidity were used for the calculation. The observed daily precipitation, maximum and minimum temperatures, amount of solar radiation within the 3rd order mesh (ca. 1-km resolution) were provided by the National Institute for Agro-Environmental Science (NIAES). The relative humidity at Kawaguchiko and wind speeds at Ogochi, Hachioji, Otsuki, Furuseki, Kawaguchiko, and Yamanaka were obtained from JMA (2017).

**Parameter calibration and validation**

The model performance was evaluated by the reproducibility of the average daily inflow rate (m³/s) from the watershed to the reservoir. The observation data used for the evaluation were obtained from Kanagawa Prefecture, the administrator of the reservoir. Two performance indexes
were used for the evaluation, namely, Nash–Sutcliffe efficiency coefficient (NSE) (Equation (1)) and percent bias (PBIAS) (Equation (2)) (Moriasi et al. 2007):

\[
NSE = 1 - \frac{\sum_{i=1}^{n} (O_i - N_i)^2}{\sum_{i=1}^{n} (O_i - O_{i,ave})^2}
\]

\[
PBIAS = \frac{\sum_{i=1}^{n} (O_i - N_i) \times 100}{\sum_{i=1}^{n} (O_i)}
\]

where \( n \) is the number of observations, \( O_i \) is the observed inflow (m\(^3\)/s), \( N_i \) is the predicted inflow (m\(^3\)/s), and \( O_{i,ave} \) is the average of the observed inflow (m\(^3\)/s).

A good parameter set from the viewpoint of these indexes was sought by sensitivity analysis followed by parameter calibration and validation. Here, it is clear that the value of NSE tends to depend on the reproducibility of the floods (i.e., high flow rate days). Considering this feature, the method shown in Figure 4 was suggested and employed to obtain a good parameter set. SWAT-CUP (Arnold et al. 2012) ver. 5.1.5.4 was used for parameter calibration. In the calibration, the algorithm SUFI-2 was employed with 2,000 calculations for one calibration. According to Karim (2015), the warm-up period of approximately 2 to 3 years is recommended for the SWAT-CUP calibration. Three to five years of data that include average, wet, and dry years should be used for calibration (Gan & Bitfu 1996; Moriasi et al. 2007). Based on this information, the periods from 2001 to 2003, 2004 to 2006, and 2007 to 2009 were used as watershed initialization, calibration, and validation, respectively. Note that the annual precipitation in 2004, 2005, and 2006 in the watershed were 2,078 mm, 1,236 mm, and 1,590 mm, respectively. On the other hand, the average annual precipitation in 2004–2009 was 1,621 mm.

**Demonstration of the effects of climate change**

The effects of climate change were demonstrated by comparison of the river flow simulation in the past (from 1981 to 2000) and in the future (from 2081 to 2100). The meteorological data provided by NIAES and JMA were used for simulation in the past. The calculations obtained with version 5 of the Model for Interdisciplinary Research on Climate (MIROC5) (Watanabe et al. 2010) under the assumption of Representative Concentration Pathway (RCP) 2.6, 4.5, and 8.5 which stabilize radiative forcing at 2.6, 4.5, and 8.5 W/m\(^2\) in 2100, respectively (Thomson et al. 2011), were used for future simulation. These weather data near the watershed (i.e., latitude = 35.72°; longitude = 139.2°) of MIROC5 were first obtained from the Coupled Model Intercomparison Project Phase 5 (CMIP5) (DOE & LLNL 2016). Then, the data of each point shown in Figure 2 were estimated using the cumulative density function (Iizumi et al. 2010; Matsuda et al. 2013). In this estimation, observed data provided by JMA or NIAES from 1981 to 2000 and MIROC5 calculations within the period from 1981 to 2000 (initialized in 1980) at the representative point were used. The differences in each set of meteorological data between the representative point and each point in Figure 2 were then estimated by the cumulative density function. Finally, the prediction of each point was obtained by subtracting the difference from the representative point data with reference to the order of the value.

**Software used for analyses**

ArcSWAT Ver. 2009.93.7b (Texas A&M Agrilife Research et al. 2016) was used as the SWAT interface with GIS software ArcGIS (Ver. 9.3; Esri Japan, Tokyo, Japan). ArcGIS was also used for drawing maps. The processing of SWAT input data was performed with VBA in Microsoft Office Excel (Ver. 2013; Microsoft, WA, USA). Statistical analyses were performed with Excel-Toukei 2010 (Social Survey
RESULTS AND DISCUSSION

Parameter estimation and model reproducibility

Various types of information about parameter values of SWAT are available, and it is therefore possible to tentatively perform SWAT calculation using these values. Ideally, feasible predictions would be given by these parameters. However, it is also true that the parameter values should be calibrated for better prediction. Here, improvement of the predictive capability by the parameter calibration method shown in Figure 4, i.e., the effectiveness of the suggested calibration method, was confirmed by comparing the predictabilities of the models with the pre-calibrated tentative values and the post-calibrated values. The resultant NSE and PBIAS using the tentative values shown in Table 2 were −4.7 and −6.2, respectively. These tentative values were determined based on the default values of ArcSWAT, etc. This result indicated the need for parameter calibration.

According to the procedure shown in Figure 4, 14 parameters shown in Table 2 were found to have strong effects on river inflow by sensitivity analysis equipped with ArcSWAT. Furthermore, based on our experience, another seven parameters regarding snow events and a parameter about lateral flow travel time were selected for calibration. As a result, a total of 22 parameters, shown in Table 2, were selected as the calibration target. These parameters were also calibrated in other studies (Arnold et al. 2012; Shimiizu et al. 2013). The SUFI-2 trial by SWAT-CUP indicated that 11 of these 22 parameters have high sensitivity for PBIAS compared to their sensitivity for NSE (indicated as ‘PBIAS-influencing parameter’ in Table 2). These PBIAS-influencing parameters consisted of soil-related parameters, such as SOL_K, snow-related parameters, such as SFTMP, and groundwater-related parameters, such as GWQMNN. Some of these parameters have high sensitivity for NSE, and were therefore recalibrated in the next step.

A hydrograph with better reproducibility was obtained by the method employed in this study compared to the method referring only to NSE. Arnold et al. (2012) recommended a method involving separation of base flow and runoffs in the target hydrograph, and calibrating one after another. The calibration method employed in this study is another option that can perform parameter calibration more simply without hydrograph separation. The calculated water inflow from 2004 to 2009 using the finally calibrated parameters (Table 2) is shown in Figure 5 with the observed water inflow and precipitation. The values of NSE and PBIAS in each period are also shown in this figure. In the calibration period, NSE was 0.837 and PBIAS was 2.73. In the validation period, NSE was decreased to 0.751. The value of PBIAS in the validation period was changed to −2.67. No marked decrease in model prediction performance was observed in the validation period. The predictive capability for the monthly average inflow was calculated (Figure 6) to estimate the model performance with comparison of the rating suggested by Moriasi et al. (2007). As a result, NSE and PBIAS in both the calibration and validation periods were within the range of rating ‘very good’ (year 2004–2006: NSE = 0.958, PBIAS = 2.79; year 2007–2009: NSE = 0.909, PBIAS = −2.63).

To confirm the uncertainty of the model prediction, the plot of observation versus prediction with reliability interval is shown in Figure 7. Here, the days were categorized into three types with reference to precipitation on the day and the preceding day considering the lag time. One was the ‘heavy precipitation day’ with 48-hour precipitation >100 mm, and the other was the ‘dry day’ with 48-hour precipitation <1 mm. The remaining days were categorized as ‘normal day.’ The range of ±50% of the calculation and the +100% of calculation are indicated in this figure as the reliability interval. With regard to prediction uncertainty range of ±50%, 96.2%, 96.8%, and 63.2% confidence levels were found for all days, dry days, and heavy precipitation days, respectively. On the other hand, for heavy precipitation days, four of 19 predictions were >150% of each observation. If the uncertainty range was expanded from −50% to +100%, 73.7% confidence level was found for the heavy precipitation days. The distributions of normal days and dry days almost overlapped, and there were cases in which the flow rate in some dry days surpassed that in some heavy precipitation days. Note that the predictions of these days were sufficient despite the
Table 2 | Parameters calibrated in this study

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Tentative value(s)</th>
<th>Value after calibration</th>
<th>Calibration method</th>
<th>Selected parameter based on sensitive analysis of SWAT</th>
<th>PBIAS-influencing parameter</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 ALPHA_BF</td>
<td>Base flow alpha factor</td>
<td>0</td>
<td>1</td>
<td>0.048</td>
<td>0.7073</td>
<td>V</td>
<td>o</td>
<td>o</td>
</tr>
<tr>
<td>2 BLAI</td>
<td>Maximum potential leaf area index</td>
<td>−0.2</td>
<td>+0.2</td>
<td>0–6†</td>
<td>0.0199</td>
<td>R</td>
<td>o</td>
<td>o</td>
</tr>
<tr>
<td>3 CANMX</td>
<td>Maximum canopy storage (mm)</td>
<td>0</td>
<td>100</td>
<td>0</td>
<td>7.000</td>
<td>V</td>
<td>o</td>
<td>o</td>
</tr>
<tr>
<td>4 CH_K2</td>
<td>Effective hydraulic conductivity in main channel alluvium (mm)</td>
<td>250</td>
<td>500</td>
<td>0</td>
<td>399.625</td>
<td>V</td>
<td>o</td>
<td>o</td>
</tr>
<tr>
<td>5 CH_N2</td>
<td>Manning’s ‘n’ value for the main channel</td>
<td>0</td>
<td>0.1</td>
<td>0.014</td>
<td>0.02993</td>
<td>V</td>
<td>o</td>
<td>o</td>
</tr>
<tr>
<td>6 CN2</td>
<td>Initial SCS runoff curve number for moisture condition II</td>
<td>−0.2</td>
<td>+0.2</td>
<td>59–98†</td>
<td>0.0707</td>
<td>R</td>
<td>o</td>
<td>o</td>
</tr>
<tr>
<td>7 ESCO</td>
<td>Plant uptake compensation factor</td>
<td>0</td>
<td>1</td>
<td>0.95</td>
<td>0.0578</td>
<td>V</td>
<td>o</td>
<td>o</td>
</tr>
<tr>
<td>8 GW_DEREY</td>
<td>The delay time, cannot be measured directly</td>
<td>0</td>
<td>500</td>
<td>31</td>
<td>42.38</td>
<td>V</td>
<td>o</td>
<td>o</td>
</tr>
<tr>
<td>9 GWQMN</td>
<td>Threshed depth of water in the shallow aquifer required for return flow to</td>
<td>0</td>
<td>5,000</td>
<td>0</td>
<td>2,736</td>
<td>V</td>
<td>o</td>
<td>o</td>
</tr>
<tr>
<td>10 RCHRG_DP</td>
<td>Deep aquifer percolation fraction</td>
<td>0</td>
<td>1</td>
<td>0.05</td>
<td>0.4663</td>
<td>V</td>
<td>o</td>
<td>o</td>
</tr>
<tr>
<td>11 LAT_TTIME</td>
<td>Lateral flow travel time (days)</td>
<td>0</td>
<td>180</td>
<td>0</td>
<td>97.07</td>
<td>V</td>
<td>o</td>
<td>o</td>
</tr>
<tr>
<td>12 SOL_AWC</td>
<td>Available water capacity of the soil layer</td>
<td>0</td>
<td>1</td>
<td>0.074</td>
<td>0.8353</td>
<td>V</td>
<td>o</td>
<td>o</td>
</tr>
<tr>
<td>13 SOL_K</td>
<td>Saturated hydraulic conductivity (mm/h)</td>
<td>0</td>
<td>2,000</td>
<td>220</td>
<td>1,391</td>
<td>V</td>
<td>o</td>
<td>o</td>
</tr>
<tr>
<td>14 SOL_Z</td>
<td>Depth from soil surface to bottom of layer (mm)</td>
<td>−0.2</td>
<td>+1.0</td>
<td>1.000</td>
<td>0.3859</td>
<td>R</td>
<td>o</td>
<td>o</td>
</tr>
<tr>
<td>15 SARLUG</td>
<td>Surface runoff lag coefficient</td>
<td>0.05</td>
<td>24</td>
<td>4</td>
<td>16.75</td>
<td>V</td>
<td>o</td>
<td>o</td>
</tr>
<tr>
<td>16 SFTMP</td>
<td>Snow fall temperature (°C)</td>
<td>0</td>
<td>5</td>
<td>1</td>
<td>0.3713</td>
<td>V</td>
<td>o</td>
<td>o</td>
</tr>
<tr>
<td>17 SMTMP</td>
<td>Snow melt base temperature (°C)</td>
<td>0</td>
<td>5</td>
<td>0.4</td>
<td>3.516</td>
<td>V</td>
<td>o</td>
<td>o</td>
</tr>
<tr>
<td>18 SMFMX</td>
<td>Melt factor for snow on June 21 (mm/(°C·day))</td>
<td>0</td>
<td>20</td>
<td>4.5</td>
<td>13.875</td>
<td>V</td>
<td>o</td>
<td>o</td>
</tr>
<tr>
<td>19 SMFMIN</td>
<td>Melt factor for snow on December 21 (mm/(°C·day))</td>
<td>0</td>
<td>20</td>
<td>4.5</td>
<td>13.245</td>
<td>V</td>
<td>o</td>
<td>o</td>
</tr>
<tr>
<td>20 TIMP</td>
<td>Snow pack temperature lag factor</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0.9328</td>
<td>V</td>
<td>o</td>
<td>o</td>
</tr>
<tr>
<td>21 SNOCOVMX</td>
<td>Minimum snow water content that corresponds to 100% snow cover (mm)</td>
<td>0</td>
<td>500</td>
<td>1</td>
<td>185.625</td>
<td>V</td>
<td>o</td>
<td>o</td>
</tr>
<tr>
<td>22 SNO50COV</td>
<td>Fraction of snow volume represented by SNOCOVMX that corresponds to 50% snow</td>
<td>0</td>
<td>0.75</td>
<td>0.5</td>
<td>0.638</td>
<td>V</td>
<td>o</td>
<td>o</td>
</tr>
</tbody>
</table>

Values differ depending on land use for the part marked with †.

aV: The existing parameter value is to be replaced by a given value.

R: An existing parameter value is multiplied by (1 + a given value).

bParameters more sensitive for PBIAS than NSE.
variation in preceding precipitation, indicating that the effect of water retained in the watershed is replicated satisfactorily.

Demonstration of the effects of climate change simulation

To discuss adequate policy for water resource management to address future climate change, it is important to understand the differences in risks under different pathways of global warming. Here, we calculated the water flows in three representative concentration pathways, i.e., RCP 2.6, 4.5, and 8.5. The time courses of the inflow rates in the past (1981–2000) and in the future (2081–2100) under each pathway were calculated by the model with the finally calibrated parameters. Note that the inflow in the past was not actual observations but the simulated values. Therefore, the comparisons of the inflow described here should be considered as potential-based discussion.

The resultant hydrograph in daily time step is shown in Figure 8. Three large peaks surpassing about 1,000 m$^3$/s were found in August 1982, September 1982, and August 1983. In all of these cases, heavy precipitation caused by typhoons was observed upstream and midstream of the
Sagami River. In the two cases in 1982, flood damage caused by river inundation and storm sewer pipe backflow occurred in Hiratsuka City located at the mouth of the Sagami River. The raising of the water level of Lake Kawaguchi caused flood damage in both September 1982 and August 1983 (MLIT 2007). Furthermore, such high inflow may cause long-term turbidity problems in the reservoir (Hotta et al. 2005). In fact, 1,000 m$^3$/s = 86 × 10$^6$ m$^3$/day is about 1.8 times the effective volume of the Sagami Dam reservoir.

The maximum precipitation observed in the watershed within 1981–2000 was 299 mm/day (averaged in the watershed). The numbers of days with >300 mm of precipitation were 2, 2, and 1 in RCP 2.6, 4.5, and 8.5, respectively. On 2 days, the daily average inflows were unprecedented in the past (1981–2000). One day with average daily inflow of 2,500 m$^3$/s was predicted under the scenario RCP 2.6. This extremely high inflow was calculated under a continuous heavy precipitation (260 mm in the previous day, and 365 mm in the day). Under the scenario RCP 4.5, a flood of about 1,600 m$^3$/s was calculated with a day of 305 mm precipitation. Here, precipitation levels of 28 mm and 60 mm were expected in the 2 days and 1 day before the day, respectively. Meanwhile, the shorter time step of the calculation is another reason why such high inflows were calculated. For example, the 3-day averages of these floods were 1,397 and 1,063 m$^3$/s in RCP 2.6 and 4.5, respectively. These were almost in the range of 1.0–1.3 times the maximum inflow observed in the past (1981–2000). Comparisons of each month are described below.

The drought risk was discussed with the low inflow calculated in this simulation. In 1996, the restriction on water
intake and service restriction occurred in the Yokohama Waterworks and others during the periods from February 26 to April 24 and July 5 to 23 because of the significant decrease in storage volume of the Sagami Dam reservoir and other reservoirs upon which Yokohama Waterworks and others depend. The inflow in these periods was lower than 10 m$^3$/s. The numbers of such low-inflow days were expected to be 57 days, 24 days, 289 days, and 22 days in the calculations of the past, RCP 2.6, 4.5, and 8.5, respectively. Especially in RCP 4.5, almost five months from December 2099 to April 2100 were expected to have average daily inflow of 8–12 m$^3$/s, indicating the possibility of serious drought.

Furthermore, statistical analysis of the differences in daily inflow was also performed. The maximum, 75th percentile, median, 25th percentile, and minimum daily inflow in each month are shown in Figure 9. The statistical significance of differences between the past and the future was assessed by the Brunner–Munzel test. Based on the results, the inflow rates from September to April (except March under RCP 2.6) are expected to decrease significantly in the future. The decrement in April is especially marked (median value changed from 25.0 m$^3$/s to 18.9 m$^3$/s; 24% decrease). As mentioned above, restriction of water intake occurred from February to April 1996. Thus, the low inflow in February and April can be considered to represent a high risk of water shortage. The inflow rates in June, July, and November are expected to increase. The increments in June and July are especially marked. In June, median values changed from 30.8 m$^3$/s to 60.7 m$^3$/s under RCP 2.6, 53.0 m$^3$/s under RCP 4.5, and 44.5 m$^3$/s under RCP 8.5 (44%–97% increase), and 75th percentile changed from 38.7 m$^3$/s to 124.6 m$^3$/s under RCP 2.6, 96.5 m$^3$/s under RCP 4.5, and 86.2 m$^3$/s under RCP 8.5 (122%–222% increase); in July, the median value changed from 33.2 to 49.8 m$^3$/s under RCP 2.6, 43.9 m$^3$/s under RCP 4.5, and 43.7 m$^3$/s under RCP 8.5 (32%–50% increase). That is, risks caused by flooding, e.g., high turbidity or damage to facilities near the stream, in June and July will be increased in future, and adequate countermeasures for flooding should be discussed and designed.

As mentioned above, to avoid the effects of short time steps in the calculations, a discussion using monthly average inflow, which is a broader prediction, was given. Comparison of monthly average inflow is shown in Figure 10. The drought months mentioned above are also indicated in Figure 10. Especially, the monthly average inflow rate in February 1996 was calculated as 10.8 m$^3$/s (indicated by a broken line in the figure), which is the second lowest value during the period 1981–2000. That in March 1996 was calculated as the third lowest value, 11.5 m$^3$/s. Two months with the same inflow level (i.e., <12.0 m$^3$/s) were calculated in the past (in 1984 and 1988). However, each was finished in a single month and was not continuous.
On the other hand, the continuous months with average inflow <12.0 m³/s were expected as indicated in Figure 10. In the future under scenario RCP4.5, such months are predicted to appear in 2094, 2096, 2098, 2099, and 2100 (up to a maximum of five continuous months). This means that an increase in drought risk is expected in the future under scenario RCP 4.5 from the viewpoint of the Sagami Dam reservoir inflow. In the study by Mouri (2015), the wash load, which is considered to be increased with river flow, under RCP 4.5 would be expected to be lower than other pathways throughout Japan. This tendency is comparable to this study.

In fact, a large reservoir (Miyagase Dam reservoir) was constructed and operated since 2001, and the drought risk has decreased. However, the increase in drought potential should be taken into consideration.

**Uncertainties**

In this study, model uncertainty was estimated by its reliable interval as shown in Figure 7. To reduce model uncertainty, Li et al. (2016) demonstrated two methods, namely, multimodel combination using two hydrological models (i.e., variable infiltration capacity model and ‘abcd’ model) and data assimilation (i.e., ensemble Kalman filter) using one hydrological model (i.e., ‘abcd’ model) regarding daily and monthly streamflow prediction. Concerning the multimodel combination, tank model (Ishihara & Kobatake 1979) is one of the candidates. We have already assessed its suitability for flood prediction in Sagami Dam reservoir (Momiyama et al. 2016). Another candidate is distributed surface–subsurface coupled fluid model (Sagehashi et al. 2016). Due to detailed consideration about the subsurface flow, it is adequate for the prediction of base flow (i.e., drought prediction) as well as peak flow. Meanwhile, new data accumulation with the development of environmental monitoring technology as well as monitoring for the effects of climate change is expected. Data assimilation to reduce the model uncertainty using such information is also expected.

On the other hand, there is still room for uncertainty in future climate prediction, which was used as the climate input in the simulation. Only one climate change prediction model (MIROC5) was employed in this simulation. Anyway, the question about uncertainty of future climate prediction remains unsettled in this study. Further simulations using other GCMs, such as MRI, HadGEMS, and GFDL (DOE & LLNL 2016) are needed to discuss the possibility of drought risk with more reliable prediction. Therefore, the simulation results shown in this study should be considered as just one demonstration under one set of assumptions.
However, the assessment procedure of climate change effects on flood and drought using a hydrological model has been demonstrated in this study.

**CONCLUSIONS**

The hydrology of the Sagami Dam reservoir inflow was modeled using SWAT. The hydrological parameters were successfully calibrated and validated for the observed inflow in the years 2004–2006 and 2007–2009, respectively, by a parameter calibration procedure suggested in this study. The effects of climate change on the inflow in the future (from 2081 to 2100) under RCP 2.6, 4.5, and 8.5 predicted by MIROC5 were simulated by the model with comparison of the simulated inflow rates in the past (from 1981 to 2000). As a result, flood peak not calculated in the past was expected under RCP 2.6 and 4.5, whereas a long-term low inflow not calculated in the past was expected under RCP 4.5. The increases in drought risk in February and April, and the flood risk in June and July were elucidated by analysis of the changes in inflow in each month. Although further discussions are required regarding the uncertainty of future climate prediction, a procedure for assessment of the risks of flood and drought under future climate change was demonstrated in this study.

**ACKNOWLEDGEMENTS**

In this study, observed inflow rate of Sagami Dam and flow rate from the external watershed at Doushi Daichi Power Plant were provided by Kanagawa Prefecture. This study was partially supported by a Health Labour Sciences Research Grant (H27-Kenki-Ippan-003) from the Ministry of Health, Labour and Welfare, Japan.

**REFERENCES**


Li, W., Sankarasubramanian, A., Ranjithan, R. S. & Sinha, T. 2016 Role of multimodel combination and data assimilation in improving streamflow prediction over multiple time scales. Stochastic Environmental Research and Risk Assessment 30 (8), 2255–2269.


First received 30 March 2017; accepted in revised form 21 September 2018. Available online 23 October 2018