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Impact analysis of long-term stochastic inflow prediction and its uncertainty on reservoir operation during drought situations

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Abstract Impacts of long-term stochastic inflow predictions (SIPs) and their uncertainties on reservoir operation for water supply under drought situations are analysed and discussed in this study. Multiple sets of SIPs are pseudo-randomly generated with five-day resolution for three months, arbitrarily changing the two kinds of prediction's uncertainty, namely reliability and discrimination, for a comprehensive analysis of the impact of the SIP. Monte Carlo simulations of long-term reservoir operation for water supply under drought situations are then conducted considering generated multiple SIPs with various uncertainties. The proposed analysing method was applied to an assumed reservoir whose data was derived from Sameura Reservoir in Japan, demonstrating expected impacts of SIPs and their uncertainties on the long-term reservoir operation, and giving a suggestion as to what type of uncertainty in SIP is more important in real-time reservoir operation for more effective drought management.

Key words stochastic inflow prediction; reservoir operation; drought management; impact analysis; uncertainty; reliability; discrimination; Monte Carlo simulation

INTRODUCTION

Reservoirs play an important role in drought management by adjusting river waters so as to resolve mismatches between natural water supply and water demand downstream. Efficient reservoir operation with consideration of hydrological conditions expected in the target river basin during oncoming months is therefore crucially needed for effective drought management.

As information on future hydrological conditions, long-term stochastic predictions of hydrological variables such as precipitation or inflow to reservoirs for the coming several months have been provided by meteorological or hydrological authorities. Krzystofowicz (2001) remarked on four advantages of considering stochastic hydrological forecasts in that they are scientifically more honest; enable risk-based warnings of water disasters like floods; enable rational decision making; and offer additional economic benefits in light of his analysis. Long-term stochastic predictions on hydrological variables for the coming several months are also useful to be taken into consideration in decision making for long-term reservoir operation as they include not only the expected value, but also information on uncertainty contained in the predictions with stochastic representation, which is also considered important when reservoir managers decide on the operation policy for drought management based on possible tendencies of water balance in the target river basin in the future. From this viewpoint, many studies have been reported to promote utilization of information on uncertainty contained in hydrological predictions in long-term reservoir management (Kelman *et al.*, 1990; Karamouz & Vasiliadis, 1992; Faber & Stedinger, 2001; Kim *et al.*, 2007 Georgakakos & Graham, 2008; Pianosi & Ravazzani, 2010; Zhao *et al.*, 2011).

However, stochastic hydrological predictions have not been explicitly considered in decision making for reservoir operation in actual reservoir management. This is because effective methodologies have not been developed to utilize stochastic hydrological predictions with various degrees of uncertainty in the real-time reservoir operation based on intensive impact analysis of uncertainty in long-term stochastic hydrological predictions on improvement in reservoir operation when the predictions are considered. Intensive analyses are therefore needed to clarify impacts of stochastic hydrological predictions on performance of long-term reservoir operation for drought management in order to promote utilization of stochastic hydrological predictions in the long-term reservoir operation. From this perspective, Nohara & Hori (2012) have conducted comprehensive impact analysis of long-term stochastic inflow predictions (SIPs) and their uncertainties on improvement in water release decision making in long-term reservoir operation for water supply, employing reliability and discrimination for indices related to uncertainty of SIPs. In Nohara & Hori (2012), the analysis mainly described annually averaged impacts of SIPs, with various degrees of uncertainty on reservoir operation for water supply based on the performance of simulated reservoir operations. However, further detailed analyses are needed by focusing on the impacts of long-term SIPs on improvement in water release performance from a reservoir, especially under the drought situation, in order to provide more practical information on the way of utilizing long-term SIPs to enhance water release decision making in reservoir operation for drought management.

Considering the situation mentioned above, this paper analyses impacts of long-term SIPs with various degrees of uncertainty on performances of real-time long-term reservoir operation for water supply during drought situations where real-time coordination of water supply is inevitable.

METHODOLOGY

Outline

A Monte Carlo simulation (MCM) model of reservoir operation for water supply was developed by coupling an artificial generation process of SIPs with different attributes of uncertainty for impact analysis of them on performance of the operation based on a model developed in Nohara & Hori (2012).

At first, five-daily SIPs for the coming three months are arbitrarily generated with designed uncertainties represented by two indices for reliability and discrimination of the SIPs, respectively, so that the predictions can include arbitrary errors and vagueness against true values of inflow to the target reservoir. Actually observed inflow regimes at the target reservoir are employed for the true values of inflow in this paper in order to make the analysis more practical and detailed compared with Nohara & Hori (2012), in which the true values were also artificially generated based on the statistics estimated from historical data for general impact analysis. Optimal water release strategies are then estimated by stochastic dynamic programming (SDP) considering the generated SIPs for the coming three months with five-day resolution. Reservoir operations for water supply are conducted according to the estimated optimal strategy, updating SIPs and the water release strategy every five days through the designed period for the simulation. This simulation is repeated for a number of times as MCM considering SIPs generated in each simulation. Impact of SIPs and its uncertainty described with two indices on long-term reservoir operation is analysed by aggregating the results of the simulations under the drought situations. Impacts of SIPs with arbitrary combinations of reliability and discrimination indices are finally analysed by repeatedly conducting the MCMs described above, changing the combination of indices for reliability and discrimination of SIPs.

Concepts of two attributes related to uncertainty in SIPs

SIPs are artificially generated by adding probabilistic distribution of prediction error to the true value of inflow at each time step within the predicted period (see also Nohara & Hori, 2012). Normal probabilistic distribution is assumed for the probabilistic distribution of the prediction error. For generation of SIPs, two basic attributes of SIPs related to their uncertainty are considered here. One is reliability, and the other is discrimination (see Fig. 1).

Reliability of stochastic predictions can be considered to be a concept associated with the correspondence between predicted and observed probabilistic distribution, given the prediction is stable. In this study, the distance between centres of predicted probabilistic distribution and conditional distribution of observation, given the prediction, is considered as the correspondence of two probabilistic distributions, and variance of the distances between centres taken over the number of the predictions is employed to represent reliability of the predictions. However, discrimination is defined as a concept related to the predicted range of the occurrence of the state.

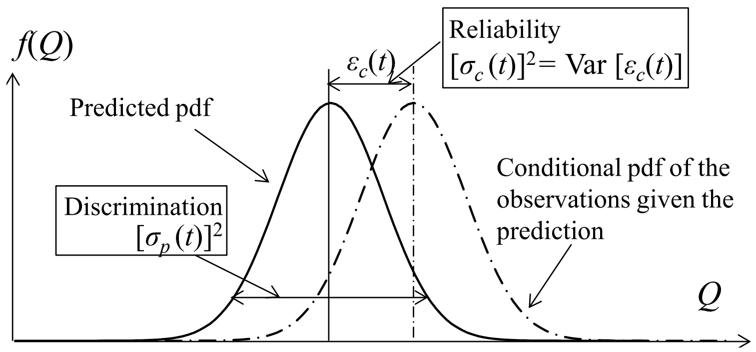

Fig. 1 Concepts of two attributes of stochastic inflow prediction considered in this study.

In this study, variance of the predicted probabilistic distribution, which also represents spread of the distribution, is employed to evaluate how the range of predicted states is specified. Discrimination is considered important, as well as reliability, because these two concepts are generally independent diagnostic measures of prediction performance and express both factorizations of the joint distribution of forecast and observation (Casati *et al.*, 2008).

The averaged difference between predicted probabilistic distribution and conditional distribution of observation given the prediction is also considered as one of important biases of stochastic predictions. This bias can, however, be comparatively easily corrected by adding (or subtracting) the averaged difference if the statistics of the prediction are available. This bias is, therefore, not considered or discussed in this study, assuming that it has already been corrected.

Generation of SIP with arbitrary uncertainty

Stochastic inflow predictions are artificially generated so as to control these two important characteristics of prediction uncertainty described in the previous section. Generation procedures of SIPs for each lead time at each time step of prediction are described as follows (see Fig. 2).

At first, a centre (average value) of a predicted probability distribution function (PDF) is randomly sampled from probabilistic distribution of the centres of predicted PDFs, which is a normal distribution $N(\mu_c(t), [\sigma_c(t)]^2)$ described in equation (1):

$$f_{\mu_p'}(\mu_p'(t)) = \frac{1}{\sigma_c(t)\sqrt{2\pi}} \exp\left[-\frac{1}{2}\left\{\frac{\mu_p'(t)-\mu_c(t)}{\sigma_c(t)}\right\}^2\right] \qquad (0 < \mu_p'(t) < \infty) \tag{1}$$

where $\mu_p'(t)$ is a sampled value of a centre of a predicted PDF for period t, $\mu_c(t)$ is average of a normal distribution which predicted PDFs' centres follow at period t. In this study $\mu_c(t)$ is assumed to be 0 because this bias of the prediction is not considered and therefore there is no difference between averaged value of prediction centres and true values. On the other hand, $\sigma_c(t)$ is the standard deviation of the normal distribution, which predicted PDFs' centres follow at period t, defined by equation (2) (see also Fig. 1):

$$[\sigma_c(t)]^2 = \mathrm{Var}[\varepsilon_c(t)] = C_c^2 [\sigma_o(t)]^2 \tag{2}$$

where $\sigma_o(t)$ is standard deviation of historically observed inflows at period t, $\varepsilon_c(t)$ is difference of centres between predicted probabilistic distribution and conditioned probabilistic distribution of observation given the prediction, and C_c is reliability index of SIPs, which is defined as proportion of $\sigma_c(t)$ to the standard deviation of historical inflow at period t ($\sigma_o(t)$). By this definition, reliability of a predicted PDF can be controlled so that the centre of predicted probabilistic distribution becomes closer to the conditioned PDF of inflow occurrence given the prediction as smaller value is employed for C_c. In case $C_c = 0$ and subsequently $\sigma_c(t) = 0$, the prediction becomes a perfect stochastic prediction, which probabilistic distribution is identical to the conditioned probabilistic distribution of observation given the prediction.

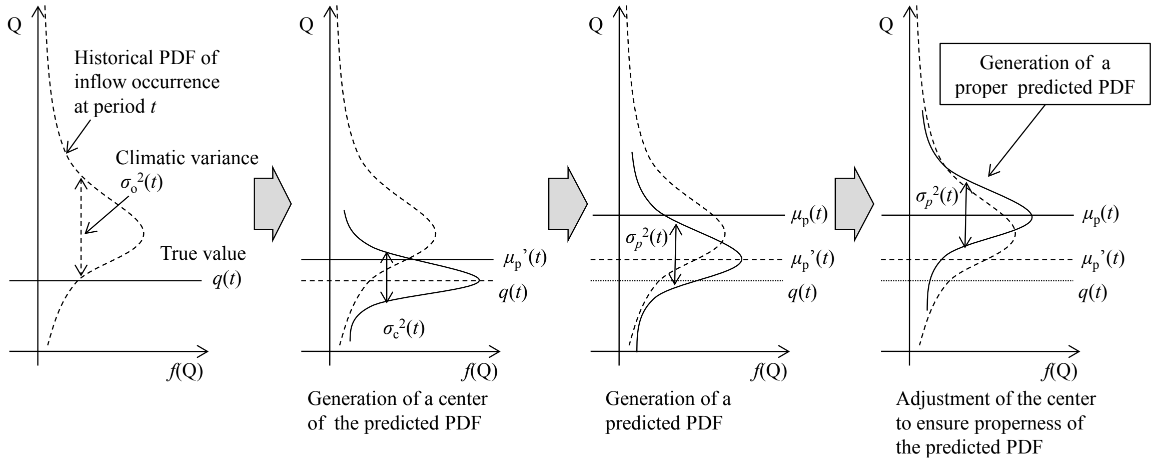

Fig. 2 Schematic diagram for generation of SIP for period *t*.

The centre of the predicted PDF sampled in the previous step is then adjusted by randomly sampling a value again from a normal distribution $N(\mu_p'(t), [\sigma_p(t)]^2)$, where the centre is $\mu_p'(t)$, the previously sampled value for the centre of the predicted PDF, and standard deviation is that of predicted PDF $\sigma_p(t)$. By this operation, the prediction can have a proper PDF which is identical to the conditioned probabilistic distribution of observation given the prediction of $\mu_p'(t) = 0$. Otherwise the prediction falls into a biased one as the centre of the predicted probabilistic distribution is always identical to the true value if $\mu_p'(t) = 0$. The predicted PDF is finally decided by considering a normal distribution with standard deviation of $\sigma_p(t)$ around the adjusted centre $\mu_p(t)$, and described as the following equation:

$$f_{q*}(q*(t)) = \frac{1}{\sigma_p(t)\sqrt{2\pi}} \exp\left[-\frac{1}{2}\left\{\frac{q*(t)-\mu_p(t)}{\sigma_p(t)}\right\}^2\right] \qquad (0 < q*(t) < \infty) \tag{3}$$

where $q*(t)$ is the predicted inflow for period *t*, $\mu_p(t)$ is the adjusted centre of the predicted PDF for period *t*, and $\sigma_p(t)$ is standard deviation of predicted probabilistic distribution defined as following equation (see also Fig. 1):

$$\left[\sigma_p(t)\right]^2 = C_p^{\,2}\left[\sigma_o(t)\right]^2 \tag{4}$$

where C_p is discrimination index of SIP, which is defined as proportion of standard deviation of a predicted PDF to $\sigma_o(t)$. By this definition, discrimination of a predicted PDF can be controlled so that width of the PDF becomes wider as C_p becomes greater. The prediction becomes a deterministic prediction if $C_p = 0$. Generation of SIPs is repeatedly conducted by following the procedures mentioned above for each time step within predicted range every time prediction is conducted.

While any non-negative number can be employed for C_c and C_p, these values must be decided so as to fulfil the condition $[\sigma_c(t)]^2+[\sigma_p(t)]^2 < [\sigma_o(t)]^2$ i.e. $C_c^2+C_p^2< 1$ in order for the prediction to be valuable to be considered. This is because the prediction can be considered no longer valuable in cases where the variation of the prediction is more than that of historical distribution of inflow, and it would rather be considered rational to consider the historical inflow distribution itself as the prediction.

The SIP is repeatedly generated for each lead time at each period in each simulation according to the procedures mentioned above.

Reservoir operation

Water release strategy for water use purpose is decided with consideration of the generated long-term SIP at each time step. The stochastic dynamic programming (SDP) approach is employed for optimization of water release strategy as stochastic prediction has to be taken into account. The optimization is conducted so as to minimize accumulated drought damage. The accumulated drought damage is described as equation (5), assuming that drought damage can be represented as the ratio of water deficit to water demand at the time step:

$$\min_{r_t} \underset{w_t}{E}\left[H_t(w_t)\right] = \min_{r_t} \underset{w_t}{E}\left\{\left[\max(d_t - w_t, 0)\right]^2 \big/ d_t\right\} \tag{5}$$

where r_t is release amount at period t, d_t is water demand at an assessed point in the downstream of the target reservoir at period t, w_t is streamflow at the assessed point calculated by adding water amount runoffs between the dam and the assessed point at period t to the release from the dam r_t, and $H_t(w_t)$ is drought damage caused by the water deficit at period t. Optimization of water release strategy is conducted so as to minimize future damage function $f_t(\cdot)$ described below:

$$f_t(s_t) = \min_{r_t} \underset{w_t}{E}\left\{H_t(w_t) + \underset{w_t}{E}\left[f_{t+1}(s_{t+1})\right]\right\} \tag{6}$$

where s_t is storage state of the target reservoir at period t.

CASE STUDY

Study area and simulation settings

The proposed model was applied to a simplified reservoir basin for which data are derived from Sameura Reservoir in the Yoshino River basin in Japan, and impact analysis of SIPs with various uncertainties was conducted for the drought period. Only the storage capacity for water use (173 000 000 m^3) was considered for the assumed reservoir, while Sameura Reservoir is actually a multi-purpose reservoir. Only one assessed point of streamflow was assumed to be located just downstream of the reservoir, and water demand d_t and streamflow w_t presented in equations (5) and (6) were replaced by target release R_t and release r_t, respectively. Time step and duration of the simulation are set to five days and three months in summer from the beginning of July (period 37 when counted from January with five-days unit) to the end of September (period 5), respectively, in which drought is often observed due to high demand of water. As for the true values of inflow, actual inflow sequence observed at Sameura Reservoir during the drought periods in typical low flow years (1994 and 2005) and an extreme low flow year (2008) were used.

Fifteen scenarios with different combinations of C_c and C_p were each considered in the generation of SIPs so as to fulfil the condition of $C_c^2+C_p^2 < 1$, which is required for the prediction to be worth being considered so that the total variance of the predicted value is less than historical variance of inflow, while only the results for five different combinations of C_c and C_p with an identical value of $C_c^2 + C_p^2$ are presented as representations in this paper. The combinations of two indices are: $C_c^2 = 0.4$ and $C_p^2 = 0.0$ (Case 1); $C_c^2 = 0.3$ and $C_p^2 = 0.1$ (Case 2); $C_c^2 = 0.2$ and $C_p^2 = 0.2$ (Case 3); $C_c^2 = 0.1$ and $C_p^2 = 0.3$ (Case 4); and $C_c^2 = 0.0$ and $C_p^2 = 0.4$ (Case 5) all of which values of $C_c^2+C_p^2$ are 0.4 r. Reservoir operation was simulated 1000 times with consideration of the SIPs artificially and repeatedly generated for each case of reliability and discrimination indices for SIP with five initial storage percentages which are 20%, 40%, 60%, 80% and 100%. Numbers of discretization in the reservoir optimization by SDP were set to 100 levels for inflow, release and storage states.

Simulation results and analysis

Simulated results of averaged drought damage over the simulated period with different initial storages for each case of SIP's uncertainty are shown in Tables 1–3. In the results for typical low flow years, 1994 (Table 1) and 2005 (Table 2), it can be seen that more damage was simulated as C_c became larger and C_p became smaller with comparatively smaller initial storages from 20% to 60%. It can be also seen that more damage were simulated as SIPs with smaller C_c and greater C_p were considered for the simulation results with larger initial storages from 80% to 100%. However, contrasting results are seen in the simulation results for the extreme low flow year (in 2008, Table 3).

Table 1 Simulated results of averaged drought damage over the simulated period in 1994.

Initial storage (%)	Case 1 (m^3/s)	Case 2 (m^3/s)	Case 3 (m^3/s)	Case 4 (m^3/s)	Case 5 (m^3/s)	Difference (m^3/s)	Rate of difference (%)
20	5.280†	4.990	4.817	4.734	4.674*	0.607	11.5
40	2.725†	2.450	2.262	2.174	2.113*	0.613	22.5
60	0.639†	0.515	0.433	0.421	0.420*	0.219	34.3
80	0.066	0.064*	0.099	0.109	0.142†	0.078	55.0
100	0.019*	0.023	0.073	0.085	0.118†	0.100	84.4

*Maximal damage over cases with each initial storage; †minimal damage over cases with each initial storage.

Table 2 Simulated results of averaged drought damage over the simulated period in 2005.

Initial storage (%)	Case 1 (m^3/s)	Case 2 (m^3/s)	Case 3 (m^3/s)	Case 4 (m^3/s)	Case 5 (m^3/s)	Difference (m^3/s)	Rate of difference (%)
20	6.416†	6.209	6.128	6.092	6.028*	0.387	6.0
40	3.292†	3.070	2.920	2.866	2.812*	0.480	14.6
60	0.781†	0.650	0.562	0.527	0.503*	0.278	35.6
80	0.018*	0.020	0.044	0.056	0.086†	0.069	79.7
100	0.011*	0.014	0.039	0.050	0.082†	0.071	86.5

*Maximal damage over cases with each initial storage; †minimal damage over cases with each initial storage.

Table 3 Simulated results of averaged drought damage over the simulated period in 2008.

Initial storage (%)	Case 1 (m^3/s)	Case 2 (m^3/s)	Case 3 (m^3/s)	Case 4 (m^3/s)	Case 5 (m^3/s)	Difference (m^3/s)	Rate of difference (%)
20	20.25†	20.37	20.42	20.49	20.56*	0.304	1.5
40	14.68†	14.82	14.95	15.06	15.15*	0.471	3.1
60	10.12	10.11†	10.19	10.31	10.37*	0.261	2.5
80	6.60*	6.42	6.36†	6.37	6.42	0.236	3.6
100	3.80*	3.52	3.42	3.36	3.32†	0.478	12.6

*Maximal damage over cases with each initial storage; †minimal damage over cases with each initial storage.

It can be seen that more damage was calculated as SIPs with smaller C_c and greater C_p were considered when initial storage was comparatively small (20%, 40% and 60%), whereas the model simulated more damage when SIPs with greater C_c and smaller C_p were employed in the simulations with larger initial storages (80% and 100%).

Figures 3 and 4 show a comparison in time series of simulated results for Cases 1 and 5 for inflow regime in 1994 with 80% of initial storage, and for inflow regime in 2008 with 20% of initial storage, respectively. It can be also seen in Fig. 3 that more damage was simulated in Case 5 which has larger C_p before low inflow regime continued. However, Fig. 4 illustrates that smaller damages were simulated in the earlier periods before period 43 in Case 5 while simulation in Case 5 demonstrated larger damages in the subsequent periods from period 44 to period 47 by conducting large amount of water savings due to a sudden drop in storage volume.

Considering the actual inflow regime in 2008 was extremely low, the results described above can be summarized as below. In the mild drought situations such as the situations under low flow regimes observed in 1994 and 2005 with larger initial storages (e.g. 80% or 100%), the results suggest that it is more important to consider long-term SIPs with less C_p, in other words, more discriminated stochastic predictions for effective drought management. It can be considered because the reservoir operation model considering SIPs with less discrimination conducted more water savings by considering the possibility of extreme low flow situation covered with wide predicted probabilistic distributions, although they were actually not necessary as the reservoir had

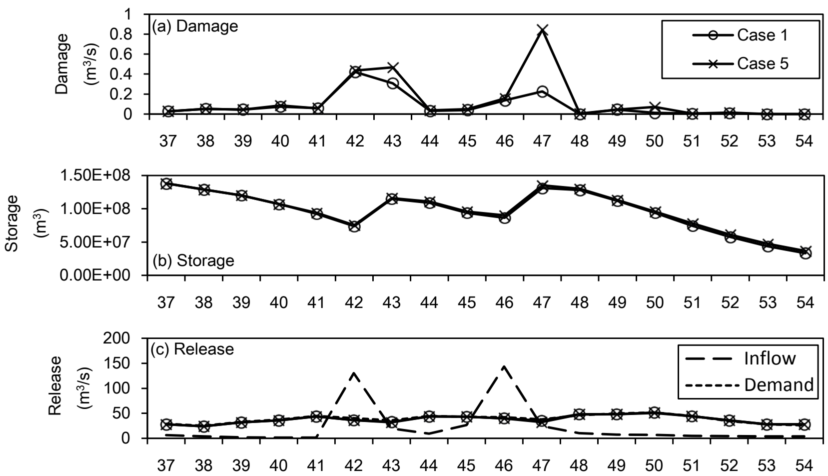

Fig. 3 Simulated time series of: (a) damage; (b) storage; and (c) release (1994, 80% of storage).

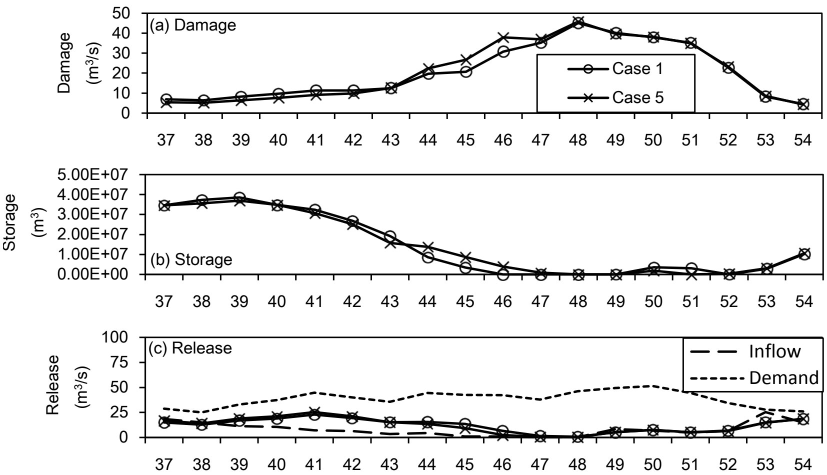

Fig. 4 Simulated time series of: (a) damage; (b) storage; and (c) release (2008, 20% of storage).

storage and inflow sufficient to release water so as to mitigate water savings. For moderate drought situations such as the situation under low flow regimes (1994 and 2005) with smaller initial storages or under extremely low flow regimes like 2008 with larger initial storage (e.g. 80% or 100%), the results illustrated that SIPs with less C_c, in other words, more reliable stochastic predictions, were preferable for effective drought management by reservoir operation. It can be considered because water savings were gradually and adequately conducted by considering SIPs with smaller C_c and greater C_p, which tended to keep forecasting occurrence of drought with some probability. However, less C_p was again preferred by long-term reservoir operation with consideration of SIPs under severe drought situations with extreme low flows and small initial storages (e.g. 20–60% in 2008). This can be considered because the reservoir operation model tended to relax water savings influenced by prediction of large inflow, which is also covered with predicted probabilistic distributions with wide skirts, and tended to subsequently increase drought damage after storage completely dropped off, when SIPs with large C_p were considered.

CONCLUSION

Impacts of long-term SIPs and their uncertainties on reservoir operation for water supply under drought situations were analysed and discussed. Through the impact analysis by the Monte Carlo simulation of reservoir operation considering SIPs with various degrees of reliability and discrimination, it was suggested that impacts of SIPs and their uncertainties can vary depending on the seriousness of droughts at the target reservoir: discrimination index C_p is considered more important in mild droughts; reliability index C_c is considered more important in moderate droughts; and discrimination index C_p is considered more important in severe droughts. The further investigations are, however, considered necessary to generalize the results observed in this application as the impact analysis was conducted for only one reservoir basin. The impacts of the persistence in the prediction errors or uncertainties are also considered important issues to be analysed and discussed in the future.

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