https://doi.org/10.5194/hess-2019-175
Preprint. Discussion started: 6 June 2019

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Evaluating robustness of dynamic reservoir management under diverse climatic uncertainties: Application to the Boryeong Reservoir in South Korea

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https://doi.org/10.5194/hess-2019-175
Preprint. Discussion started: 6 June 2019

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ABSTRACT

The implications of forecast-based reservoir operation have been considered to be innovative approaches to water management. Despite the advantages of forecast-based operations, climate-related uncertainty may discourage the utilization of forecast-based reservoir operation in water resources management. To mitigate this concern, a systematic evaluation proves helpful. This study presents an evaluation framework for reservoir management under a variety of potential climate conditions. In particular, this study uses Monte Carlo simulations to quantify the robustness of the forecast-based operation in a scenario of degraded ability of forecast skill, and demonstrates a new performance metric for robustness. This framework is described in a case study for a water supply facility in South Korea. To illustrate the framework, this study also proposes dynamic reservoir operation rules for our case study, utilizing seasonal climate information and a real-option instrument from an interconnected water system. Results provide system robustness evaluated over a wide range of defined uncertainties related to climate change. Results also suggest that the dynamic operation management adopted in this study can substantially improve reservoir performance for future climates compared to current operation management. This analysis may serve as a useful guideline to adopt dynamic management of reservoir operation for water supply systems in South Korea and other regions.

Keywords: **Dynamic reservoir operation, Climate change, Robustness, Boryeong Reservoir**

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1. Introduction

Population growth, resultant water demand, and recent climate change have increased the likelihood of water deficits in many regions of the world (Padowski et al., 2015; Schewe et al., 2014). Efficient of hydrologic infrastructure is required to cope with present and future uncertainty (Ahmad et al., 2014). To meet these demands, considerable improvement in water resources system operations has been achieved over the last decade, including multi-objective operations (Tsai et al., 2015; Yang et al., 2015), the use of inflow forecasts (Giuliani et al., 2015; Sankarasubramanian et al., 2009), conjunctive use with groundwater (Liu et al., 2013; Singh et al., 2015), and optional transfers from an adjunct system (Jeuland and Whittington, 2014; Palmer and Characklis, 2009).

The utility of forecasts in reservoir operations has long been investigated (e.g., Bai et al., 2014; Giuliani et al., 2015; Yao and Georgakakos, 2001; Zhao et al., 2012). To manage interannual hydrologic oscillation, seasonal climate forecasts (1-6 months) have been often coupled with reservoir operations (Block, 2011; Gong et al., 2010; Najibi et al., 2017; Sankarasubramanian et al., 2009; Steinschneider and Brown, 2012). These forecast-based operations are notably beneficial to conserve water supplies during low-flow periods (Block, 2011; Golembesky et al., 2009). Despite the advantages of forecast-based operations, the possibility of forecast skill degradation diminishes their utility in water resources management. Forecast skill degradation indicates that predictive ability is decreased when an adopted covariate (e.g., climate teleconnection) is utilized for estimating inflow in a reservoir. To better assess this concern, a systematic approach is required to assess the impact of the possibility of forecast skill degradation on the reliability of forecast-based operations, which has received little attention

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in previous studies. This study supports the field of reservoir operations by proposing a framework to examine how altered forecast skills could influence the behavior of system design.

To achieve the primary objective, we newly identify a useful seasonal climate pattern, which can be utilized to develop seasonal climate-based operations for the study's water supply facility. Seasonal climate-based operations and their climate covariates are becoming more widely suggested in many reservoir systems in many regions seeking multiple objectives (Broad et al., 2007; Gong et al., 2010; Najibi et al., 2017; Steinschneider and Brown, 2012). Also, seasonal climate-based operations have been considered as improved system operation rules (Block, 2011; Visser, 2017). Because the impacts and roles of climate covariates are diverse depending on geographical location (Ashbolt and Perera, 2018), reservoir operations incorporating teleconnections from large-scale atmospheric oceanic circulation patterns must pertain specifically to each system. To be tailored for our water supply facility, a forecast-based operation algorithm is also described to incorporate the large-scale oceanic circulation pattern identified in this study. Following Gong et al. (2010) and Steinschneider and Brown (2012), forecast information is used to determine water rationing to circumvent severe shortfalls by diminishing the normal supply.

Climate-based operations have further been used as reliable climate change adaptation strategies (Steinschneider and Brown, 2012; Whateley et al., 2014). However, as noted by Romsdahl (2011) and Whateley et al. (2014), water resource managers may not be receptive to the use of forecast-based reservoir operations for their long-term operation plans (i.e., climate change adaptation plans) for various reasons such as financial constraints, insufficient skill,

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and institutional obstacles. In particular, the possibility of forecast skill degradation may be one of the main reasons for this reluctance. Global climate change may accelerate unexpected alterations in the relationship between large-scale synoptic circulation and local hydrology. For instance, Allan et al. (2014) describe possible changes in future surface hydrology related to the Pacific-North American (PNA) teleconnection pattern. A similar interpretation can be found for ENSO with local hydrology (Kohyama et al., 2018). In these cases, a forecast with unreliable predictions may lead water managers to make inappropriate operation decisions, resulting in subsequent critical shortages and severe criticism from stakeholders. One possible way to mitigate this concern is to explicitly evaluate the impacts of changes in forecast skill in the relationship between large-scale synoptic circulation and local hydrology by simultaneously considering potential shifts in climate. Such an evaluation may identify adequate bounds ensuring acceptable performance at a reasonable risk.

The impact of climate change on water resources management has been widely investigated (Zhang et al., 2017). Global circulation models (GCMs) are commonly employed for understanding potential shifts in climate, but due to biases and incomplete sampling of uncertainties, they are limited for risk assessments exploring potential climate change (Brown and Wilby, 2012). Poorly understood climate physics and computational complexity further exacerbate limitations in incorporating information from these scenarios into climate change assessments (Koutsoyiannis et al., 2009). Alternatively, robustness-based methods have been proposed without direct use of climate model projections, focusing on analysis that quantifies the range of climate space over which a water resource system can provide acceptable performance. Examples include info-gap analysis (Korteling et al., 2013), robust decision making (Lempert and Groves, 2010; Matrosov et al., 2013) and decision scaling (Brown et al.,

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2012; Turner et al., 2014). The robustness-based method has been increasingly used to assess system vulnerability and to propose alternative policy decisions (Brown et al., 2011; Ghile et al., 2014; Hassanzadeh et al., 2016). Based on the robustness-based method (decision scaling is adopted in this study), we develop an evaluation framework to systematically account for uncertainties related to internal climate variability when determining if altered forecast skills are reliable.

In South Korea, drought risk has not been an explicit concern as an increase in precipitation over South Korea has been documented in various studies (Ho et al., 2003; Kim and Jain, 2011; Lee et al., 2012). However, many regions of Korea have recently been experiencing water deficit (Kwon et al., 2016). To be specific, the Korean peninsula experienced severe droughts in 2002 and 2014-2016 (Kim et al., 2018). During the 2014-2016 drought, local water managers executed water supply restrictions for many areas of the west coast of South Korea, thereby adversely affecting the environment and living conditions for people (Ihm et al., 2019). This multi-year drought drew water managers' attention in South Korea because it was an exceptional event considering the regularly recurring flood season (June to August) every year. Multi-year drought poses a new and substantial challenge to water managers deciding current strategies to ensure prudent future reservoir operations.

Cognizant of the risk of a multi-year drought, local water managers in South Korea have constructed real-option water transfers enabling offsetting local water shortfalls by drawing water from distant water resource systems. For example, the Korean Water Resources Corporation (K-water) recently constructed a water transfer pipe from the Baekje Weir to the

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Boryeong Reservoir in anticipation of water shortages (Kim et al., 2017). Although many studies have advocated the use of option instruments for mitigating water resource system failures (Palmer and Characklis, 2009; Zeff et al., 2016; Zhu et al., 2015), many scientists in South Korea question whether water transfer options are valuable (Jang et al., 2017). However, even if water transfers may not be worthwhile for the present, they could prove promising in the face of unexpected future climate conditions. Accordingly, we utilize the proposed framework to investigate the utility of water transfer options for both the present and a future with climate change. We also examine if more effective water management would result during critical drawdowns when water transfer is utilized concurrently with our new climate-based operation curve.

In summary, this study seeks to answer the following questions in a case study of daily streamflow for water supply facilities (the Boryeong Reservoir and Baekje Weir) in South Korea. The water supply facilities recently experienced the worst drought in the historical record, highlighting that reliable and effective operation rules are urgently required for both the present and the future.

1. Can a forecast-based operation rule improve performance for the Boryeong Reservoir compared to the status quo operation rule?
2. Will the real-option water transfer installed between the Baekje Weir and the Boryeong Reservoir prove useful to curtail water shortages? What are the potential contributions of real-option water transfer when utilized concurrently with our operation rule?

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3. If the dynamic operation rule was adopted, how responsive would our improved reservoir system be under long-term climate change as well as changes in seasonal forecast skill?

The rest of this paper is described as follows. Section 2 delineates a theoretical background of the dynamic reservoir operation and the proposed framework. Section 3 introduces a specific application to the Boryeong Reservoir system, the primary water supply system for Boryeong in South Korea. Results are presented in section 4. The paper concludes with a discussion of some limitations of our approach as well as potential research needs in section 5.

2. Methodologies

In this study, the methodology is comprised of three major components. The first follows Steinschneider and Brown (2012) to develop dynamic reservoir management incorporating forecast-based operations and real-option water transfer from an interconnected water system (Section 2.1). We then present how to generate future streamflow scenarios using a stochastic weather generator and a hydrologic model (Section 2.2). Finally, we introduce a new framework using Monte Carlo methods to explore whether different operation rules provide appropriate performance over a wide array of uncertainties (Section 2.3). To be specific, three reservoir operation rules are evaluated. The first rule $\boldsymbol{C_{Baseline}}$ presents a baseline and status quo operation, comparable to that currently used in our study case. The second rule $\boldsymbol{C_{Forecast}}$ employs forecast-based operations without the ability to hedge risk with a real-option. The real-option from an interconnected water system is then added to bolster the dynamic operation in

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the third rule $\boldsymbol{C}_{\boldsymbol{Dynamic}}$. Following Field et al. (2012), robustness is defined when an operation plan performs well across many feasible scenarios. Accordingly, the operation rule options can be robust to a specific type of long-term alterations if they produce an acceptable performance for overall simulations associated with that long-term alteration. A detailed explanation of each step is provided in the following sections.

2.1 Dynamic reservoir management

The operation rule curve $\boldsymbol{C}$ can be formalized as $\boldsymbol{C} = f(\boldsymbol{Q})$, where $\boldsymbol{C}$ is a set of daily reservoir storage levels, $\boldsymbol{Q}$ is a set of daily inflow sequences, and $f(\cdot)$ represents the function used to derive the rule curve. Each inflow sequence q covers one calendar year with total n years. The dynamic operation rule is designed for d different phases of a climate teleconnection utilized for forecast use. To be specific, the historical record is divided by year into d mutually exclusive sets, $\boldsymbol{Q}_1, \dots, \boldsymbol{Q}_d$ such that for all years in a given set, the climate index is in one particular phase.

$$\boldsymbol{Q}_d = \{q_{\breve{n}} | \breve{n} \in \breve{N}_d\} \qquad \text{(Eq. 1)}$$

$$\breve{N}_d = \{\breve{n} | I_{\breve{n}} \in (\acute{\imath}_d, \grave{\imath}_d), \breve{n} \in [1, 2, \dots, N]\} \qquad \text{(Eq. 2)}$$

where, $I_{\breve{n}}$ is an index measuring climate teleconnection for the $\breve{n}$ calendar years in the historic record, $\acute{\imath}_d$ and $\grave{\imath}_d$ indicate minimum and maximum values, respectively, to delimitate the d^{th} phase of the climate conditions, and $\boldsymbol{Q}_d$ is a set of inflow that occurred during years

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for the d^{th} phase of the climate conditions. To drive the dynamic operation rule, inflow sequences are limited to $\boldsymbol{Q}_d$ associated with that particular phase of climate variability $\boldsymbol{C_d} = f(\boldsymbol{Q}_d)$.

During real-time operations, forecast-based operations are maintained for one calendar year. The month following the release of climate information, reservoir operations are altered corresponding to the rule curve obtained by the current phase of the climate information. After one calendar year, the reservoir operation is changed by the new forecast. Note that the forecast-based operation applied in this study is relatively straightforward. Perhaps monthly updating of the rule curve could be more promising as noted in Aboutalebi et al. (2015).

The specific dynamic operation rule associated with that particular phase of climate variability ($\boldsymbol{C_d}$) is determined by a stochastic analysis. The methodology of a stochastic analysis is described in detail elsewhere (Steinschneider and Brown, 2012; Westphal et al., 2007) so is only briefly reviewed here. At its core, $\boldsymbol{C}$ is defined such that it has a certain chance that a reservoir system is drawn down below the critical storage level C^{***} over a period given different initial reservoir conditions and time of year. $\boldsymbol{C}$ is designed across time by month so is constant for all period in a given calendar month. To consider the multi-year drought, resampled two year sequences of inflow, drawn from a set of yearly inflow sequences, are utilized. After identifying the minimum-maximum storage levels for the certain chance, linearly interpolation is employed between the two minimum-maximum storage levels for each month.

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In addition, water transfer (*TR*) from an interconnected water system is operated during specific periods when the storage level of the target reservoir falls below a certain storage level (C^{**} used in this study). The decision rule to facilitate the option is formulated as

$$TR_t = \begin{cases} \min(C^{**} - S_{t-1}, TR_{max}) & \forall S_{t-1} < C^{**} \\ 0 & \forall S_{t-1} \geq C^{**} \end{cases} \quad \text{(Eq. 3)}$$

where S_{t-1} is the reservoir storage at *t-1* and TR_{max} is the maximum volume of water which can be transferred from the interconnect water system. Here, the amount of water transferred in the option is designed as a function of how far the current storage falls below the predefined storage C^{**} and is limited by physical constraints (e.g., maximum pipe volume).

2.2 Future inflow realization under climate alternatives

The operation rule curve is evaluated though an exhaustive sampling of changes in climate variables, such as mean precipitation and temperature changes. A weather generator developed by Cordano and Eccel (2016) is used to provide climate sequences that exhibit similar climate statistics. To be specific, daily precipitation, maximum, and minimum temperatures are generated for each specified mean climate future in this study. The weather generator utilizes a vector autoregressive (VAR) model (Pfaff, 2008) to preserve temporal and spatial correlations among generated daily precipitation and temperatures. The auto-regression order must be

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determined prior to scenario generation, and is decided based on the AIC (Akaike, 1981) calculated from the observed data. Then the VAR model is calibrated on the transformed time series which is transformed into Gaussian-distributed random variables through deseasonalization and Principal Component Analysis (PCA). Details on the methodologies about the weather generator can be found in Cordano and Eccel (2016).

Climate sequences can be developed over any range of potential climate change. While the selection of this range remains still an open question, the range can specify a large sufficient range that can cover the climate space that is explored by GCM projections and ensure that the endpoints of the range do not emerge in a meaningful implication (Whateley et al., 2014). Also, a number of climate simulations (e.g., 100-1000) are needed to adequately explore possible climate fluctuations (Guimarães and Santos, 2011). Following these two logical strategies, 40-year daily simulations of climate are generated 200 times with different climate changes imposed on the mean of precipitation and maximum/minimum temperatures in this study. Climate changes include percent changes in mean precipitation (-25% to 30% in 5% increments) and absolute changes in mean maximum and minimum temperatures ($-2.0°C$ to $2.0°C$ in $0.5°C$ increments) from baseline values. Therefore, $21600 = 200 \times 12 \times 9$ different 40-year climate sequences are developed in this study.

A conceptual, lumped parameter hydrologic model, the Sacramento Soil Moisture Accounting (SAC-SMA) model (Burnash, 1995; Burnash et al., 1973) is used to simulate future daily streamflow from the generated climate sequences. The SAC-SMA divides the basin into two soil zones, an upper zone and a lower zone, which is its most representative feature compared

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to other typical hydrologic models (e.g., PRMS, VIC, and HBV). The upper zone simulates the short-term storage of the basin; the lower zone represents the underground soil in the long-term storage. Each zone is affected by evapotranspiration and free water, thereby representing the water that evaporates and the water that flows or percolates downward (Najafi et al., 2011). The generation processes are delineated by a total of 16 unknown parameters, but 3 parameters (SIDE, RIVA, RSERV) are set to their default values as in other studies (e.g., Chu et al. (2010)), leaving 13 parameters for calibration. In addition, effective rainfall and snowmelt input to SAC-SMA is considered to simulate snow accumulation/melting processes using a snow model similar to those of Ahn et al., (2016a) and Martinez and Gupta (2010) based on daily mean temperature, with an additional 3 parameters. Lastly, to account for biases in climate variables, an input data error model is employed based on two formulations, a multiplier form (Li and Xu, 2014) and an additive form (Huard and Mailhot, 2006), which have been widely applied (Jin et al., 2010; Zhang et al., 2016). Errors in temperature (precipitation and evapotranspiration) is assumed to be additive (multiple) which can be formulated as follows:

$$\begin{aligned}\widehat{T}_t &= T_t + e_T\\ \widehat{P}_t &= P_t e_P \qquad \text{Eq. (4)}\\ \widehat{PET}_t &= PET_t e_{PET}\end{aligned}$$

where e represents the bias correction term for temperature (T), precipitation (P), and evapotranspiration (PET). The Hargreaves method (Hargreaves and Samani, 1982) is used for estimating PET from maximum and minimum temperatures. Radiation values for the

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Hargreaves method are estimated by the method proposed by (Allen et al., 1998).

In total, the 19 parameters of the model (presented in Table 1) are calibrated by maximizing Kling-Gupta efficiency (KGE; Gupta et al., 2009) using the differential evolution optimization algorithm (Mullen et al., 2009). KGE (ranging between $-\infty$ and 1) is composed of three independent error components, including terms for mean bias, variability bias, and correlation between the simulated and observed flows. This performance metric has advantages over traditional skill measures like Nash-Sutcliffe efficiency (NSE) because it removes interactions between error components and reduces negative variability bias in simulation results (Revilla-Romero et al., 2015).

2.3 Framework to evaluate robustness of diverse alternatives

The framework focuses on demonstrating how robust the alternatives of forecast skills function under various potential climate conditions. To be specific, we evaluate a reservoir plan under three alterations in climate (changes in precipitation, temperatures and seasonal forecast skills related to teleconnection). A plan is considered robust to a set of alterations if it offers satisfying performance for overall Monte Carlo simulations related to the three alterations. Although three climate-related alterations are considered here, the framework can be easily expanded to consider other feasible alterations such as changes in water supply demands.

The following procedure is used to define robustness in this study.

[1] For a reservoir operation plan, $g = 1, \ldots, G$ future precipitation, maximum and minimum temperatures are generated under each long-term climate change scenario under $h = 1, \ldots, H$. In this study, $G = 200$ climate sequences are produced under $H = 117$ change scenarios (as stated in Section 2.2). Thereby, G streamflow simulations are obtained for each long-term change scenario.

[2] For each of $j = 1, \ldots, J$ conditions of forecast skills, a future teleconnection index is developed by a bivariate conditional expectation with the generated streamflows. Here, the forecast skill ability is defined by the correlation ($\rho_{\tilde{\imath}\tilde{q}}$) between the seasonal index value ($\tilde{\imath}$) and the generated seasonal streamflows ($\tilde{q}$). Therefore, future seasonal values of the forecast-informed index are generated by $N(\mu_{\tilde{\imath}} + \frac{\sigma_I}{\sigma_{\tilde{q}}}\rho_{\tilde{\imath}\tilde{q}}(\tilde{q} - \tilde{\imath}), (1 - {\rho_{\tilde{\imath}\tilde{q}}}^2){\sigma_{\tilde{\imath}}}^2)$. In this study, $J = 5$ future forecast skills are generated to examine the impacts of forecast skill degradation, along with G streamflow simulations for each long-term change (illustrated in Section 4.1).

[3] After a reservoir plan is operated with future streamflow simulations, a binary performance score, $U(h, g, j)$, is developed to characterize system performance. The binary performance score returns a value of 1 if the reservoir operation shows acceptable performance; otherwise it obtains a value of 0. In this study, performance is considered acceptable if simulated storages S_t are maintained above a predefined threshold (the critical storage C^{***} used here is described in Section 3.1). Instead, acceptable performance can be defined by comparing any performance variable (e.g., deficit in water supply) with a predefined threshold.

[4] For h^{th} long-term climate change scenario and j^{th} condition of forecast skill, the robustness index (RI) of the specific reservoir operation, similar to (Steinschneider et al., 2015), is developed by integrating the binary performance scores (Eq. 5).

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$$RI_{h,j} = \frac{1}{G}\sum_{g=1}^{G} U(h,g,j) \qquad \text{Eq. (5)}$$

In this study, averaging binary scores is used to summarize a sufficiently large number of future scenarios ($G = 200$). We note that an additional process (e.g., providing a different weight to each scenario) may be considered to develop the RI if limited sets of scenarios are used. Then, assigning normalized weights for each scenario can be used.

Although other performance metrics are available (e.g., reliability, resilience, and vulnerability described in Fowler et al. (2003) and Hashimoto et al. (1982)), the RI is preferred in this study because the three metrics may be more appropriate under conditions where the single time series is believed to fully represent the uncertainty of future inflows but is less appropriated in the analysis with many possible future scenarios (Whateley et al., 2014).

[5] The RI offers a mapping, which can be used to determine whether a reservoir plan is robust under potential climate conditions considered. If the RI for the defined climate condition is greater than the adequate threshold ($\wedge^{RI} = 0.9$ in this study), we consider the reservoir plan robust for the climate condition. In addition, an ensemble of GCM projections is superimposed on these surfaces to provide the likelihood of different climate changes.

[6] Finally, the degradation robustness index (DRI) of the forecast-based reservoir operation is developed under j^{th} forecast skill change as follows:

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$$DRI_j = \frac{1}{G \times H} \sum_{h=1}^{H} \sum_{g=1}^{G} U(h,g,j) \qquad \text{Eq. (6)}$$

Similar to the RI, an adequate threshold is defined for the DRI ($\wedge^{DRI}$ = 0.7 in this study). Although this threshold is arbitrary, it is quite useful in a decision-making process. Also, the lower threshold is acceptable because it must consider a plan under a sufficiently large range of long-term climate change scenarios. Alternatively, system planners can decide the value of the threshold based on their expertise after reviewing the robustness.

3. Case Study Description

3.1 Overview of water supply system and its rule curve

This study focuses on the water supply systems in two adjacent basins including the Geum River Basin and the western Geum River Basin, located in midwest of South Korea (Figure 1). The basins receive an annual average of 1,250 mm precipitation. Similar to other regions in South Korea, the basins are affected by a monsoon climate that often generates extraordinarily heavy rainfall and corresponding floods in the summer (Yan et al., 2015). Accordingly, two-third of annual precipitation is concentrated in the summer spanning from June to early September (flood season) while only one-thirds of annual precipitation falls during the remaining months (drawdown season). The drawdown season is generally dry, contributing to periodic droughts to the basins (Ahn and Kim, 2019). These distinct seasonal climate fluctuations pose significant water management challenges including requiring deliberate operation of the local reservoirs (Sohn et al., 2013).

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This study uses the Boryeong Reservoir in the western Geum River Basin, and the Baekje Weir in the Geum River Basin (Figure 1). The Boryeong Reservoir with a storage capacity of 116.9 MCM (1 MCM is equal to 10^6 m^3) was constructed in 1998 to serve four main purposes: (1) flood control, (2) water supply, (3) water quality, and (4) hydropower generation, and is operated by the Korean water resources corporation (K-water). The reservoir serves as the principal municipal and industrial water supply (WS^{MI}) source for eight cities such as Boryeong, Dangjin, and Seosan, and is also operated for hydropower generation (WS^{HP}), environmental demand (WS^{EN}), and supply of seasonal irrigation demand (WS^{IR}). Therefore, total controlled releases for water supply at time t are expressed as $R_t = WS_t^{MI} + WS_t^{EN} + WS_t^{IR} + WS_t^{HP}$. While the reservoir has a flood control storage capacity (106.3 MCM) for the flood season, the dead storage capacity is limited to 8.1 MCM for the drawdown season.

Our study basin experienced severe droughts in 2002 and 2014-2016. In particular, during the 2014-2016 drought, the Boryeong Reservoir failed to satisfy the designed demands including municipal, agricultural, and environmental water supplies, adversely affecting the environment and inadvertently harming people. During the multi-year drought, storage of the reservoir was depleted to just 18.9% of its capacity—which is the minimum percentage in the historical record (Hong et al., 2016). To protect the system against other extreme droughts and changes in climate, two alternatives have been suggested. First, a new operation rule, comprised of three storage levels, was developed for the Boryeong Reservoir (Figure 2; Ministry of Land, Infrastructure and Transpor, 2015). If the reservoir level drops below the mild storage level C^*, water allocation for WS^{EN} is terminated the water level rises above C^*. Then, if the reservoir level falls below than the severe level C^{**}, three water demands (WS^{EN}, WS^{IR}, WS^{MI}) are restricted by 100%, 30% and 10%, respectively. Here, additional water restriction of 10% is conducted for WS^{MI} if the reservoir level drops below the critical storage level C^{***}. In the analysis, we adopt the water restriction policies across the three operation rules ($\boldsymbol{C_{Baseline}}$, $\boldsymbol{C_{Forecast}}$, $\boldsymbol{C_{Dynamic}}$). Also, the current critical level C^{***} is employed to make a fair comparison between strategies whereas C^{*} and C^{**} of the forecast-based operations are determined by a stochastic model (see Section 2.1).

Next, K-water recently constructed a 21 km, 110 cm water transfer pipe connecting the Baekje Weir (storage capacity: 28.7 MCM) to the Boryeong Reservoir in preparation for water shortages. The Baekje Weir was completed in 2013 to mainly support agricultural demand with the flood control storage capacity (28.6 MCM) and dead storage capacity (5.7 MCM). The new pipe can draw water from the Baekje Weir with a maximum of 115,000 m^3 per day before depleting storage of the Boryeong Reservoir. For this strategy, the water transfer option is triggered when storage of the Boryeong Reservoir falls below the severe level C^{**} and continues until the Boryeong Reservoir rises above C^{**}.

Finally, the storage (S) of the Boryeong Reservoir can be formulated as follows:

$$S_t = S_{t-1} + q_t + TR_t - SP_t - R_t \quad \text{Eq. (7)}$$

where SP_t indicates any water that spills out from the reservoir. We define that SP_t occurs only when $S_t > S_{max}$

3.2 Data

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Historic daily climate data, including precipitation, maximum and minimum temperatures were gathered from 60 of the Korea Meteorological Administration's Automated Surface Observing System (ASOS) gauges. The climate data was interpolated onto a 1/8 degree resolution (~140 km^2) by using the Thiessen polygons (Thiessen, 1911). The final historic data set was obtained over the period of 1 January 1973 to 31 December 2018 by averaging the values within the grid cells overlapping our study basin areas. In addition, monthly sea surface temperatures (SSTs) were obtained from the Extended Reconstructed Sea Surface Temperature version 5 dataset (Huang et al., 2017).

Daily historical inflow data for the Boryeong Reservoir was gathered online from the "Water Resources Management Information System" webpage (http://www.wamis.go.kr/) for the period of 1 January 1998 to 31 December 2018. The same hydrologic dataset for the Baekje Weir was collected from the "My water" webpage (http://www.water.or.kr/) over the period between 1 January 2013 and 31 December 2018. Note that both sets of hydrologic data were available only upon completion of their construction, respectively. Current demand data for all water use were obtained from our partners in K-water.

Mean changes in precipitation and maximum/minimum temperatures were collected from the World Climate Research Programme's Coupled Model Intercomparison Project Phase 5 (CMIP 5) multimodel data sets. The climate model projections were bias corrected using the detrended quantile mapping (DQM; Bürger et al., 2013; Eum and Cannon, 2017) method. These projected changes in precipitation and temperatures were calculated across the entire Boryeong Basin using 30-year windows between 1976 and 2005 (baseline) and 2051 and 2080 (future). Two emission scenarios (Representative Concentration Pathways 4.5 and 8.5) and initial condition

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members of 26 models (presented in Table S1) were employed in the analysis.

4. Results

4.1 Climate teleconnections for Boryeong Reservoir

Many studies have well documented the global impacts of the El Niño-Southern Oscillation (ENSO), a large-scale oceanic circulation pattern in the tropical Pacific Ocean (Kug et al., 2009; Sharma et al., 2016; Ward et al., 2014) whereas further examination is necessary to investigate its effects on the Korean Peninsula (Yoon and Lee, 2016). We identify that ENSO exhibits a lagged influence over hydroclimate in the western Geum River Basin and is used to construct hydrologic forecasts for the region during early spring, the most crucial period for reservoir operation in drawdown season. Figure 3a shows the Pearson correlation coefficients between June-August (JJA) SST at each ocean grid cell and average February-April (FMA) streamflow in the coming year for the Boryeong Basin over the period of 1998-2018 (21 years). Similar analysis is conducted for seasonal low flows defined here by seasonal 20 day low flows (Figure 3b). These correlation patterns reveal that the FMA inflows are significantly and positively related with lagged ENSO, implying that summer ENSO provides some predictability. Wang and Fu (2000) reported that during El niño, an anticyclonic flow over the Philippine Sea develops, intensifying during the previous seasons and can affect climate in the following winter, bringing warm and moist air to East Asia. Following this pattern, hydrologic conditions are wetter (dryer) than usual with lagged effect during El niño (La Niño) events in our study area. For simplicity, we use Niño 3.4 (Gergis and Fowler, 2005) to represent the magnitude of ENSO (Figures 3c and 3d). The correlation (ρ) between Niño 3.4 and seasonal average flows (seasonal low flows) is 0.72 (0.58), indicating that the relationship is fairly significant. For

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developing forecast-based operations, the binary forecasts of Niño 3.4) are issued based on the state of the Niño 3.4 indices being greater than or less than median values (Niño 3.4^{+} and Niño 3.4^{-}) in this study. Also, seasonal low flows are utilized to investigate the potential impacts of forecast skill change from the relationships with Niño 3.4 because seasonal low flows are more directly associated with drought conditions than average flows. Accordingly, future forecast skills ($J = 5$) of Niño 3.4 are defined by absolute changes in the correlation with seasonal low flows (ranges between 0.15 and 0.75).

4.2 Performances of weather generator and hydrologic modeling

Figure 4 shows a brief evaluation to demonstrate the ability of the weather generator to simulate historical climate conditions for the Boryeong and Beakje Basins. Here, 400 simulations with no changes imposed are compared against observed statistics for each calendar month. The average, standard deviation, skew of daily precipitation, and kurtosis of daily precipitation are displayed in Figure 4a-d. Similarly, the average and standard deviation of maximum/minimum temperatures are presented in Figure 4e-f. Overall, the results suggest good performance for all variables and statistics with observation values falling within the range of the simulations. Note that the simulations are slightly biased in regard to standard deviations of maximum/minimum temperatures for some months (e.g., maximum temperatures are underestimated in August while overestimated in September). We also confirm that the cross-correlations of all three variables for calendar months are fairly preserved in the simulations (not shown). The performance confirms that the weather generator used in this study is appropriate to reproduce climate scenarios for our study basins.

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Figure 5 shows observed daily streamflow for the last three years of calibration and two years in the validation period. Note that different calibration and validation periods are selected for each basin due to the imbalance in the records of hydrologic data (see Section 3.2). For the Boryeong Basin, augmented SAC-SMA is calibrated (validated) by using the observed daily data from January 1999 to December 2013 (January 2014 to December 2018). The KGE, NSE, and percent bias (PB) are 0.79, 0.58, and 0.2% for the calibration period and 0.77, 0.61, and 0.8% for the validation period, respectively. The PB is expressed as a percentage of observed values. For the Beakje Basin, SAC-SMA is calibrated (validated) by using the data from January 2013 to December 2016 (January 2017 to December 2018). The KGE, NSE, and PB equal 0.83, 0.66, and 0.5% for the calibration period and 0.75, 0.55, and -8.3% for the validation period. Based on performance criterion suggested by Martinez and Gupta (2010) and Moriasi et al. (2007), these performances are considered either "good" or "efficient" for daily simulation. Note that because the NSE is not adopted for the objective of calibration, it is not significantly decreased from the calibration to the validation period. The parameters calibrated for the two basins are also presented in Table 1.

4.3 Rule curve comparison in historical period

Figure 6 shows a time-series of Boryeong Reservoir storage operated by three rule curves ($\boldsymbol{C_{Baseline}}$, $\boldsymbol{C_{Forecast}}$, and $\boldsymbol{C_{Dynamic}}$) as well as three rule curves themselves for the most recent seven years (2012-2018). This period is selected since it reflects the worst drought on record (see Section 3.1). Note that simulated inflow for the Beakje Weir is utilized for $\boldsymbol{C_{Dynamic}}$ based on the assumption that the water transfer option is available from the initial date of the Boryeong Reservoir. Figure 6a presents the status quo operation curves exhibiting

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a pronounced and seasonal pattern whereas Figures 6b and 6c also show the forecast-based rule curves which are changed year to year on the basis of a hydrologic forecast associated with lagged ENSO events. Here, Niño 3.4^{+} $\boldsymbol{C_{Forecast}}$ is shifted downward especially for the severe storage level (C**) compared to Niño 3.4^{-} $\boldsymbol{C_{Forecast}}$ which is consistent with the ENSO forecasting signal identified in Section 4.1.

Several insights emerge from Figure 6. In Figures 6a, $\boldsymbol{C_{Baseline}}$ experiences critical drawdowns during the 2016-2017 drought event with storage falling below C^{***} for 272 days. Under $\boldsymbol{C_{Forecast}}$, critical drawdowns are somewhat moderated with storage falling below C^{***} for 243 days albeit with little benefit. The marginal improvement is from a potential drawback of the forecast-based operation. In 2017 when the drought was most severe, the risk of water shortage is incorrectly predicted by the summer ENSO, leading to the storage level falling below the critical level. That highlights that the risk associated with seasonal forecasts in an individual year can increase even if average performance is better from reliable forecast information. A potential drawback is alleviated when the real-option water transfer is adopted ($\boldsymbol{C_{Dynamic}}$). The real-option from the Beakje Weir eliminates critical drawdowns even in 2016-2017 which are the driest periods on record. This indicates that the real-option is beneficial in preventing the Boryeong Reservoir from falling below critical storage levels even for a multi-year drought event.

4.4 Robustness in climate uncertainties

Figure 7 shows the RI of three operation rule curves ($\boldsymbol{C_{Baseline}}$, $\boldsymbol{C_{Forecast}}$, and $\boldsymbol{C_{Dynamic}}$) for

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changes in mean precipitation and temperature with the teleconnection forecast skill held at baseline level (ρ=0.55). $\boldsymbol{C_{Baseline}}$ provides robust performance for all temperature changes when mean precipitations exceed 110% of historical means but when mean precipitations drop, the operation is fairly vulnerable. In addition, the operation rule is not robust for current precipitation and temperature conditions (RI = 0.71). On the other hand, $\boldsymbol{C_{Forecast}}$ shows improved performance for current conditions (RI = 0.83). In comparison, $\boldsymbol{C_{Forecast}}$ improves overall system performance compared to $\boldsymbol{C_{Baseline}}$, suggesting that improved operation performance is expected when the forecast-based operation is applied as described in previous studies (Block, 2011; Visser, 2017). When $\boldsymbol{C_{Dynamic}}$ is utilized, we may expect more reliable performance, which is confirmed in the analysis using historical records. Even though mean precipitation is reduced by 10% of the historic value, a high level of robustness (RI= 0.90) could be expected by $\boldsymbol{C_{Dynamic}}$, supporting the use of option instruments for the Boryeong reservoir.

In the results, we also confirm nonlinear results by changes in mean temperature whereas changes in mean precipitation lead to consistently dominant changes. The nonlinear performance in warmer conditions may be due to a shift in the hydrograph that accompanies changes in temperature due to changes in the timing and magnitude of snow accumulation and melting. Figure 7 also includes pdfs developed by an ensemble of GCM projections. Projections are centered on an increase of 11% mean precipitation and 1.78 °C. For the centered projections, three operation rules achieve a similarly reliable performance. However, approximately 38% (25%) of the GCM projections are located in the relatively risky climate surfaces for $\boldsymbol{C_{Baseline}}$ ($\boldsymbol{C_{Dynamic}}$). The portion of the GCM (11%) is further decreased for

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$C_{Dynamic}$. Taken together, an improved operation rule may be urgently needed and can be achieved by our dynamic operation rule if teleconnection forecast skills are preserved.

Next, Figure 8 summarizes the results for all of the combinations of climate change considered in this study. Also, the DRI is calculated for each forecast skill (see Section 2.3) and is presented in Table 1. Note that the status quo operation is not shown here because it is not affected by degradation of the forecast skill therefore the results of Figure 7a are equally obtained for each forecast skill. Several insights emerge from these results. First, the robustness of two dynamic operations, $C_{Forecast}$ and $C_{Dynamic}$, are decreased when the forecast skill abilities decline. Second, $C_{Forecast}$ provides adequate performance across a wide range of the forecast skill degradation when compared to $C_{Baseline}$ (DRI = 0.632). This also includes very low forecast ability ($\rho = 0.15$) although the results may be caused by the higher reservoir levels used in $C_{Forecast}$ than in $C_{Baseline}$ (see Figure 6). However, improved $C_{Forecast}$ does not still satisfy our predefined threshold (Λ^{DRI}) in all forecast skills. Third, $C_{Dynamic}$ is very effective when the forecast-based operation is incorporated with the real-option water transfer. $C_{Dynamic}$ shows the reliable robustness (DRI = 0.706) even with lower forecast ability ($\rho = 0.35$) for the forecast-based operation. It suggests that the real-option can manage both the downside risk of faulty seasonal forecasts and severe changes in climate. These results advocate the use of the real-option for the Boryeong Reservoir as a powerful instrument in the future. We note that the economic analysis to maintain infrastructure to facilitate water transfers is not conducted in this study. However, the cost may be significantly less than those required to install a new impoundment to expand system storage, which is another advantage for the

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real option. Lastly, we may conclude that $C_{Dynamic}$ is quite robust even though the forecast skill ability is significantly reduced by 40% of the current skill.

5. Summary and Conclusions

Dynamic reservoir operations have received widespread interest in the field of reservoir operations and climate change adaptation strategy, but little attention to quantifying their robustness to a variety of climate uncertainties. Using a robustness-based method, we develop an evaluation framework that can be applied based on a range of defined climate change space over which acceptable performance can be achieved. In particular, a new metric, the degradation robustness index (DRI), is proposed to scrutinize the robustness of a forecast-based operation rule under the possibility of forecast skill degradation and climate variable alterations.

The novel contribution is also achieved by proposing new dynamic reservoir operation rules for our case study, the Boryeong Reservoir, which has recently experienced the worst drought in its historical record. For developing forecast-based operations, we newly identify lagged ENSO effects on inflows during early spring the most crucial period for the Boryeong operation. The comparative results suggest that a forecast-based operation may be favorable compared to the status quo operation currently utilized in the reservoir system. In addition, we also examine the effects of a water transfer option that recently questioned whether a real-option water transfer from the Baekje Weir is useful. Using such an option would bolster system performance by enabling the reallocation of water when the Boryeong Reservoir is in a precarious condition. Furthermore, we confirm the real-option can support a forecast-based operation for our reservoir system when ill-informed operation adjustments would be happened by misguided climate information.

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There are opportunities to further extend our evaluation. To simplify the analysis, we assume that current water demand scenarios will persist under future climate changes. While this simple assumption is acceptable for this study, future work needs to explore the impacts of various water demand scenarios (e.g., expansion of irrigation). Also, hydrologic uncertainty is not considered here even if the uncertainty may be significant for reservoir operations focusing on water supply objectives (Marton and Paseka, 2017; Steinschneider et al., 2015). A forecast-based operation could be designed to better utilize seasonal forecast information by using a specific optimization algorithm (e.g., Denaro et al. (2017)). However, the optimized operation policies should be re-evaluated in a cross-validation framework to ensure the calibration sets are robust. Given that only the relatively limited hydrologic data is available in our case study (21 years), the optimized policies is not considered.

Our framework is rather computationally intensive because a large set of future ensemble scenarios is employed to represent natural fluctuations in climate uncertainties. The limitation may be acceptable since the mandatory simulation time could be prohibitive for multi-reservoir systems, and thus high performance computing may be required (Kasprzyk et al., 2013). However, local water managers may prefer simple and concise techniques for their practical management. Future work could address devising concise approaches, which could effectively reduce computational burden.

In addition to the urgent need for effective reservoir operations, the western Geum River Basin has also faced many water-related issues including controlling water quality and combatting eutrophication from rising water temperature (Ahn and Kim, 2019). Perhaps, the most essential research is to estimate local streamflow after taking into account the impacts of water withdrawal networks. Although our study basin, the Boryeong Basin, is relatively free from human adjustments, most parts of the western Geum River Basin are regulated, indicating that relying on traditional hydrological models without accounting for human activity modules may not accurately represent the regional hydrology. Therefore, a network of hydrological models with feedback in coupled local reservoirs (e.g., Lv et al. (2016)) is required for hydrologic analysis. We believe that such large-scale coupled hydrologic and system models will be an attractive avenue for future research.

Acknowledgements

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) (No. 2019R1C1C1002438). The authors would like to thank Byoung-Dong Oh at the Korean Water Resources Corporation for providing data of the Boryeong Reservoir and Beakje Weir during the development of this paper. We also appreciate the APEC Climate Center (APCC) for offering the downscaled climate projections.

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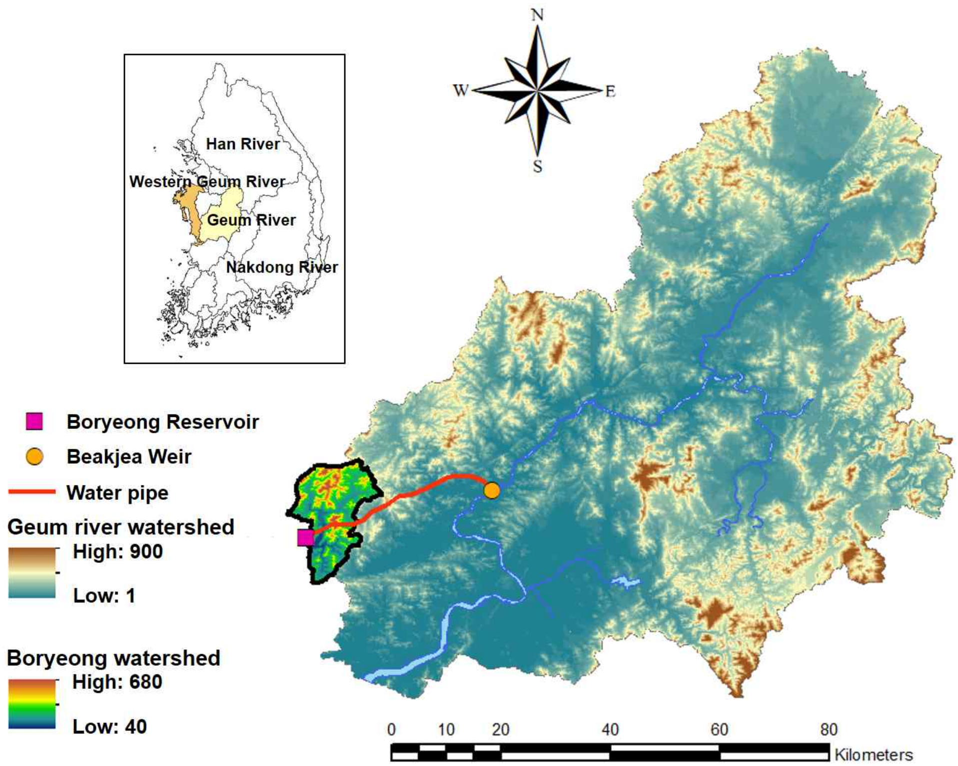

Figure 1 Map of the Geum River basin and the two Reservoirs (Boryeong Reservoir and Beakje Weir). Inset: the location of our study area in the Korean peninsula is presented.

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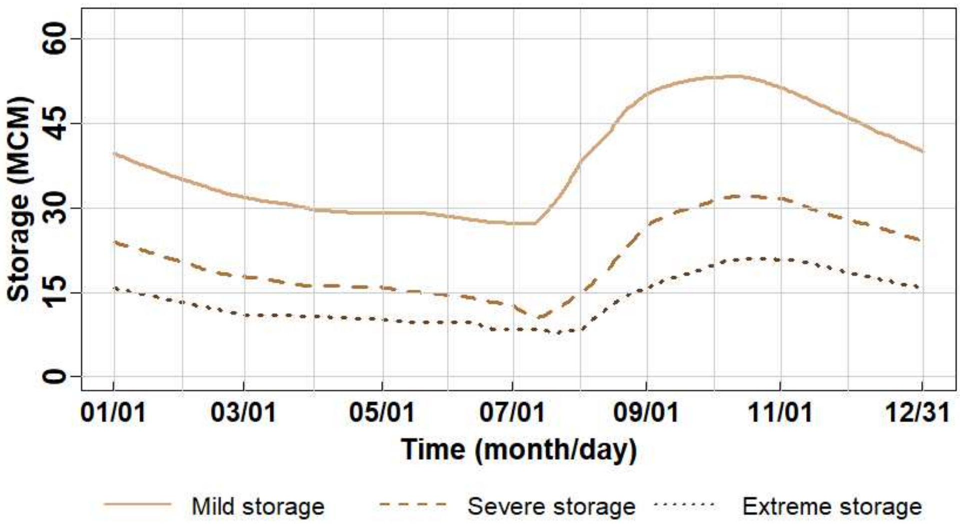

Figure 2 Standard operation rule curves currently used for the Boryeong reservoir.

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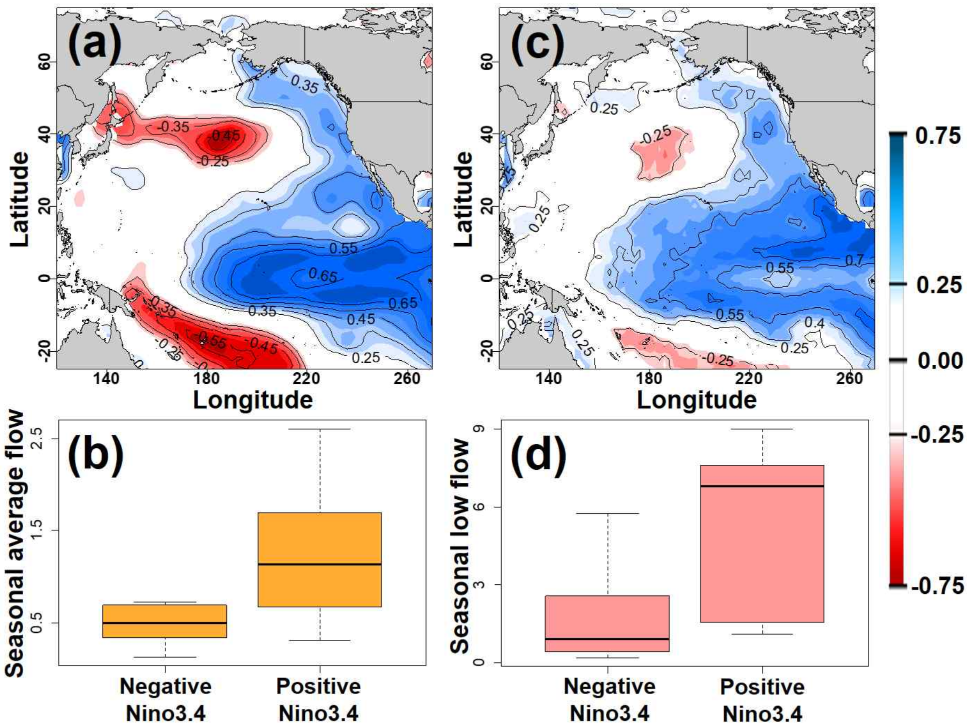

Figure 3 Pearson correlation coefficients between seasonal SSTs in JJA at each grid cell and (a) averaged FMA streamflow (c) FMA low flows in the following years, and Box plots for (b) averaged FMA streamflow (d) FMA low flows during previous years in which the JJA Nino 3.4 index is above or below its seasonal median.

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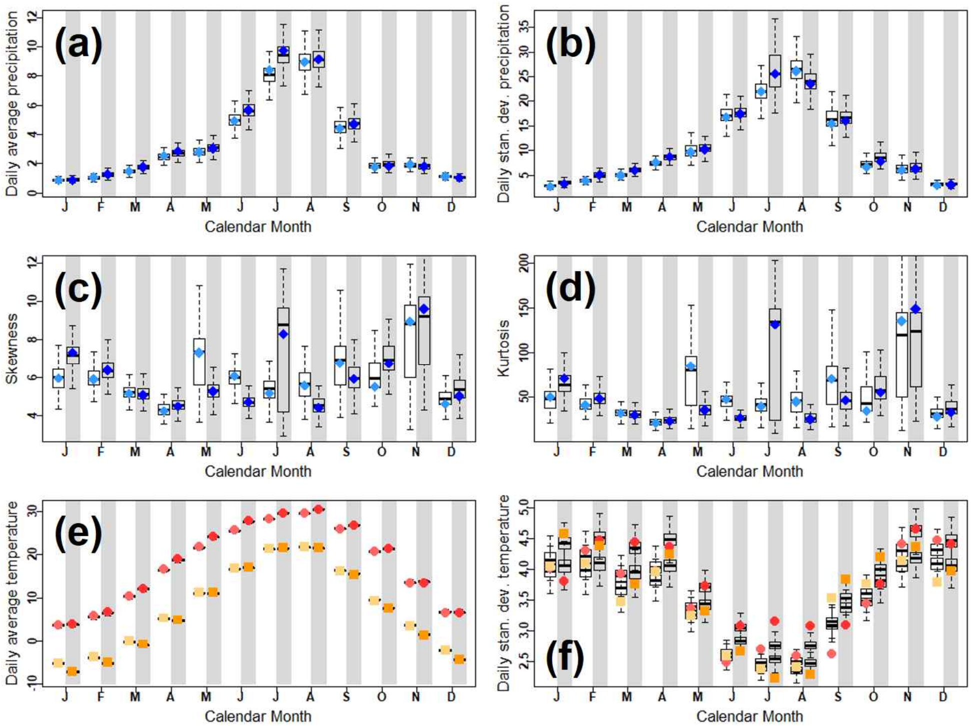

Figure 4 Evaluation of historical climate simulations for the Boryeong and Beakje Basins, including the (a) average (b) standard deviation (c) skewness (d) kurtosis (e) average and (f) standard deviation for maximum and minimum temperatures. Simulations for the Beakje Basin are highlighted (gray color). Also, observed precipitation, maximum and minimum temperatures are shown by using three colors (blue, red, and yellow).

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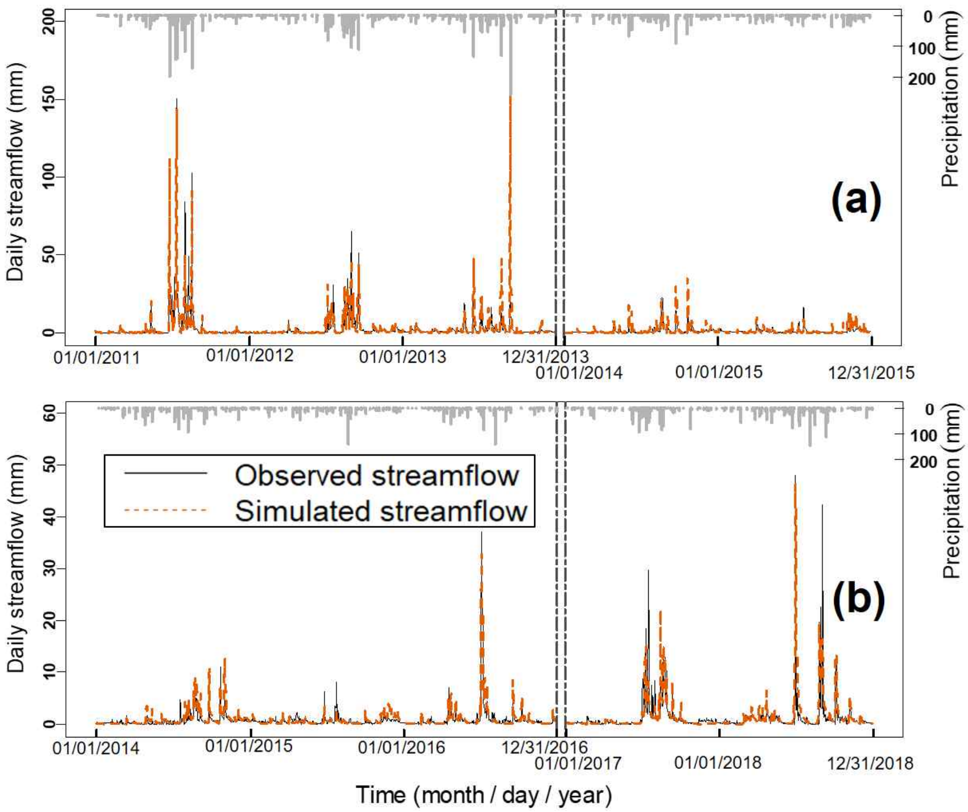

Figure 5 Simulated and observed inflows over the calibration (left) and validation (right) periods (a) for the Boryeong reservoir and (b) for the Beakje reservoir. Basin precipitation is also presented.

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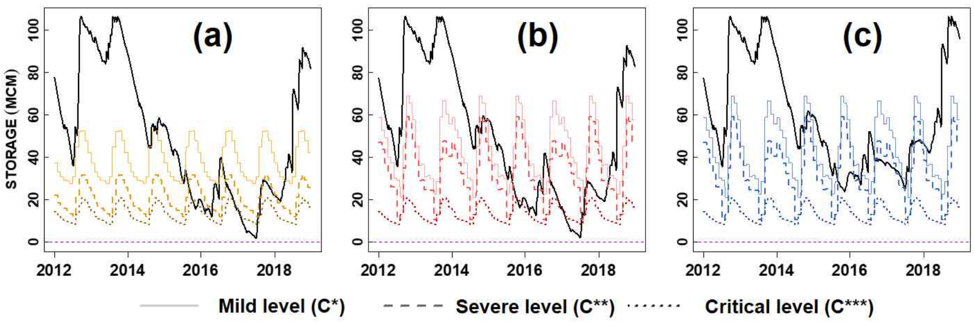

Figure 6 Storage simulation (Black line) of the Boryeong reservoir over historical data (2012-2018) using (a) status quo operation rule, (b) forecast-based operation, and (c) forecast-based operation with the real-option water transfer from the Beakje Weir. The critical storage level (C***) is commonly employed in three strategies.

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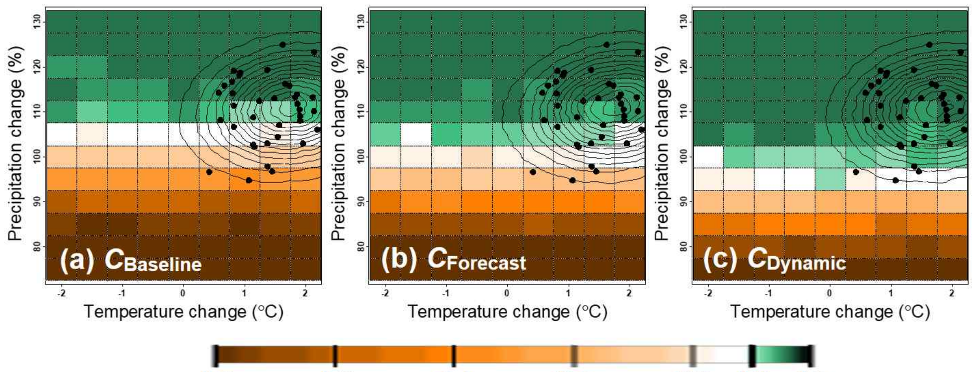

Figure 7 Robustness of three operation rules ($C_{Baseline}$, $C_{Forecast}$, and $C_{Dynamic}$) under future changes in precipitation and temperature with historical forecast skill ability (ρ=0.55). The green color indicates that the operation rule is robust for the defined changes. PDFs from GCM projections are superimposed over climate space to present the likelihood of different climate changes.

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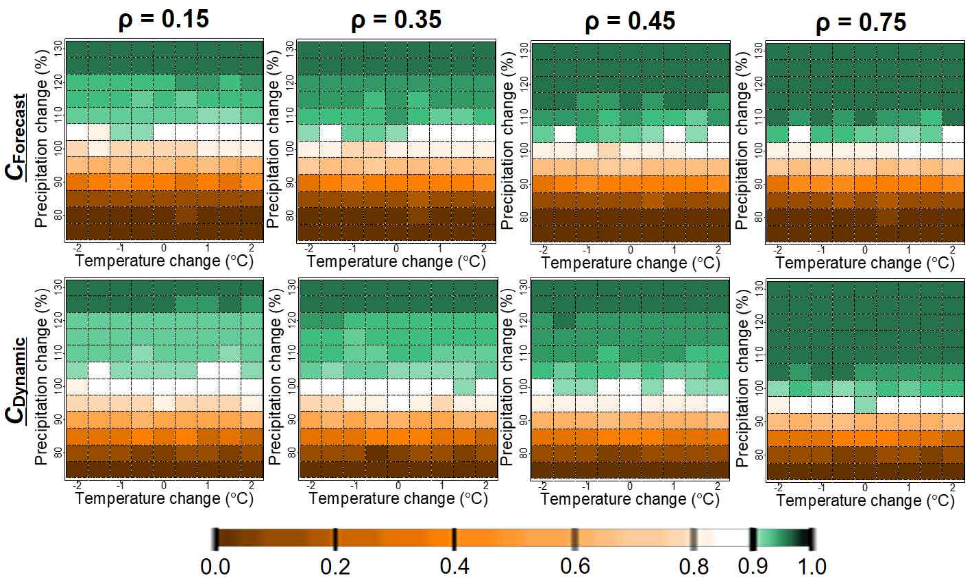

Figure 8 Robustness of two dynamic operation rules for changes in mean precipitation, mean temperature, and forecast skill ability. Here, the green color indicates that the operation rule is robust for the defined changes.

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Table 1 The parameters of the augmented Sacramento Soil Moisture Accounting (SAC-SMA) model used in this study

Parameter	**Description**	**Range**	**Calibrated value**	
			Boryeong	**Beakje**
UZTWM	Upper zone tension water capacity (mm)	(1 - 150)	5.80	3.30
UZFWM	Upper zone free water capacity (mm)	(1 - 150)	92.71	137.96
LZTWM	Lower zone tension water capacity (mm)	(1 - 500)	10.41	75.16
LZFPM	Lower zone primary free water capacity (mm)	(1 - 1000)	29.28	75.15
LZFSM	Lower zone supplementary free water capacity (mm)	(1 - 1000)	9.09	48.66
UZK	Upper zone free water lateral depletion rate (1/day)	(0.1 - 0.5)	0.50	0.31
LZPK	Lower zone primary free water depletion rate (1/day)	(0.0001-0.25)	0.00	0.10
LZSK	Lower zone supplementary free water depletion rate (1/day)	(0.01 - 0.25)	0.24	0.12
ZPERC	Percolation demand scale parameter	(1 - 250)	249.08	69.93
REXP	Percolation demand shape parameter	(0.0 – 5)	0.00	4.52
PFREE	Percolating water split parameter	(0.0 - 0.6)	0.03	0.23
PCTIM	Impervious fraction of the watershed area	(0.0 - 0.1)	0.10	0.00
ADIMP	Additional impervious areas	(0.0 - 0.4)	0.07	0.00
MLT	Snow melting parameter	(0.0 - 1.0)	0.66	0.36
TRAN	Temperature above which all precipitation falls as rain (°C)	(-3.0 - 3.0)	-2.93	-2.88
TDIF	Nonnegative temperature difference from the TRAN for water stored as snow (°C)	(0 - 3.0)	0.83	0.64
e_T	Error term for temperate	(-1.0 - 1.0)	0.97	0.98
e_P	Error term for precipitation	(0.95 - 1.05)	1.03	0.98
e_{PET}	Error term for evapotranspiration	(0.95 - 1.05)	1.04	1.03

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Table 2 Results of the degradation robustness index (DRI) under three operation rules ($C_{Baseline}$, $C_{Forecast}$, and $C_{Dynamic}$). Acceptable values for the DRI are italicized and bolded.

Operations	$C_{Baseline}$	$C_{Forecast}$	$C_{Dynamic}$
Forecast skill ability (ρ)		**DRI**	
0.15	0.632	0.634	0.693
0.35	0.632	0.647	***0.706***
0.45	0.632	0.655	***0.718***
0.55	0.632	0.660	***0.725***
0.75	0.632	0.675	***0.739***