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Skill of seasonal flow forecasts at catchment-scale: an assessment across South Korea

Yongshin Lee[1], Francesca Pianosi[1], Andres Peñuela[2], Miguel Angel Rico-Ramirez[1]
[1] School of Civil, Aerospace and Design Engineering, University of Bristol, Bristol, BS8 1TR, UK
[2] Department of Agronomy, Unidad de Excelencia María de Maeztu, University of Cordoba, Cordoba, 14071, Spain

Correspondence: Yongshin Lee (yongshin.lee@bristol.ac.uk)

Abstract.
Recent advancements in numerical weather predictions have improved their forecasting performance at longer lead times for several months. As a result, seasonal weather forecasts, providing predictions of weather variables for the next several months, have gained significant attention from researchers due to their potential benefits for water resources management. Many efforts have been made to link seasonal weather forecasts with Seasonal Flow Forecasts (SFFs) using diverse hydrological models. However, generating SFFs with good skill at finer scales such as catchment remain challenging, hindering their application in practice and adoption by water managers. Consequently, water management decisions, not only in South Korea but also in many other countries, continue to rely on worst-case scenarios and the conventional Ensemble Streamflow Prediction (ESP) method. This study examines the potential of SFFs in South Korea at a catchment-scale. The analysis was conducted across 12 operational reservoir catchments of various size (from 59 to 6648 km2) over a last decade (2011-2020). Seasonal weather forecasts data (precipitation, temperature and evapotranspiration) from the ECMWF (European Centre for Medium-Range Weather Forecasts, system5) is used to drive a Tank model (conceptual hydrological model) to generate the flow ensemble forecasts. The actual skill of the forecasts is quantitatively evaluated using the Continuous Ranked Probability Skill Score (CRPSS), and it is probabilistically compared with ESP, which is the most popular forecasting system. Our results highlight that precipitation is the most important variable in determining the skill of SFFs, while temperature also plays a key role during the dry season in snow-affected catchments. Given the coarse resolution of seasonal weather forecasts, a linear scaling method to adjust the forecasts is applied, and it is found that bias correction is highly effective in enhancing the skill of SFFs. Furthermore, bias corrected SFFs showed higher skill than ESP up to 3 months ahead, and it was particularly evident during abnormally dry years. To facilitate future applications to other regions, freely available Python packages for analysing seasonal weather and flow forecasts have been made accessible.

Keywords: Seasonal weather forecasts, Seasonal flow forecasts, Skill assessment, Ensemble Streamflow Forecast, CRPSS, Linear scaling

1. Introduction

Over the last decade, numerical weather prediction systems have improved their forecasting performance at longer lead times, ranging from 1 to several months ahead (Alley et al., 2019; Bauer et al., 2015). The water management sector may benefit considerably from these advances. In particular, predictions of weather variables such as precipitation and temperature several months ahead ('seasonal weather forecasts' from now on) might be exploited to anticipate upcoming dry periods and implement management strategies for mitigating future water supply deficits (Soares and Dessai, 2016).

To increase relevance for water resource management, seasonal weather forecasts can be translated into Seasonal Flow Forecasts (SFFs) via a hydrological model. SFFs can be provided and evaluated at different temporal and spatial resolutions: a coarser resolution, e.g., magnitude of total next-month runoff over a certain region (Arnal et al., 2018; Prudhomme et al., 2017) or a finer resolution, e.g., daily/weekly streamflow at a particular river section over the next month (Crochemore et al., 2016; Lucatero et al., 2018). The distinction is important here because coarser resolution SFFs can only be used to inform water management in a qualitative way, whereas finer resolution SFFs can also be used to force a water resource system model for a quantitative appraisal of different management strategies. Proof-of-principle examples of the latter approach are provided by Boucher et al. (2012), Chiew et al. (2003), and Peñuela et al. (2020). These papers have demonstrated, through model simulations, the potential of using SFFs to improve the operation of supply reservoirs (Peñuela et al., 2020), irrigation systems (Chiew et al., 2003) and hydropower systems (Boucher et al., 2012).

Obviously, generating seasonal flow forecasts with good skill at finer scale is challenging and lack of skill is often cited as a key barrier to real-world use of SFFs by water resources managers (Jackson-Blake et al., 2022; Soares

https://doi.org/10.5194/egusphere-2023-2169
Preprint. Discussion started: 16 October 2023

and Dessai, 2016; Whateley et al., 2015). In practice, if a Water Resource System (WRS) model is used to simulate and compare different operational decisions, this is done by forcing the WRS model against a repeat of a historical low flow event ("worst-case" scenario) (Yoe, 2019) or against ESP. ESP is a widely used operational forecasting method whereby an ensemble of flow forecasts is generated by forcing a hydrological model forced with historical meteorological observations (Baker et al., 2021; Day, 1985). Since the hydrological model is initialised at current hydrological conditions, ESP are expected to have a certain level of skill particularly in "long-memory" systems where the impact of initial conditions last over long time periods (Li et al., 2009). Previous simulation studies that examined the use of SFFs to enhance the operation of water resource systems (e.g., Peñuela et al., 2020, as cited above) did indeed show that ESP serves as a 'hard-to-beat' benchmark. Similar to other countries, in South Korea, the worst-case scenario and ESP are used for informing water management activities, whereas SFFs are not currently used. Before the use of SFFs can be proposed to practitioners, it is thus crucial to understand the skill of such products and how it compares to ESP.

Numerous research has been conducted on the skill of SFFs in different regions of the world. Some of these studied focused on the 'theoretical skill', which is determined by comparing SFFs with pseudo-observations produced by the same hydrological model when forced with observed temperature and precipitation. This experimental set-up enables to isolate the contribution of the weather forecast skill to the flow forecast skill, regardless of structural errors that may be present in the hydrological model. In general, most studies have found that the theoretical skill of SFFs may be only marginally better than that of ESP in specific region and lead time. For example, Yoseff et al. (2013) analysed multiple large river basins worldwide and found that SFFs generally perform worse than ESP. Likewise, the findings of Greuell et al. (2019) indicated that SFFs are more skillful than ESP for the first lead month only. Across Europe, the theoretical skill of SFFs was found to be higher than the theoretical skill of ESP in regions with long hydrological memory, and notably lower in cold and semi-arid areas (Pechlivanidis et al., 2020) as well as coastal and mountainous regions (Greuell et al., 2018).
Although important to how the information content of seasonal weather forecasts vary across regions with different climatic characteristics, from a water management perspective, the theoretical skill may not be the most appropriate metric, as it reflects the performance within the modelled environment (Pechlivanidis et al., 2020) rather than the real-world. The 'actual skill', which is determined by comparing SFFs to streamflow observations, would be more informative for water managers to decide on whether to use SFFs and when. Previous studies that investigated the actual skill showed that, as expected, the actual skill is lower than the theoretical skill due to errors in the hydrological model and in the weather input observations (Greuell et al., 2018; van Dijik et al., 2013). In addition, due to the coarse horizontal resolution of seasonal weather forecasts (around 1°×1°), the forecast skill can be significantly improved through bias correction, particularly of precipitation forecasts (e.g., Crochemore et al., 2016; Lucatero et al., 2018; Tian et al., 2018). However, even after bias correction, SFFs were found unable to surpass the (actual) skill of ESP in many previous applications (e.g., Crochemore et al., 2016; Greuell et al., 2019; Lucatero et al., 2018).
Previous studies reviewed above have mainly used the seasonal weather forecasts provided by the European Centre for Medium-Range Weather Forecasts (ECMWF). Here, it is important to note that the majority of these studies have utilized ECMWF's system 3 (e.g., Yossef et al., 2013) or 4 (e.g., Crochemore et al., 2016; Greuell et al., 2019; Lucatero et al., 2018; Tian et al., 2018). Only a few studies have been conducted based on ECMWF's cutting-edge forecasting system version 5, which became operational in November 2017. These include Peñuela et al., 2020 and Ratri et al., 2023, which however did not analysed the skill of the SFFs in much detail but rather focused on their operational implementation. Given that the upgrade of forecasting system can lead to substantial enhancement in overall performance (e.g., Johnson et al., 2019; Köhn-Reich and Bürger, 2019), it is interesting to assess whether improved skill of weather forecasts delivered by the System 5 translates into improved skill of flow forecasts.

Our previous research (Lee at al., 2023) on the skill of seasonal precipitation forecasts (SPFs) across South Korea, showed that the ECMWF's system 5 provides skilful seasonal precipitation forecasts that outperform the climatology (based on historical precipitation observations), particularly during the wet season (June to September) and in dry years, where skill can be high also at longer lead times beyond the first month. Considering the significant correlation between precipitation and streamflow in the country (Ministry of land, infrastructure, and transportation, 2016), South Korea is an interesting test bed to investigate if the skill of seasonal precipitation forecasts is mirrored into the skill of SFFs at the catchment scale.

Specifically, in this study we focus on 12 catchments of various size (from 59 to 6648 km^2) which include the most important multipurpose reservoirs across South Korea, and where the use of SFFs may considered for assisting operational decisions and mitigating impacts of droughts. Given this practical long-term goal, our study focuses on assessing the actual skill and comparing it with ESP, which is a simpler to implement (and already in use) forecasting system. As a hydrological model, we use the lumped Tank model (Sugawara et al., 1986) which

https://doi.org/10.5194/egusphere-2023-2169
Preprint. Discussion started: 16 October 2023

is the rainfall-runoff model currently in use for the national water management and planning. For all catchments, we briefly analyse the hydrological model performance and gap between theoretical and actual skill. We also investigate which weather forcing input (precipitation, temperature, and potential evapotranspiration) mostly contribute to the actual skill of SFFs across different catchments, before and after bias correction. Finally, we look at how the actual skill varies across seasons, years, and catchment, to draw conclusions on when and where SFFs may be more informative than ESP for practical water resources management. In doing so, we develop a workflow for SFFs analysis, implemented in a Python Jupyter Notebook, which can be utilized by readers to evaluate and test SFFs in other regions.

2. Material and methodology

2.1 Study site and data

2.1.1 Study site

The spatial scope of this study is defined as 12 multi-purpose reservoir catchments across South Korea. While there are 20 multi-purpose reservoirs nationwide (Korea Water Resources Corporation (K-water), 2022), we have specifically selected 12 reservoirs with no external flows from other rivers or reservoirs. The selected reservoirs have at least 10 years of historical flow data as reported in Table 1. The location of the catchments and the mean annual precipitation, temperature, and potential evapotranspiration (PET) are shown in Figure 1(a-c). Generally, the catchments located in the southern region exhibit higher mean annual precipitation, temperature, and PET.

Table 1. Properties of the 12 multipurpose reservoirs and the catchments they drain (K-water, 2022). P is precipitation, T is temperature and PET is potential evapotranspiration.

Catchment		Soyanggang	Hoengseong	Chungju	Andong	Imha	Yongdam	Buan	Sumjingang	Hapcheon	Milyang	Namgang	Jangheung
Area (km^2)		2703	209	6648	1584	1361	930	59	763	925	95	2285	193
Mean annual	P (mm)	1220	1336	1197	1079	956	1317	1292	1343	1279	1375	1477	1439
	T (°C)	10.8	10.9	11.1	11.1	12.2	11.8	13.5	12.6	12.8	14.2	13.5	13.8
	PET (mm)	874	870	881	896	947	884	960	919	933	993	952	896

https://doi.org/10.5194/egusphere-2023-2169
Preprint. Discussion started: 16 October 2023

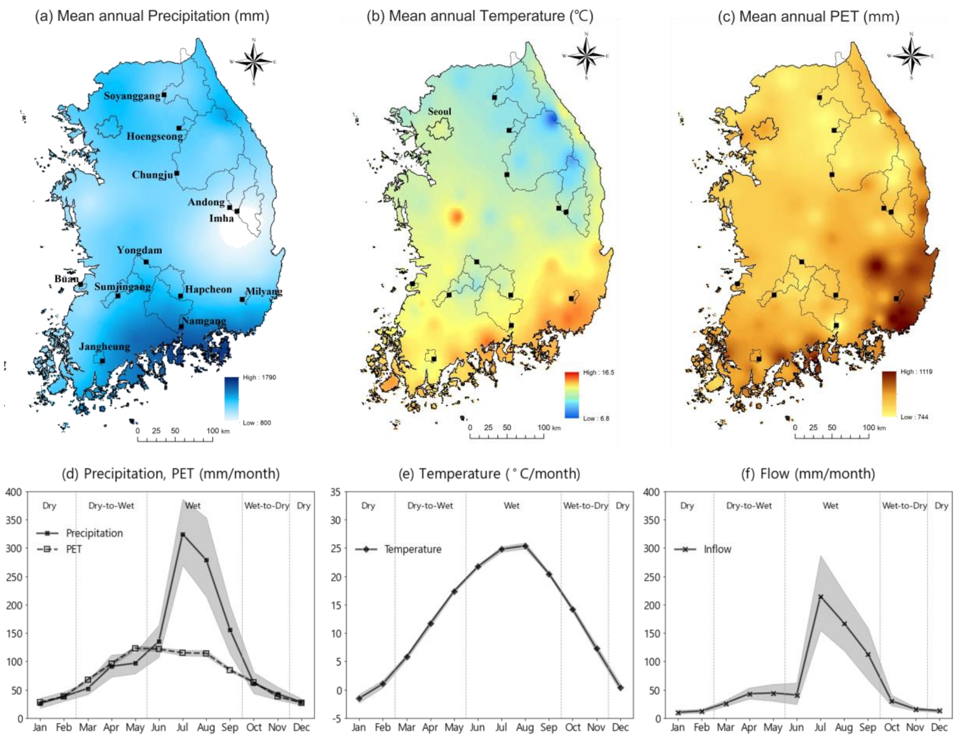

Figure 1: Mean annual (1967-2020) (a) precipitation (mm/year), (b) temperature (℃/year) and (c) PET (mm/year) across South Korea; the boundaries of the 12 reservoir catchments are shown in the figures. Mean monthly (d) precipitation and PET, (e) temperature and (f) flow averaged over the 12 reservoir catchments from 2001 to 2020. The grey area represents the variability of each weather variable. Note that the figures a to c were produced by interpolating the point measurements using the inverse distance weighting method for displaying purposes.

Figure 1(d-f) show the monthly changes in precipitation and PET (d), flow (e), and temperature (f) averaged over the 12 selected catchments from 2001 to 2020. In order to examine how the skill of seasonal weather and flow forecasts varies across a year, we divide a year into four seasons: dry (December to February), dry-to-wet Transition (March to May), wet (June to September), wet-to-dry Transition (October to November). As shown in this figure, most of the total annual precipitation (and the corresponding flow) occurs during the hot and humid wet season, while the dry season is characterized by cold and dry conditions. Precipitation and flow show high inter-annual variability during the wet season due to the impacts of Typhoons and Monsoon. On the other hand, PET and temperature exhibit marginal inter-annual variability.

2.1.2 Hydrologic data and seasonal weather forecasts

Precipitation, temperature, and potential evapotranspiration are the key variables required to simulate flows using a hydrological model. To this end, daily precipitation data from 1318 in-situ stations produced by the Ministry of Environment, the Korea Meteorologic Administration, and the national water resources agency (K-water) (Ministry of Environment, 2021), and daily temperature data from 683 in-situ stations generated by KMA were obtained. Both precipitation and temperature data cover the period from 1967 to 2020 (see Figure 1). Potential evapotranspiration (PET) data was computed using the standardized Penman-Monteith method suggested by UN Food and Agriculture Organization. The precipitation and temperature measurements have been quality-controlled by the Ministry of Environment. We used the Thiessen polygon method to calculate the catchment average precipitation and temperature.
Specifically, the flow data used in this study refers to the flow to the reservoir from their upstream catchment (see Table1 and Figure 1). Streamflow data was generated via field measurement and a rating curve, flow data is calculated using a mass balance equation, which takes into account the daily changes in reservoir volume (from storage-elevation curve) caused by the water level fluctuations and water supplies. However, to date, the reservoir

https://doi.org/10.5194/egusphere-2023-2169
Preprint. Discussion started: 16 October 2023

evaporation has not been considered in estimating the flow of reservoirs in South Korea. In this study, quality-controlled daily flow data for each reservoir produced by K-water is used.

Several weather forecasting centres, including European Centre for Medium-Range Weather Forecasts (ECMWF), the UK Met Office and the German Weather Service (DWD), provide seasonal weather forecasts datasets through the Copernicus Climate Data Store (CCDS). According to our previous study (Lee et al., 2023), ECMWF was found to be the most skilful provider of seasonal precipitation forecasts for South Korea. Since the precipitation is one of the most important weather forcings in hydrological forecasting (Kolachian and Saghafian, 2019), we have utilized the seasonal weather forecasts datasets from ECMWF (System 5) in this study. Since 1993, ECMWF has been providing 51 ensemble forecasts (a set of multiple forecasts equally likely) on a monthly basis (25 ensembles prior to 2017) with a horizontal resolution of 1° × 1° and daily temporal resolution up to 7 months ahead. The time period from 1993 to 2020 was selected and the ensemble forecasts for the selected catchments have been downloaded from the CCDS.

2.2 Methodology

The methodology of our analysis is summarized in the schematic diagram shown in Figure 2. Firstly, we compiled seasonal weather forecasts ensemble from ECMWF for precipitation (P), temperature (T), and potential evapotranspiration (PET) over the 12 reservoirs for 10 years from 2011 to 2020. To downscale the datasets, a linear scaling method was applied to each weather forcing (Sec. 2.2.1). Additionally, to calculate the Ensemble Streamflow Prediction (ESP), 45 ensemble members of each weather variable were also generated using historical observations (1966-2010). Each ensemble member of ESP represents simulated flow using a hydrological model initialized with observed meteorological data to simulate current conditions and forced by historical meteorological observations for the forecasting period. Secondly, we estimated the parameters of the hydrological model and validated its performance (Sec. 2.2.2). Utilizing the Seasonal weather forecasts datasets as input data to the hydrological model, we generated an ensemble of seasonal flow predictions (SFFs), and using historical weather observations as input to the hydrological model we produced the ESP. The Continuous Ranked Probability Skill (CRPS) method was applied (Sec. 2.2.3) to calculate actual skill (compared with observed flow data) and theoretical skill (compared with pseudo-observation flow data) (van Dijk et al., 2013). Here, pseudo-observation refers to the flow time-series computed based on the calibrated hydrological model and in-situ weather observations.

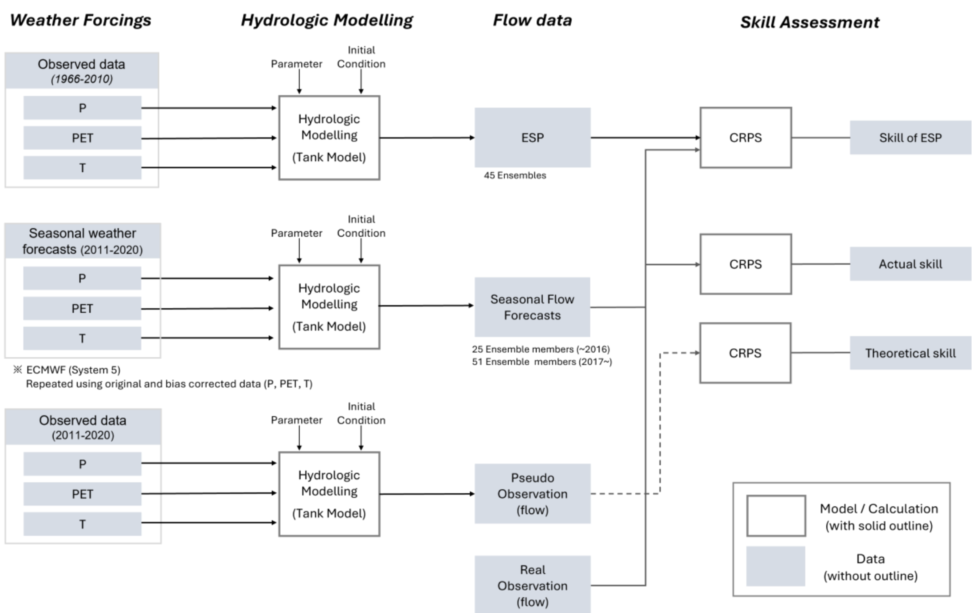

Figure 2: Schematic diagram illustrating analysis method of the study.

https://doi.org/10.5194/egusphere-2023-2169
Preprint. Discussion started: 16 October 2023

2.2.1 Bias correction (Statistical downscaling)

The seasonal weather forecasts datasets from CCDS have a spatial resolution of 1°×1°, which is too coarse for the catchment-scale analysis. Previous studies also have reported that seasonal weather forecasts generated from General Circulation Models contain systematic biases and this can cause forecast uncertainty (Manzanas et al., 2017; Maraun, 2016; Tian et al., 2018). Moreover, the usefulness of bias correction in enhancing the forecast skill has been shown in many previous studies (Crochemore et al., 2016; Ferreira et al., 2022, Pechlivanidis et al., 2020; Tian et al., 2018). Hence, it is imperative to investigate the potential enhancement in the skill of hydrological forecasts resulting from the bias correction of weather forcings.

Numerous bias correction methods have been developed including linear scaling method, local intensity scaling and quantile mapping (Fang et al., 2015; Shrestha et al., 2017). Thanks to its simplicity and low computation cost (Melesse et al., 2019), a linear scaling method is widely adopted. Despite its simplicity, this method has demonstrated practical usefulness in various studies (Azman et al., 2022; Crochemore et al., 2016; Shrestha et al., 2017). Therefore, the linear scaling method was used in this study.

Previous studies found that additive correction is preferable for temperature whereas multiplicative correction is preferable for variables such as precipitation, evapotranspiration, and solar radiation (Shrestha et al., 2016). Consequently, the equations for linear scaling method for each variable can be expressed as:

$$P^*_{forecasted} = P_{forecasted} \cdot (b_P)_m = P_{forecasted} \cdot \left[\frac{\mu_m(P_{observed})}{\mu_m(P_{forecasted})} \right] \tag{1}$$

$$PET^*_{forecasted} = PET_{forecasted} \cdot (b_{PET})_m = PET_{forecasted} \cdot \left[\frac{\mu_m(pET_{observed})}{\mu_m(pET_{forecasted})} \right] \tag{2}$$

$$T^*_{forecasted} = T_{forecasted} + (b_T)_m = T_{forecasted} + \left[\mu_m(T_{observed}) - \mu_m(T_{forecasted}) \right] \tag{3}$$

where $X^*_{forecasted}$ is the bias corrected forecast variable (X) at daily time scale, $Y_{forecasted}$ is the original forecast variable (Y) before bias correction, $(b_P)_m$, $(b_{PET})_m$ and $(b_T)_m$ are the bias correction factors for precipitation, PET and temperature respectively at month m, μ_m means monthly mean, and *observed* represents the observed daily variable. In this study, daily precipitation forecasts were bias corrected using the monthly bias correction factor (b_m) for each month (m = 1 to 12). The bias correction factor was computed using the observations and original forecasts datasets from 1993 to 2010, and these were then applied to adjust each seasonal weather forecasts for later years (2011 to 2020).

2.2.2 Hydrologic modelling

The Tank model was first developed by Sugawara of Japan in 1961 (Sugawara et al., 1986; Sugawara, 1995) and has become a widely used conceptual hydrologic model in many countries (Goodarzi et al., 2020; Ou et al. 2017). A modified version of the Tank model, incorporating soil moisture structure and snowmelt modules, is commonly used in South Korea for long-term water resources planning and management purposes due to its higher performance (Kang et al., 2004; Lee et al., 2020). As shown in Figure 3, the modified Tank model used in this study comprises four storage tanks representing the runoff and baseflow in the target catchment (Phuong et al., 2018; Shin et al., 2010) and incorporates water-balance module suggested by United States Geological Survey (McCabe and Markstrom, 2007).

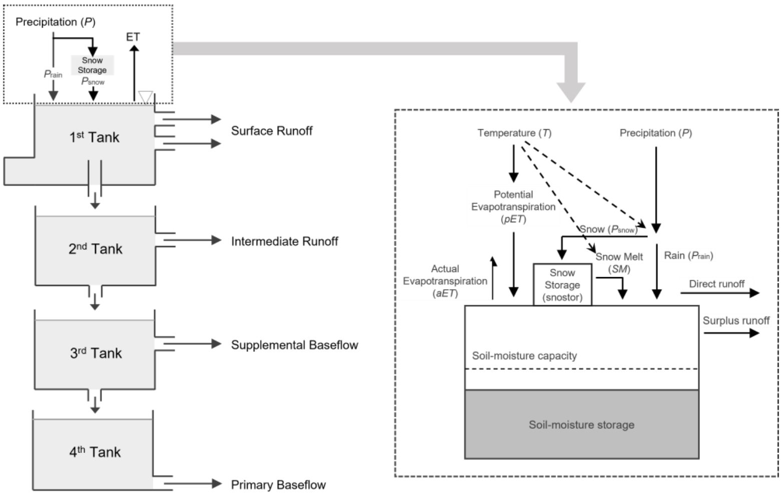

Figure 3: The structure of modified Tank model (Left) and its water -balance module (Right)

This model has 21 parameters (see the Table S1 in Supplementary material), which were calibrated based on historical observations. We calibrated the model parameters using observations for the period from 2001 to 2010, and the validation was done using the time period 2011 to 2020. To estimate the model parameters, the Shuffled Complex Evolution global optimization algorithm (SCE-UA), developed at the University of Arizona (Duan et al., 1992, 1994), is utilized. This algorithm has widely been used for the calibration of hydrologic models and has shown more robust and efficient performance compared to many traditional optimization methods such as Genetic Algorithm, Differential Evolution, and Simulated Annealing (Rahnamay-Naeini et al., 2019; Yapo et al., 1996). The following Objective Function (OF) proposed by Sugawara (Sugawara et al., 1986), is applied to estimate the parameters using the SCE-UA algorithm, because a previous study demonstrated that this function shows higher performance in calibrating the Tank model in South Korean catchments with calibration periods longer than 5 years (Kang et al., 2004).

$$OF = \sum_{t=1}^{N} \left| q_t^{obs} - q_t^{sim} \right| \, / \, q_t^{obs} \quad (4)$$

where *t*, *N* represent time (in days) and total number of time steps, q_t^{obs} and q_t^{sim} represent the observed and simulated flow at time *t*, respectively. The optimal parameter set is the one that produces the lowest value from the objective function.

In order to evaluate the model performance in diverse perspectives, we used three different evaluation indicators: Nash-Sutcliffe model Efficiency coefficient (*NSE*), Percentage Bias (*PBIAS*), and Ratio of Volume (*ROV*). The calculation of each indicator was carried out as described by the following equations.

$$NSE = 1 - \sum_{t=1}^{N} (q_t^{obs} - q_t^{sim})^2 \, / \, \sum_{t=1}^{N} (q_t^{obs} - q_{mean}^{sim})^2 \quad (5)$$

$$PBIAS = \sum_{t=1}^{N} (q_t^{obs} - q_t^{sim})^2 \, / \, \sum_{t=1}^{N} q_t^{obs} \times 100 \quad (6)$$

$$ROV = \sum_{t=1}^{N} q_t^{sim} \, / \, \sum_{t=1}^{N} q_t^{obs} \quad (7)$$

where *t*, *N*, q_t^{obs} and q_t^{sim} are as defined in Eq. 6, and q_{mean}^{sim} represents simulated mean flow across the total number of time steps (*N*).

The *NSE* can range from negative infinity to 1. A value of 1 indicates a perfect correspondence between the simulated and the observed flow. *NSE* values between zero and 1 are generally considered acceptable levels of performance (Moriasi et al., 2007). *PBIAS* is a metric used to measure the average deviation of the simulated values from the observation data. The optimal value of *PBIAS* is 0, and low-magnitude values indicate accurate simulation. Positive (negative) values of *PBIAS* indicate a tendency for overestimation (underestimation) in the

https://doi.org/10.5194/egusphere-2023-2169
Preprint. Discussion started: 16 October 2023

simulation (Gupta et al., 1999). *ROV* represents the ratio of total volume between the simulated and observed flow. An optimal *ROV* value is 1, and a value greater (less) than 1 suggests overestimation (underestimation) of total flow volume (Kang et al., 2004).

2.2.3 Skill assessment

In this study, we adopted the Continuous Ranked Probability Score (CRPS) developed by Matheson and Winkler (1976) which measures the difference between the cumulative distribution function of the forecast ensemble and the observations. The CRPS has the advantage of being sensitive to the entire range of the parameter of interest (the forecast ensemble) and being clearly interpretable, as it is equal to the Mean Absolute Error for a deterministic forecast (Hersbach, 2000). Moreover, it is a widely used metric to assess the skill of ensemble forecasts (Leutbecher and Haiden, 2020). The CRPS can be calculated as:

$$\mathrm{CRPS} = \int [F(x) - H(x \geq y)]^2 \, dx \tag{8}$$

where *F(x)* represents the cumulative distribution of the SPFs ensemble, *x* and *y* are respectively the forecasted and observed flow, *H* is called the indicator function and is equal to 1 when $x \geq y$ and 0 when $x < y$. If the SPFs were perfect, i.e., all the ensemble members exactly matched the observations, the CRPS would be equal to 0. Conversely, the higher the CRPS, the lower the skill of the SPFs.

The assessment of the absolute skill of ensemble climate forecasts is essential for understanding the model performance. In this study, we used the Continuous Ranked Probability Score (CRPS) as a tool to evaluate the skill of SFFs. However, interpreting the CRPS alone can be challenging in terms of determining the quality of the skill. To address this issue, we also employed the Continuous Ranked Probability Skill Score (CRPSS), which presents the forecast skill in a relative manner by comparing it to a benchmark forecasting method. In assessing the skill, benchmarks are important to understand the performance of a forecasting system (Pappenberger et al., 2015). The Major reasons that we use ESP as a benchmark are because it is a widely used method in flow forecasting (Pappenberger et al., 2015; Peñuela et al., 2020) and also computationally inexpensive (Baker et al., 2021; Harrigan et al., 2018). Here, we generated weather forcing ensemble using the Tank model fed with historical daily meteorological records available from 1966 to 2010, hence leading to an ensemble of 45 members for each catchment. The CRPSS is defined as the ratio of the forecasted and benchmark CRPS, and it is expressed as follows:

$$\mathrm{CRPSS} = 1 - \frac{\mathrm{CRPS}^{Sys}}{\mathrm{CRPS}^{Ben}} \tag{9}$$

where CRPS^{Sys} is the CRPS of the SPFs and CRPS^{Ben} is the CRPS of the benchmark. The values of CRPSS can range from -∞ to 1. When the CRPSS is positive, i.e., from 0 to 1, the forecasting system is more skilful than the benchmark and when the skill scores are negative, i.e., from -∞ to 0, the system is less skilful. When CRPSS is equal to zero, the forecasting system (SPFs) and the benchmark have the same skill and when it is equal to 1, the forecast is perfect.

Since the CRPSS has a range from -∞ to 1, simply averaging the CRPSS can result in negative values and be greatly influenced by the presence of some abnormally high or low events. Hence, in this study, we have adopted the concept of 'overall skill' (Lee et al., 2023) as a comprehensive and probabilistic measure to assess the forecast skill. The overall skill represents the probability of being more skilful than the benchmark forecasts (i.e., when CRPSS is greater than 0) over the entire period and is calculated as:

$$\text{Overall skill (\%)} = \frac{\sum_{y=1}^{N_y} [\, H\ (\mathrm{CRPSS})\ (\mathrm{y})\,]}{N_y} \times 100\ (\%) \tag{10}$$

where N_y is the total number of years, the indicator function H is equal to 1 when CRPSS (y) > 0 (SFFs are more skilful than ESP in year y) and 0 when CRPSS (y) ≤ 0 (ESP beats SFFs). If the overall skill is greater (lesser) than 50%, we conclude that the SPFs are generally more (less) skilful than benchmark across the period (years).

3. Results

https://doi.org/10.5194/egusphere-2023-2169
Preprint. Discussion started: 16 October 2023

3.1 Contribution of hydrological model performance to the skill of SFFs

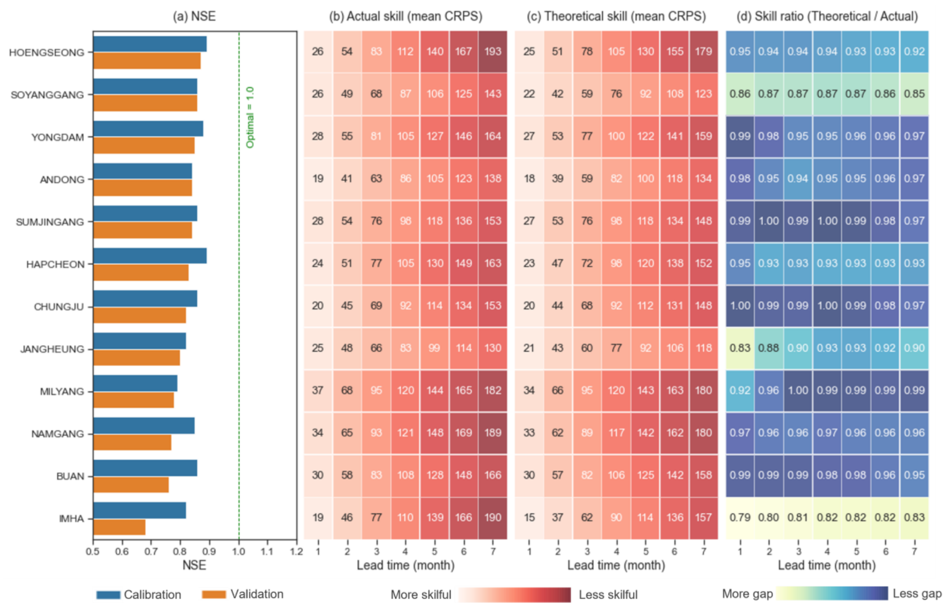

Figure 4. (a) Nash-Sutcliffe Efficiency (NSE) of the hydrological models for the 12 catchments analysed in this study; (b) actual skill and (c) theoretical skill of the SFFs, (d) skill ratio (theoretical / actual skill) in terms of mean CRPS at different lead times (x-axis) (all skill values calculated before bias correction of weather forcings).

Figure 4(a) shows the NSE of the modified Tank model for each catchment during the calibration period 2001-2010 (blue bars) and the validation period 2011-2020 (orange bars). As seen in this figure, the NSE values for the 12 catchments are generally high (within the range of 0.7 to 0.9) during both the calibration and validation periods, and the relative difference in performance between the two periods is small for all catchments but the last three. The NSE results indicate a 'good' performance through comparative analysis (Chiew and Mcmahon, 1993; Moriasi et al., 2015). A detailed model performance evaluation, including other performance metrics such as PBIAS and ROV, is given in the Supplementary Material, and it demonstrates that the Tank model utilized in this study shows an excellent performance to simulate streamflow.

Figures 4(b-c) represent the actual and theoretical skill measured by the mean CRPS over the period 2011-2020. Again, these are calculated by comparing the simulated flows with the observed flows (actual skill), and with pseudo-observations (theoretical skill). Since the CRPS is calculated based on accumulated monthly mean flow at a given lead time, forecast errors also accumulate over time. Therefore, both skills deteriorate considerably as the lead time increases. Generally, the actual skill shows slightly lower performance (higher CRPS) compared to the theoretical skill, but the difference is not large.

To facilitate comparison, the ratio between the actual and theoretical skill is shown in Figure 4(d). For most catchments, the ratio values are close to 1, confirming the small gap between actual and theoretical skill. The noticeable exception is only seen in the Imha catchment.

3.2 Contribution of weather forcings to the skill of SFFs

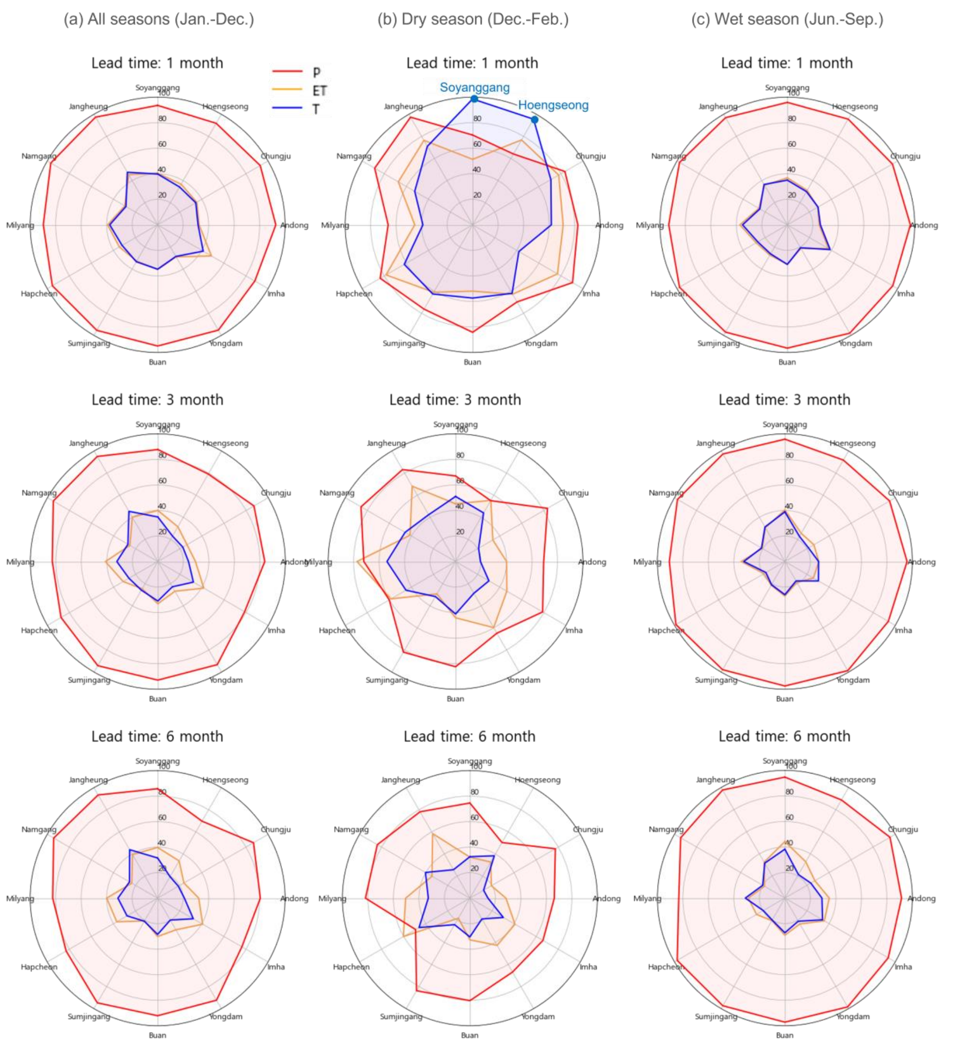

Figure 5. Relative skill (%) of each weather forcings (Precipitation: red, ET: orange, Temperature: blue) before bias correction to the skill of SFFs averaged over 10 years (2011-2020) during (a) all seasons, (b) dry and (c) wet season at 1, 3 and 6 lead months from the top to bottom (Catchments are ordered by their location from the northernmost (Soyanggang) to the southernmost (Jangheung) in right-angle direction, see Figure 1).

In this section, we quantify the contribution of each weather forcing to the skill of Seasonal Flow Forecasts (SFFs). In doing so, we assess and compare the skill of the flow forecasts obtained by forcing the hydrological model with seasonal weather forecasts for one meteorological variable and observational data for the other two. For instance, to assess the contribution of precipitation, we used seasonal precipitation forecasts, and observations for PET and temperature. This workflow is illustrated in Figure S2 (Supplementary material).
Figure 5 shows the relative skill of each non-bias corrected weather forcing to the SFFs skill across all seasons (a), dry (b) and wet (c) seasons at different lead times (1, 3, and 6 months). The relative skill is calculated as the ratio of the CRPS for flow computed using seasonal weather forecasts for all weather forcings (P, T and PET), to the CRPS calculated solely based on individual weather forcing (only P or T or PET).

https://doi.org/10.5194/egusphere-2023-2169
Preprint. Discussion started: 16 October 2023

As shown in Figure 5(a), the contribution of each weather forcing to the skill of SFFs varies with catchment and lead time, but overall precipitation plays a dominant role. Specifically, the contribution of precipitation (red) accounts for almost 90% of the total CRPS which forced by seasonal weather forecasts for all weather forcings, while PET (orange) and temperature (blue) contribute a similar level between 30% and 40%.
During the dry season (Figure 5(b)) however, PET and temperature show comparable levels of contribution to precipitation. This is more evident in the Soyanggang and Hoengseong catchments, which are both located in the northernmost region of South Korea (see Figure 1). These catchments are characterized by low temperatures and heavy snowfall in the dry (Winter) season. Correct prediction of temperature is thus crucial here as temperature controls the partitioning of precipitation into rain and snow, and hence the generation of a fast or delayed flow response. Further analysis (shown in Supplementary Material, Figure S7), reveals that temperature forecasts in these two catchments are consistently lower than observation, which means that the hydrological model classifies rain as snow for several events, and hence retains that 'snow' in the simulated snowpack what in reality should produce a flow response. This explains the significant increase in skill when forcing the model with observed temperature instead (blue line in Figure 5(b)).
In order to enhance the forecasts skill, we applied bias correction to each weather forcing and re-generated the SFFs with bias-corrected weather forcings. The overall skill increases by 46% to 54% on average across all seasons, and more specifically from 31% to 50% in the dry season and from 54% to 55% in the wet season. The largest increase in overall skill is found in the Imha catchment, which had the lowest skill before correcting biases. For a detailed account of the skill before and after bias correction, see Figure S3 and S4 in Supplementary material.

Figure 6 illustrates the change in the relative skill of each weather forcing after bias correction, focusing on the dry season and the first forecasting lead month. One notable finding is that, in the snow-affected catchments (Soyanggang and Hoengseong), there is a significant decrease in the relative skill of temperature after applying bias correction. As shown in detail in Figure S7 in the Supplementary Material, this is due to the correction of systematic underestimation biases in temperature forecasts, which lead to a more correct partition of precipitation into snow and rain, and thus better flow predictions. The relative skill of the forecasts for all seasons and lead times after bias correction are reported in Figure S5 in the Supplementary material.

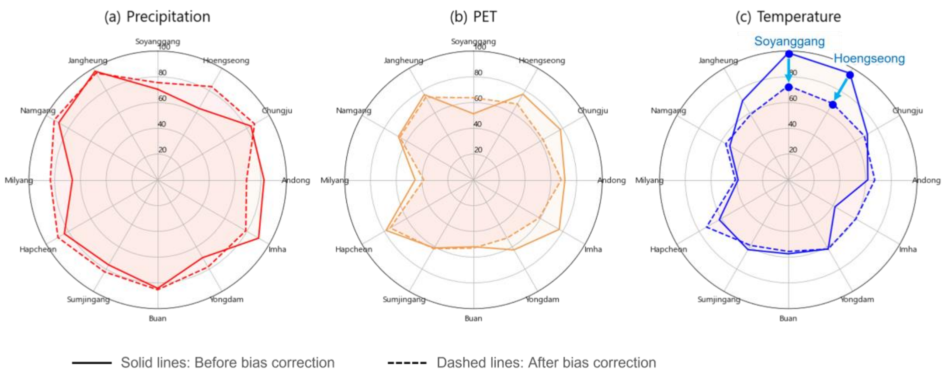

Figure 6. Relative skill (%) of each weather forcings ((a) Precipitation, (b) PET, (c) Temperature), before (solid line) and after (dashed line) bias correction, to the skill of SFFs averaged over 10 years (2011-2020) during the dry season and first lead month.

3.3 Comparison between SFFs and ESP across seasons and catchments

In order to comprehensively compare the performance of SFFs and Ensemble Streamflow Predictions (ESP), we employ the overall skill, which quantifies the frequency with which SFFs' skill surpasses ESP's skill, as outlined in section 2.2.3 (Eq.10). Figure 7 shows the seasonal and regional variations of overall skill (after bias correction) for all seasons (a), for the dry season (b) and the wet season (c). For each catchment, the results are visualised through a table showing the overall skill at lead times of 1 to 6 months. The table cells are coloured in green (pink) when SFFs (ESP) are more skilful than ESP (SFFs). Yellow colour indicates that both systems have equivalent skill. In principle, this happens when the overall skill is around 50%, however in order to avoid misinterpreting small differences in skill, we decided to classify as equivalent all cases when the overall skill is between 45% and 55%.

As shown in Figure 7(a), the overall skill of SFFs varies according to the lead time, season and catchment. SFFs generally outperform ESP, particularly until 3 months ahead. At longer lead times the results vary from catchment to catchment. For instance, the SFFs outperform ESP for some catchments (Janheung, Namgang, Hapcheon), SFFs show similar skill than EPS in other catchments (Soynahggang, Hoengseong, Chungju, Milyang), and SFFs also show less skill than ESP in other catchments (Imha, Buan, Sumijngang). In specific, two catchments, Buan, which is located in the Western coastal region and has the smallest catchment area, and Imha, which is the driest catchment, show the lowest skill. Nevertheless, we could not identify a conclusive correlation between catchment size or mean annual precipitation and overall skill.
Comparing the results for the dry and wet seasons, Figure 7(b-c) shows that SFFs are much more likely to outperform ESPs in the wet season, and particularly in the catchments in northernmost region. During the dry season the overall skill of SFFs is lower, and particularly in the Buan, Imha and Sumjingang catchments SFFs outperform ESP only for the first lead month.

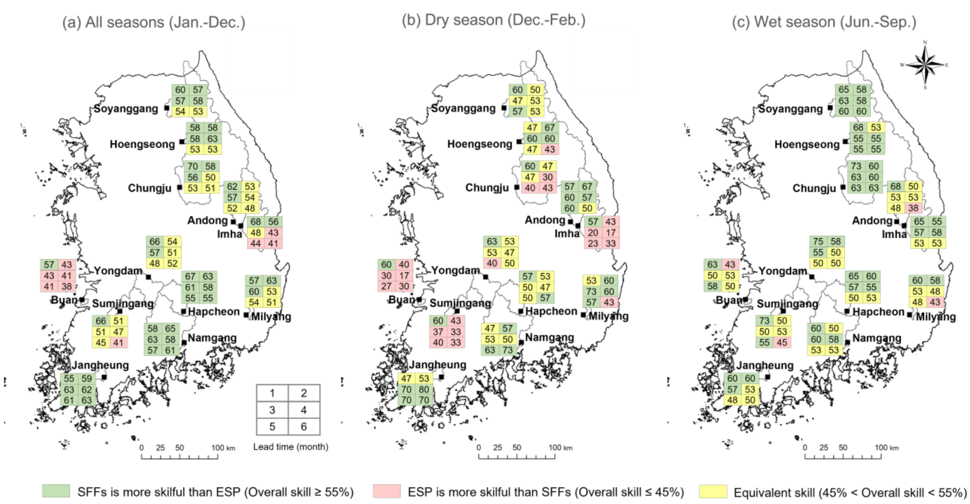

Figure 7. Map of overall skill of bias corrected SFFs for 10 years (2011-2020) over (a) all seasons, (b) dry season and (c) wet season. The colors represent whether SFFs outperform EPS or not for each catchment and lead time (1 to 6 months).

3.4 Comparison between SFFs and ESP in dry and wet years

We now assess the influence of exceptionally dry and wet conditions on the skill of SFFs. Based on the mean annual precipitation across 12 catchments within the period 2011-2020, we classified the years 2015 and 2017 as dry (P < 900 mm), and the years 2011 and 2020 as wet (P > 1500 mm). Figure 8 shows the overall skill of the SFFs averaged over 12 catchments for the entire period (a), dry years (b), and wet years (c), during all seasons (black solid line), dry (red dashed line) and wet (blue dashed line) seasons, respectively.

Figure 8(a) shows that SFFs outperform ESP for lead times of up to 3 months across seasons, while maintaining equivalent skill levels thereafter. In addition, it is evident that SFFs is more skilful during the wet season than during the dry season. In dry years (Figure 8(b)), in contrast to the typical decrease in overall skill with lead time, we find that SFFs maintain a significantly higher skill than ESP at all lead times, and particularly during the wet season (blue line). On the other hand, in wet years (Figure 8(c)), the overall skill is generally poor, and ESP generally has higher skill than SFFs, especially during the wet season.
Last, we analyse the spatial variability of overall skill by looking at the spread of the overall skill in individual catchments (grey dots). We see that the spread in dry and wet years (Figure 8(b-c)) is larger than in average years (Figure 8(a)). A more detailed analysis of the overall skill for each catchment (described in Figure S6 in Supplementary material) shows that the catchments located in southern region consistently exhibit higher skill, regardless of lead times and dry/wet years.

https://doi.org/10.5194/egusphere-2023-2169
Preprint. Discussion started: 16 October 2023

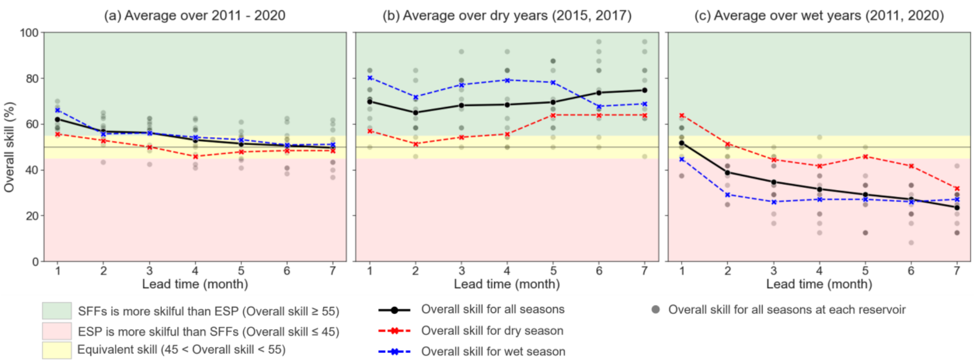

Figure 8. Overall skill of bias corrected SFFs over 12 catchments averaged over (a) entire years (2011 to 2020), (b) dry years (mean annual P < 900mm) and (c) wet years (mean annual P > 1500mm) during all seasons (black lines), dry seasons (red dashed lines) and wet seasons (blue dashed lines). Here, mean annual precipitation is averaged across the catchments and years.

3.5 Example of flow forecasts time-series

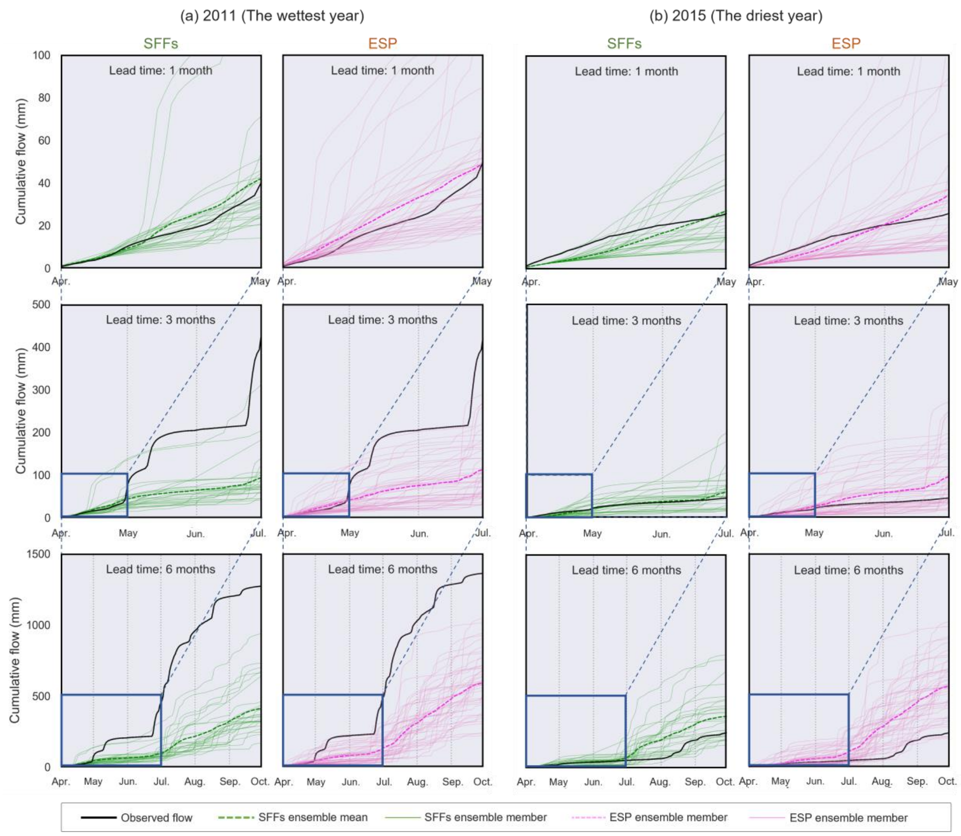

Figure 9. Observed cumulative flow (black lines) and forecasted cumulative flow representing SFFs after bias correction (left, green lines) and ESP (right, pink lines) in the Chungju reservoir for 1, 3, and 6 months of lead times over (a) the wettest year (2011, 1884mm/year), and (b) the driest year (2015, 742mm/year).

https://doi.org/10.5194/egusphere-2023-2169
Preprint. Discussion started: 16 October 2023

Figure 9 shows an example of the flow into the Chungju reservoir, which holds the largest storage capacity in South Korea. It compares the observed and forecasted cumulative flow forced by seasonal weather forecasts (SFFs, green lines) and historical weather records (ESP, pink lines) for lead times of 1, 3, and 6 months from April during the wettest (2011) and the driest year (2015), respectively.

In this specific catchment and years, SFFs show equivalent or slightly higher performance than ESP at a 1-month lead time. However, as the lead time increases, the performance of both methods tends to deteriorate. In particular, considerably higher performance was found in SFFs compared to ESP in the driest year (Figure 9(b)). On the other hand, it is obvious that both methods have insufficient sharpness in forecasting flow in the wettest years. Examining each ensemble member of both SFFs and ESP, we found higher variability in ESP. Furthermore, since ESP utilizes the same weather forcings, the forecasted flows are generally similar in terms of its quantity and patterns, regardless of the wettest and driest years. Conversely, the forecasted flow ensemble members of SFFs show distinctive patterns for each year.
Although, these results are confined to a single catchment and specific years, this analysis is valuable in quantitatively illustrating the forecasted flow results under dry and wet conditions and different lead times. Furthermore, these features are generally shown in other catchments, and align with our previous findings in section 3.4.

4. Discussion

4.1 The skill of seasonal flow forecasts

This study offers a comprehensive view of the skill of SFFs as compared to the skill of conventional – and easier to implement - ESP method. In contrast to the majority of previous studies, which assessed the skill of SFFs at continental or national level or over large river basins, our study focuses on 12 relatively small catchments (59 - 6648 km^2) across South Korea.

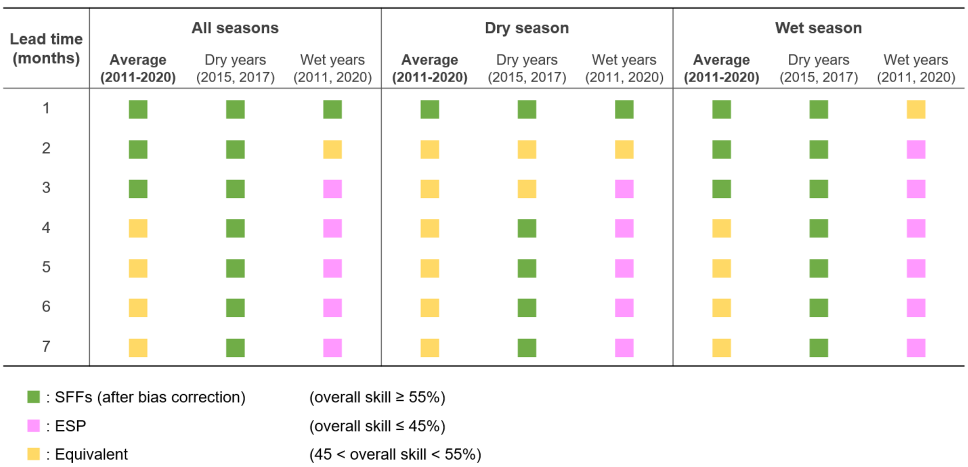

Figure 10. Summary of key findings regarding the skill of SFFs and ESP at different lead times, seasons, and years.

Figure 10 summarizes the key findings of this study regarding the overall skill of SFFs, i.e., their chances of being skilful than ESP across different seasons and years. It demonstrates that SFFs outperform ESP in almost all the cases for forecasting lead times of one month. This result is consistent with previous literature (e.g., Lucatero et al., 2018; Yossef et al., 2013). In addition, the higher skill of SFFs compared to ESP is also shown at lead times of 2 and 3 months in several situations as shown in Figure 10, and at even longer lead times in dry years. This is more surprising as this considerable skill of SFFs was not found in previous studies.
Particularly, since the earlier studies (Crochemore et al., 2016; Lucatero et al., 2018) have explored actual skill within a similar catchment scale to our study, comparing their results with our findings holds interest. In brief, their results suggest that ESP remains a ‘hard-to-beat’ method compared to SFFs even after bias correction. Crochemore et al. (2016) showed that SFFs using bias corrected precipitation, is in equivalent level of skill with

https://doi.org/10.5194/egusphere-2023-2169
Preprint. Discussion started: 16 October 2023

ESP up to 3 months ahead. Lucatero et al. (2018) concluded that SFFs still face difficulties in outperforming ESP, particularly at lead times longer than 1 month.

The difference of our results compared to the literature stems from a combination of several important factors. First, it is worth noting that these two previous studies were conducted at the catchment-scale, with a specific focus on Europe, namely France (Crochemore et al., 2016) and Denmark (Lucatero et al., 2018). The skill of SFFs vary according to the geographic locations, meteorological conditions of given study area, as confirmed by numerous studies (e.g., Greuell et al., 2018; Pechlivanidis et al., 2020; Yossef et al., 2013). Therefore, the skill of SFFs could also be influenced by distinct spatial and meteorological conditions between Europe and South Korea. Second, we can attribute the difference to the utilization of a more advanced seasonal weather forecasting system. Unlike previous studies which applied ECMWF system 4, our study is conducted based on ECMWF's cutting-edge forecasting system version 5. It is reported that ECMWF system 5 has many improvements compared to the previous version including improvements in the predictive skill of the El Niño Southern Oscillation (ENSO) (Johnson et al., 2019) and rainfall inter-annual variability (Köhn-Reich and Bürger, 2019). While it is challenging to quantitatively evaluate the impact of system advancements in this study, given the significance of meteorological forecast in hydrological forecasts, it is highly probable that the development of the system has had a positive influence on the results. Although a few studies have analysed the skill of SFFs based on ECMWF system 5 (e.g., Peñuela et al., 2020; Ratri et al., 2023), direct comparisons with our research were deemed difficult due to differences in catchment scale and analysis methods, such as the absence of a comparison with ESP.
Last, the performance of the hydrological model also contributes to differences in the results. To evaluate the impact of model performance, we compared actual skill (forecast skill compared to observed flow data) and theoretical (forecast skill compared to pseudo flow observation) skill and found that the actual skill is generally lower than theoretical skill. This finding is consistent with previous studies, and the difference in skill between the actual and theoretical skills is highly linked to the performance of hydrological model (Greuell et al., 2018; van Dijk, 2013). When a model's actual skill closely approximates its theoretical skill, it may suggest that the model is operating at a best possible level, given the inherent uncertainties and limitations associated with the available data and methods. Although our results showed that the theoretical skill is higher than actual skill, their difference was generally marginal. This close agreement between the two skills indicates that the model is well-calibrated and capable of effectively capturing the underlying hydrological processes in those catchments.

Our findings on the impact of bias correction quantitatively showed that generally precipitation controls the skill of SFFs, however, we also found that temperature plays a substantial role in specific seasons and catchments. Specifically, the Hoengseong and Soyanggang catchments, located in the northernmost part of South Korea and affected by snowfall in the Winter (dry) season (December to February), exhibit a higher temperature contribution than precipitation for a forecasting lead time of one month during the dry season. The main reason for this is the underestimation of temperature forecasts. Our supplementary experiments provide evidence that using bias-corrected temperature forecasts significantly improves the accuracy of flow forecasts (see Figure S7 in Supplementary material). Although the positive impact of bias correction of precipitation forecasts in enhancing the skill of SFFs has been well-documented in numerous previous studies (Crochemore et al., 2016; Lucatero et al., 2018; Pechlivanidis et al., 2020; Tian et al., 2018), our result demonstrates the importance of bias correction of temperature too, at least in snow-affected catchments.
An alternative approach to bias correction has been proposed by (Lucatero et al., 2018; Yuan and Wood, 2012), who argued that directly correcting the biases in the flow forecasts may result in better performance at lower computational cost. However, we tested this alternative approach and found conflicting outcomes (Figure S8 in Supplementary material). Therefore, caution should be exercised when directly correcting biases for flow, as this approach may exclude the contribution of initial conditions, which is one of the most crucial factors in hydrological modelling. In cases where the performance of hydrological model is the major source of error, bias correction of the flow might be useful, however, if the model shows an acceptable performance, as demonstrated in this study, incorporating bias correction for the simulated flow could add more errors.

Another noteworthy finding is that SFFs were considerably more skilful than ESP for all lead times during the wet season in dry years. Conversely, the performance of SFFs during the wet season in wet years was not satisfactory. This is because SFFs skill is commonly dominated by skill of precipitation forecasts, and we previously found skill of precipitation forecasts is the lowest in wet years (Lee et al 2023). The systematic biases of seasonal precipitation forecasts, which tend to underestimate (overestimate) the precipitation during the wet (dry) season, led to the consistent results in flow forecasts. This finding also hints that SFFs hold the potential to provide valuable information for effective water resources management during dry conditions which are important for drought management.

4.2 Limitations and directions for future research

https://doi.org/10.5194/egusphere-2023-2169
Preprint. Discussion started: 16 October 2023

In this paper, we investigated the skill of seasonal weather forecasts provided by ECMWF and their application in SFFs at the catchment-scale. Based on our previous research, it has been demonstrated that amongst four forecasting centres, ECMWF provides the most skilful seasonal precipitation forecasts (Lee et al., 2023), thus we utilized seasonal weather forecasts datasets from ECMWF in this study. However, the skill for other weather forcings such as temperature and PET, have not tested across South Korea. Therefore, more broadly research is needed to determine the seasonal weather forecasts provider that can lead to skilful hydrological forecasts in the regions or seasons of interest.

Given the distinct climatic conditions in South Korea, it is important to acknowledge that our results may not be applicable to other regions or countries. Therefore, further work needs to be carried out to reproduce this analysis in different regions. To facilitate this process, the two Python-based toolboxes, SEAFORM (SEAsonal FORecasts Management) and SEAFLOW (SEAsonal FLOW forecasts) can be useful. The SEAFORM toolbox developed in a previous study (Lee et al., 2023) offers multiple functions for manipulating seasonal weather forecast datasets (e.g. download the datasets, time-series generation, bias correction). On the other hand, the SEAFLOW toolbox, developed in this study, is specifically designed for the analysis of SFFs based on the modified Tank hydrological model (but it could be useful to apply to other hydrologic models).

In terms of forecast skill, our study showed the potential of SFFs at catchment-scale for real water management. However, it is also crucial to recognize the difference between 'skill', which indicates how well the hydrological forecasts mimic observed data, and 'value', which refers to the practical benefits obtained from utilizing those forecasts in real water management. Previous studies have addressed this issue, showing that better skill does not always result in positive value (Boucher et al., 2012; Chiew et al., 2003). Although, in terms of 'skill', earlier findings argue that SFFs are generally less skilful than ESP (e.g., Lucatero et al., 2018; Yossef et al., 2013), in terms of 'value', a recent study has demonstrated that the use of seasonal forecasts in semi-arid regions offers significant economic benefits by mitigating hydro-energy losses in a dry year (Portele et al., 2021). Therefore, our future research efforts should concentrate on a quantitative evaluation of the value of SFFs for reservoir operations to informing decision-making in water resources management. This evaluation is of significant importance as it directly relates to assessing the potential utilization of SFFs in practical water management.

5. Conclusions

This study assessed the actual skill of Seasonal Flow Forecasts (SFFs) across 12 catchments in South Korea using a hydrological model forced by seasonal weather forecasts from the ECMWF (system 5). By focusing on operational reservoir catchments with relatively small catchments, our findings showed the potential of SFFs for practical water resources management.

The main conclusions from this study are summarized as follows: First, theoretical skill outperforms the actual skill, yet their skill gap was insignificant. This result suggests that the hydrological model, used in this study, demonstrates a reliable performance. Second, compared to other weather forcings, precipitation plays a dominant role in the skill of SFFs, and this is particularly evident during the wet season. However, temperature can be also highly important at specific season and catchments, and this result highlights the significance of bias correction of temperature. Third, at small catchment-scale, which is more suitable for water resources management, SFFs (utilizing bias-corrected seasonal weather forecasts) were more skilful than ESP up to 3 months ahead. Particularly, the highest skill of SFFs during the wet season in dry years highlights the potential of SFFs for adding values in drought managements. Last, although our research highlights the superior skill of SFFs at the catchment-scale in South Korea, it is important to note that the outcomes may vary depending on factors such as the type of seasonal weather forecasts system used, the study area, and the performance of the hydrological model.

As seasonal weather forecasting technologies continue to evolve, it is also crucial to concurrently pursue their application and validation in flow forecasting. We hope that our findings contribute to the continuous validation efforts of the skill of SFFs across various regions and, furthermore, serve as a catalyst for their practical application in real water management. At the same time, our proposed research approach and the analysis package we have developed using Python Jupyter Notebook, can offer valuable support to water managers in gaining practical experience to utilize SFFs more effectively.

Code and data availability. The SEAFLOW (seasonal flow forecasts) and SEAFORM (seasonal forecast management) Python packages are available at https://github.com/uobwatergroup/seaflow, and https://github.com/uobwatergroup/seaform, respectively. ECMWF data are available under a range of licences. Inflow data are made available by the K-water and can be downloaded from https://www.water.or.kr/.

Author contributions. YL designed the experiments, with suggestions from the other co-authors. YL developed the workflow and performed simulation. FP and MAR participated in repeated discussions on interpretations of results and suggested ways forward in the analysis. AP provided YL with modelling technical support and reviewed the manuscript.

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Preprint. Discussion started: 16 October 2023

Competing interests. The authors declare that they have no conflict of interest.

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