Monthly Reservoir Inflow Forecasting for Dry Period Using Teleconnection Indices: A Statistical Ensemble Approach

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Featured Application: The work can be applied to reservoir operation for water supply by foreseeing the inflows to a reservoir for the coming months to take necessary action in advance to save water for an expected drought situation.

Abstract: Reliable long-range reservoir inflow forecast is essential to successfully manage water supply from reservoirs. This study aims to develop statistical reservoir inflow forecast models for a reservoir watershed, based on hydroclimatic teleconnection between monthly reservoir inflow and climatic variables. Predictability of such a direct relationship has not been assessed yet at the monthly time scale using the statistical ensemble approach that employs multiple data-driven models as an ensemble. For this purpose, three popular data-driven models, namely multiple linear regression (MLR), support vector machines (SVM) and artificial neural networks (ANN) were used to develop monthly reservoir inflow forecasting models. These models have been verified using leave-one-out cross-validation with expected error S as a measure of forecast skill. The S values of the MLR model ranged from 0.21 to 0.55, the ANN model ranged from 0.20 to 0.52 and the SVM from 0.21 to 0.56 for different months. When used as an ensemble, Bayesian model averaging was more accurate than simple model averaging and naïve forecast for four target years tested. These were considered to be decent prediction skills, indicating that teleconnection-based models have the potential to be used as a tool to make a decision for reservoir operation in preparing for droughts.

Keywords: reservoir inflow forecasting; teleconnection indices; Bayesian model averaging

1. Introduction

Like many regions in developed countries, demands on water resources of the Southern Chungnam province, fourth largest in South Korea, are continuously growing, but there is only one water source—Boryeong multi-purpose Dam. The available reservoir storage of Boryeong Dam is 116.9 million tons and designed to supply 23,800 tons per day for agricultural, residential and industrial use serving 420,000 of people in Western Chungnam Province [1]. Boryeong Dam is also supplying water to four major steam power plants, which generate about 25% of South Korea’s electricity.

Currently, the water use of Southern Chungnam Province is about 21,000 tons per day, which is approaching 90% of design demand. Water demand from steam power plants is expected to increase because of population growth. Furthermore, because of the region’s adjacency to Seoul, the capital of South Korea, construction of an industrial complex has been planned in the near future, which will also increase water demand. These increasing water demands have raised several concerns.
and triggered discussions on additional dam building and water allocation issues. However, those structural measures need at least 5–10 years to solve the water shortage problem in Chungnam Province, which means, if the operational failure of the dam occurs in the meantime during drought, water availability may be threatened because of the storage shortage.

In 2015, Western Chungnam Province had to reduce water supply by 20% for 5 months because of serious drought. Thus, reliable long lead-time reservoir inflow forecasting is essential because water resources manager must decide when to reduce environmental flows to secure more water during water shortage or to increase water release to prevent dam overflows. To reduce the negative impacts of climatic variability on dam operation, dam inflow forecasting model with at least 3 months lead time is needed to prepare for potential threat such as floods and droughts. For the water supply purpose, it is important to know in advance to save some water if the shortage in water is on the horizon of the near future. Boryeong Dam is very vulnerable to drought as its effective storage to annual water supply is 1:1 and is related with many different types of stakeholders including government, municipalities, agriculture, environmental organizations, enterprises, etc. [1]. To address the complex need for water resources before any decision on the adjustment of dam releases to be reached, a month or two is not a sufficient amount of time to do so. Thus, at least 3-months lead time, thus a season-ahead forecast, is needed, and it is quite common in forecasting practices [2–4]. In summary, the time required for local stakeholders to take operational actions and also the medium time horizon for forecasting needs were factored into the selection of lead time to be 3 months.

There are two basic approaches for long-range hydroclimatic predictions: dynamic models and empirical statistical models. The dynamic approach is based on process models for climate and hydrology. The statistical approach is based on data driven models where the predictor–predictand relationship is the essence of the technology. Although it is anticipated that dynamic models may become superior to empirical models in the future, empirical forecasting models are still able to compete because they are less expensive to develop and use [5].

The hydroclimatic models used to forecast seasonal precipitation or streamflow are still far from perfect, and there are a lot of uncertainties to be considered. Especially, the models need to be in better compliance with climatic observations such as ocean-atmospheric indices, which are connected to climatic variability globally. These ocean-atmospheric forcing predictors, called hydroclimatic teleconnections are widely used to forecast long range seasonal streamflow or precipitation. Since weather and climate are linked with atmospheric circulation over the continents, previous studies have suggested the relationships between the extreme phases of El Niño southern oscillation (ENSO) and the fluctuations of stream flow and precipitation [6,7]. There is growing evidence of the effects of atmospheric-oceanic features on the hydrology of the western basins [8–10]. Moss et al. [11] used the southern oscillation index (SOI) as a predictor of the probability of low flows in New Zealand. Chiew et al. [12] pointed out the effect of ENSO on Australian rainfall, streamflow and drought. More recently, Chen and Lee [13] suggested variations in correlations and possible climate regime shifts.

There are also several past studies for streamflow prediction with long lead times using ocean-atmospheric oscillation indices. Chiew et al. [14] used the ENSO–streamflow relationship to forecast streamflow. Xu et al. [15] showed the possibility for seasonal streamflow forecasting using climate teleconnections at the Three Gorges Dam. Chandimala and Zubair [16] tried to forecast streamflow and rainfall, based on ENSO, for water resource management. Karla et al. [17] predicted annual streamflow volume with a 1-year lead time by a data-driven model, the support vector machine (SVM), using the North Atlantic oscillation (NAO), ENSO and sea surface temperature (SST). Ouachani et al. [18] also showed the impact of teleconnection pattern on precipitation and streamflow. More recently, Hidalgo-Munoz et al. [19] employed multiple linear regression using large-scale atmospheric and oceanic information for seasonal streamflow forecasting and found fair forecasting skill.

Although previous studies revealed a significant relationship between large-scale climate teleconnections and stream flow, most of those applications have investigated the correlation between
teleconnection indices and streamflow in the large-scale basins on a yearly or seasonal basis. However, there have been few studies evaluating the applicability of climate indices in predicting monthly runoff in a small watershed such as Boryeong Dam watershed (163 km$^2$) in South Korea [20,21]. At the same time, there were no attempts to use multiple data-driven models as an ensemble for a monthly reservoir inflow forecasting purpose in the context of simple model averaging (SMA) and Bayesian model averaging (BMA), which is an ensemble averaging technique based on multiple model results. BMA considers the uncertainty of each model’s forecasts explicitly and uses this uncertainty to calculate a predictive distribution. This method has two desirable advantages. One is that it provides deterministic forecast and the other is that it offers prediction interval of forecast distribution, which is very helpful to make a decision probabilistically.

The main objective of this research is identifying the monthly best combination of climate indices and developing a monthly reservoir inflow forecasting model based on them with a three-month lead time. For the efficient dam operation, monthly reservoir inflow prediction with a lead time of at least three months is needed, which means climate predictors measured at least three months in advance are used. Another objective is to evaluate whether the ensemble prediction by BMA with data-driven models for reservoir inflows in a small basin is reliable or useful in forecasting monthly reservoir inflows, which is a very important tool for the stable dam operation.

2. Materials and Methods

2.1. Study Site and Data Used

Boryeong Dam watershed located in South Chungcheong Province of South Korea was selected as the study site (Figure 1). It is near the coast of the West Sea and belongs to a monsoonal climatic region with seasonal cycle of precipitation. The dam’s height and crest length are 50 m and 291 m, respectively [22]. The dam has an effective storage of $108.7 \times 10^6$ m$^3$ and supplies municipal and industrial waters to three cities (Boryeong, Seosan and Dangjin), five counties (Seocheon, Cheongyang, Hongseong, Yesan and Taean) and two electrical power plants (Dangjin and Seobu). The watershed drainage area upstream of the dam site is 163 km$^2$ [1]. The average slope is 36.9%, and the average elevation is 233.4 m. The basin’s topography is mainly covered with forest (72%) and agricultural land (17%) and had undergone very little changes since early 1900s [23]. This watershed is a fluvial system, which is governed by rainfall-driven peak in wet season. The annual average precipitation of the watershed is about 1305 mm/year, and approximately two-thirds of the annual precipitation occurs during warm seasons from June to September. The annual mean discharge and runoff ratio are 4.19 m$^3$/s and 0.58. The average annual temperature, monthly maximum temperature and monthly minimum temperature are 12.8, 36, and $-13.6$ °C, respectively.

In this study, monthly reservoir inflow data of Boryeong Dam are obtained from Water Resources Management Information System [24] of Korea (1998–2016) to be used as predictands. Our target seasons for forecasts are dry periods spanning from January to May and from November to December, and the wet seasons (June to October) are excluded because the prediction of reservoir inflow becomes more important for water supply during this season. In the literature, there are similar studies in spirit, which focused on forecasting specifically for dry season streamflow, which is the critical season that allows for the decision to be made on optimal allocation of precious water resources in the context of the drought condition [25–27]. Monthly long-term observed precipitation data, which are the areal precipitation from stations within Boryeong Dam watershed, were taken from WAMIS and K-water and were used for the analysis. The gauging stations are located in Figure 1. The monthly average precipitation, dam inflow and runoff coefficient are shown in Table 1 and Figure 2.
Inflow depth (mm) and runoff coefficient are updated monthly (Table 2).

resources in the context of the drought condition [25]. The critical season that allows for the decision to be made on optimal allocation of precious water is the dry season. During this season, inflow becomes more important for water supply. Similar studies focused on forecasting streamflow specifically for the dry season. In the literature, target seasons for forecasts are dry periods spanning from January to May and from November to December, and the wet seasons (June to October) are excluded because the prediction of reservoir inflow is less accurate during these periods.

We also used time series of many climatic indices available from the Climate Prediction Center [28] for the same period, which are updated monthly (Table 2).

Figure 1. Location of the Boryeong Dam watershed and its elevation.

Table 1. Monthly average precipitation, reservoir inflow depth and runoff coefficient (1998–2016).

| Data                  | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec |
|-----------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| Precipitation (mm)    | 28.7| 38.6| 50.3| 96.3|103.4|163.4|326.6|274.8|165.2|67.7 |45.6 |39.9 |
| Inflow depth (mm)     | 10.9| 17.0| 18.4| 44.6| 50.3| 63.8|237.9|198.5|119.1|33.6 |13.5 |15.0 |
| Runoff coefficient    | 0.38| 0.44| 0.37| 0.46| 0.48| 0.39| 0.72| 0.72| 0.72| 0.50| 0.30| 0.38 |

Figure 2. Monthly average precipitation, inflow depth and runoff coefficient of study area.

We also used time series of many climatic indices available from the Climate Prediction Center [28] for the same period, which are updated monthly (Table 2).
Table 2. List of teleconnection indices used in this study.

| Abbreviation | Definition |
|--------------|------------|
| AAO          | Antarctic Oscillation is the first leading mode from the EOF analysis of monthly mean height anomalies at 700-hPa. |
| AMM          | Atlantic Meridional Mode is the atmosphere-ocean variability in the tropical Pacific and tropical Atlantic. |
| AMO          | Atlantic Multidecadal Oscillation is an index of the North Atlantic temperature. |
| AO           | Arctic Oscillation is a pattern of atmospheric pressures of the Arctic and North Atlantic oceans. |
| EA           | East Atlantic Pattern is associated with surface temperatures in Europe and US. |
| EAWR         | Eastern Asia/Western Russia index is the second prominent mode of low-frequency variability over the North Atlantic. |
| ERSST        | Extended Reconstructed Sea Surface Temperature is a global grid monthly sea surface temperature. |
| MEI          | Multivariate ENSO Index is related to sea-level pressure, surface wind, sea surface temperature, surface air temperature and total cloudiness fraction of the sky. |
| NAO          | North Atlantic Oscillation is a dominant teleconnection patterns ranging from North America to Europe and North Asia. |
| NINA3        | NINA3 is the average of sea surface temperature anomalies over the region from 5N to 5S and 150W to 90W. |
| PDO          | Pacific Decadal Oscillation is associated with monthly SSTs across the North Pacific. |
| SOI          | Southern Oscillation Index is the development and intensity of El Nino or La Nina events in the Pacific Ocean. |
| TNA          | Tropical Northern Atlantic Index is the anomaly of the average of the monthly SST from 5.5N to 23.5N and 15W to 57.5W. |
| WP           | Western Pacific Index is a primary mode of low-frequency variability over the North Pacific in all months. |

2.2. Methodology

2.2.1. Predictor Selection

A time-lagged (3–12 months backward) correlation analysis between the monthly climatic indices and reservoir inflow at Boryeong Dam was performed to select the best monthly candidate predictors associated with teleconnection impact on the monthly reservoir inflow. Correlation analysis of less than a 3 months lagged period was not considered in this study because 3-months lead time forecasts were needed for the study area to prepare for a drought, allowing for about a month for multi-stakeholders to reach a decision and 1 or 2 months to take managerial actions [1]. Significance tests were then performed based on a two-tailed t-test for correlation coefficients between predictors (observed climate indices) and predictand (observed reservoir inflow) values. A multiple linear regression analysis was used to select predictors using the stepwise regression method, which is an iterative process of adding or removing candidate predictors based on the F-statistics of their estimated coefficients and their p-values, which are significant for a value of less than 5% [19,29]. Multicollinearity check was also considered for the regression modeling. Multicollinearity results in difficulty in coming up with reliable estimates of parameters in regression models. Multicollinearity checks were run for the models, calculating variance inflation factor (VIF) as described in Equation (1):

$$VIF_i = \frac{1}{1 - R_i^2}$$  \hspace{2cm} (1)

where $R_i^2$ is the coefficient of determination of the regression of predictor $i$. A VIF above 5 indicates high correlation [30].

2.2.2. Statistical Models

For the monthly dam inflow forecasts with a 3-month lead time, multiple linear regression model (MLR), support vector machines (SVM) and artificial neural networks (ANN) methods were
applied, which are very popular approaches well identified as mainstream in a recent review [31] of streamflow forecasting using data-driven models and powerful statistical techniques that have found many applications in this field [17,29,32–42]. However, thorough the comparison of models was not the main focus of our work. The MLR method is a multivariate technique that determines a linear relationship between multiple independent variables (predictors) and a dependent variable [43]. The chosen climatic indices are the independent variables and monthly reservoir inflow is the dependent variable. The formula for the multiple linear model used is shown below in Equation (2):

\[ y = C + D_1x_1 + D_2x_2 + \cdots + D_nx_n \]  

where \( y \) is the output variable; \( x_i \) represent the climatic indices; \( D_i \) is the regression coefficients and \( C \) is the intercept.

SVM is a useful tool for data classification and pattern recognition in the field of data mining [44,45]. It has shown to provide excellent performances in regression and time series prediction. The general framework of SVM involves (1) separating data into training and test sets, (2) producing a model with training data set and (3) predicting the target value based on test data set. Support vector regression has the same concepts as the SVM for classification. The main goal of support vector regression is to find a function \( f(x) \) that has at most \( \varepsilon \) deviation from the target variable \( y \) as described in Equations (3)−(5).

\[ f(x) = \langle \omega, x \rangle + b \]  

\[ \text{Minimize } P(f) = \frac{1}{2}||\omega||^2 + c \sum_{i=1}^{n} (\xi_i + \xi_i^*) \]  

\[ \text{Subject to } \begin{cases} y_i - \langle \omega, x_i \rangle - b \leq \varepsilon + \xi_i \\ \langle \omega, x_i \rangle + b - y_i \leq \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \geq 0 \end{cases} \]  

where \( C \) determines the tradeoff between flatness of \( f \) and tolerance of the prediction error \( \varepsilon \), \( \xi_i \) and \( \xi_i^* \) are the slack variables to deal with optimization problems. A detailed description of statistical principles of SVM can be found in [46]. The kernel function is used to consider nonlinearities in the model. A radial basis kernel that has been known to perform better than other kernels was used.

ANN, in contrast to MLR, has a flexible mathematical configuration that can analyze nonlinear relationships between dependent and independent variables. ANN generally consists of input layers, one or more hidden layers and an output layer [47]. However, there are different schemes for ANN depending on the number of layers and nodes. The general definition of ANN is as shown in Equation (6):

\[ y = g \left( \sum_{i=1}^{l} w_i x_i \right) \]  

where \( y \) is a summation function of weighted \( (w) \) output, \( x \) is a neuron with inputs and \( g \) is an activation function used to generate an output. There are many different activation functions, we used the typical sigmoid logistic non-linear function, which varies from 0 to 1 as in Equation (7):

\[ g(t) = \frac{1}{1 + e^{-t}} \]  

The optimization process of finding an appropriate connection between the input layer and hidden layer by changing \( w \) and the bias was determined through learning or training the system. Therefore, training was the process to minimize the difference between the ANN output and the observed value (the target data).

The application of ANN algorithms in hydrology is well documented in the paper by Govindaraju [48]. Matlab was the software used for developing the ANN model. The scheme
used in this study, shown in Figure 3, was the input–hidden–output layer, which means the network had input neurons (chosen climatic indices) in the input layer (4 at the most as determined in this study), ten neurons in the hidden layer and one neuron (monthly reservoir inflow) in the output layer. When we added to or subtracted from 10 hidden layer nodes, which is a default value in Matlab, the result was not significantly better. Therefore 10 hidden layer nodes were used as recommended by the software. A two-layer feedforward network, which is the most common training method in ANN called the multilayer perceptron, was used and trained using the Bayesian-regularization algorithm [49].

![Figure 3. The designed network diagram for artificial neural network (ANN).](image)

2.2.3. Model Validation

The traditional framework of hydrologic modeling includes preparing data sets, dividing a data set into training and test data sets, training the model and assessing the results from the trained model on a test data set. However, the general process described above can cause period-specific output for reservoir inflow forecasts using climate indices such as different combinations of predictors depending on how the data is split. This is because of different periodicity exhibited by predictors. Additionally, the second reason is the difference between the recent and past climate characteristics due to the climate change impact. For example, the average inflows in November and December in the period of 1998–2012 (training data) were 1.4–1.5 million tons, while the average inflows in the recent period of 2013–2016 (test data) were 5.0–6.3 million tons [1]. In this case, there is a lack of learning data for high inflow, which lowers the reliability of the machine learning method because training data did not reflect the recent increasing precipitation trend in winter season. These results indicate the necessity of considering the recent seasonal or monthly streamflow characteristics when we build a statistical model. In order to solve that issue, k-fold cross-validation was proposed instead of dividing the data sets into specific training and testing term. The target area had 19 observed data sets. Each sample data was removed, and the model was trained with the remaining \((k - 1)\) sample data. Finally, the removed sample data was tested using the trained model, and this process is repeated for \(k\) times. For each month that is to be predicted in a given year, a separate model is built and trained using the data recorded in the same month for the remaining 18 years.

2.2.4. Model Evaluation

To evaluate the ability of above models’ forecast skill, correlation coefficient \((r)\) and expected error, \(S\) [50] were used. Correlation coefficient describes the degree of collinearity between the predicted value and measured data. The coefficient \(S\) is computed as Equation (8):
\[ S = 1 - \frac{\sqrt{\text{var}(Q' - Q_s)}}{\sqrt{\text{var}(Q_s)}} \]  

where \( Q' \) and \( Q_s \) are forecasted and observed values of reservoir inflow, respectively. The coefficient \( S \) can range from \(-\infty \) to 1. The coefficient of 1 means a perfect match of predicted value to the observed data. The coefficient above 0 indicates that the model has certain skill in prediction. Consequently, the closer the model’s efficiency coefficient is to 1, the more accurate the model’s prediction is.

The overall methodology adopted for monthly reservoir inflow prediction can be visualized in Figure 4.

**Figure 4.** Flowchart of small basin scale dam inflow prediction by multiple linear regression (MLR), a support vector machine (SVM) and ANN.

### 3. Results and Discussion

#### 3.1. Selection of Oceanic-Atmospheric Indices

Table 3 shows the best-fitting predictors having the highest correlations with \( p \)-values of less than 5% and VIF of less than 5. We described the correlation strength between predictors and reservoir inflow of 0.80 and higher as “very strong”, those from 0.60 to 0.79 as “strong” and those from 0.40
to 0.59 as moderate correlations [51]. In January, two predictors were selected, Tropical Northern Atlantic index (TNA; lag-10 months) and extended reconstructed sea surface temperature (ERSST; lag-3 months), and showed strong correlation (−0.67, 0.61) with p-values of less than 1%. Additionally, WP (lag-4 months) and the multivariate ENSO index (MEI; lag-8 months) have strong correlations (−0.67 and 0.68) with p-values of less than 1% in February. The East Atlantic pattern (EA) was well correlated during the month of the March (−0.71) and May (0.67). Four climate indices were selected in April with NINA3 (lag-10 months) showing a very strong correlation (0.83), and the remaining predictor’s correlation coefficients lie between the values 0.44 and 0.66. The ERSST (lag-3 months) has a strong correlation in November (0.75) and December (0.66).

A different set of climate factors was selected for each month as is found in Table 3. The lag month as little as 3 months to as long as 12 months were found for climate factors exhibiting the different levels of lags of climate indices that have influence on streamflow. The spring season (March-May) were found to be the months that take the most advantage of good number of climate indices (four) as predictors for streamflow. A similar pattern of results was presented in previous work [52], indicating the variability of climatic factors that have influences on each month for medium-range forecasting on the study area. Among the climate indices considered, TNA, Arctic oscillation (AO), EA and ERSST were found to be selected repeatedly more than once with different lagged months as major predictors in several months. The ERSST, which is the climate index representing the sea surface temperature, was identified to be most frequent predictor (selected in five different months) that has the influence on streamflow.

Table 3. List of teleconnection indices used for each month (the number in the ( ) means the months lagged).

| Month | Climatic Indices | Correlation Coefficient | p-Value | VIF |
|-------|------------------|-------------------------|---------|-----|
| Jan   | TNA(10), ERSST(3) | −0.67, 0.61              | 0.001, 0.005 | <1.0 |
| Feb   | WP(4), MEI(8)    | −0.67, 0.68              | 0.001, 0.001 | <1.3 |
| Mar   | EA(4), AO(5), AMM(3), ERSST(3) | −0.71, −0.64, −0.59, 0.45 | 0.0007, 0.002, 0.007, 0.05 | <1.7 |
| Apr   | NINA3(10), SOI(5), EAWR(6), PDO(8) | 0.83, −0.57, 0.44, 0.66 | 0.0001, 0.009, 0.05, 0.001 | <4.1 |
| May   | EA(9), AO(9), AAO(12), ERSST(3) | 0.67, 0.45, −0.47, 0.47 | 0.001, 0.04, 0.03, 0.03 | <1.3 |
| Nov   | TNA(8), ERSST(3) | −0.54, 0.75              | 0.01, 0.0002 | <1.1 |
| Dec   | NAO(8), NINO3(5), ERSST(3) | 0.46, 0.57, 0.66 | 0.04, 0.01, 0.002 | <1.3 |

In many papers, ocean SST were identified to influence streamflow [20,53,54]. The correlation analysis between the ERSST value of the waters around the Korean Peninsula and the reservoir inflow was investigated in order to find the region highly correlated with the inflow with 3-month lead time. As a result, ERSST was identified to be useful for lead time forecasting of reservoir inflow except February and April. Table 4 lists the selected locations for ERSST for the months being considered in this study. Figure 5 shows the moving correlation coefficients with lags considered between Q’ and Qs for the entire period 1998–2016. Except the ERSST(Mar, Dec) and TNA(Nov), the remaining factors exceeded a significance level of 95%.

Table 4. Selected locations from the global climate data for the extended reconstructed sea surface temperature (ERSST).

| Month | Jan | Feb | Mar | Apr | May | Nov | Dec |
|-------|-----|-----|-----|-----|-----|-----|-----|
| Locations selected | 48° N, 40° N, 26° N, 24° E, 198° E, 146° E, 152° E, 210° E | 48° N, 40° N, 26° N, 24° E, 198° E, 146° E, 152° E, 210° E | 48° N, 40° N, 26° N, 24° E, 198° E, 146° E, 152° E, 210° E | 48° N, 40° N, 26° N, 24° E, 198° E, 146° E, 152° E, 210° E | 48° N, 40° N, 26° N, 24° E, 198° E, 146° E, 152° E, 210° E | 48° N, 40° N, 26° N, 24° E, 198° E, 146° E, 152° E, 210° E | 48° N, 40° N, 26° N, 24° E, 198° E, 146° E, 152° E, 210° E |
| Correlation coefficient | 0.61 | 0.40 | 0.45 | 0.64 | 0.47 | 0.75 | 0.66 |
Figure 5. Moving correlations (years 1998–2016) between the monthly reservoir inflow and the climatic indices.
3.2. Individual Model Performance

The performance of each model in terms of $r$ (correlation coefficient) and $S$ are listed in Table 5. The $r$ values of the three models ranged from 0.62 to 0.90, which shows that the pattern of the observations was well simulated. The $r$ value of 0.7 or more means a strong relationship between the observed and predicted values based on the criteria given by Hinkle et al. [55]. In terms of skill score, the monthly prediction skill score was larger than 0 for all three models and showed some predictive skill. The $S$ values of the MLR model ranged from 0.21 to 0.55, the ANN model ranged from 0.20 to 0.52, and the SVM from 0.21 to 0.56. Except for January and December, the maximum prediction score of the models was above 0.4. One of the reasons why the forecasting score was low in January and December compared with the other months is that the variation in monthly inflow was large, which made the model prediction more difficult for these two months. The MLR model has a relatively simpler method than the other two models, however the forecast performance shows similar results and is considered to be an applicable and useful method with short computation time. Among the three models, MLR model depicted best results in April ($r = 0.86$, $S = 0.49$), and ANN model showed the best result in February ($r = 0.83$, $S = 0.44$), May ($r = 0.81$, $S = 0.41$) and November ($r = 0.88$, $S = 0.52$). SVM model indicated the best skill score in the cases of January ($r = 0.67$, $S = 0.26$), March ($r = 0.9$, $S = 0.56$) and December ($r = 0.76$, $S = 0.34$). The comparison of the observed and predicted values is shown in Figure 6. It can be concluded that the statistical method using climatic indices to predict dam inflow for small basin scale gives reasonable forecasts, with a 3-months lead time.

With the increase of observed data, the accuracy of forecasts will be improved. This issue of the effect of the training set size on the forecast performance of data-driven models is well confirmed in the literature. Foody et al. [56] showed for the remotely sensed data set the classification accuracy was increased significantly as a result of increasing the number of training cases using ANN method. Sug [57] discussed the effect of training set size for the performance of neural networks of classification and showed the tendency that multilayer perceptrons have better performance in relatively larger training data sets. Sordo et al. [58] investigate the dependency between sample size and accuracy of SVM. As a number of cases increases, SVM showed a substantial improvement in performance. Raquel et al. [59] analyzed the influence of training set size on the prediction accuracy of SVM model and indicated that the predictions became stable with increasing size of training sets.

| Month | MLR $r$ | MLR $S$ | ANN $r$ | ANN $S$ | SVM $r$ | SVM $S$ |
|-------|---------|---------|---------|---------|---------|---------|
| Jan   | 0.65    | 0.21    | 0.67    | 0.20    | 0.67    | 0.26    |
| Feb   | 0.69    | 0.26    | 0.83    | **0.44**| 0.62    | 0.21    |
| Mar   | 0.89    | 0.55    | 0.86    | 0.49    | 0.90    | **0.56**|
| Apr   | 0.86    | **0.49**| 0.76    | 0.35    | 0.83    | 0.44    |
| May   | 0.78    | 0.33    | 0.81    | **0.41**| 0.71    | 0.30    |
| Nov   | 0.81    | 0.41    | 0.88    | **0.52**| 0.80    | 0.32    |
| Dec   | 0.75    | 0.31    | 0.75    | 0.27    | 0.76    | **0.34**|

Table 5. Monthly forecast skill scores ($r$ and $S$) between the observed and predicted dam inflow with a 3-months lead time. The bold numbers represent the best prediction skill score of each month.
Figure 6. Cont.
Figure 6. Cont.
where weight as described in Equation (9):

\[ \alpha_{\text{sma}} = \left( \frac{1}{k}, \ldots, \frac{1}{k} \right) \] (9)

where \( k \) is the total number of models.

Forecast density of the BMA model, \( g_j \) is computed as follows in Equation (10):

\[ g_j = \sum_{k=1}^{k} \beta_k f_k \bar{y}_j \] (10)

where \( \beta_k \) denotes the weight vector, \( f_k \) is unknown forecast distribution and \( \bar{y}_j \) is a measurement vector. If a normal distribution is used as a forecast distribution, \( f_k \) can be described as Equation (11):

\[ g_j = \sum_{k=1}^{k} \beta_k g_k \bar{y}_j \] (11)
\[ f_k(\bar{y}_j|D_{jk}, \sigma^2_k) = \frac{1}{\sqrt{2\pi \sigma^2_k}} \exp\left(\frac{-1}{2} \sigma^{-2}_k (\bar{y}_j - D_{jk})\right) \]  

(11)

where \( D_{jk} \) is the point forecasts, and \( \sigma^2_k \) is variance. The MODELAVG tool box was used for BMA analysis and the details are explained in the manual [61].

3.3.2. Application of Ensemble Prediction

In order to assess the utility of this approach, we compared each forecast with the naive forecast (NF) that is average of the streamflow recorded for that month over the previous years. The Nash–Sutcliffe efficiency (NSE, [62]) and the percent bias (PBIAS) were chosen as the metrics for performance evaluation.

NSE is a normalized value that describes the relative magnitude of the residual variance (“noise”) compared to the observed data variance [36] and is computed as follows in Equation (12):

\[
\text{NSE} = 1 - \frac{\sum_{t=1}^{T} (Q_{ot} - Q_{tm})^2}{\sum_{t=1}^{T} (Q_{ot} - \overline{Q_o})^2}
\]

(12)

where \( Q_{ot} \) and \( Q_{tm} \) is the observed and forecasted value of the dam inflow, respectively, at time \( t \), and \( \overline{Q_o} \) is the mean observed value. NSE can range from \(-\infty\) to 1 and the coefficient of 1 means a perfect match of predicted value to the observed data. The coefficient of 0 indicate that the model predictions are same as the mean of the observed data, whereas the coefficients less than zero indicate that the observed mean is more accurate than the model’s predicted value. Consequently, the closer the model’s efficiency coefficient is to 1, the more accurate the model’s prediction is.

The PBIAS was calculated according to the Equation (13):

\[
PBIAS (\%) = \frac{\sum_{t=1}^{T} (Q_{ot} - Q_{tm})}{\sum_{t=1}^{T} (Q_{ot})} \times 100
\]

(13)

The PBIAS is the forecast error normalized by the observation and quantifies the tendency of predicted value being either greater (over-forecast: negative values) or smaller (under-forecast: positive values) than the observed data.

NSE values greater than 0.5 and PBIAS within 25% are considered “adequate” [63]. Table 6 shows the forecast results of SMA, BMA and NF with the value of NSE, PBIAS. BMA results showed that NSE was above 0.7 and PBIAS values were within 25% for all years. BMA and SMA methods showed more reliable prediction results than NF. Overall, the BMA method resulted in more accurate forecasts than the other two methods. In addition, the 95% prediction uncertainty ranges of the BMA method for the target year 2016, which is given as an example, envelop most observations in Figure 7. The dam watershed suffered severe meteorological droughts in 2015 with precipitation of 668.6 mm/year, approximately 60% of 40-year (1976–2015) average precipitation (1188 mm/year) [22]. The forecasting results show that the BMA method presented reliable predictability in drought year. These results showed the applicability that the proposed models could be used as a decision-making tool to manage dam operation for water supply in the context of BMA.
Table 6. Performance statistics for Bayesian model averaging (BMA), simple model averaging (SMA) and naive forecast (NF).

| Year | NSE | PBIAS (%) | NSE | PBIAS (%) | NSE | PBIAS (%) |
|------|-----|-----------|-----|-----------|-----|-----------|
| 2013 | 0.78| 6.45      | 0.77| 14.41     | -0.02| 37.37     |
| 2014 | 0.77| 3.08      | 0.52| 10.37     | -1.68| 14.92     |
| 2015 | 0.89| -1.33     | 0.71| -7.11     | -1.34| 36.41     |
| 2016 | 0.71| -21.87    | 0.43| -36.34    | 0.31 | 44.19     |

Figure 7. Cont.
Figure 7. Comparison of forecasts between SMA and BMA for January (a), February (b), March (c), April (d), May (e), November (f) and December (g) of target year 2016. The red line displays the mean point forecast of the BMA method, whereas the block dots are observations. Grey region indicates 95% prediction interval.

4. Conclusions

Water resources managers consider accurate lead time forecasting of streamflow as one of the most fundamental components for preparing water hazards such as droughts. For the streamflow prediction with the statistical method, the most basic method is a naive forecast. Additionally, an improved forecast skill has been shown by more advanced models ranging from simple regression method to the data-driven modeling approach such as ANN, SVM, etc. [3, 16]. Many hydrologists focus on predicting hydrologic conditions using teleconnection between streamflow and climate indices [17, 65].

This study was motivated by the recognition of worsening water shortage in Southern Chungnam Province in South Korea due to emerging development and increasing demand on water resources. We developed statistical reservoir inflow forecast models with a lead time of 3 months based on MLR, ANN and SVM methods using lagged teleconnection between streamflow and regularly updated climate indices. For the model building, a 19-year-long hydrologic data set for the Boryeong Dam basin and various climatic indices were used. In addition to individual model building, we expanded the scope to investigate their integrated predictive capability as an ensemble prediction method in the context of BMA for improving predictability. The important results obtained in this study are summarized as follows.

First, we found that monthly teleconnection variables can be useful predictors for forecasting the monthly reservoir inflow for a small basin. Although the forecast performance of three models in Boryeong Dam basin were not perfect, the results have shown the possibility that climatic indices based models could be applied to a small basin for sustainable water resources management. Though ANN and SVM were better than MLR, the MLR method still has the advantage of being more directly based on the relationship between climatic indices and reservoir inflow over the forecasts obtained from SVM and ANN model. Ensemble prediction results showed that BMA is more accurate and useful than SMA and NF. In addition, the prediction interval provided by BMA can be very helpful for early decision-making in response to drought situations.

Wind, temperature and geomorphologic characters are key factors affecting precipitation and reservoir inflow. Despite remarkable recent progress in atmospheric science, our understanding of climatic forcing and how they influence climate variability and predictability at different lead times and over different time scales remains far from being complete [66]. Further understanding of climatic forcing is needed to develop more accurate statistical and numerical streamflow forecasting models.
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This study is considered a promising first step for stable dam operation using statistical model to forecast reservoir inflow at a reasonable lead time. Despite being the promising approach to forecast reservoir inflow from a small basin, the proposed models need to be tested for other basins for more general applicability. In the future study, climatic indices can be further combined with local variables such as precipitation and flows for current and previous months so that the direct cause of the inflow is supplemented by the remotely influential climate variables for better prediction performance.

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