Probabilistic long-term hydrological drought forecast using Bayesian networks and drought propagation

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Abstract
Effective drought mitigation plans that can handle severe drought conditions require reliable drought forecasts. A probabilistic hydrological drought forecasting method was developed using Bayesian networks that incorporate dynamic model predictions and a drought propagation relationship. The resulting model, Bayesian networks based drought forecasting with drought propagation (BNDF_DP), was designed using current and forecast lead time drought conditions of a multi-model ensemble. Hydrological drought conditions were represented by the Palmer Hydrological Drought Index. The ranked probability score (RPS) and receiver operating characteristic (ROC) curve analysis were employed to measure forecast proficiency. The BNDF_DP model showed good performance, with an RPS 4–50% higher than a climatological model. ROC analysis indicated that the BNDF_DP offered superior forecasting skills for long-term drought, with a 2 and 3 month lead time, compared with a model that does not consider drought propagation. The overall results indicated that the BNDF_DP model was a promising tool for probabilistic drought forecasting that can provide water managers and decision-makers with the flexibility to respond to undesirable drought risks, prepare drought mitigation action plans and regulate policies based on future uncertainties.

KEYWORDS
Bayesian networks, drought propagation, hydrological drought, probabilistic forecast

1 | INTRODUCTION
Hydrological drought is a deficiency in surface and subsurface water resources (Fleig et al., 2006). A wide variety of water sectors can be affected by drought, and society is particularly vulnerable to hydrological drought, with reductions in water supply, crop yield and industrial products now commonplace. In this context, a hydrological drought forecasting system that includes a systematic monitoring framework is primarily responsible for effective operation of the global water supply system (Van Loon, 2015; Yuan et al., 2017; Shin et al., 2018). In South Korea, the Korea Meteorological Administration has produced meteorological drought forecasts using the dynamic model of Global Seasonal Forecasting System 5. Residential and industrial water drought outlooks conducted by the Department of the Environment that compare water supply and demand provide deterministic drought forecasts.

Drought forecasting models can be categorized into two groups: statistical and dynamic (Yan et al., 2017). Several
types of statistical models for drought forecasting are available, depending on the method used: autoregressive such as autoregressive moving average and autoregressive integrated moving average models; Markov chain; machine learning, such as artificial neural networks, support vector machines and meta-Gaussian; and their combinations (Kim and Valdes, 2003; Mishra and Desai, 2005; Mishra et al., 2007; Morid et al., 2007; Durdu, 2010; Mishra and Singh, 2011; Belayneh et al., 2014; Mehr et al., 2014; Hao et al., 2016). Statistical models for hydrological forecasting are based on a set of assumptions that rely only on available data. The climate system can be modelled by dynamic models defined by a mathematical representation of the interactions between land, ocean and atmosphere. Various dynamic models such as the Climate Forecast System of the National Oceanic and Atmospheric Administration National Centers for Environmental Information and the Ensemble Forecast of the European Centre for Medium-Range Weather Forecasts are used extensively for climate prediction, and their variables are subsequently used as input for hydrological models to generate streamflow ensemble forecasts (Yuan et al., 2013; Trambauer et al., 2015; Xu et al., 2018). Although reasonable skills in terms of correlation can be obtained through statistical models, dynamic models offer the advantage of detailed representations of the climate system at high spatio-temporal resolutions (Liu et al., 2015; Xu et al., 2018). Despite the increased use of dynamic models in hydrological applications, the direct use of model outputs must still deal with biases in climate models that reduce the efficiency beyond a 1 month lead time (Yuan et al., 2013; Yan et al., 2017).

Hydrological drought forecasting in South Korea remains a difficult task. First, relatively long-term data are not available for South Korea, most notably for streamflow and groundwater data. To apply a dynamic model simulation to a hydrological drought forecast, a hydrological model is forced with dynamically predicted meteorological data (e.g. precipitation and temperature) to produce future hydrological variables. The resulting forecasts include greater uncertainties than those produced by meteorological drought forecasting because of model error and uncertainty, in addition to input uncertainty associated with dynamic model simulations (AghaKouchak, 2014). Therefore, a new approach to predicting droughts is required.

A Bayesian networks based drought forecasting model is proposed to quantify prediction uncertainties based on probability. This model can easily consider various forecast predictors from the relationships between the variables. Because hydrological drought forecasting is accompanied by higher uncertainty than forecasts for other types (Yuan et al., 2017), uncertainty estimates are needed to provide reliable forecasts. A probabilistic presentation allows our model to assess uncertainty explicitly. Bayesian networks are probabilistic models within a graphical structure, which describes a network of interacting variables of interest and acquires probabilistic inferences over those variables. Bayesian networks have been applied to economics, climatology, social statistics and natural sciences, and are particularly useful for forecasting (Van Koten and Gray, 2006; Amstrup et al., 2008; Eisuke et al., 2012). The naive Bayesian classifier (Van Koten and Gray, 2006) and the Bayesian network modelling shell Netica (Amstrup et al., 2008) have been used for Bayesian networks based forecasting. Recently, an integrated learning model in a Bayesian network model combined with a copula function that describes dependences has been proposed for drought monitoring and forecasting (Madagar and Moradkhani, 2014; Avilés et al., 2016). In the present study, a Bayesian networks based drought forecasting (BNDF) framework is proposed for hydrological drought forecasting informed by three predictors: drought persistence, drought propagation and dynamic forecasts from the Asia-Pacific Economic Cooperation (APEC) Climate Center (APCC) Multi-Model Ensemble (MME) (Min et al., 2014). The APCC MME products are available to all registered users for non-commercial research or climate operations, through the APEC Data Service System (http://cis.apcc21.org).

Drought propagation is a dominant factor in the BNDF model. Because atmospheric, surface and subsurface water storage are closely interconnected within the hydrological cycle, all droughts (whether meteorological, agricultural or hydrological) are related to each other. Meteorological drought is usually defined by the degree of dryness and the duration of the dry period that represents a departure from a region’s normal climate. Agricultural drought focuses on the impacts on agriculture, including soil water deficits, reduced groundwater or low irrigation reservoir levels. Hydrological drought usually follows periods of extended precipitation shortfalls that affect water supply, resulting in potentially significant societal impacts. Through the drought propagation process, meteorological drought acts as the starting point of hydrological drought (Apurv et al., 2017). There is a significant relationship between hydrological and meteorological droughts (Heim, 2002), and several studies have concluded that understanding drought propagation mechanisms between different types of drought may provide more accurate forecasts of agricultural and hydrological droughts, with the use of meteorological drought as a precursor (Hao et al., 2016; Wang et al., 2016). In the case of drought propagation, some researchers (Van Loon and Van Lanen, 2012; Van Loon, 2015; Barker et al., 2016; Melo and Wendland, 2016;...
Wang et al., 2016; Huang et al., 2017) have investigated drought propagation using various drought indicators. However, a statistical approach to the drought propagation phenomenon has not been developed (Shin et al., 2018) and only a few studies have focused on estimating drought propagation lag time (Sattar and Kim, 2018). In South Korea, Shin et al. (2018) found that the transition from meteorological to hydrological drought and the lag time of drought propagation could be estimated using the Palmer Hydrological Drought Index (PHDI) and the Standardized Precipitation Index (SPI). The PHDI is a hydrological indicator that has been used to assess the long-term impact of drought on hydrological systems (Palmer, 1965), and the SPI is a meteorological indicator that has been used to represent precipitation deficit (McKee et al., 1993). Drought propagation lag time and meteorological drought conditions were applied to the hydrological drought forecasting model.

In this section, a brief overview of previous studies has been provided. The study area and data used in the present study are summarized in the following section, and theoretical aspects of the Bayesian networks modelling framework considering drought propagation are discussed in Section 3. The results are described and discussed in Section 4. A summary and concluding remarks follow in Section 5.

2 | STUDY AREA AND DROUGHT INDICES

Monthly precipitation and temperature data for South Korea were obtained from the Korea Meteorological Administration (www.kma.go.kr), as shown in Figure 1, and then used to calculate the PHDI and SPI for 1973–2015.

To predict hydrological drought more effectively, the present study used APCC seasonal forecasts, which are an ensemble of simulations from multiple dynamic models. The APCC provides deterministic 3 month and 6 month MME predictions of precipitation and temperature from the simple composite method (Min et al., 2014). The 3 and 6 month APCC MME provided prediction information from 2008 and 2014, respectively. The APCC MME precipitation and temperature, which are gridded at a resolution of 2.5° × 2.5° for the study area (longitude 35.0°–37.5° E, latitude 127.5°–130.0° N), were extracted from the APCC data service web portal. A statistically downscaled APCC MME prediction was used to estimate the SPI. The focus was on developing a drought forecasting method, and a spatial downscaling approach to link APCC MME simulations at local sites of interest was not considered. Instead, APCC MME outputs were collected from the adjacent grid centred on the location of the weather station of interest, and their values (APCC MME precipitation and temperature data) were transformed into site based data by applying a predictive anomaly to the monthly historical mean values (Shin et al., 2016).

Because most South Korean streamflow and groundwater data for the past 30 years are limited, the PHDI was selected as a hydrological drought indicator. The PHDI can be easily calculated from a simple water balance model using only temperature and precipitation. The PHDI was derived from the Palmer Drought Severity Index (PDSI), which is based on a primitive water balance model; this allows for computation of the PHDI during calculation of the PDSI. The concept of drought in the PDSI involves the moisture anomaly between actual precipitation and precipitation that is Climatologically Appropriate for Existing Conditions (CAFEC). The CAFEC precipitation was computed using a water balance equation and four hydrological parameters (evapotranspiration, runoff, soil moisture loss and recharge), which were calculated using temperature and precipitation records and estimates of the available water capacity of the soil. The computational procedure for the hydrological parameters is described by Palmer (1965). Shin et al. (2018) compared the PHDI and the Standardized Runoff Index to naturalized streamflow of the sub-basin, which is simulated from the TANK model. A similar drought pattern appeared in the two indices.
In the present study, a meteorological drought was identified by the SPI, which has been widely used to describe drought conditions because the SPI computation is simple and uses only monthly precipitation as a predictor of hydrological drought. The long-term precipitation record at monthly time scales was first fitted to the gamma probability distribution. The resulting distribution was transformed into a standard normal distribution with a value of 0 for the mean and 1 for the standard deviation. Drought events were defined when the SPI fell below −1.0 and the PHDI became −2.0, as shown in Table 1.

3 | PROBABILISTIC DROUGHT FORECASTING FRAMEWORK

3.1 | Bayesian networks and a likelihood weighting algorithm

Bayesian networks are probabilistic models that can describe the conditional dependences of a set of random variables using a directed acyclic graph (Pearl, 1985). The networks consist of a set of nodes and directed arcs; the nodes of the networks represent random variables (discrete and/or continuous) and the arcs connect pairs of nodes. The direction of the arcs is denoted by arrows that indicate the causal relationship between the nodes. The arcs start from a causal or preceding event of the parent node and progress to an outcome event of the child node. The relationship between nodes is defined as a conditional probability, which is based on prior information or a statistically observed correlation (Dey and Stori, 2005). The conditional probability is calculated based on Bayes's theorem. There are three basic sequential connections in Bayesian networks: converging, diverging and linear. The converging type was primarily used in our study. In the network, causes of Y are X1 and X2, which means that Y is conditionally dependent on X1 and X2.

The joint probability distribution of variables can be written as:

\[ P(X_1, X_2, Y) = P(Y|X_1)P(Y|X_2)P(Y) \] (1)

and the conditional probability of Y given X1 and X2 is expressed as:

\[ P(Y|X_1, X_2) = \frac{P(Y, X_1, X_2)}{P(X_1, X_2)} \] (2)

To estimate the posterior probability, \( P(Y|X_1, X_2) \), a likelihood weighting algorithm based on a Monte Carlo simulation was applied. The conditional probability of \( P(Y|X) \) can be estimated using the relative approximation of probabilities \( P(Y = y, X = x) \) (Lee and Lee, 2006). It is assumed that \( X \) denotes a set of observed nodes \( (X = \{X_1, X_2, ..., X_n\}) \) of the network and Y is the nodes not contained in \( X \). The path probability distribution \( \rho(y, x) \), the weighting distribution \( \omega(y, x) \) and a binomial random variable \( (l, y, x) \) were used to generate the posterior probability \( P(Y = y|E = x) \), as given by:

\[ \rho(y, x) = \prod_{Y_i \in Y} P[Y_i|\text{Parents}(Y_i/E)]_{Y = y, X = x} \] (3)

\[ \omega(y, x) = \prod_{X_i \in X} P[E_i|\text{Parents}(E_i)]_{y = y, E = e} \] (4)

\[ \chi(y, x) = \begin{cases} 
\text{True, if } X = x \text{ in } y \\
\text{False, if } X \neq x \text{ in } y
\end{cases} \] (5)

The expectation of the random variable \( E(\chi \cdot \omega) \) becomes:

\[ E(\chi \cdot \omega) = \sum \chi(y, x)\rho(y, x)\omega(y, x) = P(Y = y, X = x) \] (6)

and the expectation of the weight distribution is represented by:

\[ E(\omega) = \rho(x, y)\omega(x, y) \]

\[ = \sum \chi(x, y)\rho(x, y)\omega(x, y)|_{\chi(y, x) = \text{True}} + \sum \chi(x, y)\rho(x, y)\omega(x, y)|_{\chi(y, x) = \text{False}} \]

\[ = P(X = x) \] (7)

The posterior probability can be then calculated using:

\[ P(Y = y|X = x) = \frac{P(Y = y, X = x)}{P(X = x)} \] (8)

| Categories       | PHDI          | SPI          |
|------------------|--------------|-------------|
| Extremely dry    | \( \leq -4.0 \) | \( \leq -2.0 \) |
| Severely dry     | −3.99 to −3.00 | −1.99 to −1.50 |
| Moderately dry   | −2.99 to −2.00 | −1.49 to −1.00 |
| Near normal      | −1.99 to 1.99 | −0.99 to 0.99 |
| Moderately wet   | 2.00 to 2.99  | 1.00 to 1.49 |
| Severely wet     | 3.00 to 3.99  | 1.50 to 1.99 |
| Extremely wet    | \( \geq 4.0 \)  | \( \geq 2.0 \)  |
3.2 Drought propagation from meteorological drought to hydrological drought

Drought can be forecasted using different variables, including hydro-meteorological variables (e.g. precipitation, temperature), drought indices (e.g. PHDI, SPI) and climate indices (e.g. North Atlantic oscillation, Pacific decadal oscillation, sea surface temperature) (Mishra and Singh, 2011; Hao et al., 2016). Among these variables, different climate indices of atmospheric tele-connection that may have an effect on the distribution of precipitation have been considered in drought forecasting models (Cutore et al., 2009; Chen et al., 2013; Santos et al., 2014). Despite their potential predictability, climate indices are seldom used to estimate the likelihood or severity of drought due to low correlation with South Korean data. For example, analyses of the SPI and various climate indices by Kim et al. (2017) found correlation co-efficients ranging from −0.2 to 0.2. In our case, various factors (e.g. annual precipitation patterns, topographical characteristics) have influenced drought conditions, and it is difficult to find a significant relationship between climate indices and drought indicators.

Given this background, the use of both drought persistence and transition properties is suggested for hydrological drought forecasts. To be more specific, meteorological drought originates from a lack of precipitation and then propagates to soil moisture storage, streamflow and groundwater systems, which results in agricultural and hydrological drought (Van Loon, 2015; Hao et al., 2016) in a process called drought propagation. In other words, hydrological drought lags behind meteorological drought, and the severity of hydrological drought is attenuated by consideration of drought propagation. In the present study, the definition of drought propagation was used as described by Shin et al. (2018) and demonstrated propagation from meteorological drought (3 month and 6 month SPI) to hydrological drought (PHDI) over South Korea.

Drought propagation lag times were estimated at each station using 6 month SPI and PHDI values for 1973–2015. Figure 2 depicts drought propagation lag times in two cases. For the 1994 drought event (Figure 2a), a hydrological drought occurred 2 months after a meteorological drought began. In the 2014–2015 drought (Figure 2b), meteorological drought on the basis of the SPI was detected 1 month earlier than the PHDI. As there were different delayed responses in each drought event, the average drought propagation lag time was calculated at 54 stations, as shown in Figure 3. Hydrological drought was delayed from 1 to 7 months, and this drought propagation lag time and the 6 month SPI were used in the BNDF model.
3.3 Bayesian networks based drought forecasting with drought propagation (BNDF_DP)

Our Bayesian networks based hydrological drought forecasting model was designed to consider both dynamic forecasts (i.e. APCC MME) and the lagged SPI with consideration of propagation to represent hydrological drought better. The framework of the hydrological drought forecasting model was based mainly on the Bayesian networks approach proposed by Shin et al. (2016). The main difference with the existing model was the combined use of dynamic MME prediction outcomes and the drought propagation relationship, as described in Section 3.2. The hydrological drought forecasting network model is shown in Figure 4.

The structure of the forecast model was composed of four nodes: three parent nodes (HDn, MHDn+l, SPIn+l−lt) and one child node (HDn+l). A different lead time (l) from 1 to 6 months was considered. It represents the lag time, which is defined as the time difference between the onset of drought (i.e. SPI and PHDI); the lag time of each station is presented in Table 1. Three parent nodes represent the current hydrological drought condition (i.e. HDn), the predicted hydrological drought condition derived from the APCC MME model for an l month lead time (i.e. MHDn+l) and the lagged meteorological drought condition for the month l−lt (i.e. SPIn+l−lt).

Node HDn is described by the probability density function (PDF) of the PHDI for the current month (nth month), which can be constructed using nth month historical records. Node MHDn+l is similarly represented by the PDF of the PHDI for the next month ((n + l)th month), which is estimated by APCC MME forecasts. Finally, it was assumed that the node of SPIn+l−lt can be typically defined by the PDF under the drought propagation relationship, which plays an important role in improving the forecasting skill in the BNDF_DP model. In the BNDF_DP model, each node was treated as a continuous variable with an assumed Gaussian distribution. The predictive posterior probability of the HDn+l node was then formulated as in:

\[
P(HD_{n+l}|HD_n,MHD_{n+l},SPI_{n+l−lt}) = \frac{P(HD_{n+l}|MHD_{n+l},SPI_{n+l−lt})}{P(HD_n|MHD_{n+l},SPI_{n+l−lt})}
\]

where \(P(HD_{n+l}|MHD_{n+l},SPI_{n+l−lt})\) represents the PDF of the PHDI for the next month (n+l)th month, which is estimated by APCC MME forecasts. The probability forecast events is n. A lower RPS value indicates a small forecast probability error and a perfect forecast result in an RPS value of 0 (Wilks, 2011). The ranked probability skill score (RPSS) is the skill score of the RPS, as given by:

\[
RPSS = 1 - \frac{RPS}{RPS_{clim}}
\]

where RPSclim is the RPS of the climatological forecast, which was selected as the reference forecast model. A positive RPSS implies that the proposed forecast model is superior to the reference forecast model.

The ROC assesses the forecast ability to discriminate between alternative outcomes (Trambauer et al., 2015). The reliability of the forecast results was evaluated by classifying the observed and forecasted products as “true” or “false.” Given a classifier, there were four possible outcomes: true positive, false positive, false negative and true negative. A 2 × 2 confusion matrix (a contingency table) was constructed.
to represent the disposition of the set of instances. Table 2 shows the confusion matrix, hit rate (HR) and false alarm rate (FAR), which are calculated using:

$$HR = \frac{H}{H + M}$$ (12)

$$FAR = \frac{F}{F + N}$$ (13)

where $H$, $M$, $F$ and $N$ are the numbers of true positives, false negatives, false positives and true negatives, respectively. The value of the HR and FAR produces the ROC curve, and the area under the ROC curve is the ROC score. A perfect forecast has an ROC score of 1, while 0.5 or less indicates negative skill. To evaluate the drought forecast performance with the ROC, the number of occurrences and non-occurrences of a drought event is used to calculate the HR and FAR (Bae et al., 2017; Seibert et al., 2017). However, non-occurrence drought events (no drought) can affect model verification, as they are generally more common than drought events. In our study, multi-class ROC analysis (Wandishin and Mullen, 2009) was applied to verify the agreement of drought forecasts with a drought state. The example of a multi-class confusion matrix is given in Figure 5.

4 | RESULTS

4.1 | Probabilistic drought forecasting with the BNDF_DP model

The newly developed probabilistic drought forecasting model, BNDF with drought propagation (BNDF_DP), is able to provide different types of probabilistic hydrological drought forecasting in accordance with the MME products (3 month and 6 month APCC MME). The probabilistic forecast results obtained from the BNDF_DP model are represented mainly by a Gaussian probability distribution that is described by the mean value and variance (i.e. uncertainty bounds). The monthly PHDI forecast results for Seoul station with various lead times are illustrated in Figure 6.

### Table 2

| Forecasted outcome | True | False |
|--------------------|------|-------|
| True               | True positive ($H$) | False positive ($F$) |
| False              | False negative ($M$) | True negative ($N$) |

### Figure 5

Multi-class receiver operating characteristic (ROC) confusion matrix

### Figure 6

Forecast results of 3 and 6 month ahead probabilistic Palmer Hydrological Drought Index forecast for Seoul station, October 2014. (a) Probabilistic drought forecasting results for 3 month lead time; (b) probabilistic drought forecasting results for 6 month lead time.
Different MME models were considered for different lead times of 3 and 6 months in Figures 6a,b, and the forecast was issued in October 2014. Figure 6a shows that the forecast PDF tends to shift toward the right side when the lead time increased, indicating that the drought will weaken. Similarly, Figure 6b demonstrates that the drought decreased as lead time increased. Long-term drought forecasting allows the changes in drought conditions to be better understood for developing a mitigation plan.

Figure 7 presents the boxplots for the 1 month lead time PHDI probabilistic forecasts. The boxplots illustrate the uncertainty of drought forecasts with the median and interquartile range (i.e. the 25th and 75th percentiles), while the red asterisks in Figure 7a indicate the observed PHDIs. As illustrated, all observations fell within the 50% credible interval. In addition, Figure 7b displays the drought occurrence probability represented by bar charts, which is defined by the cumulative probabilities of the forecasted PHDI that are less than or equal to −2.0. Compared with the observed drought states (represented by the coloured background bars), the drought occurrence probability represents a high value for a drought condition. In the context of water resources management, the predicted drought occurrence probability could be useful for rapid evaluation and the onset of a future drought event.

### 4.2 Forecast verification

The performance of PHDI forecasts for various lead times in terms of the selected skill scores (i.e. RPS, RPSS and ROC) was then explored. The RPS and RPSS were used to evaluate the probabilistic forecast performance for the 3 month and 6 month lead times. The RPSs of 3 and 6 month forecasts during January 2008 to December 2015 are shown in Tables 3 and 4, in which the RPS of drought forecasts was compared with the climatology for the representative stations (Seoul, Daejeon, Daegu and Gwangju) as well as the average of the 54 stations. The average RPSs over the 54 stations ranged from 1.069 to 1.361 and from 1.062 to 1.733 for the 3 month and 6 month MME forecasts, respectively. Here, the probabilistic climatology forecast was estimated using the historical PHDI from 1974 to 2008, as summarized in Tables 3 and 4. If the RPS was lower than the climatology RPS, the proposed model performed better than the reference forecast model. In our case, the RPS using the 3 month MME was substantially lower than that of the climatology RPS, the proposed model performed better than the reference forecast model. In our case, the RPS using the 3 month MME was substantially lower than that of the climatology, as shown in Table 4. The use of seasonal forecasts effectively increased performance that may not be obtained by

![Figure 7](image-url)
climatology. Specifically, a 10–50% increase in accuracy in terms of the RPS was reported with the use of MME forecasts, and model accuracy tended to increase with lead time.

For the 6 month MME forecasts, the BNDF_DP model results are summarized in Table 4, and the overall performance is better than the climatology in terms of RPS values. The RPSS values for different lead times for the BNDF_DP model over 54 stations are represented in Figures 8 and 9. In all stations, the RPSS of the BNDF_DP using 3 month MME forecasts was positive, as shown in Figure 8. The averaged RPSS using 6 month MME forecasts showed positive values under the 6 month lead time, and vice versa, as shown in Figure 9. The short verification period of the 6 month lead time MME induced a low forecast skill.

To assess the prediction performance of the BNDF_DP model using ROC analysis, our model was compared with the BNDF model, which is the Bayesian networks based drought forecasting model without consideration of the drought propagation relationship. Because the BNDF_DP and BNDF models produced probabilistic forecast results, the forecast mean value (50% of the forecast PDF) was applied to assess and compare forecast performance. The ROC score evaluated the forecast skill to distinguish between various drought states (no drought, mild drought, severe drought, extreme drought). Figure 10 illustrates the ROC curve for the BNDF_DP model as four different drought states and Table 5 presents the ROC score corresponding to Figure 10. In this figure, the markers denote the HR and FAR of each station in different drought classes, and the ROC curve is linked by each drought class. In Figures 10a,b, most of the ROC scores (the area under the ROC curve, x- and y-axes) are greater than 0.5, meaning that the forecast model provided reliable results. The ROC scores, based on the ROC curves for 1 to 3 month lead times, are supplied in Table 5. In the ROC analysis, the 3 month lead time MME model was used as it has short verification periods, i.e. 2 years. Comparing the ROC scores of the BNDF_DP with the BNDF

| Station | RPS for forecast lead time | RPS<sub>clim</sub> |
|---------|--------------------------|-------------------|
| Seoul   | 0.900 0.942 1.058 1.133 1.242 1.408 2.067 |
| Daejeon | 1.025 1.333 1.542 1.842 2.083 2.242 2.000 |
| Daegu   | 1.092 1.367 1.417 1.542 1.742 1.692 1.317 |
| Gwangju | 1.075 1.358 1.575 1.842 1.858 1.933 1.517 |
| Average of 54 stations | 1.062 1.260 1.423 1.542 1.635 1.733 1.737 |

FIGURE 8 Ranked probability skill score (RPSS) values during January 2008 to December 2015 using 3 month Asia-Pacific Economic Cooperation Climate Center Multi-Model Ensemble forecasts

FIGURE 9 Ranked probability skill score (RPSS) values during January 2014 to December 2015 using 6 month Asia-Pacific Economic Cooperation Climate Center Multi-Model Ensemble forecasts
model in Table 5, the 1 month lead time forecast shows that the BNDF model (except the extreme drought state) presented a high score. In the case of 2 and 3 month lead time forecasts, the BNDF_DP model discriminated well between no/severe/extreme drought occurrences and non-occurrences.

5 | CONCLUDING REMARKS

Reliable hydrological drought forecasting is important for effective water management, as hydrological drought affects society more than other types of drought. Hydrological drought forecasts show greater uncertainty than meteorological drought forecasting because of input and parameter uncertainties (AghaKouchak, 2014). A new probabilistic hydrological drought forecast model has been developed using drought propagation relationships and Bayesian networks. The Bayesian networks based forecasting model was easy to construct; its structure is based on a cause and effect relationship between variables, and the probabilistic presentation is advantageous to assess uncertainty specifically. The proposed Bayesian networks based drought forecasting with drought propagation (BNDF_DP) model is composed of four nodes of current data, the dynamic prediction model of Asia-Pacific Economic Cooperation Climate Center Multi-Model Ensemble forecasted information, the drought propagation relationship and forecast results.

To measure forecast performance, ranked probability score (RPS), ranked probability skill score (RPSS) and receiver operating characteristic (ROC) analyses were employed. The RPS and RPSS analyses showed that the BNDF_DP model had better forecasts than a climatological forecast model. The ROC was applied to measure the forecast performance of drought states according to the forecast lead time compared with the previous drought forecast models (BNDF model). The drought forecast performance showed that the BNDF_DP model performed better with a higher ROC score than models with a long lead time.

The developed hydrological drought forecasting model can provide reliable forecasts with uncertainty bounds. The probabilistic forecasting results can inform water managers responsible for drought mitigation and efficient response.

**FIGURE 10**  Receiver operating characteristic curves of four drought categories for 1 month drought forecasts: (a) Bayesian networks based drought forecasting with drought propagation (BNDF_DP) model; (b) BNDF model

**TABLE 5**  Receiver operating characteristic (ROC) scores for 1–3 month ahead Bayesian networks based drought forecasting with drought propagation (BNDF_DP) and Bayesian networks based drought forecasting (BNDF) of four drought categories

| Lead time | Forecast model | No drought | Mild drought | Severe drought | Extreme drought |
|-----------|----------------|------------|--------------|----------------|-----------------|
| 1 month   | BNDF_DP        | 0.947      | 0.910        | 0.941          | 0.980           |
|           | BNDF           | 0.949      | 0.919        | 0.946          | 0.977           |
| 2 month   | BNDF_DP        | 0.904      | 0.849        | 0.893          | 0.972           |
|           | BNDF           | 0.900      | 0.836        | 0.887          | 0.973           |
| 3 month   | BNDF_DP        | 0.860      | 0.783        | 0.891          | 0.964           |
|           | BNDF           | 0.854      | 0.747        | 0.863          | 0.966           |
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