Nat. Hazards Earth Syst. Sci. Discuss., https://doi.org/10.5194/nhess-2017-163
Manuscript under review for journal Nat. Hazards Earth Syst. Sci.
Discussion started: 19 June 2017

Natural Hazards and Earth System Sciences
Open Access
Discussions

The Probabilistic Drought Forecast Based on the Ensemble Technique Using the Korean Surface Water Supply Index

Suk Hwan Jang[1], Jae-Kyoung Lee[2], Ji Hwan Oh[3], Jun Won Jo[4], and Younghyun Cho[5]

1. Professor, Department of Civil Engineering, Daejin University, Pocheon-si, Gyeonggi-do, Korea, drjang@daejin.ac.kr
2. Assistant Professor, Innovation Center for Engineering Education, Daejin University, Pocheon-si, Gyeonggi-do, Korea, myroom1@daejin.ac.kr
3. Ph.D Candidate, Department of Civil Engineering, Daejin University, Pocheon-si, Gyeonggi-do, Korea, ojh4525@naver.com
4. Master course, Department of Civil Engineering, Daejin University, Pocheon-si, Gyeonggi-do, Korea, yhjowon@naver.com
5. Principal Researcher, Hydrometeorological Cooperation Center, Gwacheon-si, Gyeonggi-do, Korea, yhcho@kwater.or.kr

Corresponding Author: Jae-Kyoung Lee, Innovation Center for Engineering Education, Daejin University, Pocheon-si, Gyeonggi-do, Korea
E-mail : myroom1@daejin.ac.kr

Nat. Hazards Earth Syst. Sci. Discuss., https://doi.org/10.5194/nhess-2017-163
Manuscript under review for journal Nat. Hazards Earth Syst. Sci.
Discussion started: 19 June 2017

Abstract

This study proposes the new hydrological drought index, Korean Surface Water Supply Index (KSWSI), which overcomes some of the limitations in the calculation of previous SWSI applied in Korea and conducts the probabilistic drought forecasts using KSWSI. In this study, all hydrometeorological variables in the Geum River basin were investigated and appropriate variables were selected as KSWSI components for each sub-basin. And whereby only the normal distributions are applied to all drought components, probability distributions suitable for each KSWSI component were estimated. As a result of verifying KSWSIs, the accuracy of KSWSIs showed better drought phenomenon in drought events. The monthly probabilistic drought forecasts were also calculated based on ensemble technique using KSWSI. In 2006 and 2014 drought events, the accuracy of the drought forecasts using KSWSIs were higher than those using previous SWSI, demonstrating that KSWSI is able to enhance the accuracy of drought forecasts. The influence of expanding hydrometeorological components and selecting appropriate probability distributions for each KSWSI component were analyzed. It is confirmed that the accuracy of KSWSIs may be affected by the choice of hydrometerological components, the station data obtained, the length of used data for each station, and the probability distributions selected. Furthermore, the uncertainty quantification of the KSWSI calculation procedure was also carried out using the Maximum Entropy (ME) theory. The large MEs and standard deviations of KSWSIs in the flood season cause uncertainties, implying that the selection of the appropriate probability distributions for selected drought components in the flood season is very important.

Key words: Hydrological drought, Korean surface water supply index, Probabilistic drought forecast, Uncertainty quantification, Maximum entropy

Nat. Hazards Earth Syst. Sci. Discuss., https://doi.org/10.5194/nhess-2017-163
Manuscript under review for journal Nat. Hazards Earth Syst. Sci.
Discussion started: 19 June 2017

1. INTRODUCTION

From 2014 to 2015, a great deal of economic damage has occurred because of the shortage of agricultural water due to drought throughout the Korean Peninsula, especially in the northern part of Gyeonggi-do. Droughts have dramatic impacts on the socio-economic state and their occurrence is becoming more frequent. Drought management is difficult not only because of the seasonal characteristics (which means that more than 60% of the annual average rainfalls occur in the summer season), but also because of the dry flood season caused by global warming. The water shortage stresses the small agricultural and municipal water reservoirs, making it difficult to manage water resources plans and policies (Choi, 2002). In order to effectively mitigate these droughts, continual improvement of drought indexes should be prioritized; because the drought occurs due to various conditions and circumstances, it is difficult to reflect all of these in the drought index. The various drought indices used in Korea have some problems as follows: determining the hydrological meteorological factors to be utilized, determining whether the improved or developed drought index can be extended in all regions, and determining how to set thresholds to distinguish among the stages of the drought index. These considerations make it difficult to accurately monitor and forecast actual droughts.

In hydrological drought, the effects of hydrological variables on drought such as streamflow, soil water, and groundwater are physically delayed compared to meteorological variables such as precipitation and evapotranspiration, so that these characteristics can be reflected in the hydrological drought index. Recently, various hydrological drought indices have been developed and improved. Shukla and Wood (2008) developed the Standardized Runoff Index (SRI) using hydrological variables and contrast results of a SRI with that of a Standardized Precipitation Index (SPI) during drought events in a snowmelt region. Karamouz et al. (2009) developed an integrated index, the Hybrid Drought Index (HDI), which was combined with the well-known SPI, Water Surface Supply Index (SWSI), and Palmer Drought Severity Index (PDSI) and applied to the Gavkhooni/Zayandeh-rud basin in the central part of Iran. Karamouz et al. concluded that the results of the HDI show its significant value for drought prediction. Dogan et al. (2012) compared and analyzed six different drought indices for intensity and duration of drought in Kenya, and concluded that the Effective Drought Index (EDI) was consistent with other drought indices for various time-steps and was preferable for monitoring long-term droughts in arid/semi-arid regions. Ahn and Kim (2010) developed the Water Ability Index (WAI) based on the amount of water available in a basin, which could replace the SWSI as a hydrological drought index in Korea. Park et al. (2011) then proposed the Water Availability Drought Index (WADI) to improve the shortcomings of previous domestic hydrological indices which did not reflect water supply and water intake or reservoir and dam facilities.

Drought forecast should also be performed in preparing for drought and creating proactive drought policies and preparedness plans. White et al. (2004) utilized the optimized Canonical Correlation Analysis (CCA) to forecast principal components of summer precipitation anomalies to predict the duration of drought over eastern and central Australia. Belayneh and Admowski (2013) proposed the use of three machine learning techniques, Artificial Neural Network (ANN), Support Vector Regression (SVR), and coupled WAvelet-ANNs (WA-ANN), to forecast short-term drought for short lead times with SPI in the Awaash river basin of Ethiopia. The results revealed that the WA-ANN model was the most accurate for forecasting SPI3 and SPI6 values over lead times of one and three months. Son and Bae (2015) reviewed the availability of the Ensemble Streamflow Prediction (ESP) technique for hydrological drought forecasting and showed that it is effective for a 1-2 months outlook in Korea. However, studies of domestic drought forecast are only at the beginning stage, and projected meteorological data is necessary for drought forecast. However, it is difficult to utilize the data due to the uncertainty of the future projected meteorological data and the limitation of data acquisition and connection.

Therefore, this study proposes the new and improved hydrological drought index and conducts the methodology to forecast droughts in future for the Korean Peninsula as follows: Firstly, in this study, the limitations of the existing hydrological drought index are analyzed, improvements are made, and a new drought index is applied called the Korean Water Surface Supply Index (KSWSI). Secondly, the probabilistic monthly drought forecasts are estimated using the KSWSI based on the

Nat. Hazards Earth Syst. Sci. Discuss., https://doi.org/10.5194/nhess-2017-163
Manuscript under review for journal Nat. Hazards Earth Syst. Sci.
Discussion started: 19 June 2017

Natural Hazards and Earth System Sciences
Discussions

ensemble technique. Lastly, the effect of the selection of drought components and their probability distributions is analyzed and a method is proposed to quantify their uncertainties.

2. Methodology

2.1 Study basin

This section describes the Geum River basin as the applicable area for improving the drought index and verifying the drought forecast (Fig. 1). The Geum River basin flows north-westerly to about its mid-point, then generally south-westerly for 401km. It consists of 21 sub-basins, and drains into an area of 9,810km^2. The Geum River basin has two multi-purpose dams, Daecheong Dam and Yongdam Dam. Daecheong Dam provides municipal and industrial water supply to Daejeon and Chungju, and Yongdam Dam (which is only one-fifth the size of the Daecheong Dam drainage area) supplies water to Jeonju. Analyzing the river flow in the Geum River basin is relatively simple because it has fewer dams and a simpler river system than other basins. The region of the Geum River basin has been affected by considerable drought since 2000 year and has been widely used in previous drought studies in Korea.

[Fig. 1. Study basin: 14 sub-basins in Geum River basin]

2.2 Improvement of hydrological drought index: Surface Water Supply Index (SWSI)

The Surface Water Supply Index (SWSI) (Shafer and Dezman, 1982) was selected as the well-known hydrological drought index. SWSI is advantageous as it can flexibly utilize various hydrometeorological components depending on the study basin. SWSI is based on probability distributions of monthly time series of individual component indices and is calculated using four hydrometeorological components: snowpack, precipitation, streamflow, and reservoir storage. It is also an appropriate drought indicator in snow-dominated regions. The drought classification of SWSI is divided into seven categories (extremely dry (-4.2 to -3.0; 7th category), moderately dry (-2.9 to -2.0;

6th category), slightly dry (-1.9 to -1.0; 5th category), near average (-0.9 to 1.0; 4th category), slightly wet (1.1 to 2.0; 3rd category), moderately wet (2.1 to 3.0; 2nd category), and extremely wet (3.1 to 4.2; 1st category)) and is similar to the typical categories of the Palmer Drought Severity Index (PDSI). The mathematical formulation of SWSI is given by:

$$\mathrm{SWSI_t} = \frac{w_1 P_t^{snow} + w_2 P_t^{prec} + w_3 P_t^{strm} + w_4 P_t^{resv} - 50}{12} \quad (1)$$

where w_1, w_2, w_3, and w_4 are the weights for each hydro-meteorological component and $w_1 + w_2 + w_3 + w_4 = 1$, and where t represents the monthly time-step. P_t^i is the non-exceedance probability (in percentage) for component i where the superscripts of *snow*, *prec*, *strm*, and *resv* represent the snowpack, precipitation, streamflow, and reservoir storage in time t, respectively. In calculating the SWSI, depending on regions, a snowpack component is applied from December to the subsequent May, and a streamflow component is applied during the remaining periods. Kwon et al. (2006) and Kwon and Kim (2006) then developed a Modified SWSI (called MSWSI) by improving SWSI for the Korean Peninsula. In MSWSI, the snowpack parameter is replaced by groundwater because the portion of underground water is more important to snowpack in the water resources management in Korea:

$$\mathrm{MSWSI_t} = \frac{w_1 P_t^{gw} + w_2 P_t^{prec} + w_3 P_t^{strm} + w_4 P_t^{resv} - 50}{12} \quad (2)$$

where *gw* represents the groundwater component. The process of MSWSI calculation is as follows:

Step 1: Analysis of available hydrometeorological components by basins

Step 2: Selection of available hydrometeorological components and collection of observed data

Step 3: Calculation of weights for each hydrometeorological component

Nat. Hazards Earth Syst. Sci. Discuss., https://doi.org/10.5194/nhess-2017-163
Manuscript under review for journal Nat. Hazards Earth Syst. Sci.
Discussion started: 19 June 2017

Step 4: Estimation of probability distributions for each hydrometeorological component

Step 5: Calculation of MSWSI values using Eq. (2)

However, this process of MSWSI calculation has several limitations. Firstly, only four hydrometeorological components are used in the previous MSWSI calculation in Steps 1 & 2 and the MSWSI is not able to reflect more various components. Different hydrometeorological components actually impact drought events depending on data length, the urban area, and upstream & downstream areas of dams; therefore, the available components should be widely investigated. Secondly, in Step 4, probability distributions of all components were fitted to the only normal distribution in the MSWSI calculation process. Estimating the appropriate probability distribution for each component yields accurate non-exceedance probability values, which can be used to estimate the near actual drought index.

Therefore, in this study, an improved MSWSI was developed, called the Korean SWSI (KSWSI), with two improvements. The first improvement involves investigating all available hydrometeorological components and selecting the appropriate components for each sub-basin. The second improvement involves estimating and applying a suitable probability distribution for each selected hydrometeorological component. The detailed improvements are as described in the following section and Fig. 2 shows the process of the MSWSI calculation and its improvements.

Investigation and selection of available hydrometeorological components

In this section, all hydrometeorological data from each sub-basin in the Geum River basin were investigated and classified into 9 types: precipitation data, water level data in dam, meteorological data, national streamflow data, local streamflow levels 1 & 2 data, multi-regional water supply, local water supply, and groundwater (Table 1(a)). The precipitation data, water level data, water discharge data, streamflow data, dam data (included in inflow, release, and storage data), and groundwater data were selected as practical hydrometeorological components on the basis of ease of data acquisition, data quality control, and data length. These data were then collected from each observation station

(Table 1(b)). Table 2 shows the final hydrometeorological components selected for each sub-basin. The values of the previous MSWSI are calculated using precipitation data obtained from six stations, streamflow data obtained from 10 stations, groundwater data obtained from 3 stations, and dam inflow data for calculating the values of KSWSIs in this study. However, the types of data were extended to include (areal-averaged) precipitation data from 42 stations, streamflow data from 28 stations, groundwater data from 7 stations, and dam data included in inflow, release, and storage data. The sub-basins were also classified into upstream of dam, downstream of dam, streamflow, groundwater, precipitation, and water supply-dominant basin depending on the most influential hydrometeorological component that has the largest weight for each sub-basin. Doesken et al. (1991) proposed a method that can reflect the relative contribution of hydrometeorological components to estimate the weights (w_1, w_2, w_3, and w_4). The initial weights of each month for each component were calculated as monthly values divided by the annual total of the component. The calculated monthly values of selected components of KSWSI were summed for each month. Then, the twelve monthly sums, calculated using this procedure, were divided by their total sum to find the sum of the final weights as 1. As shown in Fig. 3, sub-basins adjacent to the upstream and downstream of dams were affected by components related to dam data and streamflow and precipitation components had an important impact in other sub-basins. Especially, the effects of streamflow and precipitation components are varied slightly month by month, with the effect of the precipitation component being greater in the flood season.

Improvement of probability distribution estimation for each hydrometeorological component

In this section, the probability distributions (Generalized Extreme Value (GEV), Gumbel, normal, 2-parameter log-normal, log-normal, and 3-parameter log-normal distribution) applicable to each hydrometeorological component and parameter estimation methods (e.g. maximum likelihood method, probability weighted moment method, and method of moment) are applied and then log-likelihood test is also used for the goodness of fit test. Table 3 shows final selected probability distributions for each hydrometeorological component and sub-basin.

[Fig. 2. Procedure of KSWSI calculation and two improvements proposed by this study]

[Table 1. Basic investigation of hydrometerological components at each sub-basin]

[Table 2. Selected hydrometerological components and stations at each sub-basin]

[Fig. 3. Example of weights of each hydrometeorological variable for each month at sub-basin 3001 and 3007]

[Table 3. Selected suitable probability distributions to hydrometerological components at each sub-basin]

2.3 Application results of KSWSI

In this study, 2001, 2006, and 2014-year events were used, when the severe drought occurred nationally. In the 2001 event, the average rainfall amounts were as high as 377mm from March to May, which was 20%~30% of the annual rainfall amounts in some regions in Korea. The rainfall amounts from August to October was only 30% of the annual rainfall amounts in the south part of the Korean Peninsula in 2006 and the national reservoir storage ratio was 67% on average (NEMA, 2009). In 2014, a severe drought occurred in northern Korea, where average rainfall amounts were 50%~61% compared to the normal-year, where the normal-year is the mean of the last 30-year average rainfall (KMA, 2014).

Fig. 4 shows the results of the MSWSI and KSWSI for April in 2001, 2006, and 2014 in Geum River basin. In 2001, both MSWSI and KSWSI generally showed a similar drought trend; while the MSWSI in the Daecheong Dam had moderate and extreme droughts, the KSWSIs showed near normal and slight droughts. In 2006 and 2014, the KSWSIs showed stronger drought intensities in some sub-basins than the MSWSIs; especially, KSWSIs indicated that droughts in the western sub-basins were more severe.

Comparison of MSWSIs and KSWSIs in sub-basin 3001

Fig. 5(a) shows the time series for the MSWSIs and the KSWSIs in sub-basin 3001 for the 2014 event. In the MSWSI, slightly severe or severe droughts were simulated to occur continuously; however, KSWSIs were overall above the near normal droughts. Fig. 5(b) shows the time-series of non-dimensional ratios to the normal droughts during in the 2013-2014 years for each hydrometeorological component such as precipitation, streamflow, and dam inflow. In block A of Fig. 5(a), the ratios of precipitation and dam inflows were lower than the normal-year in January-February 2014, but inflows and streamflow were abundant due to the increased precipitation (up to 164%) compared to the normal-year from September to December 2013. As these effects continued until early 2014, it is more reasonable to assume that hydrological drought did not occur in sub-basin 3001. In the flood season, the amount of precipitation and dam inflow were lower than the normal-year, but water shortage did not occur due to the abundant precipitations from March to April. In block B of Fig. 5(a), MSWSI showed sub-basin 3001 under drought conditions, but the dam inflow and streamflow increased due to the significantly higher precipitation than normal-year, and KSWSIs showed that sub-basin 3001 was more moderately wet.

Comparison of MSWSIs and KSWSIs in sub-basin 3014

Fig. 5(c) shows the time series for the MSWSIs and the KSWSIs in sub-basin 3014 for the 2001 event. The MSWSIs were somewhat varied; however, most of them were above the normal drought level and no dry condition occurred, except in July and August. On the other hand, in the KSWSIs, most of the droughts occurred in 2001, and severe drought occurred in early 2001. Fig. 5(d) shows the time-series of the non-dimensional ratios to the normal-year during the 2001-2002 years for each hydrometeorological component such as precipitation, streamflow, and dam inflow. During the block period shown in Fig. 5(c), the amount of precipitation and streamflow, which were only 40%~60% of the normal-year, contributed to the water storage, resulting in severe drought (Fig. 5(d)). Therefore, it is more reasonable to conclude that hydrological drought occurred in sub-basin 3014.

Nat. Hazards Earth Syst. Sci. Discuss., https://doi.org/10.5194/nhess-2017-163
Manuscript under review for journal Nat. Hazards Earth Syst. Sci.
Discussion started: 19 June 2017

Natural Hazards and Earth System Sciences
Discussions

As shown in the previous examples, compared to the MSWSIs, the KSWSIs calculated more accurate drought results in the Geum River basin. Therefore, it is confirmed that the KSWSI is more appropriate in hydrological drought monitoring and forecasting.

[Fig. 4. Comparison of the MSWSI and KSWSI results in April 2001, 2006, and 2014 years]

[Fig. 5. Verification of KSWSI results in sub-basin 3001 and 3014]

3. Probabilistic Drought Forecasts with the KSWSI

3.1 Monthly drought forecasts based on ensemble technique

Application outline

This study considered 16 historical scenarios (1990~2005) and 24 historical scenarios (1990~2013) with variables of hydrometeorological components for monthly drought forecast for 2006 and 2014, respectively. For drought forecasting to January 2006, for example, 16 historical scenarios (1990~2000) of precipitation and temperature were inputted into hydrological models to generate streamflows and groundwater level ensembles. For each forecasting period, the hydrological model was executed with the hydrometeorological variables for the preceding 12 months to determine the initial conditions. The historical data of each hydrometeorological component were then fitted to their proper probability distribution to make the variable dimensionless. These ensembles finally served as inputs in the calculation of the values of KSWSI with their weights. Fig. 6 shows the procedure of monthly probabilistic drought forecasts.

[Fig. 6. Example of the procedure of the monthly probabilistic drought forecast]

Calibration of the hydrological model: abcd water balance model

In this study, the *abcd* water balance model was used, which has parameters of *a*, *b*, *c*, and *d* to determine the streamflow and groundwater. The parameters of the *abcd* model are estimated with a regional regression for ungauged basins because streamflow is gauged only at Yongdam and Daecheng Dam. The regional regression equation was then formulated using the relationship between each of the calibrated parameters and the site specific basin characteristics such as basin length, drainage area, basin annual average precipitation, basin annual average potential evapotranspiration, basin average land height, basin average land slope, basin drainage density, basin average temperature, basin monthly maximum precipitation, basin monthly maximum potential evapotranspiration, drainage relief, soil type, and basin total stream length. The calibrated parameters, *a*, *b*, *c*, and *d* of the *abcd* model were obtained using gauged stations in nine multipurpose dams in Korea. Table 4 shows the regional regression equations over all of Korea as a result of a step-wise regression technique. Using these equations with basin characteristics of an ungauged basin, *a*, *b*, *c*, and *d* can be computed and consequently the streamflow of the basin can be computed from the calibrated *abcd* model.

[Table 4 Regression equations for the *a*, *b*, *c*, and *d* parameters]

To verify the estimated parameters of the *abcd* model using the regional regression equations, the *abcd* model was applied to generate the monthly inflows at Yongdam Dam from 2002 to 2004 (period #1) and from 2010 to 2013 (period #2). The calculated values of the R-Bias, R-RMSE, and R^2 during period #1 were -0.06, 35, and 0.92, respectively, and those during period #2 were 0.11, 0.55, and 0.91, respectively, suggesting that the model parameters are accurately estimated.

3.2 Results of monthly drought forecasts

Fig. 7 showed the forecast results of monthly drought using MSWSI and KSWSI equations in April and December of 2006 and 2014, respectively. Drought-intensities in the drought forecasts using the KSWSIs were stronger than in the MSWSI, and the drought occurred widely throughout the Geum River basin. While the MSWSI-based drought forecasts for April 2006 and 2014 predicted slight and moderate drought in some sub-basins of downstream and near Yongdam Dam, the results of the KSWSI forecasted severe and moderate droughts in most sub-basins of the Geum River basin. Then, in December 2006 and 2014, drought forecasts of MSWSIs were similar to those of KSWSIs; especially, in December 2014, drought forecasts by KSWSIs showed severe droughts in some sub-basins of downstream and near Yongdam Dam. Table 5 shows the occurrence probabilities of droughts for each sub-basin by drought forecast using MSWSIs and KSWSI for April and December 2014. From the drought forecasts using KSWSI, the probabilities of severe droughts in both April and December 2014 were over 70%, showing droughts were highly likely to occur.

In this study, the accuracy of the probabilistic forecast was measured using the Average Hit Score (AHS) and Half Brier Score (HBS) (Wilks, 1995). The AHS scored the probabilities of occurrences of drought forecasts for the drought category by the actual drought, and the ensemble drought forecasts can be considered to be effective if their AHS is higher than the AHS of the naive forecasts. The concept of HBS is similar to the mean square error and is a way to give a high score when ensemble drought forecasts match the actual drought, but gives a penalty for wrong categories. The drought forecast becomes increasingly more accurate as the HBS becomes smaller than the naive forecast. The equations of AHS and HBS are as follows:

$$\text{AHS}=\frac{1}{N}\sum_{i=1}^{N} f_i^{o} \tag{3}$$

$$\text{HBS}=\frac{1}{N}\sum_{j=1}^{J}\sum_{i=1}^{N}(f_{i,j}-o_{i,j})^2 \tag{4}$$

where f^{o} is the probability of drought forecast for the category of actual drought, N is the number of drought forecasts, J is the number of drought categories, $f_{i,j}$ is the probability of the ith forecast in the jth category, and $o_{i,j}$ is the actual drought in the jth category. The category of actual drought score is 1 at the ith drought forecast and the scores of the remaining categories are zero.

The drought forecasts were compared to the corresponding observed event for a verification period of 12 months in 2006 and 2014. As shown in Table 6(a), the AHS of the 2006 and 2014 events are 0.201 and 0.200, respectively, which are higher than that of the naive forecast (=0.174). Especially, the AHSs of drought forecasts using KSWSI are 0.249 and 0.325 for 2006 and 2014, respectively, which is more accurate than the drought forecast using MSWSI. The overall accuracy of the drought forecasts was better in the dry season (October to the following May) than in the flood season (from July to September), and the accuracy of drought forecasts using KSWSIs was improved from 0.219 to 0.397 by AHS. As shown in Table 6(b), while the accuracy of drought forecasts using the MSWSI is 0.848 in 2006, which is smaller than that of the naive forecast (=0.857) for 2006 and 2014, the accuracy of MSWSI in 2014 (=0.865) was low. The accuracy of drought forecasts using KSWSI was confirmed to be superior to that of the MSWSI because the HBS of K-SWSIs is 0.824 and 0.795 in 2006 and 2014, respectively. The occurrence ranges of actual forecasts and drought forecasts of MSWSI and KSWSI were compared. Fig. 8(a) and 8(b) show the actual droughts (black dots) and occurrence ranges of drought forecast ensembles (between the first and third quartiles of the box-plot) from January to December 2014 for sub-basin 3001. The actual droughts exist in the range of the drought forecast ensembles, implying that the drought forecasts consider the extent of the actual drought and as the range of drought forecast ensembles narrows, including the occurrence of actual drought, the accuracy of drought forecasts increases. While the ranges of drought forecasts using MSWSI include most actual droughts in Fig. 8(a), the actual droughts are outside of the range of drought forecasts of KSWSI in Fig. 8(b). As shown in Figs. 8(c) and 8(d) in sub-basin 3007, the drought forecasts with MSWSI are effective because most categories of drought forecast ensembles (red dashed boxes) include actual droughts. Especially, in Fig. 8(d), the box-plot is very small in the drought forecasts, implying that the values of the KSWSI drought forecast ensemble are very concentrated in the category of ‘severely dry’ and the actual drought also occurs in the same category, so that the accuracy of the drought forecasts with KSWSI is very high. Fig. 8(e) and 8(f) show a similar tendency to that of sub-basin 3007, confirming the high accuracy of the drought forecast using the KSWSI.

[Fig. 7. Comparison of the drought forecasts using the MSWSI and KSWSI on April and December in

2006 and 2014]

[Table 5. Comparison of the most probable drought categories and their probabilities for each sub-basin in April and December on 2014 year]

[Table 6. Accuracy of the MSWSI and KSWSI results]

[Fig. 8. Comparison of the drought forecasts ranges for each month at sub-basin 3001, 3007, and 3014 in 2014 year]

4. Uncertainty Analysis of the Calculation Procedure for the KSWSI

In steps 1, 2, and 4 in the KSWSI calculation process described in Section 2.2, the researcher's experience and subjective judgment are involved. For example, the researcher selects the hydrometeorological variables as drought components and fits the probability distributions to the selected drought components. This means that the final results using the KSWSI can differ according to the researcher's subjective judgment; this likely results in uncertainty about the drought monitoring and forecasts. The subjective judgments of the researchers for each stage of the KSWSI calculation are as follows.

- Step 1&2: Analysis and selection of available hydrometeorological components for each basin
  (a) selection of available hydrometeorological components
  (b) data quality verification of selected hydrometeorological components
  (c) selection of observation stations to acquire hydrometeorological data as drought components
- Step 4: Estimation of probability distributions for each hydrometeorological component
  (a) estimation of probability distributions for each drought component
  (b) selection of proper probability distributions for each drought component

Therefore, in this section, the influence of researcher's subjective judgment on the KSWSI calculation and its corresponding uncertainty are analyzed.

4.1 Analysis of the influence of expanding hydrometeorological components as KSWSI components

As mentioned above, in this study, the precipitation data, water level data, discharge data, streamflow data, dam data (included in inflow, release, and storage data), and groundwater data were selected as hydrometeorological components that can be practically applied as KSWSI drought components. Table 7 shows that, for the MSWSI, observed data in only one station was used for each drought component (K-water, 2005); however, averaged data were used from several stations in the KSWSI calculation. Especially, in the case of precipitation, areal-averaged data using the Thiessen method was used rather than point data. Secondly, only the data of Daecheong Dam was reflected in MSWSI, because the data length of Yongdam Dam was insufficient at the time of the MSWSI study. This study used the observation data of dams as follows: (1) for applying dam data, the sub-basins in Geum River basin were divided into those that were affected by Yongdam Dam and those affected by Daecheong Dam; (2) sub-basins around dams were also divided into upstream and downstream sub-basins, and the observation data of dam inflow and storage in the upstream and dam release in downstream were then applied to the KSWSI calculation, respectively. Finally, the MSWSI calculation only reflected four drought components, but the K-SWSI reflected a maximum of six drought components and the number of observation stations used to obtain meteorological data in all drought components was increased.

In order to investigate the influence of the selection of hydrometeorological components, the KSWSIs for 2001 and 2006 drought events were calculated using the drought components selected in Table 2. Similar to the MSWSI studies (K-water, 2005), the probability distributions of all drought components were assumed to be normal distributions. In Table 8, the results of both MSWSI and KSWSI showed drought as a whole in all of the sub-basins. Especially, the same values of MSWSIs were calculated from the same drought components from sub-basin 3001 to 3004, but KSWSIs show

Nat. Hazards Earth Syst. Sci. Discuss., https://doi.org/10.5194/nhess-2017-163
Manuscript under review for journal Nat. Hazards Earth Syst. Sci.
Discussion started: 19 June 2017

slightly different drought indices. In the 2006 drought event, MSWSI indicated that the water resources of the entire Geum River system were very low, resulting in drought. However, the opposite results were recorded for the KSWSI, where drought was avoided due to the abundant water resources.

Comparison of MSWSIs and KSWSIs in sub-basin 3001

Fig. 9(a) shows the time series for the MSWSIs and the KSWSIs in sub-basin 3001 for the 2006 drought event. In both the MSWSIs and KSWSIs, drought occurred in the beginning of 2006, but the drought was somewhat resolved as the flood season passed. However, the drought-intensity calculated by KSWSIs is stronger than that by MSWSI. Fig. 9(b) shows the time-series of non-dimensional ratios to the normal-year for the 2005-2006 years for each hydrometeorological component of precipitation, streamflow, and dam inflow. In block A1 of Fig. 9(b) (same as block A of Fig. 9(a)), the amount of precipitation and dam inflows were lower than the normal-year from January to April 2005, and the streamflow was almost the same as normal-year. In block B1 of Fig. 9(b) (same as block B of Fig. 9(a)), in July 2006, the dam inflow and streamflow both increased due to very large precipitation compared to the normal-year, and since August, the dam inflow also decreased because precipitation was very low. For the observed hydrometeorological data for March, June, and August 2006, while the amount of streamflow is maintained, it is more reasonable that hydrological droughts occurred because of the low precipitation and dam inflow.

Comparison of MSWSIs and KSWSIs in sub-basin 3010

Fig. 9(c) shows the time series for the MSWSIs and the KSWSIs in sub-basin 3010 for the 2006 drought event. While the results of MSWSIs show no drought in early 2006 but severe droughts in the flood season, KSWSIs was below the category of ‘near normal’, except for July, and indicated that water shortage occurred for the entire period. In block C1 of Fig. 9(d) (same as block C of Fig. 9(c)), MSWSIs indicated that water resources were abundant, but some water shortages did actually occur, and the accuracy of the KSWSI results is considered to be superior to that of MSWSI because precipitation is very influential in this season. In block D1 of Fig. 9(d) (same as block D of Fig. 9(c)), in July 2006, a large amount of precipitation occurred compared to the normal-year, so the amount of both dam release and streamflow was increased and the water shortage was then resolved. After August, the amounts of both dam release and streamflow decreased. The MSWSIs showed severe drought in July when the amount of precipitation, streamflow, and dam release were larger than normal-year, but the KSWSI results indicated that the drought was resolved. In 2006, the streamflow and dam release were smaller than normal-year and their variation was not significant. Reflecting the water resources, KSWSIs showed that droughts were resolved due to the occurrence of precipitation, but water shortages had generally occurred.

As shown in the previous results, the results of KSWSIs may affect whether or not the actual droughts are accurately simulated by the KSWSI calculation depending on the hydrometerological components used as the drought components, which station data are obtained, and the length of used data for each station, respectively.

[Table 7. Comparison of hydrometeorological components in each sub-basin between the MSWSI and this KSWSI studies]

[Table 8. Comparison of MSWSI and KSWSI results in July in each sub-basin]

[Fig. 9. Verification of previous results and these MSWSI results in sub-basins 3001 and 3010: (a) & (b) at 3001 and (c) & (d) at 3010]

4.2 Analysis of the influence of the selection of probability distributions for each KSWSI component

In Section 2.2, the precipitation component was fitted to the Gumbel and GEV distributions, the normal and Gumbel distributions for streamflow, 2-parameter log-normal and Gumbel distributions for dam data (inflow, release, and storage), and the 3-parameter log-normal distribution for groundwater. Since the drought components which are applied for each sub-basin differ and several probability distributions can be applied in the even same sub-basin, the KSWSI results can differ depending on the probability distributions selected. In this study, we determined how the results could be changed by calculating KSWSIs by applying all the probability distributions (including the normal distribution) that are shown to be appropriate. Table 9 shows the probability distributions applied to each drought component. In the application process, the maximum number of scenarios for probability distributions applicable to the sub-basins is 36 (= 3 probability distributions for precipitation × 2 for river flow × 3 for dam data × 2 for groundwater), and the ranges of KSWSIs are indicated using the maximum and minimum values among these combinations (Fig. 10).

In Fig. 10(a), the maximum and minimum values of KSWSIs showed a similar tendency in the 2006 drought event, but the KSWSI ranges were separated by two to three categories. The time-series of the maximum values of KSWSIs was located above the category 'near normal', which means droughts did not occur, but the minimum values of KSWSIs showed droughts due to water shortage except for July. The KSWSIs using only normal distribution are similar to the averages of the maximum and minimum KSWSIs. In the 2014 drought event shown Fig. 10(b), the maximum values of KSWSIs are also above the category 'near normal', which means the water resources are abundant in 2014; however, the minimum KSWSIs shows continuous severe drought, similar to the results of KSWSIs using only the normal distribution. The difference between the maximum and minimum values of KSWSIs was significant (maximum five categories). In sub-basin 3008 shown Fig. 10(c), the time-series of the maximum and minimum KSWSIs showed similar trends in the 2006 drought event, and the ranges of the maximum and maximum KSWSIs differed by one to two categories. Furthermore, most of the maximum KSWSIs did not show water shortages, and the minimum KSWSIs showed droughts in March, August, and September. In Fig. 10(d) for the 2014 drought event, while the maximum KSWSIs were almost similar to the minimums of them from January to May, the maximum and minimum KSWSIs showed large differences in the flood season.

The scenario ranges of KSWSI generally varied according to the selection of probability distributions, and their results of droughts significantly differed depending on the probability distributions selected for each drought component. Therefore, it was confirmed that the selection of the probability distributions could affect the accuracy of results of the KSWSI calculation.

[Table 9. Available probability distributions to each hydrometerological component at each sub-basin]

[Fig. 10. Comparison of MSWSI time series of max, min, and normal at sub-basin 3001 and 2008 in 2006 and 2014: (a) & (b) at 3001 & 3008, respectively, in 2006 and (c) & (d) at 3001 & 3008, respectively, in 2014]

4.3 Quantification of Uncertainty in the KSWSI calculation procedure

Methodology: Maximum entropy principle

Shannon (1948) first introduced the use of entropy as a method to estimate uncertainty quantitatively if the information context is obtained from probability distributions of a given set of information. If probabilities of occurrences of a certain set of information are large, the amount of information is small, and if their probabilities are small, the amount of information becomes large. If X is defined as a random variable with probability p, and $I(X)$ is the information context of X, entropy $H(X)$ is given as follows:

$$H(X) = -\sum p_X(x) \ln p_X(x) = \sum p_X(x) I(X) = E[I(X)] \tag{5}$$

Maximum Entropy (ME) based on Shannon's entropy theory (1948) was proposed by Jaynes (1957). When a certain set of information is given, based on the information, maximum entropy theory provides the probability density function which maximizes the entropy. If a given set of information is the minimum value a and maximum value b, the distribution maximizing the entropy is a uniform distribution on [a, b], and the corresponding entropy $H(X)$ (i.e. maximum entropy) is given as (Gay and Estrada, 2010):

$$H(X) = -\int_a^b f_X(x) \ln f_X(x) dx = -\int_a^b \frac{1}{b-a} \ln \frac{1}{b-a} dx = -\ln(b-a) \tag{6}$$

Uncertainty quantification of KSWSIs

In this section, KSWSIs calculated by selected drought components and their probability distributions in Section 4.2 are inputted into the formula (Eq. (6)) of ME to estimate and analyze uncertainties of KSWSIs. The results are shown in Table 10 and Fig. 11. Of the ME values for each sub-basin in Table 10(a), the ME value (=1.002) in sub-basin 3001 is the largest and the minimum ME is 0.521 in sub-basin 3006 in the 2001 drought event. In 2006 and 2014, sub-basins 3002 and 3001 have the largest values of MEs of 1.120 and 1.503, respectively, and the smallest MEs of 0.578 and 0.578, respectively, in sub-basin 3012. Especially, even though the ME values of each sub-basin slightly differ, MEs showed a similar tendency in the same sub-basin despite different drought events. This tendency is more evident in the comparison of the number of ME values for each drought event, drought component, and number of selected drought components for each sub-basin. In other words, the ME values of the sub-basins with many drought components are large, and sub-basins with few drought components, have relatively small ME values. The different drought components for each sub-basin include the data of dam inflow, dam release, groundwater, and data of precipitation and streamflow components, and were used in all sub-basins. Because the data of different observation stations was used for each sub-basin, it could not be determined whether the difference of ME values for each sub-basin was more influenced by dam and groundwater components than by precipitation and streamflow. From the above results, it can be deduced that the increased number of drought components does not necessarily improve the accuracy of the KSWSIs calculation to the actual droughts. In other words, the large values of MEs imply that the results of KSWS have large uncertainty. Therefore, only drought components that can represent the hydrometeorological characteristic of each sub-basin should be selected and applied.

In the monthly MEs for each drought event in Table 10(b), the ME values (1.215 and 1.379) in July are the largest and the minimum ME at 0.562 and 0.650 in January in the 2001 and 2006 drought events, respectively. In 2014, the seasonal ME value was the highest at 1.053 in the flood season. Furthermore, in all drought events, although the values of MEs decreased in the dry season, they increased in the flood season as shown in Fig 11(b). To determine the reasons for this result, the standard deviations of KSWSI according to the selected probability distributions in Section 2.3 are also shown in Fig. 11(b). The trend of standard deviations of KSWSI was similar to the monthly MEs for each drought event, which decreased in the dry season and increased in the flood season. The large standard deviations of KSWSIs mean that the variation of calculated KSWSIs depending on the selection of probability distributions is large, which affects the uncertainty of the KSWSI results. In other words, the large MEs and standard deviations of KSWSIs in the flood season cause uncertainties, which mean that the selection of the appropriate probability distributions for selected drought components in the flood season is very important.

[Table 10. Maximum entropy results for each sub-basin and month in each drought event]

[Fig. 4. Comparison of maximum entropy results between sub-basins and months for each drought event]

5. Conclusion

In this study, the new hydrological drought index, KSWSI, was proposed, which overcomes some of the limitations in the calculation of MSWSI applied in Korea. The probabilistic drought forecasts based on ensemble technique were also conducted using KSWSI. The summary of the study is as follows. Firstly, all hydrometeorological variables in the Geum River basin were investigated and then classified into nine types. Based on these results, appropriate variables were selected as drought components for each sub-basin. It was confirmed that the effect of precipitation component is greater in the flood season. Secondly, to overcome the limitation of MSWSI, whereby only the normal distributions are applied to all drought components, probability distributions suitable for each hydrometeorological component were estimated. As a result of verifying the accuracy of KSWSIs using historical observed meteorological data, the results of KSWSIs showed better drought phenomenon in drought events. Thirdly, in this study, the monthly probabilistic drought forecasts were calculated based on ensemble technique using KSWSI. The drought forecasts of both MSWSIs and KSWSIs were more accurate than the naïve forecasts. In addition, in 2006 and 2014, both AHS and HBS of the drought forecasts using KSWSIs were higher than those using MSWSI, demonstrating that KSWSI is able to enhance the accuracy of drought forecasts. Finally, the influence of expanding hydrometeorological components as KSWSI components was analyzed and the probability distributions for each KSWSI component were selected. It is confirmed that the accuracy of KSWSIs may be affected by the choice of hydrometerological components used as drought components, the station data obtained, the length of used data for each station, and the probability distributions selected for each drought component. Furthermore, the uncertainty quantification of the KSWSI calculation procedure was also carried out. The large MEs and standard deviations of KSWSIs in the flood season cause uncertainties, implying that the selection of the appropriate probability distributions for selected drought components in the flood season is very important.

In order to monitor accurate droughts and manage water resources to mitigate droughts, in future research, analysis will be needed not only of the spatially segmented sub-basin divisions, but also the municipal district units in the administrative districts. This is because it is very important to distinguish between the waterworks and the dam beneficiation regions and, for these regions, the dams should be assessed individually by using the dam water supply capacity index. Further studies should also be conducted on the practical use of meteorological forecasting data to improve the accuracy of drought forecasts.

Acknowledgement

This study was funded by the Korea Meteorological Administration Research and Development Program under Grant KMIPA-2015-6190

References

Ahn, Kuk-hyun and Kim, Young-Oh, 2010” A study on improving drought indices and developing their outlook technique for Korea. *Proceeding of Korea Water Resources Association*, 6-12.

Belayneh, A and Adamowski, J, 2013: Drought forecasting using new machine learning methods. *Journal of Water and Land Development*, 18, 3-12.

Choi, Y., 2002: Trends in daily precipitation events and their extremes in the southern region of Korea.

Korea Soc, Environmental Impact Assessment, 11, 189-203.

Doesken, N. J., Mckee, T. B., and Kleist, J., 1991: *Development of a surface water supply index for the Western United States*. Colorado Climate Center, Department of Atmospheric Science, Colorado State University. Climatology Report #91-3.

Dogan, S., Berktay, A., Singh, V. P., 2012: Comparison of multi-monthly rainfall-based drought severity indices, with application to semi-arid Konya closed basin, Turkey. *Journal of Hydrology*. 470, 255-268.

Gay, C. and Estrada, F., 2010: Objective probabilities about future climate are a matter of opinion. *Climatic Change*, 99, 27-46.

K-water, 2005: *Development of the monitoring system for the drought management*.

Karamouz, M., Rasouli, K., and Nazif, S., 2009: Development of a Hybrid Index for Drought Prediction: Case Study. *Journal of Hydrologic Engineering*, 10.1061/(ASCE) HE.1943-5584.0000022, 617-627.

Korea Meteorological Administration, 2014: *2013 The abnormal climate report*. Korea Meteorological Administration.

Kwon, Hyung Joong and Kim, Seoung Joon, 2006: Evaluation of semi-distributed hydrological drought using SWSI (Surface Water Supply Index). *Journal of the Korean Society of Agricultural Engineers*, 48(2), 37-43.

Kwon, Hyung Joong, Park, Hyun Jin, Hong, Dae Oui, and Kim, Seoung Joon, 2006: A study on semi-distributed hydrologic drought assessment modifying SWSI. *Journal of Korea Water Resources Association*, 39(8), 645-658.

National Emergency Management Agency, 2009: *Performance report for the progress to overcome drought*. National Emergency Management Agency.

Park, Min Ji, Shin, Hyung Jin, Choi, Young Don, Park, Jae Young, and Kim, Seong Joon, 2011: Developing of a hydrological drought index considering water availability. *Joournal of the Korean Society of Agricultural Engineers*, 35(6), 165-170.

Shafer, B. A. and Dezman, L. E., 1982: Development of surface water supply index - A drought severity indicator for Colorado. *Proceeding of Western Snow Conference*, 164-175.

Shannon, C. E., 1948: A mathematical theory of communication. *Bell System Technical Journal*, 27, 379-423.

Shukla, S., and Wood, A.W., 2008. Use of a standardized runoff index for characterizing hydrologic dought. *Geophysical Research Letters*, doi:10.1029/2007GL032487.

Son, Kyung Hwan and Bae, Deg Hyo, 2015: Applicability assessment of hydrological drought outlook using ESP method. *Journal of Korea Water Resources Association*, 48(7), 581-593.

White, W. B., Gershunov, A., Anns, J. L., Mckeon, G., and Syktus, J., 2004: Forecasting Australian drought using south hemisphere modes of sea-surface temperature variability. *International Journal of Climatology*, 24, 1911-1927.

Wilks, D. S., 2006: *Statistical Methods in the Atmospheric Sciences*. Academic Press, Elsevier.

Nat. Hazards Earth Syst. Sci. Discuss., https://doi.org/10.5194/nhess-2017-163
Manuscript under review for journal Nat. Hazards Earth Syst. Sci.
Discussion started: 19 June 2017

List of Tables

Table 1. Basic investigation of hydrometerological components at each sub-basin

Table 2. Selected hydrometerological components and stations at each sub-basin

Table 3. Selected suitable probability distributions to hydrometerological components at each sub-basin

Table 4 Regression equations for the *a*, *b*, *c*, and *d* parameters

Table 5. Comparison of the most probable drought categories and their probabilities for each sub-basin in April and December on 2014 year

Table 6. Accuracy of the MSWSI and KSWSI results

Table 7. Comparison of hydrometeorological components in each sub-basin between the MSWSI and this KSWSI studies

Table 8. Comparison of MSWSI and KSWSI results in July in each sub-basin

Table 9. Available probability distributions to each hydrometerological component at each sub-basin

Table 10. Maximum entropy results for each sub-basin and month in each drought event

Nat. Hazards Earth Syst. Sci. Discuss., https://doi.org/10.5194/nhess-2017-163
Manuscript under review for journal Nat. Hazards Earth Syst. Sci.
Discussion started: 19 June 2017

Table 1. Basic investigartion of hydrometerological components at each sub-basin

(a) Investigation of available hydrometerological components

Basin No.	Sub-basin name	Pcp. station	WL station	W station	NS	LS level 1	LS level 2	WWS	LWS	GW
3001	Yongdam dam	O	O	O	X	O	O	O	O	O
3002	Downstream of Yongdam dam	X	O	X	X	O	O	X	X	O
3003	Muju Namdaecheon	O	O	X	X	O	O	X	O	O
3004	Youngdongcheon	O	O	O	X	O	O	X	O	O
3005	Chogang	O	O	O	X	O	O	X	O	O
3006	Upstream of Daecheong dam	O	O	X	O	O	O	X	O	O
3007	Bocheongcheon	O	O	O	O	O	O	X	O	O
3008	Daecheong dam	O	O	X	O	X	O	O	O	O
3009	Gapcheon	O	O	O	O	O	O	X	O	O
3010	Downstream of Daecheong dam	O	O	X	O	X	O	X	O	O
3011	Mihocheon	O	O	O	O	O	O	O	O	O
3012	Geum river Gongju	O	O	O	O	O	O	O	O	O
3013	Nonsancheon	O	O	X	O	O	O	X	O	O
3014	Geum river estuary bank	O	O	X	O	O	O	O	O	O

* Pcp: Precipitation; WL: Water Level, W: Weather; NS: National Stream; WWS; Wide Water Supply; LWS; Local Water Supply; GW: GroundWater

(b) Analysis and collection of hydrometerological components

Components	Stations	Data length	Description
Precipitation	KMA: 9, MOLIT: 24, K-water: 8	Maximum: 1966-2015	. Data quality & length . Priority to KMA . Areal average with Thiessen method
Water level & streamflow	87	Maximum: 1990-2015	. Data quality & length
Dam	Yongdam, Daecheong	Yongdam: 2001-2015 Daecheong: 1981-2015	. Total nine dams located . non-available 6 dams in KRC
Groundwater	7	Maximum: 1998-2015	. Used in GIMS . Data quality & length

Table 2. Selected hydrometerological components and stations at each sub-basin

Basin No.	Subbasin classification	Hydrometeorological components			
		Precipitation	Streamflow	Dam	Groundwater
3001	Upstream of dam	Jangsu, Daebul, Buksang, Jinan	Donghyang, Chunchun	Inflow & water-level in Yongdam dam	Jangsu-Jangsu
3002	Downstream of dam	Muju(KW)	Anchun	Release discharge in Yongdam dam	
3003	Precipitation, Streamflow	Muju(KW), Buksang, Muju(M)	Sulchun, Jangbaek		
3004	Precipitation, Streamflow	Geumsan(K), Geumsan(KW), Youngdong	Sutong, Hotan		Geumsan-Geumsan, Geumsan-Boksu
3005	Precipitation, Streamflow	Chupoongryung, Hwanggan, Buhang2	Songchun, Simchun		
3006	Precipitation, Streamflow	Iwon	Okchun		
3007	Precipitation, Streamflow	Boeun(K), Boeun(KW), Neungwol	Gidaegyo, Chungsung		
3008	Upstream of dam	Gunbuk, Annae	Okgakgyo, Daechung dam, Hyundo	Inflow & water-level in Daechung dam	
3009	Downstream of dam	Daecheon	Bangdong, Sindae		Daejeon-Moonpyung, Daejeon-Taepyung
3010	Precipitation, Streamflow	Bugang	Bugang, Maepo	Release discharge in Daechung dam	
3011	Precipitation, Groundwater	Cheongju, Chunan, Gaduk, Sunghwan, Byungcheon, Jeungpyung, Jinchun, Oryu	Chungju, Hapgang, Mihogyo		Chungwon-Gaduk, Jinchun-Jinchun
3012	Precipitation, Streamflow	Buyeo, Chungyang, Jungsan, Banpo, Bokryong, Gongju, Hongsan, Jungan	Guryong, Gyuam		
3013	Precipitation, Streamflow	Yeonsan, Jangsun, Ganggyung	Hangwol, Nonsan		
3014	Precipitation, Streamflow	Gunsan, Hamyeol, Ganggyung	Ippo, Okpo		

* KW: K-water; K: KMA; M: MLIT

Table 3. Selected suitable probability distributions to hydrometerological components at each sub-basin

Basin No.	Hydrometeorological components			
	Precipitation	Streamflow	Dam	Groundwater
3001	Gumbel	Gumbel	2-Log-Normal	3-Log-Normal
3002	Gumbel	Normal	2-Log-Normal	
3003	Gumbel	Normal		
3004	Gumbel	Gumbel		3-Log-Normal
3005	Gumbel	Gumbel		
3006	Gumbel	Gumbel		
3007	Gumbel	Gumbel		
3008	Gumbel	Gumbel	2-Log-Normal	
3009	Gumbel	Normal		3-Log-Normal
3010	Gumbel	Gumbel	2-Log-Normal	
3011	Gumbel	Gumbel		3-Log-Normal
3012	Gumbel	Gumbel		
3013	Gumbel	Gumbel		
3014	Gumbel	Gumbel		

Table 4. Regression equations for the *a*, *b*, *c*, and *d* parameters

	Regression equations
a	= 0.1472 - 0.6002×(basin average temperature) + 0.01236×(basin annual average potential evapotranspiration) - 0.0602×(basin drainage density)
b	= -895.3440 + 1.0696×(basin annual average potential evapotranspiration) + 256.8310 × (basin drainage density) + 1.3901×(basin monthly maximum precipitation) + 0.0789×(basin total stream length)
c	= -0.3893 + 0.9773×(basin average temperature) + 0.0196× (basin annual average potential evapotranspiration) - 0.10182×(basin drainage density) - 0.0006×(basin monthly maximum precipitation)
d	= -3.7841 + 0.0128×(basin annual average potential evapotranspiration) + 0.0427×(basin annual average precipitation) + 0.3206×(basin drainage density)

Nat. Hazards Earth Syst. Sci. Discuss., https://doi.org/10.5194/nhess-2017-163
Manuscript under review for journal Nat. Hazards Earth Syst. Sci.
Discussion started: 19 June 2017

Table 5. Comparison of the most probable drought categories and their probabilities for each sub-basin in April and December on 2014 year

Basin No.	With the MSWSI				With the KSWSI			
	April 2014		December 2014		April 2014		December 2014	
	Category	Prob.	Category	Prob.	Category	Prob.	Category	Prob.
3001	4	41.9	3	32.3	7	32.3	4	48.4
3002	4	48.4	7	22.6	4	35.5	7	29.0
3003	6	32.3	6	32.3	7	38.7	6	41.9
3004	4	64.5	3	38.7	5	51.6	4	51.6
3005	6	25.8	4	29.0	7	77.4	7	77.4
3006	4	32.3	6	32.3	7	77.4	7	77.4
3007	6	25.8	4	25.8	7	77.4	7	77.4
3008	4	67.7	4	71.0	5	35.5	6	35.5
3009	4	54.8	3	45.2	4	54.8	3	51.6
3010	4	74.2	4	64.5	7	38.7	5	29.0
3011	4	51.6	3	32.3	5	51.6	4	54.8
3012	6	29.0	4	25.8	7	77.4	7	77.4
3013	6	32.3	7	41.9	7	77.4	7	77.4
3014	5	32.3	7	25.8	7	77.4	7	77.4

Nat. Hazards Earth Syst. Sci. Discuss., https://doi.org/10.5194/nhess-2017-163
Manuscript under review for journal Nat. Hazards Earth Syst. Sci.
Discussion started: 19 June 2017

Natural Hazards and Earth System Sciences
Open Access
EGU
Discussions

Table 6. Accuracy of the MSWSI and KSWSI results

(a) Average Hit Score

Month	MSWSI		KSWSI	
	2006	2014	2006	2014
1	0.230	0.212	0.348	0.491
2	0.273	0.260	0.342	0.507
3	0.093	0.240	0.354	0.182
4	0.258	0.309	0.096	0.369
5	0.239	0.157	0.134	0.392
6	0.224	0.242	0.177	0.332
7	0.099	0.129	0.075	0.459
8	0.180	0.182	0.388	0.272
9	0.199	0.141	0.360	0.237
10	0.252	0.210	0.286	0.104
11	0.193	0.152	0.099	0.187
12	0.171	0.171	0.329	0.366
Average	0.201	0.2	0.249	0.325

Season	MSWSI		KSWSI	
	2006	2014	2006	2014
Spring	0.197	0.235	0.195	0.314
Summer	0.168	0.184	0.213	0.354
Autumn	0.214	0.167	0.248	0.176
Winter	0.225	0.214	0.340	0.455

Nat. Hazards Earth Syst. Sci. Discuss., https://doi.org/10.5194/nhess-2017-163
Manuscript under review for journal Nat. Hazards Earth Syst. Sci.
Discussion started: 19 June 2017

(b) Half Brier Score

Month	MSWSI		KSWSI	
	2006	2014	2006	2014
1	0.851	0.840	0.694	0.494
2	0.730	0.761	0.627	0.442
3	1.059	0.805	0.665	1.081
4	0.724	0.680	1.133	0.693
5	0.748	0.931	1.090	0.630
6	0.768	0.755	0.961	0.780
7	1.023	0.977	1.180	0.554
8	0.878	0.885	0.613	0.929
9	0.853	0.969	0.638	0.937
10	0.789	0.899	0.792	1.232
11	0.857	0.962	0.886	1.067
12	0.891	0.910	0.613	0.698
Average	0.848	0.865	0.824	0.795

Season	MSWSI		KSWSI	
	2006	2014	2006	2014
Spring	0.844	0.805	0.963	0.801
Summer	0.889	0.872	0.918	0.754
Autumn	0.833	0.944	0.772	1.079
Winter	0.824	0.837	0.645	0.545

Nat. Hazards Earth Syst. Sci. Discuss., https://doi.org/10.5194/nhess-2017-163
Manuscript under review for journal Nat. Hazards Earth Syst. Sci.
Discussion started: 19 June 2017

Table 7. Comparison of hydrometeorological components in each sub-basin between the MSWSI and this KSWSI studies

Basin No.	MSWSI Study	KSWSI study	Subbasin classification
3001	D_DF., SF(1 OB), Pcp(1 OB)	Y_DF & Y_DWL, SF(2 OBs), Pcp(4 OBs), GW(1 OB)	Upstream of dam
3002	D_DF, SF(1 OB), Pcp(1 OB)	Y_DRD, SF(2 OBs), Pcp(4 OBs)	Downstream of dam
3003	D_DF, SF(1 OB), Pcp(1 OB)	SF(2 OBs), Pcp(3 OBs)	Precipitation, Streamflow
3004	D_DF, SF(1 OB), Pcp(1 OB)	SF(3 OBs), Pcp(2 OBs), GW(2 OBs)	Precipitation, Streamflow
3005	D_DF, SF(1 OB), Pcp(1 OB)	SF(2 OBs), Pcp(3 OBs)	Precipitation, Streamflow
3006	D_DF, SF(1 OB), Pcp(1 OB)	SF(1 OB), Pcp(1 OB)	Precipitation, Streamflow
3007	D_DF, SF(1 OB), Pcp(1 OB)	SF(2 OBs), Pcp(3 OBs)	Precipitation, Streamflow
3008	D_DF, Pcp(1 OB)	D_DF & D_DWL, SF(3 OBs), Pcp(2 OBs)	Upstream of dam
3009	SF(1 OB), Pcp(1 OB), GW(1 OB)	SF(2 OBs), Pcp(1 OB), GW(2 OBs)	Downstream of dam
3010	Pcp(1 OB)	D_DRD, SF(2 OBs), Pcp(1 OB)	Precipitation, Streamflow
3011	SF(1 OB), Pcp(1 OB), GW(1 OB)	SF(3 OBs), Pcp(8 OBs), GW(2 OBs)	Precipitation, Groundwater
3012	SF(1 OB), Pcp(1 OB)	SF(2 OBs), Pcp(8 OBs)	Precipitation, Streamflow
3013	Pcp(1 OB)	SF(2 OBs), Pcp(3 OBs)	Precipitation, Streamflow
3014	Pcp(1 OB)	SF(2 OBs), Pcp(3 OBs)	Precipitation, Streamflow

* Y_: Yongdam dam, D_: Daecheong dam, DF: Dam Inflow, DWL: Dam WaterLevel, DRD: Dam Release Discharge, Pcp: Precipitation, SF: StreamFlow, WL: WaterLevel, GW: GroundWater, OB: Observed station

Nat. Hazards Earth Syst. Sci. Discuss., https://doi.org/10.5194/nhess-2017-163
Manuscript under review for journal Nat. Hazards Earth Syst. Sci.
Discussion started: 19 June 2017

Natural Hazards and Earth System Sciences
Open Access
Discussions

Table 8. Comparison of MSWSI and KSWSI results in July in each sub-basin

Basin No.	MSWSI result (category)		KSWSI result (category)	
	2001	2006	2001	2006
3001	-1.95(5)	2.91(2)	-0.49(4)	3.48(1)
3002	-1.95(5)	2.91(2)	-0.41(4)	0.98(4)
3003	-1.95(5)	2.91(2)	-2.08(6)	4.03(1)
3004	-1.95(5)	2.91(2)	-1.09(5)	3.68(1)
3005	-2.76(6)	0.739(4)	0.87(4)	3.80(1)
3006	**-0.91(4)**	2.01(2)	-2.46(6)	3.74(1)
3007	-2.66(6)	1.45(3)	-3.55(7)	3.50(1)
3008	-2.80(6)	2.69(2)	-2.47(6)	3.69(1)
3009	-3.16(7)	1.89(3)	-3.21(7)	1.41(3)
3010	-2.49(6)	2.39(2)	-2.41(6)	3.36(1)
3011	-2.14(6)	1.65(3)	-1.94(5)	3.35(1)
3012	0.53(4)	0.40(4)	-1.76(5)	2.51(2)
3013	-1.45(5)	2.70(2)	-3.20(7)	3.49(1)
3014	-0.77(4)	2.70(2)	-1.92(5)	3.23(1)

Table 9. Available probability distributions to each hydrometerological component at each sub-basin

Basin No.	KSWSI components			
	Precipitation	Streamflow	(related to) Dam	Groundwater
3001	·Gumbel ·GEV ·Normal	·Gumbel ·Normal	·2-Log-Normal ·Gumbel ·Normal	·3-Log-Normal ·Normal
3002	·Gumbel ·GEV ·Normal	·Gumbel ·Normal	·2-Log-Normal ·Gumbel ·Normal	
3003	·Gumbel ·GEV ·Normal	·Gumbel ·Normal		
3004	·Gumbel ·GEV ·Normal	·Gumbel ·Normal		·3-Log-Normal ·Normal
3005	·Gumbel ·GEV ·Normal	·Gumbel ·Normal		
3006	·Gumbel ·GEV ·Normal	·Gumbel ·Normal		
3007	·Gumbel ·GEV ·Normal	·Gumbel ·Normal		
3008	·Gumbel ·GEV ·Normal	·Gumbel ·Normal	·2-Log-Normal ·Gumbel ·Normal	
3009	·Gumbel ·GEV ·Normal	·Gumbel ·Normal		·3-Log-Normal ·Normal
3010	·Gumbel ·GEV ·Normal	·Gumbel ·Normal	·2-Log-Normal ·Gumbel ·Normal	
3011	·Gumbel ·GEV ·Normal	·Gumbel ·Normal		·3-Log-Normal ·Normal
3012	·Gumbel ·GEV ·Normal	·Gumbel ·Normal		
3013	·Gumbel ·GEV ·Normal	·Gumbel ·Normal		
3014	·Gumbel ·GEV ·Normal	·Gumbel ·Normal		

Nat. Hazards Earth Syst. Sci. Discuss., https://doi.org/10.5194/nhess-2017-163
Manuscript under review for journal Nat. Hazards Earth Syst. Sci.
Discussion started: 19 June 2017

Natural Hazards and Earth System Sciences
Open Access
Discussions

Table 10. Maximum entropy results for each sub-basin and month in each drought event

(a) For each sub-basin

Basin No.	Maximum entropy			Average
	2001	2006	2014	
3001	1.002	1.198	1.503	1.234
3002	0.985	1.210	1.352	1.182
3003	0.845	0.785	0.985	0.872
3004	0.985	1.002	1.052	1.013
3005	0.789	0.812	1.005	0.869
3006	0.521	0.651	0.785	0.652
3007	0.742	0.584	0.712	0.679
3008	0.854	0.888	0.616	0.786
3009	0.795	0.875	0.687	0.786
3010	0.891	0.985	0.871	0.916
3011	0.841	0.784	0.852	0.826
3012	0.668	0.578	0.363	0.537
3013	0.784	0.652	0.514	0.650
3014	0.781	0.587	0.612	0.660

(b) For each month

Month	Maximum entropy			Average	Season	Averaged ME
	2001	2006	2014			
1	0.562	0.650	0.541	0.584	Spring	0.787
2	0.701	0.716	0.629	0.682		
3	0.825	0.765	0.882	0.824		
4	0.795	0.827	0.722	0.781	Summer	1.053
5	0.721	0.847	0.697	0.755		
6	0.854	0.785	0.865	0.835		
7	1.215	1.379	1.174	1.256	Autumn	0.904
8	1.125	1.087	0.992	1.068		
9	0.987	1.182	1.077	1.082		
10	1.002	0.843	0.883	0.909	Winter	0.676
11	0.785	0.686	0.695	0.722		
12	0.625	0.889	0.768	0.761		

Nat. Hazards Earth Syst. Sci. Discuss., https://doi.org/10.5194/nhess-2017-163
Manuscript under review for journal Nat. Hazards Earth Syst. Sci.
Discussion started: 19 June 2017

Natural Hazards and Earth System Sciences
Open Access
Discussions

List of Figures

Fig. 1. Study basin: 14 sub-basins in Geum River basin

Fig. 2. Procedure of the previous MSWSI calculation and two improvements proposed by this study

Fig. 3. Example of weights of each drought component for each month at sub-basin 3001 and 3007

Fig. 4. Comparison of the MSWSI and KSWSI results in April 2001, 2006, and 2014 years

Fig. 5. Verification of KSWSI results in sub-basin 3001 and 3014

Fig. 6. Example of the procedure of the monthly probabilistic drought forecast

Fig. 7. Comparison of the drought forecasts using the MSWSI and KSWSI on April and December in 2006 and 2014 years

Fig. 8. Comparison of the drought forecasts ranges for each month at sub-basin 3001, 3007, and 3014 in 2014 year

Fig. 9. Verification of MSWSI and KSWSI results in sub-basins 3001 and 3010: (a) & (b) at 3001 and (c) & (d) at 3010

Fig. 10. Comparison of KSWSI time series of max, min, and normal at sub-basin 3001 and 3008 in 2006 and 2014 years: (a) & (b) at 3001 & 3008, respectively, in 2006 year and (c) & (d) at 3001 & 3008, respectively, in 2014 year

Fig. 11. Comparison of maximum entropy results between sub-basins and months for each drought event

Fig. 1. Study basin: 14 sub-basins in Geum River basin

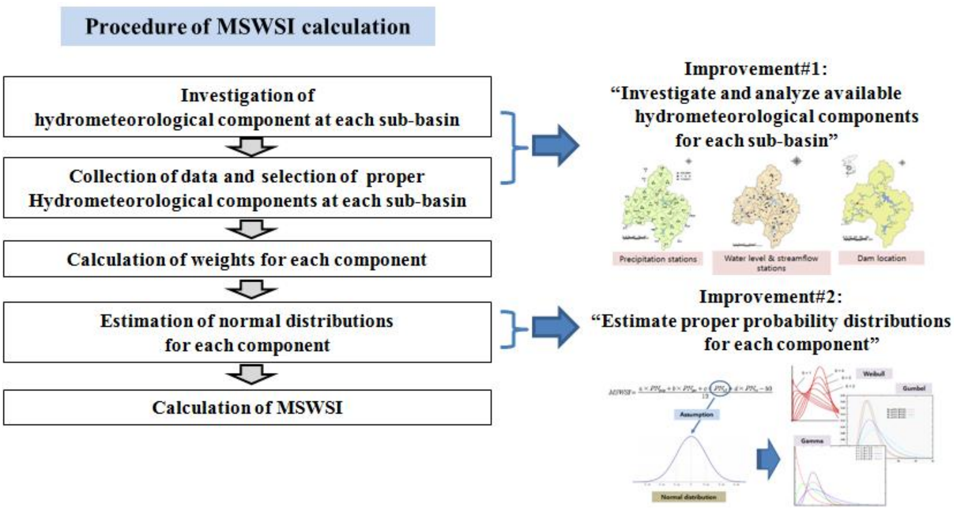
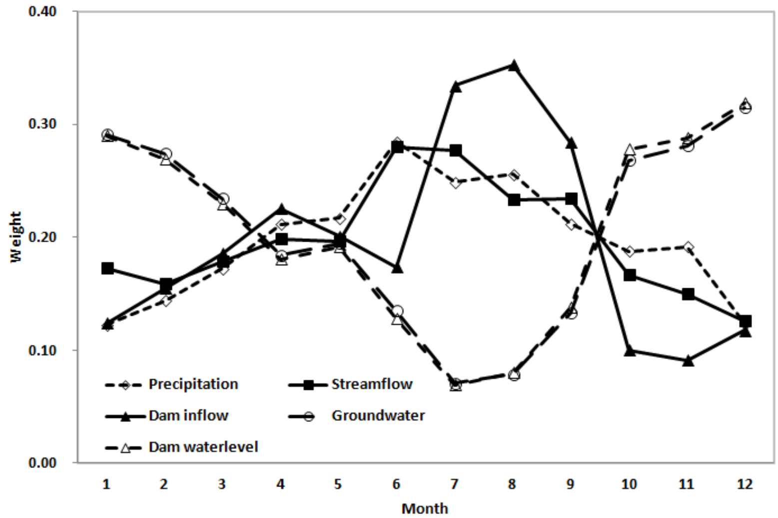
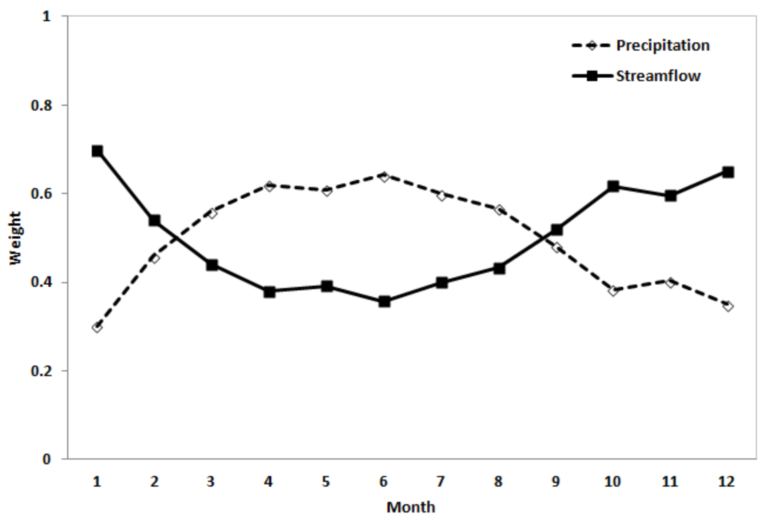


Fig. 2. Procedure of the previous MSWSI calculation and two improvements proposed by this study



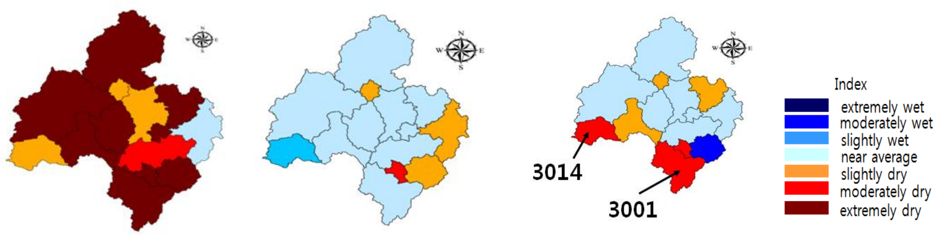
(a) Sub-basin 3001



(b) Sub-basin 3007

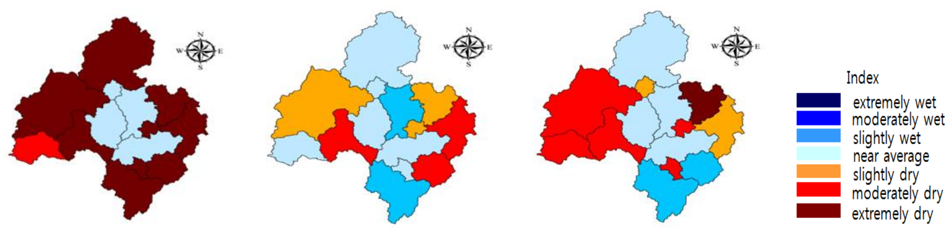
Fig. 3. Example of weights of each drought component for each month at sub-basin 3001 and 3007

Nat. Hazards Earth Syst. Sci. Discuss., https://doi.org/10.5194/nhess-2017-163
Manuscript under review for journal Nat. Hazards Earth Syst. Sci.
Discussion started: 19 June 2017



April 2001 April 2006 April 2014

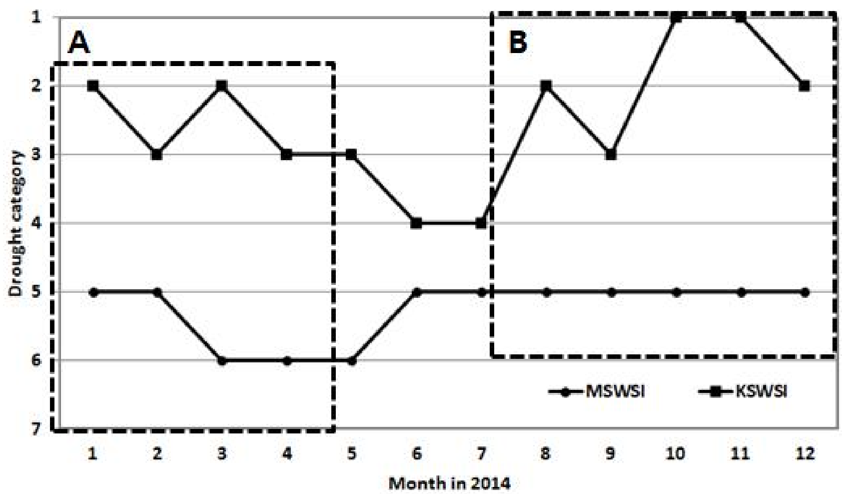
(a) MSWSI results



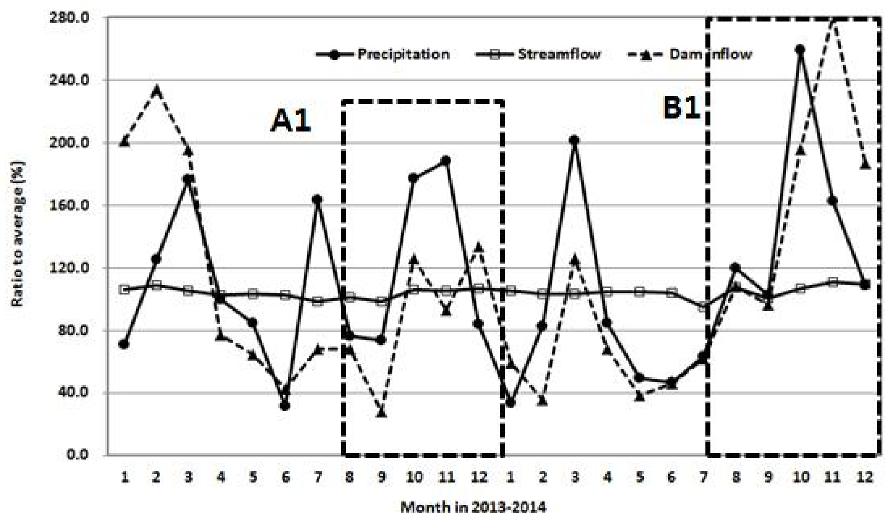
April 2001 April 2006 April 2014

(b) KSWSI results

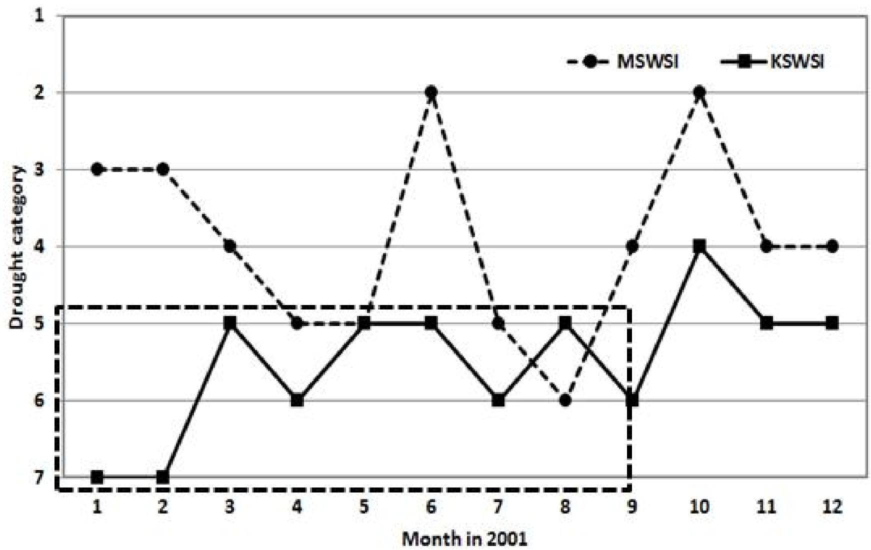
Fig. 4. Comparison of the MSWSI and KSWSI results in April 2001, 2006, and 2014 years



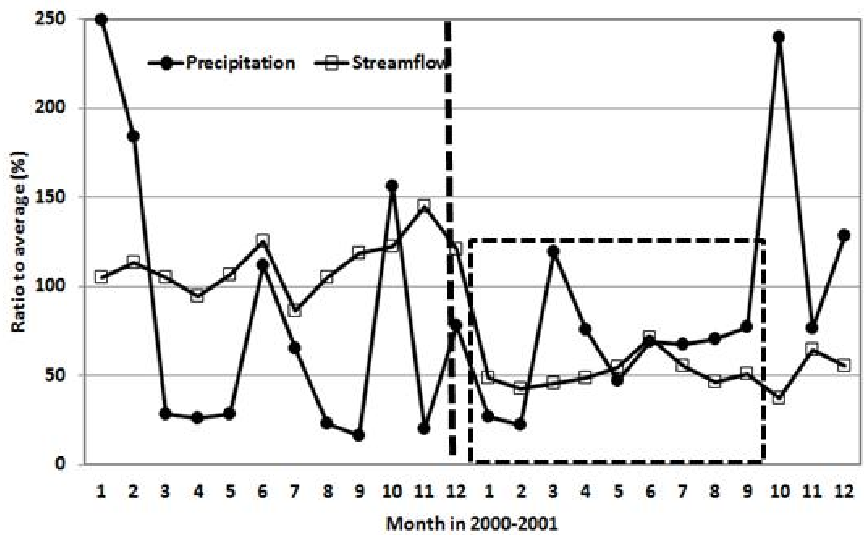
(a) Time series of the previous and improved monthly MSWSIs in 2014 year



(b) Time series of monthly precipitation, water level, and dam inflow in 2014 year



(c) Time series of the previous and improved monthly MSWSIs in 2001 year



(d) Time series of monthly precipitation and streamflow in 2001 year

Fig. 5. Verification of improved MSWSI in sub-basin 3001 and 3014: (a) & (b) at 3001 and (c) & (d) at 3014

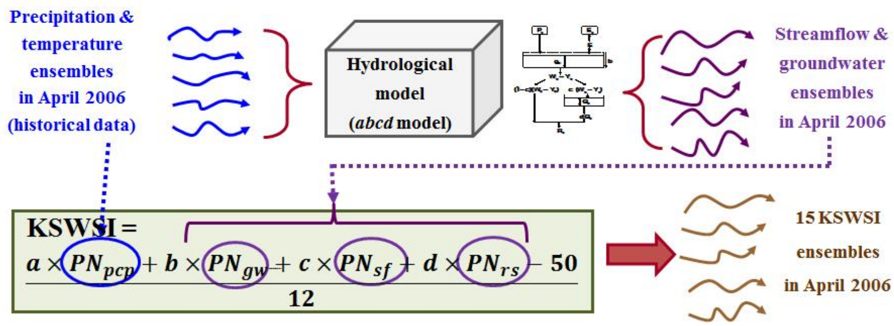


Fig. 6. Example of the procedure of the monthly probabilistic drought forecast

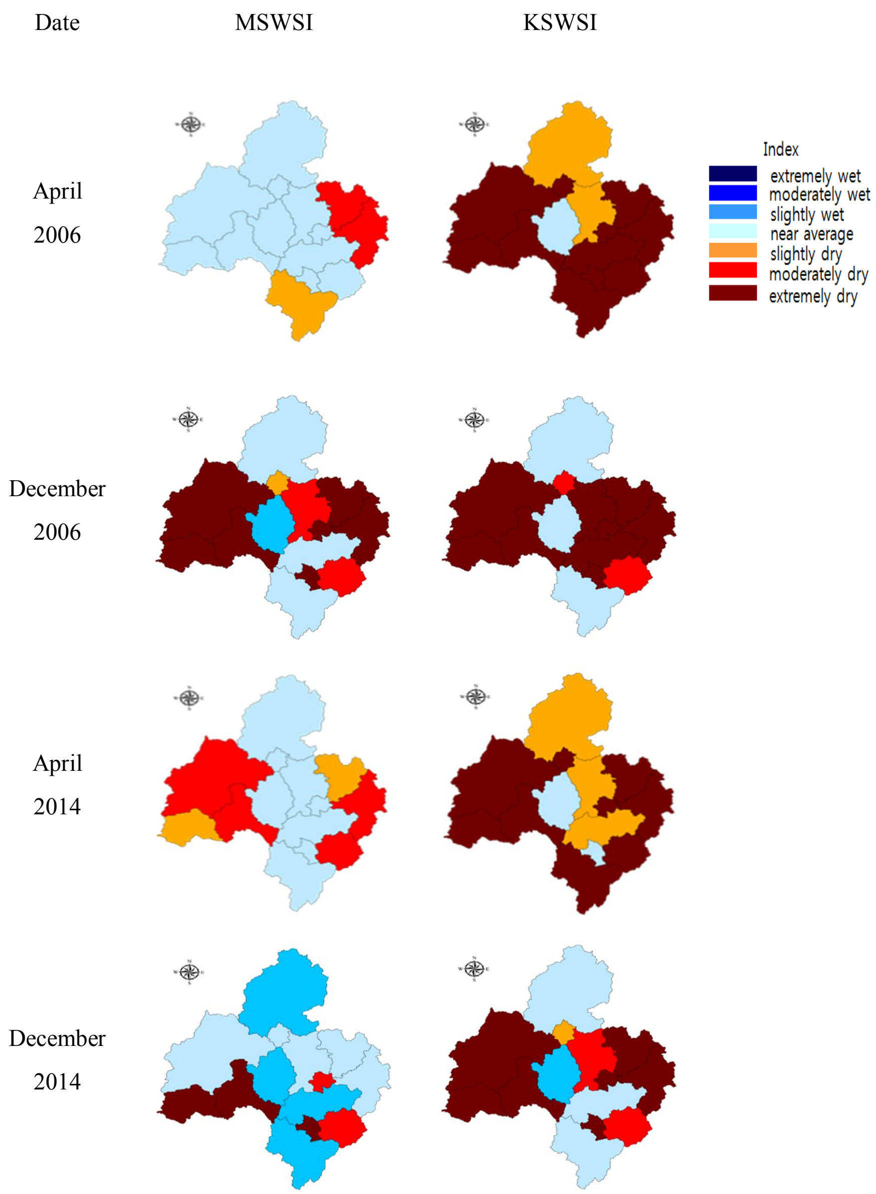
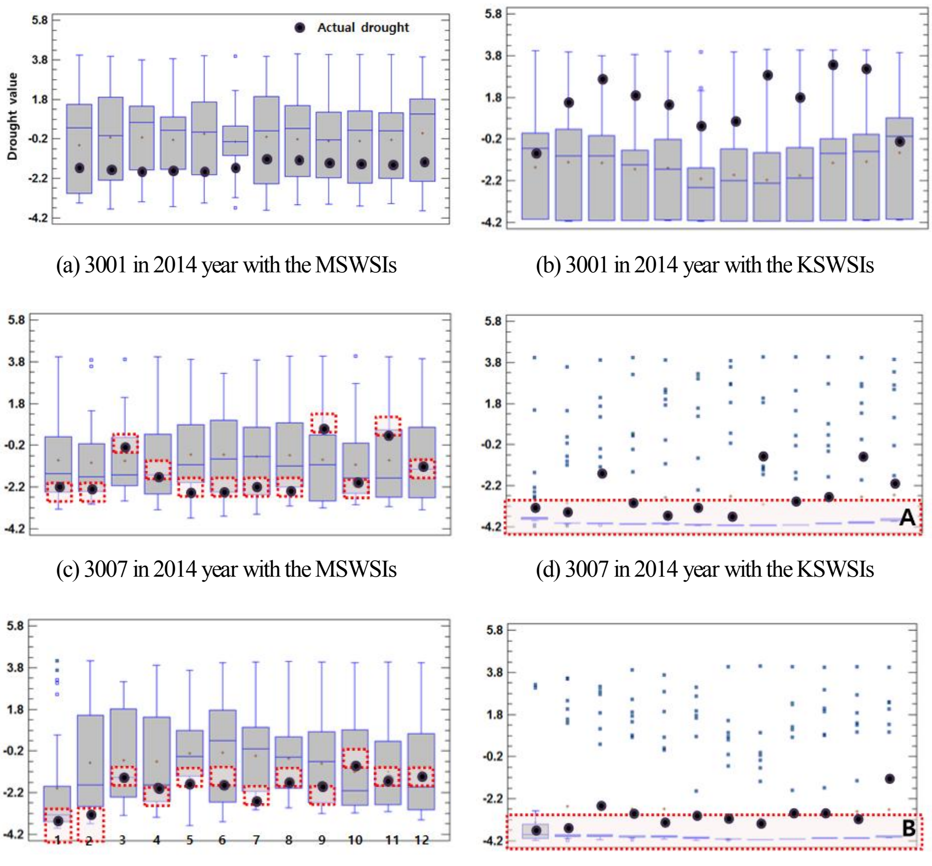


Fig. 7. Comparison of the drought forecasts using the MSWSI and KSWSI on April and December in 2006 and 2014 years

Nat. Hazards Earth Syst. Sci. Discuss., https://doi.org/10.5194/nhess-2017-163
Manuscript under review for journal Nat. Hazards Earth Syst. Sci.
Discussion started: 19 June 2017

Natural Hazards and Earth System Sciences
Open Access
Discussions



(a) 3001 in 2014 year with the MSWSIs

(b) 3001 in 2014 year with the KSWSIs

(c) 3007 in 2014 year with the MSWSIs

(d) 3007 in 2014 year with the KSWSIs

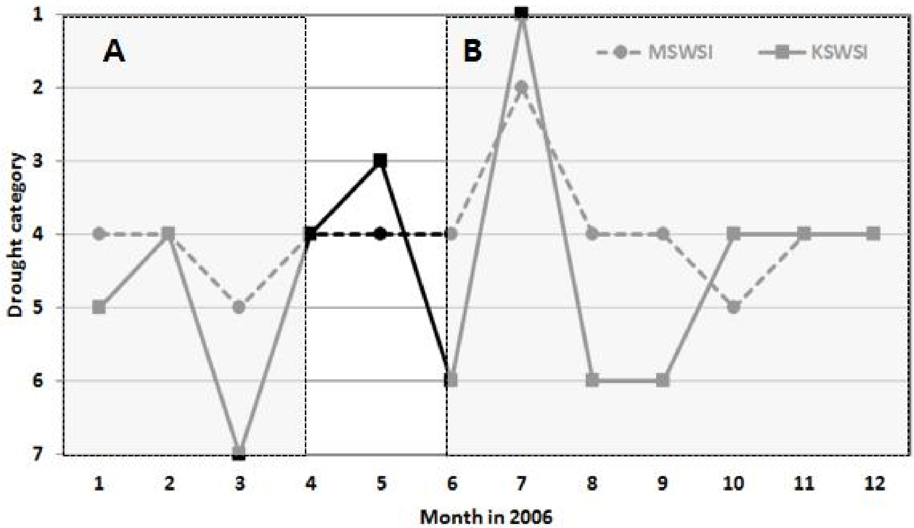
(e) 3014 in 2014 year with the MSWSIs

(f) 3014 in 2014 year with the KSWSIs

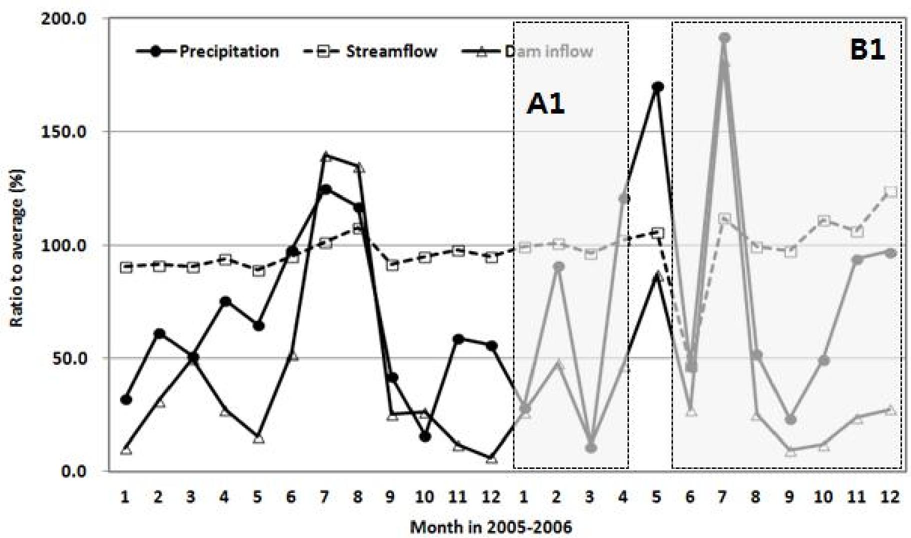
Fig. 8. Comparison of the drought forecasts ranges for each month at sub-basin 3001, 3007, and 3014 in 2014 year

Nat. Hazards Earth Syst. Sci. Discuss., https://doi.org/10.5194/nhess-2017-163
Manuscript under review for journal Nat. Hazards Earth Syst. Sci.
Discussion started: 19 June 2017

Natural Hazards and Earth System Sciences
Open Access
Discussions



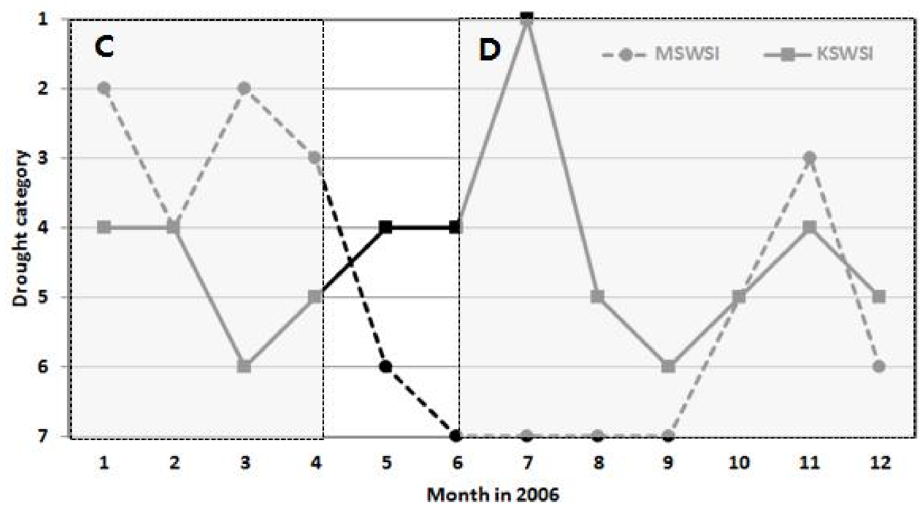
(a) Time series of the previous and this monthly MSWSI results in 2006 year at 3001



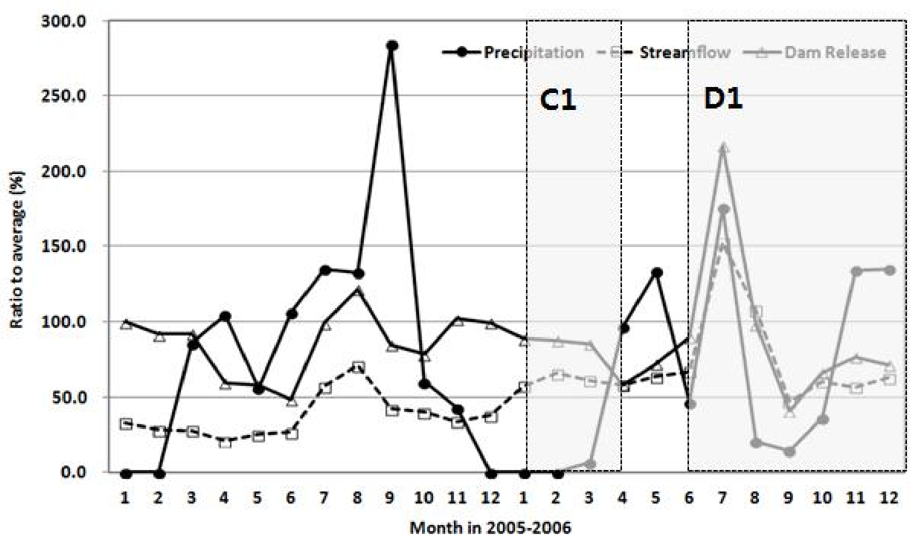
(b) Time series of monthly precipitation, streamflow, and dam inflow in 2005-2006 years at 3001

Nat. Hazards Earth Syst. Sci. Discuss., https://doi.org/10.5194/nhess-2017-163
Manuscript under review for journal Nat. Hazards Earth Syst. Sci.
Discussion started: 19 June 2017

Natural Hazards and Earth System Sciences
Open Access
Discussions

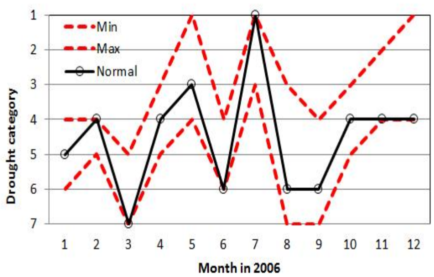


(c) Time series of the previous and this monthly MSWSI results in 2006 year at 3010

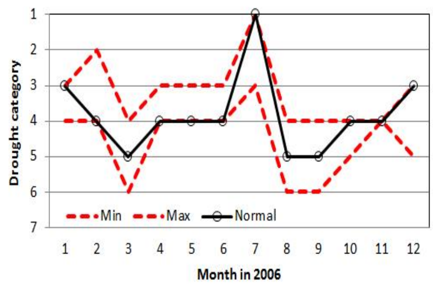


(d) Time series of monthly precipitation, streamflow, and dam release in 2005-2006 years at 3010

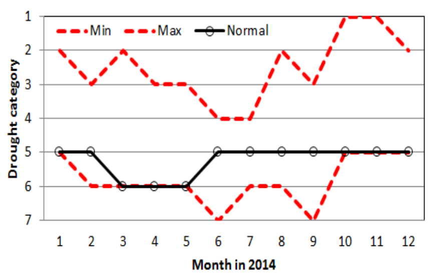
Fig. 9. Verification of MSWSI and KSWSI results in sub-basins 3001 and 3010: (a) & (b) at 3001 and (c) & (d) at 3010



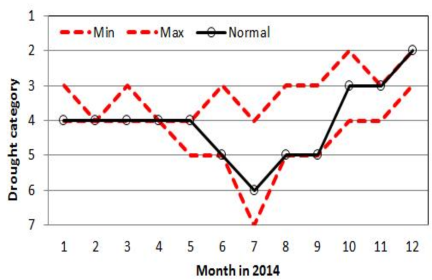
(a) Sub-basin 3001 in 2006 year



(b) Sub-basin 3008 in 2006 year

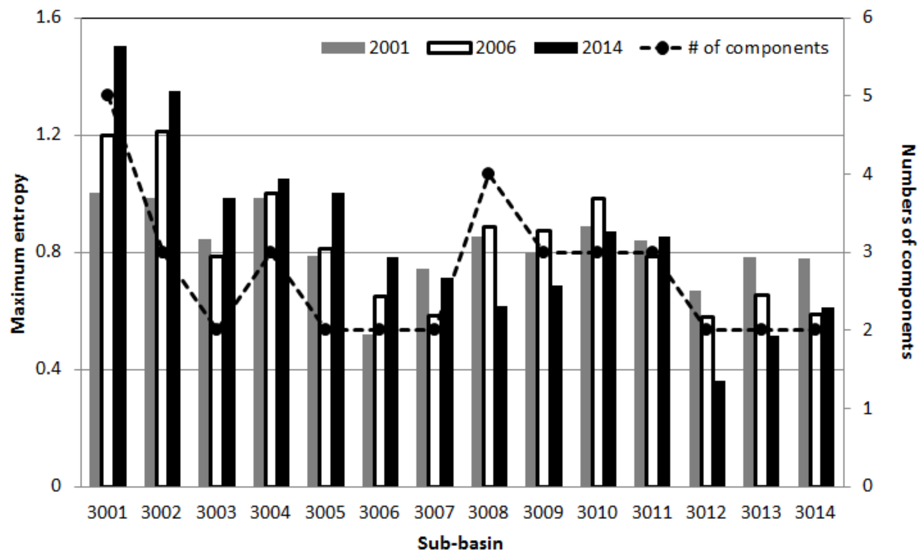


(c) Sub-basin 3001 in 2014 year

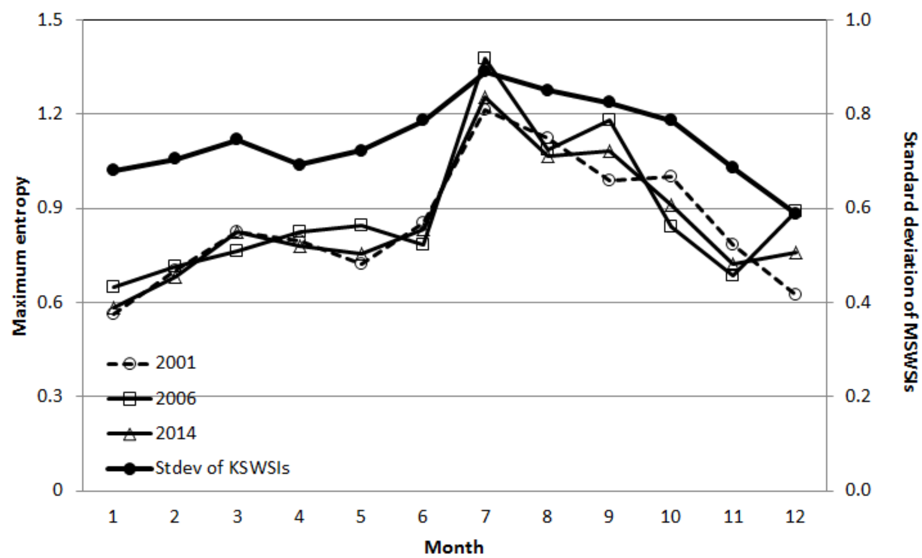


(d) Sub-basin 3008 in 2014 year

Fig. 10. Comparison of KSWSI time series of max, min, and normal at sub-basin 3001 and 3008 in 2006 and 2014 years: (a) & (b) at 3001 & 3008, respectively, in 2006 year and (c) & (d) at 3001 & 3008, respectively, in 2014 year



(a) For each sub-basin



(b) For each month

Fig. 11. Comparison of maximum entropy results between sub-basins and months for each drought event