Drought Definitions and Forecasts for Water Resources Management

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Abstract

Interest in the potential impacts of climate variability on existing and planned water resource projects is commonplace. Climate impact investigations have focused primarily on evaluating extreme events with large potential impacts, like floods and droughts. Droughts, in particular, are difficult to analyze because of their slow onset, spatial variability, heterogeneous impacts, and uncertain management actions. Recent studies have attempted to define drought characteristics as a function of precipitation, streamflow, soil moisture, and storage level (for developed systems). This paper extends these other studies by focusing on drought in the Geum River basin of Korea with three primary goals: 1) generating an operational definition of drought, 2) creating mid-term forecasts of climate variability, and 3) developing a decision support system for drought management that incorporates these other two features. The drought definition is derived from a series of computer simulations that use past precipitation, past and current streamflow, and reservoir storage to anticipate the onset and continuation of a drought event. Next, ensemble climate forecasts (developed from NCEP forecasts) are used to generate predictions of streamflows for the basin. These forecasts are mid-range in length (up to six month) and are derived from global spectral models (GSMs). These monthly meteorological forecasts are then interpolated to the finer hydrologic model scale. Finally, a decision support system is created to integrate the current degree of drought intensity and streamflow forecasts into a management plan. The decision support system indicates the likelihood of inadequate supplies and proposes management actions.

Introduction

For decades, researchers have attempted to provide operationally useful definitions of drought to aid water resource managers. Wilhite and Glantz (1985) summarized several drought definitions and identified six general categories of drought: meteorological, climatological, atmospheric, agricultural, hydrologic, and water management. Useful definitions of drought require that the context of water use and availability be considered. Furthermore, a primary objective of water management is the maintenance of a reliable and sustainable water supply through varying climatic and hydrologic conditions. To better manage limited water resources and optimize the system operation, droughts must be monitored and analyzed as they are identified, moved through various stages of development, and then resolved.

In addition to identifying droughts, it is important to manage operation during droughts. Developing an adaptive management system during periods of large climate variability is one of the most significant challenges facing water resource engineers. This paper describes the development of an adaptive method for drought curtailment planning as well as real-time drought monitoring using simulation tools. Such methods are necessary to support decision making in river basins, particularly those with a history of conflict over water.

Methodology

<u>Drought indicators</u>

Drought indicators are widely used to identify the onset, continuation, and/or termination of a drought. Drought indicators can include measures of streamflow, precipitation, reservoir storage, composite indices like the Palmer Drought Severity Index (which uses precipitation, temperature, and the available water content of the soil) and other similar measures (Fisher and Palmer 1997). To ensure that a drought indicator includes all necessary features, it is suggest that they contain at least four separate components: a characterization of the climatologic component (e.g., precipitation), essential hydrologic features (e.g., streamflow), a measure of the infrastructure related to storing and distribution water (e.g., stored water, distribution capacity, etc.), and a reasonable calculus to integrate these features into a representative drought index that could be used to trigger appropriate management responses.

McKee et al. (1993) suggests the Standardized Precipitation Index (SPI) for characterizing climatological droughts. This index incorporates the historical record of 3, 6, 12, 24, or 48 months of precipitation and their relationship to their mean values. The index is normalized according to the mean of its month using the Gamma function to define the relationship of probability to historical precipitation. The SPI values ranges from -2 to +1 when the index value reaches a value of above the zero into drought. Similarly, 3 month SPI is applied in this study.

Another needed component of a drought index is streamflow. Streamflow is of vital concern for water management. In this study, a four month total inflow from January to April into a reservoir is calculated.

Reservoir storage level is another important indicator of the drought definition procedure because it represents the degree of development and the current robustness of the system.

Table 1 presents three drought indicators and their range of values (1-5). The three indicators include the 3-Month SPI, four month total inflow, and average active storage in April. A composite index is calculated by averaging the values of each of the drought indicators.

<u>Streamflow forecast associated with climate variability</u>

Typically, streamflow forecast derived from forecasts of the future state of the climate can play a key role in identifying the possibility of extreme events (drought

Table 1. Three drought indicators and their values

3 Month SPI (Cum. probability, %)	Four month total inflows (Cum. probability, %)	Average storage in April (% of storage)	Indicator Value
> 80	> 80	> 80	1 - (Very Good)
60 – 80	60 – 80	60 – 80	2 - (Good)
40 – 59	40 – 59	40 – 59	3 - (Normal/Warning)
20 – 39	20 – 39	20 – 39	4 - (Drought)
< 20	< 20	< 20	5 - (Severe Drought)

and flood) as well as managing regional water resources. The National Center for Environmental Prediction (NCEP) provides six-month predictions of temperature and precipitation in association with Global Spectral Model (GSM). These forecasts are made with a resolution of 1.9 degree spatial domain and between 5 and 15 minutes temporal domain. NCEP also provides ten different hind-casts of the GSM for each year from 1979 to 1999. These hind-casts are the estimates that would have been made of temperature and precipitation if the forecasting system had been in place during this period. The hind-casts can be used to compare the GSM result associated with forecasts and historic weather conditions. For application to a smaller watershed (not a continental size system), the NCEP forecasts must be bias-corrected to minimize the error generated with associating them to a coarse grid point. In addition, the bias-corrected forecasted data must be spatially distributed throughout the basin to be available for a hydrology model. Miller and Palmer (2003) have presented the bias correction procedure as well as spatial distribution technique. The hydrologic model used in this research is a combination of the Better Assessment Science Integrating Point and Nonpoint Sources (BASINS 3.0, EPA 1996) and the Hydrologic Simulation Program-Fortran (HSPF, EPA 1970's). BASINS has been updated to include more modern spatial tools that are quickly becoming essential to application of emerging distributed hydrology models. BASINS operates under the ArcView GIS environment. The main components of BASINS are: 1) a data management tool that allows the user to get nationally archived hydrologic and metrologic database; 2) watershed delineation tools; 3) utilities for classifying the digital elevation maps, land use, soils, and water quality data; 4) watershed characterization reports that allows the user to present the output of information on selected watershed (http://www.epa.gov/waterscience/basins/basinsv3.htm).

BASINS provides a primary data set to be available for the Hydrologic Simulation Program-Fortran (HSPF) and the Soil Water Assessment Tool (SWAT, USDA 1995). HSPF is a semi-distributed model in support with BASINS consisting of discrete grid cells associated with DEM resolution. Each subbasin can be simulated using HSPF pervious land segment (Forest, Agricultural, and Urban Built-up), impervious land segment (Urban Built-up), and stream or mixed reservoir segment (RCHRES). The RCHRES simulates the flow of water in the tributary that drains each sub-watershed. Each subbasin consists of two soil layers including a upper-zone soil layer and lower-zone soil layer. The upper-zone soil layer responds quickly to storm events, while the lower-zone soil layer impacts interflow and ground base flow. To create a forecast with the model, three years of existing meteorological data just prior to the forecast is run through the model to minimize the modeling error driven by the initial condition.

To estimate the most appropriate meteorological data for the model, HSPF simulates streamflow as an input of neighboring precipitation and temperature data to compare historical flows and simulated flows. Next, an appropriate weather station is determined by evaluating the annual water balance and monthly streamflow pattern. Next, a spatial adjustment is used for the NCEP grid points that surround the study area. In this study, a total of nine NCEP grid points were selected as initial candidate (Figure 1). Eventually, only one of nine points (the one closest to study area) was used because it best represented the monthly spatial and temporal distribution of precipitation and temperature. In a last step, the forecasts are temporally downscaled from a monthly to an hourly time step as an input data set for HSPF hydrologic model.

Application and Discussion

The application site for this research is the Guem River basin, one of the largest watersheds in Korea (Figure 1). Guem River basin is 9,810 square kilometers with a mainstem length of 396 kilometers. Two major dams are located on the Guem River. Daechong Dam (which creates a reservoir of approximately 1,500 million cubic meters) provides water to several major cities. Yongdam Dam (which creates a reservoir of approximately 815 million cubic meters) is located in upstream of Daechong Dam and was completed in 2001. The river flows from south to north. In this study, the first week of May in every year is determined to be an appropriate day to initiate the drought monitoring procedure. If the day is delayed, the drought response is too late to be effective, while when it is activated early in the day, cost-benefit associated with hydropower release is infeasible.

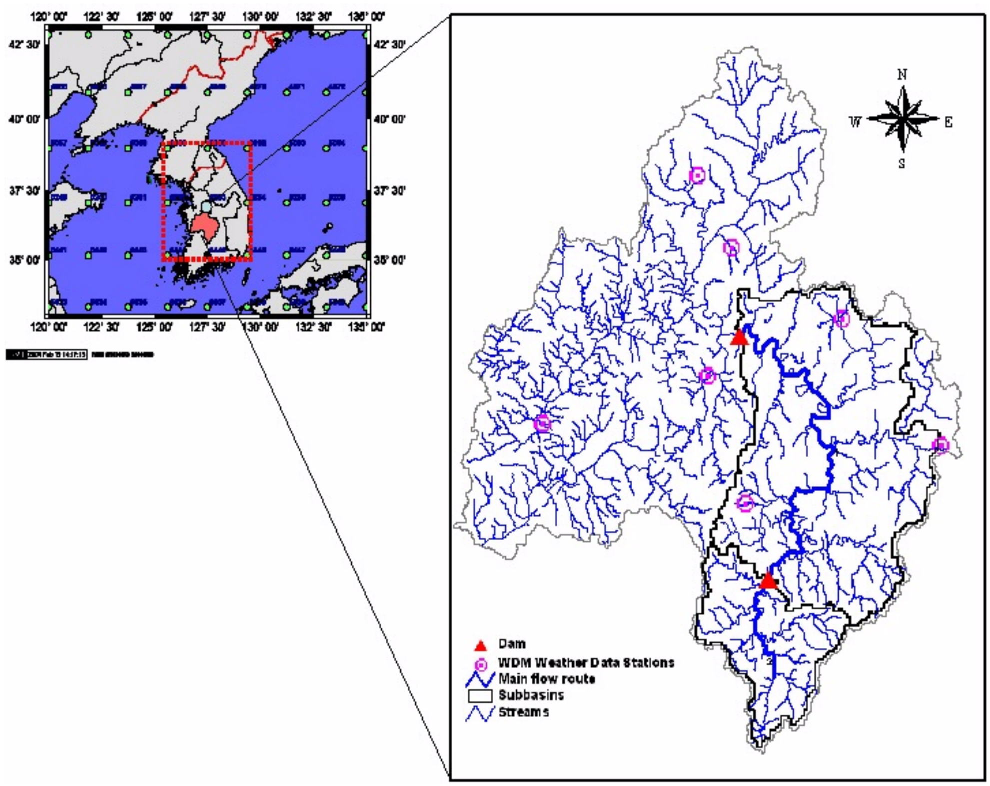

Figure 1. Schematic Overview of Guem River Basin with NCEP Grid Points

To verify that the composite index evaluated in the first week of May can identify droughts, statistical analysis (Analysis of Variance: ANOVA) was used of historic drought records. The analysis indicated that weightings of 45%, 25%, and 30%, three-month SPI, four month total reservoir inflows, and reservoir storage in April, respectively, resulted in the best characterization of the composite drought index. Table 2 shows the recalculated representative drought indices for a given year. Note that the year corresponding to the five recalculated drought indices covers most years of historical drought records. This suggests that a drought curtailment plan should have been activated in that year.

Figure 2 presents the streamflow forecast for January through June of 2004 into Daechong water supply reservoir. The streamflow runoff is measured just upstream of the reservoir. Figure 2 presents the projected total monthly inflows by month for each ensemble. The upper solid line and middle solid line indicate the maximum historic flow and average historic flow. The bottom solid dotted line represents the minimum historic flow. In general, the twenty ensembles lie between historic maximum and minimum flow. The graph also suggest that during the critical late spring and summer season, the flows are forecasted to be normal. From a water resource management perspective, normal reservoir operation is expected.

Table 2. Recalculated Five drought indices associated with weighted value for historical calendar year

Year	Drought index			Value of recalculated composite drought index	Value of recalculated drought index
	P	S	R		
1981	4	4	5	4.3	4
1982	4	5	4	4.2	4
1983	2	3	4	2.8	3
1984	3	5	2	3.2	3
1985	3	4	5	3.8	4
1986	4	4	1	3.1	3
1987	3	2	3	2.7	3
1988	3	5	4	3.8	4
1989	3	3	2	3.2	3
1990	1	2	1	1.2	1
1991	3	3	2	2.7	3
1992	3	4	4	3.5	4
1993	3	4	2	2.9	3
1994	4	5	3	3.9	4
1995	3	5	5	4.1	4
1996	3	5	3	3.5	4
1997	3	5	4	3.8	4
1998	2	2	1	1.7	2
1999	3	3	1	2.4	2
2000	4	5	2	3.6	4
2001	4	4	3	3.7	4
Note: P:3 month SPI,S: four month streamflow into reservoir, R: average active storage in April					

A six-month forecast beginning in the end of each year indicates the amount of water availability for next year's demand. Since precipitation and temperature are the forcing parameters that determine streamflow forecasts, it is important to evaluate their sensitivity on the results. Figure 3 and Figure 4 include the total monthly precipitation and average monthly temperature, respectively. The average monthly temperature is shown as the deviation from the 30-year historical monthly average, 1973 to 2002. The upper bold line represents the historic maximum monthly temperature and second bold line shows the historic average monthly temperature. The majority of ensembles had temperatures that are projected to be normal during January through March, while most of ensembles from April to June are projected to be above normal. Ensemble 5 in April had temperatures similar to the historic minimum temperature. Figure 4 shows that the prediction for precipitation fluctuates with similar deviation on average over six months. The total monthly precipitation is shown as the ratio of total monthly precipitation of an ensemble to the 30-year historic average of total monthly precipitation, 1973 to 2003. The upper bold line represents the maximum historic monthly precipitation, and second bold line shows the average of historic monthly precipitation.

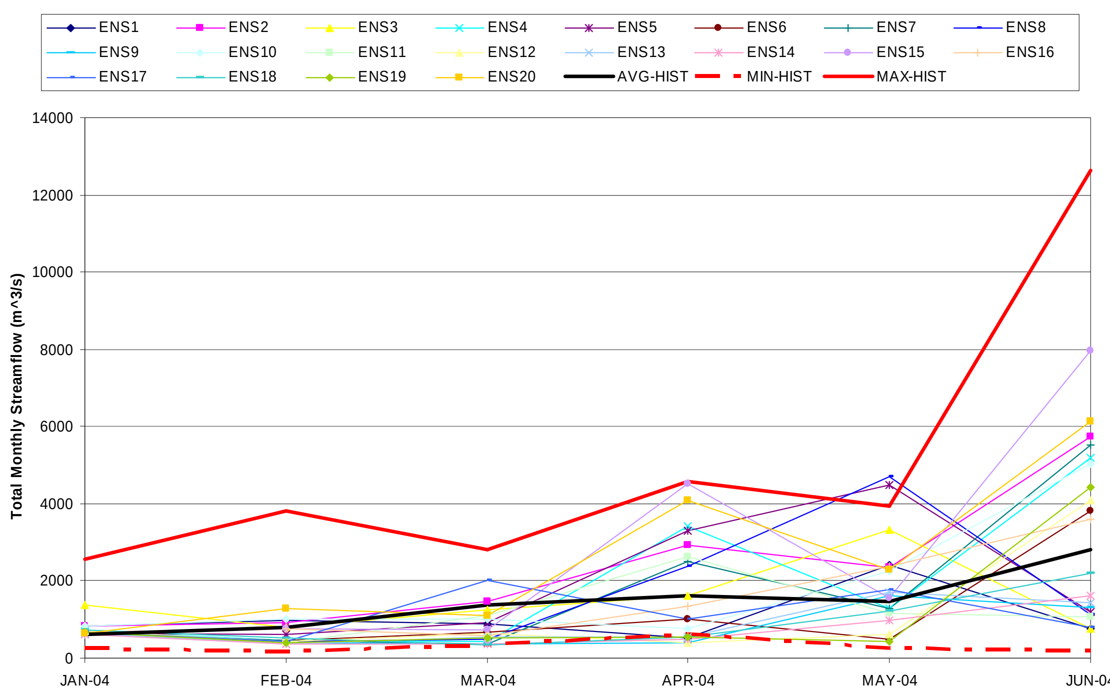

Figure 2. Projected Inflow into Daechong Reservoir for January through June

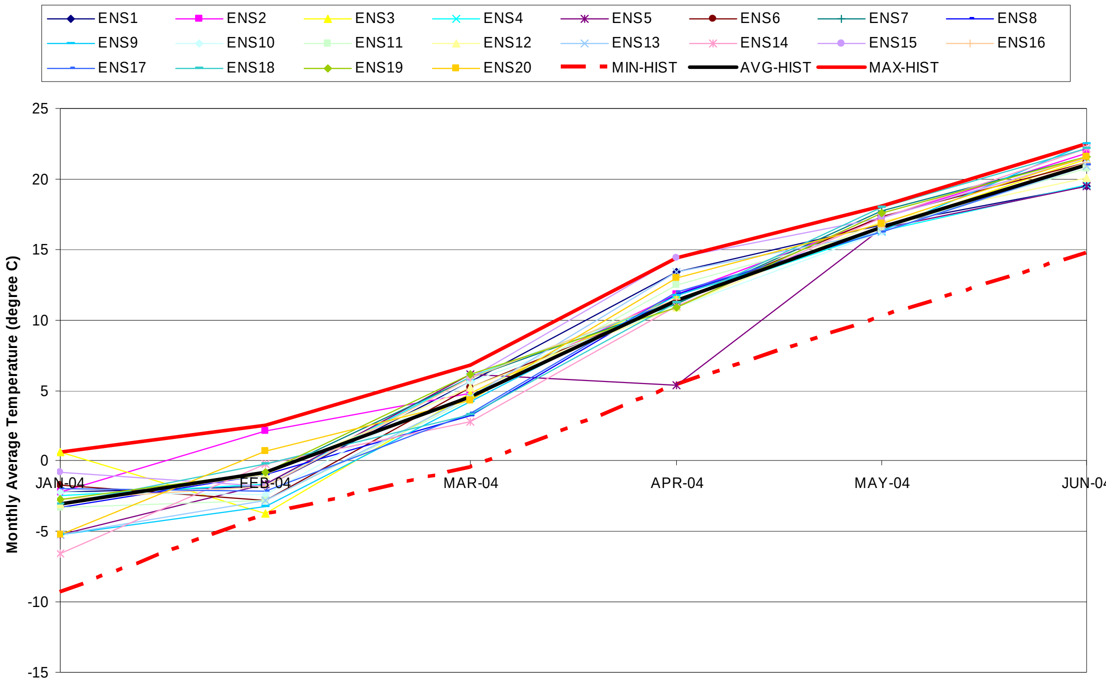

Figure 3. Monthly average temperature at Guemsan weather station

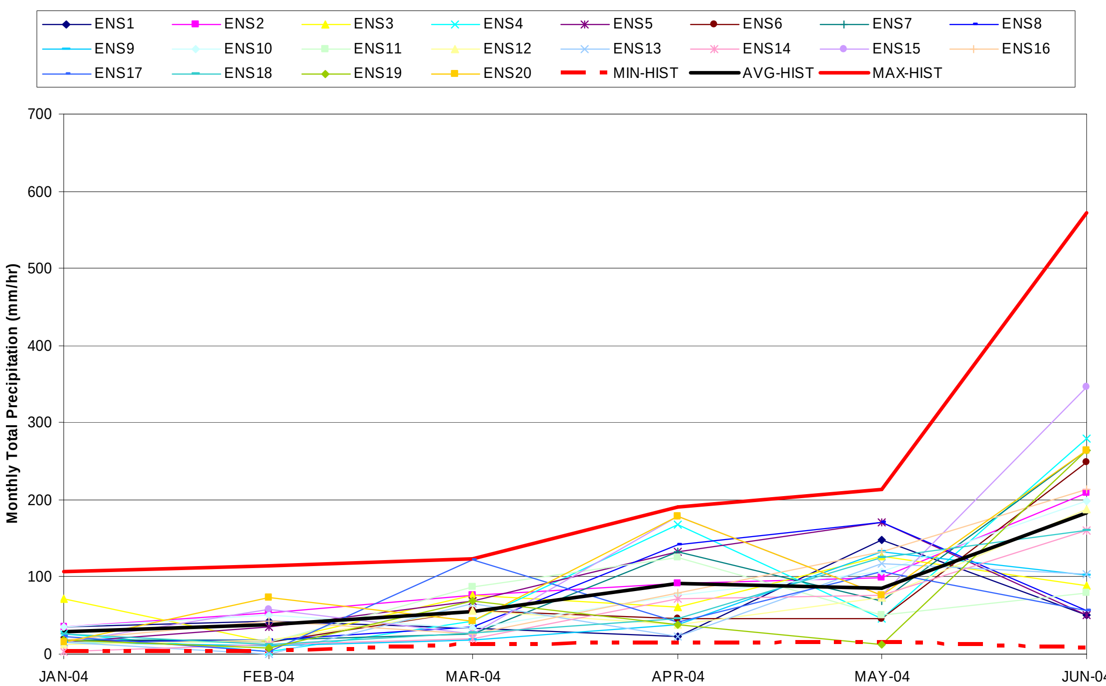

Figure 4. Monthly total precipitation at Guemsan weather station

From January through March, 15 of the 20 ensembles have below normal precipitation as 5 and 8 ensembles with the same precipitation for May and June, respectively. These data indicate that the forecast for the next six months is for average precipitation and temperature over historical records. Obviously, the averages in runoff predicted from January through June are caused by both average forecasts of precipitation and temperature. From May to June, although average precipitation is predicted, this is a critical period and the result should be analyzed with extreme caution because a drought event can occur shortly after a wet season (June thru September). To minimize an economic loss associated with these events, it is necessary to continue monitoring hydrologic status by doing consecutive forecasts.

Adaptive simulation model to monitor on-going drought

A normal year (Figure 6) and drought year (Figure 7) are examined to evaluate adaptive computer algorithms associated with an on-going drought. Figure 5 presents a schematic of storage behavior associated with adaptive computer algorithm defined by the drought index. In Figure 6, starting with the first week of May (19^{th} week in week Axis), the adaptive model doesn't respond to the ongoing drought because current hydro releases at that time are not higher than curtailment of the hydro release defined in the algorithm (500 m^3/s). While continuing monitoring on-going drought until 29^{th} week, there is no other action implemented. But, as it approaches 30^{th} week, the drought level goes up to stage 4, under this situation, the adaptive model responds to help storage levels increase by reducing the amount water released for hydropower. If the adaptive model meets satisfactory condition (Figure 5), the drought index goes back to normal condition, and drought actions will be terminated.

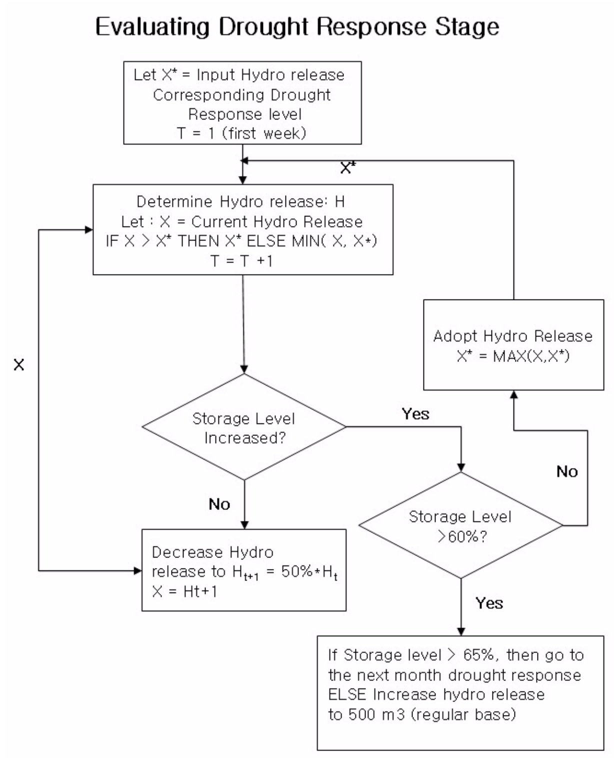

Figure 5. Adaptive computer algorithm responds to on-going drought.

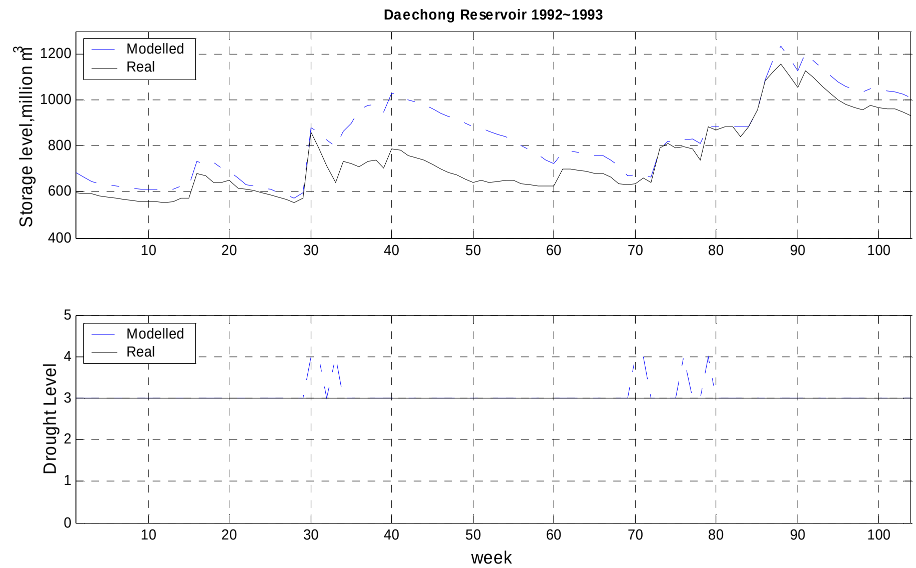

Figure 6. Adaptive drought response during normal years (1992~1993)

In addition to normal years, the model performs well for drought events. Figure 7 represents the storage behavior associated with a severe drought period (1994-1995). Unlike normal years, the model responds by activating drought responses that restrict the amount of hydropower generated.

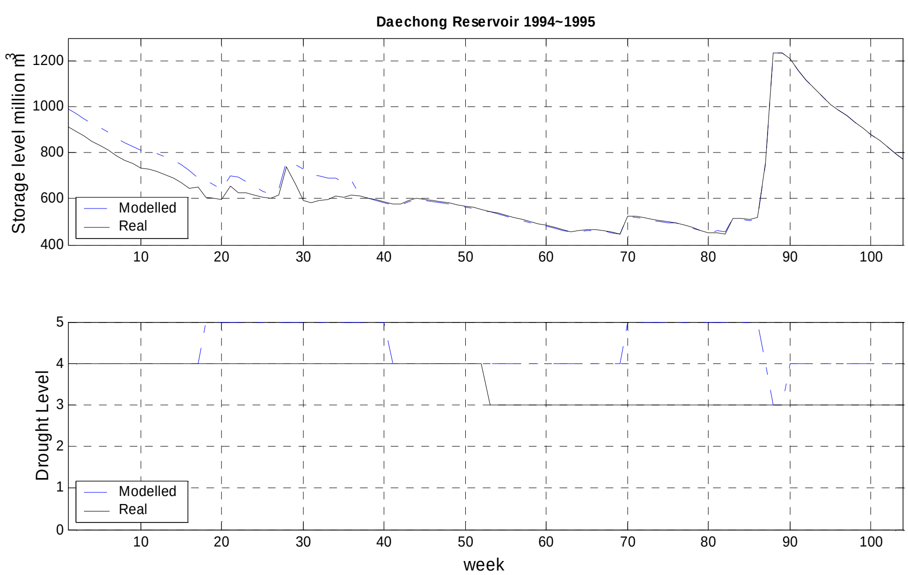

Figure 7. Adaptive drought response during drought years (1994~1995)

The implementation of forecast into adaptive drought monitoring algorithms would be very useful to better manage regional water resources. The 3 month SPI and four month streamflow should be replaced by forecasted 3 month SPI and four month streamflow to define the drought.

As seen in Figure 6, the adaptive drought model works well during normal conditions. This implies that a water resource manager can increase their revenue using available water. If the streamflow forecast component is applied in the adaptive model with a 6 month-lead forecast, the reservoir management would be improved.

Future work

Future research will include: (1) applying the drought definition to more basins to verify its applicability; (2) analyzing historic six-month NCEP forecasts and comparing these to other forecast approaches; (3) investigating the value of daily NCEP; (4) developing heuristic downscaling methods to minimize spatial error from grid point to hydrologic subbasin; (5) evaluating confidence intervals of forecasts.

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