

DECLARING DROUGHT FOR EFFECTIVE WATER MANAGEMENT

S. Kyle McKay¹ and Todd C. Rasmussen²

AUTHORS: ¹U.S. Army Corps of Engineers, Environmental Laboratory, 248 Georgia Ave, Athens GA 30606-2712; ²University of Georgia, Warnell School of Forestry and Natural Resources, Athens GA 30602-2152

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Abstract. Water managers are tasked with resolving conflicts between freshwater resource uses, which range from municipal water supply, to recreation, and to sustaining aquatic ecosystem integrity. Further complicating management, hydrologic processes experience numerous sources of periodic, quasi-periodic, and episodic variation. Water allocation trade offs are often most complex and contentious when availability is low. Drought is a “recurring extreme climatic event over land characterized by below-normal precipitation over a period of months to years” (Dai 2011).

Water managers often apply indicators of climatologic and hydrologic conditions to identify when drought conditions are reached (e.g., Palmer Drought Severity Index, streamflow, respectively). These indicators inform drought declarations, with associated drought responses such as watering restrictions.

Herein, we suggest techniques for predicting and declaring oncoming drought to improve the accuracy of drought declarations. We hypothesize that drought indicators in preceding months are predictive of future drought levels. Specifically, we develop predictive models using the Palmer Hydrologic Drought Index, a common drought indicator. We then demonstrate the utility of our model for drought declarations for the Middle Oconee River near Athens.

INTRODUCTION

Hydrology in the Southeastern United States undergoes numerous sources of variation, such as daily river fluctuations, seasonal climate dynamics, and extreme events. Drought is a common and normal component of this naturally fluctuating regime (Stooksbury 2003). Although the societal costs of recent droughts have been significant, more severe droughts have been observed in both instrumented and modeled history (Campana et al. 2012, Pederson et al. 2012).

Over twenty indicators of drought are commonly applied to measure and evaluate ambient and historical moisture conditions (Heim 2002, Dai 2011). These indicators help water managers identify, declare, and respond to drought conditions (Campana et al. 2012).

We address techniques for identifying oncoming drought conditions in order to declare drought and preemptively adjust water use and management schemes.

Specifically, we develop an approach which relies on varied applications of the Palmer Hydrologic Drought Index for comparing alternative drought prediction techniques.

STUDY SITE

The Middle Oconee River watershed is a 398-mi² basin in the rapidly developing Georgia Piedmont. In 1997, Barrow, Clarke, Jackson, and Oconee counties jointly constructed Bear Creek Reservoir under the auspices of the Upper Oconee Basin Water Authority (UOBWA 1997). This 500-acre off-channel reservoir is filled using water pumped from the Middle Oconee River and is a primary water source for these counties.

The four-county water authority (herein referred to as UOBWA) maintains a contingency plan to respond to — and mitigate the effects of — drought (UOBWA 2003). This plan specifies three primary drought indicators that are used to declare five levels of drought:

- Palmer Hydrologic Drought Index (PHDI),
- Middle Oconee River streamflow at Arcade GA, and
- Bear Creek reservoir levels.

For the purpose of this paper, we focus only on PHDI to evaluate our proposed method; however, similar analyses could be undertaken for drought declaration using other indicators. The PHDI assesses long-term hydrologic conditions for the region on a non-dimensional scale from 6 (extremely wet) to -6 (extremely dry). The UOBWA plan identifies five drought levels based on PHDI values (Table 1), with each level having specific water conservation targets.

Table 1: Palmer Hydrologic Drought Index (PHDI) for determining UOBWA drought levels.

Drought Level	Palmer Hydrologic Drought Index (PHDI)	Water Use Reduction Goal (%)
0	$-0.5 < \text{PHDI}$	0
1	$-1 < \text{PHDI} \leq -0.5$	2.5
2	$-2 < \text{PHDI} \leq -1$	5
3	$-3 < \text{PHDI} \leq -2$	10
4	$\text{PHDI} \leq -3$	20

METHODS

Real-time drought indicators are rarely available due to data and computational burdens. Thus, water management decisions typically rely on data from a previous time period. For instance, August decisions may use July's PHDI data, or this week's decisions may use last week's stream-flow.

Here, we demonstrate the application of simple time series models for predicting current PHDI values and associated drought levels. PHDI values are computed monthly by the National Climatic Data Center for the north-central region of Georgia (NOAA 2012; state code = 09, region code = 02).

Application of prior conditions to predict current (or future) conditions is generally referred to as time series analysis. We used standard time-series methods to analyze data from 1895-2011 ($n=1404$) for the purpose of demonstrating the prediction accuracy of three alternative PHDI models. For each model, PHDI was predicted at time t based on the following equations:

- Current method (UOBWA)
 - $PHDI_t = PHDI_{t-1}$
- Differenced auto-regressive model (Model 1)
 - $PHDI_t = PHDI_{t-1} + (PHDI_{t-1} - PHDI_{t-2})$
- Auto-regressive model (Model 2)
 - $PHDI_t = (PHDI_{t-1} + PHDI_{t-2}) / 2$

Drought levels were computed for each PHDI prediction as well as observed PHDI data at each time step. Because drought levels have associated management actions, models were evaluated based on their capacity to predict drought level, rather than PHDI.

The primary evaluation metric is the number of drought levels different from the observed drought level. For instance, if observed drought level at time t is 2, but a model predicted drought level is 3, then the departure is 1.

We summed the number of data points at each level of departure (ϵ_d) and normalized this by the total number of data points ($\epsilon_p = \epsilon_d / n$). The range of predictive error is bounded between $-4 \leq \epsilon_p \leq 4$, because a prediction error cannot exceed four drought levels. Importantly, positive values indicate a Type-I error (false prediction of drought) and negative values indicate a Type-II error (drought occurred undetected).

To compare our three competing models, an overall score (S) was computed as a weighted average of the magnitude and probability of errors. A low value of this metric indicates high predictive capability, whereas high values indicate low predictive capability (perfect prediction occurs when the score is $S = 0$). This formulation penalizes larger over smaller errors.

RESULTS

While all three models track PHDI values with reasonable certainty (Figure 1A), large discrepancies between observed and predicted values may occur (Figure 1B). In general, these PHDI predictions provide relatively accurate drought declarations, with all three models predicting over 66% of drought levels correctly and over 88% of values within one drought level (Figure 2). However, dramatic 2-, 3-, and 4-drought level errors occasionally occur. Interestingly, the models do not demonstrate a bias toward Type-I (false positive) or Type-II (false negative) errors.

Although all models demonstrate similar efficacy, the scores favor the UOBWA method over models 1 and 2 with scores of 0.338, 0.489, and 0.409, respectively. This is attributable to the UOBWA method's low prevalence of drought-level differences of more than one level (5.6%).

DISCUSSION

Early detection of dry conditions and accompanying drought declaration is critical to water management. This analysis demonstrates a simple method for comparing alternative detection methods using three simple time series models, and compared their utility in declaration decisions. In this analysis, the existing UOBWA model proved superior to the other two formulations. However, additional research is needed to reduce the number of declaration errors, including:

Time series models. Time series analysis has a wealth of applications, from tracking markets to weather forecasting. We present three simple models, but additional analyses may reveal that more complex models would better detect drought. For instance, Rugel et al. (2012) demonstrate predictability of river discharge in Georgia on time scales as long as six months.

Drought indicators. Drought detection is a complex multi-metric process, and we have only considered a single variable, the PHDI. The UOBWA also relies on river discharge at weekly and monthly time scales to make withdrawal decisions (UOBWA 2003). Furthermore, other indicators such as the Standard Precipitation Index (SPI) are also quite useful in drought decision-making (Campaña et al. 2012).

The UOBWA declares drought levels based on an average of indicators from PHDI, discharge, and reservoir levels. The first two indicators are not influenced by local managers, and thus respond to ambient conditions. Reservoir levels, however, may be manipulated out-of-sync with ambient moisture levels, and are likely to be poor drought indicators.

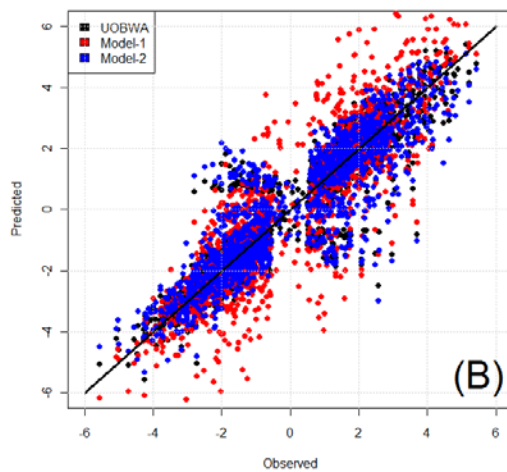
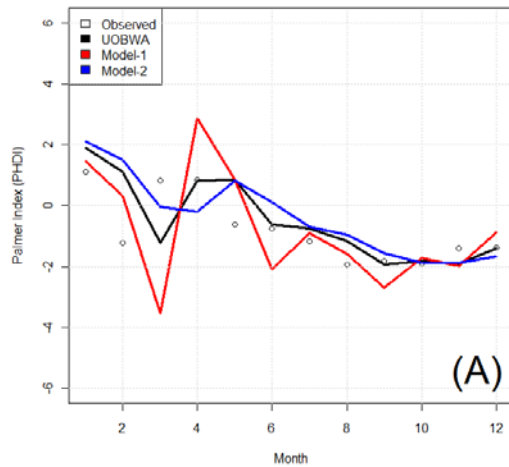


Figure 1: Model evaluation: (A) model predictions over a sample time period in 2011, and (B) observed vs. predicted PHDI.

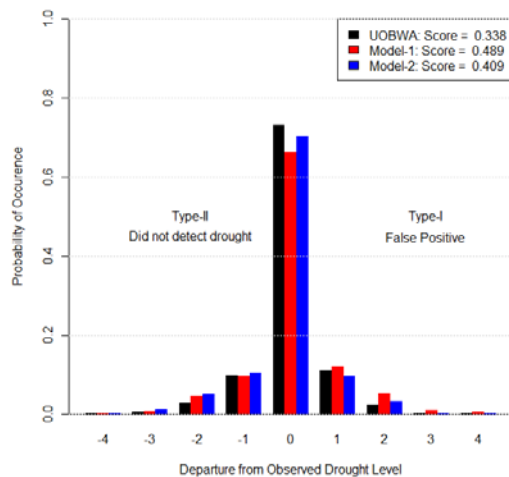


Figure 2: Departures from observed drought levels.

Reservoir levels are response variables to management actions, and we recommend a more nuanced approach for their incorporation into drought declaration decisions. For instance, if drought levels based on PHDI, discharge, and reservoir levels were 4, 3, and 0, the overall drought level would be only 2, which is a clear understatement of the existing conditions.

What is needed is a metric that relates the reservoir volume to the predicted total demand for water for the remainder of the season. Thus, low water levels late in the season should be managed differently than low levels early in the season. The difference between the total reservoir volume (plus projected river withdrawals) and the predicted demand for the rest of the season would provide such a metric. In fact, the drought response could be managed so that conservation reduces the gap between available and needed supplies.

Methods such as those presented here help water managers preemptively respond to drought by making informed drought declaration decisions. Methods for accurate, reliable, and repeatable drought detection and declaration are challenging to develop. However, this topic is likely to become more important in light of increased demand for freshwater in the Georgia Piedmont and the relative wetness of the late-20th century (Pederson et al. 2012).

We have presented a simple method for analyzing alternative drought declaration schemes, and although we have focused on simple models, we believe this general framework is transferrable to other basins, drought indicators, and more complex models.

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NOTATION

- ϵ_d Number of incorrect drought-declaration predictions
- ϵ_p Probability of incorrect drought-declaration predictions
- n Number of PHDI observations
- S Weighted-averaged of model accuracy and probability of error

PHDI Palmer Hydrologic Drought Index
 UOBWA Upper Oconee Basin Water Authority

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² <http://www.ncdc.noaa.gov/temp-and-precip/drought/>

³ www.bearcreekwtp.com

⁴ www.bearcreekwtp.com