Value of ENSO-Forecasted Drought Information for the Management of Water Resources of Small to Mid-Size Communities

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2 authors:

Vaishali Sharda
Kansas State University

Puneet Srivastava
University of Maryland, College Park

VALUE OF ENSO-FORECASTED DROUGHT INFORMATION FOR THE MANAGEMENT OF WATER RESOURCES OF SMALL TO MID-SIZE COMMUNITIES

V. Sharda, P. Srivastava

ABSTRACT. *There have been great advances in climate forecasting ability in recent years. However, the use of this information in water management decision-making has been lacking. The temporal and spatial scales of forecasts and the difficulty of understanding forecast products have been cited as key reasons for the lack of use of these forecasts. The Community Water Deficit Index (CWDI) was previously developed as a tool to use El Niño Southern Oscillation (ENSO) forecasts to forecast droughts in small to mid-sized communities of the southeastern U.S. This study investigated the monetary value and benefits of using CWDI as a seasonal drought forecasting technique. The efforts were focused on determining the usefulness of drought information for municipal water management, the usefulness of water restrictions imposed by municipal water management, and the extent to which advance knowledge of probabilistic drought forecasts mitigates negative impacts. The results indicate that water use restrictions are effective for coping with drought, and the benefits of using forecasts and water management adjustments should involve planning. It was also found that by using drought forecasts, and thus having a drought preparedness plan, communities can save both water and money.*

Keywords. *Climate variability, Mitigation, Municipal, Saving, Stakeholder, Water availability, Water management.*

Drought can be defined as scarcity of precipitation over a geographic area for an extended period, resulting in water shortages (NWS, 2008). Drought or the threat of drought has become a constant problem in many parts of the U.S. and, apart from being a costly natural disaster across many sectors, has become one of the most serious and complex problems confronting water resource planners. Walker et al. (2008) stated that because it is hard to tell exactly when a drought starts and when it is over, a drought can be compared to an economic recession. Despite the fact that droughts cost billions of dollars every year in the U.S. (Ryu et al., 2010), there is no methodical effort to determine its complete impact. Most states now implement drought management plans, a crucial aspect of which is to establish a link between drought status in a basin and management actions. It has been suggested that, to mitigate adverse impacts of drought, proactive planning is more effective than reactive crisis management (USACE, 1993; Wilhite, 1991; Wilhite and Rhodes, 1993). As such, it is important to develop tools for water managers whose systems are vulnerable to drought to assist them with advance planning.

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The authors are **Vaishali Sharda, ASABE Member,** Graduate Student, and **Puneet Srivastava, ASABE Member,** Professor, Department of Biosystems Engineering, Auburn University, Auburn, Alabama. **Corresponding author:** Vaishali Sharda, 152 E. J. Frick Dr., Manhattan, KS 66503; phone: 510-305-4262; e-mail: vzs0003@tigermail.auburn.edu.

Improved information about future climate fluctuations can help decision-makers take advantage of climatic good fortune and mitigate the impact of adverse situations. Recent advances in seasonal climate forecasting offer the potential to improve the ability and willingness of stakeholders to respond to forecasts of climate fluctuations. Despite the potential usefulness of seasonal forecasts, they currently remain underused, with forecasts playing a marginal role in decision-making (Callahan et al., 1999; Pulwarty and Melis, 2001). Many obstacles to forecast use have been stated in the literature, including unawareness of their existence, distrust of their accuracy, perceived irrelevance to management decisions, and competition from other innovations (Carbone and Dow, 2005). Other concerns about the use of seasonal forecasts include the forecasts being difficult to understand and apply in decision-making (Pulwarty and Redmond, 1997; Stern and Easterling, 1999). While the use of forecast products by themselves cannot decrease the vulnerability of a community water system to drought, past observations and available projections of climate variables such as precipitation and temperature at seasonal to decadal timescales can potentially help communities prepare for water shortages (Lowery et al., 2009). Water authorities in most parts of the world use very conservative tactics in managing their water supply systems, and very few make use of seasonal forecasts (Chiew et al., 1998).

The southeastern U.S. is an area that is vulnerable to drought, given the extreme interannual variability of water availability as well as growing water demands and shrinking supplies. Demand for water has increased in the region due

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to rapid residential, industrial, and recreational growth; climate variability in the region intensifies the situation. Seasonal climate variability influences water supply availability, which is important for municipal water management as well as for other important phenomena that depend on water availability, such as agricultural productivity, animal and human disease epidemiology, populations of plants and wildlife, and many others (Barrett, 1998). Coping with the problem of maintaining a balance between water demand and water supply has become the focus of most surface water managers in the region. Water supply enhancement in the form of purchasing water, groundwater mining, interbasin transfers, and construction or enhancement of reservoir storage has been the traditional method for dealing with drought conditions (Pagano et al., 2001). However, most of the approaches are expensive and do not have social or political support (WWPRAC, 1998).

In the southeastern U.S., most climate variability is attributable to the El Niño Southern Oscillation (ENSO) (Hansen et al., 1998; Schmidt et al., 2001), with drier conditions associated with the La Niña phase and wetter conditions associated with El Niño. ENSO is a climate pattern driven by cyclical warming and cooling of sea surface temperatures in the equatorial Pacific Ocean. Because detailed scientific understanding of ENSO began around 1997, the ability to provide reasonably reliable ENSO-based forecasts of climatic variables is a very recent development (Chiew et al., 1998; Crane et al., 2011). That said, ENSO is being extensively used as an indicator to study precipitation and temperature patterns at different scales (Andrews et al., 2004; Sharda et al., 2012). For forecasting, there is a vast difference between forecasting the ENSO phase and the ability to forecast the impact of ENSO on the climatic variables that matter to stakeholders (Barrett, 1998). This indirect relationship makes the value of ENSO-related forecast information dependent on the strength of the intervention. Although the accuracy and lead times of ENSO phase predictions have improved considerably over the past few years, these predictions can explain only a small part of the variation in the variables most important to decision-makers (Hansen, 2002). Despite the above-mentioned constraints, there is increased interest in the relationship between ENSO and hydrologic variables, and several recent studies have investigated the benefits and risks associated with using hydrologic forecasts for drought management, reservoir operation, and other hydrologic applications (Chiew et al., 1998).

The value of forecasts is in improved decision-making, which could reduce costs and losses to water users and reduce social disruption. A study in Arizona (Pagano et al., 2001) found that the use of ENSO forecasts in the "wet" winter of 1997-1998 saved the Salt River Project $1 million by reducing groundwater pumping. However, there are counter examples of "failed" forecasts (Changnon, 2002), the short-term effects of which were still considered positive for the water management sector, whereas the long-term effects were generally negative. Therefore, a certain level of uncertainty needs to be included in the forecasts.

The main challenge for forecasters is to provide reliable and useful forecast products that can be understood and used by stakeholders who may or may not be technically qualified. A myriad of forecast products are freely available on the internet that include outlooks provided by the National Weather Service (NWS), Climate Prediction Center (CPC), International Research Institute for Climate and Society (IRI), along with several other research groups, such as the U.K. Meteorological Office (UKMO) (Evans et al., 1998) and the European Center for Medium-Range Weather Forecasting (ECMWF) (Stockdale et al., 1998), that work on development of numerical model forecasts. None of these products are tailored specifically to the needs of water resource managers who primarily rely on surface water resources, especially those of small to mid-size communities in the southeastern U.S. To deal with these circumstances, communities in the southeastern U.S. would benefit from a sophisticated surface water management system that can measure drought impacts, management actions, and incorporate climate information. This is a prerequisite for estimating the value of climate forecasts in water management.

Given the complex relationship between climate forecast adaptation and water management, and in a time increasing water scarcity and climatic uncertainty (Kenney et al., 2014), there is a need for an approach that aims at water conservation by cutting demand, especially in regions like the southeastern U.S. where climate variability significantly impacts water availability (Sharda et al., 2012). Keeping this in mind, the Community Water Deficit Index (CWDI) was developed to forecast ENSO-based drought for the small to mid-sized communities of the region (Sharda et al., 2013). This tool forecasts hydrologic drought, defined as drought associated with periods of precipitation shortfall on surface and subsurface water resources (Dracup et al., 1980), three to four months in advance and operates at the spatial scales most desired by water resource managers. More importantly, it is based on a novel approach that considers both the water availability and water demand of a community.

However, the usefulness and value of CWDI remain to be established. The purpose of this study was to assess the value of this unique ENSO-based hydrologic drought forecast tool for small to mid-size communities of the region. The value or usefulness of drought information available through CWDI was assessed by studying the seasonality of water demand, the impact of drought (climate variables) on municipal water demand (i.e., how consumption changes with precipitation and temperature), and the use and effectiveness of water restrictions in curtailing seasonal demand. The study also dealt with how drought forecasts can influence the decision-making process or mitigate the negative impacts of drought, i.e., how forecasts can help in imposing conservation measures and in arranging alternate or supplemental water supplies. The key contribution of this study is to demonstrate the value of CWDI as a seasonal drought forecasting tool and thereby increase the adoption and use of forecast products by water managers in the southeastern U.S.

Methods

Study Area

To investigate the value and usefulness of drought forecast information, a case study that uses the consequences from the intended users' viewpoint was used. Past researchers have reported that the use of perspective studies to examine forecast information can be helpful to increase the understanding and implementation of forecasts (Katz and Murphy, 1997). Because the usefulness of any forecast is based on the opinion of potential users, it can be best achieved through the cooperation of forecasters and users (Pagano et al., 2001). Instead of making assumptions, a cooperative approach that ensures the needs of the users are known and targeted by the forecaster is required to avoid the risk of issuing forecasts that do not inspire confidence among the users (Ritchie et al., 2004).

Keeping the above points in mind, the methodology presented in this article was tested for the city of Auburn, Alabama. Auburn, located in Lee County, is a city of around 55,000 people. For 85% of its water supply, the city relies on Lake Ogletree, which is situated to the southeast of the city. Apart from Lake Ogletree, the city has an agreement with the neighboring city of Opelika to purchase water on a monthly basis. The storage in Lake Ogletree is also supplemented by water pumped in from two quarries in the area. Increasing water demand and recent droughts in the region (2000 and 2007) associated with the La Niña phase of ENSO (fig. 1) have put the city's water managers in a dire water availability situation many times in the past (Auburn, 2011). Because the city relies on a surface water source, is a mid-size community, and is located in the southeastern U.S., it is an ideal subject for this case study. A case for the dependence of community water demand on climate variables was built first, followed by studying the effectiveness of use restrictions on water demand, and then the importance and value of drought forecast information for water resource managers were studied.

Data

Historical precipitation and temperature data were required to run various components of this study, and these data were obtained from the National Climate Data Center (NCDC, 2010). Historic water demand data (gallons per day) were obtained from the city of Auburn for a period of eleven years (1998-2010). Auburn also provided historic lake level data for the years 1980 to 2011. The ENSO forecast from the International Research Institute for Climate and Society (IRI), which was used in this study, provides sea surface temperature anomalies in the Niño 3.4 region of the Pacific Ocean based on an average of 22 different dynamic and statistical models (http://iri.columbia.edu/climate/ENSO/currentinfo/SST_table.html). Auburn provided unit cost of production and unit cost of purchase per 1000 gallons of water. The cost of production includes costs for pumping, purification, distribution, meter reading, billing and collection, operational administration expenses, and general operation expenses. Auburn has a purchase agreement with the neighboring city of Opelika and has to purchase a minimum of 8 million gallons per month and can buy up to 3.6 million gallons per day (table 1).

Table 1. The city of Opelika's schedule of rates for sale to resellers of water to public water systems (source: www.owwb.com).

	Monthly Consumption (gal)	Unit Price (per 1000 gal)
Min	25,000	\$2.77
Next	50,000	\$2.54
Next	75,000	\$2.48
Next	100,000	\$2.43
Next	125,000	\$2.36
Next	150,000	\$2.25
Next	175,000	\$2.15
Next	700,000	\$2.06

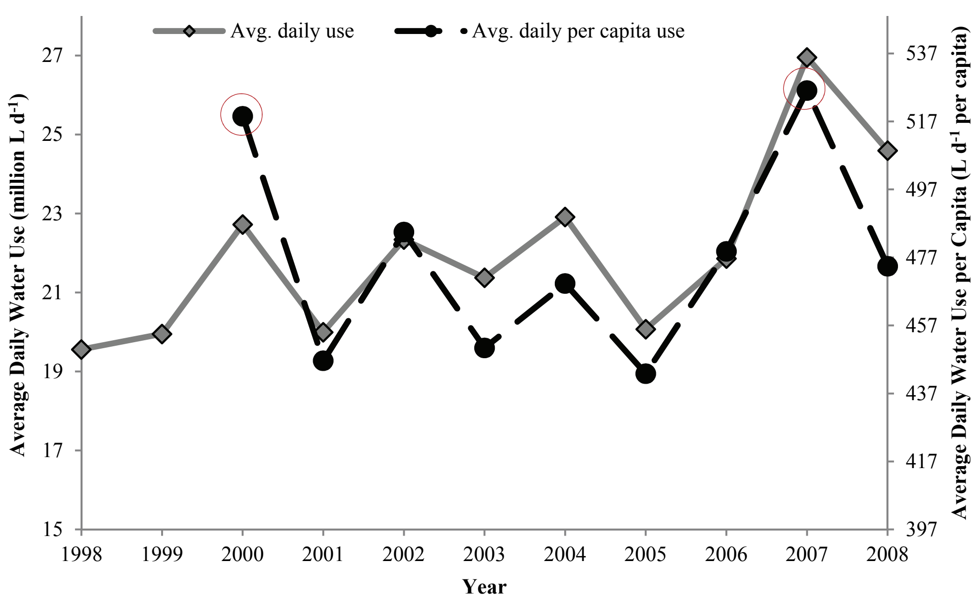

Figure 1. Average daily water use in Auburn, Alabama, for the past 12 years in million liters per day (solid line) and per capita (dashed line) (Sharda et al., 2013). Note that 2000 and 2007 were drought years caused by La Niña. Per capita water demand increased significantly during these years.

Water Demand and Effectiveness of Restrictions

The two main reasons for forecasting water demand of a community are long-term planning and short-term operation (Polebitski and Palmer, 2010). The variation in annual water demand of a community is driven by climate variables, such as precipitation and temperature, due to outdoor water use in urban and suburban areas. This seasonality of water demand is an important basis to study the impact of climate variables on daily water demand of a community. The historic daily demand data (gallons per day) showed that this variable was highly variable across the dataset. Generally, water managers compare daily water use (demand) during periods of restricted water use to water use during the same periods in the past to determine the effectiveness of municipal water restrictions during periods of drought or low water availability. However, this approach does not consider the impacts of climate on water use and demand. Therefore, in this study, daily water use during periods of restricted use was compared to an estimate of "expected use" of water. "Expected use" was defined as water that would have been used in the absence of restrictions, given the temperature and precipitation conditions. This comparison would thus help in evaluating the impact of climate on water use and the true effectiveness of water restrictions. Daily precipitation and temperature data were used as predictors in a multiple regression model to predict expected use of water along with a one-day lag variable to account for temporal persistence in the time series of community daily water use. Because population is the largest factor determining water demand (Gutzler and Nims, 2005), it was important to isolate the demand component related to climate variability. Therefore, water use data were converted to per capita water consumption. Similar approaches to study the impacts of climate on water use were mentioned by Kenney et al. (2004) and Shaw et al. (1992). The regression model developed was in the form of equation 1:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \varepsilon \qquad (1)$$

where y is the per capita water use; x_1, x_2, and x_3 are the predictor variables (daily maximum temperature, daily precipitation, and one-day lag variable of water use, respectively); β_0 is the regression constant; β_1, β_2, and β_3 are the slope coefficients for the predictor variables; and ε is the error. The regression model was developed using SAS software (SAS Institute, Inc., Cary, N.C.), and the coefficients were estimated using data from years in which no restrictions were issued by the community. The coefficients in the regression equation were estimated using data from the year 2002 and tested for the years 2003 and 2004. The R^2 values obtained from the regression model were used to establish the accuracy of the model in predicting water use using the climate variables (eq. 5).

Forecasting Drought Using CWDI

Based on Auburn's drought management plan, phases of drought are defined by the percentage of lake storage available. Drought phases are assigned according to the level of storage desired and may depend on the season of the year. This information was provided by Auburn water managers. According to the city's drought plan, it is assumed that Lake Ogletree can meet peak water supply needs during droughts if it is at full pool on May 1 (after winter and spring rains) in any given year. If the lake level is less than full pool on May 1 in any given year, a phase 1 drought is declared to manage water use by Auburn's customers. A phase II drought is declared when the water level reaches approximately 65% of the lake's storage volume. A phase III drought is declared when the storage volume is 50% of the full pool volume, and a phase IV drought is declared if the lake level reaches approximately 40% of the full storage volume. Figure 2 shows the drought phases during the 1999-2001 droughts for Lake Ogletree, ranging from moderate (phase I) to extreme (phase IV). These droughts coincided with a strong La Niña phase, as described by the Niño 3.4 index, indicating the impact that ENSO has on water availability for the city. This relationship between La Niña and water scarcity in the southeastern U.S. (Sharda et al., 2012) formed the basis for developing CWDI as a tool to forecast ENSO-induced drought in the region. CWDI is a supply-and-demand water balance model that considers the decrease in supply and increase in demand for irrigation during drought conditions (Sharda et al., 2013). During the low-precipitation and high-temperature ENSO phase (La Niña) in the southeastern U.S., the loss of soil moisture through evapotranspiration increases the demand for outdoor water use by residents (e.g., watering lawns), which increases the stress on water availability for the community. In CWDI, demand is divided into two components: static demand, which is not dependent on climate and consists of water use for indoor purposes, and dynamic demand, which is dependent on climate (ENSO) and arises from outdoor use. The supply-and-

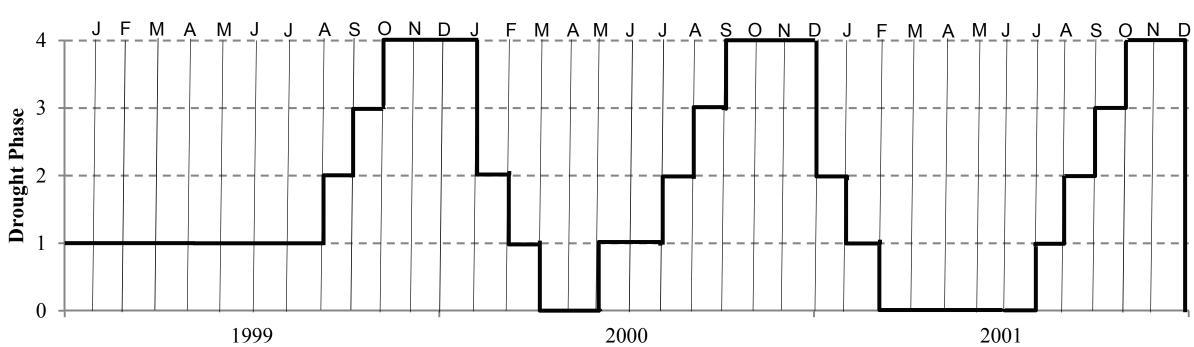

Figure 2. Droughts of record for the period 1999-2001 for Auburn, Alabama (source: city of Auburn).

demand water balance in the watershed leads to the total available storage in the reservoir.

The CWDI was estimated as the ratio of the available storage and the desired level of water storage in the reservoir of the community and is given as:

$$\mathrm{CWDI} = \frac{S}{S_d} - 1 \tag{2}$$

where S is the available storage in the reservoir, and S_d is the desired storage in the reservoir. The available storage (S) in the reservoir is calculated as a part of the CWDI model, whereas the desired storage (S_d) is a user input or is supplied by the water managers:

$$\text{If } S \geq S_d,\ \mathrm{CWDI} \geq 0, \Rightarrow \text{No deficit} \tag{3}$$

$$\text{If } S < S_d,\ \mathrm{CWDI} < 0, \Rightarrow \text{Deficit} \tag{4}$$

Previous studies have shown that multimodel climate forecasts outperform single-model forecasts, thereby reducing uncertainty and false alarms (Golembesky et al., 2009). Using IRI's ENSO forecasts, Spectral Weather Generator (Schoof et al., 2005; Schoof, 2008) was used to generate ENSO-constrained climatic variables, which were then used to forecast CWDI three to four months in advance. To account for uncertainty in the dataset, ensembles of daily data constrained by the seasonal forecast were used. CWDI has been tested and validated for Auburn to show that the CWDI forecast has skill and is consistent. More detail on how CWDI forecasts drought can be found in Sharda et al. (2013). Figure 3 shows CWDI forecasts in terms of percentage lake capacity for some of the past drought years.

Based on the ENSO phase (La Niña) during a year, the CWDI model was run to create an ensemble forecast for each year beginning in November to show what the drought forecast would have looked like during November through March. This period was chosen to coincide with the principal recharge period for reservoirs in the southeastern U.S. (especially Alabama and Georgia). This period was selected in discussions with Auburn water managers. To obtain the CWDI forecast ensemble (95% confidence band), IRI's ENSO forecast value in the Niño 3.4 region was used to constrain the weather generator.

Value of Forecast Information

The potential value or usefulness of this forecast information for water resource managers was determined by assessing how this information might allow mitigation of negative impacts. The model was run to estimate how demand management could be changed through practices such as conservation measures, imposing voluntary and mandatory restrictions, and altering transfer or purchase agreements. The value of CWDI forecast information was studied by quantifying the water and cost savings for the community

Month	1998-99	1999-00	2007-08
Nov	30.70	46.13	48.90
Nov	36.02	43.66	45.44
Nov	37.56	50.73	43.95
Nov	40.42	48.64	52.21
Dec	38.85	47.69	53.03
Dec	39.29	47.33	49.72
Dec	40.74	50.27	47.44
Dec	41.97	55.28	47.40
Dec	41.87	53.81	44.82
Jan	42.36	51.67	44.93
Jan	42.56	49.19	43.19
Jan	40.74	52.96	46.43
Jan	40.34	54.19	54.65
Jan	43.90	55.21	65.54
Feb	45.70	52.98	63.64
Feb	45.70	49.86	61.49
Feb	45.13	46.77	59.17
Feb	43.38	45.06	65.17
Mar	47.30	45.50	65.29
Mar	49.60	48.66	62.78
Mar	52.40	64.03	68.16
Mar	54.10	72.62	72.23

Phase I
Phase II
Phase III
Phase IV

Figure 3. Weekly drought phases assigned to percentage lake capacity as forecasted by CWDI for La Niña years studied for the Auburn, Alabama, water supply system. Drought phases were attributed according to Auburn's proposed drought plan.

based on the assumption that this information was used to plan ahead and create awareness or impose voluntary or mandatory restrictions depending on the drought severity.

The conservation measures adopted by the city, the supply enhancement policies, and other water management options were studied in the context of using CWDI as a planning tool. Because ENSO has a clear impact on climate variables in the southeastern U.S. during winter months (October to March) and the predictability decreases over summer months (Sharda et al., 2012), CWDI was forecasted only until March.

For estimating the value of drought information over summer months, observed historic climate data were used along with target conservation measures depending on the drought phase. Based on past strategies used by the water managers, the following three elements were studied:

1. The first element is planning for drought before it occurs. This planning can include water conservation programs and increasing public awareness about the possibility of a drought.

2. The second element is identifying and classifying drought based on the water supply. The CWDI forecast indicates the status of water availability in the system. This water availability information can be used to identify and classify droughts, and interventions can be planned accordingly. The best time to identify and classify a drought will be during the recharge period, i.e., December to March. Once the drought is identified, it can be communicated to the public in March or April, rather than in June or July when the community is already well into the drought and there is no way to recover. When the reservoir levels improve, water managers can officially lift restrictions and remove fines and surcharges. To identify and classify droughts, a demand reduction goal was set, and it was assumed that the water managers, looking at the severity of the forecasted drought, would take measures to conserve water or curtail demand. The goals used for demand reduction were adapted from Walker et al. (2008) and are given in table 2.

3. The third element is responding to a drought by increasing supply and decreasing demand. Increase in water supply can be achieved by purchasing water from an outside source with which the community already has a contract or other supplemental supply options depending on the system structure, for example, groundwater withdrawal. Measures for decreasing water demand include reducing the water budget of the municipality as a whole. Individual water budgets can be reduced by percentages specific to the outdoor use of water, and wise water use practices can be emphasized.

These three elements can help evaluate the drought information available to water managers and help guide how they use this information to formulate drought response plans and

Table 2. Demand reduction goals with the use of Community Water Deficit Index (CWDI) (adapted from Walker et al., 2008).

Drought Phase	Drought Description	Conservation Goal	Proposed Actions
I	Incipient	5%	Public awareness
II	Moderate	15%	Voluntary restrictions
III	Severe	20%	Mandatory restrictions
IV	Extreme	25%	Mandatory restrictions plus drought rates

policy changes. This information can also help water managers cope with drought and help communities be well prepared and aware of forthcoming drought.

Based on the drought phase at the beginning of the forecast period, target conservation percentages were applied in the dynamic demand component of the CWDI model to achieve better storage levels in the reservoir. The changes in storage level were then converted to volumetric savings of water as well as economic savings.

The water savings arise from conservation achieved by the community in compliance with the water restrictions or conservation measures imposed by the city in anticipation of approaching drought. This saving was calculated as the difference between the storage levels forecasted (using CWDI) and the observed storage levels at end of each month. The CWDI model was run at a daily time step, and the results were presented at a weekly time step to meet the expectations of the water managers. A monthly time scale was used to calculating savings because the conservation measures are usually issued by the communities once every month. The economic component was analyzed by using the unit cost of production and the unit cost of purchase per 1000 gallons of water. The monthly savings in the cost of water arise mainly from reducing the need to purchase water from Opelika. Along with these costs, the cost arising from loss of revenue due to target conservation measures was also accounted for. Although this information is community-specific, it illustrates the potential importance of drought forecast information for water resource managers of small to mid-size communities.

RESULTS AND DISCUSSION

WATER DEMAND AND EFFECTIVENESS OF RESTRICTIONS

Patterns of precipitation, temperature, and monthly water use are presented in figure 4. Monthly water use was obtained by averaging population-weighted data across the entire sample. The seasonality of water use is evident in figure 4c, but other interesting details are also apparent. Demand in winter months is rather invariant from year to year, whereas water use during summer months can be highly variable from year to year. Figure 4c shows a definite seasonality in water demand during drought years. Water demand increased during these years, compared to normal years, because temperatures were high and there was not enough precipitation. As the residents watered their lawns to keep the grass alive, water use spiked during May through August. To date, Auburn has not enforced mandatory water restrictions. However, the city has raised public awareness and implemented voluntary restrictions. These efforts include asking residents to water their lawns only two or three times a week, alternating the watering schedule between odd and even numbered addresses. Voluntary restrictions also call for residents to water only between 6:00 p.m. to 8:00 a.m., when because evapotranspiration is lowest.

Equation 5 is an example regression equation for the year 2000, which was a drought year when no water restrictions were imposed:

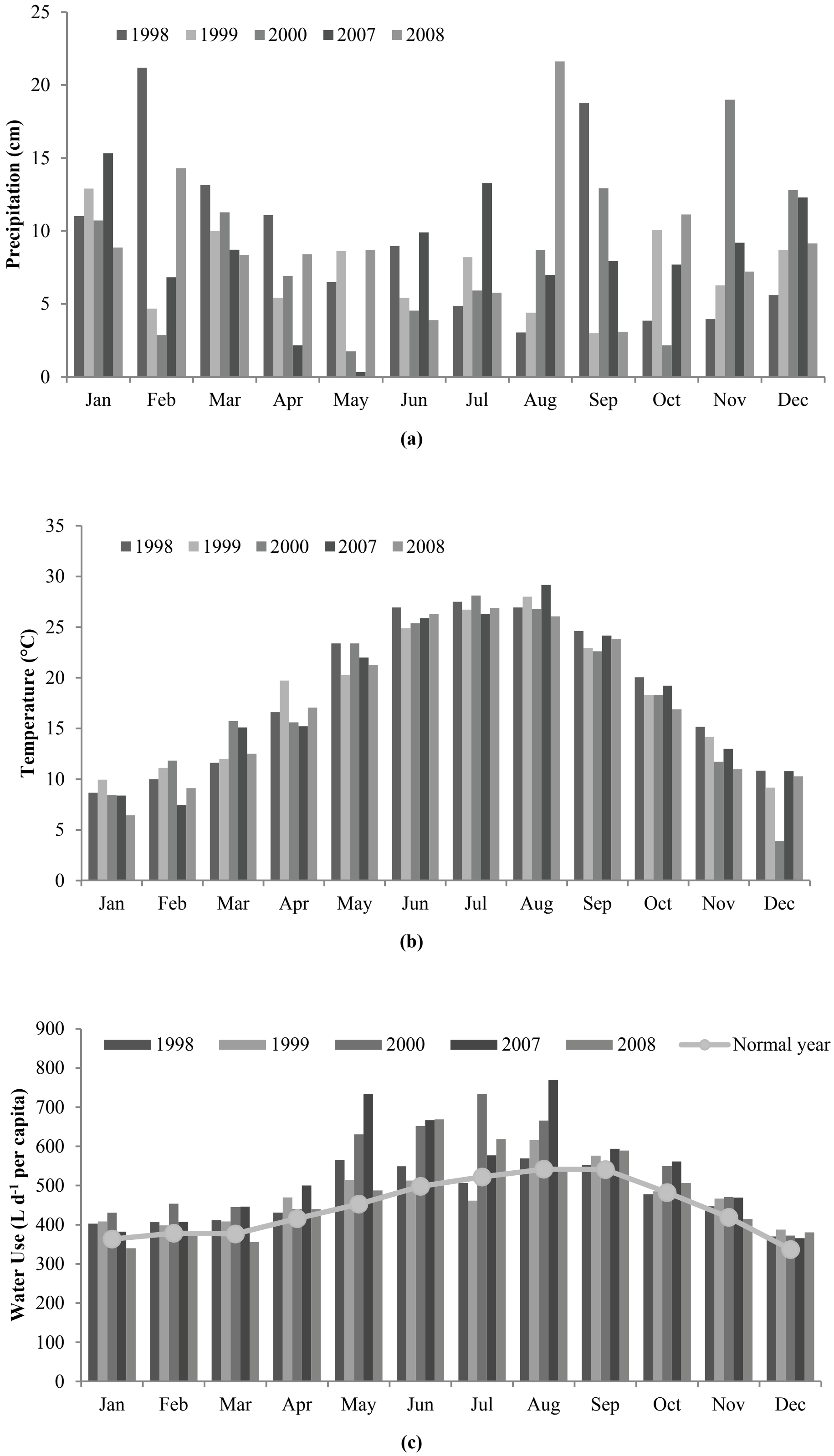

Figure 4. (a) Total monthly precipitation pattern for Auburn during some historic drought years, (b) average monthly temperature pattern for Auburn during some historic drought years, and (c) monthly water use for drought years showing seasonality of water demand.

$$y = -0.46R + 0.19T + 0.71L + 0.18 \quad (5)$$

where R is daily precipitation, T is daily maximum temperature, and L is the one-day lag variable of water use.

The regression model showed skill in predicting water use, with R^2 values ranging from 0.65 to 0.81. Greater accuracy could be achieved using more sophisticated regression techniques. However, this regression model addresses the purpose of our investigation, which was to describe drought response in this case study. The regression model also shows that water use and demand have a positive relationship with temperature, indicating that water use increases with increase in temperature. An inverse relationship was observed for precipitation. A strong relationship was observed for the one-day lag variable for current demand, indicating that water use on a given day is a function of water use on the previous day. This outcome was expected and provides an assessment of anticipated water savings that could be attributed to climate.

The developed equation was then applied to data from a period when restrictions were in effect (2007 and 2008) to estimate the expected use. The difference between actual and expected water use during that period was calculated to estimate the effectiveness of water restrictions during drought.

Water savings over the period of restrictions were also investigated to study the effectiveness of water restrictions. Total water savings were calculated by comparing the 2007 and 2008 water use with the average of 2002, 2003, and 2004, whereas expected use was a comparison of actual per capita use during 2007-2008 with the water use expected due to climatic conditions, which were calculated using the regression model. These values were calculated both for the entire study period and for the restriction period, i.e., 1 October 2007 to 30 June 2008. The difference between expected (calculated using eq. 5) and actual (observed) water use is shown in figure 5. This figure provides an estimate of the water savings that can be attributed to the drought-inspired water restrictions imposed during this period (October 2007 to June 2008 La Niña). It is important to note that only voluntary restrictions were in effect during this period. Higher water savings can be seen during fall to winter months, when residents do not water their lawns as much. However, as temperatures soar during late spring, along with low precipitation due to typical La Niña conditions, the differences between observed and expected water use decrease, indicating that voluntary restrictions are relatively ineffective conservation measures. Imposing mandatory restrictions results in higher water savings during summer months (Kenney et al., 2004). However, because Auburn did not impose any mandatory restrictions, we do not have any results to report.

Past studies have shown that imposing mandatory restrictions in April 2008 (after drought conditions did not improve from October 2007 to April 2008) would have resulted in better water savings and would have improved the drought conditions (Kenney et. al., 2004). Because per capita water use was investigated, the present results evaluate water restrictions effectiveness from an individual user standpoint.

Calculation of the effectiveness of water restrictions in terms of percent savings for Auburn showed that total water use increased, whereas expected per capita water use slightly decreased. During the period of voluntary restrictions, expected per capita water use showed a saving of 14%, indicating the effectiveness of these restrictions in saving water in terms of per capita expected use. These results show that the water use of a community depends on climate and that management decisions, such as imposing voluntary or mandatory water use restrictions, can be effective tools for saving water and averting severe drought conditions.

Forecasting Drought Using CWDI

CWDI forecasted severe to extreme drought during November through March for all the years discussed here. These results agree with some of the observed drought data discussed earlier (fig. 2). These forecast results reflect the

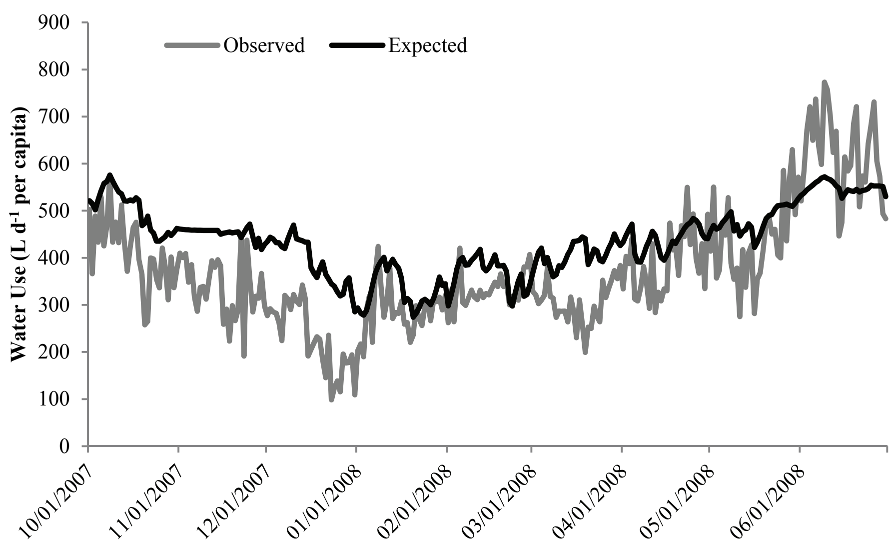

Figure 5. Observed and expected water use for Auburn from 1 October 2007 to 30 June 2008 demonstrating the impact of water restrictions.

situation when no conservation measures were adopted by the city. However, to evaluate and quantify the value of this forecast information, the results of hypothetical scenarios using different conservation measures, restrictions, or public awareness measures were studied in terms of volumetric water savings as well as economic benefit to the community. The analysis of total savings in water and cost was extended to cover summer months.

Figure 6 shows the ensemble forecast of CWDI for two drought years (1999-2000 and 2007-2008) as well as the observed lake levels converted to CWDI values. The figure includes the 95% confidence interval, indicating that there is a 95% probability that the forecast drought will lie between the upper and lower bounds. Figure 6 is another way of presenting the results in table 3, the difference being that the table presents percentage lake levels, whereas the figure

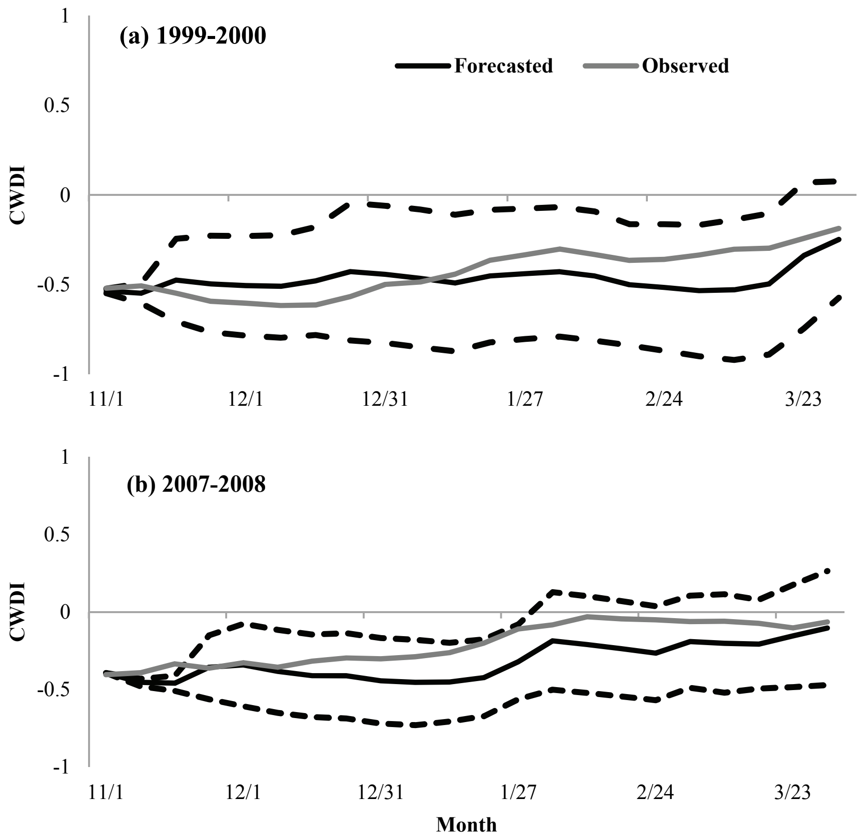

Figure 6. Examples of CWDI forecasts showing 95% confidence interval (dashed lines) and median (black line) for Auburn (November through March) for two drought years: (a) 1999-2000 and (b) 2007-2008.

Table 3. Comparison of reservoir storage levels with and without the use of forecast information in terms of volumetric and economic savings.

Year	Month	Starting Storage ($\times10^6$ L)	Ending Storage ($\times10^6$ L)	Ending Drought Phase	Conservation Measure	Change from Case without Forecast Information: Volume ($\times10^6$ L)	Change from Case without Forecast Information: Cost (USD)	Cumulative Savings: Volume ($\times10^6$ L)	Cumulative Savings: Cost (USD)
1999-2000	Nov.	1791	1983	IV	25%	496	$166,539	496	$166,539
	Dec.	1970	2302	IV	25%	717	$279,614	1213	$446,153
	Jan.	2267	2345	III	20%	-162	-$52,735	1051	$393,418
	Feb.	2388	2059	III	20%	-1580	-$64,630	-528	$328,788
	Mar.	2003	2946	IV	25%	-1805	-$118,890	-2333	$209,898
	Apr.	3381	3923	III	20%	-1252	-$97,666	-3585	$112,232
	May	4224	5590	I	5%	178	$70,332	-3407	$182,564
	June	5553	5384	No drought	0%	920	$459,460	-2487	$642,024
	July	5210	4522	I	5%	1122	$541,284	-1365	$1,183,308
2007-2008	Nov.	2913	3201	II	15%	709	$311,060	709	$311,060
	Dec.	3349	3392	II	15%	696	$305,672	1405	$616,732
	Jan.	3658	3659	I	5%	-733	-$10,675	672	$606,057
	Feb.	3881	3864	I	5%	-1103	-$14,823	-442	$591,234
	Mar.	4324	4749	I	5%	-587	-$62,886	-1018	$528,348
	Apr.	5131	5265	I	5%	-252	-$50,728	-1270	$477,620
	May	5155	5065	I	5%	9	-$10,592	-1261	$467,028
	June	4805	4293	I	5%	80	-$3398	-1182	$463,630
	July	4171	3797	I	5%	86	$28,153	-1095	$491,783

shows the actual CWDI forecast, with negative CWDI values indicating the severity of drought and positive values indicating no drought or desired storage levels being met. As is clear from the figure, during these La Niña years, the CWDI forecasts showed less than desired storage levels during most of the recharge period. According to the Auburn drought management plan, if Lake Ogletree is at or above full pool level on May 1, the supply should last the community through summer and fall. However, this plan assumes normal precipitation and temperature conditions during the months following May 1, which may not always be the case, and storage conditions can worsen during high-demand summer and fall months. For the example years shown in figure 6, the reservoir was still in drought even after February 1, and La Niña conditions persisted until at least May (2000 and 2008) and even beyond (1999), making it difficult to reach full pool conditions by May 1 without enhancing the supply by purchasing water from Opelika.

Value of Forecast Information

The results of the example model runs (1999-2000 and 2007-2008) showing the beginning and ending storage levels at the end of each month for which CWDI was forecasted are given in table 3. The "ending drought phase" column indicates the drought phase at the end of the month after imposing respective conservation measures (according to table 2) on the dynamic demand component of CWDI. The volumetric change and the cost change (profit or loss) are reported in the right columns of the table. There was a saving at the end of November and December for both years. This saving could be due to two reasons. First, in response to the restrictions imposed during phase III and phase II drought at beginning of the month, water use declined. Because of the effectiveness of the restrictions, as established in earlier sections of this study, it can be said with confidence that the restrictions imposed on outdoor water use would have helped in reducing the dynamic demand of water as compared with observed data. Second, the cost saving could be attributed to the fact that the water managers were not aware of the approaching drought and therefore did not enhance the supply (purchase water) to raise the storage levels. However, there was a negative change in the storage volume during January through March for both years, showing that the forecast storage volume at the end of each of these months was less than the observed storage volume during the same time. This change was because Auburn purchased a large amount of water from Opelika during these periods, sometimes even more than the daily limit of 3.6 million gallons, for which they had to pay wholesale reseller rates to Opelika. This purchase allowed Auburn to increase storage, but at the added cost of purchasing water. This explains the economic gain the community could have made with the forecast information.

Similar results were obtained for April through July, and it was clear that using conservation measures according to drought phase, instead of purchasing larger quantities of water, could have resulted in volumetric and economic savings. The "cumulative savings" column indicates that Auburn could have saved $1,183,308 and $491,783 during winter to summer seasons for 1999-2000 and 2007-2008, respectively. It is important to note that higher savings are associated with more severe drought condition, as is the case for 1999-2000. Therefore, the more severe the drought conditions are, the more important this type of forecast information becomes, leading to substantial water savings as well as cost savings.

Communities that rely on surface water supplies could use forecasts tailored to their needs to manage reservoirs over a longer period and provide better allocation of water resources over time. During the winter, water managers in the southeastern U.S. follow predicted precipitation and temperatures very closely because these factors drive the storage levels in reservoirs during the spring (Callahan et al., 1999). Accurate forecasts delivered during these months could prove very helpful in water management during hot and dry summer months.

From the starting and ending storage levels in the reservoir for both study periods, it was observed that, with the use of forecast information, the community could have increased storage in the reservoir and mitigated drought conditions. For 1999-2000, drought conditions improved from phase III to no drought by the end of June 2000, and during 2007-2008, drought conditions improved from phase II in November 2007 to phase I by the end of July 2008.

However, concerns remain about the accuracy of forecasting, which has become one of the main barriers to the use of climate information by water managers. Studies in the past have found that forecasts need to be evaluated at a regional scale for their accuracy and to identify conditions or seasons during which the forecasts have consistently performed well (Pagano et al., 2001). Jin et al. (2008) reported that the skill of ENSO forecasts starting in August and November is better than that of forecasts starting in February and May. In a previous study, we established that ENSO has a significant impact on the climate of Alabama during winter (Sharda et al., 2012). This gives us confidence in the use of CWDI forecasts during the recharge season for the planning and mitigation of drought. Several other actions could be taken to address this issue, including maintaining interactions between scientists and forecasters in the drought planning process and involving stakeholders in the development of forecast products and prediction processes. More accurate forecasts with appropriate lead times need to be developed and in a format that is easily understood and used for decision-making by water managers. It is also important to hold forums that bring stakeholders and forecasters together.

Summary and Conclusions

This study was undertaken to explore the usefulness and value of seasonal drought forecast information for water resource managers of small to mid-sized communities in the southeastern U.S. and demonstrate the use of climate forecasts for drought management. The city of Auburn, Alabama, was used as a case study to demonstrate the benefits of CWDI as a tool for forecasting ENSO-induced drought in the region. The city of Auburn provided historic reservoir levels, consumption data, drought plans, rates for calculating the cost of production of water, and purchase agreements and cost of purchasing from the neighboring city of Opelika. The Niño 3.4 forecast provided by IRI was used to constrain the Spectral Weather Generator for generating ENSO-constrained climate variables for creating an ensemble forecast of CWDI. The CWDI was forecasted three or four months in advance to study the utility of drought forecast.

The study investigated the benefits and water management actions that might occur if Auburn water management decisions were conditioned on ENSO-based CWDI forecast information. The seasonality of water demand and the developed regression model showed that there were statistically significant relationships between climatic conditions and water use in Auburn. These results formed the basis for imposing water restrictions to deal with water shortages in the community. Per capita water consumption responded to the imposed voluntary water restrictions during the period studied and resulted in water savings. Similar results have been found in other studies (Kenney et al., 2004), indicating that voluntary and mandatory water restrictions are effective tools for reducing per capita water consumption.

Having established that water use restrictions are effective tools for handling drought conditions, CWDI forecasts for late winter and early spring months (recharge period) were selected to study the value of this forecast information for water resource managers. To study the value of CWDI forecast information, it was important to consider the net economic benefits resulting from its use. Economic benefits were calculated by taking into account the cost of purchasing additional water to bring the reservoir levels up during the recharge season along with any loss of revenue due to imposing water use restrictions. Based on the results of using CWDI forecasts in historic years, there would have been savings in the costs associated with purchasing water if CWDI drought forecasts were used.

In conclusion, it can be suggested that small to mid-sized communities that predominantly rely on surface water sources should have clear plans for droughts of all levels of severity based on forecasted supplies and demands. Application of CWDI as a tool to forecast drought has been shown to result in benefits for Auburn, as compared to water supply operation using no forecast information. Further, CWDI can be used to ensure the end-of-season water supply by invoking appropriate restrictions depending on the ENSO forecast. Drought forecasting with a tool such as CWDI, which can be customized for the specific needs of a community, operates at the desired spatial and temporal scales, and considers both supply and demand related to climate variables, holds great value for the water resource managers of the region.

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The historic water demand and lake level data used in this study are property of the city of Auburn, Alabama. The city of Auburn does not guarantee these data to be free from errors or inaccuracies. Additionally, the city of Auburn disclaims any responsibility or liability for interpretations of these data or decisions based thereon.

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