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Increasing the usability of drought information for risk management in the Arbuckle Simpson Aquifer, Oklahoma

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ABSTRACT

Tools are needed that can add value to existing drought information and customize it for specific drought management contexts. This study develops a generalized framework that can be used to link local impacts with readily available drought information, thus increasing the usability of existing drought products in decision making. We offer a three-step risk-based framework that can be applied to specific decision-making contexts: (i) identify hydrologic impact thresholds, (ii) develop threshold exceedance model, and (iii) evaluate exceedance likelihood. The framework is demonstrated using a study site in south-central Oklahoma, which is highly susceptible to drought and faces management challenges. Stakeholder input from interviews are used to identify "moderate" and "extreme" thresholds below which water needs are not met for important uses. A logistic regression model translates existing drought information to the likelihood of exceeding the identified thresholds. The logistic model offers an improvement over climatology, and the 12-month Standardized Precipitation Index is shown to be the best drought index predictor. The logistic model is used in conjunction with historical drought information to give a retrospective look at the risk of drought impacts from the beginning of the century. Results show the 1980s to early 2000s to be an anomalously wet period, and that recent drying trends and impacts do not appear to be unusual for the 20th century. This drought risk analysis can be used as a baseline by local managers to guide future decision making under climate uncertainty.

1. Introduction

Drought is one of the costliest climate hazards impacting the U.S. (NCDC, 2015), which has led to an increase in demand for research and products to aid in drought understanding and management. In the U.S., drought conditions are routinely monitored and assessed to understand where drought is occurring and how it may evolve (Svoboda, 2000). There are also national efforts to provide a suite of drought products and tools to assist with water management and drought response, such as through the National Integrated Drought Information System's U.S. Drought Portal (www.drought.gov). In addition to widespread interest in current drought, climate change studies have been undertaken to provide insight into how drought will change in the future (Dai, 2011, 2013; Sheffield and Wood, 2007; Georgakakos et al., 2014).

A challenge to providing drought information is that drought cannot be universally defined. Although there are four overarching definitions of drought: meteorological, hydrological, agricultural and socioeconomic (e.g., Wilhite and Glantz, 1985),

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many different drought indices have been developed (Mishra and Singh, 2010). This is because what constitutes as a "drought" often depends on the location and impact sector of interest. Thus, a key component of drought management is to identify, assess, and report local impacts (Wilhite et al., 2007). However, even if local impacts are identified, they are often not directly diagnosed by routinely available drought products. For example, the most common meteorological drought index, the Palmer Drought Severity Index (PDSI; Palmer, 1965), corresponds to particular drought categories: e.g., PDSI values between -1 and -1.99 correspond to a "Mild Drought" classification. However, particular local impacts – such as a stream running dry – may be felt at either higher or lower PDSI values. As such, stakeholders in local communities are likely to make decisions in the context of local impacts, rather than in light of a drought classification such as "Mild Drought". This makes many of the routinely developed drought products not readily useable in local management efforts. Tools are needed that can add value to existing drought information and customize it for specific decision-making contexts (Lemos et al., 2012). The goal of this study is to develop and demonstrate a generalized framework that can be used to link local impacts with readily available drought information, thus increasing the usability of existing drought products in decision making.

Recent calls to improve decision support have generally focused on using climate information (NRC, 2007, 2009), but can also apply to drought information. For climate information to be useable, it must be credible, salient, and legitimate (Cash et al., 2003), as well as perceived to be useful to users' decision-making contexts (see Lemos et al., 2012 and references therein). Successful use of climate information requires some iteration between knowledge producers and users (Dilling and Lemos, 2011) and efforts to close the usability gap can open up new opportunities for interdisciplinary approaches to creating knowledge (Kirchhoff et al., 2013). In the drought planning process, the involvement of community stakeholders has been acknowledged as an important component (Wilhite et al., 2005).

Stakeholder involvement is also a key component of risk-based management approaches (Jones, 2001), which have been touted as the most suitable framework for decisions related to climate risk (Jones and Preston, 2011). Jones (2001) put forth a risk-management approach that is organized around the likelihood of exceeding critical impact levels. The advantage of risk-based approaches is that they offer a systematic process for weighing likelihood and consequence, but are also flexible in that they can be tailored to incorporate the methods that are most suitable for the context (Jones and Preston, 2011).

Here we put forth a generalized risk-based framework that is demonstrated for the Arbuckle Simpson Aquifer (ASA), a critical groundwater resource located in south-central Oklahoma. The ASA is the main source of the area's water resources, which are essential for a variety of uses and activities. Management of the aquifer faces significant challenges that include planning for climatic stressors and balancing competing needs. Drought conditions and a recent water management dispute (Shriver and Peaden, 2009; Lazrus, 2016) and resulting legislation prompted a 6-year investigation to set a basin-wide limit on the amount of water that can be pumped to protect stream flows. It focused on many aspects of drought, hydrology, and groundwater extraction in the ASA (Osborn, 2009); however, a gap still exists between research findings and concrete methods that can help to manage the aquifer through prolonged times of drought in accordance with local stakeholder values. This study examines the influence of drought on ASA hydrology, but focuses on particular drought impacts that are found to be relevant to stakeholders. These drought impacts are used to develop a risk-based model that translates existing drought information to locally meaningful knowledge. The model is used in conjunction with historical drought information to give a retrospective look at the risk of drought impacts in the ASA, and can be used as a baseline by local managers to guide future decision making under climate uncertainty. The paper is organized by first developing a framework that can be applied to generic decision-making contexts (Section 2), and is then applied to the ASA (Section 3).

2. Methods

To increase the usability of existing drought information, we offer a three-step risk-based framework that can be applied to specific decision-making contexts: (i) identify hydrologic impact thresholds (Section 2.1), (ii) develop threshold exceedance model (Section 2.2.), and (iii) evaluate exceedance likelihood (Section 2.3).

2.1. Step 1. Identify hydrologic impact thresholds

Identifying impact thresholds are key to developing risk-based strategies (Jones, 2001), in particular for guiding action in light of climate-related risks (Jones and Preston, 2011; Yohe and Leichenko, 2010). Impact thresholds can be quite diverse, ranging from simple "rules of thumb" to more formalized criteria (see Jones, 2001 for examples). Important considerations for identifying and setting thresholds are provided by Jones (2001); the main role for a threshold is to provide "an agreed upon frame of reference linking different knowledge systems". Thus, thresholds provide an effective link between stakeholder values and technical modeling.

Because water use decisions are typically made at the local level, stakeholders are mostly concerned about a relatively small geographic region and about local impacts relevant to their values, needs and decision-making, e.g., water needs among ranchers in south-central Oklahoma. As such, to ensure that hydrologic impact thresholds are meaningful, first it is necessary to understand how diverse groups interact with and place value on local water resources and how they may be impacted by drought conditions. One way of exploring this is through ethnographic methods, including interviews. Data from interviews with stakeholders can be used to determine important water uses and needs. Interviewee observations can also help contextualize and enhance hydrologic records. Thus, providing drought information that uses interview results to address local priorities helps to ensure the information is useable in decision making (Lazrus, 2016); that is, it is salient to user communities and legitimately reflects diverse user needs (Lemos et al., 2012).

Stakeholder input can then be used to determine thresholds below which water needs are not met for important uses. However, threshold selection also needs to consider technical constraints. This is because for a numerical risk-based model, thresholds need to be quantitatively linked to an existing drought variable. Thus, the threshold selection is limited by data availability and how well the threshold can be represented by a model.

2.2. Step 2. Develop threshold exceedance model

Risk-based approaches can accommodate a variety of modeling methods (Jones and Preston, 2011), and here we adopt statistical logistic regression (Helsel and Hirsh, 1995), which is part of the family of generalized linear models (GLM) that assumes the binomial distribution with the logit link function (McCullagh and Nelder, 1989). Logistic regression is an appealing choice because it is a simple, flexible, and transparent methodology for directly estimating the probability of an event occurring (or not occurring). To develop a logistic regression, the first step is to identify an impact threshold, as outlined above (Section 2.1). For example, minimum streamflow standards are often set to ensure the health of aquatic ecosystems. Next, the continuous data time series is converted to a categorical time series (i.e., value becomes a "1" if it exceeds the threshold and a "0" if it does not exceed the threshold). The categorical data is then fit by logistic regression, expressed as:

$$p = \frac{\exp(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots \beta_k X_k)}{1 + \exp(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots \beta_k X_k)}$$

where p is the probability of exceeding the threshold, the coefficients $(\beta_1, \beta_2, \cdots \beta_k)$ are the model parameters fitted to the predictors $(X_1, X_2, \cdots X_k)$. Maximum likelihood estimation is used to estimate the coefficients (Helsel and Hirsh, 1995). In this analysis, the *glm* library was used in the statistical software R (R Core Team, 2014).

In this formulation of risk, the consequence is the probability (or risk) of exceeding the threshold (Jones and Preston, 2011). As such, we use the terms "risk", "probability", and "likelihood" interchangeably in this paper, but see discussion section for further details on this point.

The logistic models are evaluated by examining the objective Akaike Information Criterion (AIC) (Akaike, 1974)

$$AIC = 2k - 2L$$

where k is the number of parameters in the model and L is the logarithm of the likelihood function. Models with lower AIC values are considered better models in terms of both goodness-of-fit and parsimony (i.e., the AIC penalizes models with more parameters). Further, to provide an estimate of the uncertainty explained by the logistic model, the likelihood R^2 was calculated:

$$R^2 = 1 - \frac{L}{L_0}$$

where L is the same as above and L_0 is the log likelihood for the intercept-only model (Helsel and Hirsh, 1995). The predictions are also evaluated using the Brier Skill Score (BSS) (Wilks, 1995):

$$BSS = 1 - \frac{BS_{Prediction}}{BS_{Climatology}}$$

where the $BS_{Prediction}$ is the Brier Score (*BS*) predicted by the model, defined as:

$$BS_{Prediction} = \frac{\sum_{i=1}^{N}(p_i - o_i)}{N}$$

where p_i refers to the predicted probabilities, o_i refers to the observed probabilities ($o_i = 1$ if the observed exceeds the threshold, 0 otherwise), and N is the sample size. $BS_{Climatology}$ is also calculated from the above equation, but for every year uses climatological probabilities, i.e., the "stationary" probability of exceeding the threshold that is calculated from the historical record. For example, if the threshold is the median, then $p_i = 0.50$. BSS values span negative infinity to 1. Compared to climatology, BSS < 0 indicates that the prediction has less skill, BSS = 0 indicates equal skill, and a BSS > 0 indicates more skill, with 1 being a "perfect" prediction. The BSS is evaluated using all of the fitted data, as well as in across-validation mode (i.e., systematically leave-out and then predict each observation).

2.3. Step 3. Evaluate exceedance likelihood

The advantage of developing a model that relates local impact thresholds to drought indices is that it can readily incorporate a wide variety of climate information. Often, regional historical drought information is available for a longer and more complete time series than local hydrologic information. Further, drought indices such as PDSI are routinely calculated in climate change studies, and can be used to translate abstract climate change projections to concrete local implications. Here we focus on using historical information since it has the advantage of being less uncertain than future projections, but the approach could be readily applied to climate change predictions and projections. Using historical information can help to quantify past or current climate risks (Wilby and Dessai, 2010) and in some cases be adequate for making decisions about the future (Briley et al., 2015).

The historical drought information is used in conjunction with the threshold exceedance model, resulting in estimates of the exceedance likelihood. These probabilities provide a measure of the uncertainty of event occurrence. For instance, in a given month, there might be a 60% chance of exceeding the threshold. However, up to this point, this is just an *assessment* of the risk. To be used in risk *management*, the question is raised: what is the level of risk that is needed to motivate action? And what actions, if any, are possible? For instance, is a 60% chance enough to implement water restrictions? Or does it need to be a 70% chance? In this paper, an action cutoff of 50% is utilized (i.e., a probability = 0.5), as it is readily interpretable as the point above which a threshold exceedance is more likely than not. However, when applied in practice, these action cutoffs would be determined with stakeholder input. Despite these subjective aspects, the advantage of risk management is that once these values are set, there is a systematic way to estimate risk and initiate action.

3. Case study application

3.1. Background

The ASA is a critical groundwater resource located beneath about 520 square miles (1350 square kilometers) in south-central Oklahoma. The aquifer is the main source of drinking water for local municipalities, as well as being important for mining and ranching activities in the area. In addition, the aquifer feeds many springs and streams in the watershed, providing water for recreation, tourism, and ecosystems. The aquifer is recharged by precipitation (Christenson et al., 2011), which has been highly variable over the last century, and the area is therefore prone to periodic drought conditions (Silvis et al., 2014). In recent years (e.g., 2006, 2011–2012), the region has experienced several devastating droughts (Shivers and Andrews, 2013), with adverse impacts for the economy, environment, and quality of life.

Given these ongoing issues as well as a recent water management dispute (Shriver and Peaden, 2009; Lazrus, 2016), a 6-year investigation was undertaken to better understand the hydrology of the area. In particular, a groundwater modeling study was conducted (Christenson et al., 2011) to establish the quantity of water that can be sustainably extracted from the aquifer on an annual basis without negatively affecting springs and streams in the area. Results from this study led to a ruling that reduced the amount of water that could be pumped from the aquifer annually by an order of magnitude (OWRB, 2013). Given its susceptibility to drought and importance to a diverse community of users with competing needs, the ASA is an excellent case study to examine.

3.2. Impact thresholds for the ASA

Lazrus (2016) conducted interviews with stakeholders in the ASA to explore how they valued water for different activities and perceived drought impacts. Interviewees were selected following a snowball sampling strategy whereby initial interviewees were contacted for an interview based on their connection to water management and use in the area, and were asked to suggest other people who they thought should also be interviewed on these criteria. Interviews were conducted with 38 stakeholders who were actively engaged in relevant sectors including ranching, municipal water management, and tourism and recreation. The study revealed that most interviewees place a high value on several of the hydrologic services supplied by the aquifer, including drinking water supply, habitat for plants and animals, and livelihoods (Lazrus, 2016; Towler et al., 2016a). Interviewees recognized that many of these services were related to groundwater levels in the area, many of which are monitored by the U.S. Geological Survey (USGS) and the Oklahoma Water Resources Board (OWRB). As such, it was decided that at least one of the impact thresholds should be based on groundwater depth. The OWRB is the water agency that is responsible for managing hydrologic services identified by the interviewed stakeholders. The OWRB has the mission "to enhance the quality of life for Oklahomans by managing, protecting, and improving the state's water resources to ensure clean, safe, and reliable water supplies, a strong economy, and a healthy environment."

To determine the groundwater threshold, we used a groundwater well with one of the longest available records that is closely monitored by the OWRB: the USGS Fittstown well (USGS 343457096404501). This well was also identified by interviewees as an important source of information: "I've seen the graphs. It must have been from Fittstown [well] that sort of shows the recharge and drought and how much water… is in the aquifers" (Interview #34). The Fittstown well has field measurements of the groundwater depths from 1959-the present, as well as continuous monitoring since October of 1980. The correlation between the overlapping periods was high ($r = 0.98$), so the records were combined, resulting in a record from 1959 to 2014. From this record, monthly averages were calculated, and only about 7% of the monthly data were missing. The monthly times series is shown in Fig. 1, and shows that there is considerable variability, with monthly averages for the well depth ranging from a minimum of 93–128 feet below the surface, representing a 35-foot fluctuation. The smoother shows that the groundwater levels peaked in the mid-1990s, and have since been decreasing. One of the metrics that can be used is a Z-score, whereby the well levels are standardized by subtracting the mean and dividing by the standard

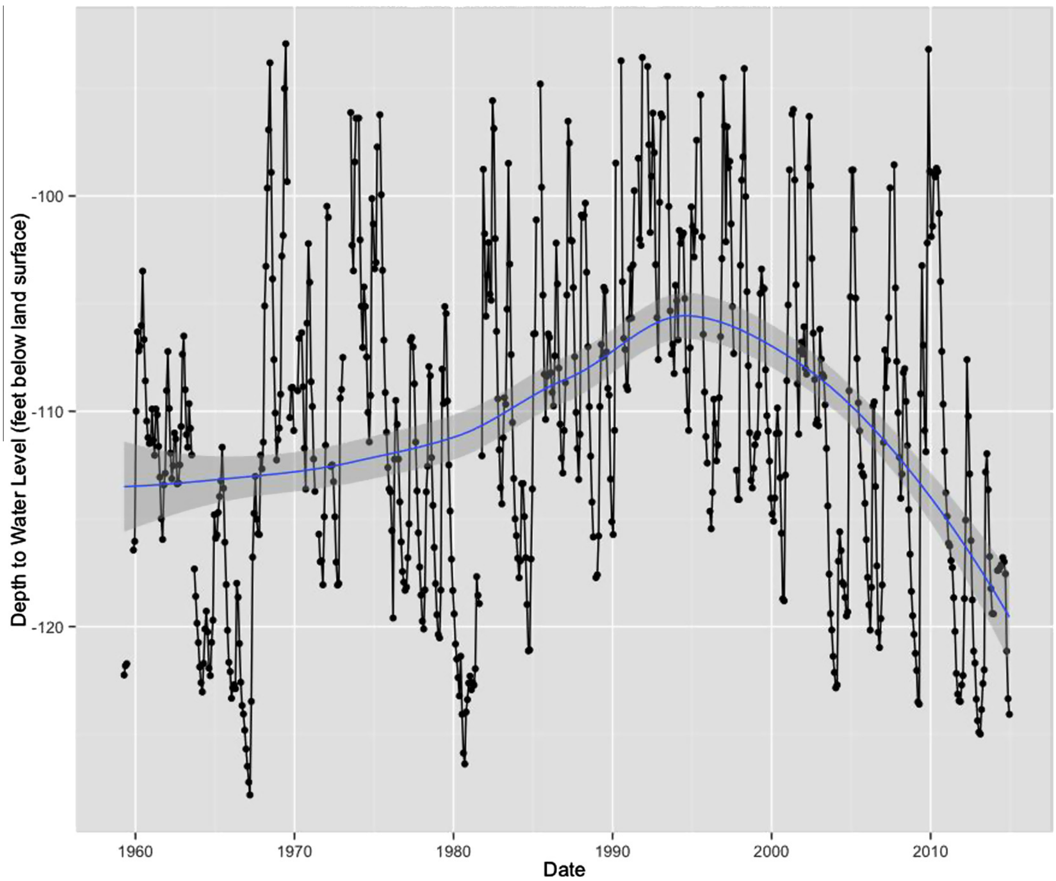

Fig. 1. Monthly average time series of groundwater depths from the Fittstown well with smoother (blue line). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

deviation. This way, everything is centered on zero: values above zero would indicate a "healthy" aquifer and values below zero signifying a "stressed" aquifer. A Z-level of zero corresponds to the mean of the Fittstown groundwater depths, or an actual groundwater level of 111 feet below the surface. This 111-foot threshold was used in the analysis as an indicator for the risk to the three most important hydrologic services – drinking water, habitat, and livelihoods – mentioned previously. In this study, we call the 111-foot (or Z-score = 0) threshold the "moderate" threshold.

The previous study by Lazrus (2016) also found that some, though not all, stakeholders placed a high value on several other water uses from the aquifer, including recreation, spiritual fulfillment, and cultural practices (Lazrus, 2016; Towler et al., 2016a). The Chickasaw National Recreation Area (CNRA) provides recreational opportunities, and several of its springs hold cultural and historical significance. In addition, the springs are unique ecosystems and recent survey work of 23 springs in Oklahoma revealed the ASA to have the greatest diversity of species of the areas surveyed (Tarhule and Bergey, 2006). As such, it was decided that one of the thresholds would be based upon spring flows.

To determine a threshold to represent spring flows, we examined data availability for springs in the CNRA, including the Antelope Spring at Sulphur, OK (USGS 07329849). The spring's flow was monitored briefly in the late 1980s (11/1985 – 9/1989), and then continuously from October 2002 through the present. The spring is highly influenced by drought, and National Park Service files indicate that it has been reduced to no flow at some points during the past century (Hanson and Cates, 1994). The connection between drought and springs was also noted by interviewees, for example this person referring to the drought in 2011: "Your last year was the worst [drought], I guess in the history, I mean according to anything I've ever read. That's worse than even the 1930s, in terms of here. But to give you an example, there used to be 39 springs in that little – in the [Chickasaw Recreational Area]. There is two – two good ones left – two... there may be some during high water tables, but they don't last long. So we have two, Buffalo and Antelope" (Interview #1). Although the record is not particularly long, the Antelope Spring flows are highly correlated with the Fittstown well ($r = 0.87$; Fig. 2). Fig. 2 shows that the spring typically stops flowing when the Fittstown groundwater levels fall between 117 and 124 feet. From this, 120 feet was selected as another threshold for the Fittstown well to serve as a proxy for the risk of no flow at Antelope Springs. In short, this was considered an indicator for the risk to the other hydrologic services of interest to some stakeholders in the

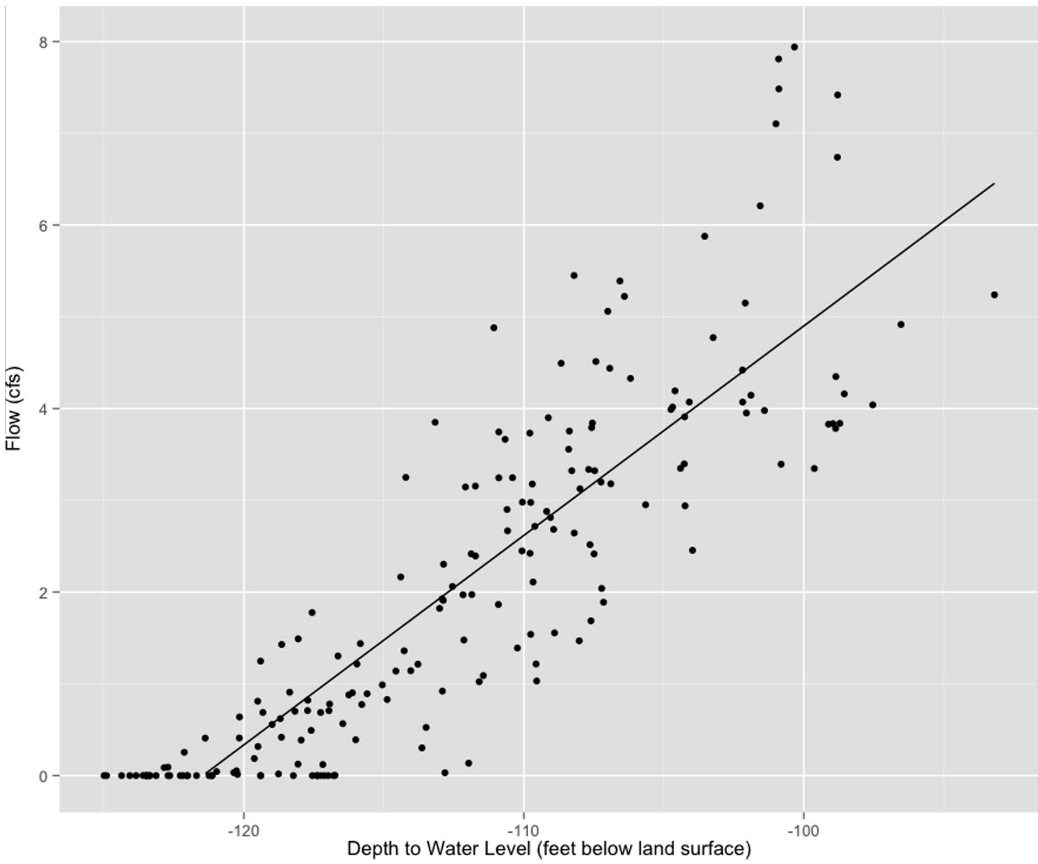

Fig. 2. Scatterplot of monthly Fittstown groundwater depths and Antelope Springs flows ($r = 0.87$).

region: recreation, spiritual fulfillment, and cultural practices. However, an added benefit is that this threshold also relates to the most important hydrologic services identified (i.e., drinking water, habitat, and livelihoods), but it is more stringent than the previously determined "moderate" threshold. This is referred to as the "extreme" threshold.

3.3. ASA logistic regression model

To develop the logistic regression between the thresholds identified in Section 3.2 and drought indices, we examine two of the most popular and common drought indices: the Palmer Drought Severity Index (PDSI) and the Standardized Precipitation Index (SP). PDSI is a well-known index of meteorological drought (Palmer, 1965) that is based on a water balance of precipitation, soil moisture, potential evapotranspiration, and runoff. SP only considers how precipitation variability affects drought (McKee et al., 1993), but can be calculated to consider different time scales. For example, the 1-month SP (SP01) considers short-term conditions, and the 24-month SP (SP24) considers longer-term conditions (i.e., precipitation from the last 2 years). Monthly U.S. climate division data, including PDSI and SP, are available through the National Oceanic and Atmospheric Administration's (NOAA) National Climatic Data Center (NCDC; http://www7.ncdc.noaa.gov/CDO/CDODivisionalSelect.jsp). We examine Oklahoma climate Division 8, wherein the ASA is located, for the period of 1959–2014 to correspond with the Fittstown groundwater depths period of record. Although the thresholds were identified from analyses based on all the months of the year, the logistic regression is developed to focus specifically on the summer, June–July–A ugust–September (JJAS). JJAS includes the hottest months of the year as well as the low recharge months for the ASA (Christenson et al., 2011), thus corresponding to the season of the worst drought impacts. To fit the regression, drought indices are averaged over JJAS, but to understand the extent of the impacts, we use the minimum groundwater level that occurred during the JJAS season for each year.

The linear correlations between the average JJAS drought indices and the minimum JJAS Fittstown groundwater levels show the close association between drought and ASA hydrology (Table 1). Results show that SP12 has the strongest relationship ($r = 0.87$), indicating that the aquifer has a 12 month "memory" of precipitation in the watershed. PDSI's correlation with the Fittstown groundwater levels is 0.75. Although PDSI is not as predictive as SP12, we include PDSI results because it is such a commonly used index. Fig. 3 shows the scatterplot of SP12 and PDSI versus groundwater levels, both in terms of

Table 1
Linear correlations (r) between average Jun–Sep (JJAS) drought indices and minimum JJAS Fittstown groundwater depths.

Index	r
PDSI	0.751
SP01	0.505
SP02	0.564
SP03	0.603
SP06	0.699
SP09	0.815
SP12	0.874
SP24	0.752

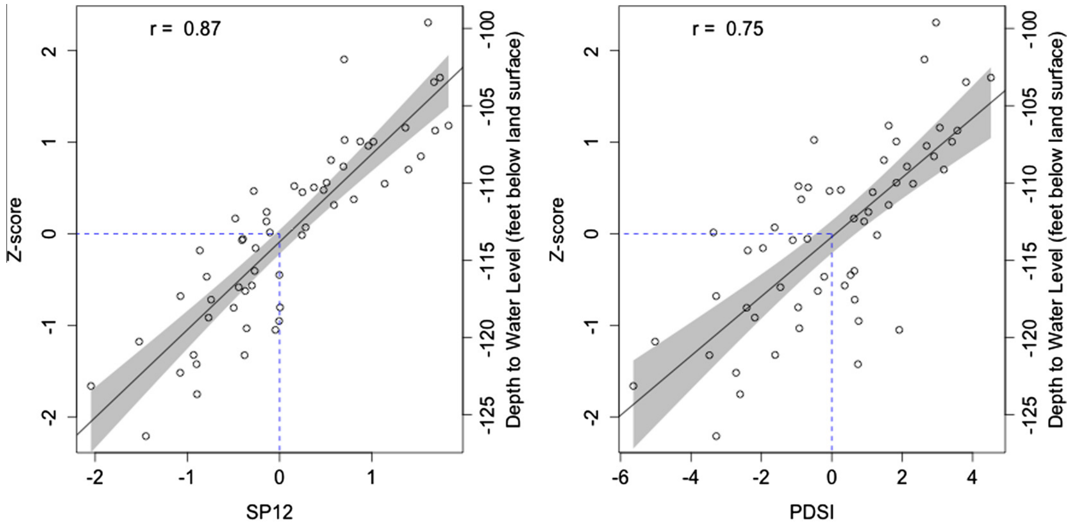

Fig. 3. Scatterplot of minimum JJAS Fittstown groundwater Z-scores (left axis) and depths (right axis) versus average JJAS SP12 (left) and PDSI (right). Black line is best fit with 95% confidence intervals (gray shading).

Z-values (left axis) and actual values (right axis). Results for the moderate threshold show that a Z-value of zero corresponds to an SP12 value of zero, underscoring the close relationship between precipitation and groundwater. Similarly, a Z-value of zero corresponds to about a PDSI of zero. This suggests that any time SP12 or PDSI values go below zero, the aquifer has some risk of becoming stressed.

For the moderate threshold, we fit a logistic regression using SP12 and PDSI (Table 2, top). As expected, the SP12 model has a lower AIC value than the PDSI model (32 versus 48) and a higher R^2 value (0.63 versus 0.42). In addition, the BSS scores for SP12 and PDSI (0.69 and 0.46, respectively) indicate that both models show skill over just using climatology. That is, it is better to use this model than to just use the historical probability, where we would have assumed that every year the likelihood of exceedance was 61% (i.e., the percent of time the minimum JJAS levels went below the moderate threshold). Fig. 4a shows that as the SP12 decreases (gets drier), the likelihood of exceeding the moderate threshold increases. This is

Table 2
Coefficients and goodness-of-fit statistics for moderate and extreme thresholds using SP12 and PDSI.

Threshold	Intercept (se[a])	SP12 (se[a])	PDSI (se[a])	AIC[b]	R^2	BSS[c]	BSS_xval[d]
Moderate[e]	1.43 (0.58)	−4.50 (1.2)	–	32	0.63	0.69	0.65
	1.08 (0.45)	–	−1.09 (0.29)	48	0.42	0.46	0.42
Extreme[f]	−4.98 (1.7)	−5.50 (2.1)		22	0.60	0.60	0.51
	−3.08 (0.85)	–	−1.01 (0.34)	31	0.41	0.43	0.36

[a] se = standard error.
[b] AIC = Akaike Information Criterion.
[c] BSS = Brier Skill Score.
[d] BSS_xval = BSS cross-validated.
[e] Depth < 111 feet or Z-score < 0.
[f] Depth < 120 feet.

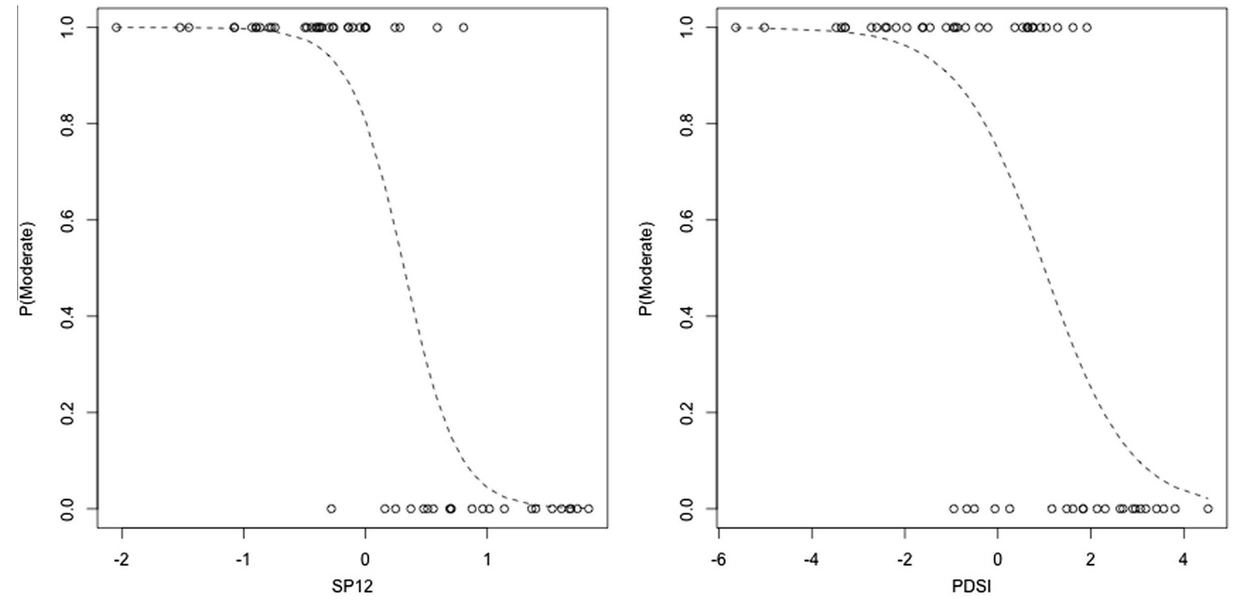

Fig. 4. Logistic regression of average JJAS SP12 (left) and PDSI (right) and the probability of the Fittstown groundwater depth exceeding the moderate threshold.

Table 3
Likelihood of exceedance for moderate and extreme thresholds using average JJAS SP12 and PDSI.

SP12	P (Moderate)	P (Extreme)	PDSI	P (Moderate)	P (Extreme)
2	0	0	3	0.1	0
1.5	0	0	2	0.25	0.01
1	0.04	0	1	0.50	0.02
0.5	0.31	0	0	0.75	0.04
0	0.81	0.01	−1	0.90	0.11
−0.5	0.98	0.10	−2	0.96	0.26
−1	1	0.63	−3	0.99	0.49
−1.5	1	0.96	−4	1	0.72
−2	1	1	−5	1	0.88
−2.5	1	1	−6	1	0.95

quantified in Table 3. We can see that from SP12 = 1 to SP12 = 0 to SP12 = −1, the risk of exceedance rapidly jumps from 4% to 81% to 100%, indicating how quickly the aquifer can be designated as "stressed" by this metric. Results for PDSI are shown in Fig. 4b, and in Table 3, showing that the likelihood of exceedance increases more gradually for decreasing PDSI values.

For the extreme threshold, a logistic regression is also fit. From Table 2 (bottom), we can see that similar to the moderate threshold, the AIC and R^2 values indicate that the SP12 model is preferable to the PDSI model (i.e., 22 versus 31 for AIC, and 0.60 versus 0.41 for R^2). The BSS scores again indicate that including SP12 or PDSI in the logistic model is better than climatology (0.60 and 0.43). That is, if we had used climatology, we would have assumed that every year the likelihood of exceedance was 14% (as calculated using the minimum JJAS level from each year of the historical record). These results also show that for both thresholds, the cross-validated BSS is very similar to the fitted BSS, indicating that these models are also skillful in a predictive mode. Fig. 5 shows the logistic fits for both predictors, and the likelihoods of exceedance are quantified in Table 3. In terms of exceeding the extreme threshold, the risk also increases rapidly for SP12: from SP12 = 0 to SP12 = −1 the risk moves from 1% to 63%.

3.4. Historical exceedance likelihoods for the ASA

Although monthly drought data from 1959 to 2014 were used to develop the exceedance model (Section 3.3), NOAA's NCDC has drought data that is available from 1896. This longer time series of PDSI and SP12 is used with the logistic regressions to reconstruct the likelihood of exceeding the thresholds. Results for SP12 and PDSI are similar, but results are only shown for SP12.

The monthly exceedance likelihoods for the moderate threshold shows considerable variability (Fig. 6a), and does not show any notable regime-type behavior. This is not surprising, given that this moderate threshold was derived from the

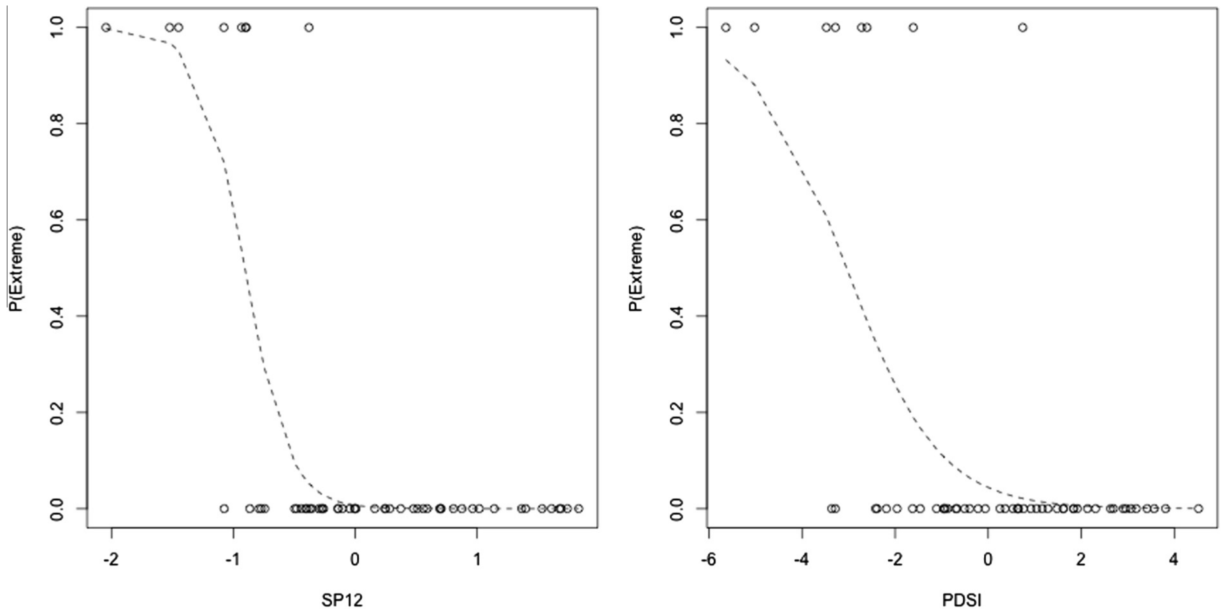

Fig. 5. Logistic regression of average JJAS SP12 (left) and PDSI (right) and the probability of the Fittstown groundwater depth exceeding the extreme threshold.

mean groundwater level. Likelihoods for the extreme threshold show more discernable peaks and valleys (Fig. 6b) than are seen for the moderate threshold (Fig. 6a). For the extreme threshold, most recently, the highest likelihoods occurred in 2011, which was a recent severe drought year which corresponded to no flow at Antelope Springs, as well as in 1956, another severe drought year (Silvis et al., 2014), which according to National Park Service files also corresponded to a period of no flow (Hanson and Cates, 1994).

Figs. 6a and 6b are useful for a risk assessment, but to be relevant to risk management, we need to identify a level of risk that can initiate some hypothetical action. We emphasize that further work with stakeholders would be needed to determine one or more operational action cutoffs, but here we illustrate the results using a value of 0.5 (Fig. 6c and 6d). That is, if the exceedance probability from Fig. 6a and 6b was >0.5, then it is represented by a black vertical bar (Fig. 6c and 6d), which indicates months in which a hypothetical action would be warranted. We point out that an action cutoff of 0.5 is equivalent to an odds ratio of "1", which is the point at which a threshold exceedance is more likely than not.

Results for the moderate threshold with a cutoff of 0.5 indicates that some sort of action would have been prudent quite frequently (Fig. 6c). Again, this is expected for several reasons. First, the threshold is quite conservative. In addition, the groundwater levels are closely tied to precipitation in this area, which has historically been quite variable and drought-prone (Silvis et al., 2014). The fact that it is so frequently "risky" to exceed this threshold is partially why the groundwater levels are so closely monitored. This indicates that the risk-based approach may not be as useful for moderate thresholds, as compared to more stringent thresholds.

Results for the extreme threshold using the 0.5 cutoff show more regime-type behavior (Fig. 6d). Here, the need for action is more intermittent than it was for the moderate threshold, but it also shows that the last century is punctuated with periods when the risk of the springs going dry is quite high. The notable exception to this is the 1980s to the early 2000s, which appear to be an anomalously wet period. Aside from that wet period, the higher likelihoods of exceedance for the recent period (since the early 2000s) seem representative of the likelihoods seen in the rest of the 20th century.

We also validated the results by comparing years where there was a need for action (i.e., the probability was >0.5) and whether or not the Fittstown groundwater level actually went below the extreme threshold. We found that in the 56 years of the Fittstown record (1959–2014), the minimum JJAS groundwater level went below the extreme threshold in 8 years. Using the 0.5 cutoff, the model predicted this correctly in 7 out of 8 years, as well as one year (1963) that was incorrectly predicted to exceed the threshold.

4. Discussion

Understanding which drought impacts are important to local stakeholders, given their values and uses of local water resources, can help identify impact thresholds for local management. However, management challenges can arise when stakeholders have diverse perspectives and value water differently. In this study we were able to identify two thresholds, a "moderate" and "extreme" threshold. We note that even though the latter threshold was developed for the hydrologic services for which there was less consensus among stakeholders (i.e., recreation, spiritual fulfillment, and cultural practices),

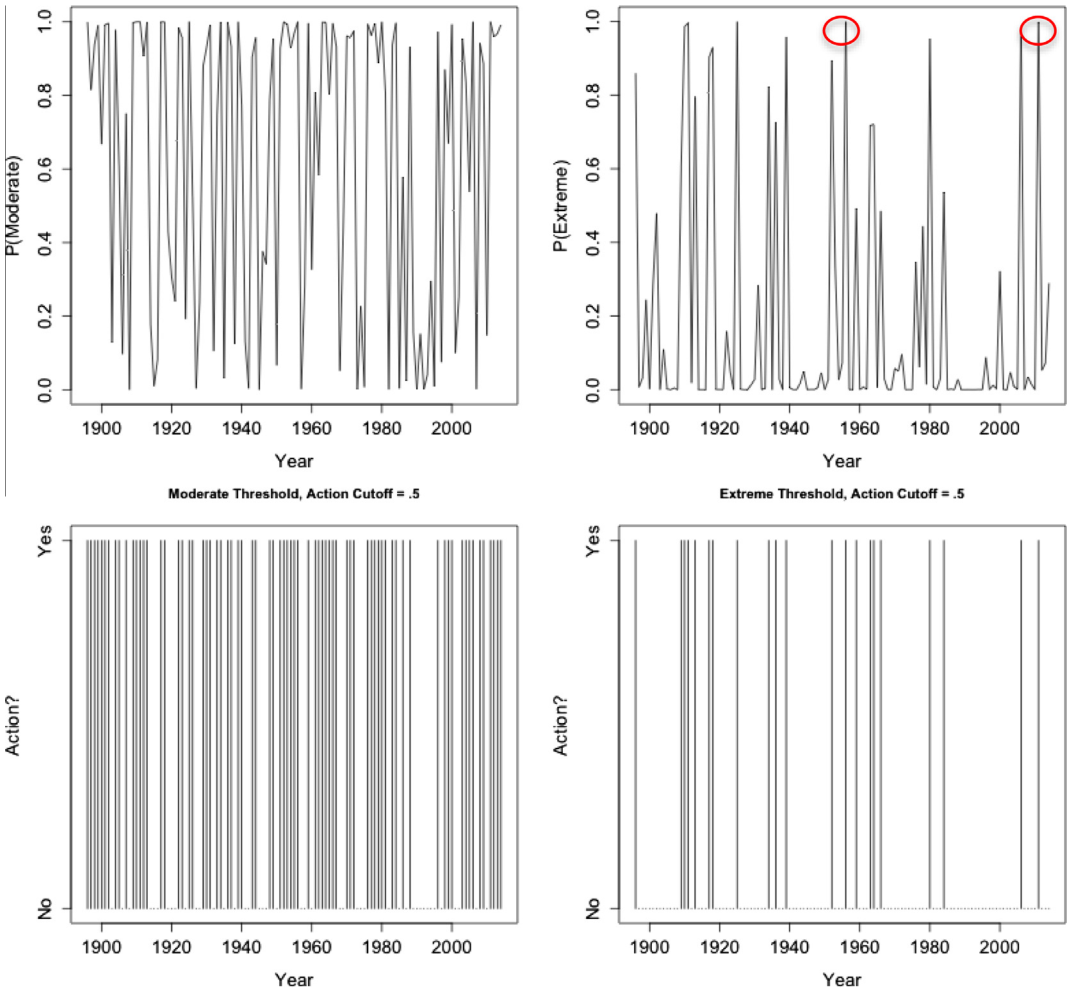

Fig. 6. a, b: Reconstruction of the probability of exceeding the moderate (left) and extreme (right) threshold from average JJAS SP12. Red circles are 1956 and 2011. c, d: Results from a & b are reduced to "Yes" or "No" for action cutoff of 0.5 for the moderate (left) and extreme (right) threshold.

it actually also covers the hydrologic services that were valued by all stakeholders (i.e., drinking water, habitat, and livelihood). Thus, the extreme threshold could be used as a way of combining different perspectives, which has been found to be a key to developing successful solutions (Verweij et al., 2006). Further, increased understanding of the diverse and opposing viewpoints held by stakeholders in the ASA (Lazrus, 2016) can help to understand how to reduce disagreement among stakeholders and promote sustainable water management in a changing climate (Towler et al., 2016a).

It is important to note that at present, groundwater use from the ASA is relatively small (Christenson et al., 2011), which is likely why we were able to discern such a strong climate signal. The opposite has been found in some other areas of Oklahoma, where trends in groundwater levels seem to be more closely associated with human activities than to climate (Tarhule and Bergey, 2006). In those cases, it might be necessary to add another explanatory variable to the model, such as groundwater pumping, to better quantify the risk. In the ASA there are increasing demands to extract more groundwater from the area, and so these results provide a useful baseline to consider in future management decisions.

We also point out that in our formulation of risk, we are only quantifying the risk in terms of physical variables, i.e., drought indices. However, it is being increasingly acknowledged that climate-related risks result from both physical climate hazards and societal vulnerability (Oppenheimer et al., 2014). In this paper, we addressed the latter through using interviews to understand stakeholder values, but there are other important socio-demographic characteristics that were not considered here. We also note that thresholds and action cutoffs may change over time, underscoring the importance of sustained interaction with stakeholders (Dilling and Lemos, 2011).

5. Summary and conclusions

This paper provides a general three-step risk-based framework for identifying, modeling, and evaluating drought risks for local impacts. The framework is applied to the ASA, a critical groundwater resource in south-central Oklahoma. Although several hydrologic studies have been commissioned in the ASA (Osborn, 2009), additional methods may provide local managers with tools to better manage their water rights under increasing climate strain and demands for growth. This study develops a generalized approach that elucidates local risks by querying stakeholder knowledge and leveraging existing drought information.

Impact thresholds are determined by weighing stakeholder input from interviews and technical constraints. From this, two thresholds were identified, including an "extreme" threshold that was relevant to the hydrologic services that were valued by all of the stakeholders surveyed. To quantify the risk of exceeding the threshold, a logistic regression is developed between the identified thresholds and existing drought indices. The logistic models offer an improvement over climatology, and SP12 is shown to be the best drought index predictor. The logistic model is used in conjunction with historical drought information to give a retrospective look at the risk of drought impacts in the ASA from the beginning of the century. Results show the 1980s to early 2000s to be an anomalously wet period, and that recent drying trends and ceased spring flows do not appear to be unusual for the 20th century. This is complementary to recent studies that have looked at the longer term: for instance, using tree-ring reconstructions, Tarhule (2009) concluded that droughts in the area were most common during 1700–1770 and 1900–1960. The 1800s were found to be a period of modest and infrequent droughts, as was the period from 1960 to 2004 (the last year of their analysis).

Historical context provides important perspective for preparing for future climate impacts. This is critical in an already drought-prone region, as studies suggest that there is likely to be increased drying over the ASA in the future (Towler et al., 2016b; Liu et al., 2012). In future work, the logistic regression can be paired with climate model predictions and projections to examine potential future trends and implications for risk management and planning.

Given the importance of adequate water resources for societal and ecological needs, there is an imperative to provide drought risk information that can facilitate decision making. By developing tools that can directly bridge existing drought information with local impacts, a more comprehensive understanding of current and future drought risk can be gained to inform management and planning.

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