A control chart for severity index to detect drought compares favourably to logistic regression

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ABSTRACT

We describe the discovery of how a traditional control chart for the Palmer Drought Severity Index (PDSI) to detect drought compares favourably to a theoretically appropriate statistical (logistic regression) model of drought as a function of PDSI. Our empirical results are based on monthly observations of PDSI, precipitation and temperature made in Kansas since 1895. Results from the study suggest that a relatively simple statistical approach based on Shewhart control charts may provide a more accessible method for relevant government agencies to predict droughts, improving resource management and preparation. Moreover, utilizing such an approach over more sophisticated methods may come at little expense regarding prediction errors.

Key words | control charts, drought detection, drought indices, logistic regression, quality control

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INTRODUCTION

Drought remains one of the most climatologically significant events encountered by society; even in developed countries, the repercussions can be devastating. Every society in the world is vulnerable to the economic and environmental consequences of drought (NDMC 2006) as it is a naturally occurring event. A drought can be described as an unexpected decrease in precipitation compared to the normal pattern. This shortfall is relative to the region in question and can occur in any area; both wet and arid climates can experience droughts (WMO 2006). Droughts are by nature and definition temporary. Due to the severe consequences of drought and humanity's inability to prevent its occurrence, emphasis is placed on drought prediction and monitoring as a tool for the proper implementation of consequence management and mitigation policies.

Although it is relatively straightforward for most people to agree on the general description of a drought, determining when a drought is officially occurring or attempting to measure its severity is a different matter. Despite the relative prominence of droughts and the shared familiarity most societies have with this natural disaster, a clear quantifiable definition is hard to come by.

An abundance of performance measures related to droughts are available and in use. A large number of factors including precipitation levels (the most well-known measure), soil moisture, groundwater levels and stream/river volume are popular, as are indices that take multiple factors into account. The Palmer Drought Severity Index (PDSI) is one such index, incorporating soil moisture, precipitation and several other factors through a computational technique to create a single value measuring drought severity. Although criticisms of the PDSI exist, it remains one of the most utilized indices for the past 40 years since its creation (Lohani & Loganathan 1997).

Measures of drought severity are crucial; governments often rely on such measures to determine whether drought preparedness policies should be implemented in order to reduce economic and environmental impacts (Kansas Office of the Governor 2003). The failure to recognize an imminent drought can lead to grave consequences. For example, the state government in Kansas enacts specific policies such as burn bans or water conservation on the basis of the combined analysis of various indices and meteorological factors (Tom Lowe, Kansas Water Office, personal communication,

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October 23 2008); the negative effect of the drought would be exacerbated if such policies were not implemented in a timely manner. However, similar to situations in which quality control tools are applied, appropriate economic design (with predetermined costs of false alarms and misses) is essential in order to minimize the total cost associated with making decisions.

One of the most challenging aspects of defining and measuring droughts is the fact that the label is almost always applied in hindsight (James Putnam, US Geological Survey, personal communication, October 23 2008); a drought period is usually declared as such only after it has passed or as it is occurring, making monitoring and prediction even more nebulous. Some state governments (such as Virginia) enact drought policies only if several consecutive time periods display characteristics of a drought (Lohani & Loganathan 1997); in this case, a drought is only officially acknowledged after it has begun.

Evidently, drought monitoring contains some similarities to quality control. Similar to the manufacturing industry, there is a need to monitor processes (in this case the level of moisture in an area) and to be alerted when something out of the ordinary occurs so that appropriate measures can be enacted. Implementing measures involve a certain cost and, in both situations, there is a desire to avoid unnecessary expenses. False alarms should be avoided, so waste of resources is minimized. Failure to act when the situation requires action can be extremely costly. In manufacturing, the consequence may be an increased proportion of defective products leading to waste; for drought managers, the result may be crop losses, water shortages or fire outbreaks. As a result, implementation of statistical quality control tools may be of benefit to the field of drought management.

LITERATURE REVIEW

Prediction and monitoring methods

Having established how crucial foresight is in dealing with droughts, prediction models have been widespread in the literature; there has been no lack of effort in the field. Popular methods include the use of auto-regressive statistical models (Podur 2001), step-wise multiple regression (Hastenrath 1990) and Markov-chain models (Lohani and Loganathan 1997), among many others. Models can become quite complex in some cases, such as when atmospheric and meteorological factors are taken into account. In an interesting analysis of the effects of model complexity, Halide & Ridd (2008) studied the performance of a relatively simple univariate statistical model they developed in comparison with several complex statistical and dynamical models. Although performance of the simple model varied relative to more complex models, the authors concluded that the marginal gains in accuracy were outweighed by the disproportionate increase in computation time. The authors suggested that this may require a shift in philosophy regarding model improvement; perhaps future work should focus more on reducing the number of factors and honing in on the most important variables.

Several of the methods employed seek to predict the return periods of drought. In one study (Kim *et al.* 2006), non-parametric methods are used to analyze drought frequency. The authors note that one of the difficulties of creating reliable models is the insufficient volume of historical drought data; as a result, they utilized synthetic data. Freitas & Billib (1997) approached drought prediction using neural network models, and a study compared the performance of two indices (SPI and PDSI) with a proposed method based on estimating dry spells (Krysanova *et al.* 2008). This study utilized the family of generalized linear models to predict droughts based on each of the three methods. Barros & Bowden's (2008) extensive study on long-lead forecasts of drought combined linear and non-linear statistical data models in order to forecast SPI levels 12 months in advance; results suggested that an ensemble approach would be appropriate. Blenkinsop & Fowler (2007) integrated multiple models in a complex projection of future precipitation patterns.

Monitoring plays an important role in drought management. Predictive models tend to rely on the data collected through weather monitoring stations or national organizations such as the National Climatic Data Center (NCDC). Many governing entities within the United States rely exclusively on a combination of indices and data provided by the NCDC (Tom Lowe, Kansas Water Office, personal communication, October 23 2008) and forego the use of predictive models. Hence, the potential of a drought occurring is not viewed as a forecast as much as a departure from the norm. Action is more reactive than proactive.

One example of a monitoring approach in the literature is described by Ramezani (2008); the methodology consisted of utilizing a simple moving average chart with control limits in order to identify whether a drought period was occurring. Both the Normal Percent Precipitation Index (NPPI) and the Standard Precipitation Index (SPI) were used as inputs to the model created using Minitab 14, a statistical software package. The study concluded that the moving average using SPI was more effective in recognizing drought periods. Steinemann & Cavalcanti (2006) describe a systematic and statistically consistent method of selecting appropriate indicators and triggers from the large variety available to policymakers. Final methods of drought monitoring were decided on by an iterative process of expert review and evaluation, along with analytic methods such as bivariate Pearson correlation.

Although it would appear that statistical quality control methods are highly relevant to drought monitoring, little research has been devoted to this area. Predictive models remain popular among the research community, while a more straightforward monitoring practice seems prevalent among many decision makers, particularly at the regional level.

In a review of the current literature regarding drought prediction/monitoring, the type of data available plays a significant role in the selection of a predictive or monitoring methodology. Autoregressive models are popular due to the fact that most (if not all) of the environmental and meteorological data are time series; weather stations throughout the United States measure precipitation, temperature and other observations in a systematic manner, checking the status of instruments at various times. Also, as mentioned previously, the methods utilized by most state governments point to a strong assumption of autocorrelation; action is often not taken until several time periods indicating drought have occurred serially.

Data characteristics

An enormous amount of drought-related data is collected. Government agencies at the state and national levels systematically collect and store data from weather stations spread throughout the United States. Precipitation statistics for the state of Kansas are available from as early as 1895.

Although a broad range of data types exists, and the debate over which measures are more relevant to drought prediction and monitoring is ongoing, there are a few general conclusions that can be drawn. Precipitation levels have been and still remain the most easily recognizable indicator of drought. Fundamentally, drought is a lack of precipitation. Understandably, critics charge that precipitation levels alone are a poor indicator of drought conditions, and that other measures such as groundwater levels and flow rates are needed in order to recognize potential droughts (James Putnam, US Geological Survey, personal communication, October 23 2008). However, the fact remains that groundwater levels are dependent on precipitation levels. One could abstractly view precipitation as an 'input' that maintains groundwater levels. Unless 'output' changes drastically, it will be the input that will affect the possibility of a future shortage.

METHODOLOGY

Data selection

The data that were selected presented several challenges. Although plentiful, not all meteorological data is accessible. Consequently, all precipitation data obtained from NCDC was in the form of a monthly average across the entire state of Kansas for the period from 1895 to the present (NCDC 2008). This presented several potential approaches for data analysis, but decreased the purity of the data. In addition to the precipitation data, average PDSI values across the state of Kansas spanning the same time frame were obtained; this provided a convenient matching of precipitation and PDSI values.

A key decision regarding the definition of drought conditions had to be made. The United States Geological Survey (USGS) reviews historical climate conditions in the state of Kansas, officially identifying years of drought (USGS 2000). Relying on the authority of the USGS provided a clear standard for evaluating the performance of the statistical quality control monitoring tool. As mentioned previously, monthly averages for the state of Kansas were obtained for both precipitation levels and values of the PDSI. These data were selected due to their convenient availability, as well as on the basis of quantity. Both data sets contained data from as far back as January of 1895 until October 2008 at the time they were accessed. This resulted in a total of 1366 data points for precipitation and the PDSI, with twelve data points per year.

Historical accounts (USGS 2000) have identified several periods of drought: 1929–1941, 1952–1957, 1962–1972, 1974–1982, 1988–1992 and, more recently, 2000–2006. In order to represent the historical occurrences of drought during specific time periods, a response was modelled as a binary variable. A value of this variable was then assigned to each month of each year. If a drought occurred during a particular year, all values of the response variable for each month of that year were assigned a value of 1; if no drought occurred, a value of 0 was assigned. This strategy provided the needed versatility for creating a statistical model of the data as well as an opportunity to provide analysis of Type I and Type II errors.

Methods of analysis

Applying the tools of statistical quality control to the drought-monitoring problem presented several challenges and opportunities. Preliminary assessment of the data indicated that there was a significant amount of variation within the precipitation averages dataset. Combined with the effect of seasonality and auto-correlation, it appeared fairly probable that a statistical model would be theoretically appropriate for the data. Logistic regression was quickly identified as a strong candidate, considering that the occurrence of drought could be conveniently classified on a binary basis (1 for drought, 0 for lack of drought). In this case, 'success' would indicate the occurrence of a drought and 'failure' would specify lack of a drought (see Steiner *et al.* 2000 for an application of logistic regression to surgical data). A chart for the purpose of monitoring droughts would then be constructed on the basis of the regression model.

The second method of analysis selected was the application of the control chart for individual observations (the I-Chart). Several characteristics of the problem indicated that this would be a suitable approach for comparison with the logistic model. First, the official drought record for the state of Kansas (USGS 2000) provided a suitable identification of Phase I (statistical analysis to establish in-control limits) data. Only data points that were not classified as droughts under the official record would be included in the calculation of control limits; data points from drought years could be assumed to be out-of-control with an 'assignable cause' (in this case a change in precipitation or PDSI). Second, by supplementing the data obtained from the NCDC with the official Kansas drought record (USGS 2000), it would be possible to evaluate the values of the Type I and Type II errors associated with the designed chart by comparing points that plotted out-of-control with the actual occurrence of a drought.

Utilizing these two approaches to analyze the available data, a suitable comparison of the theoretically appropriate logistic regression model with the classic Shewhart control chart could be made.

RESULTS

Ultimately, all of the data was arranged in a format convenient for analysis (see Table 1), along with the response variable representing the absence or presence of a drought. Two methods of analysis were applied to the data. First, a statistical model was fitted to the data using logistic regression, which provided predictions of drought based on the comparison of the estimated probabilities for each available data point (values of precipitation and PDSI) with a specified 'cut-off' value. The second approach was to design an I-Chart (control chart for individual observations) to classify data

Table 1 | Example of data

Year	Month	Precip.	PDSI	Drought
1928	5	3.48	1.91	0
1928	6	7.31	3.28	0
1928	7	4.33	3.73	0
1928	8	3.04	3.77	0
1928	9	1.34	3	0
1928	10	2.49	2.94	0
1928	11	4.26	4.22	0
1928	12	0.95	4.2	0
1929	1	1.09	4.36	1
1929	2	0.83	4.25	1
1929	3	0.91	3.53	1
1929	4	3.28	3.56	1
1929	5	4.69	3.88	1

from specific data points as 'in-control' (no drought) or 'out-of-control' (drought occurrence).

Logistic regression model

Logistic regression is a specific instance of the class of models known as generalized linear models, and is applied to binary outcomes (1 for success, 0 for failure). The probabilities associated with each outcome are assumed to follow a binomial distribution (Cabrera 1994). An additional assumption is that the binary outcome is related to independent variables and that these relationships follow the logistic function. Consequently, the logistic regression model can be expressed as $\log\,[p\ /\ (1\text{–}p)] = \beta_0 + \beta_1 \times_1 + \ldots + \beta_n x_n$, where p is the associated probability of success, x_1 through x_n are the independent variables, β_0 is the intercept and β_1 through β_n are the coefficients of the independent variables. Hence, the binary outcomes are related to the linear combination of the independent variables via the natural log of the odds ratio (probability of success over the probability of failure). The parameters of the model (β_0 through β_n) are determined via the Maximum Likelihood Estimation.

The logistic regression model was applied to the data using Minitab 15; both data types (precipitation and PDSI) were treated as independent variables affecting the outcome (binary variable indicating drought). Although the calculation of PDSI includes precipitation (Palmer 1965), we were careful to ensure that there were no significant effects due to multicollinearity, an issue often arising when applying regression techniques to correlated independent variables. The results (summarized in Table 2) indicated that precipitation failed the test of significance, while the hypothesis that PDSI was insignificant was rejected.

Since the statistical software indicated a failure to reject the hypothesis of insignificance for precipitation in the main effects model, it was determined that further analysis would be appropriate. A second order model was fitted in order to determine whether interactions between precipitation and PDSI existed, verifying the insignificance of the precipitation factor. The newly defined independent variables for the second-order model were precipitation, PDSI, the square of precipitation, the square of PDSI and the interaction created by multiplying precipitation by PDSI. The results appear in Table 3.

Results from the second-order model confirmed the previous results: again, the PDSI variable was the only factor successfully rejecting the hypothesis of insignificance. All other factors failed to reject the hypothesis. Consequently, it was determined that the most appropriate model would be based on a single independent variable representing the PDSI values. Given the parameters of the logistic regression model, an estimated probability of a drought occurring could be calculated for each data point; these probabilities could then be compared to a particular level of probability selected as a 'cut-off' in order to predict an outcome of drought or no drought. Having obtained an acceptable logistic regression model and determined precipitation to be an insignificant factor, a second approach using statistical quality control was attempted.

SQC method

As mentioned previously, the SQC tool selected for analysis of the data was the I-Chart (control chart for individual observations); the selected variable to plot was the PDSI value. However, particular characteristics of the data required a divergence from the classic application of the individuals (I) chart.

The PDSI is structured such that a value of zero indicates normal conditions, a positive value indicates increased

Table 2 | First-order logistic regression model

Predictor	Coefficient	Standard error
Constant	−0.222616	0.105222
Precipitation	0.0663489	0.0387962
PDSI	−0.387072	0.0273294

Table 3 | Second-order logistic regression model

Predictor	Coefficient	Standard Error
Constant	−0.290687	0.152067
Precipitation^2	0.0124501	0.0190084
PDSI^2	0.0173368	0.0089751
PDSI × Precipitation	−0.0367624	0.0200058
Precipitation	0.0326959	0.111463
PDSI	−0.315272	0.0474175

moisture and a negative value indicates a moisture deficit. Since the objective was to detect droughts, the primary concern was to detect unusually low values of the PDSI; positive values of PDSI were not considered relevant. Consequently, only the lower control limit was of interest. Shewhart control charts for individuals are two-sided with an upper and lower control limit and Type I error probability of approximately 0.0027 outside of the three sigma control limits. A new chart had to be devised in order to provide performance reasonably similar to the classic Shewhart chart, but with only one control limit of interest.

Given that the Shewhart chart with three sigma limits has approximately 0.0027 Type I error probability outside of the control limits, it was assumed that a single control limit chart should retain the same level of Type I error, albeit on one side of the control limit (the lower control limit). Given a total probability of approximately 0.0027, the related Z score for the lower control limit is approximately −2.8. This would indicate that an appropriate lower control limit would be 2.8σ below the centreline.

To apply the I-Chart, appropriate estimates of sigma had to be obtained from the 'in-control' data points in order to calculate an appropriate control limit. Assuming that in-control data would be represented by months when no drought occurred, and treating drought occurrence as an 'out-of-control' situation, estimates of sigma were based on all available drought-free data. The centreline was based on the sample average of the in-control data. Using the moving range estimation of the standard deviation, the calculated lower control limit (LCL) was calculated to be 0.062583 (see Table 4 for a summary of the results).

Table 4 | One-sided I-chart design

X-bar	1.468939
MR-bar	0.56656
d_2	1.128
s	0.50227
LCL	0.062583

After implementing the I-Chart design calculated from the in-control data only, the remainder of the data (including data points when drought occurred) was also plotted (see Figure 1). As can be seen, the initial impression of all the plotted data was that a large number of points seemed to plot below the lower control limit.

Type I/Type II error analysis

Having implemented both a logistic regression model as well as a modified version of Shewhart's control chart for individuals, a comparison of the two methods was appropriate. The fact that periods of drought had already been

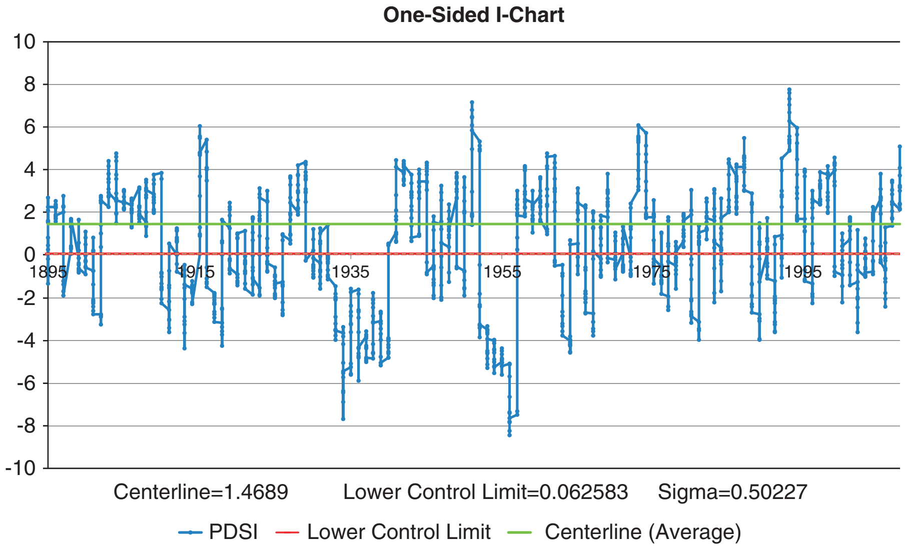

Figure 1 | One-sided I-chart.

identified for the time intervals in which the data had been collected enabled convenient estimation of Type I and Type II errors. Approximations of each type of error could be obtained for both methods of analysis, facilitating systematic comparison.

For a particular value of the cut-off probability in the logistic regression model, Type I error could be estimated by counting the number of false alarms from the model's predictions in comparison to the actual occurrence of drought and dividing by the total number of data points. Type II error could be estimated by counting the number of occurrences where the model prediction failed to specify drought when a drought actually occurred and dividing by the total number of data points.

In the case of the one-sided I-Chart, the number of points falling below the lower control limit where no drought occurred divided by the total number of data points would give the estimated Type I error rate, while the number of misses divided by the total would give an estimate of the Type II error rate. In this way, the Type I and Type II error rates could be compared to those of the logistic regression model.

It could be argued that the selection of control limits for Shewhart's control charts is rather arbitrary; three sigma limits have been the subject of much debate. Thus, in seeking a relatively reasonable comparison with the logistic regression model, an analogous cut-off value of probability had to be selected. In order to provide a good assessment of the performance of both models, several scenarios for the logistic regression model were evaluated:

1. an arbitrarily selected cut-off probability of 0.5;
2. cut-off value selected such that Type I and Type II errors are equal (equal cost scenario); and
3. cut-off value selected such that the Type I error rate is as close to 0.0027 as possible.

All three scenarios were completed and the associated Type I and Type II error rates calculated; error rates for the one-sided I-Chart were also calculated. Type I error percentages were summed with Type II percentages in order to obtain a total 'cost' due to errors associated with the models, an approach made possible by assuming an equal cost for each error type. This enabled comparisons of effectiveness for each model. The results are summarized in Table 5.

Table 5 | Type I and Type II Error Rates

Model	Cut-off	Type I	Type II	Total cost
I-Chart	N/A	0.1640	0.1728	0.3368
Logistic	0.5000	0.1325	0.2269	0.3594
Logistic	0.7637	0.0037	0.3631	0.3668
Logistic	0.3338	0.1669	0.1669	0.3338

CONCLUSIONS AND FUTURE WORK

The information in Table 5 presents several interesting results. Assuming an equal cost scenario (cost of Type I error is equal to cost of Type II error), the Shewhart chart performs surprisingly well. As indicated by the Total cost column in Table 5, if there is an equal aversion to false alarms as there is to failing to recognize drought occurrence, the I-Chart actually outperforms the logistic regression methods with the exception of the equal cost design, which demonstrates an improvement that can be considered marginal at best (0.003 difference). These results occur despite the fact that the logistic regression approach could be considered the more 'intelligent' of the two methods; even the theoretically appropriate statistical model designed specifically to produce equal Type I and Type II errors fails to produce significant improvement over the Shewhart chart.

Interestingly, this appears to coincide with the philosophy of Halide & Ridd (2008): increased model complexity does not guarantee greater model efficacy. More variables may not necessarily lead to greater accuracy. It may be that the advantages presented by the relatively simple application of statistical quality control tools may prove to be sufficiently accurate for drought management, as well as being relatively accessible in comparison to more complex models.

There is a lower total percentage of error (both Type I and Type II) for the quality control approach than for all but one of the logistic regression models. This seems to indicate that statistical quality control has the potential to reduce the number of false alarms as well as the number of failures to recognize drought. False alarms could lead to the unnecessary deployment of drought management resources, while failing to respond when a drought is in progress could amplify socioeconomic consequences. Both lead to undesirable impacts, and any reductions in the number of errors would be advantageous. Although in a perfect world the drought monitoring methodology would lead to no such errors on the part of drought management officials, seeking to minimize the total cost of both error types is applicable in a realistic manner in order to obtain the best possible utilization of resources.

The success of the Shewhart chart could be due in part to the distribution underlying the PDSI values; because the PDSI values are monthly averages, the central limit theorem suggests they may by normally distributed. Due to the effectiveness of Shewhart charts when the data are normally distributed, the PDSI data may have provided a significant enhancement to the performance of the I-Chart.

An additional characteristic of interest for the Shewhart chart is the value of the control limit (0.062583); this value is remarkably close to 0, which is defined as normal moisture conditions for the PDSI. This result would seem to indicate that the PDSI is a fairly reliable indicator, and that its popularity as a standard for determining drought conditions is well founded.

Several possibilities for future research are evident. The foremost opportunity would be to obtain other popular indices or measures utilized in drought prediction (such as stream flow volumes or groundwater levels) and apply similar analysis techniques. These might provide valuable information regarding effective methods for mitigating the consequences of drought. It may be possible that other measures and indices would provide lower costs under the equal cost scenario.

Another area warranting further investigation would be estimates of the actual costs of Type I and Type II errors; this would be of great assistance in designing the most cost-effective drought monitoring methods. In this study, false alarms and missed signals (Type I and Type II errors) were considered to be equally undesirable; future studies could perhaps determine approximate costs by interviewing officials involved with drought management in order to ascertain the effectiveness of the proposed method under actual perceptions of costs. Also, the performance of methods based on various measures and indices could be compared and contrasted to determine economic designs.

Regarding the Type I and Type II errors, it is important to note that the method of classification for drought was to classify all months in a drought year as a time of drought; further work would benefit from higher resolution information. Estimates of Type I and Type II errors would improve in accuracy if such data were obtained, shedding additional light on the subject. As mentioned previously, all the PDSI data obtained for this study was for the entire state of Kansas; consequently, one limitation of this study is in the area of spatial scale. Opportunities for future study include using data from a smaller region to assess the efficacy of the statistical method in monitoring drought. How would this analysis perform in geographically diverse regions? Is there a significant difference in performance when analyzing regions such as the Great Plains and the Rocky Mountains?

The index chosen for this analysis was the PDSI. Applying the same approach presented in this article to other indices such as the SPI (Standardized Precipitation Index), SWSI (Surface Water Supply Index), or RDI (Reclamation Drought Index) may provide a greater understanding of the efficacy of statistical quality control tools and logistic regression in this field. Several areas of further research are possible, and the field of drought monitoring and prediction stands to benefit.

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