Assessing spatiotemporal variability of drought in the U.S. central plains

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This paper examines the change in precipitation from 1900 to 2006 on a regional scale over a portion of the Central United States. Monthly precipitation data is kriged over the Kansas River Basin region. The Standardized Precipitation Index (SPI) is calculated at several time scales ranging from 1 to 12 months. The linear trend of SPI values over the time period is calculated and analyzed, showing many areas of increasing wetness throughout the area, with drying in isolated regions of the West and North. These isolated regions of drying overlap regions of heavy water use and irrigation, suggesting possible detrimental effects on agricultural production and aquifer levels if the trend continues. With the areas of increasing trend, however, it is unclear whether increased precipitation actually signifies any increase in water availability. Fourier analysis is also used to detect characteristic frequencies of SPI values. No difference in drought frequency patterns across the region was observed.

1. Introduction

Much of the recent public concern over climate change tends to focus on rising global mean temperatures. However, climate varies significantly on a regional scale and changing precipitation patterns can be particularly damaging (IPCC, 2007; Chapter 11). In fact, drought is estimated to be the most costly natural disaster in the world (Witt, 1997). The wide range of detrimental effects associated with precipitation deficits include: decreased crop yields, increased wildfires, death of cattle and wildlife, water shortages, and rising food prices (Witt, 1997, and National Drought Mitigation Center, http://www.drought.unl.edu/risk/impacts.htm). The variety of direct and indirect damages makes it difficult to enumerate the exact costs, although the Federal Emergency Management Agency (FEMA) estimates losses at between 6 and 8 billion dollars annually in the United States alone (Witt, 1997).

Precipitation quantities and patterns remain more difficult to predict and identify than changes in temperatures. Most global climate models (GCMs) parameterize cloud processes, which leads to significant differences between predicted and observed precipitation patterns (Randall et al., 2007). Moreover, the resolution of GCMs is approximately 2° latitude by 2° longitude over land (Randall et al., 2007), which not only limits the ability to simulate sub-grid scale precipitation processes but also leads to problems in the understanding and prediction of small-scale as well as regional precipitation changes that can have pronounced effects on human habitats, whether agricultural or urban.

Drought and its consequences have long plagued ecosystems and society (e.g. Le Roy Ladurie, 1971). The consequences of drought vary greatly depending on its location, timing, extent and the type of society or societal sector impacted by the drought. (e.g. Gleick, 1993). In part because of the difficulty in defining how drought might affect society there is no universal definition of drought. In addition drought is also not easily linked to fixed precipitation amounts. For example, one of the weaknesses of Koppen (1900) climate classification system is that it defines climatic boundaries of the basis of precipitation quantities. Thornthwaite (1931) recognized this problem and developed a methodology to quantify water demand or potential evapotranspiration and developed a climate classification that allowed for climate to be defined in terms of water demand and supply (Thornthwaite, 1944, 1948). These early efforts were really considered what Thornthwaite (1931) identified as permanent drought conditions as an indication of the relative aridity of a climate (i.e. a permanently dry climate as opposed to the concept of a temporary drought period). However, societal drought impacts are more often caused by relative drought conditions, where drought is a consequence of a temporary deviation from normal water demand and supply conditions (Carter and Mather, 1966; Kemp, 1994). Such temporary anomaly conditions can be well represented in a number of ways by evaluating anomalous water supply (precipitation) conditions, or through other variables such as soil moisture conditions. The combination of what defines a drought that has an impact on a particular sector of society and...
the choice of variables to use to define drought led to over 150 definitions of drought (Wilhite and Glantz, 1985). Recognizing that set precipitation amounts could not define drought conditions, since drought period attempted to distinguish between locations that observe “permanent drought,” the consequences of drought vary greatly by the length and timing of the precipitation deficit, which is often not taken into account in the interpretation of model results. More recently, Heim (2002) divides drought into four categories based on the myriad of effects: meteorological, agricultural, hydrological, and socioeconomic. Meteorological drought simply refers to the atmospheric conditions that result in the absence or reduction of precipitation. Because its definition only relies on rainfall, meteorological drought can end literally overnight, as soon as sufficient precipitation falls to bring levels close to average. Agricultural drought is a short-term dryness in soil layers that can reduce crop yields. Due to its reliance on plant and soil conditions, agricultural drought usually has a lag time in response to precipitation changes (Park et al., 2005), and the impact depends greatly on the timing of the drought in relation to crop growth. Hydrological droughts have an even longer lag time, as they are defined by deficiencies in surface and subsurface water supplies, which respond more slowly to meteorological conditions. Socioeconomic drought can be related to any of other three categories, but with a strong emphasis on the supply and demand of an economic good that is affected by these drought conditions. These drought classifications have different characteristic time scales, but often produce overlapping consequences.

For instance, in a heavily irrigated region, a precipitation deficit only a few months long could have detrimental effects if it occurs during the growing season. Crops would require additional irrigation, putting further stress on groundwater reserves and contributing to hydrological drought conditions. Conversely, long-term hydrological drought conditions can have adverse effects on agriculture by lowering aquifer levels, increasing the cost and difficulty of irrigation. Both of these scenarios would also have socioeconomic consequences, such as increased food prices and shortages of water for industrial uses. Thus, it is important to understand and predict both short- and long-term droughts and seasonal variations of drought occurrence.

Evaluation of streamflow data in Kansas shows that hydrological droughts are becoming more severe, even without larger precipitation deficits occurring (Putnam et al., 2008). Record-low streamflow levels were recorded in many Kansas rivers in 2006, and demand for water in the area is rising (Putnam et al., 2008)—implying that future droughts could be even more devastating.

This study focuses on quantifying spatial and temporal patterns in drought occurrence throughout a heavily agricultural region in the Central U.S. Specifically, patterns and changes of drought severity, amount, and characteristic frequencies are analyzed for droughts of many time scales and each season. This will further understanding of current patterns of precipitation, how it has changed with altered land use in the area, and what future areas/time scales may be vulnerable.

2. Review of drought indices

The first issue in studying drought is deciding on a meaningful, precise, and functional definition. According to the National Weather Service glossary (NOAA, 2008), drought is “a deficiency of moisture that results in adverse impacts on people, animals, or vegetation over a sizeable area.” This general definition can be widely agreed upon, but has little practical use. The definition does little to help us classify precisely when a precipitation deficit is occurring, when it ends, how anomalous the conditions are, and how conditions vary over time and space. A precise mathematical index must be used for scientific studies of precipitation, and many have been developed over the years. Some of the pertinent information used for selection of an index in this study is outlined below. For a more thorough review of drought indices the reader is referred to Heim (2002).

Early indices tended to be simplistic, specific to certain uses, and applicable only in particular regions. For example, one early criterion for drought was fifteen consecutive days with no rain (Heim, 2002). This definition is surely meaningless in an arid location, where such conditions are well within a normal range. The index also does not take into account seasonal variations and cannot be used to track normal or anomalously high precipitation conditions. Some indices are less regionally specific, defining drought as an accumulated departure from normal conditions. Although this concept of summed precipitation anomalies is very simple and easy to define at any location, it usually leaves many questions unaddressed. For instance, the exact time a drought begins, which is critical for calculating the cumulative anomaly, is often defined subjectively as a time when the cumulative anomaly begins a sharp decline (Keyantash and Dracup, 2002). The relative severity of a drought is also difficult to gauge without a standard method of relating the amount of precipitation deficit may be devastating in some regions, but no cause for concern in others.

Thornthwaite (1931, 1948) proposed indices more focused on agricultural uses. The precipitation effectiveness index, for example, is the sum of precipitation effectiveness ratio (monthly precipitation divided by evaporation) over 12 months at a location. Another index proposed by Thornthwaite is just precipitation minus evapotranspiration. These sound simple, but there are many complicating factors involved in the estimation of evaporation and evapotranspiration (Thornthwaite, 1944) that could cause errors. It should also be noted that, with no frame of reference used for normal conditions in a region, these indices are more a measurement of the climatic aridity of a location than of the temporary conditions that define drought (Heim, 2002). Thornthwaite’s proposals were innovative, however, in their emphasis on not just the amount of rainfall, but also on the amount of water needed for agriculture. His ideas were used as a basis for many indices to follow, including the Palmer Drought Severity Index (PDSI), which has been widely used in the United States (Palmer, 1965).

Palmer (1965) developed the PDSI for monitoring crop conditions. Considered the first comprehensive drought index in the U.S., it is widely hailed as a landmark development (Heim, 2002). PDSI was designed to be an appropriate index for agricultural uses, taking into account soil and crop needs. Based on a monthly water balance accounting system, PDSI incorporates precipitation, soil moisture, runoff, evapotranspiration, potential evapotranspiration, and other factors important to plant growth. The water balance equations involve many variables, steps, and assumptions, which are explained in detail by Alley (1984).

McKee et al., (1993) developed the Standardized Precipitation Index (SPI) to address the variety of time scales on which precipitation deficits/surpluses can affect different aspects of the hydrologic cycle. A relatively short-lived precipitation deficit during the growing season may have little noticeable effect on groundwater levels, but could, at the same time, be detrimental to crop growth. SPI is based on precipitation data summed at any time scale (usually between 1-month and 24-month sums depending on area of interest) and fitted to a statistical distribution. The relative simplicity of the SPI is one strong advantage of the index. The SPI, like the PDSI, is a dimensionless number in which negative/positive values indicate dry/wet conditions (Heim, 2002). However, unlike the PDSI, the values are normalized (McKee et al., 1993). Although the SPI is theoretically unbounded, in practical
application, it is usually bounded at around $\pm 3.09$, corresponding to the probabilities of .999 and .001, due to the finite number of observations (Guttman, 1999). The normalization of the index implies that SPI values should occur with the same frequency everywhere, so the index should be useful at any location and be spatially consistent. Additionally, because only precipitation values are used and the data is standardized, the exact meaning of an SPI value is clear and easy to compare to historical records. Since SPI can be calculated on any desired time scale, droughts of different characteristic lengths that affect different aspects of the hydrologic cycle can be analyzed. Other advantages of the SPI include the fact that wet and dry conditions are represented in a similar way, meaning that wet conditions can also be monitored (McKee et al., 1993).

Unfortunately, there is a caveat with the universal application of SPI. For arid regions and short time scales, the large number of zero precipitation values could skew the SPI towards positive numbers (Wu et al., 2007). If there are many zero precipitation values, $q$ (equation (5)) will be a high probability, resulting in SPI values that are non-normally distributed and effectively lower bounded (Wu et al., 2007). Given that zero values of precipitation are more likely to happen on smaller scales and in drier locations/seasons, it is important to keep this in mind and use time scales appropriate for the location being studied.

Other weaknesses of the SPI include its lack of consideration of snow/frozen ground, soil conditions, distribution of rainfall within the time scale evaluated, or temperature data. It is important to point out that even if precipitation in an area is greater, a corresponding increase in temperature could negate the positive effects of increased moisture from an agricultural perspective. Although McKee et al. (1993) originally used a gamma distribution, any distribution function can be used to fit the data. Guttman (1999) compared SPI values computed using six different distributions and concluded that Pearson type III and the two-parameter gamma distribution matched a standard model best. He suggested that Pearson type III distribution be used universally, because, with its three parameters, it is more flexible for fitting simple precipitation data. However, the two-parameter gamma distribution is used especially often (e.g. Lloyd-Hughes and Saunders, 2002, Moreira et al., 2006, Sonmez et al., 2005, Wu et al., 2005, 2007), as it was originally specified by McKee et al., (1993) and has been distributed for use in over 60 countries (Wu et al., 2005).

As with the PDSI and other indices, the length and consistency of record can affect the accuracy of SPI values. McKee et al., (1993) originally specified that a period of at least 30 years should be used for SPI calculations. Guttman (1994) found that records of 40–60 years are needed for stability in the central area of the precipitation distribution, and records of 70–80 are years needed for stability in the tails of the distribution. Wu et al. (2005) also studied the effect of record length on SPI, and warn users of SPI that incomparable values can be obtained if different periods of precipitation record are used in SPI calculation.

Many studies have been done to compare a variety of drought indices, or to specifically compare PDSI and SPI. In one such comparison, Guttman (1998) analyzed the spectral density of PDSI and the cross-spectra of PDSI and SPI at 111 stations across the U.S. He found that there was a high level of consistency between SPI and PDSI and noted that PDSI tends to lag the SPI on time scales shorter than a year and is in phase with the 12-month SPI. A correlation of .73 between PDSI and 12-month SPI was found by Lloyd-Hughes and Saunders (2002). This indicates that precipitation is the dominant factor of PDSI. When looking at PDSI spectral density alone, Guttman (1998) found 8 distinct characteristic spectra, indicating a lack of spatial consistency in the PDSI. For instance, in some areas PDSI values have a memory of soil conditions for at least 9 years prior, while in other places the index has a memory of only about 2.5 years. Due in part to this spatial inconsistency, Guttman (1998) recommended the use of SPI for drought studies. Alley (1984) also concluded that PDSI lacks spatial consistency due to the large variability in the rate of occurrence of “extreme” and “severe” droughts across the U.S.

In a more comprehensive study of indices, Keyantash and Dracup (2002) evaluated the relative effectiveness of 14 different commonly used drought indices. They used their own admittedly subjective evaluation criteria of robustness (over a wide range of physical conditions), tractability (simplicity of computation), transparency (clarity of objective of the index), sophistication, extendibility (across time), and dimensionality (connection of

Fig. 1. Locations of data stations (black dots) and area of analysis (outlined by dashed rectangle), also outlined is the boundary of the Kansas River Basin.
values with real world data). The index with the highest ranking was the rainfall deciles, scoring 116/145, followed closely by the 1-month SPI (the study ignored other possible time scales) with 115. PDSI received one of the lowest 3 scores. Although this scoring was subjective, the study does provide interesting results that echo many of the considerations of PDSI and SPI presented above.

3. Methodology

In this study, data covering the central US from the Global Historical Climatology Network (GHCN) is analyzed for spatial and temporal precipitation patterns and trends. Each of the 337 stations used (Fig. 1) has records of at least 30 years of monthly sum precipitation during the period from 1900 to 2006. The analysis presented focuses on the region over the Kansas River Basin (KRB) (Fig. 1), an area of stark precipitation gradient (Fig. 2; see below for discussion of the data used in the calculation), with the Western region drier in the rain shadow of the Rockies and the Eastern/Southern regions receiving more moisture from the Gulf of Mexico.

An issue that must be addressed is that of missing data. When looking at spatial trends, a uniformly distributed set of stations with no missing data would be ideal. However, regional data for the entire record of study on a consistent grid is, of course, unavailable. In order to account for this spatially and temporally varying data

![Fig. 2. Average annual precipitation (mm) from 1900 to 2006.](image)

![Fig. 3. Example of transformation from fitted gamma distribution cumulative probability to standard normal distribution values.](image)
set, the data is kriged to create a .05 degree grid of monthly precipitation values for 1900–2006 over the area around the Kansas River Basin (Fig. 1). This choice of region and time period ensures that more than 150 stations spread in and around the area are used to calculate the grid at each month. While there are more advanced methods for quantifying the spatial distribution of precipitation, ordinary kriging is deemed sufficient as opposed to a model-data combined approach (e.g. Haberlandt and Kite, 1998) as there is little topography in the area and we are only interested in data at a monthly time scale.

As this study analyzes spatial and temporal trends over a zone of such diverse climatic norms, one of the primary concerns in picking an index is the ability to compare values across many different locations. For this reason and the many advantages outlined above, SPI was chosen as the evaluation tool. However, since the western region of study is relatively dry, appropriate time scales of SPI must be used to maintain normality. Wu et al. (2007) tested for the normality of SPI at several scales in many locations across the U.S. They found non-normal SPI distributions in Kansas and Nebraska at time scales of up to 6-weeks. In order to avoid this possible discrepancy, SPI is only calculated at time scales of 3-, 6-, 12-, and 24-months in this study.

Lloyd-Hughes and Saunders (2002) outline in detail the calculation of SPI, which is summarized here. The most commonly used distribution for SPI calculation is the two-parameter gamma distribution, with a shape and scale parameter, which has the probability density function defined by:

$$g(x) = \frac{1}{\beta^a \Gamma(a)} x^{a-1} e^{-x/\beta} \quad \text{for } x > 0,$$

where $a$ is a shape parameter, and $\beta$ is a scale parameter, $x$ is the amount of precipitation, and $\Gamma$ is the gamma function. Initial estimates for the shape and scale parameters are calculated by:

$$a = \frac{1}{4A} \left( 1 + \sqrt{1 + 4A^3} \right),$$

and

$$\beta = \frac{x}{a},$$

with

$$A = \ln(x) - \frac{\sum \ln(x)}{n},$$

where $x$ is the precipitation (averaged at any time scale, denoted by the overbar) and $n$ the number of observations. Using these as initial shape/scale estimates, an iterative procedure for maximum likelihood estimate is applied, resulting in a better fitting of $a$ and $\beta$ to the precipitation data.

By integrating the probability density function with estimated parameters, the cumulative probability of a given precipitation value for each month can be calculated, denoted $G(x)$. However, since the gamma distribution is undefined at 0, the probability of no precipitation is not yet included in this value. Obviously, there is a chance of no observed precipitation within the time scale, so this must be corrected for, and the new cumulative probability becomes:

$$H(x) = q + (1 - q)G(x),$$

Table 1

<table>
<thead>
<tr>
<th>SPI</th>
<th>Condition</th>
<th>Cumulative probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>-3.0</td>
<td>Extremely dry</td>
<td>0.0014</td>
</tr>
<tr>
<td>-2.0</td>
<td>Severely dry</td>
<td>0.0228</td>
</tr>
<tr>
<td>-1.0</td>
<td>Moderately dry</td>
<td>0.1587</td>
</tr>
<tr>
<td>0.0</td>
<td>Normal</td>
<td>0.5000</td>
</tr>
<tr>
<td>1.0</td>
<td>Moderately wet</td>
<td>0.8413</td>
</tr>
<tr>
<td>2.0</td>
<td>Very wet</td>
<td>0.9772</td>
</tr>
<tr>
<td>3.0</td>
<td>Extremely wet</td>
<td>0.9986</td>
</tr>
</tbody>
</table>

Fig. 4. 12-month sum precipitation in mm (top), 6-month SPI values (middle), and 12-month SPI values (bottom) for kriged data at Topeka (38.95°N, 95.95°W) from 1900 to 2006.
where $q$ is the probability of zero precipitation (simply the number of observations of zero precipitation divided by the total number of observations). This can cause errors in some arid regions. The cumulative probability distribution $H(x)$ is then transformed into the standard normal distribution using a conversion approximation to generate the SPI values for each month (e.g. Fig. 3). The conversion approximation is given in detail in Lloyd-Hughes and Saunders (2002). SPI values calculated this way should have an expected value of 0 and a standard deviation of 1. McKee et al., (1993) defined drought categories for SPI values as seen in Table 1.

From the kriged precipitation results SPI is calculated using the two-parameter gamma distribution at 3-, 6-, 12- and 24-month time scales. Mean annual precipitation totals are also calculated from the kriged results at each location, (Fig. 2).

To examine temporal changes over the period of study, a simple linear regression is calculated at each grid point for each time scale of SPI. The slopes of the linear trends are then mapped to see spatial differences in temporal trends across the KRB. Trends for 3-month SPI are calculated using February, May, August, and November values separately, so that trends in short-term drought occurrence can be investigated by season (winter, spring, summer, and fall, respectively). Recall that the 3-month SPI value of May, for instance, is based on the sum of precipitation of March through May, while August is based on the sum of June–August. So, in order to avoid overlap, only one month is chosen to represent each season.

To further analyze temporal patterns of precipitation anomalies, Fourier analysis is used to decompose each time series of kriged 12-month SPI values. 12-month SPI is chosen as the time scale of analysis because of the common use of this time scale and correlation with other drought indices, such as PDSI. The Fourier spectra are used to compare characteristic frequencies of anomalous precipitation incidents by longitude and are averaged over the entire region to examine characteristic drought frequencies of the area as a whole.

4. Results and discussion

Considering amount of irrigation already required in some counties in the KRB, water limitation due to drought is a viable threat to the agricultural production in the region. Additional water is especially needed in the Western (Eastern Colorado) and in the Northern (Southern Nebraska) portions of the basin where there is
less precipitation annually and/or more water-intensive crops are grown. Precipitation differs across the region by up to 790 mm annually (Fig. 2), with the driest western grid point receiving an average of only 229 mm yr$^{-1}$ and the wettest Eastern region averaging 1019 mm yr$^{-1}$. Because there is such a strong gradient over a region spanning approximately 10 degrees longitude, small changes in the precipitation pattern could have large effects locally. A shift in the gradient too small to be detected on the scale of most global climate models could potentially cause detrimental effects on the largely agricultural region.

From a straight monthly precipitation time series (Fig. 4, top) it is difficult to locate any historical time periods of drought, much less interpret the frequency of droughts or changes in severity over time. In the calculation of SPI, the cumulative probability of each precipitation value is assigned a standard normal value (Fig. 3). Thus, any month with the mean summed precipitation value becomes 0 SPI. After this transformation, it is readily apparent which time periods have below/above average precipitation based on values being less/greater than 0 SPI (Fig. 4, middle and bottom). It is also easy to distinguish periods of drought, as defined in Table 1, and recognize historical extremes, such as the severe droughts in the 1930s and 1950s. The longer the SPI scale, the smoother the time series becomes, since precipitation values used in SPI calculation are summed on the scale of interest. Hence, the 12-month SPI (Fig. 4, bottom) shows longer-term drought conditions, is a much smoother time series, and tends to lag slightly behind the 6-month SPI (Fig. 4, middle) drought occurrences. With this the historical record of droughts in the area can be seen at each station.

Fig. 6. Slope ($\Delta$SPI/year) of the linear regression of 24-month (top), 12-month (middle), and 6-month (bottom) SPI values for the period of 1900–2006.
Plots of SPI values for specific months (Fig. 5) prove that the index can have a wide range of conditions across the KRB, with some areas capable of being in ‘extremely wet’ conditions during the same month that others regions are in drought conditions. Although, in extreme drought conditions, it is also possible for nearly the entire region to be in a drought at once. For instance, over 81% of the region is classified as experiencing drought in July of 1956 (Fig. 5, top).

The linear trends in 24-, 12-, and 6-month SPI also exhibit a wide range of values across the area (Fig. 6). A similar spatial variation is seen for all three of these SPI time scales. There is an increasing trend of SPI in most of the region, especially in the Southern area. Eastern Colorado, far Northwestern Kansas, and Central Nebraska all have decreasing rates of SPI from 1900 to 2006. Thus, the largest decrease in SPI is seen in areas that already have lower mean precipitation values and rely more heavily on irrigation. This is illustrated in Fig. 7, where the average trend in SPI is plotted along with the mean annual precipitation. The SPI trend is decreasing between $-104$ to $-102$ degrees longitude, or in far Western Kansas/Eastern Colorado, where precipitation averages below 500 mm per year. All Eastern latitudes, which already average much more precipitation, show increasing SPI trends.

Severity of the consequences of drought vary greatly by season, and the trend in SPI of drought across the region also varies by season. Linear trends in 3-month SPI for winter, spring, summer, and fall seasons were plotted (Fig. 8). The greatest decrease is seen in winter, where most of the region has a decreasing trend in SPI that is especially prevalent in the same areas of strong decreases on
larger time scales. Spring shows the most increase in precipitation throughout the East, with some areas of decrease confined mostly to the area around Eastern Colorado. Summer has a drying trend in the North, with increases SPI in the far South and East, while fall shows little change or variation.

In order to analyze patterns in drought frequency over the time period, the Fourier spectra of the 12-month SPI time series were computed for each grid cell and averaged by longitude. Comparison of the frequencies of anomalous precipitation events in the West/ East showed no major variation with longitude. The average spectrum for the entire region (Fig. 9) illustrates a tendency for anomalous precipitation to occur periodically about every 2.17, 2.54, 3.23, 4.82, 7.77, and 23.77 months.

5. Conclusions

The SPI is a valuable tool for quantifying the impacts of drought and comparing the intensity of drought across time and space. Here, we examine the trend in SPI for a heavily agricultural region in the central U.S. Kriged monthly precipitation data shows that the areas of the basin which receive less than 500 mm of precipitation annually are showing decreasing trends (becoming drier) over the twentieth century.

These areas in the western portions of the basin are heavily agricultural and make use of the Ogallala aquifer for irrigation. Given the likelihood of increased air temperatures in the region (Brunsell et al., in press) combined with a continued trend in decreasing precipitation, the Kansas River Basin becomes extremely vulnerable to the occurrence of drought. The eastern portions of the basin are generally showing increases in the SPI (wetter conditions). It must be pointed out that if temperatures increase across the region, an increase in precipitation may still result in a decrease in moisture availability and therefore a net drying of the area. There is a sensitive balance between increases in air temperature and precipitation that will result in a net gain precipitation in the region. Given the functional form of the Clausius–Clapeyron equation, it is likely that the increases in precipitation will not be sufficient to offset the atmospheric evaporative demand and the area will experience a net drying.

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