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Journal of Arid Environments 133 (2016) 125–133

Contents lists available at ScienceDirect

Journal of Arid Environments

journal homepage: www.elsevier.com/locate/jaridenv

Spatial and temporal variability in minimum temperature trends in the western U.S. sagebrush steppe☆

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ARTICLE INFO

Article history:
Received 14 October 2015
Received in revised form
10 May 2016
Accepted 6 June 2016
Available online 5 July 2016

Keywords:
Climate trend
Spatial variation
Aridland
Time series analysis

ABSTRACT

Climate is a major driver of ecosystem dynamics. In recent years there has been considerable interest in future climate change and potential impacts on ecosystems and management options. In this paper, we analyzed minimum monthly temperature (T *min*) for ten rural locations in the western U.S. sagebrush steppe. Oregon and Nevada each had five locations, and the period of record ranged from 69 to 125 years. We used structural time series analysis to evaluate trends over time at each location. We also used box plots to compare variation within months at each location. We concluded: 1) T *min* variation over years is much higher during the winter than during other seasons, 2) there is evidence of decadal trends in both directions (hotter and cooler) for most, but not all sites, and 3) sites exhibited individualistic patterns rather than following a general regional pattern. The analysis shows that sites in relatively close proximity can exhibit different temperature patterns over time. We suggest that ecologists and land managers make use of any available weather data from local weather stations when planning for the future or interpreting past changes in plant and animal populations, rather than relying on regional averages.

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1. Introduction

The western U.S. sagebrush steppe is a region that has experienced large historical climatic shifts (Nowak et al., 1994). Because of the aridity of the region, relatively small shifts in climate can influence ecosystem dynamics. Some projections suggest that temperature increases in the future could be substantial (about 2.0–6.0 °C), although predictions for precipitation are less clear (Mote et al., 2013). Precipitation is generally considered more difficult to predict than is temperature (Webb and Stokes, 2012). Of the various temperature-related parameters, minimum temperature (T *min*) is thought to be the more sensitive to atmospheric induced climate change than other temperature variables (Easterling et al., 1997; Tang and Arnone, 2013).

In this paper we analyze trends in monthly average minimum temperatures (T *min*) for 10 rural locations in the northern Great Basin/sagebrush steppe of the U.S. Time series such as these exhibit autocorrelation: monthly temperatures are correlated with adjacent months. Many standard statistical analyses carry an assumption that observations are independent. Autocorrelation within the series limits the usefulness of traditional regression analysis, in part because the assumption of independence of errors is violated. Thus, as appealing as regression analysis may appear, it was necessary to explore other analysis approaches. Autoregressive, integrated, moving average (ARIMA) models have been used to analyze time series data (Visser and Molenaar, 1995; SAS Institute, 2008; Kärner, 2009). State space modeling (SSM), another technique with general application to time series data, has grown out of the field of control engineering. Kalman (1960) described the approach, and the filtering technique he proposed is now known as the Kalman filter. Harvey (1989) presented a class of models referred to as structural models, which utilized SSM and the Kalman filter in macroeconomics. Harvey and Todd (1983) had previously discussed the relative merits of ARIMA and SSM methods and concluded that while both methods provided similar forecast functions, structural models were desirable because the individual components (such as cycle, season and trend) have direct interpretation, and the model's well-defined structure leads to appropriate forecast functions. For our purposes, we chose structural modeling because it allows separation of the model into individual components. Harvey and Souza (1987) utilized SSM

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http://dx.doi.org/10.1016/j.jaridenv.2016.06.003
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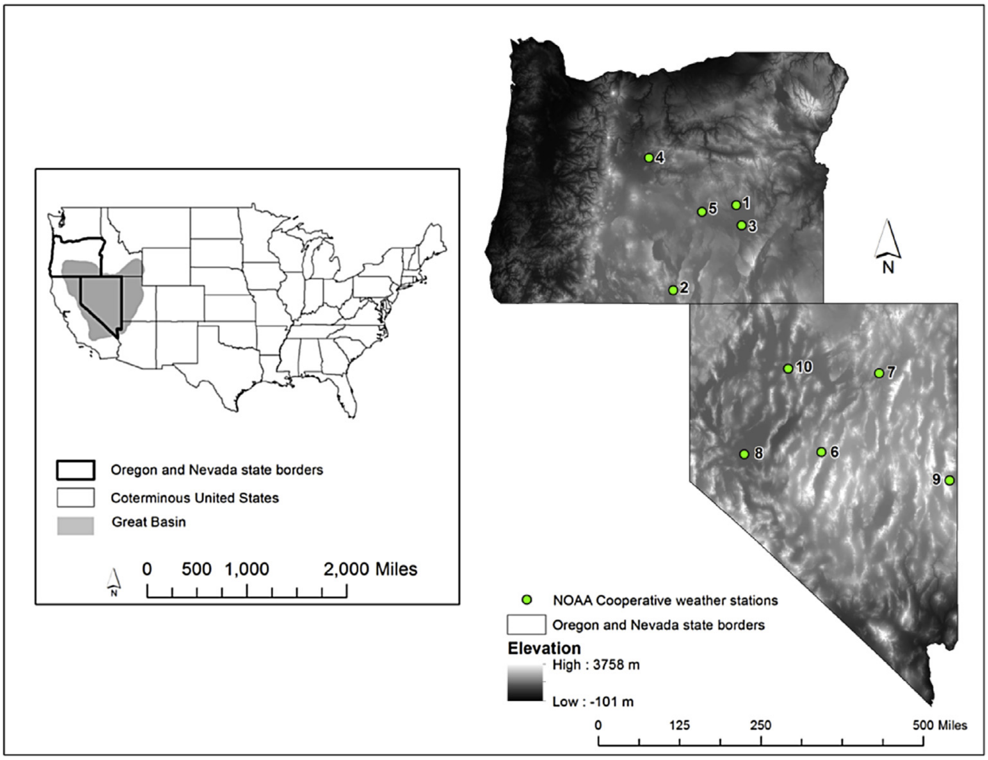

Fig. 1. Map of the USA showing location of the Great Basin (inset), and elevation map of Oregon and Nevada showing weather station locations as described in Table 1.

techniques to investigate the presence of cyclical precipitation patterns in Brazil. Others have investigated the North Atlantic Oscillation (Mills, 2004), central England temperature record (Harvey and Mills, 2003); and global warming signals (Stern and Kaufmann, 2000).

Prior analyses have shown increasing temperature trends both globally (Folland et al., 2001) and regionally (dos Santos et al. 2011; Mote et al., 2013). Thus our hypothesis was that the majority of locations will exhibit statistically significant warming during the period of record. Our second hypothesis was that warming would not be uniform over time. In other words, even if there was a significant overall warming trend, individual decades might show no warming, or even cooling. To test these hypotheses, we applied time series analysis to monthly T *min* data from the 10 locations. We discuss the relevance of our analysis to sagebrush steppe ecology.

2. Methods

2.1. Temperature data

Daily minimum surface air temperature data were obtained for 10 National Weather Service (NWS) cooperator stations in Nevada and Oregon, USA. The monthly data we present in this paper are the averages of all daily T *min* values within a month. Stations were located between 39 and 44°N and 114–122°W. Nine stations were within the boundary of the Great Basin (Fig. 1). We selected 10 stations that had generally continuous data records between 1940 and 2010, with two beginning before 1900 (Table 1). Data for this study was obtained from the National Climatic Data Center (NCDC), Global Historical Climatology Network, (GHCN) Version 3 data repository (see: http://www.ncdc.noaa.gov). These data have received extensive quality assurance testing by NCDC prior to public release (Durre et al., 2010; Menne et al., 2012). These tests include non-climatic influences such as changes in instrumentation, station environment, and observing practices that occur over time (Peterson et al., 1998). Initially, the data were visually inspected for trends, discontinuities and outliers. Boxplots of T *min* were constructed to assist with this and to describe the general seasonal dynamics of each station (Fig. 2).

2.2. Analysis

We analyzed each station's record of average minimum monthly air temperature by using Unobserved Components Model (UCM) as implemented in the SAS 9.2 release (SAS Institute, 2008).[1] These structural models provide a regression-like decomposition of the response series into unobserved, or latent, components. Seasonal, cyclical, trend and regression components can be extracted from the series, leaving the irregular (random error) component. A UCM can always be viewed as a generalized regression model where the regression coefficients can be *time varying* (SAS Institute, 2008). Modeled components can be deterministic or stochastic, linear or nonlinear. Harvey (1989) provides a thorough discussion of UCM development and it's relation to ARIMA and exponential smoothing models. An objective of time series analysis is to model the responses across time so that no structure remains in the residuals.

Here each series was modeled separately, by starting with stochastic seasonal, cyclical and trend components in a basic structural model (BSM). The following stochastic model can capture this type of series in UCM:

$$y_t = \mu_t + \gamma_t + \varepsilon_t, \quad \varepsilon_t \sim NID\left(0, \ \sigma_\varepsilon^2\right), \qquad t = 1, \ldots, n \qquad (1)$$

Here y_t is the temperature time series, μ_t is a stochastic trend, γ_t

[1] Mention of tradename does not indicate endorsement by USDA.

Table 1
Station metadata for the ten NOAA cooperative weather stations used in this report. Data were obtained from the Global Historical Climate Network (GHCN). Station numbers refer to location numbers on the map in Fig. 1, and GHCN ID references the GHCN database ID for that station. Percent complete data are for the monthly data summaries provided in the GHCN-Monthly dataset.

Station #	GHCN ID	GHCN principle name	Elev. meters	Coordinates		Start year	End year	% Missing
				North	West			
1	USW00094185	BURNS MUNICIPAL AIRPORT	1262	43.60	118.96	1939	2010	1
2	USC00354670	LAKEVIEW 2 NNW	1314	42.24	120.37	1914	2008	4
3	USC00355162	MALHEUR REFUGE HDQ	1254	43.27	118.84	1937	2010	5
4	USC00356883	PRINEVILLE	867	44.30	120.81	1897	2010	6
5	USC00358029	SQUAW BUTTE-NORTHERN GREAT BASIN EXP RANGE[a]	1427	43.49	119.72	1937	2010	3
6	USC00260507	AUSTIN #2	2012	39.49	117.07	1939	2008	6
7	USW00024121	ELKO REGIONAL AIRPORT	1539	40.83	115.79	1911	2010	2
8	USC00262780	FALLON EXPERIMENT STATION	1210	39.46	118.78	1938	2010	3
9	USC00263340	GREAT BASIN NATIONAL PARK[b]	2083	39.01	114.22	1937	2010	4
10	USW00024128	WINNEMUCCA AIRPORT	1310	40.90	117.81	1885	2010	0

[a] Referred to as NGBER in text.
[b] Referred to as GBNP in text.

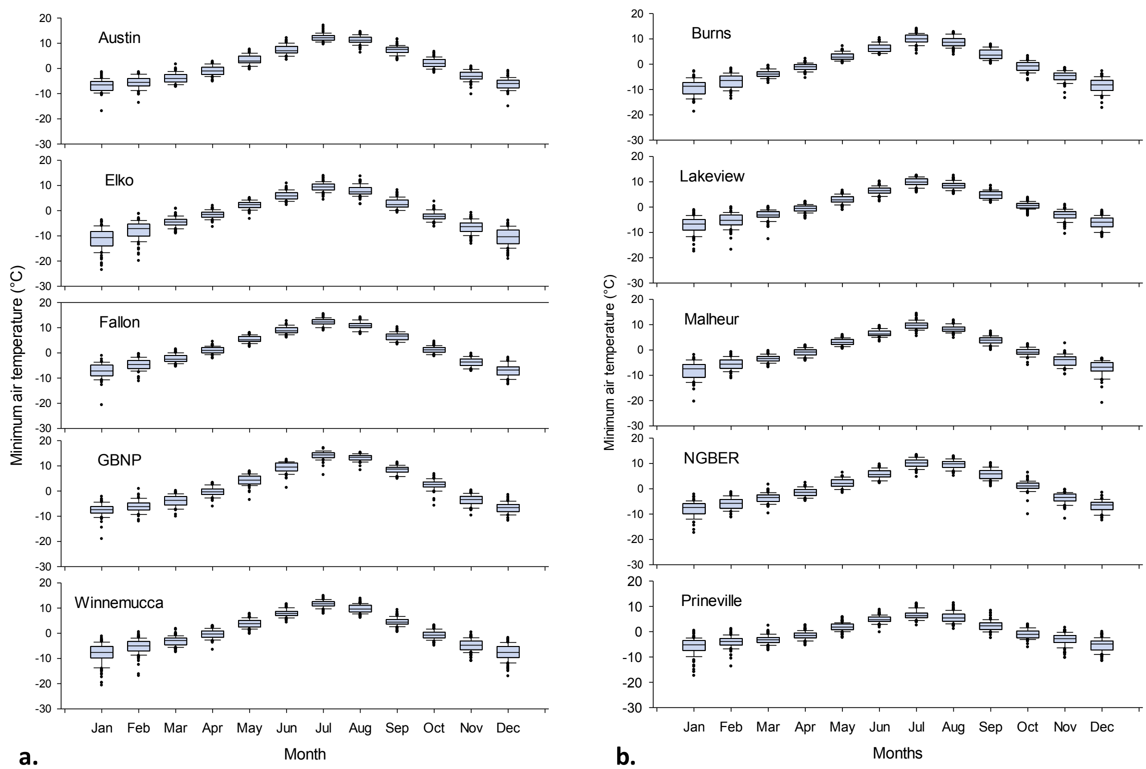

Fig. 2. a, b. Mean monthly minimum surface air temperature (°C) for 10 locations in Nevada (a) and Oregon (b), for period of record. Boxes span the 25th and 75th interquartile range and the horizontal line identifies the median temperature. Upper and lower whiskers show the range of data between the 10 and 90 percentiles. Extreme values beyond these percentiles are dots above or below the whiskers.

represents a stochastic seasonal component, and the irregular, or error, term is ε_t with a normal, independent distribution (NID) of mean zero and variance σ_ε^2 . Trend μ_t is the tendency of the series in the absence of seasonality γ_t. The UCM procedure provides two alternative models for the trend component. First is as a random walk (RW) which implies that the series has no persistent upward or downward tendency. The RW model for trend μ_t becomes:

$$\mu_t = \mu_{t-1} + \eta_t \ , \quad \eta_t \sim NID\left(0, \ \sigma_\eta^2\right) \tag{2}$$

where μ_t has no net movement up or down and in the case of $\sigma_\eta^2 = 0$, μ_t becomes constant. In the second case trend is modeled as local linear trend (LLT). Here trend has independently varying level μ_t and slope β_t. These terms are analogous to intercept and slope terms in ordinary linear regression, but with time-varying coefficients. This model can be represented as:

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t \ , \quad \eta_t \sim NID\left(0, \ \sigma_\eta^2\right) \tag{3}$$

where $\beta_t = \ \beta_{t-1} + \ \xi_t \ , \quad \xi_t \sim NID(0, \ \sigma_\xi^2)$

As noted, the disturbance terms η_t and ξ_t are assumed independent and each can be zero, which, when $\sigma_\xi^2 = 0$ creates a linear trend with deterministic slope. If $\sigma_\eta^2 = 0$ the trend becomes smoother but still varies based on the slope disturbance term (σ_ξ^2).

The BSM was modified by removing non-significant components. Significance tests (p |t|≤0.10) determined whether components were stochastic or deterministic. After models were revised based on these results, each component was tested to determine whether it contributed significantly to the model. We used UCM to examine the trend component for each series and properly account for serial correlation common to temperature time series. At all locations the cyclical component was not significant and was dropped. After each model was developed, white noise tests of residuals were performed to verify that remaining variation was random error.

Temperature data for Burns, Oregon will be considered in detail to illustrate the use of UCM in SAS. The data are 99% complete, with only short gaps in the monthly sequence. The station was moved 8 km east, from the Post Office to the Burns Airport in May 1980. The data were prepared for analysis and then analyzed in UCM beginning with Eq. (1) modeling trend as a LLT Eq. (3). The station move required that an intervention term be added to the model:

$$y_t = \mu_t + \gamma_t + \sum_{j=1}^{m} \beta_j x_{jt} + \varepsilon_t \quad (4)$$

The station move in 1980 was coded as a dummy variable x_{jt}, having two levels (0, 1). The dummy variable allows for removal of the effect of the station move from the model. This model (4) fit the data well (adj. $R^2 = 0.88$), however inspection of the residual autocorrelation function (ACF) showed significant lag 1 correlation. Therefore the model (4) was modified to include a lag (1) term on the dependent variable y_t. All stations in this report required the lag term.

$$y_t = \mu_t + \gamma_t + \sum_{i=1}^{p} \varphi_i y_{t-i} + \sum_{j=1}^{m} \beta_j x_{jt} + \varepsilon_t \quad (5)$$

Addition of the lag term to account for serial correlation improved the R^2 slightly (0.9) and examination of the residual ACF indicated the time series had been stabilized; that is, there is no remaining structure in the residuals. In its final form the model (5) fit the data well. The likelihood optimization algorithm in UCM converged after 8 iterations and indicated that trend components (level and slope) were not stochastic (*Pr*>|t| = 0.8 and 0.81, respectively). Therefore these components were treated as constants by constraining σ_η^2 and σ_ξ^2 in (3) to zero, yielding a constant trend similar to ordinary regression. Seasonality remained as a stochastic component although its variance term was not highly significant (*Pr*>|t| = 0.1). Our objective in this paper is to determine trend components of each series. We do not discuss the modeling of seasonal and irregular terms here. For details of the UCM procedure the reader can consult the ETS User's Guide, Chapter 31 (SAS Institute, 2010). Each of the remaining 9 station temperature series were analyzed similarly.

2.3. Descriptions of terms

2.3.1. Stochastic vs. deterministic

Deterministic model output is an exact result of parameter values and the initial conditions. Temperature on day two can be fully described by temperature on day one and the model parameters. Stochastic (probabilistic) model output on day two is not fully determined. The parameters vary with time and therefore the same initial conditions can have multiple outputs based on the variance associated with the model parameters. Ecologists are quite familiar with the randomness inherent in natural systems. This leads to an effort to develop probabilistic (stochastic) models to describe the system under study. If the variances associated with the parameters approach zero the model then reduces to a deterministic statistical representation of the phenomenon being studied.

2.3.2. Level and slope

Trend is modeled using two components. Level and slope together describe the trend of the system. At each time step the temperature is estimated as the sum of level and slope estimates. Level is based on previous temperatures, and slope represents the expected change in temperature at each time interval. Both level and slope have a variance term which creates a range of possible temperature estimates.

3. Results

The ten locations included in this analysis cover a wide cross-section of the Great Basin (Fig. 1). Elevations were generally in the 1200–1550 m range with Prineville below (867 m), and Austin (2012 m) and GBNP (2083 m) above that range (Table 1). We calculated long term minimum and average temperatures to provide an indication of the relative temperatures across locations (Table 2). The three most southerly locations did have the highest average T *min* over the period of the record. Winnemucca and Elko were both colder than some Oregon locations, with Elko registering as the coldest of the 10 locations (at least for T *min*). Six of the locations fell within a 1.0 °C range (0.6 to −0.4 °C) for T *min*. The relative rankings were different for average than for minimum temperature. The location with the largest shift in ranking was Winnemucca, which was fourth coldest for minimum, but second warmest for average temperature. Again the three most southerly locations tended to be warmer than locations to the north. The two highest elevation locations were also the most southerly (GBNP and Austin) and the lowest elevation location (Prineville) was the most northerly. So there was complete confounding of latitude and elevation.

All locations were fitted using a lag of one to account for serial correlation in the temperature series. Coefficients (φ_i) ranged from 0.008 to 0.279. Prineville required an additional lag of 6 months to minimize the ACF. Two locations, Burns and Prineville were moved during the period studied here, and in both cases significant (Pr>|t| <0.05) change was noted (−1.2 °C and 1.6 °C, respectively) after the station was moved.

Two locations, Burns and Malheur, had deterministic level and slope (Table 3). In other words, these two locations showed no trends over the period of record (Fig. 4). The remaining locations were found to have stochastic level terms, but in all cases slope was deterministic. Austin had the highest level estimate (2.2 °C) while Elko had the lowest (−0.237 °C). The slope term (Table 3) was negative for Burns, NGBER, Fallon, Great Basin NP, and

Table 2
Annual average of daily minimum and average temperature (°C), averaged across all years in the period of record for each location in the study.

Location	Station period of record			
	Minimum	SE	Average	SE
Austin	1.2	0.2	8.5	0.2
Elko	−1.0	0.2	7.9	0.1
Fallon	1.6	0.1	10.7	0.1
GBNP	1.9	0.1	8.9	0.1
Winnemucca	0.1	0.1	9.4	0.1
Burns	−0.3	0.1	7.5	0.1
Lakeview	0.6	0.2	7.9	0.2
Malheur	0.2	0.1	8.2	0.1
NGBER	0.2	0.3	7.3	0.3
Prineville	−0.4	0.1	8.4	0.1

Winnemucca, however all slope estimates were within 1 S.E of zero. None of the locations showed a large trend (Fig. 3). All locations with stochastic level components show evidence of multi-year deviations as the time series developed.

We evaluated variability, patterns, and trends in the T min data. Monthly variability was assessed with box plot diagrams (Fig. 2). The consistent pattern across locations was that year-to-year variation in T *min* was highest in the winter months (December, January and February). For many locations, spring was not as variable as we might have thought, especially April and May. In general, there was relatively low variability during the summer months.

Scatter plots (Fig. 3) represent all the monthly T *min* values for the period of record. Consistent scaling was used on figures to improve across location comparison. Scatter plots allow a visual assessment of the extreme monthly values that are not evident in other parts of the data analysis. For example, many, but not all locations, experienced a very cold January 1949. This was among the coldest months on record for all sites except Winnemucca and Malheur. In several cases January 1949 was a clear outlier (approaching −20 °C), well below other cold months in the period of record (e.g. GBNP, Fallon, and Burns). Several locations had colder than normal temperatures during the 1980's than in surrounding decades. Prineville, Fallon and Austin all had slightly warmer summer months since 2000 than during the decades immediately preceding 2000, as indicated by higher levels in the upper portion of the graph.

The black line in the scatter plots represents trend, but scaling on these plots makes it difficult to visualize the magnitude of trend. To improve visual assessment of the trend line, we re-plotted the data and scaled the graphs from +3 to −3 °C in Fig. 4. Two of the locations (Burns and Malheur) were deterministic and showed no significant trend over the period of record. These locations were only 50 km apart, and the Malheur site is in close proximity to Malheur and Harney Lakes which are relatively large (about 30,000 ha of area) internally drained Great Basin lakes. The other locations demonstrated some degree of trend over the period of record, in both directions. The exception was Austin which showed only small tendencies for trend, and only upward trend. The decade of the 1940's was cool at many locations, with all non-deterministic sites except Austin exhibiting some degree of downward trend. From the 1950's onward, trends were generally flat or increasing with several exceptions. For many locations, the 1980's experienced a cooling trend; in the case of Elko, cooling during the decade was nearly 2 °C. Smaller declines were seen in Fallon, NGBER, and Prineville. Half of the locations (Elko, Fallon, GBNP, Lakeview and NGBER) had T *min* declines during the late 1990's to 2010.

The slopes generated from location data was used to calculate a 100 yr change (Table 3). Several locations showed increases (Elko, Austin, Lakeview, and Prineville) and several decreased more than a fraction of a degree (Winnemucca, GBNP, and NGBER). However, when a confidence interval was calculated for the slopes or 100 yr estimate, the interval included 0.0 for all locations.

4. Discussion

The U.S. Great Basin has experienced dramatic climate shifts in the past (e.g. Nowak et al., 1994). We chose to evaluate one aspect of climate during the relatively short period for which weather records are available. The parameter we present here is T *min*, in part because it is thought to be more sensitive to atmospheric induced climate change than other temperature variables (Easterling et al., 1997; Tang and Arnone, 2013), and is important to the adaptive genetic variation of native species (Richardson et al., 2014). Temperature in general is of great interest because it influences rates of biological processes and interacts so strongly with precipitation (Schimel, 2013). Our analysis provides a mixed picture of monthly T *min* trends during the past century (datasets range from 69 to 125 years for the 10 sites). The changes calculated for a 100 yr interval tend to increase for some locations such as Elko and Prineville, and cool slightly for others, such as Winnemucca and NGBER. But for all locations, the absolute value of the slope standard error is greater than the value of the slope. A confidence interval around the slope would include zero. So even for sites with apparent trends, there was no statistical significance associated with the trend. Other T *min* analysis of the Great Basin has shown temperature increases (dos Santos et al. 2011; Tang and Arnone, 2013). Both these studies found that T *min* trends of individual sites could be positive, neutral or negative. In their analysis there were more sites with positive T *min* trends, so on a regional basis (Tang and Arnone, 2013) or a state basis (dos Santos et al. 2011), these authors concluded there has been warming in the past century. The synthesis of these results shows that temperature trends are not uniform across space. We did not analyze monthly trends, although we do discuss variability during different months and seasons.

While larger global and regional trends are certainly of interest, we focused more on evaluation of trends within and across sites. There have been major changes in vegetation patterns in the Great Basin during the past century, but it is unclear if these changes are related to climatic oscillations, directional changes in climate, human impacts, or other factors such as rising atmospheric CO_2. Our analysis of the ten locations yielded the following general

Table 3
Trend information, based on the model final state, for 10 locations in Oregon and Nevada. Monthly mean minimum temperature (°C) records were decomposed into season, trend and irregular components by structural time series modeling. Level and slope together represent the trend component. Change in minimum temperature per 100 y is estimated from the slope component.

Station	State	Level		Slope		°C per 100 y	S.E.
		Estimate	Std. Err.	Estimate	Std. Err.		
Austin	NV	2.175	0.312	−0.00102[a]	0.00215	1.224	2.58
Elko	NV	−0.237	0.441	0.00142[a]	0.00257	1.704	3.084
Fallon	NV	1.39	0.395	−0.00003[a]	0.00308	−0.036	3.696
GBNP	NV	1.483	0.475	−0.0003[a]	0.00447	−0.408	5.364
Winnemucca	NV	0.253	0.303	−0.0008[a]	0.00114	−1.008	1.368
Burns	OR	0.187[a]	0.334	−0.0002[a]	0.00053	−0.012	0.624
Lakeview	OR	0.534	0.366	0.00098[a]	0.00213	1.176	2.556
Malheur	OR	0.212[a]	0.137	0.0001[a]	0.00068	0.12	0.816
NGBER	OR	0.377	0.435	−0.0005[a]	0.00349	−0.528	4.188
Prineville	OR	0.859	0.684	0.00133[a]	0.00183	1.596	2.196

[a] Level or slope estimate for this location was deterministic (Pr> |t| = 0.1).

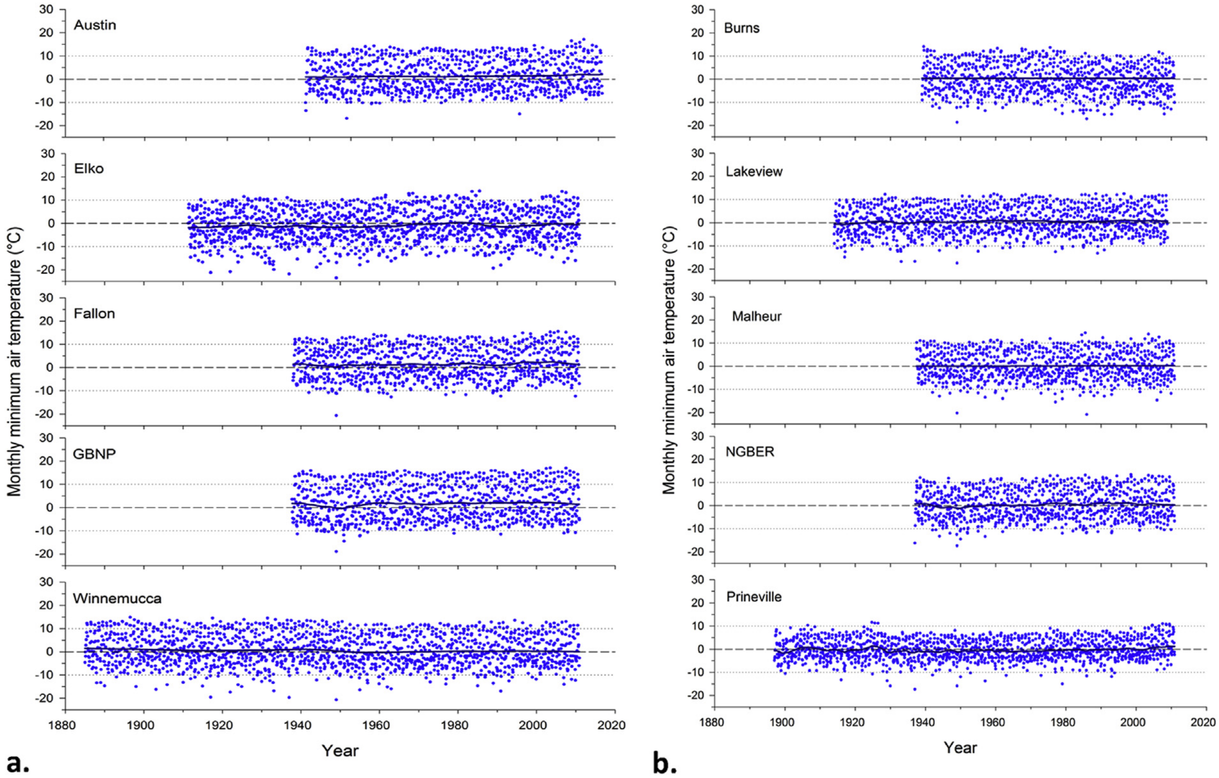

Fig. 3. a, b. Plots of Nevada (a) and Oregon (b) monthly average minimum temperature (°C) and the smoothed trend line extracted from the data using structural time series modeling.

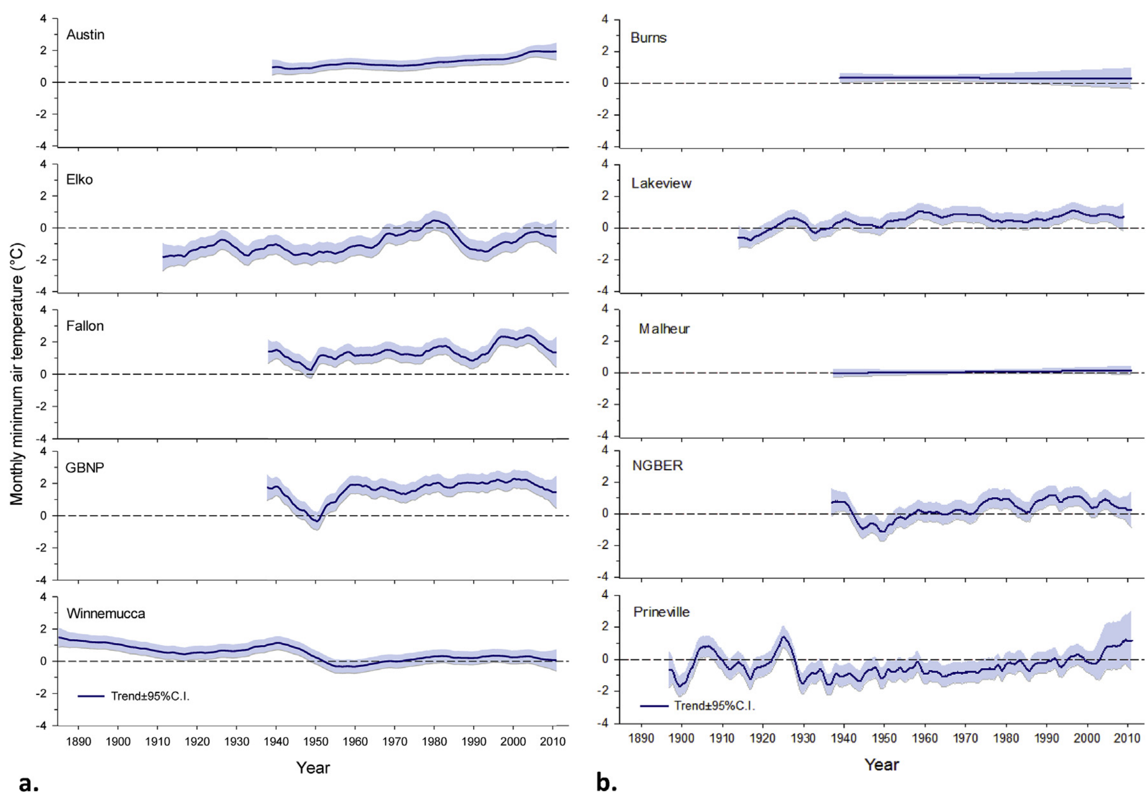

Fig. 4. a, b. Smoothed trend lines of monthly minimum air temperature are shown for five Nevada (a) and Oregon (b) locations. Smoothed trend lines were obtained by time series analysis using unobserved components models containing trend, season and irregular terms. Burns and Malheur stations in Oregon had deterministic trends; all other locations were modeled with stochastic, locally linear trends. Shaded bands cover the modeled 95% confidence interval.

conclusions: 1) T *min* variation over years is much higher during winter months (especially December and January) than during other seasons, 2) there is evidence of decadal trends in both directions (hotter and cooler) for most sites, and 3) sites tended to follow individualistic patterns rather than general regional patterns. Vegetation trends in the Great Basin include an increase in invasive annual grasses such as cheatgrass (*Bromus tectorum* L.), and expansion of woodlands. In an analysis conducted over a decade ago, cheatgrass dominated about 20,000 km^2 or 7% of the land area of the Great Basin (Bradley and Mustard, 2005). Several invasive Bromus species are thought to benefit from increasing temperatures in this region (Bradley et al., 2016). Mild temperatures are also thought to benefit some species involved in woodland expansion (Miller et al., 2005). Our analysis may not detect subtle changes in temperature within individual months, but at a year-long scale it is difficult to show that past warming could account for the dramatic increases in invasive annuals during the 1900s. We did not evaluate precipitation patterns, which can also influence expansion of invasive annual grasses (Bradley, 2009). Cheatgrass in particular may also benefit from increasing atmospheric CO_2 (Ziska et al., 2005), as do woodland species (Knapp et al., 2001). If temperature change did not have a major impact on cheatgrass expansion, then increasing atmospheric CO_2 may be an important factor. Our personal observations suggest that cheatgrass has become much more common at higher elevations and minimally disturbed sites than it was 20 years ago (Chen et al., 2012). The reduction in very cold months in the period after 1980 may have improved survival and recruitment of woodland species such as western juniper (*Juniperous occidentalis* var. *occidentalis Hook*). This species may be sensitive to very low temperatures or sudden changes in temperature (e.g. Soule and Knapp, 2007).

The level of variation within months over the period of record was unexpected. Spring is often viewed as the most variable time of year, and that may be true on a day-to-day basis. But over years, winter is clearly most variable in terms of mean monthly T *min* (Fig. 2). The nature of that variability can be seen in Fig. 3, with the rough boundary on the cold edge of the monthly data (generally in the −10 to −20°C range) and a much smoother upper edge (around 10°C) which represents the warmer months. In terms of trend, Shen et al. (2012) found that over the contiguous U.S. from 1895 to 2008, February had the largest positive temperature trend for any month. Similarly, Vogelsang and Franses (2005) found temperature increases in winter, but not in spring or summer for northwestern Europe. The effect of extreme cold periods on vegetation is difficult to predict and may depend on an array of factors including snow cover, soil moisture, plant phenology and timing of stress relative to plant developmental stage (Gornish et al., 2015). For seeds and seedlings of several dominant sagebrush steppe bunchgrasses, high winter mortality is common, so we anticipate that extreme cold periods would negatively impact recruitment (James et al., 2011; Boyd and Lemos, 2013). There appear to be more very cold months (<−10°C) for many sites during 1940–1960 than in subsequent 20 yr intervals.

Climatic variability can be analyzed for both short term and long term trends. While much recent focus has been on longer term trends, multi-year or even multi-decade trends may be critical for understanding climate/vegetation relationships. Climatic oscillations in the data we analyzed are most obvious from the smoothed trendlines in Fig. 4. Some sites showed clear decadal trends; for example, Elko cooled about 2 °C during the 1980's, GBNP cooled from 1940 to 1950 and then warmed an equal amount from 1950 to 1960. Three of the locations (Burns, Malheur and Austin) exhibited no trend line shifts over decade or shorter time frames. The region experienced general cooling in the 1980's and for many locations cooling from 2000 to 2010, which could influence vegetation trends. We have not analyzed precipitation data, but cooler temperatures are generally associated with lower evapotranspiration and thus higher soil moisture. An analysis of climate in the northwestern U.S. from 1675 to 1978 also demonstrated a tendency for decadal and interdecadal-scale climatic oscillations (Hessburg et al., 2005). In their summary of recent climatological studies from the western U.S., Hessburg et al. (2005) found substantial evidence for a dry or warm period in the 1920's to 1940's, but little agreement among studies for other periods of the timeline. They compared eight studies which evaluated varying periods between the years 1600 and 2000 and used a variety of analytical methods. In our analysis of T *min* there are a few general trends that are common to a portion of the sites, (warming in the 1920's to 1940's and cooling in the 1980's and 2000 to 2010), but clearly site-to-site comparisons are influenced by factors other than regional climatic patterns.

The combination of yearly fluctuations during winter (Fig. 2a, b) and decadal trends (Fig. 4a, b) in T *min* suggests that recruitment of existing species and success of restoration projects may be episodic. Neilson (1986, 1987) suggests that the influence of oscillations between different climatic regimes can control both establishment and mortality of individual species. Recruitment of individuals is a critical parameter for establishing vegetation trajectories or maintaining stable plant communities. Sequences of favorable establishment years may be particularly important for western U.S. sagebrush steppe rangelands because: 1) the region's aridity creates challenges for seedling establishment (e.g. James et al., 2011), and 2) the native perennial bunchgrasses which are important for stabilizing the sagebrush steppe may be relatively short-lived with average life spans of a decade or less (Svejcar et al., 2014).

An interesting aspect of our analysis is the overall lack of consistent trends across sites (Fig. 4). We previously mentioned some of the regional trends that were evident across a portion of the sites (eg., the cooling trend in the 1940's), but there are only a few sites that exhibited parallel trends. Burns and Malheur were both deterministic in nature (did not exhibit random trends). But these sites were only 50 km apart and both were influenced by flat topography and the buffering capacity of flowing or standing water. Burns is surrounded by the flood meadows of the Harney Basin which are generally wet during spring and early summer, and Malheur is influenced by Malheur and Harney Lakes to its north. We don't intend to characterize each site, but only point out that the two most similar sites were physically close and at least to some extent influenced by similar factors. In contrast, NGBER was only 64 km from Burns, but exhibited a much different pattern. This site was not influenced by proximity to water. There were periods where other sites showed parallel characteristics; for example, Elko and Fallon from 1975 to present. In their analysis of Pacific coast climate (from Oregon to Alaska), Gedalof and Smith (2001) found a "step-like climate shift" in 1976–1977. This roughly corresponds to T *min* declines in Elko, Fallen and NGBER.

In general, we could not find reasonable ways to group sites, based on geography (Fig. 1), elevation (Table 1), or relative ranking based on T *min* or T *ave* (Table 2). There was confounding of elevation and latitude in that our southernmost site was at the highest elevation (GBNP) and our northernmost site was at the lowest elevation (Prineville). The critical message would appear to be that caution must be exercised in extrapolating yearly weather data from one site to another. Precipitation is more variable than temperature in space and time (e.g. Donat et al., 2014), and it is more difficult to predict (Webb and Stokes, 2012), but that does not necessarily mean that temperature is easily estimated across space. Our analysis demonstrates the uniqueness of T *min* within sites.

Others have also shown that century or longer, site-level temperature trends can be either positive or negative at the scale of a state (dos Santos et al. 2011), the Great Basin (Tang and Arnone, 2013), western North America (Booth et al., 2012), or globally (Wickham et al., 2013).

5. Conclusions

Analyses of past and present climatic trends provide ecologists and land managers a starting point for adapting to future climate. Climate is a major driver of vegetation dynamics, but separating climatic and management impacts on vegetation can be very difficult. Our analysis of ten locations in the U.S. Great Basin yielded the following major conclusions related to trends in T *min*: 1) variation in T *min* is much greater during the winter than in other seasons, 2) most, but not all sites, experience multi-year or multi-decade trends in either direction (colder or hotter), and 3) the sites had individualistic patterns of T *min* rather than following general regional patterns. We suggest ecologists and managers in this region access past climate data for sites important to them from the Global Historical Climatology Network (http://www.ncdc.noaa.gov), via the Regional Climate Centers. There is a tremendous amount of available data for a wide variety of locations (http://www.wrcc.dri.edu, click "Historical Data", "Climate Summaries", then "Western U.S. Climate Summaries – NOAA Coop Stations" for data in the western U.S.). The large number of cooperating sites ensures that climate data need not be generalized across large areas at least in the U.S. While the density of weather stations may be highest in North America and Europe, there is a substantial global network of weather stations. For example, Wickham et al. (2013) compiled data sets from 36,869 sites globally for their analysis. Evaluating past trends for an area is a reasonable first step in planning for the future. A great deal of work is needed to link past climate to changes in plant and animal populations. Even during periods of relatively stable climate, the western U.S. sagebrush steppe is subject to large yearly variation, which complicates trend analysis.

Acknowledgements

We thank Dr. Bruce Mackey for advice and review of statistical procedures used for data analysis, and Drs. Roger Sheley and Stuart Hardegree for critical reviews.

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