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Empirical modeling of spatial and temporal variation in warm season nocturnal air temperatures in two North Idaho mountain ranges, USA

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ABSTRACT

Accurate, fine spatial resolution predictions of surface air temperatures are critical for understanding many hydrologic and ecological processes. This study examines the spatial and temporal variability in nocturnal air temperatures across a mountainous region of Northern Idaho. Principal components analysis (PCA) was applied to a network of 70 Hobo temperature loggers systematically distributed across 2 mountain ranges. Four interpretable modes of variability were observed in average nighttime temperatures among Hobo sites: (1) regional/synoptic; (2) topoclimatic; (3) land surface feedback; (4) canopy cover and vegetation. PC time series captured temporal variability in nighttime temperatures and showed strong relationships with regional air temperatures, sky conditions and atmospheric pressure. PC2 captured the topographic variation among temperatures. A cold air drainage index was created by predicting PC2 loadings to elevation, slope position and dissection indices. Nightly temperature maps were produced by applying PC time series back to the PC2 loading surface, revealing complex temporal and spatial variation in nighttime temperatures. Further development of both physically and empirically based daily temperature models that account for synoptic atmospheric controls on fine-scale temperature variability in mountain ecosystems are needed to guide future monitoring efforts aimed at assessing the impact of climate change.

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1. Introduction

Surface air temperatures drive many ecological processes and are a key input to many vegetation and hydrologic models (Running and Coughlan, 1988). Much of the concern about the potential biophysical and ecological impacts of climate change (e.g., snowmelt timing, shifts in species occurrence) centers on high-elevation and mountain systems (Diaz et al., 2003). Accurate predictions of temperature in mountains are therefore essential if we are to reduce physical uncertainty in predictions of ecological impacts of climate warming.

Input data for surface air temperature models come from surface weather stations, the majority of which are located in cities, valleys, and generally at low elevations (Di Luzio et al., 2008). Climate stations in high elevation mountains are sparse or absent, and those that do exist often have short or incomplete records (Daly et al., 2007). In the absence of climate station data, statistical methods have been developed to predict temperatures in complex topography, using either fixed lapse rates or empirical approaches (e.g., thin plate splines) (Daly, 2006; Daly et al., 2008; Hutchinson, 1991).

Temperature varies at fine spatial scales in complex terrain. It has been known for decades that radiatively cooled air drains into valleys and basins at night. A number of studies have contributed important knowledge about the physical processes controlling nocturnal cold air drainage. Barr and Orgill (1989) identified external meteorological factors that influence magnitude of cold air drainage and nocturnal winds. Kondo et al. (1989) describe physical mechanisms of heating and cooling related to nocturnal cold air flow in a single basin. A number of studies by Whiteman and others explore the mechanisms influencing the development and break-up of inversion patterns in mountain valleys across different valley basins (Whiteman, 1982; Whiteman et al., 1999, 2001; Whiteman and McKee, 1982). Chung et al. (2006) developed a statistical model for predicting cold air drainage accumulation for a small basin in Korea. These studies and others (Dobrowski et al., 2009; Lundquist and Cayan, 2007) indicate that cold air drainage and pooling are physically interpretable processes that occur across diverse topographic settings throughout the western United States. However, direct objective measurement and modeling of this phenomenon requires micrometerological observations and modeling techniques that were unavailable until recently

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(Lundquist et al., 2008). Similarly, mid-slope thermal bands that complicate standard temperature lapse rate modeling approaches were described as early as 1862 (Barry, 2008) and are widely noted (Barry, 2008; Whiteman, 2000). These effects are not well accounted for by available interpolated temperature models and PRISM is the only interpolation model in extensive usage that attempts to account for temperature inversions (Daly et al., 2008). Spatial and temporal patterns of nocturnal temperatures are likely to vary with physiography, synoptic atmospheric patterns (Daly et al., 2009) and vegetation characteristics, and across a range of spatial scales. Furthermore, work by Daly et al. (2009) shows that atmospheric conditions influence the degree to which nighttime air temperatures become decoupled from free air conditions. Thus the magnitude of cold air drainage and minimum nighttime temperatures in mountains vary from night to night. Methods are needed for linking synoptic atmospheric controls with fine-scale physiographic variation to predict daily temperature variation in mountains. Further analysis of high resolution temperature data provided by new sensor networks across different physiographic types and across a range of spatial extents may be needed to better understand spatial and temporal patterns of topoclimatic variability.

The availability of inexpensive temperature sensors opens the door for high-resolution topoclimatic analyses. Hubbart et al. (2007) used thermochron ibuttons to quantify the impacts of cold-air pooling on nighttime conifer tree transpiration. Lundquist and Cayan (2007) used a combination of inexpensive sensors to show influences of physiography on temperature patterns. Past studies have also used several topographic indices such as elevation, aspect, distance from streams and flow accumulation grids to quantify and model microclimate variability in complex terrain (Chung et al., 2006; Daly et al., 2009; Dobrowski et al., 2009; Fridley, 2009). However, many additional terrain indices have yet to be evaluated as potential tools for quantifying topoclimatic variability.

This study examines the temporal and spatial variability in nocturnal air temperatures using a network of temperature sensors distributed in a systematic stratified sample across two North Idaho mountain ranges. Principal components analysis (PCA) was used to independently identify and then model the spatial and temporal variation among Hobo sensors. PC loadings, representing the spatial variation among stations, are projected onto indices derived from a 30 m digital elevation model to create a nocturnal cold air drainage index. Multiple linear regression models predicting the temporal variation in PC time series are constructed. By applying PC time series back to predicted PC loading surfaces, daily nighttime temperature maps are created for the Bonners Ferry study area.

2. Study area and methods

2.1. Study area

Our study area encompasses Boundary County, Northern Idaho, USA (Fig. 1). The Selkirk and Purcell Mountain ranges lie to the west and east respectively, separated by the Kootenai River. Topographic relief in the area is extreme, with elevation rising from 530 m in the valley to 2350 m in the Selkirk Mountains over a distance of about 10 km. Bonners Ferry lies in a climatically unique region of the US, where both maritime and continental climates influence seasonal weather patterns (WRCC 2010; http://www.wrcc.dri.edu/narratives/IDAHO.htm).

2.2. Instrumentation

One hundred and twenty Hobo microloggers, instrumented with temperature sensors were installed across the Selkirk and Purcell mountains in a systematic random sample design, stratified by elevation, solar radiation (Fu and Rich, 1999) and a compound topographic index (CTI) (Moore et al., 1993). Sensors were installed unshielded at 2 m height on the north side of large diameter trees beneath the forest canopy. Lundquist and Huggett (2008) suggest that with proper positioning, trees and vegetation can be used to shield sensors from direct incoming radiation from above. Because snow albedo would have likely caused bias in spring temperatures at many sensor locations, we evaluate only nocturnal temperatures. Because spring snowpack may have covered higher elevation sensors, only July 7th to October 31st data were used. Temperature at each site was recorded at 10 min intervals from June 7th, 2008 to October, 2008. Fifty dataloggers failed or were destroyed by animals, therefore only 70 stations are analyzed here.

2.3. Analysis methods

Principal components analysis (scaled and centered PCA) was used to explore nighttime temperatures with princomp in the stats package in R (R core development team, 2008). Terminology describing PCA varies among different disciplines, with the atmospheric sciences favoring “empirical orthogonal function (EOF)” analysis. In this instance, PCA and EOF analysis are the same, and the analysis described here is similar to that of Lundquist and Cayan (2007). We examined spatial and temporal patterns in both nighttime minimum and average nighttime temperatures, where daily average nighttime temperature was calculated using a sunrise and sunset table so that for each day, only temperature observations from 1 h after sunset and 1 h before sunrise were included. Preliminary evaluation of PCA results showed that PC loadings (EOF’s) represented the topographic variability among stations while PC time series showed sensitivity to daily variation in regional air temperatures and atmospheric conditions.

2.3.1. Analysis of PCA time series

PC scores (principal component time series) were first interpreted using correlation analysis, with temperature, solar radiation and relative humidity from the Saddle Pass Remote Automated Weather Station (RAWS) and 700 mbar geopotential heights over the study area from the North American Regional Reanalysis (NARR) Data (Mesinger et al., 2006) (http://www.esrl.noaa.gov/psd/data/reanalysis/reanalysis.shtml, accessed October 2009). Daily variation in principal component time series was then modeled using ordinary least squares regression. Temperature, relative humidity and solar radiation from the Saddle Pass RAWS station (Lat/Long = 48.78, −116.35; Elev. = 1720 m) were used as independent variables. RAWS data were plotted and visually inspected but no missing data or anomalous values were found. Two indices were derived from the North American Regional Reanalysis (NARR) data. These indices, representing the gradient in free atmosphere lapse rates across the study area were calculated by first determining the 850–500 mb lapse rates (°C/km) in each NARR grid cell and then differencing grid cell lapse rates at the north–south and east–west edges of the study domain. These indices were developed to capture any potential changes in free atmosphere stability across the study area that may in turn impact surface microclimate temperature regimes. Henceforth, these indices are abbreviated EWP (east–west pattern) and NSP (north–south pattern). A number of candidate regression models were compared using the Akaike Information Criterion (Akaike, 1974). The AIC is a means of assessing model parsimony, and imposes a penalty such that addition of an independent variable that does not improve the model results in a larger AIC, indicating a weaker model. Model with the fewest variables and lowest AIC was selected, with a reduction in AIC score of less two considered to be insignificant.

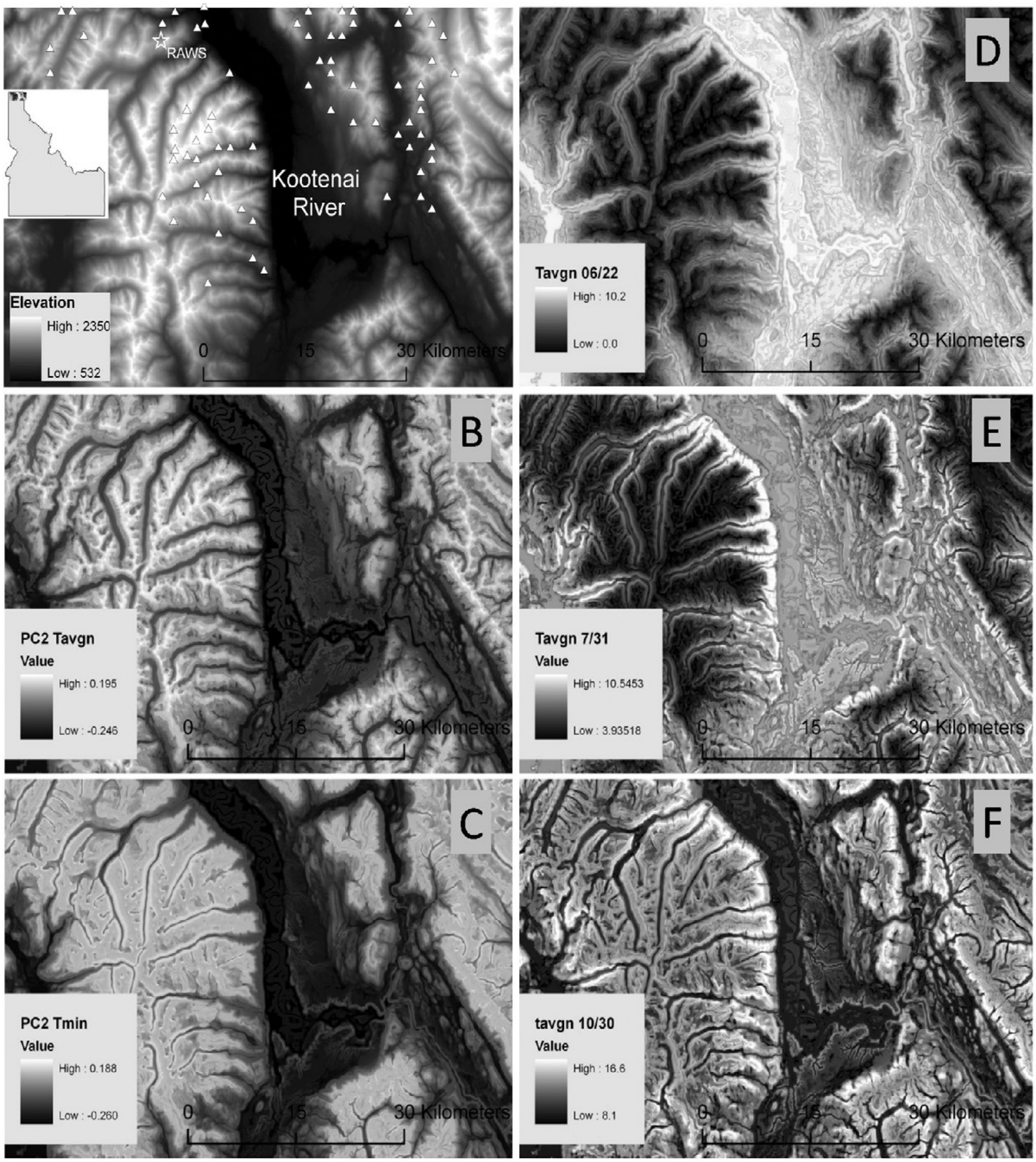

Fig. 1. Bonners Ferry study area (upper left panel) in Northern Idaho, USA showing: (A) Elevation map and location of 70 Hobo temperature sensors (white triangles). (B) PC loadings on nighttime average temperatures predicted to 30 m topographic variables. (C) PC loadings on nighttime minimum temperatures predicted to 30 m topographic variables. (D–F) Selected nighttime average predicted temperatures.

2.3.2. Analysis and modeling of PCA spatial loadings

We examined relationships between PC loading patterns and 14 topographic indices described by Evans and Cushman (2009) and Holden et al. (2009). These indices were created for the Bonners Ferry study area using a 30 m digital elevation model (DEM) from the Shuttle Radar Topography Mission (Farr et al., 2007), and they included several measures of topographic complexity and relative slope position. Similar to Chung et al. (2006), terrain complexity indices were calculated across a range of pixel window sizes ($3 \times 3 \ldots 27 \times 27$ pixels). All of the variables in Holden et al. (2009) were examined. However, dissection and relative slope position variables were of particular interest, because they have not previously been evaluated as potential topoclimatic predictors. A 30 m Normalized Differenced Vegetation Index grid (NDVI) was derived from a terrain and reflectance corrected July, 2006 Landsat Thematic Mapper 5 image (Rouse et al., 1974). Values for each raster at the location of each Hobo sensor were extracted using Hawth's Tools in ArcGIS version 9.2.

Correlation analysis was first used to examine relationships among PC loadings and independent variables. Principal component 1 captured the daily temperature signal common among all Hobo stations and were spatially uniform (mean = 0.129; standard deviation = 0.01). PC2 explained 4% of the variation among the 70 Hobo sensors and PC2 loadings showed sensitivity to several topographic indices, including elevation, terrain complexity and relative slope position. These results indicated that PC2 captured variation in nighttime temperatures associated with topography. PC2 loadings were fit to three topographic variables using the Ran-

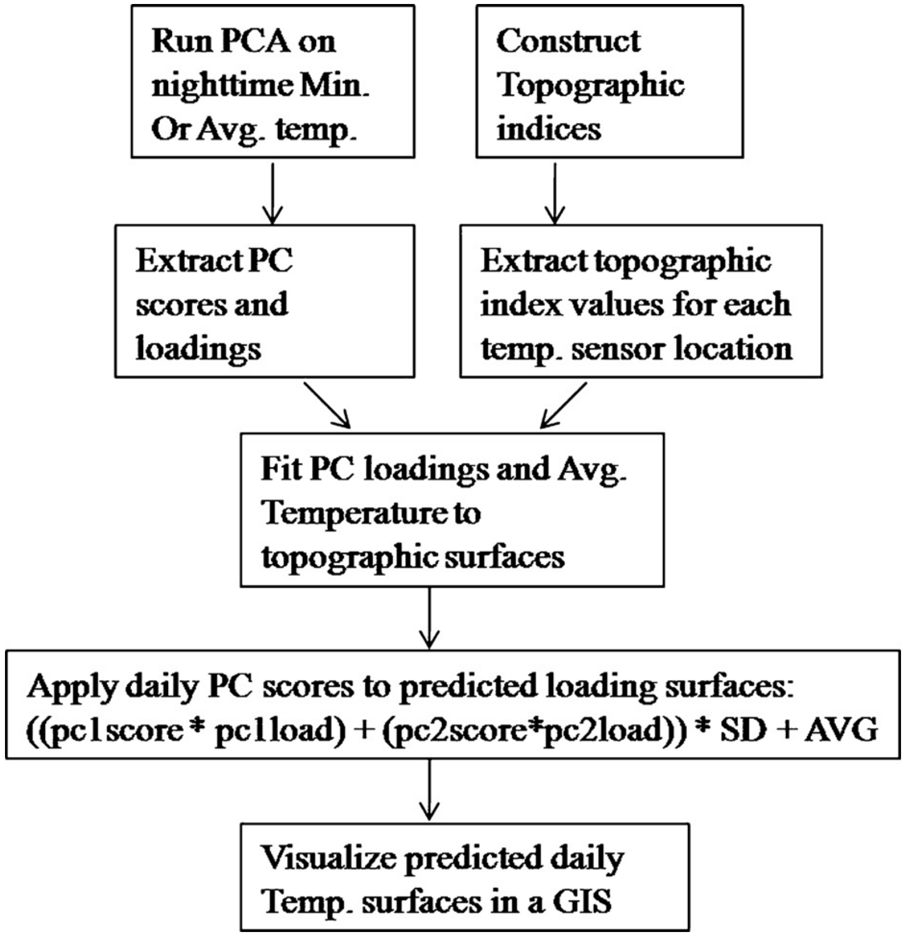

Fig. 2. Flowchart describing steps in PCA reconstruction of daily average nighttime temperatures.

dom Forest algorithm (Breiman, 2001) and the Model Improvement Ratio tool of Murphy et al. (2010) was used to select a parsimonious model with the highest variance explained and lowest mean squared error. Table 2 gives equations and references for each topographic index. Random Forests is a bootstrapped classification tree algorithm that has superior predictive capabilities over most other classification and regression algorithms. Readers unfamiliar with Random Forests or the topographic indices described here can refer to Breiman (2001), Holden et al. (2009) or Cutler et al. (2007) for more information. The resulting PC2 Random Forest model was predicted to 30 m grids to produce PC2 loading surfaces for the study area. The same methods were applied to average July–October nighttime temperatures for each Hobo temperature station.

2.3.3. Reconstruction of daily nighttime temperatures using PCA

By applying principal component time series back to modeled PC loading surfaces, daily nighttime average temperatures maps were produced. A flowchart describing the PCA reconstruction procedure is shown in Fig. 2. This method entails predicting the spatial component of the PCA to new feature space, applying the modeled PCA time series back to the predicted loading surfaces, then restoring the standard deviation and the mean. Spatial prediction of the mean and standard deviation of temperatures at each Hobo site and each principal component loading are required to reconstruct actual temperature values, which introduces significant error. An attempt to predict temperatures in this manner resulted in large (>2 °C) errors. Thus, these predicted daily temperatures are produced for visual interpretation only.

3. Results

3.1. PCA results and daily variation in principal component time series

Results of analyses using nighttime average and nighttime minimum temperatures were very similar. We present results for only nighttime average temperatures. PCA on nighttime average temperatures from 70 Hobo stations yielded 4 retained principal components that explain 99.2% of the variability among hobo stations, with PC1, PC2, PC3 and PC4 explaining 93.0, 4.0, 1.4 and .08 percent of variation respectively. Scatter plots and coefficients of determination (R^2 values) from linear models between PC scores and select environmental variables are shown in Fig. 3. Table 1 summarizes regression models for each PC time series. PC1 captures the average daily temperature signal across all stations and is well correlated with average daily temperature ($R^2 = 0.89$) and solar radiation ($R^2 = 0.38$) from the Saddle Pass RAWS station. A regression model with daily temperature and solar radiation at that station explains 96% of the variation in PC1. PC2 identifies the difference in free air versus valley bottom temperatures (calculated as the difference between sensors at 530 and 2300 m in elevation, the lowest and highest points in the study area), and shows sensitivity to 700 Mb geopotential height which is representative

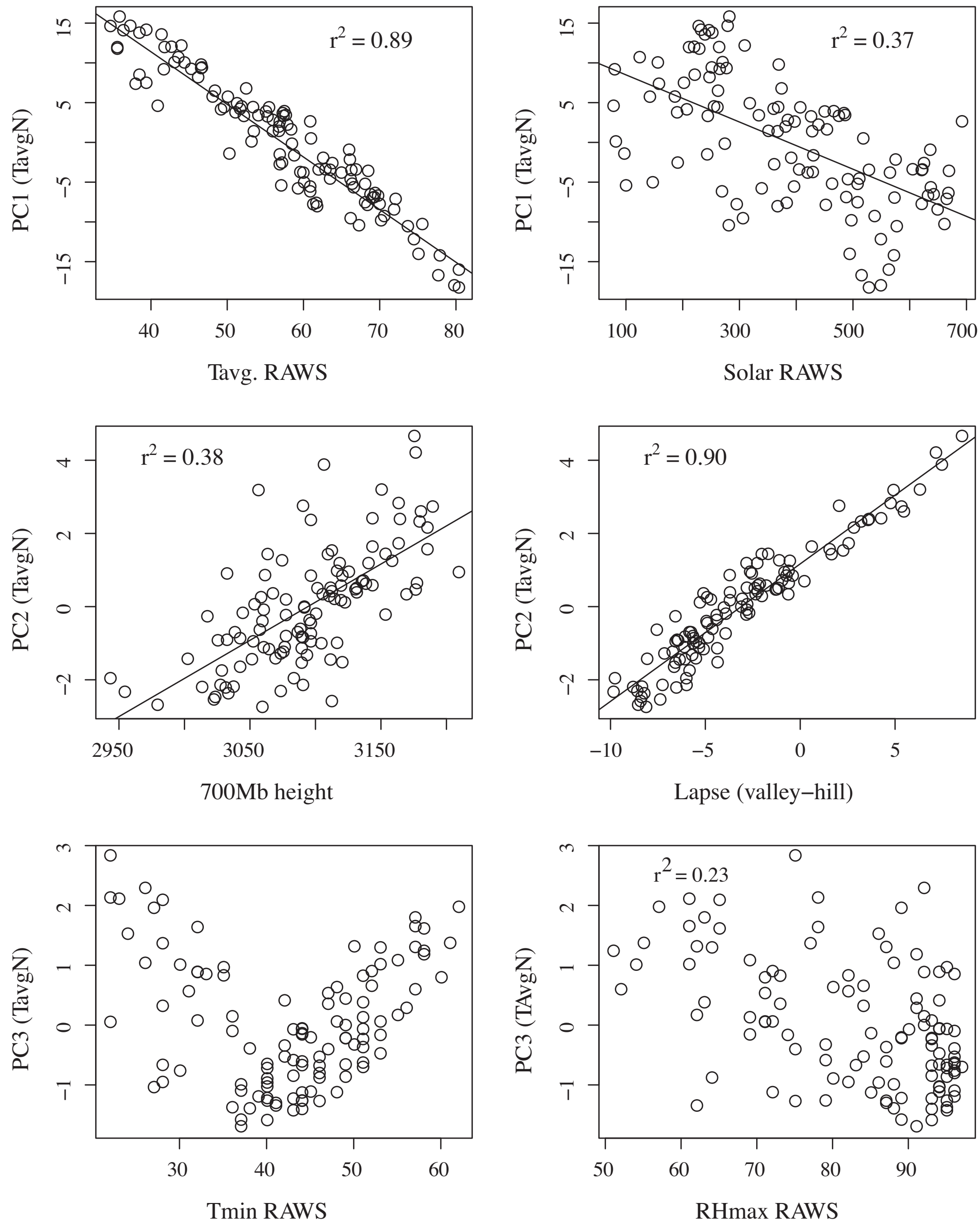

Fig. 3. Relationships between average nighttime temperature PC time series and radiation, windspeed and atmospheric pressure. Each point represents a single day.

of the regional free-air temperature (Fig. 3). A regression model with Tmin, Tmax, solar radiation, 700 mb geopotential height and NSP explained 79% of the variance in PC2 time series (Table 1). PC3 time series shows sensitivity to RAWS Tmin, and RHmax. When PC3 loadings are correlated with nighttime average temperature, two distinct groups of days are evident, and reveal a differential response to minimum temperature (Fig. 3).

Table 1
Independent variables and coefficients of determination used in regression models predicting principal component time series. Tavg, Tmin and Tmax and solar come from the Bonners Ferry RAWS station. NSP is the North–South difference in 800–500 mb geopotential heights from NARR.

Model	Ind. variables	R^2 (adj.)
PC1	Tavg, Solar	0.96
PC2	Tmin, Tmax, solar, NSP, 700 Mb	0.79
PC3	Tmin, Tmax, RHmax, Solar	0.72

3.2. Spatial variation in principal component loadings

PC spatial loadings are highly interpretable. PC1 loadings are spatially uniform (mean/SD = 0.129/0.01) and show no correlation with topographic variables. PC2 loadings on nighttime temperature are well correlated with elevation ($R^2 = 0.69$), hierarchical slope position (Murphy et al., 2010) ($R^2 = 0.42$) and a topographic dissection index calculated on a 450 m × 450 m window (DISS15; $R^2 = 0.24$) (Table 2; Fig. 4). A Random Forest model with these three variables explains 82% of the variance in PC2 loadings on nighttime average temperature and 74% of the variability in nighttime minimum temperature (Table 3). Predicted PC2 loading surfaces on nighttime average and minimum temperatures are shown in Fig. 1B and C. These surfaces are physiographic indices that capture the relative vulnerability of landscape positions to cold air drainage, with divergent patterns in valley and basin bottoms. PC3 shows weak but significant correlation with longitude ($R^2 = 0.26$; Fig. 4), reflecting

Table 2
Description of topographic indices used to create predicted PC2 loading surfaces.

Index	Abbrev.	Description	Reference
Elevation	ELEV	Shuttle Radar Topography Mission	Farr et al. (2007)
Hierarchical slope position	HSP	Cross-slope decomposition function calculated on a moving window: 3 × 3. . .27 × 27 pixels	Murphy et al. (2010)
Dissection	DISS15	$(z - z(\min))/(z(\max) - z(\min))$, where z = elevation of the focal cell in a 15 × 15 cell window	Evans (1972)

Table 3
Random Forest model results predicting spatial variability in principal component 2 loadings and July–October average nighttime temperatures. Independent variables are presented in order of importance.

Model	Independent variables	Pseudo-R^2
PC2 Tmin	ELEV, HSP, DISS15	0.74
PC2 Tavg night	ELEV, HSP, DISS15	0.82

small differences in air temperatures on the East and West slopes of the Selkirk and Purcell mountain ranges. PC4 loadings show weak but significant relationships with NDVI ($R^2 = 0.36$), suggesting the influence of canopy cover or vegetation abundance on nighttime temperatures.

3.3. Reconstruction of nightly temperatures with PCA

Following the methods described in Section 2.3.3, principal component scores were restored to PC loading surfaces to produce daily maps of predicted nighttime average temperatures for each night of the study period (July–October, 2008). Reconstructed daily temperature time series show fine-scale, complex spatial variations in nighttime air temperatures. Three example nights are shown in Fig. 1. Some nights show linear lapse rates (Fig. 1D; 6/22). However, non-linear lapse rates occur, resulting in mid-slope thermal bands which are most evident on mountain fronts directly facing the Kootenai river valley, and in areas upslope from valley bottoms (Fig. 1E; 07/31). Cold air drainage is evident in valley bottoms and on the Kootenai river valley bottom on most nights. Strong inversion patterns are evident during periods of stable high atmospheric pressure (Fig. 1F; 10/30). On these nights, nighttime temperatures at the highest elevations are much warmer than in the valley bottom 1800 m below, while nighttime temperatures are coldest in mid and upper-elevation valley bottoms.

4. Discussion

Temperature variability in both time and space across the Bonners Ferry study area is remarkably complex, reflecting interactions of synoptic atmospheric conditions with terrain, vegetation and spatial location. A dominant feature of nighttime temperature in this region is cold air drainage. This phenomenon has been described in several recent studies (Chung et al., 2006; Dobrowski et al., 2009; Lundquist and Cayan, 2007; Lundquist et al., 2008) and has been well documented in small basins and watersheds (Chung et al., 2006; Kondo et al., 1989; Whiteman, 1982; Whiteman et al., 2001).

Our analysis and results were similar in many ways to that of Lundquist and Cayan (2007) who describe relationships between PC time series and patterns of atmospheric pressure, and (Lundquist et al., 2008) who describe an empirical method for identifying areas vulnerable to cold air pooling. Similar to these analyses, both the spatial and temporal variation in primary modes of variability in nocturnal air temperatures were interpretable, with PC time series showing correlations with sky conditions and atmospheric pressure. Importantly, in this analysis, PC2 loadings were mapped to topographic variables, resulting in an empirically based physiographic index. PC2 loadings, representing the topographic variation in temperatures among these 70 mountain stations were fit to three indices with greater than 80% accuracy. The PC2 loading surface is scaled around zero and areas with significant drainage (valley bottoms and concave basins) show strongly positive loadings, while exposed areas with little drainage (ridges, hilltops) have negative loadings. Consistent with Dobrowski et al. (2009), approximately 28% of the study area shows negative PC2 loadings, indicating that cold air drainage influences nearly a third of the study area to varying degrees.

Two terrain indices (HSP and DISS15; Table 2) previously described by Holden et al. (2009) were significant predictors of spatial variation in nighttime air temperatures. A compound topographic index (also referred to as topographic convergence index in Dobrowski et al. (2009) and Chung et al. (2006)) was evaluated, but was not significantly correlated with any PC loadings. HSP and DISS15 both provide measures of topographic position relative to surrounding terrain. HSP quantifies the relative position between valley bottom and adjacent ridgetops (Murphy et al., 2010), while DISS15 calculates the degree to which a pixel is above or below adjacent cells in a 15 pixel radius window. Both measures are potential indicators of nocturnal cold air drainage. In the absence of fine-scale physically-based models of air flow and drainage, these indices may be useful for improving empirically-based models of topoclimatic variability.

The examination of larger-scale, synoptic variables assisted in the interpretation of potential mechanisms influencing variability captured in PC2 (Table 1). Geopotential heights and especially the north–south gradient in free air lapse rates (NSP) were significant predictors in regression modeling of PC2 scores, indicating that subtle gradients in synoptic conditions across the study area impact cold air drainage patterns. A gradient in background atmospheric stability captured in the NSP index would most likely impact the development of anabatic and katabatic flows and inversion heights differentially across the study area. This would in turn lead to spatial variability in surface microclimatic regimes captured in the PC2 loading maps.

Examination of PC3 spatial loadings and time series revealed what appears to be a land surface-atmospheric interaction. PC3 time series plotted against RAWS Tmin shows two distinct groups of days with opposite linear trends that separate where nights are at or near freezing (Fig. 3). PC3 loadings show a trend with longitude, indicating temperature differences between the Selkirk and drier Purcell Mountains to the East. Taken together, the spatial and temporal patterns in PC3 suggest a land surface–atmospheric interaction and a differential response of local nighttime temperatures to both atmospheric conditions and local site conditions. Without additional meteorological and biophysical data at these locations (e.g. humidity and soil moisture data), we can only speculate about the physical mechanisms driving this apparent variation. It is possible that radiative cooling at night varies as a function of solar loading during the day and atmospheric moisture at night, and that this temporal pattern in turn is sensitive to site conditions. The Purcell Mountains lie in the rain shadow of the Selkirks, and are significantly drier. Drier sites, depending on vegetation cover and substrate, would channel more energy into sensible heat gains and losses over the course of day leading to larger diurnal temperature swings than sites with more moisture. Sky conditions, atmospheric moisture and nighttime temperatures, in turn, could influence the

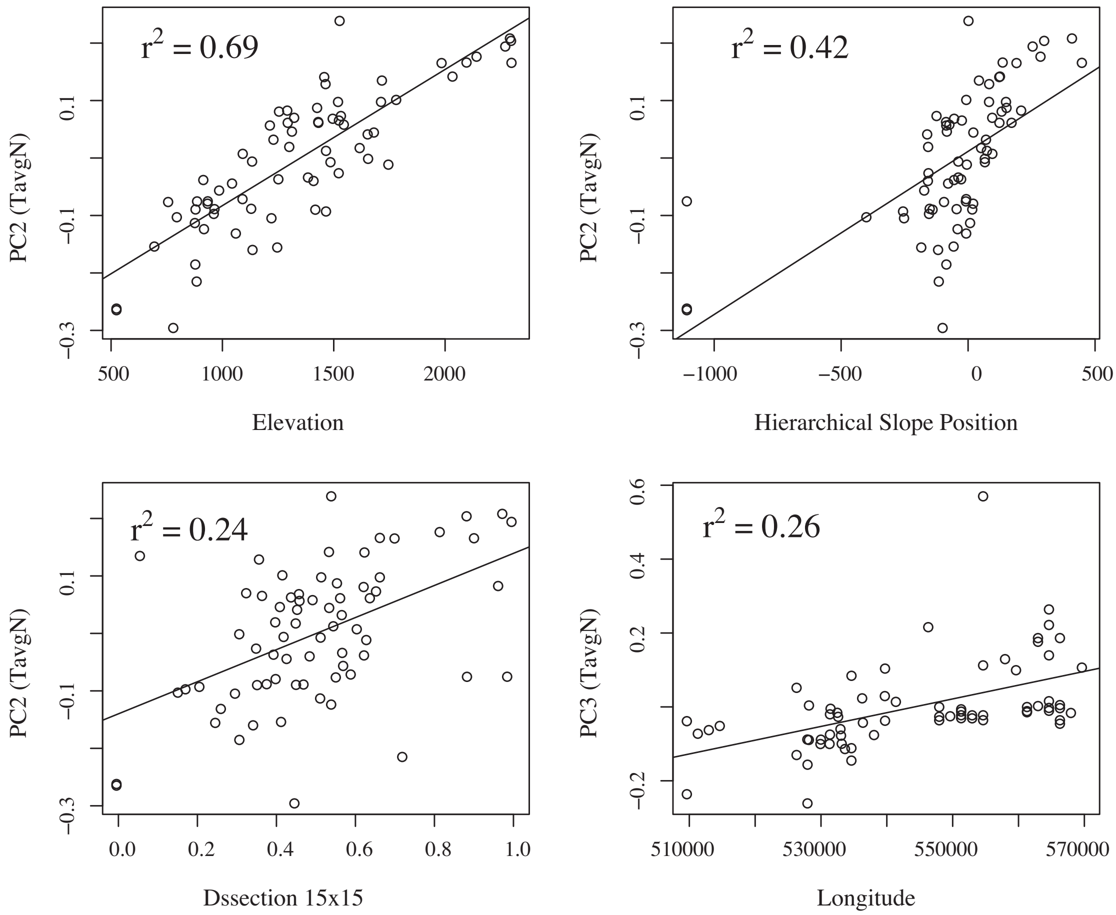

Fig. 4. Correlations between PC loadings (EOF's) and topographic variables. Each point represents a temperature sensor location.

magnitude and direction of energy exchange between the air and ground. For example, on warm, overcast nights, the ground could absorb heat differentially depending on the soil water balance, while on cold, clear nights, the transfer of heat would be from the soil to the air. Physically based models would be needed to better understand these mechanisms; however, the patterns we observe in these data suggest interactions between local biophysical conditions and synoptic atmospheric patterns that to our knowledge are not accounted for in available temperature models.

The influence of canopy cover or vegetation abundance on night-time surface air temperatures in this study was weak (less than 1% variance explained) but is still noteworthy. One of the primary drivers of landscape-scale vegetation change in the western US will likely be insect-induced tree mortality and wildfires. Additionally, changes in site water balance associated with climate warming or altered precipitation patterns will likely result in shifts in site-specific leaf area. How landscape-scale or site-level changes will influence cold air drainage is unknown. However, in combination, changes in canopy cover interacting with site water balance could significantly alter surface air temperatures via mechanisms that will be impossible to account for given available data and models. Interactions among land surface-air temperature feedbacks, vegetation and surface air temperatures warrant further investigation.

Topographic variation in this region is extreme. The average elevation in the Selkirk Mountains changes 600 m in 1 km. Where fine-scale topoclimatic variation occurs, coarse resolution (e.g. 800 m or greater) interpolated gridded models will have limited utility for predicting local air temperatures, particularly where slopes are steep or valleys extremely narrow relative to the model resolution. Micrometeorological measurements from relatively inexpensive data loggers can be useful for developing appropriately scaled observations and analyses that provide detail currently impossible with physical interpolation from long-term climate networks. Conducting field campaigns to characterize microclimatic regimes within small management units is a challenging task, but may be necessary to gather baseline information for planning efforts. Short-term field campaigns can describe local microclimatic patterns, which then may be monitored over longer time periods to elucidate their full dynamics and relationships to topographical and synoptic climate drivers. This would perhaps enable robust prediction of local topographic control on daily to monthly lapse rates. The challenge then would lie in relating these patterns to longer-term datasets and operational data sources in order to gauge potential microclimatic changes within the context of broader-scale regional temperature changes.

Ecologists have long been aware of the influence of microclimatic variation on vegetation distribution. Efforts to manage ecosystems under current and future climate scenarios may require data at resolutions much finer than are currently available in a consistent and timely manner (Millar et al., 2007). Topoclimatic variability is likely to be particularly important in mountains of the western United States where extreme topographic gradients create complex microclimates that support diverse ecosystems within small management units. Resource managers engaged in climate change adaptation planning often require high-resolution climate data for efforts like baseline species distribution mapping that can be used with climate change scenarios to predict potential species range changes (Iverson et al., 2007; McKenzie et al., 2003). Fine-scale surface air temperature models may be critical for accurate assessments of the potential impacts of climate warming on shifts in species distribution and abundance (Dobrowski, 2010).

There are several important limitations in the analysis presented here. First, with only six months of data, we can say nothing about the degree to which the patterns described here are consistent over time. Clearly, interannual and decadal climatic variation driven by coupled ocean/atmosphere processes (e.g., ENSO, or the Pacific Decadal Oscillation) could affect the frequency of high and low pressure systems and their influence on the relationships described here. Daly et al. (2009) note that some of the synoptic patterns that influence cold air drainage and pooling may change over time. Thus, while the topographically driven, spatial component of relationships between stations is likely to remain robust through time, local relationships to regional climate may change, and could be important for understanding the impacts of combined future climate change impacts. Further analyses using high-resolution data and with a range of statistical methods across longer time periods are clearly warranted. Finally, while PCA can sometimes capture important features of data related to physical processes, it is nonetheless an empirical method. True physical models of the nocturnal temperature variability are ultimately needed.

5. Conclusions

This study examined spatial and temporal variation in nighttime air temperatures, using a network of 70 temporary stations distributed across two mountain ranges in a topographically complex landscape. PCA revealed four interpretable modes of variability in average nighttime temperatures. By isolating and then predicting the spatial variation associated with topography, a nocturnal cold air drainage index was produced. Our analysis also revealed land surface-air temperature feedbacks and small variations in temperature associated with a greenness index derived from Landsat. These results contribute to a growing body of research describing the influence of physiography on air temperatures in mountains and highlight the challenges of predicting mountain temperatures where weather stations are sparse or absent. The influence of fine-scale topoclimatic temperature variation on ecological pattern and process is largely unknown. However, as efforts to predict the ecological impacts of climate change advance, issues of scale and resolution should be considered, as significant temperature variability occurs at resolutions finer than what is currently available.

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