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Empirical downscaling of daily minimum air temperature at very fine resolutions in complex terrain

Zachary A. Holden[a,*], John T. Abatzoglou[b], Charles H. Luce[c], L. Scott Baggett[d]

[a] USDA Forest Service Northern Region, 200 East Broadway, Missoula, MT 59807, United States
[b] Department of Geography, University of Idaho, Moscow, ID 83844, United States
[c] USDA Forest Service, Rocky Mountain Research Station, Boise, ID, United States
[d] USDA Forest Service, Rocky Mountain Research Station, Ft. Collins, CO, United States

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ABSTRACT

Available air temperature models do not adequately account for the influence of terrain on nocturnal air temperatures. An empirical model for night time air temperatures was developed using a network of one hundred and forty inexpensive temperature sensors deployed across the Bitterroot National Forest, Montana. A principle component analysis (PCA) on minimum temperatures showed that 98% of the spatiotemporal variability could be accounted for using the first two modes which described the coupling and decoupling of surface temperature from free air temperatures, respectively. The spatial character of these modes were strongly correlated with terrain variables and were then modeled to topographic variables derived from a 30 m digital elevation model. PCA scores were modeled using independent predictors from *in situ* observations and regional reanalysis that incorporate temperature, solar radiation and relative humidity. By applying modeled PC scores back to predicted loading surfaces, nighttime minimum temperatures were predicted at fine spatial resolution (30 m) for novel locations across a broad (~45,000 km^2), topographically complex landscape. Our results suggest that this modeling approach can be used with retrospective and projected predictors to model fine scale temperature variation across time in regions of complex terrain.

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1. Introduction

Surface air temperatures vary at fine spatial scales in complex terrain. There is growing recognition among ecologists of the need for higher resolution temperature models for understanding climate change impacts in mountains (Millar et al., 2007). Perhaps the largest source of uncertainty and error in spatial estimation of air temperatures in heterogeneous terrain occurs at night where radiative cooling and advection can foster cold air drainage (CAD). CAD has been studied at the basin scale around the world and its physical basis is well understood (Chung et al., 2006; Geiger, 1966; Kondo et al., 1989; Whiteman, 2000, 1982; Whiteman et al., 1999, 2001; Whiteman and McKee, 1982). Several recent studies have noted the importance of CAD on nighttime air temperatures at broader scales (Dobrowski et al., 2009; Lundquist and Cayan, 2007; Lundquist et al., 2008). Despite the growing awareness in the scientific community of the potential ecological significance of CAD (Dobrowski et al., 2009; Hubbart et al., 2007), it is currently not well accounted for in any available interpolated surface air temperature models. Two models currently employed in mapping temperature surfaces in the United States, PRISM (Parameter Regression on Independent Slopes Model) and DAYMET both create moderate-resolution (~1-km) temperature maps. PRISM accounts for CAD by identifying stations that lie above and below inversions (Daly et al., 2002, 2008, 2007). DAYMET temperature surfaces are derived using a Gaussian weighting filter and empirically derived relationships. However these models suffer in their ability to resolve fine-scale air temperature (sub-km scale) at the timescales relevant to biota living in narrow mountain valleys (e.g. 10–30 m).

The demand for fine-scale climate fields has escalated in recent years with growing interest in climate change adaptation While statistical and dynamical downscaling methods bridge the gap between the coarse scale of global climate models and that needed for local application, the scale of resultant datasets is still too coarse for ecological applications. This is a particularly acute problem in areas of complex terrain where interpolation-based approaches fail to resolve steep climate gradients.

Long-term mountain meteorological observations are sparse and inadequately distributed across the spectrum of terrain to fully resolve high-resolution temperature surfaces. Most long-term weather stations in regions of complex terrain are located at lower elevation (i.e. valleys), with a few snow pack telemetry (SNOTEL)

* Corresponding author. Tel.: +1 406 329 3119.
E-mail address: zaholden@fs.fed.us (Z.A. Holden).

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stations and Remote Automated Weather Stations (RAWS) broadly distributed across complex topography. However, the siting of weather stations is done with the intent to minimize influences of local relief on weather, thereby not encompassing a representative sample of heterogeneous physiography. Thus available weather stations alone may not be suited for accurately capturing physiographic influences on surface air temperatures across the diverse and complex topography.

Truly inexpensive temperature sensors (e.g. Thermochron ibuttons and Logtags costing less than $30) are increasingly being used to monitor air temperatures for short-term ecological studies (Beever et al., 2010; Hubbart et al., 2007; Lundquist et al., 2008). Distributed networks of sensors can yield insight into spatial variation in mountain air temperatures. However, short-term (e.g. <5 years) mountain temperature studies are labor intensive, provide only retrospective data and are difficult to incorporate into existing data and models.

In complex terrain characteristic of much of the western US, accurate, high spatial resolution daily models should simultaneously account for the synoptic atmospheric and topographic variation in surface air temperatures (Daly et al., 2009). Furthermore, it should be possible to integrate empirical algorithms derived from short-term, high-spatial resolution data collection efforts into existing models based on long-term climate station data to better account for physiographic influences on nighttime air temperatures. Analyses like those of Daly et al. (2009), Lundquist et al. (2008) and Holden et al. (2011) point in this direction. This paper describes a method of empirically downscaling daily nocturnal air temperatures by combining short-term data from a distributed network of ibutton temperature sensors with independent long-term observational or modeled datasets. This study builds on work by Holden et al. (2011) and resolves challenges encountered in their analysis. The primary goal was to develop empirical models from a set of short-term, high spatial resolution temperature measurements that once developed, could be used in near real-time applications or climate projections.

2. Study area and methods

2.1. Study area and data

This study was conducted on the Bitterroot National Forest, Montana, and includes portions of the Lolo and Clearwater National Forests, all on lands managed by the northern region of the U.S. Forest Service (Fig. 1). A total of 175 Thermochron ibuttons were distributed across the study area by the author and the local wildland firefighters along elevational transects across the Bitterroot National Forest, Montana, starting at valley bottoms, then every 50–100 m until the ridgetop was reached. The number of sensors varied in each transect, ranging from 6 to 14. Transects were deployed near RAWS and thirty-five additional sensors were distributed opportunistically across the study domain using roads and hiking trails. Each sensor was programmed to record at 90 min intervals beginning at midnight on 01 May 2009 and ending on 28 September 2009. Sensors were housed in two inverted funnels following Hubbart et al. (2005) and placed on the north side of trees at two meters height. 35 sensors failed or were lost, leaving 140 sensors used in this analysis.

We separately assessed two independent data sets for modeling air temperatures. These included a network of *in situ* independent surface observations from 12 RAWS, and regional reanalysis data from the North American Regional Reanalysis (NARR; 3-hourly; 32-km resolution; Mesinger et al., 2006). Reanalysis datasets assimilate a variety of observations and are able to capture macroscale surface meteorological features despite not directly

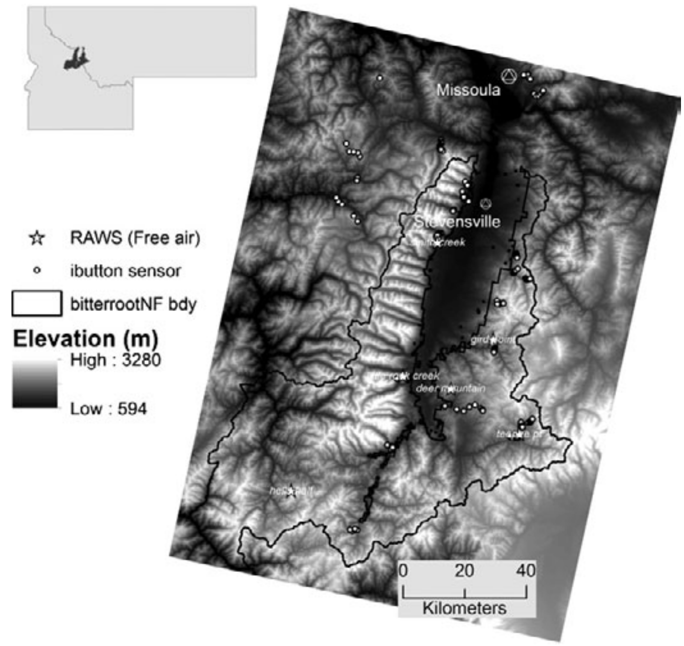

Fig. 1. Bitterroot Valley with RAWS and ibutton locations.

assimilation surface temperature observations. While previous studies have shown a strong link between surface air temperatures in observations and lower-tropospheric temperature from reanalysis, reanalysis are unable to resolve the influence of complex topography on surface temperatures at very fine (< 1km) scales.

2.2. Overview of the modeling methodology

The overall modeling approach presented here is a sequence of nested models depicted in Fig. 2. Four digital elevation model (DEM) tiles (1 × 1 degree) were selected that encompassed all ibuttons within the study area. The modeling procedure described below was applied separately to each DEM tile. First, a nearest neighbor algorithm was used to select the nearest predictor variable (RAWS or NARR grid cell) to the DEM cell center. Data for that station or cell was subsequently used to fit the PC time series models for that DEM tile. Models based on RAWS used Temperature (T_{min} and T_{max}), solar radiation and relative humidity (RH) from each station. Models based on NARR used 850 hPa temperature and specific humidity, downward shortwave radiation flux and 700 hPa geopotential height. For RAWS data, each of these variables was interpolated to a mean elevation using thin plate spline regression models and the library "fields," (Furrer et al., 2010). (See supplementary materials for more detail on the RAWS selection and the interpolation procedure.) Second, 60 ibutton temperature sensors nearest to each DEM tile center were selected to begin the modeling procedure. PCA was used in the third step to identify, separate and then model the spatial and temporal variability in nighttime minimum temperatures, initially using all 60 sensors nearest each DEM tile. Model selection follows an iterative process of one-by-one removing non-nearest neighbor ibuttons and then fitting models of PC time series. The model fitting and validation procedure was repeated with fewer and fewer ibuttons until model accuracy did not improve (i.e. following a root mean squared error (RMSE) test statistic). Once model validation was complete a final set of models were produced for each DEM tile. Using the PCA reconstruction procedure described by Holden et al. (2011), predicted temperature maps were produced at 30 m spatial resolution across the study

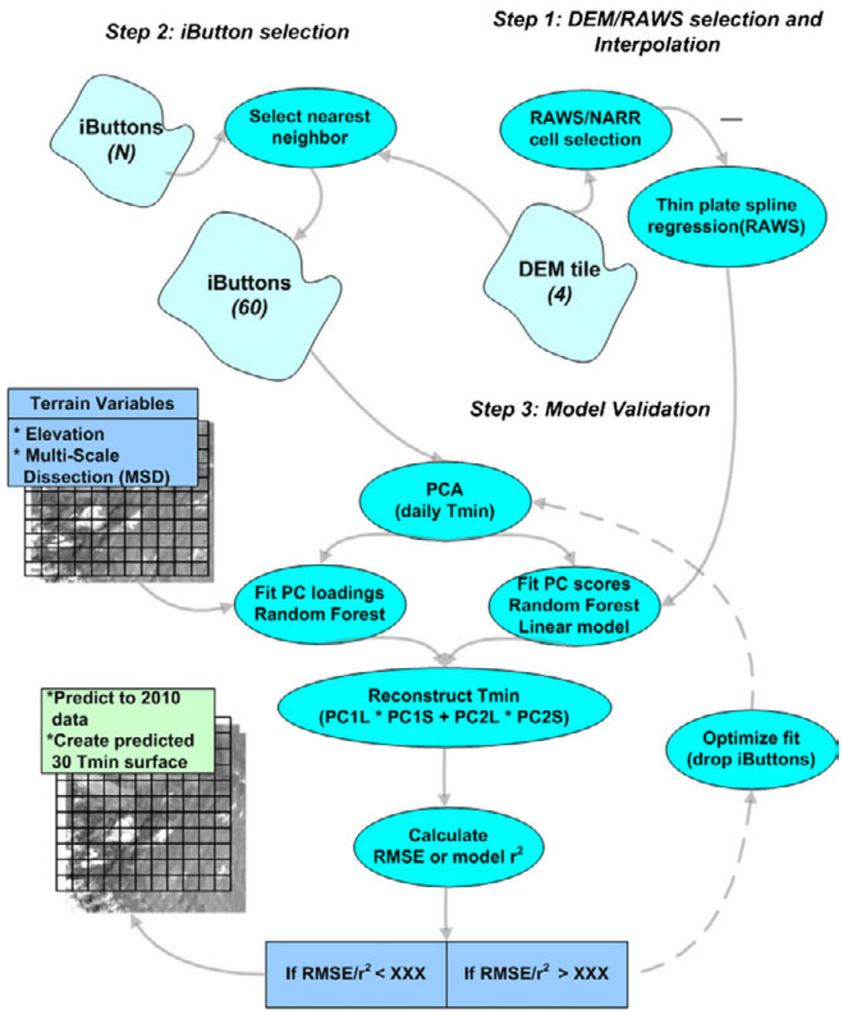

Fig. 2. Conceptual diagram of model fitting procedure.

domain. More detailed descriptions of the various components of the modeling procedure follow below.

3. Statistical analysis

3.1. Principal components analysis

PCA (also referred to as EOF analysis) involves decomposition of the covariances among several station time series, yielding two orthogonal matrices called "loadings" and "scores". Each principal component comprises a time series of scores much like the original data values, and the loadings are weights for each principal component at each station:

$$X_a = L_{a1}P_1 + L_{a2}P_2 + \cdots + L_{an}P_n \tag{1}$$

where X_a is data at station a, P_1–P_n are the principal components derived from n stations of time series, and the L_{ai} are the loadings of each principal component at station a. While the original set of station time series X_a–X_n may have had some degree of correlation between them, the n principal components derived from them have the property of being mutually uncorrelated. If the variations from the n time series are somewhat correlated, the principal components also have the property that most of the information can be represented in an efficient form using the first few principal components. PC time series and loadings can be recombined to reproduce the original values on which the decomposition was performed using Eq. (1), and a reasonable approximation may be gained using only the first few principal components (Holden et al., 2011), e.g.:

$$X_a \approx L_{a1}P_1 + L_{a2}P_2 \tag{2}$$

In this analysis, loadings were extracted from each sensor (140 columns) and the scores (time series) were retained from each row of 136 daily minimum temperature observations.

The idea behind the analysis presented here was derived from (Smith et al., 1996) who used EOF analysis in their meteorological investigation relying on fairly complete mapped information (e.g. from satellites). They developed a model of the temporal dependence of each mode of spatial variability (map) to allow them to estimate the sea surface temperature maps from years before satellite data were available but buoy and ship data were available. In other words they wanted to extrapolate maps through time. In our application, we focus on the geographic dependence of each mode of temporal variability, e.g. maps of time series. If the time series of each pixel in a map can be estimated as the weighted sum of the principal components derived from the many ibuttons, the primary challenge is estimating the loading values between observation points.

Because a large number of ibuttons are not always available to build PCs, there is also an interest understanding the connection between the time series measured at the sparse weather stations and the PCs measured from the diverse settings in which the ibuttons were placed. In essence if both the spatial loadings and time series are predictable and strongly linked to topographic metrics, then the PC loadings can be mapped to new feature space. Thus, when a PC time series observation is applied back to each pixel of the predicted loading surface, the temperature is reconstructed at new locations where no previous observations were available. Separately modeling the temporal and spatial component of the original data allows for dynamic modeling of spatial variation over time.

Several factors made using PCA for spatial prediction problematic. First, data are typically scaled and centered (i.e. the standard deviation and mean are removed from each column of data) prior to running PCA (Johnson and Wichern, 2002). However, in order to reconstruct the original air temperature values, the mean and standard deviation must later be restored to the data. Therefore, accurately reconstructing temperature values at a new location would require predicting the standard deviation and the mean at that location, introducing several sources of error. Scaling is recommended when the difference in variances in samples is large (Johnson and Wichern, 2002), or when the size of measurements varies by orders of magnitude. Here, the day-to-day variance in nighttime temperatures was similar among ibutton sensors. Therefore, data were not scaled or centered prior to PCA extraction. As a consequence, small but significant variation is introduced into the first principal component loading. This variation must be modeled, in order to accurately reconstruct air temperatures at new locations. Therefore, in this analysis, both PC1 and PC2 loadings were predicted to 30 m DEM data.

The second challenge of PCA as applied here is that at the spatial extent of this analysis (a 2×2 degree window; $\sim$45,000 km^2), weather and climate begin to vary significantly. In 2009, for example, RAWS in the southern portion of the study area received over 50% more precipitation than the northern Bitterroot valley and free air temperatures often vary by several degrees across the horizontal extent of the study area. When all ibutton temperature data were analyzed together, regional-scale temperature differences were introduced and became difficult to isolate. In our initial analyses using all 140 ibuttons, we found that latitude and longitude were significantly correlated with PC loadings, partially obscuring and diminishing local relationships among loadings and topographic variables. This problem was overcome by running and fitting models of PC scores and loadings locally around the center of each digital elevation model tile, using a nearest neighbor algorithm to select ibuttons to include in the model for each DEM tile.

3.2. Modeling PC time series

PC1 represents the regional air temperature dictated by synoptic variability (Holden et al., 2011). The PC1 time series captures the average air temperature among a group of ibuttons and showed strong correlations with regional minimum air temperatures. A simple linear model was used to fit PC1 to either daily $T_{\min}$ from the nearest RAWS or the minimum temperature at 850 hPa height from the nearest NARR cell. The PC2 time series captures the temporal and spatial variability of decoupling of the boundary layer from free air temperatures consistent with Holden et al. (2011). PC2 showed correlations with solar radiation the previous day, maximum temperature and maximum (nighttime) relative humidity. For models based on RAWS observations, models of PC2 time series were constructed using minimum and maximum temperature, maximum relative humidity and solar radiation from RAWS distributed around the study domain. Models of PC2 time series based on NARR data included 700 hPa geopotential height, downward solar radiation flux the previous day, minimum temperature and 850 hPa specific humidity. Initially, a variety of statistical models were compared as methods for fitting PC2 time series models. Although linear models and General Additive Models often yielded similar or even higher accuracies (in terms of adjusted r^2 values), Random Forest models produced better cross validation accuracies and were used for the final model fitting. The Random Forest algorithm, introduced by Breiman (2001) is a bootstrapped classification and regression tree algorithm that has gained popularity in ecology in recent years based on its ability to find signals in complex data.

3.3. Modeling PC spatial loadings

Correlation analysis, linear models and Random Forest were used to explore relationships among PC1 and PC2 loadings and a suite of topographic variables described in Holden et al. (2009) and derived from ASTER (Advanced Spaceborne Thermal Emission Radiometer) DEM data. these included a measure of topographic dissection (Evans, 1972) calculated across a range of window sizes, where dissection (D) is calculated as:

$$D = \frac{z - z_{\min}}{z_{\max} - z_{\min}}, \tag{3}$$

where z = elevation. Variable window sizes can be used to define cells included in the calculation. *D3*, *D15* and *D27* indices calculated at 3×3, 15×15 and 27×27 pixel window sizes were used. In addition, a multi-scale dissection index (MSD) was created by calculating the sum of the topographic complexity of a pixel relative to adjacent pixels across 11 increasingly large window sizes (3, 5, 7, 9, 11, 13, 15, 21, 27, 30 pixels). The result was a multi-scale measure of the position of each 30 m pixel relative to surrounding terrain. Valley bottoms and areas that are low relative to their surrounding pixels have values close to zero, while ridges and areas lying above surrounding areas have high values approaching 11. We compared a number of models constructed with different combinations of topographic variables. Ultimately, a model with elevation and MSD had the highest variance explained and lowest mean squared error with only two explanatory variables. PC1 and PC2 loadings were predicted to 30 m elevation and MSD grids.

3.4. Spatio-temporal modeling of daily minimum temperatures

Predicting PC1 and PC2 loadings to topographic indices derived from DEM data produces indices representing the response of landscape position to daily variation in nocturnal air temperatures and CAD. By applying the predicted PC1 and PC2 time series (both indices with a single value for each night) back to the static PC2 loading surface, time series of air temperature maps can be reconstructed across the landscape.

3.5. Model validation

Two separate model validations were performed. First, for each of the four models locally fitted around each DEM tile, 10% of the ibutton data were randomly selected and withheld from the model fitting procedure. The temperature for each of 136 nights at each withheld ibutton location was then predicted with the model parameterized using the remaining 90% of data, using only the latitude and longitude of the withheld ibuttons to extract topographic indices (elevation and MSD). The RMSE of observed versus predicted temperatures was calculated for each withheld station and then summarized across all withheld stations. This procedure was repeated 1000 times. We note that because of spatial autocorrelation among sensors arrayed in transects, this type of validation is likely to yield artificially high accuracies, since some adjacent sensors will have similar air temperatures and topographic features. Therefore, we assessed the transferability of the model in time and space by using the model parameterized with 2009 data

Table 1
Model accuracies for PC1 and PC2 loadings by DEM tile.

DEM tile	# sensors	PC1load pseudo-R^2	PC2 load pseudo-R^2
N45W114	54	0.36	0.90
N45W115	54	0.38	0.91
N46W114	55	0.49	0.95
N46W115	52	0.50	0.96

Table 2
Accuracies for models of PC1 and PC2 time series for each DEM tile. Models based on RAWS included T_{min}, T_{max}, RH_{max} and solar radiation the preceding day as independent variables. Models based on NARR included 850 hPa T_{min}, T_{max} and specific humidity, surface downward shortwave radiation flux, and 700 hPa geopotential height.

Input data source	RAWS		NARR	
DEM tile	PC1 R^2	PC2 (RF) pseudo-R^2	PC1 R^2	PC2 (RF) pseudo-R^2
N45W114	0.89	0.62	0.83	0.44
N45W115	0.90	0.63	0.84	0.43
N46W114	0.95	0.68	0.87	0.55
N46W115	0.96	0.69	0.85	0.58

to predict temperatures the following year (2010) at both old and new locations. Six inexpensive sensors (Thermochron ibuttons and Thermoworks Logtags) that had been recording temperatures in 2010 were retrieved for this purpose and used as validation data. Two of these sensors were located either outside the study domain or at locations where no 2009 data was collected. In addition, data from the Ninemile RAWS (previously dropped from analysis because it showed significant decoupling) was also used for validation. Again, only the latitude and longitude and derived topographic information of the new 2010 stations were assumed to be known. RMSE statistics were calculated by comparing observed versus predicted temperatures at each withheld temperature sensor.

4. Results

Fig. 3 shows observed temperatures from a transect of ibutton sensors from four nights in the Big Creek drainage. Predicted minimum temperature surfaces for three of these nights are shown in Fig. 5. Model accuracies for PC spatial loadings and time series are shown in Tables 1 and 2. The PC1 time series, representing the mean temperature among all ibuttons, was well explained by minimum temperature from RAWS and 850 hPa minimum temperatures from NARR (Table 2). PC1 time series were well predicted by RAWS T_{min}, with coefficients of determination (r^2) ranging from 0.90 to 0.96. PC1 models using T_{min} from NARR were weaker, but still high (Table 3). PC1 loadings, representing the spatial weight after removing the mean were only moderately well explained by topography (Table 2). However, the total spatial variation in

Table 3
Cross validation RMSE accuracy distributions for 2009 data. Results of models fitted using both RAWS and NARR are shown. Modeling was done separately for each DEM tile. 10% of the data were withheld and used for validation 1000 times. Min, max, mean and median represent the distribution of the RMSE across all validation runs.

	N	Min.	Max.	Mean	Median
DEM tile/RAWS					
N45W114	58	0.74	3.20	1.34	1.24
N45W115	59	1.07	3.02	1.48	1.56
N46W114	62	1.13	2.52	1.46	1.61
N46W115	64	0.70	3.1	1.49	1.63
DEM tile/NARR					
N45W114	58	1.57	2.2	2.11	2.05
N45W115	59	1.41	1.6	1.70	1.70
N46W114	62	1.52	2.39	1.91	1.91
N46W115	64	1.51	1.96	1.78	1.74

PC1 loadings was relatively small, ranging from 0.10 to 0.16. Most information about the topographically driven variation in air temperatures was isolated in PC2 which showed strong correlations with elevation and MSD. The accuracy of PC2 loading models fit around each DEM tile was generally high, ranging from 85 to 96% variance explained. Predicted PC1 and PC2 loading surfaces created by fitting models to 30 m elevation and MSD layers resulted in physiographic indices for the entire study area, shown for a single DEM tile in Fig. 3). Random Forest model accuracies of PC2 time series ranged from 62 to 69% variance explained for RAWS models, and 44–58% variance explained for NARR models. Cross validation summary statistics for 2009 data are shown separately for each DEM tile in Table 4. Mean root mean squared errors (RMSE) ranged from 1.34 °C to 1.59 °C for RAWS and from 1.74 to 2.05 °C for NARR. The accuracy of models parameterized using 2009 data and predicted to 2010 data are shown in Table 4. The average RMSE across all 7 locations from 2010 was 1.64 °C using RAWS data.

5. Discussion

Visual examination of the modeled PC1 and PC2 loading surface indicates the spatial variation associated with each principal component (Fig. 4). PC1, which represents the spatial weight after removal of the mean from all ibutton sensors shows spatial variation in average temperatures and coupling to the free atmosphere. Relatively little spatial variation resides in PC1. Most of the localized spatial variation resides in the PC2, which capture the relative vulnerability of landscape positions to decoupling from the atmosphere and cold air pooling. Valley bottoms and areas with significant upslope contributing area show strongly positive loadings (Fig. 4). A narrow transitional zone is evident in areas just above what appear to be areas of cold air pooling. Ridges, hills and exposed areas have negative loadings, indicating locations more synchronized with free air temperatures with little CAD influence. The 30 m topographic index is similar to that of Lundquist et al. (2008) and could be useful outside the daily modeling framework, for example as a gradient modeling layer or to understand potential bias associated with climate and weather station locations.

The PCA-based model described above provides one potential modeling framework for utilizing data from inexpensive sensors to empirically downscale daily nighttime temperatures at fine spatial resolutions across a large (>45,000 km^2) region of complex terrain. Our modeling approach, while empirical, has a strong physical basis. Daily variation in minimum temperatures is driven by variability in regional air temperature, maximum temperatures and solar radiation during the preceding day, and atmospheric moisture and static stability at night. The latter two properties influence radiative cooling rates and the formation of the nocturnal boundary layer, with calm nights with low humidity and a stable atmosphere being conducive to cold air pooling at valley bottoms. The model generally appears to capture both the spatial and temporal variation in warm season nocturnal cold air drainage patterns characteristic of this region. The statistical tools, predictor variables from RAWS and NARR as well as DEM data are all publicly available and the methods presented here could easily be applied to any basin-scale or larger study area given temperature observations from sensors distributed across the study domain.

The empirical temperature model presented here differs significantly from other efforts to model air temperatures in complex terrain. The spatial resolution of daily temperature surfaces are produced at a daily time step and at much higher spatial resolutions than PRISM (800 m; Daly et al., 2008), DAYMET (1 km; Thornton and Running, 1997) or the spline-based temperature models of (Rehfeldt, 2006). Second, by independently identifying, then modeling the two principal modes of variability in a dense network of

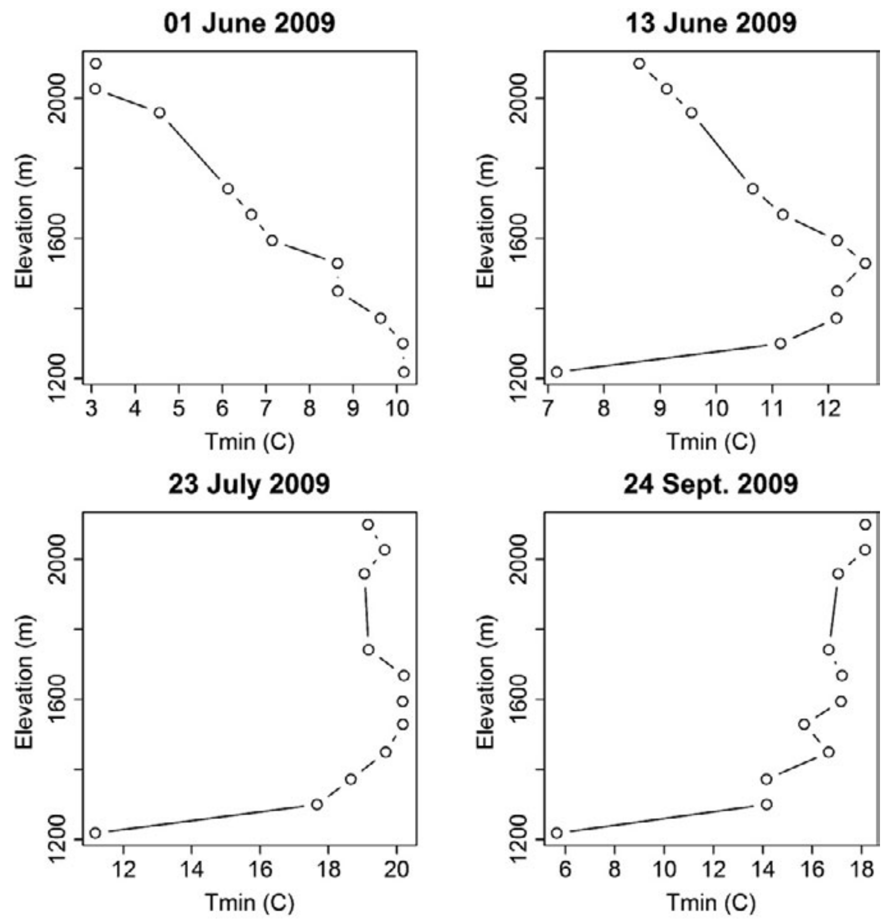

Fig. 3. Temperature profiles for 4 nights at the Big Creek drainage transect. June 1st showed temperatures that decreased with elevation. The majority of nights show large mid-slope thermal belts, as in June 30th. Some nights like July 23rd and September 24th showed full inversions with temperatures that increased continuously with elevation.

data, we were able to capture time-space interactions by incorporating atmospheric covariates (humidity and solar radiation) and their interaction with physiographic indices. Thus, this model integrates both the regional temperature and the physiographic variation associated with night-to-night variation in the magnitude of cold air drainage.

Traditional empirical temperature downscaling techniques ignore fine-scale topographic variation (Benestad, 2001). However, this variation is a major component of surface air temperature variation in complex mountainous terrain. Many ecological processes vary at fine spatial scales mountains, due principally to variation in solar radiation (aspect) and surface air temperatures (elevation gradients). Accurate modeling of changes in, e.g. productivity and plant species occurrence will require similarly scaled biophysical predictions. Generally, our results suggest that a variety of gridded data sources such as global and regional climate models could be used as predictors in this empirical model. Researchers are now beginning to run the Weather Research and Forecasting model (WRF) at relatively high (1 km) spatial resolutions (Gary Clow, pers. Comm.). Inputs or outputs from such models could also be used in conjunction with the methodology presented here to downscale mountain temperatures, ultimately building on efforts to downscale climate model projections to study the potential ecological effects of warming temperatures at finer spatial scales (Fig. 5).

5.1. Scope and limitations

There are many limitations to the work presented here. First, the time series of data used in this analysis is very short (136 days). Longer series of observations may be needed to capture and model inter-annual variability in atmospheric patterns and interactions with land surface conditions. Second, it is unclear how well these empirically derived algorithms will continue to predict temperature over time. Empirical modeling of time-space interactions remains a challenge in statistics and these models assume

Table 4
Model validation accuracies (RMSE) predicted to 2010 data.

Sensor	Elevation (m)	Dates	Description	RMSE (RAWS)	RMSE (NARR)
T63_S1	1377	July 01–August 13	Valley	2.02	2.22
T63_S3	1420	July 01–August 13	Toe slope	2.07	2.17
T63_S8	1480	July 01–August 13	Mid-slope	1.62	1.64
T63_S10	1770	July 01–August 13	Ridge	1.20	1.45
Skalkaho	2078	July 01–August 13	Ridge	1.66	2.36
Ninemileibutton 1	1330	July 01–August 13	Valley bottom	1.72	1.89
Ninemile RAWS	1260	July 01–August 13	Low elevation hilltop	1.89	2.10

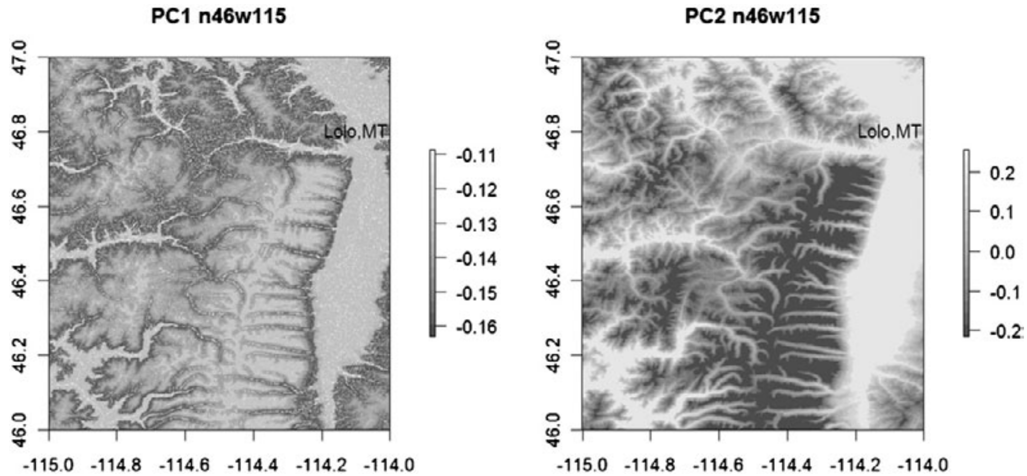

Fig. 4. Predicted PC1 and PC2 loading surface for DEM tile n46w115, located just South of Missoula, MT. The town of Lolo, MT is visible in the upper right.

stationarity through time. Additional work will be needed to adapt these methods for downscaling winter temperatures, as the physical mechanisms and scale of processes governing air temperature-land surface feedbacks will be very different with snow cover. The nearest neighbor approach to model fitting by DEM tile is simplistic and the 1×1 degree scale was chosen for convenience. We did not investigate the influence of scale here, and more sophisticated methods of integrating variation in the *X*, *Y* domain with topographic variation in air temperatures are clearly needed. Ibutton sensors were programmed to sample at 90 min intervals because memory of these sensors is currently limited to 8000 observations. It is unknown what influence this sampling interval will have the precision of our air temperature model. It is likely that there could be considerable variation in nocturnal air temperatures with a 90 min period. Ultimately, physically based models that predict air temperatures at high spatial resolutions will

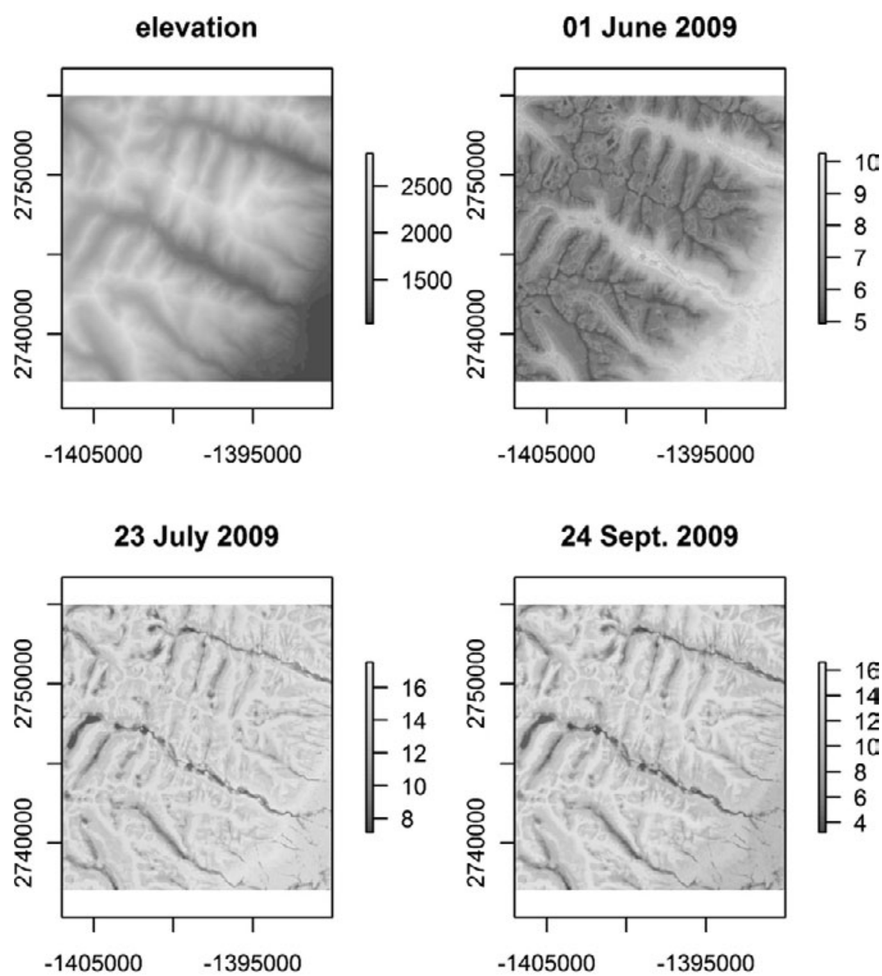

Fig. 5. Predicted minimum temperature surfaces for three nights in the Big Creek drainage. Elevation (upper left) is included as a reference.

likely be developed, although the computational demands of applying such models to the >50 million grid cells in this study domain alone would make this a challenge.

6. Conclusions

There is growing awareness of the need for finer-scale surface air temperature data in mountains for ecological modeling and forecasting climate change impacts. This paper demonstrates one method for predicting daily minimum air temperatures in complex terrain using *in situ* air temperature measurements from inexpensive sensors. Empirical models describing daily variation in cold air drainage were developed using the time series of scores derived from PCA on a network of inexpensive temperature sensors. These models, when applied to physiographic indices created from PC loadings derived from the same data captured with reasonable accuracy the daily variation in nighttime minimum temperatures during a single growing season. The same models predicted minimum temperatures to new locations the following year with similar accuracies. These methods offer a relatively inexpensive, computationally efficient means of producing daily maps of nocturnal mountain air temperatures at very high (30 m) spatial resolution that could be useful for ecological studies. With additional data, integration of observational and modeled data, inclusion of canopy cover, modeled soil moisture data, and more thoughtful selection of time series models, it should be possible to improve the empirical models of PC time series and overall model performance. The model presented here has been programmed to flexibly ingest sensor data distributed across a large spatial domain using a range of gridded climate data sources. The author and the USFS have begun monitoring surface air temperatures across the intermountain West. The anticipated three years of data at more than 2000 sites will provide new opportunities to further develop high spatial and temporal resolution temperature products across a large region of the western US.

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