High-Resolution Ground Surface Temperature Modeling in California's North Coast Region

Farrah Tyler

10 May 2024

Introduction

Methods of modeling microclimatic variability in areas with complex terrain and weather patterns such as California's North Coast Region are evolving in the field of geospatial analysis. Several different fine-scale interpolated climate gridded datasets exist that have been used in varying applications to different efficacies (Stern *et al.*, 2022).

Access to microclimatic datasets at sufficient resolution to support detailed projections of ecological impacts of climate change is currently limited. Climate surface models are rarely generated or interpreted to a resolution as fine as 1 km (Suggit *et al.*, 2011). Operating on a microclimate scale, a piece of naturally bounded land 1 km or smaller, air temperature is difficult to measure on its own (Daly *et al.*, 2007).

The OSU department of Geosciences, College of Oceanographic and Atmospheric Sciences developed a statistical regression model, PRISM (parameter-elevation regressions on independent slopes model) for climate mapping. PRISM utilizes weighted parameters based on spatial patterns of climate and their relationships with geographic features. The model integrates discrete data from weather monitoring stations as well as digital elevation models (DEM) to generate estimates of annual, monthly, and event-based climatic elements (Daly *et al.*, 2002). PRISM parameters include aspect and topographic exposure, precipitation, and coastal proximity.

Applications of PRISM for the use of interpolated climate-datasets in areas lacking robust observation-based dataset have proven effective at estimating minimum and maximum temperature at an 800-meter resolution cell size in the California-Nevada basin (Strachan *et al.*, 2017). We intend to use this approach in coastal Northern California, a heterogenous landscape influenced by the climate regimes of the Pacific Ocean and the topography of the Klamath and Trinity Mountains. Local verification from weather stations is accessible to support higher-resolution modeling.

The goal of this analysis is to determine specified climatic variability in the North Coast region at higher spatial resolution than is currently available as open-source datasets, while maintaining clear and comprehensible implementation. The study develops existing methodology from Daly and PRISM to produce modeled data sets of continuous surfaces representing ground surface temperature for future use in resource management. The deliverable will address the current data gaps by generating 20-year average (2000-2022) gridded temperature datasets at 30-meter spatial resolution.

PRISM

This work was guided by the research of Dr. Christopher Daly and the PRSIM Climate Group, who develop datasets representing short- and long-term climate patterns as part of he Northwest Alliance for Computational Science and Engineering. For our research purposes, we applied the methods to a 30 m resolution prediction raster in the North Coast region. Most microclimates occur on a sub kilometer level, and as such, benefit from representation with raster data in a 30 m spatial resolution (Suggit *et al.*, 2010).

PRISM integrates topographic covariates representing the major physiographic factors influencing climate patterns at scales of 1 km and greater, including elevation, coastal proximity, topographic facet orientation, vertical atmospheric layer, and topographic position (Daly *et al.*, 2002, Daly *et al.*, 2008).

A combination of dense data station sets, and the physiographically sensitive PRISM interpolation process improves gridded climate data sets in spatially heterogenous regions with variable terrain (Daly *et al.*, 2007). Greatest improvements observed in mountainous and coastal areas of the western United States characterized by sparse data coverage, large elevation gradients, rain shadows, inversions, cold air drainage, and coastal effects (Daly *et al.*, 2008). These factors were considered in the implication of the PRISM modeling approach in our North Coast region.

In Situ Data

We collected ground surface temperature data from the Western Regional Climate Center (WRCC) database for Wildland Fire Remote Operated Weather Stations (RAWS) in the North Coast Region. Figure 1 shows the location of 38 stations used in the mapping process and the North Coast Region boundary. We obtained monthly average temperature values by averaging daily values for each station for the years 2000-2022. Quality control procedures removed null values from the data, as some stations were installed after the initial year or had missing data when the station was down.

Figure 1. RAWS locations used in temperature interpolation for the North Coast region.

Raster Data

We obtained 30 m DEM tiles from the EarthData NASA Shuttle Radar Topography Mission (SRTM) dataset. CalTrout provided a North Coast region boundary (Figure 1) which we used to mask the DEM and derivative layers to the study area. All datasets and spatial analysis use the World Geodetic System 1984 (WGS84) Universal Transverse Mercator (UTM) zone 10 North projection, chosen for shape and angle preservation, and for scale in Northern California. From the DEM we created the following 30 m gridded datasets used in the PRISM algorithm: topographic facet, topographic position, and vertical atmospheric layer.

Topographic Facet

The topographic facet, herein absolute aspect, describes the exposure of the slope (a proxy to solar exposure) measured at a 180° East and West radius. We created an absolute aspect layer using the spatial analysist tool in ArcGIS Pro with the DEM input.

Topographic Position

The topographic position describes the surface roughness, or localized topography of the terrain in a given radius. We created the topographic position layer using a low-pass Gaussian filter on the input DEM to average terrain features within a 10 km radius of influence and preserve local detail around the central grid cell, maintaining 30 m resolution (Daly *et al.*, 2008). The values in the topographic position grid describe the height of the pixel relative to the surrounding terrain height (Daly *et al.*, 2007).

We performed sensitivity tests for topographic position layer parameters and found the 10 km averaging radius to be an appropriate scale to represent a site's suitability to cold air pooling based on its vertical positions relative to its local topographic features i.e. valley bottom, mid slope, or ridge top (Daly *et al.*, 2008).

Vertical Atmospheric Layer

The vertical atmospheric layer describes the potential temperature inversion height, where temperature increases with increased elevation. We created the vertical atmospheric layer using a similar Gaussian filtering method as topographic position grid to estimate the boundary layer where an inversion occurs and the free atmosphere above it (Daly *et al.*, 2008). In this case, we found the minimum elevation within an 10 km radius and averaged the results to produce a 'minimum' elevation grid. We applied the low pass Gaussian filter to the minimum elevation grid and used this value to apply the low pass filter to produce a 'base' elevation grid. To the base elevation grid, we added a constant height of 250 m to represent the mean climatological inversion height above sea level based on studies by Daly *et al.* (2008).

We performed sensitivity tests for vertical atmospheric layer parameters and found the 10 km averaging radius to be an appropriate scale to represent valleys in the boundary layer and prominent ridges in the free atmosphere layer (above the potential inversion height).

Climate-elevation regression

The climate-elevation regression function uses simple linear regression to describe the relationship between observed temperature and elevation values from the weather station data. The function is given in Daly *et al.* (2008), and implements (X,Y) coordinates of observed temperature and elevation values to form the equation:

$$Y = \beta_1 X + \beta_0$$

Where Y is the predicted temperature of the target grid cell, β_1 is the slope, β_0 is the intercept, and X is the elevation at target grid cell.

Weighted Regression

We implemented a weighted simple regression formula using a weighted least squares model (Weisberg, 2014) to calculate for the coefficients β_1 and β_0 using the weighted station values, where the optimal pair (β_0, β_1) is:

$$\beta_0 = \bar{y}_w - \beta_1 \bar{x}_w$$

$$\beta_1 = \frac{\sum_{i=1}^{n} w_i (x_i - \bar{x}_w)(y_i - \bar{y}_w)}{\sum_{i=1}^{n} w_i (x_i - \bar{x}_w)^2}$$

And where $\bar{y}_w$ and $\bar{x}_w$ are the weighted means given by:

$$\bar{x}_w = \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i}$$

$$\bar{y}_w = \frac{\sum_{i=1}^{n} w_i y_i}{\sum_{i=1}^{n} w_i}$$

Station weighting

To calculate the predicted temperature value (Y in the climate-elevation regression function), at the target cell, each station contributes a weight based on a radius of influence to the target cell and the contribution of the topographic covariates between the points. The weight of each station is given by the equation described in Daly *et al.* (2008):

$$W = [\, F_d W_d^2 + F_z W_z^2 \,]^{1/2} \; W_p W_f W_l W_t$$

Where W is the station weight, F_d is the user-specified distance weighting importance scalar of and F_z is the user-specified elevation weighting importance scalar of given in Daly *et al.* (2002), provided in Appendix A of this report. References for the weighting equations for each raster element are given in Table 1; we applied these equations as they are in the reference papers, implementing the default parameters of the user-specified values given in Daly *et al.* (2002), provided in Appendix A of this report. For each 30 m grid cell, the model performed a distance-weighted average of all surrounding grid cells within a 100km radius to predict the temperature value.

Table 1. PRISM weighting algorithms, table adapted from Daly et al. (2008).

PRISM Algorithm	Description	Reference
Elevation-Regression Function	Develops local relationships between climate and elevation	Daly et al. (2008), Section 4.1
Distance Weighting (W_d)	Upweights stations that are horizontally close (longitude)	Daly et al. (2008), Section 4.2.1
Elevation Weighting (W_e)	Upweights stations that are vertically close (latitude)	Daly et al. (2002), Section 4.1
Topographic Facet Weighting (W_f)	Upweights stations on the same exposure	Daly et al. (2002), Section 5
Coastal Proximity Weighting (W_p)	Upweights stations with similar exposure to coastal influences	Daly et al. (2002), Section 6 Daly et al. (2003), Sections 2.3.2 - 2.3.3
Vertical Atmospheric Layer Weighting (W_l)	Upweights stations in the same vertical layer (boundary layer or free atmosphere)	Daly et al. (2002), Section 7 Daly et al. (2003), Sections 2.3.2 - 2.3.4
Topographic Position Weighting (W_t)	Upweights stations with similar localized topography	Daly et al. (2007), Section 4

Evaluation

To perform cross validation on the predicted temperature values, we measured the difference between the observed station value and the model's expected value, removing one station at a time from the dataset. For each prediction value we generated root-mean-square deviation (RMSD) to measure the average difference between the observed and predicted values. RMSD was included as a performance in the sensitivity tests to evaluate the model's response to the implementation of different phases in the modeling process, as well as the contribution from individual covariates. We computed the RMSD value for each raster and averaged these values to obtain the average error in our model.

Results

Using the methods for deriving the PRISM algorithm described in Daly *et al.* (2002, 2003, 2007, 2008), we produced 264 raster datasets representing monthly average ground surface temperature in the North Coast Region for the years 2000-2022. The average RMSD value was 1.2 °C, meaning the model is accurate within 2 °C over a 20-year temporal range for generating monthly average temperature predictions. Figures 2 and 3 show the results of prediction rasters for the months of January and June, 2020 with relatively cooler temperatures in blue and relatively warmer temperatures in orange. The area to the west of the North Coast region boundary is the Pacific Ocean and was not included in temperature prediction, the values outside the DEM have been ignored as no data values and excluded from the prediction model at the current modeling stage.

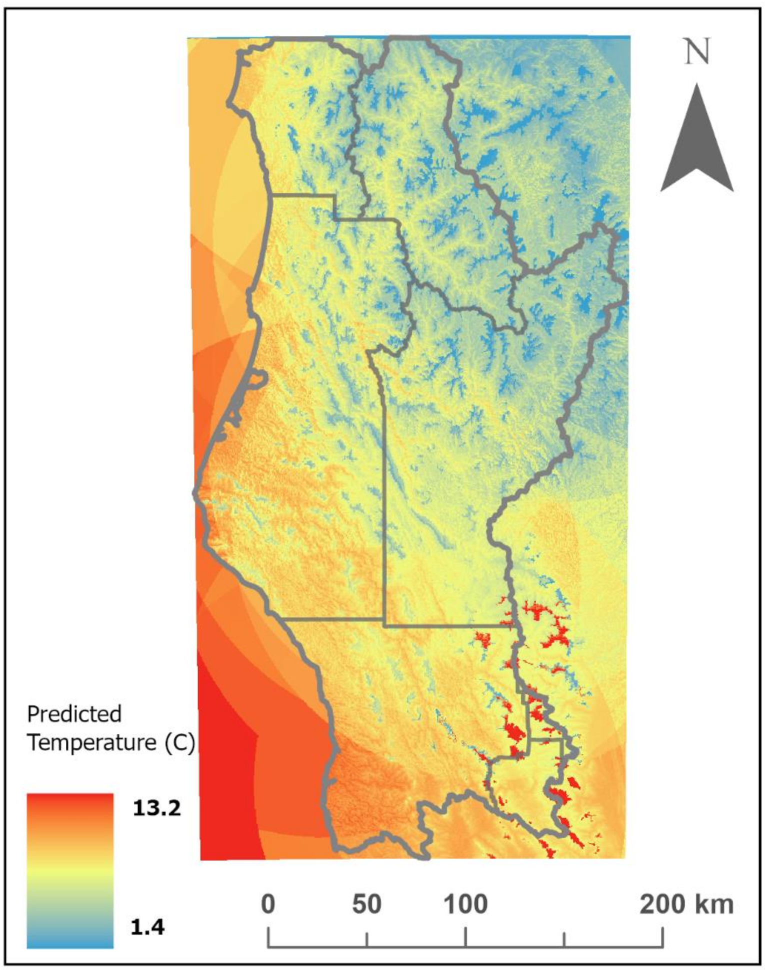

Figure 2. Predicted average monthly temperature values for January 2020 showing relatively cooler temperatures to the northeast and relatively warmer temperatures to the southwest.

The results show some error in the southwest region of the study area in dark red where predicted temperature values are outside the expected range.

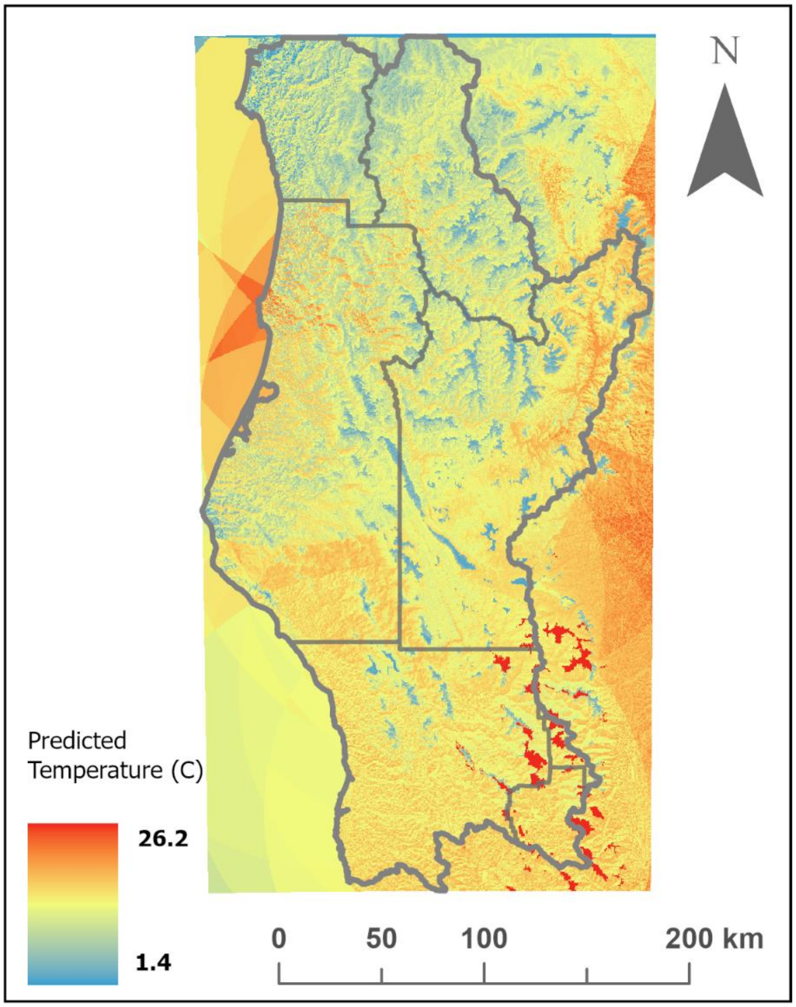

Figure 3. Predicted average monthly temperature values for June 2020 showing relatively cooler temperatures to the localized north and relatively warmer temperatures to the localized south.

.

Discussion

Dr. Daly and the PRISM Climate Group have been developing the PRISM algorithm and publishing reports with various applications and iterations of the model since 1994. Part of the efforts of this report are to represent a comprehensive analysis of the PRISM methods and generate a complete and robust resource for the supplemental equations use in the modeling process. Efforts were made to apply the most current data available in the literature when creating our 30 m temperature prediction model and supplementing our own research where methods for deriving raster covariates and function equations we ambiguous. While PRISM is widely used to analyze climatic patterns across the conterminous United States, implementing the model at higher spatial resolutions may be limited by the complexity of the topography and access to high-quality observed temperature datasets at the appropriate temporal resolution.

Producing higher-resolution data involves error handling that may not be applicable at resolutions greater than 1 km where the landscape loses some complexity. At a 30 m resolution spatial scale, however, local knowledge of climatic influences and microclimate regimes is a particularly important aspect for visual inspection and verification of the results across the study area. Evaluating the efficacy of the model in discerning the relative influence landscape-temperature interactions requires careful corroboration with local climate patterns to discern meaningful results. We accepted some fine-scale spatial error in our results for the purpose of representing large-scale temporal results. The goal of our analysis is ultimately to discern 20-year patterns for average monthly temperature, which will be used to evaluate areas of vulnerability or resiliency to climate change.

The approach at this time is to cautiously accept gross localized errors where predicted values are far outside an expected range, and to exclude any model components that are affecting the quality or generating errors in the entire study area. Currently, the coastal proximity raster and weight (W_c) is excluded from our model for this reason. To address this issue and further refine the model to represent a holistic approach of describing landscape-temperature interactions, we intend to evaluate the model using each weight separately and determining what effect it has on the result, based on its physiographic forcing property. Additionally, we intend to normalize the scale of the temperature values so they can be applied to larger-scoped projects where temperature itself will be used as a covariate in modeling landscape level climate interactions.

Appendix

A. Table 2, descriptions and typical ranges of PRISM parameters used in regression function and weighting equations given in Daly *et al.* (2008), Section 3. For our modeling purposes, we used the default values for all equations. Parameters excluded from the most current model are minimum number of on-facet stations used in regression equation (S_f) and cluster weighting (W_c), described in Daly *et al.* (2008), Appendix B.

Table 1. PRISM function and weighting parameters, sources from Daly et al. *(2008), Section 3*

Name	Description	Typical min.default/max. values		
Regression function				
r	Radius of influence	30/50/100 km[a]		
s_f	Minimum number of on-facet stations desired in regression	3/5/8 stations[a]		
s_t	Minimum number of total stations desired in regression	10/15/30 stations[a]		
			Precipitation (km^{-1})[b]	**Temperature** (°C km^{-1})
β_{1m}	Minimum valid regression slope	Layer 1	0.0	−10
		Layer 2	−0.5	−10
β_{1x}	Maximum valid regression slope	Layer 1	3.0	0/10/20
		Layer 2	0.0	0
β_{1d}	Default valid regression slope	Layer 1	0.8	−6
		Layer 2	−0.2	−6
Distance weighting				
a	Distance weighting exponent	2.0		
F_d	Importance factor for distance weighting	0.8		
Elevation weighting				
b	Elevation weighting exponent	1.0		
F_z	Importance factor for elevation weighting	0.2		
Δz_m	Minimum station-grid cell elevation difference below which elevation weighting is maximum	100/200/300 m		
Δz_x	Maximum station-grid cell elevation difference above which elevation weight is zero	500/1500/2500 m		
Facet weighting				
c	Facet weighting exponent	0.0/1.5/2.0		
g_m	Minimum inter-cell elevation gradient, below which a cell is flat	1 m/cell[c]		
λ_x	Maximum DEM filtering wavelength for topographic facet determination	60/80/100 km		
Coastal proximity weighting				
p_x	Maximum coastal proximity difference, above which proximity weight is zero	Varies with application		
v	Coastal proximity weighting exponent	0.0/1.0/1.0		
Vertical layer weighting				
y	Vertical layer weighting exponent	0.0/1.0/1.0[c]		

[a]Can be optimized automatically with cross-validation statistics
[b]Precipitation-elevation slopes are normalized by the mean precipitation in the regression function, e.g. (100 mm km^{-1} slope)/(1000 mm mean precipitation) = 0.1 km^{-1} normalized slope
[c]Can be varied dynamically by the model

Acknowledgements

This work was completed in partnership with California Trout and Christine Davis, North Coast Project Manager. This work was supported by the Cal Poly Humboldt Sponsored Programs Foundation and Dr. Jim Graham, the principal investigator.

References

Daly, C., Wayne P. Gibson, George H. Taylor, Gregory L. Johnson, and Phillip Pasteris. (2002). A Knowledge-Based Approach to the Statistical Mapping of Climate. *Climate research* 22, no. 99–113.

Daly. C., E.H. Helmer, and M. Quinones. (2003). Mapping the climate of Puerto Rico, Vieques, and Culebra. *International Journal of Climatology* 23(11): 1359-1381. doi:10.1002/joc.937

Daly, C., J.I. Smith, and R. McKane. (2007). High-resolution spatial modeling of daily weather elements for a catchment in the Oregon Cascade Mountains, United States. *Journal of Applied Meteorology and Climatology* 46(10): 1565-1586. doi:10.1175/JAM2548.1

Daly, C., Halbleib, M., Smith, J. I., Gibson, W. P., Doggett, M. K., Taylor, G. H., Curtis, J., & Pasteris, P. P. (2008). Physiographically sensitive mapping of climatological temperature and precipitation across the conterminous United States. *International Journal of Climatology*, *28*(15), 2031–2064. https://doi.org/10.1002/joc.1688

Stern, M. A., Flint, L. E., Flint, A. L., Boynton, R. M., Stewart, J. A. E., Wright, J. W., & Thornse, J. H. (2022). Selecting the optimal fine-scale historical climate data for assessing current and future hydrological conditions. *Journal of Hydrometeorology*, *23*. https://doi.org/10.1175/jhm-d-21-0045.1

Strachan, Scotty, and Christopher Daly. "Testing the Daily PRISM Air Temperature Model on Semiarid Mountain Slopes." *Journal of geophysical research. Atmospheres* 122, no. 11 (2017): 5697–5715.

Suggitt, Andrew J., Phillipa K. Gillingham, Jane K. Hill, Brian Huntley, William E. Kunin, David B. Roy, and Chris D. Thomas. “Habitat Microclimates Drive Fine-Scale Variation in Extreme Temperatures.” *Oikos* 120, no. 1 (2011): 1–8.

Weisberg, Sanford. *Applied Linear Regression*. 4th ed. Hoboken, New Jersey: Wiley, 2014. Print.