

TITLE: Surface Temperature Variability Across the East River Watershed.

AUTHORS: John Cramblitt¹, Jessica Lundquist¹

¹University of Washington, Seattle

ABSTRACT

[1] Understanding how temperature varies across space and through time is fundamental to hydrologic and ecologic study. Modeling within these fields often relies on gridded climate datasets and requires realistic representations of near-surface temperatures to accurately represent site-specific processes. In complex terrain, these representations rely on understanding how temperature varies with elevation and topography. However, numerous studies have shown commonly-used linear models of lapse rate perform poorly in complex terrain, and spatial patterns of temperature vary in response to diurnal and seasonal patterns, topography, and synoptic conditions. By leveraging a dense network of low-cost data loggers and meteorological stations, this study aims to examine spatio-temporal patterns in near-surface temperature across the East River watershed in the Colorado Rocky Mountains, a region that lacks rigorous study of this topic despite being a popular location for ecologic and hydrologic research. Linear regressions on temperature variation with elevation are used to examine the performance of linear lapse rates, the lapse rate values during times when the pattern is linear, and the corresponding synoptic conditions. Empirical Orthogonal Functions (EOFs) are used to diagnose more complex spatial patterns in observed near-surface temperatures and their corresponding temporal variability. EOF patterns reveal temperature inversions are common, particularly at night, with the coldest temperatures along the valley floor in the early morning. Additionally, a diurnal cycle of solar exposure leads to warmer temperatures at northeast-facing sites in the morning and southwest-facing sites in the evening. Correlations between 600 hPa reanalysis fields and daily EOF temporal amplitudes provide insights into large-scale weather patterns governing spatial patterns of temperature.

1. INTRODUCTION

[2] Temperature variation with elevation in complex terrain has important implications for hydrologic and ecological processes. Variability in the height of the 0°C isotherm in precipitation models can significantly impact storm runoff on mountain slopes (Lundquist et al., 2008; White et al., 2002), and estimations of April 1st SWE (Snow Water Equivalent) and spring runoff in hydrologic models are sensitive to the choice of lapse rate (the rate at which temperature cools with elevation) (Minder et al., 2010). Within ecological fields, spatial patterns of temperature in complex terrain are important for ecosystem phenology (Li et al., 2022), growing season frost risk (Inouye, 2008), animal behaviors (Beever et al.,

2017; Milling et al., 2017), and climate response (Pepin et al., 2022), and the use of in-situ measurements to correct lapse rates provided by gridded climate datasets is essential for accurate, site-specific ecological modeling (Tercek et al., 2021).

[3] Despite the importance of utilizing site-representative lapse rates, modeling efforts, including some within the East River Watershed, often use simplified representations of lapse rate in complex terrain based on a fixed mean environmental lapse rate between $6.0^{\circ}\text{C km}^{-1}$ and $6.5^{\circ}\text{C km}^{-1}$ (e.g. Cho et al., 2022; Hamlet & Lettenmaier, 2005) or linear or multiple regressions between measurements from few meteorological stations at varying elevations (e.g. Carroll et al., 2020; PRISM, Daly et al., 2002). However, numerous studies have found these simplified lapse rates to be unrepresentative of temperatures in various mountainous regions –due in part to sparsity of meteorological station observations for regression models– and suggest near-surface temperature variations are often nonlinear, following diurnal, synoptic, seasonal, and topographic patterns (Blandford et al., 2008; Daly et al., 2010; Kirchner et al., 2013; Lundquist, Pepin, et al., 2008; Lundquist & Cayan, 2007; Minder et al., 2010).

[4] A popular approach to studying near-surface lapse rates in complex terrain is to establish a dense network of distributed temperature sensors spanning a large elevational gradient in a specific region of interest (Bell et al., 2022; Blandford et al., 2008; Córdova et al., 2016; Lundquist, Pepin, et al., 2008; Lundquist & Cayan, 2007; Minder et al., 2010; Rolland, 2003; Tercek et al., 2021). However, such a study has not yet been implemented to examine near-surface lapse rates in the East River watershed, a popular region for ecological and water resources studies. To address the lack of detailed study in this region, the objectives of this study are outlined as follows. (1) Combine temperature measurements from HOBO data loggers and SNOTEL stations to create a dataset of distributed temperature measurements across the East River watershed from October 2023 - June 2024. (2) Examine the suitability of a linear lapse rate in the region. (3) Utilize an Empirical Orthogonal Function (EOF) Analysis to diagnose spatio-temporal variability in temperatures across the East River watershed. (4) Characterize synoptic conditions associated with linear temperature profiles and diagnose spatial temperature patterns. Results from this study will inform ecologic and hydrologic research in the East River Watershed and will be especially of interest for projects examining processes or ecosystem behaviors sensitive to spatial distributions of temperature in mountainous terrain.

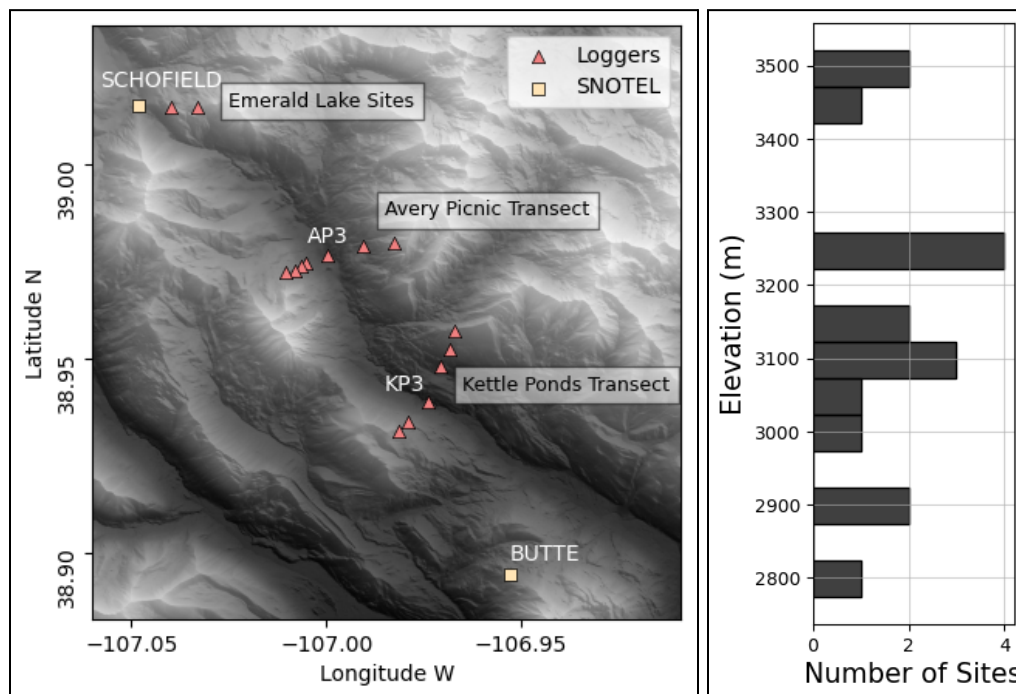
2. DATA AND METHODS

2.1. In-Situ Temperature Measurements

[5] Low-cost temperature and relative humidity loggers (Onset HOBO Model MX2301A) were deployed in three transects in the East River watershed in early October 2023 as part of the DOE grant: Seasonal Cycles Unravel Mysteries of Missing Mountain Water, led by Jessica Lundquist (U. Washington), Rosemary Carroll (DRI), Ethan Gutmann (NCAR) (see Figure 1. below). Loggers were strapped about 2 meters high on the north side of evergreen trees and took continuous half-hourly measurements of near-surface air temperature. Evergreen trees function as natural radiation shields, and thus, this deployment strategy has been shown to not introduce bias in temperature measurements (Lundquist & Huggett, 2008). The manufacturer lists maximum instrumental uncertainty as $\pm 0.25^{\circ}\text{C}$. Data are publicly available on ESS-Dive pending dataset publication (Lundquist J ; Carroll R ; Gutmann E ; Cramblitt J (estimated 2024): Time-Lapse Videos and Distributed Measurements of Air Temperature, Relative Humidity, Dewpoint, and Soil Temperature from the East River Watershed, Water Year 2024. Seasonal Cycles Unravel Mysteries of Missing Mountain Water, ESS-DIVE repository).

[6] Additional hourly near-surface air temperature data are downloaded from the Schofield Pass and Butte SNOTEL stations. Station measurements are combined with DOE grant sensor observations to create a complete dataset of hourly near-surface air temperature measurements across the East River watershed from October 7th to June 13th, 2024.

Figure 1. Locations and elevations of data loggers and SNOTEL stations.

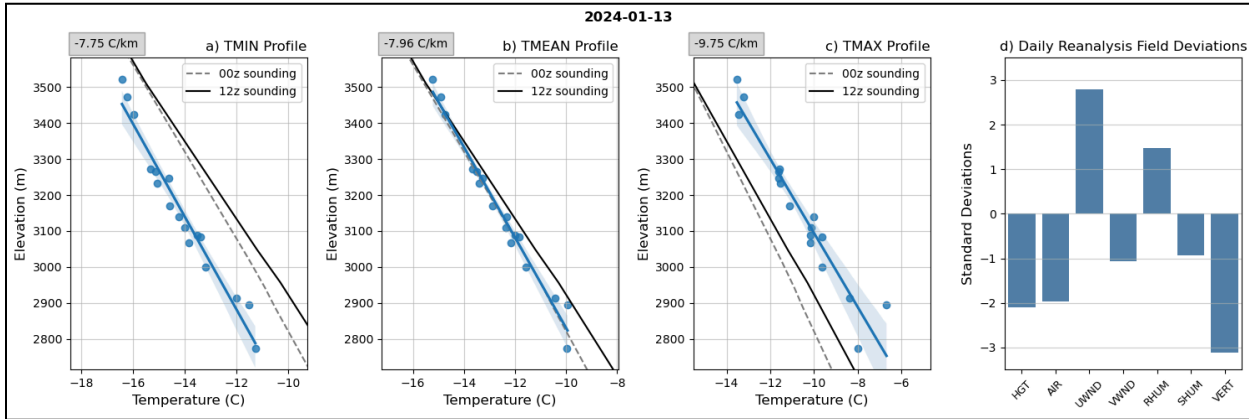


A) Map of DOE Grant data loggers (red triangles) and SNOTEL stations (yellow squares) distributed across a topographic map of the East River watershed. Sites close to the valley floor (AP3, KP3, SCHOFIELD), and transects are labeled. B) Distribution of site elevations.

2.2. Free-air Measurements: Radiosondes and ERA5 Reanalysis Data

[7] NOAA National Weather Service radiosonde data containing the free air temperature profile of the lower atmosphere are available daily at 0z and 12z from Grand Junction, CO, which is generally upwind of the East River watershed. Radiosonde data is downloaded from the University of Wyoming RAOB archive using the SounderPy python package (Gillet, 2024). 600 hPa air temperature, geopotential, relative and specific humidity, meridional and zonal winds, and vertical velocity fields are downloaded from the ERA5 Global Reanalysis Product in the 31 km grid above the East River watershed (Hersbach et al., 2023). Vertical velocity is measured in Pascals per second, where positive values correspond to sinking air and negative values correspond to rising air. Additionally, plots of daily 600 hPa fields from the NCEP North American Reanalysis are downloaded from the NOAA/ESRL Physical Science Division (Mesinger et al., 2006). The use of a coarse-resolution reanalysis product for this work is appropriate because deviation in surface temperatures from a relatively well-known baseline and variation in surface patterns with large-scale synoptic conditions are of interest. The 600 hPa level represents the approximate height of free air near the tops of surrounding peaks, and therefore less influenced by topography than surface or near-surface levels. Figure 2 shows 13 January 2024 observed temperatures fitted with linear regression, 0z and 12z temperature profiles from Grand Junction radiosondes, and 600 hPa daily field deviations from means.

Figure 2. Sample fields from 13 January 2024.



January 13th, 2024 plots of observed A) minimum daily temperatures, B) mean daily temperatures, and C) maximum daily temperatures against elevation. Blue lines are linear regressions between each set of observations, where the linear lapse rate corresponding to the slope of the regression is recorded in the grey box at the top of each plot. The dashed grey and black lines are observed temperature profiles from 0z and 12z Grand Junction soundings. D) Plot of 600 hPa daily reanalysis fields standard deviation from mean values. The lapse rate is uniquely linear on this date.

2.3. Evaluating Linear Lapse Rates

[8] Daily minimum, mean, and maximum temperatures are calculated for each site over the analysis period. Estimations of lapse rate (defined as the negative of change in temperature over change in elevation) are calculated by fitting linear regressions to daily temperature statistics and the complete hourly time series using the SciPy Python package (Virtanen et al. 2020). The R^2 value is used to assess linear model performance and acts as a measure of the linearity of temperature variation with elevation. On dates when the mean daily R^2 value from the hourly time series is greater than 0.9 (exceptionally linear days), linear lapse rates are calculated and daily mean R^2 values are correlated against daily mean ERA5 600 hPa fields to examine associated synoptic conditions. Composite NARR 600 hPa daily anomalies over the Western US provide visualizations of these conditions.

2.4. Empirical Orthogonal Function Analysis

[9] Empirical Orthogonal Function (EOF) analysis (also known as Principal Component Analysis) objectively diagnoses major modes of variability in a dataset composed of a structural dimension and a sampling dimension (in this study, the structural dimension being space, the sampling dimension being time) (Venegas, 2001). The method of Singular Value Decomposition (SVD) simultaneously calculates EOFs and Principal Components (PCs) for the dataset, where EOFs are modes of spatial variability in the dataset, and Principal Components are the corresponding time-varying amplitudes.

[10] The EOF analysis is performed on a modified dataset. 600 hPa air temperatures are subtracted from each sensor time series, such that the resulting dataset represents deviations in near-surface temperature from modeled 600 hPa temperatures. This serves to remove EOFs in which all sites vary together under forcing from synoptic conditions on much larger scales than the spatial coverage of sensors. Therefore, the analysis captures temperature variation outside variability in modeled free-air temperature that can be reasonably well predicted with reanalysis products. To complete the EOF analysis, the resulting time series are organized into a matrix, with location as rows and hourly intervals of time as columns. The method of singular value decomposition is applied to this matrix.

[11] The primary three EOFs, representing known physical patterns and explaining the greatest amount of variability in the data, are analyzed. Average daily principal component amplitudes are correlated against daily mean ERA5 600 hPa reanalysis fields. Dates in

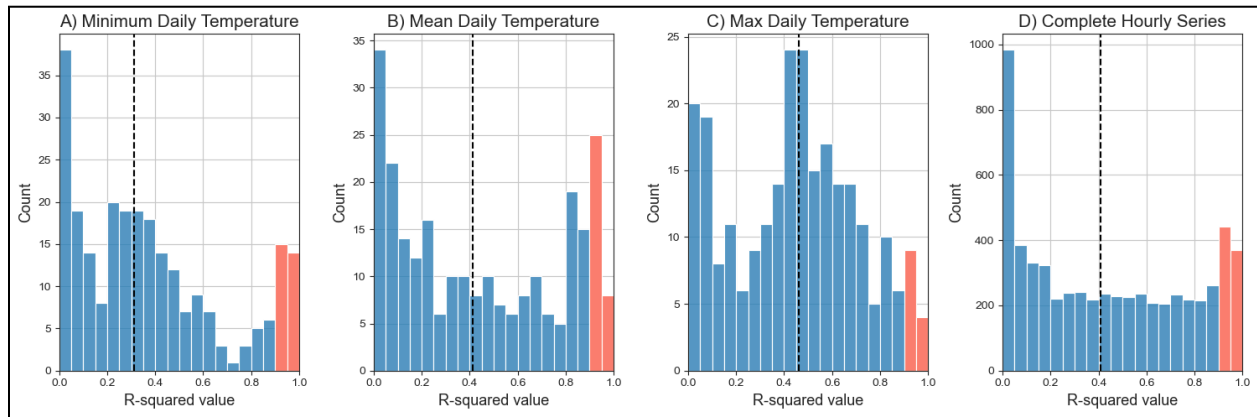
which daily mean PC amplitudes are 1 standard deviation above the mean are selected, and North American Regional Reanalysis daily 600 hPa fields are averaged over these dates to examine large-scale synoptic patterns associated with each EOF over Colorado and the Western US, respectively.

3. RESULTS AND DISCUSSION

3.1. Lapse Rate Linearity

3.1.1. How appropriate is a linear model?

Figure 3. Distribution of R^2 value for linear regressions on daily and hourly temperatures.



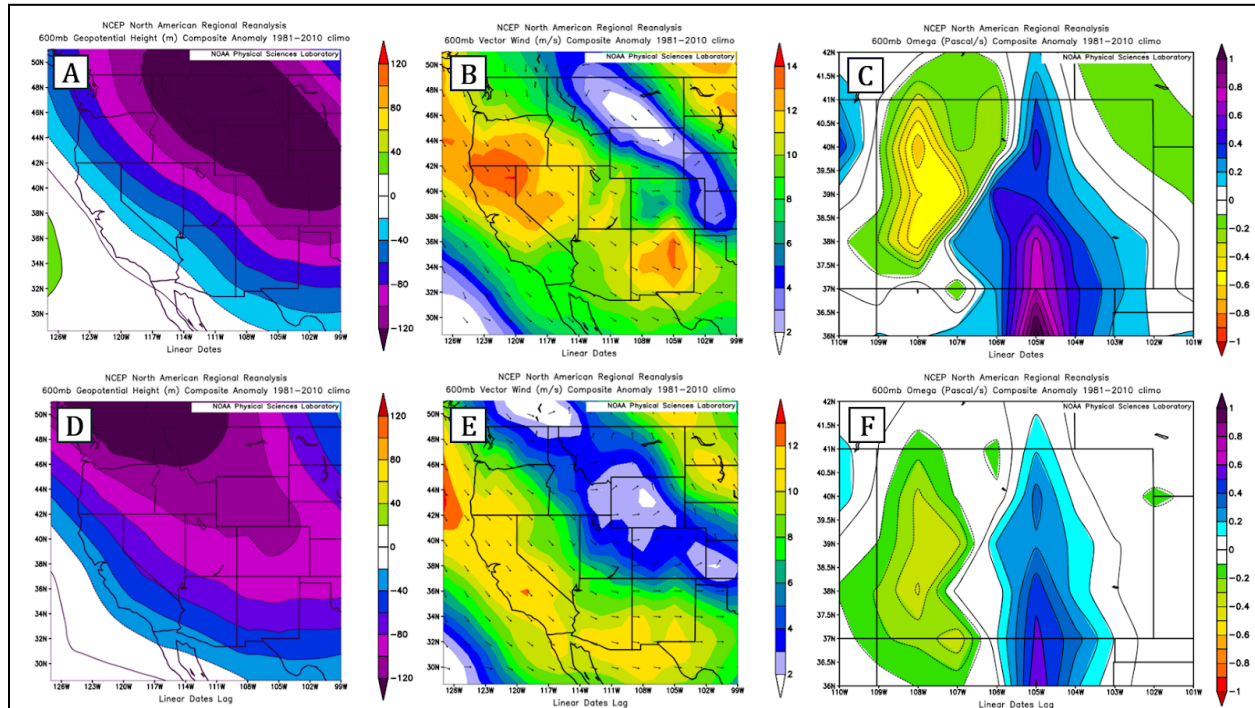
Distribution of R^2 values from linear regressions performed on A) minimum, B) mean, and C) maximum daily temperature statistics, as well as on D) the complete hourly time series. The median value for each distribution is marked with a dashed line, and bins with $R^2 > 0.9$ are colored red.

[12] The performance of a linear regression on temperature variation with elevation varies widely. Linear model performance is worse in the morning and becomes slightly more accurate as temperatures warm (Figure 3). The median R^2 value is 0.31 for daily minimum temperatures, 0.41 for daily mean temperatures, and 0.46 for daily maximum temperatures. A linear regression on the complete hourly time series explains less than half of the variance in 57% of instances. Given these generally low R^2 values, a linear model for lapse rate in the region is often an inappropriate representation for variation in temperature with elevation. These regressions are performed using a calculated line of best fit for the observed data, so linear models in which the lapse rate is assigned either a single or seasonally varying fixed value would perform worse, to a degree dependent on the accuracy of the prescribed lapse rate. However, there are some instances in which a model performs well. The conditions for these instances are explored in the following section (3.1.2.), and corresponding lapse rate values are identified in section 3.1.3.

3.1.2. Synoptic Conditions Associated with a Linear Lapse Rate

[13] Daily mean R^2 values correlate negatively with 600 hPa geopotential, vertical velocity, and temperature, and correlate positively with relative humidity and meridional wind (Table 1). Figure 4 shows the synoptic conditions on days prior to, and days with a mean R^2 value greater than 0.9. These days are characterized by cold, low-pressure systems North of Colorado moving in from the Northwest US (Figure 4a,d.), with strong northwest winds mixing air in the lower atmosphere, and regional rising air indicating unstable conditions (Figure 4b,c.). These northwest winds align with the valley's northwest orientation, which promotes the mixing of surface and upper air. Well-mixed conditions disrupt the formation of surface temperature inversions, and unstable conditions promote rising that cools air aloft, contributing to a linear decrease in temperature with elevation.

Figure 4. Synoptic conditions associated with linear temperature variation with elevation.



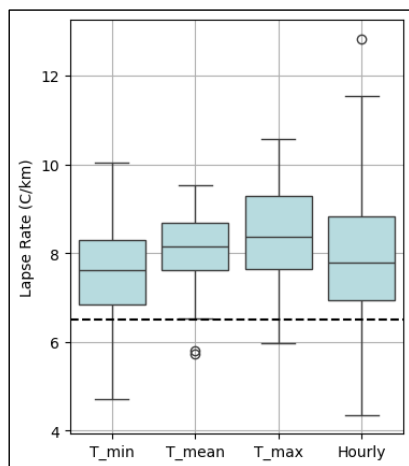
Maps of 600hPa daily anomaly A) geopotential height (m), B) vector wind (m/s), and C) vertical velocity (Pa/s) with anomalous sinking air represented by warm colors, on dates when the daily mean R^2 value for linear regression on temperature variation with elevation is greater than 0.9. C, D, E) 600 hPa daily anomalies one day before A, B, and C.

3.1.3. Linear Lapse Rate Values

[14] When temperature variation with elevation is approximately linear ($R^2 > 0.9$), the lapse rate is often steeper than the $6.5^\circ\text{C km}^{-1}$ global mean environmental lapse rate. The mean lapse rate during these conditions from the complete hourly series was $7.8^\circ\text{C km}^{-1}$, with a standard deviation of $1.4^\circ\text{C km}^{-1}$. As the day progresses and temperatures warm,

the lapse rate generally steepens, with the smallest values during daily minimum temperatures (mean of $7.5^{\circ}\text{C km}^{-1}$), and steepest values during daily maximum temperatures (mean of $8.5^{\circ}\text{C km}^{-1}$). Air in the Colorado Rocky Mountains is dry, shifting the lapse rate closer to the dry adiabatic lapse rate of $9.8^{\circ}\text{C km}^{-1}$. The tendency of lapse rate to depend on regional moisture content reflects the findings of Pepin & Losleben, 2002 and Tercek et al., 2021, who identified steep lapse rates in dry mountain regions (the US Rocky Mountains), and Minder et al., 2010, who found shallower lapse rates in more moist regions (the Washington Cascade mountains).

Figure 5. Lapse rates from linear regressions with $R^2 > 0.9$



Lapse rates calculated from linear regressions with $R^2 > 0.9$ on daily minimum, mean, and maximum temperature statistics, and the complete hourly time series.

However, lapse rates calculated in this paper were significantly steeper than regional recommendations for the Idaho central-south rocky mountains, another dry region, which varied from shallowest values of $0.1^{\circ}\text{C km}^{-1}$ during minimum daily temperatures to steepest lapse rates of $7^{\circ}\text{C km}^{-1}$ during maximum daily temperatures (Blandford et al., 2008). These differences can largely be explained by this paper's choice to conditionally calculate lapse rate when a linear model is appropriate ($R^2 > 0.9$), excluding variable temperature patterns characteristic of inversions with shallow lapse rates. When a linear model is appropriate, models using a $6.5^{\circ}\text{C km}^{-1}$ lapse rate in the region would typically overestimate temperatures at high elevations. This could lead to underestimation of snowfall at high elevations in shoulder seasons, and overestimations of the onset of spring melt and subsequent snow disappearance.

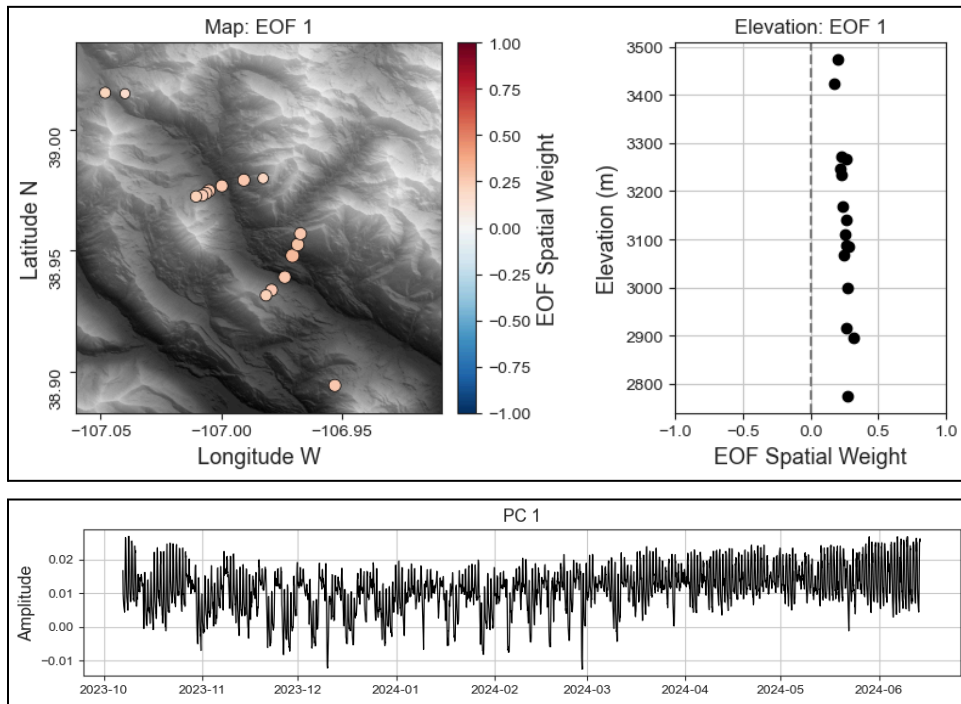
[15] While not tested in this paper, temperature profiles from Grand Junction soundings are often close in slope to observed temperature profiles over the East River watershed (see Figure 2). This reflects the results of Minder et al., 2010, which suggested soundings upwind of the Cascade mountains offer a good representation of near-surface lapse rate variability in that region and could be included in the analysis when few surface observations are available. The use of soundings to estimate a linear slope for downwind near-surface lapse rates could be more accurate than relying on a fixed value or regression between meteorological stations, or offer the potential to construct non-linear, multi-slope lapse rates. Analyzing the performance of lapse rates derived from soundings compared to fixed linear values, regressions between meteorological stations, and modeled lapse rates from gridded meteorological products such as PRISM could be a focus of future work.

3.2. EOFs and Associated Synoptic Conditions

[16] As examined in section 3.1.1, variability in temperature often cannot be explained solely by a linear decrease with elevation. In this section, Empirical Orthogonal Function analysis uncovers additional patterns controlling spatio-temporal temperature variability across the watershed.

3.2.1. EOF 1: Surface Temperatures Overall Warmer or Cooler than Free-Air Temperature

Figure 6. EOF 1 Spatial Weights and PC Amplitudes



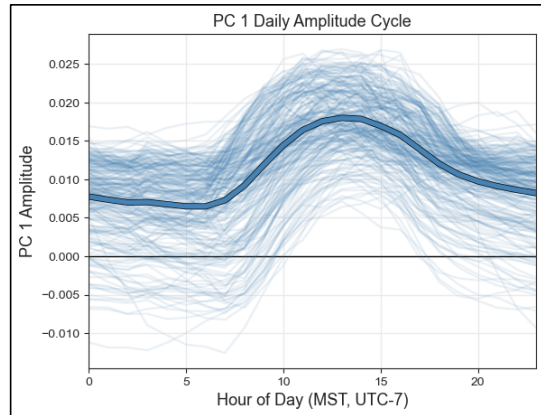
A) Map of field sites, with marker color determined by EOF 1 spatial weight at that site. B) Site elevation (m) vs. EOF 1 spatial weight at each site. C) Time series of principal component 1 amplitude.

[17] EOF 1 (50.9% of variation) has a positive spatial weight on all sites, following a regional trend for near-surface temperatures to be overall warmer than at the 600 hPa level during the analysis period (Figure 6). By multiplying average EOF 1 spatial weights by average PC 1 amplitude by the total amplitude explained by this EOF, surface temperatures are shown to be on average 6.6°C warmer than at the 600 hPa level. PC 1 amplitudes are on average positive throughout the analysis period, although negative anomalies occurred in late fall and winter. Surface temperatures colder than the 600 hPa level in the winter (negative PC 1 amplitudes) can be explained by radiative cooling from snow cover on near-surface temperatures, resulting in large-scale temperature inversions.

[18] PC 1 follows a diurnal cycle, with the largest amplitudes in the afternoon (Figure 7). Incoming solar radiation warms the land surface and heats the lower atmosphere, enhancing the temperature disparity between surface and upper air temperatures.

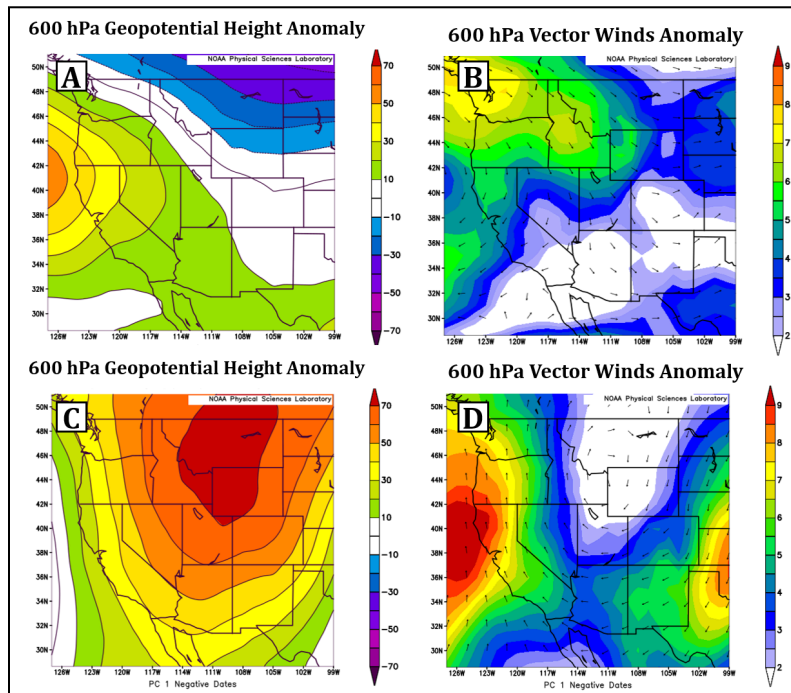
[19] PC 1 correlates positively with relative and specific humidity, and correlates negatively with vertical velocity (Table 2), indicating surface temperatures are relatively warm compared to the 600 hPa level under moist, rising air. Rising air cools adiabatically as it ascends, resulting in cooler temperatures aloft and strengthening the temperature disparity between the surface and upper air. Dates with strong PC 1 amplitude are characterized by weak synoptic conditions over Colorado, with low-pressure systems to the north in Canada, high-pressure systems over the US west coast, and weak northwest winds. Dates with strong negative PC 1 amplitudes are characterized by high-pressure systems over the Rockies and moderate Northeasterly winds (Figure 8).

Figure 7. PC 1 Daily Amplitude Cycle



PC 1 amplitude cycle for individual days shown as light lines, and the mean daily PC 1 amplitude cycle shown as a bold line.

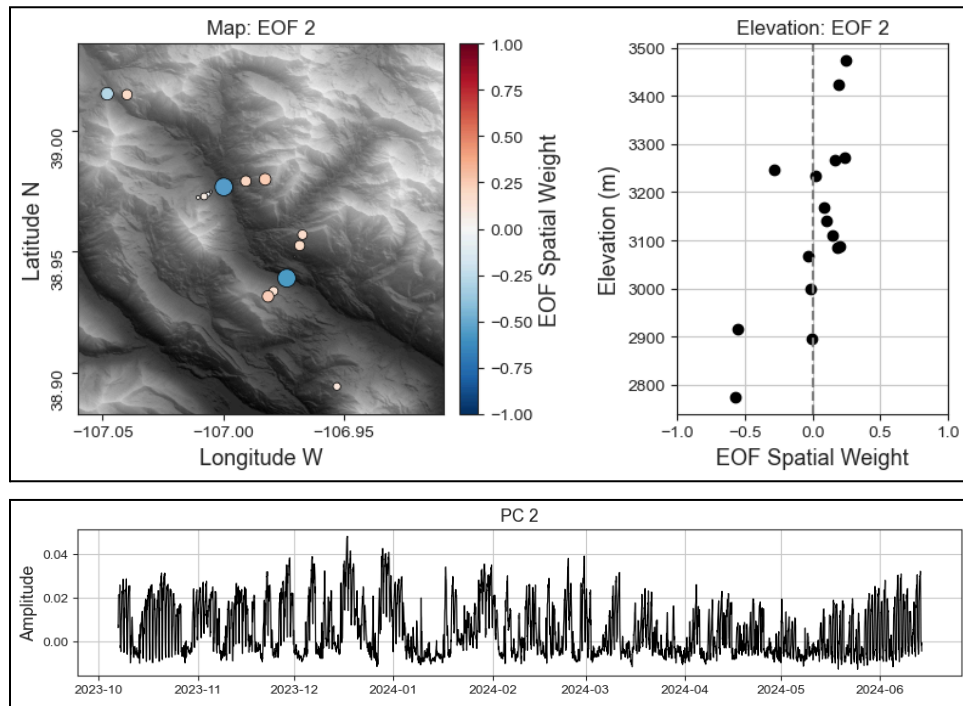
Figure 8. Synoptic conditions associated with PC 1.



Composite daily A) geopotential height and B) vector winds on dates with mean principal component 1 more than one standard deviation above the mean, and C, D) dates with mean principal component 1 less than one standard deviation below the mean.

3.2.2. EOF 2: Cold Air Pooling

Figure 9. EOF 2 Spatial Weights and PC Amplitudes



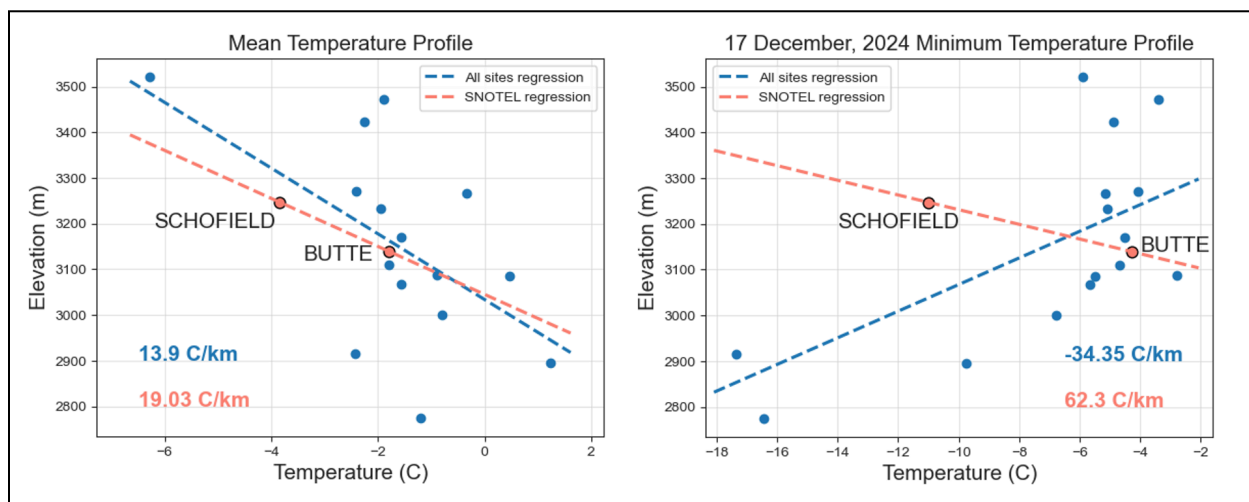
A) Map of field sites, with marker color determined by EOF 2 spatial weight at that site. B) Site elevation (m) vs. EOF 2 spatial weight at each site. C) Time series of principal component 2 amplitude.

[20] EOF 2 (9.3% of variation) corresponds to cold air pooling (CAP) and identifies sites prone to the night-time accumulation of sinking cold air. The three sites prone to CAP as identified by EOF 2 are KP3, AP3, and the Schofield Pass SNOTEL station (see labeled sites in Figure 1). KP3 and AP3 are located on the valley floor, adjacent to the East River, and the Schofield Pass Snotel station is just upslope from Elko Park and Rock Creek. Negative EOF 2 spatial weights constrained to these three sites indicate regional CAP is fairly shallow – typically limited to the valley floor. On days when the daily mean PC 2 amplitude was more than 1 standard deviation above the mean, the lowest Kettle Ponds and Avery Picnic sites (KP3 and AP3) had minimum temperatures on average 5.5°C and 6°C colder than the next highest site in each transect, respectively. Among days where cold air pooling is especially strong, these temperature disparities are stronger in winter months (valley floor sites 6.4°C and 7.1°C colder than next highest sites in December) than in the early summer (valley floor sites 4.4°C and 4.9°C colder than next highest sites in June).

Figures 11 and 12 show visual representations of the discussed temperature trends. In Figure 12, the exceptionally strong inversion between the highest sites within the Kettle Ponds transect and the secondary inversion layer in the Avery Peak transect may be explained by other site characteristics with consistent temperature effects.

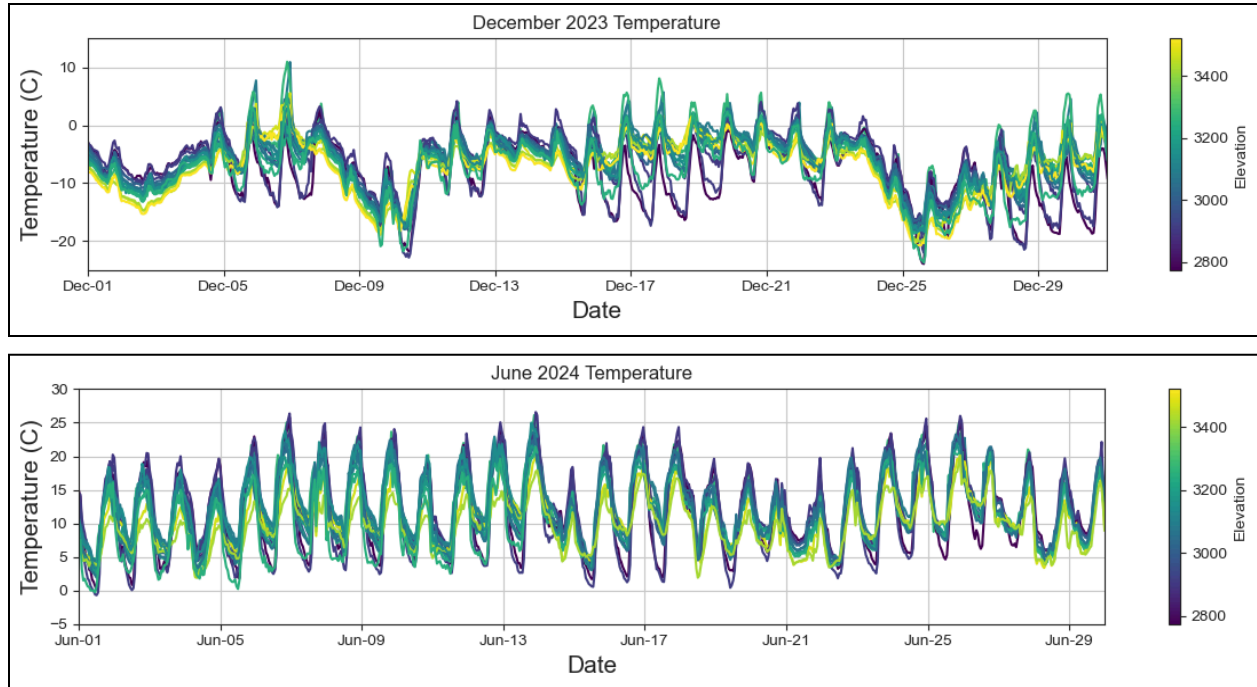
[21] Persistent wintertime cold air pooling at the Schofield Pass SNOTEL station, but not the lower elevation Butte SNOTEL station, indicates use of calculating a regional lapse rate using a linear or multiple regression between these two sites could bias models and result in a steeper lapse rate than is representative of hillside terrain. These steeper lapse rates are shown in Figure 10, which compares lapse rates calculated from linear regression between all sites, and just the two SNOTEL stations. Future work should carefully consider the topographic influences on this site before using it as a representative location of regional conditions.

Figure 10. Linear regressions on the mean temperature profile, and the 17 December 2024 minimum temperature profile



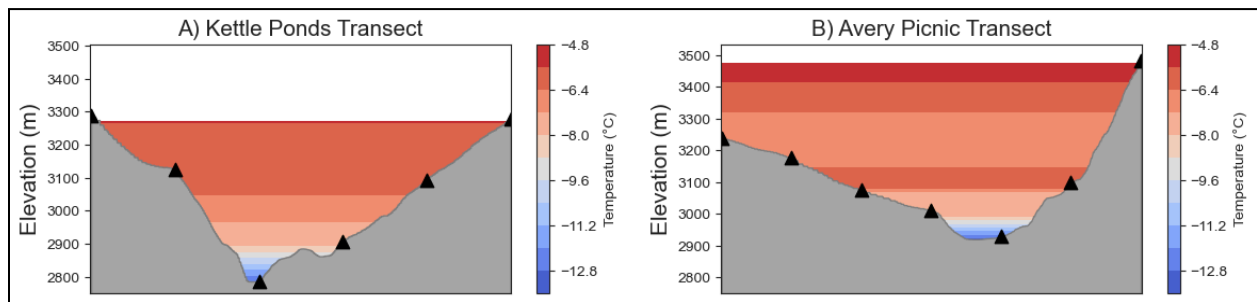
Linear regression fit to temperature variation with elevation between all sites (dashed blue line) and just SNOTEL stations (dashed red line) on A) the mean temperature profile from the analysis period and B) 17 December 2024 minimum temperatures. Blue text shows the calculated lapse rate (negative of the change in temperature with height) between all sites and red text shows the calculated lapse rate between SNOTEL stations.

Figure 11. December, 2023 observed temperature.



Time series of December 2023 and June 2024 temperatures from all 16 sites. Line color is determined by site elevation, with higher sites lighter in color.

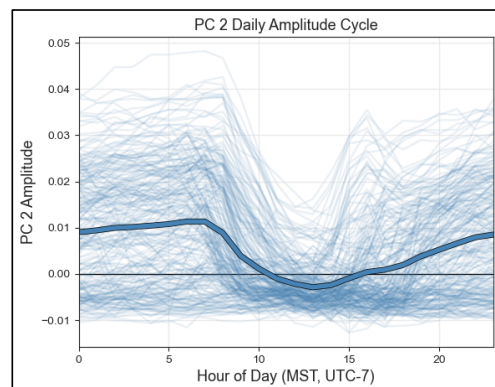
Figure 12. Elevational cross-sections of transect temperature profiles associated with strong EOF 2.



Elevational cross-sections of the Kettle Ponds and Avery Picnic transects, where the land surface is represented by the gray-shaded area, and site locations are represented by black triangles. The area between sequential site elevations is contoured by the mean daily minimum temperature profile on dates when the mean principal component 2 amplitudes are more than 1 standard deviation above the mean.

[22] PC 2 follows a diurnal pattern with on average positive but highly variable amplitudes during the night and early morning, and on average negative and more constrained amplitudes from midday to afternoon (Figure 13). Valley-floor sites have negative EOF 2 spatial weights, so positive PC 2 amplitudes indicate a night-time temperature depression and negative amplitudes indicate warmer valley-floor

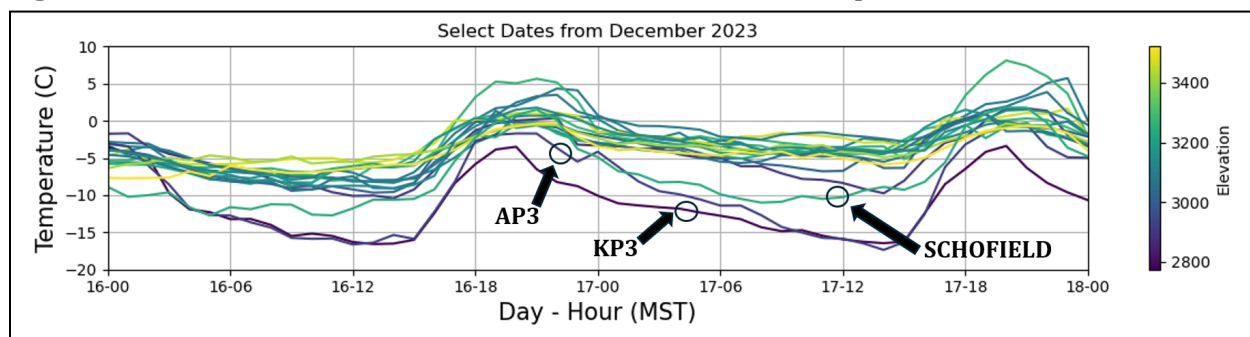
Figure 13. PC 2 Daily Amplitude Cycle.



PC 2 amplitude cycle for individual days shown as light lines, and the mean daily PC 2 amplitude cycle shown as a bold line.

temperatures. Amplitudes are greatest in the early morning after cold air has accumulated during the night (Figures 13 and 14). This reflects a cycle in which cold air pooling is common but not guaranteed during the night and early morning but becomes inhibited during the day as solar heating warms the surface and clears temperature inversions. However, solar heating does not always warm the surface enough to completely clear the temperature inversion, as shown by persistently cold valley bottom sites in Figure 14 and the extended period of positive PC 2 amplitudes in Figure 9. The cold air pool persists during the day most often in the winter months, when solar heating is weakest, and snow reflects incoming solar radiation and cools surface air temperatures.

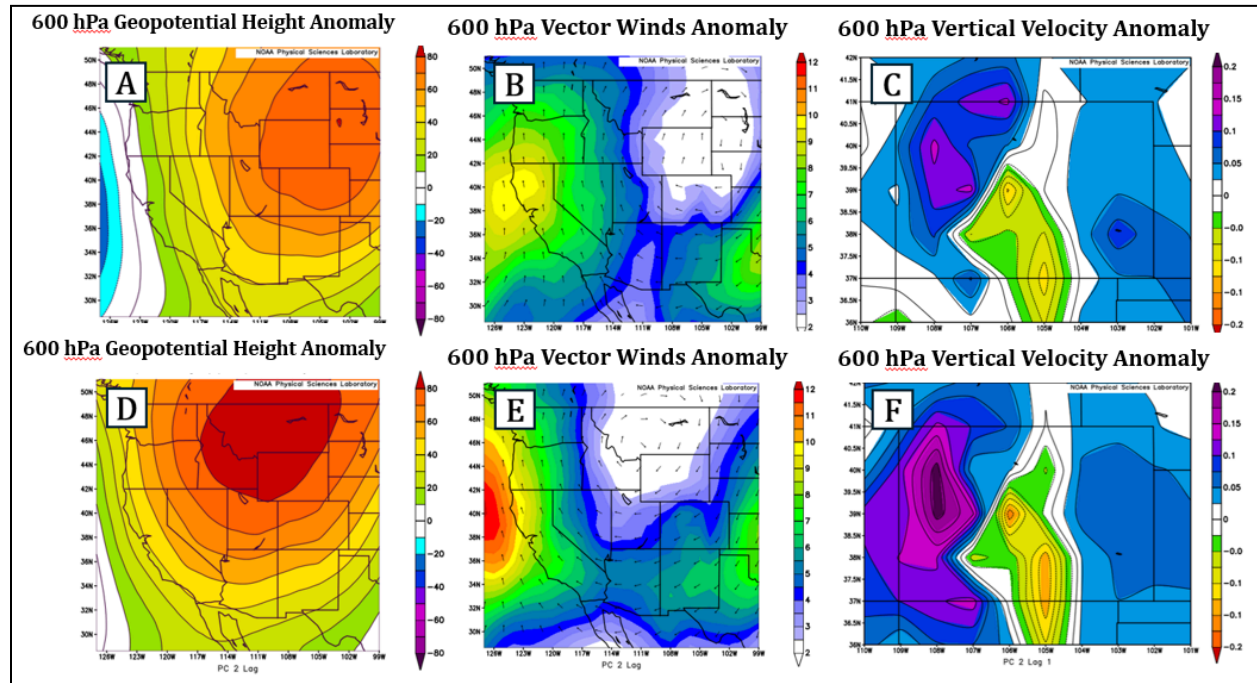
Figure 14. December 16th - 18th, 2024 observed surface temperature.



Time series temperature measurements from 15 December 00z to 18 December 00z, 2024. Lines represent individual sensors and are colored by elevation, with higher sites lighter in color. Valley-floor sites are labeled.

[23] PC 2 correlates positively with 600 hPa geopotential, temperature, and vertical velocity, and correlates negatively with relative humidity (Table 2). Figure 15 shows the synoptic conditions on days with an average PC amplitude more than 1 standard deviation above the mean (row 1), and preceding days (row 2). These days are characterized by weakening high-pressure systems north of Colorado, weak south/southeast winds, and sinking air. Together, these results are consistent with previous findings that CAP is most prominent under stable conditions with high pressure, weak winds, dry air, and clear skies (Anquetin et al., 1998; Barr & Orgill, 1989; Clements et al., 2003; Iijima & Shinoda, 2000; Lundquist, Pepin, et al., 2008). These synoptic patterns represent more or less opposing conditions to those associated with exceptionally linear lapse rates in section 3.1.1.

Figure 15. EOF 2 Synoptic Conditions

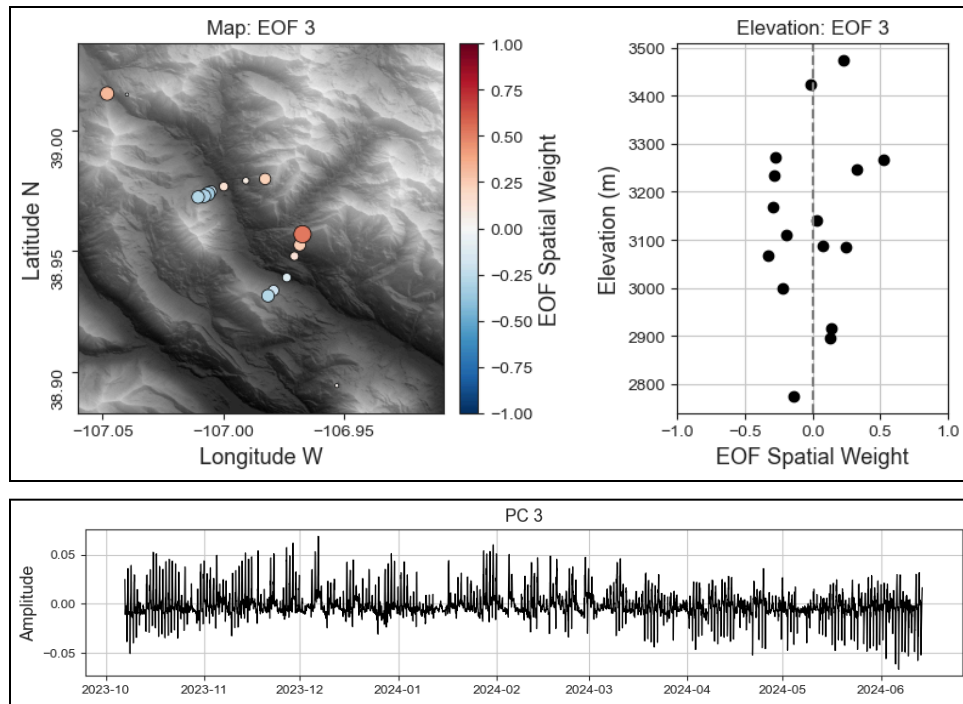


Maps of 600hPa daily anomaly A) geopotential height (m), B) vector wind (m/s), and C) vertical velocity (Pa/s) with anomalous sinking air represented by warm colors, on dates when the daily mean principal component 2 amplitude is greater than one standard deviation above the mean. C, D, E) 600 hPa daily anomalies one day before A, B, and C.

[24] In future studies, a denser network of temperature sensors could be deployed near the valley floor to more precisely identify the depth of the night-time cold air pool and characterize its variation through time.

3.2.3. EOF 3: Aspect; Southwest-facing vs. Northeast-facing

Figure 16. EOF 3 Spatial Weights and PC Amplitudes

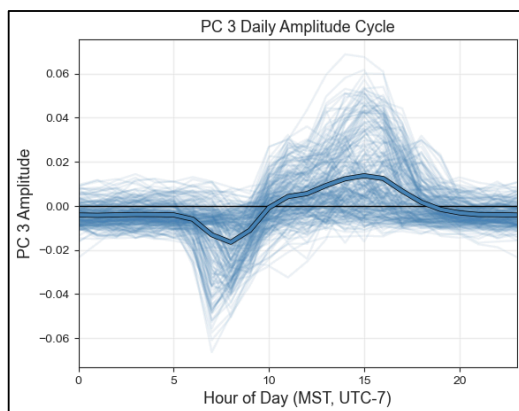


A) Map of field sites, with marker color and size determined by EOF 3 spatial weight at that site. B) Site elevation (m) vs. EOF 3 spatial weight at each site. C) Time series of principal component 3 amplitude.

[25] EOF 3 (6.8% of variation) corresponds to site aspect, with negative spatial weights on northeast-facing sites and positive spatial weights on southwest-facing aspects (Figure 16). PC 3 follows a strong diurnal cycle, with negative amplitudes in the early morning and positive amplitudes in the afternoon (Figure 17). As the sun rises in the morning,

east-facing sites are exposed to the sun first and warm before west-facing sites. As the sun sets in the afternoon, west-facing sites remain exposed to the sun while east-facing sites become shaded and begin to cool. PC 3 has predominantly positive anomalies in the winter months, indicating a tendency for the northeast-southwest component of slope aspect to dominate temperature variation in the winter when the sun is low on the horizon.

Figure 17. PC 3 Daily Amplitude Cycle



PC 3 amplitude cycle for individual days shown as light lines, and the mean daily PC 3 amplitude cycle shown as a bold line.

[28] PC 3 is associated with similar synoptic conditions as PC 2, with identical correlation signs for each reanalysis field (Table 2). Stable, poorly mixed conditions under which strong cold air pooling occurs likely allow for aspect based

temperature differences to accumulate during periods of unequal solar heating, rather than being mixed aloft.

4. SUMMARY OF RESULTS

[26] The performance of a linear regression on temperature variation with elevation varies widely, but is often a poor fit to the data with median R^2 values below 0.5. When a linear model is appropriate, the mean lapse rate from the hourly time series was $7.8^\circ\text{C km}^{-1}$, with a standard deviation of $1.4^\circ\text{C km}^{-1}$. Dates when temperature decreases linearly with elevation are characterized by low pressure systems situated north of Colorado which bring strong northwest winds and unstable, rising air.

[27] Empirical Orthogonal Function Analysis revealed three patterns governing regional near-surface temperature distributions. In the first EOF (50.9% of variance), regional near-surface temperatures were generally warmer than reanalysis air temperatures at the 600 hPa level. PC 1 showed negative anomalies in the winter due to surface radiative cooling and followed a diurnal cycle, with greater amplitudes in the afternoon after solar heating of the surface amplified temperature differences between the surface and aloft. In the second EOF (9.3% of variance), valley-floor sites prone to the night-time accumulation of cold air experienced colder temperatures. Apparent synoptic conditions for cold air pooling are consistent with previous studies. In the third EOF (6.8% of variance), greater solar exposure on southwest-facing sites resulted in these sites being generally warmer than northeast-facing sites. PC 3 followed a distinct diurnal cycle governed by solar exposure, with northeast-facing slopes warmer in the morning and southwest-facing slopes warmer in the afternoon.

[28] The ability of this paper to characterize the depth of the cold air pool was limited by sensor density. When cold air pooling was strong, the coldest surface temperatures were constrained to the lowest elevation sites in each transect, indicating a regionally shallow valley-floor cold air pool. Temperature differences between valley-floor and hillslope sites during days with strong cold air pooling were greatest in the winter (6.4°C and 7.1°C), and weaker in early summer (4.4°C and 4.9°C). Adding additional low-elevation temperature sensors to the network could enable greater precision in mapping the depth and variability of the cold air pool. Additionally, the analysis would benefit from adding temperature data through the summer and early fall to analyze a complete yearly dataset. This additional temperature data could also allow examination of the number of growing season freezing days at sites prone to cold air pooling compared to hillslope sites, relevant for ecological studies.

[29] Outlined are possible focuses for future work, and suggestions for modeling temperature in the East River watershed. Prescribing a single linear lapse rate (especially if the chosen value is not regionally specific) is likely to introduce significant errors in modeled surface temperatures. An alternative method could use lapse rates derived from daily upwind soundings, allowing non-linear profiles of free temperature, and analyzing the performance of such a method in comparison to existing procedures for calculating lapse rates could be of interest. High-resolution gridded temperature products should consider temperature variation induced by site aspect and by topographic characteristics resulting in cold-air pooling. The inclusion of the Schofield Pass SNOTEL station in the cold air pool suggests utilizing this station as representative of its elevation for the region could be a source of bias. Especially when cold air pooling is prominent, linear regression between SNOTEL stations estimates steeper lapse rates than are representative of regional temperature structure. Future modeling efforts should be careful when using this or other valley-floor meteorological stations to avoid misrepresenting the region of interest.

ACKNOWLEDGMENTS

[30] Thank you to Jessica Lundquist (University of Washington) and Rosemary Carroll (Desert Research Institute) for generous mentorship and support, to Ethan Gutmann (National Center for Atmospheric Research) for assisting with sensor installation in the fall, to Ian Breckheimer (Rocky Mountain Biological Laboratory) for providing access to local meteorological station data, and to Sophia Todorov and Jacob Ives for assisting with data collection in the field. This research was supported by funding from the Department of Energy Environmental System Science Division (Award DE-SC0024075). Additional thanks go to Willow Hoins and other students in the University of Washington Mountain Hydrology Lab for support and guidance. Hersbach, H. et al., (2018) was downloaded from the Copernicus Climate Change Service (2024). The results contain modified Copernicus Climate Change Service information 2024. Neither the European Commission nor ECMWF is responsible for any use that may be made of the Copernicus information or data it contains. Composite 600 hPa reanalysis plots were provided by the NOAA/ESRL Physical Science Division, Boulder Colorado from their Web site at <https://psl.noaa.gov>. SNOTEL station data were downloaded from the United States Department of Agriculture National Resources Conservation Service using their air and water database report generator from their website at <https://wcc.sc.egov.usda.gov/reportGenerator>.

REFERENCES

Anquetin, S., Guilbaud, C., & Chollet, J.-P. (1998). The Formation and Destruction of Inversion Layers within a Deep Valley. *Journal of Applied Meteorology*, 37(12), 1547–1560.
[https://doi.org/10.1175/1520-0450\(1998\)037<1547:TFADOI>2.0.CO;2](https://doi.org/10.1175/1520-0450(1998)037<1547:TFADOI>2.0.CO;2)

- Barr, S., & Orgill, M. M. (1989). Influence of External Meteorology on Nocturnal Valley Drainage Winds. *Journal of Applied Meteorology*, 28, 497–517.
[https://doi.org/10.1175/1520-0450\(1989\)028<0497:IOEMON>2.0.CO;2](https://doi.org/10.1175/1520-0450(1989)028<0497:IOEMON>2.0.CO;2)
- Beever, E. A., Hall, L. E., Varner, J., Loosen, A. E., Dunham, J. B., Gahl, M. K., et al. (2017). Behavioral flexibility as a mechanism for coping with climate change. *Frontiers in Ecology and the Environment*, 15(6), 299–308. <https://doi.org/10.1002/fee.1502>
- Bell, B. A., Hughes, P. D., Fletcher, W. J., Cornelissen, H. L., Rhoujjati, A., Hanich, L., & Braithwaite, R. J. (2022). Climate of the Marrakech High Atlas, Morocco: Temperature lapse rates and precipitation gradient from piedmont to summits. *Arctic, Antarctic, and Alpine Research*, 54(1), 78–95. <https://doi.org/10.1080/15230430.2022.2046897>
- Blandford, T. R., Humes, K. S., Harshburger, B. J., Moore, B. C., Walden, V. P., & Ye, H. (2008). Seasonal and Synoptic Variations in Near-Surface Air Temperature Lapse Rates in a Mountainous Basin. *Journal of Applied Meteorology and Climatology*, 47(1), 249–261.
<https://doi.org/10.1175/2007JAMC1565.1>
- Carroll, R., Williams, K., & Gochis, D. (2020). Hydrologic Model Files (PRMS) for Historical Conditions in the East River Watershed, Colorado between 1987-2019 [Data set]. United States. <https://doi.org/10.15485/1691511>
- Cho, E., Vuyovich, C. M., Kumar, S. V., Wrzesien, M. L., Kim, R. S., & Jacobs, J. M. (2022). Precipitation biases and snow physics limitations drive the uncertainties in macroscale modeled snow water equivalent. *Hydrology and Earth System Sciences*, 26(22), 5721–5735.
<https://doi.org/10.5194/hess-26-5721-2022>
- Christopher Daly, Wayne P. Gibson, George H. Taylor, Gregory L. Johnson, & Phillip Pasteris. (2002). A knowledge-based approach to the statistical mapping of climate. *Climate Research*, 22(2), 99–113.
- Clements, C. B., Whiteman, C. D., & Horel, J. D. (2003). Cold-Air-Pool Structure and Evolution in a Mountain Basin: Peter Sinks, Utah. *Journal of Applied Meteorology*, 42(6), 752–768.
[https://doi.org/10.1175/1520-0450\(2003\)042<0752:CSAEIA>2.0.CO;2](https://doi.org/10.1175/1520-0450(2003)042<0752:CSAEIA>2.0.CO;2)
- Córdova, M., Céleri, R., Shellito, C. J., Orellana-Alvear, J., Abril, A., & Carrillo-Rojas, G. (2016). Near-Surface Air Temperature Lapse Rate Over Complex Terrain in the Southern Ecuadorian Andes: Implications for Temperature Mapping. *Arctic, Antarctic, and Alpine Research*, 48(4), 673–684. <https://doi.org/10.1657/AAAR0015-077>
- Daly, C., Conklin, D. R., & Unsworth, M. H. (2010). Local atmospheric decoupling in complex topography alters climate change impacts. *International Journal of Climatology*, 30(12), 1857–1864. <https://doi.org/10.1002/joc.2007>
- Gillett, K., 2024: SounderPy: Vertical Profile Data Retrieval & Analysis Tool for Python (Version 3.0.4). Py-Pi, <https://pypi.org/project/sounderpy/>
- Hamlet, A. F., & Lettenmaier, D. P. (2005). Production of Temporally Consistent Gridded Precipitation and Temperature Fields for the Continental United States. *Journal of Hydrometeorology*, 6(3), 330–336. <https://doi.org/10.1175/JHM420.1>
- Hersbach, H., Bell, B., Berrisford, P., Biavati, G., Horányi, A., Muñoz Sabater, J., Nicolas, J., Peubey, C., Radu, R., Rozum, I., Schepers, D., Simmons, A., Soci, C., Dee, D., Thépaut, J.-N. (2023): ERA5 hourly data on pressure levels from 1940 to present. Copernicus Climate Change Service (C3S) Climate Data Store (CDS), DOI: 10.24381/cds.bd0915c6 (Accessed on 24-07-2024)
- Iijima, Y., & Shinoda, M. (2000). Seasonal changes in the cold-air pool formation in a subalpine hollow, central Japan. *International Journal of Climatology*, 20(12), 1471–1483.
[https://doi.org/10.1002/1097-0088\(200010\)20:12<1471::AID-JOC554>3.0.CO;2-6](https://doi.org/10.1002/1097-0088(200010)20:12<1471::AID-JOC554>3.0.CO;2-6)
- Inouye, D. W. (2008). EFFECTS OF CLIMATE CHANGE ON PHENOLOGY, FROST DAMAGE, AND FLORAL ABUNDANCE OF MONTANE WILDFLOWERS. *Ecology*, 89(2), 353–362.
<https://doi.org/10.1890/06-2128.1>

- Kirchner, M., Faus-Kessler, T., Jakobi, G., Leuchner, M., Ries, L., Scheel, H.-E., & Suppan, P. (2013). Altitudinal temperature lapse rates in an Alpine valley: trends and the influence of season and weather patterns. *International Journal of Climatology*, 33(3), 539–555. <https://doi.org/10.1002/joc.3444>
- Li, C., Zou, Y., He, J., Zhang, W., Gao, L., & Zhuang, D. (2022). Response of Vegetation Phenology to the Interaction of Temperature and Precipitation Changes in Qilian Mountains. *Remote Sensing*, 14(5). <https://doi.org/10.3390/rs14051248>
- Lundquist, J. D., & Cayan, D. R. (2007). Surface temperature patterns in complex terrain: Daily variations and long-term change in the central Sierra Nevada, California. *Journal of Geophysical Research: Atmospheres*, 112(D11). <https://doi.org/10.1029/2006JD007561>
- Lundquist, J. D., & Huggett, B. (2008). Evergreen trees as inexpensive radiation shields for temperature sensors. *Water Resources Research*, 44(4). <https://doi.org/10.1029/2008WR006979>
- Lundquist, J. D., Pepin, N., & Rochford, C. (2008). Automated algorithm for mapping regions of cold-air pooling in complex terrain. *Journal of Geophysical Research: Atmospheres*, 113(D22). <https://doi.org/10.1029/2008JD009879>
- Lundquist, J. D., Neiman, P. J., Martner, B., White, A. B., Gottas, D. J., & Ralph, F. M. (2008). Rain versus Snow in the Sierra Nevada, California: Comparing Doppler Profiling Radar and Surface Observations of Melting Level. *Journal of Hydrometeorology*, 9(2), 194–211. <https://doi.org/10.1175/2007JHM853.1>
- Mesinger, F., DiMego, G., Kalnay, E., Mitchell, K., Shafran, P. C., Ebisuzaki, W., et al. (2006). North American Regional Reanalysis. *Bulletin of the American Meteorological Society*, 87(3), 343–360. <https://doi.org/10.1175/BAMS-87-3-343>
- Milling, C. R., Rachlow, J. L., Johnson, T. R., Forbey, J. S., & Shipley, L. A. (2017). Seasonal variation in behavioral thermoregulation and predator avoidance in a small mammal. *Behavioral Ecology*, 28(5), 1236–1247. <https://doi.org/10.1093/beheco/arx084>
- Minder, J. R., Mote, P. W., & Lundquist, J. D. (2010). Surface temperature lapse rates over complex terrain: Lessons from the Cascade Mountains. *Journal of Geophysical Research: Atmospheres*, 115(D14). <https://doi.org/10.1029/2009JD013493>
- Pepin, N. C., Arnone, E., Gobiet, A., Haslinger, K., Kotlarski, S., Notarnicola, C., et al. (2022). Climate Changes and Their Elevational Patterns in the Mountains of the World. *Reviews of Geophysics*, 60(1), e2020RG000730. <https://doi.org/10.1029/2020RG000730>
- Rolland, C. (2003). Spatial and Seasonal Variations of Air Temperature Lapse Rates in Alpine Regions. *Journal of Climate*, 16(7), 1032–1046. [https://doi.org/10.1175/1520-0442\(2003\)016<1032:SASVOA>2.0.CO;2](https://doi.org/10.1175/1520-0442(2003)016<1032:SASVOA>2.0.CO;2)
- Tercek, M. T., Rodman, A., Woolfolk, S., Wilson, Z., Thoma, D., & Gross, J. (2021). Correctly applying lapse rates in ecological studies: comparing temperature observations and gridded data in Yellowstone. *Ecosphere*, 12(3), e03451. <https://doi.org/10.1002/ecs2.3451>
- Venegas, S. A., 2001: Statistical Methods for Signal Detection in Climate. DCESS Report #2.
- White, A. B., Gottas, D. J., Strem, E. T., Ralph, F. M., & Neiman, P. J. (2002). An Automated Brightband Height Detection Algorithm for Use with Doppler Radar Spectral Moments. *Journal of Atmospheric and Oceanic Technology*, 19(5), 687–697. [https://doi.org/10.1175/1520-0426\(2002\)019<0687:AABHDA>2.0.CO;2](https://doi.org/10.1175/1520-0426(2002)019<0687:AABHDA>2.0.CO;2)

TABLES

Table 1. R^2 values for correlation between daily mean R^2 values and 600 hPa reanalysis fields

Reanalysis Field	R^2 Value
Temperature	0.18 (-)
Geopotential	0.31 (-)
U-Wind	0.13 (+)
V-Wind	0.01 (+)
Relative Humidity	0.46 (+)
Specific Humidity	0.04 (+)
Vertical Velocity	0.23 (-)
Lag Temperature	0.04 (-)
Lag Geopotential	0.22 (-)
Lag U-Wind	0.14 (+)
Lag V-Wind	0.16 (+)
Lag Relative Humidity	0.18 (+)
Lag Specific Humidity	0.03 (+)
Lag Vertical Velocity	0.31 (-)

R^2 values between daily mean 600 hPa reanalysis fields and daily mean R^2 values from linear regressions. Lag fields are correlations between daily mean 600 hPa reanalysis fields and daily mean R^2 values.

Table 2. Principal Components Correlations with Reanalysis Fields

	PC 1	PC 2	PC 3
Temperature	0.02 (+)	0.24 (+)	0.04 (+)
Geopotential	0.00	0.38 (+)	0.13 (+)
U-Wind	0.03 (+)	0.08 (-)	0.01 (-)
V-Wind	0.08 (+)	0.01 (-)	0.00
Relative Humidity	0.16 (+)	0.61 (-)	0.33 (-)
Specific Humidity	0.38 (+)	0.07 (-)	0.17 (-)
Vertical Velocity	0.33 (-)	0.22 (+)	0.20 (+)

Lag Temperature	0.12 (+)	0.06 (+)	0.00
Lag Geopotential	0.01 (+)	0.31 (+)	0.06 (+)
Lag U-Wind	0.06 (+)	0.15 (-)	0.03 (-)
Lag V-Wind	0.19 (+)	0.25 (-)	0.19 (-)
Lag Relative Humidity	0.01 (+)	0.31 (-)	0.13 (-)
Lag Specific Humidity	0.30 (+)	0.09 (-)	0.20 (-)
Lag Vertical Velocity	0.21 (-)	0.41 (+)	0.31 (+)

R^2 values between daily mean ERA5 600 hPa reanalysis fields and daily mean principal component amplitudes. Lag fields are correlation between daily mean principal component amplitudes and daily mean reanalysis fields on the prior day.