Precipitation Downscaling Project

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Executive Summary:

The goal of this project is to predict precipitation in Texas at time point “t+1” given temperature at time “t”. This analysis uses CPC gauge-based gridded daily precipitation and daily temperature data over roughly the area of Texas from the years 2000 to 2009 to train two different predictive models. Both models applied a principal component analysis (PCA) to downscale the high dimensional temperature data, and then fit models on the selected principal components. In the first approach, K-nearest neighbors (KNN) was applied to the principal components to predict precipitation based on a subsetted testing set of temperature data to allow for comparison to actual values. In the second approach, a linear regression model was applied to the first principal component only to predict precipitation corresponding to the same testing temperature dataset.

In order to validate the fit of the models, mean squared error, mean absolute error, and residuals were calculated. These metrics were also used to compare the performance between the two models. Though upon visual inspection PCA-KNN appears to predict precipitation trends closer to observed values, the PCA-KNN approach exhibited a higher mean squared error and mean absolute error than the PCA-linear regression model despite a lower average residual value. Higher mean absolute error and mean squared error indicates that the PCA-KNN model actually performs worse than the PCA-linear regression model, likely due to large variations and inaccuracies in extreme values. The PCA-linear regression model, on the other hand, exhibits a conservative, “dreary” prediction across all time points, which leads to lower error overall when dealing with extremes.

Methods

Data Management/Preprocessing The original precipitation data was subsetted to only include the years 2000 to 2009 to correspond to the selected temperature data timeframe. Temperature data was subsetted to match the space occupied by the precipitation data and cover roughly the area of Texas. Latitude and longitude were adjusted to ensure consistent formatting across the datasets. To predict on precipitation at time t+1, the precipitation time points used in the analysis were shifted one day from the temperature data time points. Precipitation and temperature data were then split to create training and testing sets, with years 2000 to 2007 included in training and the rest allocated to testing. Temperature data was preprocessed by calculating the mean climatology and obtaining the anomalies rather than working with raw temperatures to better account for seasonal variation.

1. Setup

1.1 Load Packages

1. Data

2.1 Precipitation 2.1.1 Load data

24×24×16365 Array{Union{Missing, Float32}, 3}:  
[:, :, 1] =  
 1.37582 1.57975 1.45262 … 0.0 0.0202463 0.0  
 1.20963 1.85082 2.28766 0.0308067 0.0602374 0.114836  
 1.97182 1.45203 2.09293 0.0490085 0.121709 0.237292  
 1.5909 1.33469 1.65327 0.0664271 0.389667 0.678864  
 1.43704 1.75647 2.29071 0.0964478 0.24362 1.0564  
 1.23506 1.71966 1.24682 … 0.29584 0.192309 0.594209  
 1.34688 2.06668 1.14913 0.50683 0.345075 0.153464  
 1.45706 2.27098 0.724487 1.06509 0.576138 0.0801041  
 5.20069 3.71962 0.181735 1.43136 0.706655 0.133022  
 2.88819 0.759342 0.163341 2.08092 1.4474 0.53837  
 1.50673 0.461275 0.207048 … missing missing missing  
 1.43436 0.139224 0.290842 missing missing missing  
 3.18961 2.13086 2.59861 missing missing missing  
 5.19326 5.16296 4.65167 missing missing missing  
 5.3778 4.47193 6.19447 missing missing missing  
 2.81836 8.9879 5.9169 … missing missing missing  
 1.80613 8.12168 2.24706 missing missing missing  
 6.17247 15.1932 14.4421 missing missing missing  
 15.3935 12.0708 20.1535 missing missing missing  
 16.41 16.3307 23.8688 missing missing missing  
 12.77 20.6869 18.5016 … missing missing missing  
 14.9623 9.67723 7.38247 missing missing missing  
 21.7209 10.5213 9.88938 missing missing missing  
 20.7196 14.5443 15.6206 missing missing missing  
  
[:, :, 2] =  
 0.0 0.0 0.0 0.0 … 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 … 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0507107 0.0 0.0  
 0.0 0.0 0.0 0.0 0.170228 0.0 0.0  
 0.0344644 0.0828211 0.0 0.0 0.0242824 0.0 0.0  
 0.116297 0.232722 0.0 0.0 … missing missing missing  
 0.0780643 0.120667 0.0 0.0 missing missing missing  
 0.790819 0.209601 0.0810387 0.0836833 missing missing missing  
 0.330909 0.0694368 0.202908 0.172532 missing missing missing  
 0.0834752 0.366478 0.193584 0.041639 missing missing missing  
 0.334877 0.392715 0.221516 0.0368422 … missing missing missing  
 0.171142 0.847358 0.0837831 0.0 missing missing missing  
 0.660464 2.01706 0.12625 0.0 missing missing missing  
 0.309305 0.0865614 0.0 0.0546165 missing missing missing  
 0.206135 0.0 0.0 0.0464391 missing missing missing  
 0.397575 0.355726 0.0 0.0436917 … missing missing missing  
 1.2978 0.686435 0.064151 0.364207 missing missing missing  
 0.998617 0.906296 0.373319 2.32323 missing missing missing  
 0.708568 2.16601 2.14061 2.34233 missing missing missing  
  
[:, :, 3] =  
 0.0 0.0 0.0 0.245373 … 0.0 0.0 0.0  
 0.0 0.0 0.0 0.218143 0.0 0.0 0.0  
 0.0 0.0 0.174088 0.175847 0.0 0.0 0.0  
 0.16041 0.0296272 0.77125 0.584347 0.0 0.0 0.0  
 0.0822869 0.0 0.0870539 0.0920338 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 … 0.0 0.0 0.0  
 0.0 0.0 0.0 0.153964 0.0 0.0 0.0  
 0.0 0.0 0.0 0.377731 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.391579 0.0879667 0.0 0.0 0.0 0.0 0.0  
 0.178373 0.052071 0.0 0.0 … missing missing missing  
 0.0 0.0 0.0 0.0 missing missing missing  
 0.0 0.0 0.0621035 0.0487938 missing missing missing  
 0.0 0.0 0.509918 0.990183 missing missing missing  
 0.0 0.0 0.0975961 0.627761 missing missing missing  
 0.0 0.0 0.0 0.0 … missing missing missing  
 0.0 0.0 0.0 0.0 missing missing missing  
 0.0 0.0 0.0 0.0 missing missing missing  
 0.0 0.0 0.0 0.0 missing missing missing  
 0.0 0.0 0.0 0.0 missing missing missing  
 0.0 0.0 0.0 0.0 … missing missing missing  
 0.0707157 0.0 0.0 0.0 missing missing missing  
 0.0 0.0 0.0 0.0 missing missing missing  
 0.0 0.0 0.0 0.0 missing missing missing  
  
;;; …   
  
[:, :, 16363] =  
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 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 … 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 … missing missing missing  
 0.0 0.0 0.0 0.0 missing missing missing  
 0.0 0.0 0.0 0.0 missing missing missing  
 0.0 0.0 0.0 0.0 missing missing missing  
 0.0 0.0259045 0.0 0.0 missing missing missing  
 0.0 0.0 0.207233 0.0 … missing missing missing  
 0.0 0.0 0.0300441 0.0 missing missing missing  
 0.0 0.0 0.0296209 0.0 missing missing missing  
 0.0761566 0.228387 0.441014 0.237419 missing missing missing  
 0.275329 0.189209 0.147844 0.189911 missing missing missing  
 0.72749 0.303631 0.0207723 0.150705 … missing missing missing  
 1.02891 0.220527 0.0399159 0.0950709 missing missing missing  
 0.818845 0.127663 0.0 0.0299711 missing missing missing  
 0.641579 0.0371985 0.0 0.0 missing missing missing  
  
[:, :, 16364] =  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 … 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 … 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 … missing missing missing  
 0.0 2.37197 0.0 0.0 0.0 0.0 0.0 0.0 missing missing missing  
 0.0 0.683025 0.0 0.0 0.0 0.0 0.0 0.0 missing missing missing  
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 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 missing missing missing  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 missing missing missing  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 missing missing missing  
  
[:, :, 16365] =  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 … 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 … 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0326195 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 … missing missing missing  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 missing missing missing  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 missing missing missing  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 missing missing missing  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 missing missing missing  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 … missing missing missing  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 missing missing missing  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 missing missing missing  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 missing missing missing  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 missing missing missing  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 … missing missing missing  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 missing missing missing  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 missing missing missing  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 missing missing missing

2.1.2 Close precip dataset

closed Dataset

2.1.3 Filter data

3653-element Vector{DateTime}:  
 2000-01-01T00:00:00  
 2000-01-02T00:00:00  
 2000-01-03T00:00:00  
 2000-01-04T00:00:00  
 2000-01-05T00:00:00  
 2000-01-06T00:00:00  
 2000-01-07T00:00:00  
 2000-01-08T00:00:00  
 2000-01-09T00:00:00  
 2000-01-10T00:00:00  
 2000-01-11T00:00:00  
 2000-01-12T00:00:00  
 2000-01-13T00:00:00  
 ⋮  
 2009-12-20T00:00:00  
 2009-12-21T00:00:00  
 2009-12-22T00:00:00  
 2009-12-23T00:00:00  
 2009-12-24T00:00:00  
 2009-12-25T00:00:00  
 2009-12-26T00:00:00  
 2009-12-27T00:00:00  
 2009-12-28T00:00:00  
 2009-12-29T00:00:00  
 2009-12-30T00:00:00  
 2009-12-31T00:00:00

2.1.4 Subset data

3652-element Vector{DateTime}:  
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 2000-01-03T00:00:00  
 2000-01-04T00:00:00  
 2000-01-05T00:00:00  
 2000-01-06T00:00:00  
 2000-01-07T00:00:00  
 2000-01-08T00:00:00  
 2000-01-09T00:00:00  
 2000-01-10T00:00:00  
 2000-01-11T00:00:00  
 2000-01-12T00:00:00  
 2000-01-13T00:00:00  
 2000-01-14T00:00:00  
 ⋮  
 2009-12-20T00:00:00  
 2009-12-21T00:00:00  
 2009-12-22T00:00:00  
 2009-12-23T00:00:00  
 2009-12-24T00:00:00  
 2009-12-25T00:00:00  
 2009-12-26T00:00:00  
 2009-12-27T00:00:00  
 2009-12-28T00:00:00  
 2009-12-29T00:00:00  
 2009-12-30T00:00:00  
 2009-12-31T00:00:00

2.1.5 Reverse latitude

24×24×3652 Array{Union{Missing, Float32}, 3}:  
[:, :, 1] =  
 0.0 0.0 0.0 0.0 … 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 … 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0323414 0.0 0.0 0.0  
 0.0 0.0 0.0 0.135582 0.0 0.0 0.0  
 0.0 0.0 0.0 0.151623 0.0 0.0 0.031432  
 missing missing missing missing … 0.436169 0.167826 0.0222956  
 missing missing missing missing 0.113203 0.219052 0.0204078  
 missing missing missing missing 0.0 0.0 0.0  
 missing missing missing missing 0.0 0.0 0.0  
 missing missing missing missing 0.0 0.0696384 0.0207805  
 missing missing missing missing … 0.0450895 0.0828177 0.0338578  
 missing missing missing missing 0.0 0.0 0.0513665  
 missing missing missing missing 0.0764082 0.0628494 0.156683  
 missing missing missing missing 0.616311 0.172386 0.0214627  
 missing missing missing missing 3.26764 2.32975 3.03718  
 missing missing missing missing … 3.97116 1.08259 3.51391  
 missing missing missing missing 1.08442 0.152592 0.607323  
 missing missing missing missing 7.1412 1.6474 0.0  
 missing missing missing missing 1.00298 0.780391 0.602726  
  
[:, :, 2] =  
 0.0 0.0 0.0 … 0.0 0.861222 1.58391  
 0.0 0.0 0.0 0.0 0.142009 0.620014  
 0.0 0.0 0.0 0.0 0.0 0.0304579  
 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 … 0.0 0.0279951 0.10282  
 0.0 0.0 0.0 0.0 0.203494 0.390608  
 0.0 0.0 0.0 0.299697 1.65651 2.56886  
 0.0 0.0 0.0 2.07031 0.885224 1.6951  
 0.0 0.0 0.0 2.42535 2.01437 0.887439  
 missing missing missing … 4.94332 2.89262 1.55625  
 missing missing missing 11.1041 5.20581 2.63938  
 missing missing missing 21.9379 7.78901 4.3323  
 missing missing missing 28.1783 15.3255 10.0802  
 missing missing missing 34.7224 28.1705 13.5422  
 missing missing missing … 25.7909 27.0969 15.6146  
 missing missing missing 23.9934 25.7158 22.9741  
 missing missing missing 22.3714 23.8421 28.7882  
 missing missing missing 21.7186 23.8547 24.5314  
 missing missing missing 33.3132 19.215 14.6306  
 missing missing missing … 55.1564 27.6612 8.24005  
 missing missing missing 37.3152 56.9326 26.5516  
 missing missing missing 24.6176 73.771 51.9611  
 missing missing missing 8.29554 48.9767 73.7095  
  
[:, :, 3] =  
 0.0 0.0 0.0 … 0.0 0.0 0.119807  
 0.0 0.0 0.0 0.0640346 0.081867 0.165219  
 0.0 0.0 0.0 0.039643 0.118587 0.431731  
 0.0 0.0 0.0 0.0 0.0213695 0.271837  
 0.0 0.0 0.0 0.0226516 0.0476442 0.131516  
 0.0 0.0 0.0 … 0.0273123 0.0882924 0.112214  
 0.0 0.0 0.0 0.0 0.243156 0.652184  
 0.0 0.0 0.0 0.0254786 0.409578 1.41301  
 0.0 0.0 0.0 0.141537 1.47574 2.68291  
 0.0 0.0 0.0 0.590031 0.550419 2.79478  
 missing missing missing … 1.84155 0.927045 2.13219  
 missing missing missing 1.7651 0.957743 2.1216  
 missing missing missing 1.64877 0.612912 2.59903  
 missing missing missing 0.780635 0.469386 1.95597  
 missing missing missing 1.67376 1.71056 1.23499  
 missing missing missing … 0.883307 1.35247 1.12839  
 missing missing missing 1.0367 1.32528 3.07755  
 missing missing missing 4.9913 2.11696 0.937954  
 missing missing missing 10.4429 7.33287 2.03677  
 missing missing missing 8.51849 7.07041 4.33941  
 missing missing missing … 10.3645 10.9053 8.96606  
 missing missing missing 16.6359 18.2572 10.5232  
 missing missing missing 7.94858 18.4997 17.5984  
 missing missing missing 8.29728 18.0127 25.2627  
  
;;; …   
  
[:, :, 3650] =  
 1.91927 2.18294 4.04477 5.20947 … 0.0 0.0 0.0  
 0.203245 0.580783 2.77413 4.15098 0.0 0.0 0.0  
 0.237774 1.28198 1.22886 0.721624 0.0 0.0 0.0  
 1.80391 2.13242 1.09698 0.152618 0.0 0.0 0.0  
 2.32314 1.18486 0.259382 0.0 0.0 0.0 0.0  
 1.09869 0.124012 0.0 0.0 … 0.0 0.0 0.0  
 0.493284 0.0336855 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.210678 0.0 0.0  
 0.0 0.0 0.0 0.0 0.244225 0.0478664 0.0  
 0.0 0.0 0.0 0.0 0.883143 1.56837 0.156057  
 missing missing missing missing … 1.22156 1.51986 1.36312  
 missing missing missing missing 2.79113 3.31666 2.07084  
 missing missing missing missing 2.48622 2.86405 1.8507  
 missing missing missing missing 0.999645 7.01725 4.73033  
 missing missing missing missing 1.48617 2.80321 4.4185  
 missing missing missing missing … 0.311555 0.0501361 0.0426737  
 missing missing missing missing 0.123578 0.0 0.0  
 missing missing missing missing 0.0 0.0 0.0  
 missing missing missing missing 0.0 0.0 0.0  
 missing missing missing missing 0.0 0.0 0.0  
 missing missing missing missing … 0.0 0.0 0.0  
 missing missing missing missing 0.0 0.0 0.0  
 missing missing missing missing 0.0 0.0 0.0  
 missing missing missing missing 0.0 0.0 0.0  
  
[:, :, 3651] =  
 1.25381 1.38226 6.78581 9.23103 … 0.209643 0.06951 0.0322176  
 1.77286 1.17652 5.44695 8.42261 0.674334 0.0 0.038588  
 5.26336 2.10804 3.33561 5.37528 0.916897 0.0899668 0.0  
 4.11361 1.87916 1.61745 5.03068 0.337145 0.891777 0.0281657  
 1.10992 0.986878 1.11829 6.67025 3.08982 0.966748 0.270218  
 2.73123 2.4278 3.59609 5.59022 … 10.1729 1.6837 0.420492  
 3.33995 4.18317 3.80484 3.17682 0.469495 1.02329 0.587488  
 5.67861 5.78922 4.2321 1.34415 0.723784 1.02258 1.35627  
 5.94113 5.36736 3.45825 5.4516 1.6775 1.66165 2.03233  
 5.672 4.33358 3.37151 5.49953 2.08825 1.21806 2.91972  
 missing missing missing missing … 2.48373 1.6086 1.16387  
 missing missing missing missing 2.07946 1.88346 0.863437  
 missing missing missing missing 2.36113 1.62808 0.568243  
 missing missing missing missing 1.84581 1.57609 1.48535  
 missing missing missing missing 1.86876 1.23442 0.884178  
 missing missing missing missing … 1.79652 0.287498 1.20721  
 missing missing missing missing 2.98471 0.613985 1.21469  
 missing missing missing missing 2.01611 0.473238 0.555291  
 missing missing missing missing 1.43036 0.545582 0.477171  
 missing missing missing missing 0.386973 0.315955 0.0261992  
 missing missing missing missing … 0.0 0.0310814 0.0  
 missing missing missing missing 0.0 0.0293388 0.0  
 missing missing missing missing 0.0 0.0 0.0  
 missing missing missing missing 0.0 0.0 0.0  
  
[:, :, 3652] =  
 0.0 0.0 0.0 … 0.0 0.194001 0.229313  
 0.0 0.0 0.0 0.201 0.0 1.05024  
 0.0 0.0 0.0 0.794761 0.0 0.239922  
 0.0 0.0 0.0 0.487525 0.0712316 0.0  
 0.0 0.0 0.0 0.871535 0.725623 0.0546665  
 0.0 0.0 0.0 … 0.63043 0.834709 0.935677  
 0.0 0.0 0.0 0.737369 0.396731 1.7525  
 0.0 0.0 0.0342669 0.810175 0.914279 2.05469  
 0.0 0.0 0.418512 0.482352 0.6477 0.834548  
 0.0 0.0364437 0.121333 1.36826 1.77949 1.08005  
 missing missing missing … 1.58758 4.78649 4.96679  
 missing missing missing 3.17118 5.32441 3.90305  
 missing missing missing 3.59475 4.90733 4.06902  
 missing missing missing 1.31501 5.03513 4.85771  
 missing missing missing 1.21495 2.24849 4.07878  
 missing missing missing … 1.81574 0.2997 1.09506  
 missing missing missing 1.08286 0.0417713 0.649026  
 missing missing missing 0.0439509 0.0 0.253759  
 missing missing missing 0.0449181 0.0 1.20432  
 missing missing missing 0.264041 0.0 1.47429  
 missing missing missing … 0.779127 0.235859 0.301635  
 missing missing missing 1.42092 0.159816 0.394416  
 missing missing missing 3.98366 0.940115 1.16965  
 missing missing missing 0.545287 0.645726 1.59136

2.1.6 Convert lon to lon1 format

24-element Vector{Float32}:  
 -101.75  
 -101.25  
 -100.75  
 -100.25  
 -99.75  
 -99.25  
 -98.75  
 -98.25  
 -97.75  
 -97.25  
 -96.75  
 -96.25  
 -95.75  
 -95.25  
 -94.75  
 -94.25  
 -93.75  
 -93.25  
 -92.75  
 -92.25  
 -91.75  
 -91.25  
 -90.75  
 -90.25

2.2 Temperature

2.2.1 Load data

Dict{Int64, Array{Union{Missing, Float64}, 3}} with 10 entries:  
 2003 => [282.275 282.693 … 291.855 291.843; 282.332 282.663 … 291.725 291.825…  
 2004 => [277.587 277.948 … 292.118 292.505; 277.904 277.883 … 292.192 292.599…  
 2001 => [282.277 282.732 … 291.394 291.7; 282.241 282.585 … 291.294 291.704; …  
 2005 => [275.953 277.028 … 291.309 291.787; 276.401 277.778 … 291.375 291.761…  
 2008 => [280.872 281.42 … 290.851 291.7; 280.859 281.331 … 290.545 291.318; ……  
 2000 => [279.491 280.057 … 290.199 290.589; 279.531 280.12 … 290.026 290.425;…  
 2002 => [281.375 281.722 … 292.495 292.614; 281.622 281.596 … 291.817 292.024…  
 2009 => [276.942 277.0 … 290.54 290.873; 276.963 277.073 … 290.276 290.623; ……  
 2006 => [281.257 281.87 … 291.109 291.009; 281.398 281.981 … 290.75 291.098; …  
 2007 => [282.586 283.225 … 290.564 290.928; 282.62 283.199 … 290.448 290.725;…

2.2.2 Combine

66×27×3653 Array{Union{Missing, Float64}, 3}:  
[:, :, 1] =  
 279.491 280.057 280.607 280.917 … 289.866 290.023 290.199 290.589  
 279.531 280.12 280.553 281.077 289.713 289.881 290.026 290.425  
 279.28 280.175 280.651 281.016 289.702 289.758 289.926 290.237  
 276.178 279.946 280.693 280.98 289.692 289.883 290.018 290.189  
 273.58 279.514 280.61 280.935 289.735 290.065 290.055 290.214  
 277.067 276.623 280.496 281.015 … 289.657 289.969 289.991 290.13  
 273.442 275.95 276.05 279.896 289.52 289.897 289.96 290.041  
 269.142 278.684 276.2 278.425 289.458 289.821 289.979 290.127  
 268.997 273.748 277.069 274.384 289.484 289.773 289.944 290.203  
 268.419 268.099 269.77 271.571 289.59 289.863 289.963 290.202  
 268.58 265.679 268.572 271.113 … 289.57 289.863 289.99 290.169  
 266.085 266.211 269.975 272.546 289.445 289.784 289.933 290.244  
 264.757 265.626 270.774 273.479 289.245 289.528 289.771 290.1  
 ⋮ ⋱ ⋮   
 254.899 260.748 262.287 264.109 294.643 296.035 296.605 296.791  
 255.745 260.112 261.232 262.814 … 295.342 296.097 296.557 296.485  
 255.495 260.011 261.017 262.453 295.462 295.966 296.195 296.044  
 254.944 258.618 259.911 260.492 295.328 295.66 295.582 295.705  
 253.234 258.312 259.692 258.167 295.162 295.313 294.967 295.856  
 252.139 256.79 259.484 258.771 295.033 294.944 294.888 296.067  
 251.687 256.465 258.677 260.193 … 295.004 294.775 295.226 296.419  
 251.198 253.888 259.967 259.31 294.953 294.755 295.744 296.741  
 250.48 264.074 255.333 255.737 295.092 295.23 295.971 296.872  
 251.777 261.876 254.365 256.103 295.154 295.015 295.976 297.019  
 260.38 254.461 255.862 257.353 294.93 294.985 296.056 297.025  
 261.702 255.281 261.385 260.49 … 294.927 295.222 296.28 296.949  
  
[:, :, 2] =  
 277.785 278.38 279.159 280.1 … 289.92 290.165 290.567 290.996  
 277.716 278.507 279.004 280.103 289.754 290.153 290.443 290.939  
 277.222 278.548 279.249 279.895 289.765 290.133 290.447 290.816  
 273.583 278.09 279.134 279.774 289.607 290.211 290.484 290.76  
 270.987 277.941 278.876 279.638 289.527 290.125 290.331 290.682  
 275.653 273.91 279.103 279.61 … 289.446 289.938 290.117 290.521  
 271.838 272.446 273.632 277.845 289.418 289.856 290.03 290.381  
 267.648 276.67 274.12 276.756 289.386 289.792 289.96 290.179  
 267.639 272.867 275.305 272.49 289.276 289.648 289.91 290.173  
 267.453 266.356 268.245 270.097 289.245 289.578 289.889 290.131  
 266.813 263.233 269.017 273.323 … 289.218 289.583 289.882 290.17  
 265.723 264.585 269.935 274.421 289.139 289.587 289.797 290.14  
 264.8 265.987 270.392 273.674 289.145 289.484 289.656 290.002  
 ⋮ ⋱ ⋮   
 252.019 257.008 262.167 267.321 295.426 296.038 296.136 296.542  
 252.789 256.945 262.659 267.498 … 295.654 296.031 296.384 296.576  
 252.661 257.45 262.604 267.244 295.556 295.94 296.381 296.708  
 252.84 257.821 262.894 267.353 295.407 295.767 296.323 296.741  
 253.045 258.766 262.798 267.269 295.214 295.655 296.287 296.516  
 253.765 258.141 263.144 267.657 295.108 295.629 296.099 296.47  
 254.068 259.351 264.516 268.582 … 294.967 295.444 295.739 296.327  
 254.841 260.144 266.131 268.704 294.756 295.213 295.681 296.433  
 254.337 265.358 264.149 267.794 294.815 295.29 295.731 296.415  
 255.676 264.265 264.281 267.633 295.117 295.411 295.79 296.309  
 262.506 259.107 264.341 267.95 295.309 295.681 295.984 296.424  
 264.02 260.764 267.133 269.137 … 295.281 295.695 296.087 296.276  
  
[:, :, 3] =  
 280.828 281.828 282.706 282.996 … 289.165 289.84 290.385 290.991  
 280.566 281.458 282.289 282.929 288.986 289.586 290.269 290.903  
 279.681 281.088 281.875 282.584 288.987 289.367 290.123 290.615  
 275.337 280.444 281.437 282.134 288.897 289.346 290.005 290.397  
 271.402 278.565 280.973 281.78 288.852 289.269 289.858 290.285  
 275.433 274.647 280.394 281.478 … 288.788 289.247 289.601 290.126  
 271.669 272.666 274.223 278.408 288.709 289.104 289.461 290.028  
 267.078 275.862 273.902 276.648 288.533 288.929 289.433 289.914  
 266.979 270.142 274.794 273.056 288.451 288.853 289.353 289.877  
 266.514 265.201 267.255 269.509 288.502 288.914 289.375 289.875  
 265.282 261.934 267.185 273.036 … 288.627 289.053 289.379 289.887  
 264.581 261.941 267.859 273.294 288.549 288.959 289.247 289.778  
 264.328 264.095 269.003 272.317 288.527 288.925 289.253 289.673  
 ⋮ ⋱ ⋮   
 253.715 256.142 259.555 264.432 296.103 296.319 296.661 297.081  
 254.471 256.343 259.741 265.014 … 296.04 296.285 296.455 297.006  
 254.527 257.199 259.464 265.527 295.941 296.159 296.246 296.607  
 255.055 258.063 260.314 266.014 295.842 295.988 296.177 296.391  
 255.322 259.694 261.859 266.884 295.564 295.896 296.202 296.499  
 255.733 258.6 261.346 267.86 295.304 295.887 296.299 296.556  
 255.324 258.223 263.353 267.943 … 295.314 295.824 296.36 296.645  
 255.92 261.045 265.461 269.195 295.348 295.96 296.451 296.689  
 255.555 266.834 263.836 269.951 295.533 296.057 296.495 296.772  
 258.12 265.24 265.328 269.328 295.661 296.118 296.474 296.605  
 264.055 260.288 267.399 270.726 295.79 296.078 296.431 296.375  
 263.982 262.179 269.563 272.556 … 295.731 295.869 296.299 296.307  
  
;;; …   
  
[:, :, 3651] =  
 281.317 281.631 282.055 282.475 … 290.048 290.55 291.19 291.712  
 281.224 281.523 281.881 282.373 289.75 290.295 290.943 291.675  
 280.949 281.472 281.794 282.254 289.503 290.161 290.857 291.609  
 277.409 280.979 281.704 282.156 289.555 290.214 290.808 291.403  
 272.98 280.201 281.459 281.905 289.799 290.338 290.839 291.307  
 276.845 275.065 280.384 281.192 … 289.797 290.269 290.817 291.452  
 270.635 273.917 274.727 276.575 289.674 290.24 290.813 291.307  
 261.242 275.57 275.241 274.124 289.558 290.273 290.784 291.108  
 260.93 273.561 274.782 273.303 289.557 290.208 290.711 290.94  
 264.997 266.236 264.513 266.479 289.322 289.894 290.56 290.772  
 266.316 263.749 267.508 268.063 … 289.229 289.762 290.265 290.666  
 265.258 266.517 269.136 269.25 289.265 289.864 290.177 290.521  
 265.879 266.18 270.629 269.587 289.216 289.707 290.056 290.52  
 ⋮ ⋱ ⋮   
 253.361 252.705 252.822 255.428 293.386 294.378 295.293 296.202  
 254.197 253.381 254.299 256.346 … 293.853 294.744 295.7 296.497  
 254.319 255.045 255.828 257.537 294.197 295.051 295.971 296.718  
 254.705 257.057 258.031 259.485 294.546 295.325 296.153 296.919  
 255.491 259.084 258.295 260.563 294.833 295.686 296.518 297.227  
 257.814 258.49 257.719 263.299 295.112 295.83 296.529 296.991  
 259.65 260.214 262.346 264.149 … 295.214 295.795 296.449 297.058  
 262.037 264.046 265.519 264.893 295.595 296.247 296.771 297.537  
 261.705 269.298 264.476 266.474 295.95 296.84 297.451 298.056  
 265.553 268.9 265.503 265.871 296.193 297.139 297.758 298.104  
 271.039 264.844 269.122 268.14 296.43 297.167 297.752 298.103  
 272.069 266.797 271.938 271.56 … 296.539 297.341 297.835 298.206  
  
[:, :, 3652] =  
 280.924 281.381 281.465 281.648 … 290.272 290.567 290.694 290.878  
 280.926 281.114 281.336 281.738 290.04 290.36 290.518 290.89  
 280.686 280.924 281.356 281.76 289.859 290.191 290.436 290.894  
 276.745 280.729 281.195 281.712 289.776 290.063 290.448 290.886  
 273.125 279.941 281.124 281.767 289.607 289.957 290.539 290.992  
 276.986 275.677 280.511 281.58 … 289.408 289.944 290.686 291.071  
 271.443 274.938 275.913 277.995 289.437 290.092 290.683 290.935  
 264.532 276.826 275.71 275.997 289.46 290.124 290.51 290.797  
 264.48 273.902 275.87 273.69 289.297 289.85 290.338 290.639  
 266.745 266.052 266.847 268.699 289.037 289.586 290.106 290.673  
 266.968 264.586 269.273 269.912 … 288.935 289.517 289.817 290.912  
 266.727 268.063 269.462 270.111 288.909 289.293 290.075 291.102  
 267.132 267.341 269.07 270.322 288.931 289.572 290.579 291.034  
 ⋮ ⋱ ⋮   
 253.825 255.068 255.108 255.468 293.021 293.94 294.713 295.478  
 253.326 254.084 254.525 254.247 … 292.976 293.987 294.779 295.577  
 253.139 254.191 254.617 255.016 292.884 294.046 294.863 295.511  
 252.847 255.042 254.682 255.502 293.003 294.099 294.838 295.45  
 252.355 254.32 253.945 254.113 292.948 294.095 294.828 295.47  
 252.708 252.801 253.487 256.163 292.884 293.911 294.709 295.344  
 252.323 253.393 256.56 255.072 … 292.923 293.938 294.682 295.339  
 253.422 255.511 258.346 256.633 293.218 294.192 294.811 295.435  
 252.721 259.623 255.915 257.58 293.322 294.28 295.013 295.636  
 255.707 259.314 256.864 256.163 293.302 294.318 295.097 295.78  
 260.568 255.255 259.262 258.668 293.4 294.283 295.076 295.804  
 262.111 257.977 262.539 261.679 … 293.509 294.351 295.143 295.865  
  
[:, :, 3653] =  
 280.888 281.313 282.14 283.177 … 290.665 290.918 291.42 291.863  
 280.888 281.057 281.772 282.987 290.509 290.748 291.252 291.796  
 280.65 281.023 281.667 282.724 290.354 290.692 291.184 291.715  
 277.474 280.886 281.462 282.516 290.291 290.545 291.052 291.491  
 274.398 280.377 281.522 282.359 290.31 290.447 290.85 291.264  
 277.832 276.912 280.86 281.848 … 290.254 290.381 290.608 291.033  
 273.217 276.21 276.427 278.753 290.199 290.348 290.416 290.835  
 268.404 277.919 276.007 277.287 290.14 290.3 290.243 290.683  
 267.641 273.508 277.048 273.979 289.978 290.042 290.167 290.519  
 268.688 267.861 269.159 269.92 289.6 289.749 290.09 290.394  
 268.349 264.932 269.081 268.821 … 289.425 289.668 289.92 290.361  
 267.662 267.312 269.093 269.592 289.326 289.697 290.011 290.348  
 267.469 267.457 269.342 271.291 289.411 289.792 290.118 290.491  
 ⋮ ⋱ ⋮   
 265.747 265.947 264.79 264.938 295.352 296.136 296.881 297.443  
 264.333 264.415 264.751 265.249 … 295.32 295.854 296.607 297.26  
 263.013 264.202 263.996 263.92 294.821 295.742 296.315 296.937  
 260.457 262.073 262.738 261.584 294.357 295.263 296.039 296.637  
 258.505 261.497 263.556 261.326 293.995 294.959 295.777 296.469  
 256.852 260.006 261.386 261.116 293.811 294.556 295.434 296.124  
 254.831 257.297 260.099 260.703 … 293.698 294.391 295.111 295.891  
 254.33 256.677 259.421 258.532 293.688 294.428 294.999 295.743  
 252.638 262.568 256.035 256.655 293.43 294.324 294.987 295.735  
 254.496 261.304 255.382 256.532 293.127 294.067 294.87 295.672  
 260.685 254.638 258.74 259.026 292.917 293.757 294.664 295.52  
 261.243 257.23 261.903 261.136 … 292.844 293.684 294.548 295.45

2.2.3 Save lon, lat, time, and temp variables

open\_mfdataset (generic function with 1 method)

3653-element Vector{DateTime}:  
 2000-01-01T00:00:00  
 2000-01-02T00:00:00  
 2000-01-03T00:00:00  
 2000-01-04T00:00:00  
 2000-01-05T00:00:00  
 2000-01-06T00:00:00  
 2000-01-07T00:00:00  
 2000-01-08T00:00:00  
 2000-01-09T00:00:00  
 2000-01-10T00:00:00  
 2000-01-11T00:00:00  
 2000-01-12T00:00:00  
 2000-01-13T00:00:00  
 ⋮  
 2009-12-20T00:00:00  
 2009-12-21T00:00:00  
 2009-12-22T00:00:00  
 2009-12-23T00:00:00  
 2009-12-24T00:00:00  
 2009-12-25T00:00:00  
 2009-12-26T00:00:00  
 2009-12-27T00:00:00  
 2009-12-28T00:00:00  
 2009-12-29T00:00:00  
 2009-12-30T00:00:00  
 2009-12-31T00:00:00

2.2.4 Flip the temperature latitude

66×27×3653 Array{Union{Missing, Float64}, 3}:  
[:, :, 1] =  
 290.589 290.199 290.023 289.866 … 280.917 280.607 280.057 279.491  
 290.425 290.026 289.881 289.713 281.077 280.553 280.12 279.531  
 290.237 289.926 289.758 289.702 281.016 280.651 280.175 279.28  
 290.189 290.018 289.883 289.692 280.98 280.693 279.946 276.178  
 290.214 290.055 290.065 289.735 280.935 280.61 279.514 273.58  
 290.13 289.991 289.969 289.657 … 281.015 280.496 276.623 277.067  
 290.041 289.96 289.897 289.52 279.896 276.05 275.95 273.442  
 290.127 289.979 289.821 289.458 278.425 276.2 278.684 269.142  
 290.203 289.944 289.773 289.484 274.384 277.069 273.748 268.997  
 290.202 289.963 289.863 289.59 271.571 269.77 268.099 268.419  
 290.169 289.99 289.863 289.57 … 271.113 268.572 265.679 268.58  
 290.244 289.933 289.784 289.445 272.546 269.975 266.211 266.085  
 290.1 289.771 289.528 289.245 273.479 270.774 265.626 264.757  
 ⋮ ⋱ ⋮   
 296.791 296.605 296.035 294.643 264.109 262.287 260.748 254.899  
 296.485 296.557 296.097 295.342 … 262.814 261.232 260.112 255.745  
 296.044 296.195 295.966 295.462 262.453 261.017 260.011 255.495  
 295.705 295.582 295.66 295.328 260.492 259.911 258.618 254.944  
 295.856 294.967 295.313 295.162 258.167 259.692 258.312 253.234  
 296.067 294.888 294.944 295.033 258.771 259.484 256.79 252.139  
 296.419 295.226 294.775 295.004 … 260.193 258.677 256.465 251.687  
 296.741 295.744 294.755 294.953 259.31 259.967 253.888 251.198  
 296.872 295.971 295.23 295.092 255.737 255.333 264.074 250.48  
 297.019 295.976 295.015 295.154 256.103 254.365 261.876 251.777  
 297.025 296.056 294.985 294.93 257.353 255.862 254.461 260.38  
 296.949 296.28 295.222 294.927 … 260.49 261.385 255.281 261.702  
  
[:, :, 2] =  
 290.996 290.567 290.165 289.92 … 280.1 279.159 278.38 277.785  
 290.939 290.443 290.153 289.754 280.103 279.004 278.507 277.716  
 290.816 290.447 290.133 289.765 279.895 279.249 278.548 277.222  
 290.76 290.484 290.211 289.607 279.774 279.134 278.09 273.583  
 290.682 290.331 290.125 289.527 279.638 278.876 277.941 270.987  
 290.521 290.117 289.938 289.446 … 279.61 279.103 273.91 275.653  
 290.381 290.03 289.856 289.418 277.845 273.632 272.446 271.838  
 290.179 289.96 289.792 289.386 276.756 274.12 276.67 267.648  
 290.173 289.91 289.648 289.276 272.49 275.305 272.867 267.639  
 290.131 289.889 289.578 289.245 270.097 268.245 266.356 267.453  
 290.17 289.882 289.583 289.218 … 273.323 269.017 263.233 266.813  
 290.14 289.797 289.587 289.139 274.421 269.935 264.585 265.723  
 290.002 289.656 289.484 289.145 273.674 270.392 265.987 264.8  
 ⋮ ⋱ ⋮   
 296.542 296.136 296.038 295.426 267.321 262.167 257.008 252.019  
 296.576 296.384 296.031 295.654 … 267.498 262.659 256.945 252.789  
 296.708 296.381 295.94 295.556 267.244 262.604 257.45 252.661  
 296.741 296.323 295.767 295.407 267.353 262.894 257.821 252.84  
 296.516 296.287 295.655 295.214 267.269 262.798 258.766 253.045  
 296.47 296.099 295.629 295.108 267.657 263.144 258.141 253.765  
 296.327 295.739 295.444 294.967 … 268.582 264.516 259.351 254.068  
 296.433 295.681 295.213 294.756 268.704 266.131 260.144 254.841  
 296.415 295.731 295.29 294.815 267.794 264.149 265.358 254.337  
 296.309 295.79 295.411 295.117 267.633 264.281 264.265 255.676  
 296.424 295.984 295.681 295.309 267.95 264.341 259.107 262.506  
 296.276 296.087 295.695 295.281 … 269.137 267.133 260.764 264.02  
  
[:, :, 3] =  
 290.991 290.385 289.84 289.165 … 282.996 282.706 281.828 280.828  
 290.903 290.269 289.586 288.986 282.929 282.289 281.458 280.566  
 290.615 290.123 289.367 288.987 282.584 281.875 281.088 279.681  
 290.397 290.005 289.346 288.897 282.134 281.437 280.444 275.337  
 290.285 289.858 289.269 288.852 281.78 280.973 278.565 271.402  
 290.126 289.601 289.247 288.788 … 281.478 280.394 274.647 275.433  
 290.028 289.461 289.104 288.709 278.408 274.223 272.666 271.669  
 289.914 289.433 288.929 288.533 276.648 273.902 275.862 267.078  
 289.877 289.353 288.853 288.451 273.056 274.794 270.142 266.979  
 289.875 289.375 288.914 288.502 269.509 267.255 265.201 266.514  
 289.887 289.379 289.053 288.627 … 273.036 267.185 261.934 265.282  
 289.778 289.247 288.959 288.549 273.294 267.859 261.941 264.581  
 289.673 289.253 288.925 288.527 272.317 269.003 264.095 264.328  
 ⋮ ⋱ ⋮   
 297.081 296.661 296.319 296.103 264.432 259.555 256.142 253.715  
 297.006 296.455 296.285 296.04 … 265.014 259.741 256.343 254.471  
 296.607 296.246 296.159 295.941 265.527 259.464 257.199 254.527  
 296.391 296.177 295.988 295.842 266.014 260.314 258.063 255.055  
 296.499 296.202 295.896 295.564 266.884 261.859 259.694 255.322  
 296.556 296.299 295.887 295.304 267.86 261.346 258.6 255.733  
 296.645 296.36 295.824 295.314 … 267.943 263.353 258.223 255.324  
 296.689 296.451 295.96 295.348 269.195 265.461 261.045 255.92  
 296.772 296.495 296.057 295.533 269.951 263.836 266.834 255.555  
 296.605 296.474 296.118 295.661 269.328 265.328 265.24 258.12  
 296.375 296.431 296.078 295.79 270.726 267.399 260.288 264.055  
 296.307 296.299 295.869 295.731 … 272.556 269.563 262.179 263.982  
  
;;; …   
  
[:, :, 3651] =  
 291.712 291.19 290.55 290.048 … 282.475 282.055 281.631 281.317  
 291.675 290.943 290.295 289.75 282.373 281.881 281.523 281.224  
 291.609 290.857 290.161 289.503 282.254 281.794 281.472 280.949  
 291.403 290.808 290.214 289.555 282.156 281.704 280.979 277.409  
 291.307 290.839 290.338 289.799 281.905 281.459 280.201 272.98  
 291.452 290.817 290.269 289.797 … 281.192 280.384 275.065 276.845  
 291.307 290.813 290.24 289.674 276.575 274.727 273.917 270.635  
 291.108 290.784 290.273 289.558 274.124 275.241 275.57 261.242  
 290.94 290.711 290.208 289.557 273.303 274.782 273.561 260.93  
 290.772 290.56 289.894 289.322 266.479 264.513 266.236 264.997  
 290.666 290.265 289.762 289.229 … 268.063 267.508 263.749 266.316  
 290.521 290.177 289.864 289.265 269.25 269.136 266.517 265.258  
 290.52 290.056 289.707 289.216 269.587 270.629 266.18 265.879  
 ⋮ ⋱ ⋮   
 296.202 295.293 294.378 293.386 255.428 252.822 252.705 253.361  
 296.497 295.7 294.744 293.853 … 256.346 254.299 253.381 254.197  
 296.718 295.971 295.051 294.197 257.537 255.828 255.045 254.319  
 296.919 296.153 295.325 294.546 259.485 258.031 257.057 254.705  
 297.227 296.518 295.686 294.833 260.563 258.295 259.084 255.491  
 296.991 296.529 295.83 295.112 263.299 257.719 258.49 257.814  
 297.058 296.449 295.795 295.214 … 264.149 262.346 260.214 259.65  
 297.537 296.771 296.247 295.595 264.893 265.519 264.046 262.037  
 298.056 297.451 296.84 295.95 266.474 264.476 269.298 261.705  
 298.104 297.758 297.139 296.193 265.871 265.503 268.9 265.553  
 298.103 297.752 297.167 296.43 268.14 269.122 264.844 271.039  
 298.206 297.835 297.341 296.539 … 271.56 271.938 266.797 272.069  
  
[:, :, 3652] =  
 290.878 290.694 290.567 290.272 … 281.648 281.465 281.381 280.924  
 290.89 290.518 290.36 290.04 281.738 281.336 281.114 280.926  
 290.894 290.436 290.191 289.859 281.76 281.356 280.924 280.686  
 290.886 290.448 290.063 289.776 281.712 281.195 280.729 276.745  
 290.992 290.539 289.957 289.607 281.767 281.124 279.941 273.125  
 291.071 290.686 289.944 289.408 … 281.58 280.511 275.677 276.986  
 290.935 290.683 290.092 289.437 277.995 275.913 274.938 271.443  
 290.797 290.51 290.124 289.46 275.997 275.71 276.826 264.532  
 290.639 290.338 289.85 289.297 273.69 275.87 273.902 264.48  
 290.673 290.106 289.586 289.037 268.699 266.847 266.052 266.745  
 290.912 289.817 289.517 288.935 … 269.912 269.273 264.586 266.968  
 291.102 290.075 289.293 288.909 270.111 269.462 268.063 266.727  
 291.034 290.579 289.572 288.931 270.322 269.07 267.341 267.132  
 ⋮ ⋱ ⋮   
 295.478 294.713 293.94 293.021 255.468 255.108 255.068 253.825  
 295.577 294.779 293.987 292.976 … 254.247 254.525 254.084 253.326  
 295.511 294.863 294.046 292.884 255.016 254.617 254.191 253.139  
 295.45 294.838 294.099 293.003 255.502 254.682 255.042 252.847  
 295.47 294.828 294.095 292.948 254.113 253.945 254.32 252.355  
 295.344 294.709 293.911 292.884 256.163 253.487 252.801 252.708  
 295.339 294.682 293.938 292.923 … 255.072 256.56 253.393 252.323  
 295.435 294.811 294.192 293.218 256.633 258.346 255.511 253.422  
 295.636 295.013 294.28 293.322 257.58 255.915 259.623 252.721  
 295.78 295.097 294.318 293.302 256.163 256.864 259.314 255.707  
 295.804 295.076 294.283 293.4 258.668 259.262 255.255 260.568  
 295.865 295.143 294.351 293.509 … 261.679 262.539 257.977 262.111  
  
[:, :, 3653] =  
 291.863 291.42 290.918 290.665 … 283.177 282.14 281.313 280.888  
 291.796 291.252 290.748 290.509 282.987 281.772 281.057 280.888  
 291.715 291.184 290.692 290.354 282.724 281.667 281.023 280.65  
 291.491 291.052 290.545 290.291 282.516 281.462 280.886 277.474  
 291.264 290.85 290.447 290.31 282.359 281.522 280.377 274.398  
 291.033 290.608 290.381 290.254 … 281.848 280.86 276.912 277.832  
 290.835 290.416 290.348 290.199 278.753 276.427 276.21 273.217  
 290.683 290.243 290.3 290.14 277.287 276.007 277.919 268.404  
 290.519 290.167 290.042 289.978 273.979 277.048 273.508 267.641  
 290.394 290.09 289.749 289.6 269.92 269.159 267.861 268.688  
 290.361 289.92 289.668 289.425 … 268.821 269.081 264.932 268.349  
 290.348 290.011 289.697 289.326 269.592 269.093 267.312 267.662  
 290.491 290.118 289.792 289.411 271.291 269.342 267.457 267.469  
 ⋮ ⋱ ⋮   
 297.443 296.881 296.136 295.352 264.938 264.79 265.947 265.747  
 297.26 296.607 295.854 295.32 … 265.249 264.751 264.415 264.333  
 296.937 296.315 295.742 294.821 263.92 263.996 264.202 263.013  
 296.637 296.039 295.263 294.357 261.584 262.738 262.073 260.457  
 296.469 295.777 294.959 293.995 261.326 263.556 261.497 258.505  
 296.124 295.434 294.556 293.811 261.116 261.386 260.006 256.852  
 295.891 295.111 294.391 293.698 … 260.703 260.099 257.297 254.831  
 295.743 294.999 294.428 293.688 258.532 259.421 256.677 254.33  
 295.735 294.987 294.324 293.43 256.655 256.035 262.568 252.638  
 295.672 294.87 294.067 293.127 256.532 255.382 261.304 254.496  
 295.52 294.664 293.757 292.917 259.026 258.74 254.638 260.685  
 295.45 294.548 293.684 292.844 … 261.136 261.903 257.23 261.243

2.2.5 Subset temperature to area of Texas instead of US

11×11×3653 Array{Union{Missing, Float64}, 3}:  
[:, :, 1] =  
 291.31 290.912 290.253 289.702 … 287.914 286.397 284.341 283.857  
 291.359 292.577 291.752 290.155 288.822 287.284 284.14 283.579  
 294.291 293.043 292.334 289.887 287.999 285.853 283.505 282.566  
 293.938 292.984 290.842 289.412 285.757 285.144 283.36 283.169  
 294.653 293.992 291.703 288.774 284.997 284.048 283.946 283.252  
 296.33 295.475 293.28 287.959 … 284.874 284.03 283.941 283.375  
 296.416 295.53 293.52 290.233 284.907 283.735 282.815 283.406  
 296.158 295.471 293.695 290.598 283.788 283.558 282.356 282.317  
 296.254 295.835 294.149 291.078 285.554 283.737 282.379 280.963  
 296.419 296.219 294.747 290.463 285.086 285.36 283.302 281.299  
 296.699 296.629 295.455 291.055 … 285.868 286.188 285.094 281.852  
  
[:, :, 2] =  
 293.682 294.663 293.619 292.196 … 287.538 285.536 283.818 281.873  
 294.237 296.073 295.585 293.843 289.812 288.154 285.528 283.329  
 296.598 295.877 296.526 294.523 291.016 288.691 286.095 284.717  
 295.727 296.559 295.922 294.954 291.273 289.738 287.398 286.099  
 295.003 294.79 294.608 295.179 292.05 290.401 288.871 287.385  
 296.606 296.265 294.972 295.118 … 292.334 290.859 289.587 288.703  
 296.577 296.147 295.147 292.247 292.261 290.22 289.503 288.252  
 296.431 295.958 295.31 292.818 291.934 290.013 289.351 286.932  
 296.602 296.168 295.596 293.396 291.917 290.509 289.26 287.116  
 296.901 296.689 295.971 292.78 291.516 290.681 289.67 287.883  
 297.139 297.121 296.391 292.873 … 290.944 290.096 289.802 288.823  
  
[:, :, 3] =  
 292.085 292.854 291.909 290.942 … 282.91 281.018 278.14 274.995  
 292.797 294.604 294.149 292.369 285.145 283.904 280.893 277.093  
 295.131 294.607 294.906 293.185 286.17 284.659 282.005 278.211  
 295.704 295.811 295.002 294.017 286.947 285.41 282.396 279.592  
 294.688 294.379 294.588 294.73 288.94 286.131 283.493 280.8  
 296.732 296.152 294.6 295.283 … 290.251 287.954 285.039 281.771  
 296.851 296.422 295.191 292.597 291.292 289.293 285.617 282.495  
 296.851 296.337 295.571 292.925 292.529 290.314 287.826 282.528  
 296.955 296.507 295.852 293.724 293.374 291.678 289.932 283.792  
 297.132 296.845 296.222 293.522 293.705 292.632 291.251 287.52  
 297.489 297.374 296.658 293.777 … 294.035 292.909 291.896 290.317  
  
;;; …   
  
[:, :, 3651] =  
 277.637 279.352 280.108 281.083 … 273.931 273.617 275.306 274.236  
 279.415 281.736 281.757 281.47 273.664 273.975 275.22 274.934  
 281.824 281.551 281.937 280.699 273.825 271.055 273.781 275.18  
 283.619 282.434 281.41 279.992 274.713 274.063 272.582 272.55  
 290.401 288.971 283.602 279.458 275.537 274.975 273.296 271.246  
 291.291 289.646 286.947 279.293 … 275.802 275.287 274.882 271.582  
 291.106 289.657 287.574 283.707 275.556 275.47 274.682 273.165  
 290.998 289.551 287.295 284.176 276.106 275.714 273.903 271.966  
 290.664 289.202 287.009 283.783 276.523 275.666 273.65 272.001  
 290.345 288.809 286.681 283.336 276.449 275.371 273.636 272.243  
 290.107 288.66 286.521 282.775 … 275.964 275.335 273.596 271.933  
  
[:, :, 3652] =  
 282.926 283.67 283.073 282.293 … 278.147 277.116 276.803 275.597  
 283.743 284.613 283.219 282.454 278.879 278.547 276.846 274.946  
 283.814 283.506 282.525 281.945 278.359 276.623 276.224 274.951  
 284.123 283.35 282.25 281.368 278.279 277.436 275.468 275.422  
 289.271 288.837 284.726 281.413 278.38 277.147 275.375 274.571  
 293.833 292.335 289.518 282.214 … 277.842 277.168 276.265 274.742  
 294.774 293.582 291.862 287.782 278.187 277.193 276.447 274.786  
 294.876 294.443 292.837 289.089 278.675 277.503 275.921 273.769  
 295.069 294.504 292.929 289.629 278.731 277.876 275.461 273.733  
 294.882 293.951 292.589 288.941 279.335 278.16 275.93 273.846  
 294.284 293.195 291.91 288.445 … 279.817 278.683 276.713 274.464  
  
[:, :, 3653] =  
 287.912 288.563 288.156 285.831 … 278.462 275.737 275.032 273.965  
 289.026 288.426 287.168 285.252 279.342 277.259 275.216 273.717  
 287.971 287.57 286.571 284.772 278.773 276.701 274.801 272.97  
 287.954 285.956 285.194 284.001 279.628 277.56 273.967 273.266  
 291.792 290.58 287.419 283.298 279.328 278.125 275.064 273.112  
 293.837 292.142 289.986 282.892 … 279.816 278.361 276.646 273.587  
 294.218 293.081 290.791 287.237 279.674 279.13 277.867 274.631  
 294.547 293.709 290.968 287.526 280.181 280.313 278.919 274.998  
 295.046 293.815 291.302 287.042 280.62 280.52 279.354 275.451  
 295.541 293.893 291.453 286.918 281.327 280.75 279.292 276.5  
 295.487 294.167 291.61 287.925 … 282.428 281.333 279.876 278.086

2.2.6 Subset temperature time

3652-element Vector{DateTime}:  
 2000-01-01T00:00:00  
 2000-01-02T00:00:00  
 2000-01-03T00:00:00  
 2000-01-04T00:00:00  
 2000-01-05T00:00:00  
 2000-01-06T00:00:00  
 2000-01-07T00:00:00  
 2000-01-08T00:00:00  
 2000-01-09T00:00:00  
 2000-01-10T00:00:00  
 2000-01-11T00:00:00  
 2000-01-12T00:00:00  
 2000-01-13T00:00:00  
 ⋮  
 2009-12-19T00:00:00  
 2009-12-20T00:00:00  
 2009-12-21T00:00:00  
 2009-12-22T00:00:00  
 2009-12-23T00:00:00  
 2009-12-24T00:00:00  
 2009-12-25T00:00:00  
 2009-12-26T00:00:00  
 2009-12-27T00:00:00  
 2009-12-28T00:00:00  
 2009-12-29T00:00:00  
 2009-12-30T00:00:00

2.3 Split data into training and testing sets

24×24×731 Array{Union{Missing, Float32}, 3}:  
[:, :, 1] =  
 0.230964 0.211317 0.0417734 … 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.239267 0.203205 0.0957546 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.228309 0.229123 0.159002 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.212892 0.23749 0.212364 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.179382 0.213751 0.242253 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.083235 0.157233 0.225679 … 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0227302 0.12858 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 missing missing missing … 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 missing missing missing 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 missing missing missing 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 missing missing missing 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 missing missing missing 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 missing missing missing … 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 missing missing missing 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 missing missing missing 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 missing missing missing 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 missing missing missing 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 missing missing missing … 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 missing missing missing 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 missing missing missing 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 missing missing missing 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
  
[:, :, 2] =  
 0.0 0.0 0.0 … 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 … 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 missing missing missing … 0.0 0.0 0.0 0.0 0.0 0.0  
 missing missing missing 0.0 0.0 0.0 0.0 0.0 0.0  
 missing missing missing 0.0 0.0 0.0 0.0 0.0 0.0  
 missing missing missing 0.0 0.0 0.0 0.0 0.0 0.0  
 missing missing missing 0.0 0.0 0.0 0.0 0.0 0.0  
 missing missing missing … 0.0 0.0 0.0 0.0 0.0 0.0  
 missing missing missing 0.0 0.0 0.0 0.0 0.0 0.0  
 missing missing missing 0.0 0.0 0.0 0.0 0.0 0.0  
 missing missing missing 0.0 0.0 0.0 0.0 0.0 0.0  
 missing missing missing 0.0 0.0 0.0 0.0 0.0 0.0  
 missing missing missing … 0.0 0.0 0.0 0.0 0.0 0.0  
 missing missing missing 0.0 0.0 0.0 0.0 0.0 0.0  
 missing missing missing 0.0 0.0 0.0 0.0 0.0 0.0  
 missing missing missing 0.0 0.0 0.0 0.0 0.0 0.0203687  
  
[:, :, 3] =  
 0.0 0.0 0.0 … 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 … 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0459444  
 0.0 0.356025 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 missing missing missing … 0.0 0.0 0.0 0.0 0.0 0.0  
 missing missing missing 0.0 0.0 0.0 0.0 0.0 0.0  
 missing missing missing 0.0 0.0 0.0 0.0 0.0 0.0  
 missing missing missing 0.0 0.0 0.0 0.0 0.0 0.0  
 missing missing missing 0.0 0.0 0.0 0.0 0.0 0.0  
 missing missing missing … 0.0 0.0 0.0 0.0 0.0 0.0  
 missing missing missing 0.0 0.0 0.0 0.0 0.0 0.0  
 missing missing missing 0.0 0.0 0.0 0.0 0.0 0.0  
 missing missing missing 0.0 0.0 0.0 0.0 0.0 0.0  
 missing missing missing 0.0 0.0 0.0 0.0 0.0 0.0  
 missing missing missing … 0.0 0.0 0.0 0.0 0.0 0.0  
 missing missing missing 0.0 0.0 0.0 0.0 0.0 0.0  
 missing missing missing 0.0 0.0 0.0 0.0 0.0 0.0  
 missing missing missing 0.0 0.0 0.0 0.0 0.0 0.0  
  
;;; …   
  
[:, :, 729] =  
 1.91927 2.18294 4.04477 5.20947 … 0.0 0.0 0.0  
 0.203245 0.580783 2.77413 4.15098 0.0 0.0 0.0  
 0.237774 1.28198 1.22886 0.721624 0.0 0.0 0.0  
 1.80391 2.13242 1.09698 0.152618 0.0 0.0 0.0  
 2.32314 1.18486 0.259382 0.0 0.0 0.0 0.0  
 1.09869 0.124012 0.0 0.0 … 0.0 0.0 0.0  
 0.493284 0.0336855 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.210678 0.0 0.0  
 0.0 0.0 0.0 0.0 0.244225 0.0478664 0.0  
 0.0 0.0 0.0 0.0 0.883143 1.56837 0.156057  
 missing missing missing missing … 1.22156 1.51986 1.36312  
 missing missing missing missing 2.79113 3.31666 2.07084  
 missing missing missing missing 2.48622 2.86405 1.8507  
 missing missing missing missing 0.999645 7.01725 4.73033  
 missing missing missing missing 1.48617 2.80321 4.4185  
 missing missing missing missing … 0.311555 0.0501361 0.0426737  
 missing missing missing missing 0.123578 0.0 0.0  
 missing missing missing missing 0.0 0.0 0.0  
 missing missing missing missing 0.0 0.0 0.0  
 missing missing missing missing 0.0 0.0 0.0  
 missing missing missing missing … 0.0 0.0 0.0  
 missing missing missing missing 0.0 0.0 0.0  
 missing missing missing missing 0.0 0.0 0.0  
 missing missing missing missing 0.0 0.0 0.0  
  
[:, :, 730] =  
 1.25381 1.38226 6.78581 9.23103 … 0.209643 0.06951 0.0322176  
 1.77286 1.17652 5.44695 8.42261 0.674334 0.0 0.038588  
 5.26336 2.10804 3.33561 5.37528 0.916897 0.0899668 0.0  
 4.11361 1.87916 1.61745 5.03068 0.337145 0.891777 0.0281657  
 1.10992 0.986878 1.11829 6.67025 3.08982 0.966748 0.270218  
 2.73123 2.4278 3.59609 5.59022 … 10.1729 1.6837 0.420492  
 3.33995 4.18317 3.80484 3.17682 0.469495 1.02329 0.587488  
 5.67861 5.78922 4.2321 1.34415 0.723784 1.02258 1.35627  
 5.94113 5.36736 3.45825 5.4516 1.6775 1.66165 2.03233  
 5.672 4.33358 3.37151 5.49953 2.08825 1.21806 2.91972  
 missing missing missing missing … 2.48373 1.6086 1.16387  
 missing missing missing missing 2.07946 1.88346 0.863437  
 missing missing missing missing 2.36113 1.62808 0.568243  
 missing missing missing missing 1.84581 1.57609 1.48535  
 missing missing missing missing 1.86876 1.23442 0.884178  
 missing missing missing missing … 1.79652 0.287498 1.20721  
 missing missing missing missing 2.98471 0.613985 1.21469  
 missing missing missing missing 2.01611 0.473238 0.555291  
 missing missing missing missing 1.43036 0.545582 0.477171  
 missing missing missing missing 0.386973 0.315955 0.0261992  
 missing missing missing missing … 0.0 0.0310814 0.0  
 missing missing missing missing 0.0 0.0293388 0.0  
 missing missing missing missing 0.0 0.0 0.0  
 missing missing missing missing 0.0 0.0 0.0  
  
[:, :, 731] =  
 0.0 0.0 0.0 … 0.0 0.194001 0.229313  
 0.0 0.0 0.0 0.201 0.0 1.05024  
 0.0 0.0 0.0 0.794761 0.0 0.239922  
 0.0 0.0 0.0 0.487525 0.0712316 0.0  
 0.0 0.0 0.0 0.871535 0.725623 0.0546665  
 0.0 0.0 0.0 … 0.63043 0.834709 0.935677  
 0.0 0.0 0.0 0.737369 0.396731 1.7525  
 0.0 0.0 0.0342669 0.810175 0.914279 2.05469  
 0.0 0.0 0.418512 0.482352 0.6477 0.834548  
 0.0 0.0364437 0.121333 1.36826 1.77949 1.08005  
 missing missing missing … 1.58758 4.78649 4.96679  
 missing missing missing 3.17118 5.32441 3.90305  
 missing missing missing 3.59475 4.90733 4.06902  
 missing missing missing 1.31501 5.03513 4.85771  
 missing missing missing 1.21495 2.24849 4.07878  
 missing missing missing … 1.81574 0.2997 1.09506  
 missing missing missing 1.08286 0.0417713 0.649026  
 missing missing missing 0.0439509 0.0 0.253759  
 missing missing missing 0.0449181 0.0 1.20432  
 missing missing missing 0.264041 0.0 1.47429  
 missing missing missing … 0.779127 0.235859 0.301635  
 missing missing missing 1.42092 0.159816 0.394416  
 missing missing missing 3.98366 0.940115 1.16965  
 missing missing missing 0.545287 0.645726 1.59136

2.4 Preprocessing

2.4.1 Preprocess function

preprocess (generic function with 1 method)

2.4.2 Preprocess temperature

121×731 Matrix{Float64}:  
 -5.29162 -9.1721 -15.5382 … -12.5594 -16.6589 -11.3703  
 -6.70991 -9.24213 -14.7215 -11.7596 -15.5633 -11.2349  
 -7.4606 -8.66663 -13.3073 -12.1199 -16.0275 -14.037  
 -6.92191 -7.86488 -12.4948 -10.7737 -13.6388 -13.1353  
 -3.20601 -4.50872 -9.2725 -6.62104 -6.23282 -7.36258  
 -3.4356 -4.63927 -9.81719 … -6.78153 -6.1819 -3.63953  
 -3.22345 -4.44058 -9.73227 -6.78883 -6.39981 -2.73266  
 -2.99846 -4.25502 -9.58033 -6.43223 -6.53416 -2.6556  
 -2.86815 -4.19236 -9.76109 -6.29229 -6.88516 -2.47985  
 -2.13038 -3.76691 -9.79706 -6.33689 -7.23386 -2.69678  
 -1.22141 -3.01323 -9.46011 … -6.3053 -7.52295 -3.3459  
 -6.42715 -9.37341 -15.0048 -12.5938 -16.2631 -11.9445  
 -7.70089 -9.0709 -14.0989 -12.2314 -15.7781 -12.9018  
 ⋮ ⋱ ⋮  
 -10.2321 -12.4993 -19.5512 -17.3013 -16.7106 -13.594  
 -13.3914 -17.6619 -18.4287 … -14.2943 -13.5519 -12.1915  
 -13.0153 -17.016 -19.3798 -14.0214 -13.0043 -12.993  
 -12.6853 -16.3206 -19.573 -13.7198 -13.2715 -13.5  
 -12.877 -16.4353 -20.6092 -17.123 -16.7478 -13.8757  
 -12.8246 -15.6923 -19.4179 -18.9243 -18.1075 -14.7821  
 -12.6756 -15.5844 -20.1762 … -19.3405 -17.9994 -14.8398  
 -11.9979 -15.4558 -20.235 -16.4364 -15.8031 -14.1816  
 -11.0614 -15.3627 -20.6582 -16.4999 -15.7922 -13.9889  
 -10.5836 -14.6008 -20.3137 -15.9558 -15.87 -14.1375  
 -10.4757 -13.8554 -19.9689 -16.3106 -16.5766 -14.9735  
 -10.7302 -13.3602 -20.1791 … -16.9336 -17.4919 -14.9605

2.4.3 Reshape precip

576×731 reshape(::Array{Union{Missing, Float32}, 3}, 576, 731) with eltype Union{Missing, Float32}:  
 0.230964 0.0 0.0 0.0 … 1.91927 1.25381 0.0  
 0.239267 0.0 0.0 0.0 0.203245 1.77286 0.0  
 0.228309 0.0 0.0 0.0 0.237774 5.26336 0.0  
 0.212892 0.0 0.0 0.0 1.80391 4.11361 0.0  
 0.179382 0.0 0.0 0.0 2.32314 1.10992 0.0  
 0.083235 0.0 0.0 0.0 … 1.09869 2.73123 0.0  
 0.0 0.0 0.0 0.0 0.493284 3.33995 0.0  
 0.0 0.0 0.0 0.0 0.0 5.67861 0.0  
 0.0 0.0 0.0 0.0 0.0 5.94113 0.0  
 0.0 0.0 0.0 0.0 0.0 5.672 0.0  
 missing missing missing missing … missing missing missing  
 missing missing missing missing missing missing missing  
 missing missing missing missing missing missing missing  
 ⋮ ⋱ ⋮  
 0.0 0.0 0.0 0.0 1.8507 0.568243 4.06902  
 0.0 0.0 0.0 0.0 … 4.73033 1.48535 4.85771  
 0.0 0.0 0.0 0.0 4.4185 0.884178 4.07878  
 0.0 0.0 0.0 0.153876 0.0426737 1.20721 1.09506  
 0.0 0.0 0.0 0.0202588 0.0 1.21469 0.649026  
 0.0 0.0 0.0 0.0 0.0 0.555291 0.253759  
 0.0 0.0 0.0 0.0 … 0.0 0.477171 1.20432  
 0.0 0.0 0.0 0.0 0.0 0.0261992 1.47429  
 0.0 0.0 0.0 0.0 0.0 0.0 0.301635  
 0.0 0.0 0.0 0.0 0.0 0.0 0.394416  
 0.0 0.0 0.0 0.0 0.0 0.0 1.16965  
 0.0 0.0203687 0.0 0.0 … 0.0 0.0 1.59136

1. Principal Component Analysis 3.1 Fit PCA model

3.2 Plot variance to determine number of PCs to keep

3.3 Transform PCs

6×731 Matrix{Float64}:  
 100.247 130.942 179.171 … 159.314 159.572 128.187  
 3.03334 9.58764 -11.2996 -8.46464 -14.8938 -5.77997  
 2.22337 -3.58652 0.21244 -1.39438 -8.892 -7.86022  
 2.6004 -3.18065 -10.1462 -3.68285 -0.234302 10.0624  
 0.0852445 -1.64579 0.984028 -4.64237 -0.923782 0.668111  
 4.67906 2.65186 -1.97371 … 0.396902 0.305045 -4.68379

3.4 Save first three PCs

2921-element Vector{Float64}:  
 3.9052599528110425  
 -2.2538113042128542  
 -12.537201539433823  
 -11.024843758228124  
 -0.5726203694196917  
 4.701612681874441  
 2.5183907610932286  
 -8.215061876405912  
 -8.658143941931053  
 -6.778889657459626  
 3.078553367661374  
 7.098802390680696  
 -3.423404610358853  
 ⋮  
 -1.9310563142374508  
 -3.550451553216818  
 -6.775211071460527  
 -6.952704268141444  
 -10.052420445554452  
 -5.265265614927885  
 -6.733298155961106  
 10.088840782427953  
 -9.024376763999939  
 -3.1651858900584364  
 -6.582681154712115  
 -2.110570791578569

3.5 Plot PCA

3.5.1 Plot time series of first three PCs

3.5.2 Plot first 2 PCs and mean precipitation

3.5.3 Plot the second and third PCs with mean precipitation

1. Approach 1: KNN

Given the high dimensional structure of the gridded temperature data, a principal components analysis was performed to downscale the features while preserving variation to allow for modeling across space and time. PCA effectively reduces the number of columns (in this case, locations) by projecting the data onto new PC axes. The number of principal components to retain was determined by plotting the variance explained by the principal components and the cumulative variance. After analyzing these figures, a break in variance is observed after principal component number two. The cumulative variance explained plot reveals that approximately 97.8% of the variance is explained by the first three principal components, so three principal components were retained for further analysis. The PCA model was fit to the training temperature data and then the temperature training and testing data were transformed onto the PCA space.

KNN was then used to predict the precipitation data for the testing temperature data given temperature and precipitation over the training period.The KNN function calculates the Euclidean distance between the new datapoint and the existing K data points and assigns weights based on these distances. Weighted sampling is then conducted to obtain the predicted value based on the indexed position sampled. Three was chosen as the hyperparameter for the number of neighbors because this number of neighbors is standard in KNN analysis and serves as an appropriate baseline. The resultant predicted precipitation values were compared to the actual precipitation training data to evaluate the fit of the model using residuals, MAE, and MSE.

4.1 Define KNN function

knn (generic function with 1 method)

4.2 Combining PCA and KNN

predict\_knn (generic function with 1 method)

4.3 Test the model

24×24×731 Array{AbstractFloat, 3}:  
[:, :, 1] =  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 … 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 … 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0649847 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0218424 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 … 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0533735 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0209779 0.0901863  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0302493 0.0 0.0415976  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.19425 0.0473435 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 … 0.0884871 0.0421871 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0780542 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 … 0.0211939 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.176734  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.152089  
  
[:, :, 2] =  
 1.75447 1.41588 1.19977 0.848477 … 0.0 0.0 0.0  
 3.56247 1.01861 1.52315 1.49084 0.0 0.0 0.0  
 9.91041 1.38696 1.36932 2.96705 0.0 0.0 0.0  
 8.48843 2.42787 1.51287 2.51147 0.0 0.0 0.0  
 1.6389 1.39423 1.54824 0.957531 0.0 0.0 0.0  
 4.94228 2.9396 0.673247 0.0492278 … 0.0 0.0 0.0  
 6.01258 5.55706 4.37366 0.18723 0.0 0.0 0.0  
 7.2367 11.1376 5.32148 0.156859 0.0 0.0 0.0  
 6.91768 7.26536 1.85251 0.0910493 0.0 0.0 0.0  
 4.00505 2.66892 1.61451 0.683203 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 … 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 … 0.0334075 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 … 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0777392  
 0.0 0.0 0.0 0.0 0.0723409 0.0859267 0.147741  
 0.0 0.0 0.0 0.0 0.0262213 0.0489934 0.195904  
  
[:, :, 3] =  
 1.49692 1.99355 2.05643 … 0.0 0.0 0.0 0.0 0.0 0.0  
 0.833292 0.72057 1.09722 0.0 0.0 0.0 0.0 0.0 0.0  
 3.12063 1.12997 0.357355 0.0 0.0 0.0 0.0 0.0 0.0  
 2.17121 1.34081 0.0870448 0.0 0.0 0.0 0.0 0.0 0.0  
 0.146885 0.0664999 0.178861 0.0 0.0 0.0 0.0 0.0 0.0  
 0.464428 0.344984 0.791974 … 0.0 0.0 0.0 0.0 0.0 0.0  
 1.5742 2.66726 1.56431 0.0 0.0 0.0 0.0 0.0 0.0  
 1.55001 4.35322 2.61319 0.0 0.0 0.0 0.0 0.0 0.0  
 0.500756 2.29461 2.9136 0.0 0.0 0.0 0.0 0.0 0.0  
 0.479857 1.89894 2.37473 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 … 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.035775 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0511538 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 … 0.0340634 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0237441 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 … 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
  
;;; …   
  
[:, :, 729] =  
 0.0 0.0 0.0 0.0 0.0 0.0 … 0.140855 0.0414727 0.436889  
 0.0 0.0 0.0 0.0 0.0 0.0 0.598811 0.0493965 0.314328  
 0.0 0.0 0.0 0.0 0.0 0.0 0.240909 0.100539 0.407857  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0943053 0.266252 0.592172  
 0.0 0.0 0.0 0.0 0.0 0.0 0.082403 0.117491 0.129018  
 0.0 0.0 0.0 0.0 0.0 0.0 … 0.292574 0.660883 0.528695  
 0.0 0.0 0.0 0.0 0.0 0.0 0.236851 0.314418 0.267703  
 0.0 0.0 0.0 0.0 0.0 0.0 0.430934 0.222956 0.587176  
 0.0 0.0 0.0513685 0.0 0.0 0.0 0.180304 0.129312 0.219643  
 0.0 0.0 0.0623262 0.0 0.0 0.0 0.345806 0.176304 0.689809  
 0.0 0.0 0.0 0.0 0.0 0.0 … 0.470213 0.479811 0.99668  
 0.0 0.0 0.0 0.0 0.0 0.0 0.903811 0.805968 0.633223  
 0.0 0.0 0.0 0.0 0.0 0.0 1.55173 1.94446 1.05149  
 0.0 0.0 0.0 0.0 0.0 0.0 0.751358 2.42407 0.892646  
 0.0 0.0 0.0 0.0 0.0 0.0 0.84299 1.61934 1.53261  
 0.0 0.0 0.0 0.0 0.0 0.0 … 0.411869 1.02282 0.344983  
 0.0 0.0 0.0 0.0 0.0 0.0 0.954351 1.51298 0.313492  
 0.0 0.0 0.0 0.0 0.0 0.0 2.95927 3.57947 1.06551  
 0.0 0.0 0.0 0.0 0.0 0.0 1.85423 1.76604 1.70267  
 0.0 0.0 0.0 0.0 0.0 0.0 0.606824 0.320045 1.13114  
 0.0 0.0 0.0 0.0 0.0 0.0 … 1.41541 0.305823 0.435956  
 0.0 0.0 0.0 0.0 0.0 0.0 0.600175 0.637315 0.814799  
 0.0 0.0 0.0 0.0 0.0 0.0 0.798034 0.480626 0.410468  
 0.0 0.0 0.0 0.0 0.0 0.0 1.01349 1.12795 0.425947  
  
[:, :, 730] =  
 0.0 0.0 0.0250906 … 0.0 0.0 0.0 0.0  
 0.0 0.0 0.05093 0.0 0.0 0.0 0.0  
 0.0 0.0434867 0.163335 0.0 0.0 0.0 0.0  
 0.084721 0.455731 0.452126 0.0 0.0 0.0 0.0  
 0.376434 0.272408 0.550661 0.0 0.0 0.0 0.0  
 1.80568 0.370495 1.58513 … 0.0 0.0 0.0 0.0  
 4.14398 2.07312 4.16797 0.0 0.0 0.0 0.0  
 10.2574 9.56134 5.12458 0.0 0.0 0.0 0.0  
 9.65954 6.17192 4.32784 0.0 0.0 0.0 0.0  
 7.42415 5.88919 6.10839 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 … 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.301538 0.0756907 0.0  
 0.0 0.0 0.0 0.0 0.87682 0.408131 0.0  
 0.0 0.0 0.0 … 0.0 0.025333 0.36935 0.0624869  
 0.0 0.0 0.0 0.0 0.0 0.0766167 0.0  
 0.0 0.0 0.0 0.0 0.0 0.032296 0.100898  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0469467  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 … 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0532102  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
  
[:, :, 731] =  
 0.0 0.0 0.0 0.0 0.0 0.0 … 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 … 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0251531 … 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0208791 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 … 3.16174 0.382311 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 6.56101 1.23528 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.167616 0.41249 0.159337 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 … 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0

4.4 Analyze Fit

4.4.1 Reshape data for plotting

576×731 Matrix{AbstractFloat}:  
 0.0 1.75447 1.49692 0.0 … 0.0 0.0 0.0  
 0.0 3.56247 0.833292 0.0 0.0 0.0 0.0  
 0.0 9.91041 3.12063 0.0 0.0 0.0 0.0  
 0.0 8.48843 2.17121 0.0 0.0 0.084721 0.0  
 0.0 1.6389 0.146885 0.0 0.0 0.376434 0.0  
 0.0 4.94228 0.464428 0.0 … 0.0 1.80568 0.0  
 0.0 6.01258 1.5742 0.0 0.0 4.14398 0.0  
 0.0 7.2367 1.55001 0.0 0.0 10.2574 0.0  
 0.0 6.91768 0.500756 0.0 0.0 9.65954 0.0  
 0.0 4.00505 0.479857 0.0 0.0 7.42415 0.0  
 0.0 0.0 0.0 0.0 … 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 ⋮ ⋱ ⋮  
 0.0901863 0.0 0.0 1.0249 1.05149 0.0 0.0  
 0.0415976 0.0 0.0 0.360796 … 0.892646 0.0 0.0  
 0.0 0.0 0.0 0.414263 1.53261 0.0 0.0  
 0.0 0.0 0.0 0.108951 0.344983 0.0624869 0.0  
 0.0 0.0 0.0 0.212448 0.313492 0.0 0.0  
 0.0 0.0 0.0 0.0 1.06551 0.100898 0.0  
 0.0 0.0 0.0 0.0 … 1.70267 0.0469467 0.0  
 0.0 0.0 0.0 0.0796868 1.13114 0.0 0.0  
 0.0 0.0 0.0 0.118671 0.435956 0.0 0.0  
 0.0 0.0777392 0.0 0.0 0.814799 0.0 0.0  
 0.176734 0.147741 0.0 0.0 0.410468 0.0532102 0.0  
 0.152089 0.195904 0.0 0.0 … 0.425947 0.0 0.0

4.4.2 Time series actual vs predicted test precipitation

4.4.3 Heatmaps

4.4.4 Evaluate fit using MSE

mean\_se (generic function with 1 method)

4.4.5 Evaluate fit using MAE

mean\_abs\_error (generic function with 1 method)

4.4.6 Evaluate fit using residuals

residuals (generic function with 1 method)

1. Approach 2: PCA/Linear Regression

Similarly to Approach 1, Approach 2 employed PCA to reduce the dimensions of the temperature data. Only the first principal component was retained for further linear regression to allow for the creation of simple vectors that are compatible with linear regression syntax. Linear regression was performed on precipitation at each grid cell location following the first principal component of the temperature data. The temperature test data was then applied to this linear model to predict precipitation and was similarly compared to actual observed precipitation to evaluate the model using residuals, MAE, and MSE.

5.1 Linear Regression

576×2921 Matrix{AbstractFloat}:  
 0.0 0.0 0.0 0.0 … 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
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 0.0 10.0802 1.95597 0.103022 … 2.42879 0.0 0.0 0.0  
 0.0207805 13.5422 1.23499 0.0 2.51666 0.0 0.0 0.0  
 0.0338578 15.6146 1.12839 0.0 2.64994 0.0472129 0.0 0.0  
 0.0513665 22.9741 3.07755 0.0 2.00045 0.0460711 0.0 0.0  
 0.156683 28.7882 0.937954 0.0 1.97276 0.0751787 0.0 0.0  
 0.0214627 24.5314 2.03677 0.0 … 2.50186 0.0 0.0 0.0  
 3.03718 14.6306 4.33941 0.0 2.24995 0.0 0.0 0.0  
 3.51391 8.24005 8.96606 0.0 2.30591 0.0429012 0.0 0.0  
 0.607323 26.5516 10.5232 0.0 4.07364 0.0 0.0 0.0  
 0.0 51.9611 17.5984 0.206645 2.48726 0.659939 0.0 0.0  
 0.602726 73.7095 25.2627 1.76726 … 3.56594 2.77694 0.0 0.0

731×576 Matrix{Float64}:  
 0.288686 0.326512 0.585564 … 2.21833 2.42359 2.47836 2.48521  
 0.0693047 0.0866469 0.344425 1.94787 2.19186 2.22505 2.27144  
 -0.275387 -0.29023 -0.0344529 1.52294 1.82776 1.82705 1.93557  
 -0.293983 -0.310562 -0.0548933 1.50001 1.80811 1.80557 1.91745  
 0.0960588 0.115899 0.373833 1.98085 2.22012 2.25594 2.29751  
 0.714566 0.792159 1.05368 … 2.74335 2.87345 2.9701 2.9002  
 0.967155 1.06833 1.33132 3.05475 3.14026 3.26176 3.14632  
 1.02983 1.13686 1.40022 3.13202 3.20647 3.33413 3.2074  
 0.901364 0.996399 1.25901 2.97364 3.07077 3.18579 3.08221  
 0.343025 0.385925 0.645293 2.28532 2.48099 2.5411 2.53816  
 0.558737 0.62178 0.8824 … 2.55125 2.70885 2.79017 2.74835  
 0.2988 0.337571 0.596682 2.2308 2.43427 2.49004 2.49506  
 0.332966 0.374927 0.634237 2.27292 2.47036 2.52949 2.52836  
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 0.176906 0.204296 0.462699 2.08052 2.30552 2.34929 2.37629  
 0.0974754 0.117448 0.37539 … 1.9826 2.22161 2.25757 2.29889  
 0.269593 0.305637 0.564579 2.19479 2.40342 2.45631 2.46661  
 0.526515 0.586549 0.846982 2.51152 2.67481 2.75297 2.71696  
 0.707819 0.784782 1.04627 2.73504 2.86632 2.96231 2.89362  
 0.356321 0.400463 0.659908 2.30171 2.49503 2.55645 2.55111  
 -0.272868 -0.287476 -0.0316845 … 1.52604 1.83042 1.82995 1.93802  
 -0.178059 -0.183814 0.0725277 1.64292 1.93056 1.93943 2.0304  
 -0.066708 -0.0620658 0.194923 1.7802 2.04818 2.068 2.13891  
 -0.13347 -0.135062 0.121539 1.69789 1.97766 1.99091 2.07385  
 -0.135314 -0.137078 0.119512 1.69562 1.97572 1.98878 2.07206  
 0.0889984 0.10818 0.366072 … 1.97215 2.21266 2.24779 2.29063

5.2 Analyze Fit 5.2.1 Plot time series of actual vs predicted precipitation at different grid cells

5.2.2 Evaluate Fit using MSE

5.2.3 Evaluate fit using MAE

5.2.4 Evaluate fit using residuals

1. Compare

When plotting the predicted precipitation and the actual precipitation for the test data, upon visual inspection it seems that the PCA-KNN model more closely resembles the trends of the actual precipitation. The PCA-KNN predicted precipitation of varying levels while the PCA-linear regression model predicted nearly constant, low-level precipitation year-round, with some reflection of the seasonal trends as the maximum periods of the curves occur over the same range of time. However, upon closer analysis, the PCA-KNN model predictions differed significantly from the actual precipitation values. When considering only the residuals of actual precipitation minus predicted precipitation, the PCA-KNN model appears to perform better because the average of the residuals is lower than the PCA-linear regression model. However, when considering the mean absolute error and the mean squared error, the PCA-linear regression model outperformed the PCA-KNN model with significantly lower MAE and MSE, indicating overall that predictions are closer to actual values than the PCA-KNN model. Residuals might be lower than MSE or MAE for a model if there are both undershoots and overshoots when considering the entire dataset of predictions. For example, if the PCA-KNN model predicted 0 mm on a day that should be 40 mm and 40 mm on a day that should be 0 mm, the averaged residuals would be zero since they cancel out. MSE and MAE, however, are a more robust measure of model performance because they account for differences in sign via squaring and absolute value respectively. MSE places a greater emphasis on large errors but is sensitive to outliers, which explains why the difference in MSE is greater between the two models than MAE.

The PCA-KNN model appears to be capturing the general shape of the data better, but local predictions are not very reliable based on the MAE and MSE calculations. This model could be further optimized by optimizing the hyperparameters n\_pca and K. N\_pca is the number of principal components retained in the model. Three was selected as the n\_pca value in this analysis based on fraction of variance explained, but a systematic approach could be taken to test all values of PCs and retain the number with the lowest MSE/MAE. A similar systematic approach could be used to optimize the K parameter as well.

The PCA-linear regression model is demonstrating a “dreary” effect by predicting low level precipitation across the time series. While there are periods of slight increase and decrease over the year corresponding to seasonal variation, this model generally does not capture the shape of the data or minimum/maximum values well. Only the first principal component was retained for simplicity of the model, but to improve the predictions more principal components should be considered. Additional principal components may more accurately capture heavy precipitation patterns and predict values closer to actual precipitation on heavy rainfall days.

A limitation of both models is the handling of missing precipitation values. This analysis elected to replace missing values with 0.0, but this is likely altering predictive accuracy by introducing bias. An improvement would be to remove missing values altogether before conducting data analysis. Another major limitation of both models is only using temperature data to predict precipitation. Based on prior knowledge, pressure data is also important in predicting precipitation and model performance likely would have significantly included if more variables beyond temperature were included.

-0.23472928f0

1. Conclusion

This report provides preliminary models to predict precipitation at time t+1 based on temperature at time t over Texas. Both approaches employ a principal component analysis to downscale high dimensional spatial data while retaining variance explained within the data. Approach 1 then applies K-nearest neighbors to predict precipitation using weighted sampling indexes of the three closest neighbors. After PCA, Approach 2 applies a linear regression to the first principal component at each grid cell of precipitation following temperature. When comparing predicted and actual precipitation across the two models, Approach 1 appears to capture the range of precipitation values more accurately but exhibits a higher mean squared error and mean absolute error, indicating poorer overall model performance. Approach 2 predicts low level precipitation across the entire time series and thus has lower mean squared error and mean absolute error values due to a lack of appropriate extremes.

If the goal of the model prediction was to minimize MSE and MAE, then Approach 2 would be a better model. Both models would be significantly improved by the optimization of chosen model parameters and the inclusion of additional climate variables, including pressure, to predict precipitation.