

Lab 3: Spatial Visualization with Heat Mapping

Regional Climate Trends Project

Learning Spatial Analysis in R

EA030

January 23, 2026 v. 0.07

Contents

1	Introduction	2
1.1	Why Heat Maps?	2
2	Setup	2
3	Load Data	3
4	Learning R: Spatial Data	4
4.1	The sf Package	4
4.2	Converting Between sf and sp	4
5	Understanding Kriging	5
5.1	The Variogram	5
6	Station Location Map	6
7	Creating Heat Maps	8
7.1	Annual Maximum Temperature (TMAX)	8
7.2	Annual Minimum Temperature (TMIN)	9
8	Seasonal Heat Maps	10
8.1	Summer vs Winter TMAX	10
9	Learning R: Combining Plots	12
10	Precipitation Heat Map	13
11	Regional Summary	14
12	Export Summary	15
13	Interpreting Your Maps	15

14 Lab 3 Summary	15
14.1 What You Accomplished	15
14.2 R Concepts Learned	16
14.3 Key Results for CA	16
14.4 Using These Maps in Your Video	16

1 Introduction

In Lab 3, you will create professional spatial visualizations showing climate trends across your state. You will learn:

- Spatial data structures in R (sf and sp)
- Kriging interpolation concepts
- Creating heat maps with ggplot2
- Combining multiple maps
- Exporting publication-quality figures

1.1 Why Heat Maps?

Heat maps transform scattered point data into continuous surfaces, making spatial patterns easier to see and communicate.

2 Setup

```
## =====
## Climate Narratives Functions v7.0 Loaded Successfully!
## =====
## Run check_packages() to verify dependencies
## =====
## QUICK START:
## 1. setup_project('CA')
## 2. select_stations_for_analysis(n_stations = 50)
## 3. download_stations()
## 4. load_and_save_stations(cleanup = TRUE)
## 5. process_all_stations_for_spatial()
## 6. create_spatial_objects(all_station_trends)
##
## NEW IN v7.0:
## - Fixed figuresfolder variable handling
## - Improved error messages
## - Better documentation for teaching
##
## =====
```

```

# Set working directory (CHANGE to your path!)
setwd("/path/to/your/project/folder/")

# Load functions and packages
source("ClimateNarrativesFunctions_v07.R")
check_packages()

```

3 Load Data

```

## Loaded variables: all_station_trends
## [OK] Created spatial objects:
##       trends_sf: 50 features
##       trends_sp: 50 features
##
## [OK] Loaded spatial data for CA
##       Stations: 50
##       Longitude: -123.76 to -115.57
##       Latitude: 32.85 to 41.87

```

```

# Set your state
my.state <- "CA"

# IMPORTANT: Define folder paths before saving anything
datafolder <- "Data/"
figuresfolder <- "Figures/"

# Create Figures folder if needed
if (!dir.exists(figuresfolder)) {
  dir.create(figuresfolder, recursive = TRUE)
}

# Load the processed data
rdata_file <- paste0(datafolder, "spatial_trends_", my.state, ".RData")
load(rdata_file)

# Create spatial objects for mapping
spatial_objects <- create_spatial_objects(all_station_trends)

```

R Concept: Directory Creation

`dir.exists()` checks if a folder exists, and `dir.create()` creates it. The `recursive = TRUE` option creates parent folders if needed.

4 Learning R: Spatial Data

R has two main systems for spatial data:

- **sf** (Simple Features): Modern, tidy approach
- **sp** (Spatial): Legacy system, still used by some packages

4.1 The sf Package

```
## Structure of trends_sf (Simple Features):
## =====
## Class:      sf
## Features:   50
## CRS:        4326 (WGS84 lat/lon)
##
## First few rows:
##           ID LATITUDE LONGITUDE annual_trend_TMAX
## 1 USC00043157  41.8714 -120.1575     0.16117902
## 2 USW00023271  38.5553 -121.4183     2.53534598
## 3 USC00042294  38.5350 -121.7761    -0.04812917
## 4 USC00046074  38.2778 -122.2647     0.78330318
## 5 USC00046136  39.2467 -121.0008    -0.97059534
## 6 USC00046719  34.1483 -118.1447     2.38718896
```

```
# sf objects look like data frames with a geometry column
head(trends_sf)

# Check the coordinate reference system
st_crs(trends_sf)

# Get the bounding box
st_bbox(trends_sf)
```

4.2 Converting Between sf and sp

```
## Converting between sf and sp:  
## =====  
## trends_sf class: sf  
## trends_sp class: SpatialPointsDataFrame
```

```
# sf to sp (for packages that need sp)  
trends_sp <- as(trends_sf, "Spatial")  
  
# sp to sf  
trends_sf <- st_as_sf(trends_sp)
```

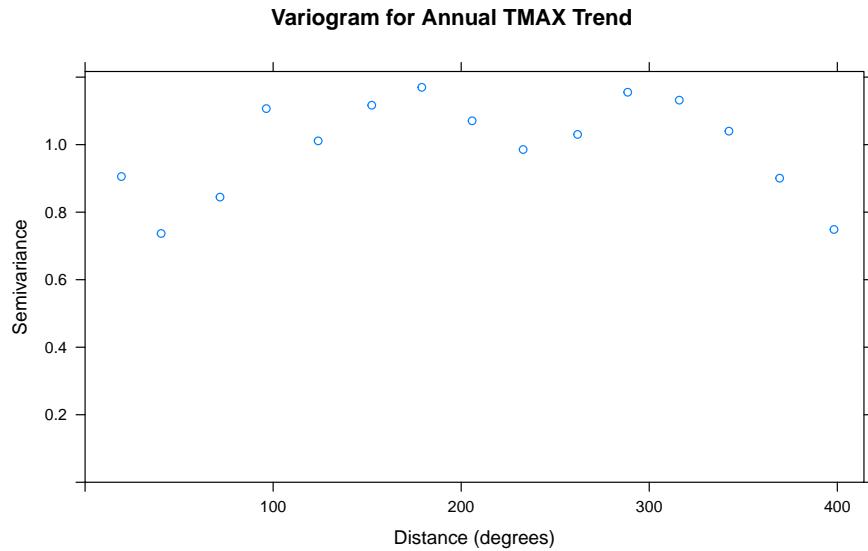
5 Understanding Kriging

Kriging is a geostatistical interpolation method that:

1. Assumes nearby points have similar values
2. Uses a **variogram** to model spatial correlation
3. Predicts values at unsampled locations
4. Provides prediction uncertainty estimates

5.1 The Variogram

A variogram describes how similar values are based on distance:



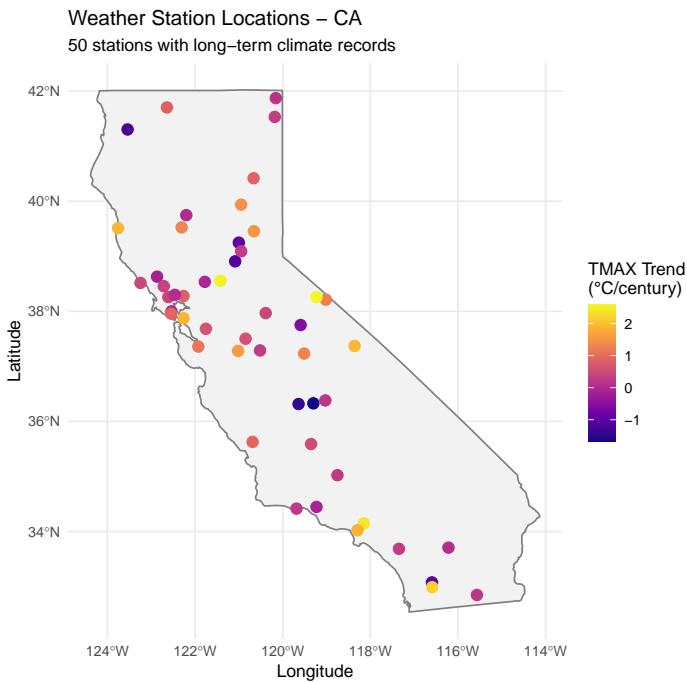
```
# Calculate empirical variogram
v <- variogram(annual_trend_TMAX ~ 1, trends_sp)

# Plot it
plot(v, main = "Variogram for Annual TMAX Trend")

# The variogram shows:
#   - Points close together are similar (low semivariance)
#   - Points far apart are different (high semivariance)
#   - The "range" is where the curve levels off
```

6 Station Location Map

Let's first see where our stations are located.



```
# Get state boundary
us_states <- map_data("state")
state_name <- tolower(state.name[state.abb == my.state])
state_boundary <- us_states %>% filter(region == state_name)

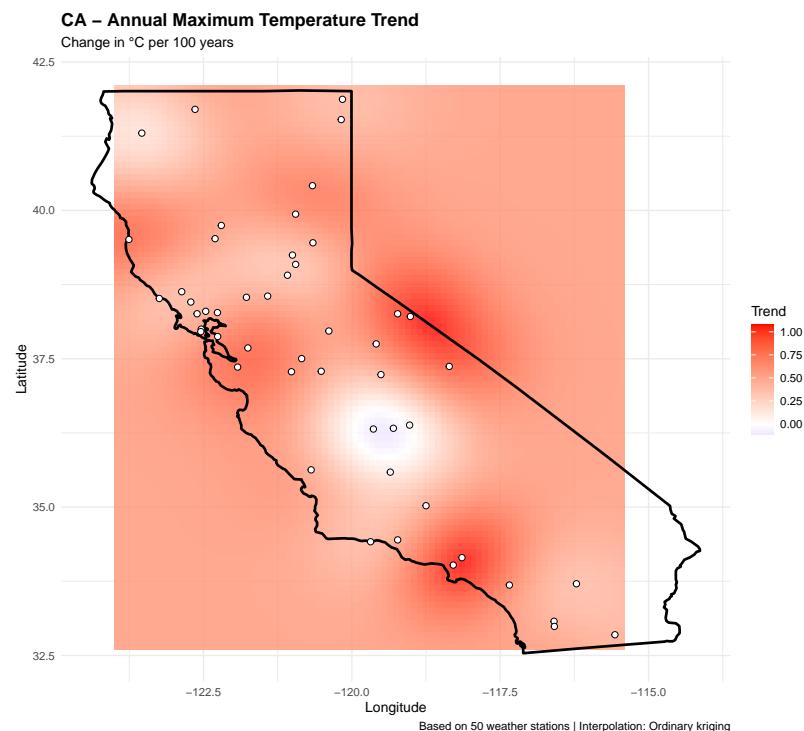
# Create map with ggplot2
ggplot() +
  # State polygon
  geom_polygon(data = state_boundary,
               aes(x = long, y = lat, group = group),
               fill = "gray95", color = "gray50") +
  # Station points colored by trend
  geom_sf(data = trends_sf,
          aes(color = annual_trend_TMAX),
          size = 3) +
  # Color scale
  scale_color_viridis_c(name = "Trend")
```

7 Creating Heat Maps

Now let's create interpolated heat maps using kriging.

7.1 Annual Maximum Temperature (TMAX)

```
## Fitting variogram for annual_trend_TMAX ...
## Performing kriging interpolation...
## [using ordinary kriging]
```



```
## 
## [OK] Saved: Heatmap_TMAX_annual_Ca.png
```

```
# Create heat map using our function
map_tmax_annual <- create_heatmap(
  trends_sp, # Spatial data
  trend_var = "annual_trend_TMAX", # Variable to map
  title = paste(my.state, "- Annual TMAX Trend"),
  subtitle = "Change in deg C per 100 years",
```

```

state = my.state,
colors = "temp",           # Color scheme
resolution = 0.1           # Grid resolution
)

# Display it
print(map_tmax_annual)

# Save high-resolution version
ggsave(paste0(figuresfolder, "Heatmap_TMAX_annual_", my.state, ".png"),
       map_tmax_annual,
       width = 10, height = 8, dpi = 300)

```

R Concept: ggsave()

`ggsave()` saves ggplot figures with professional quality:

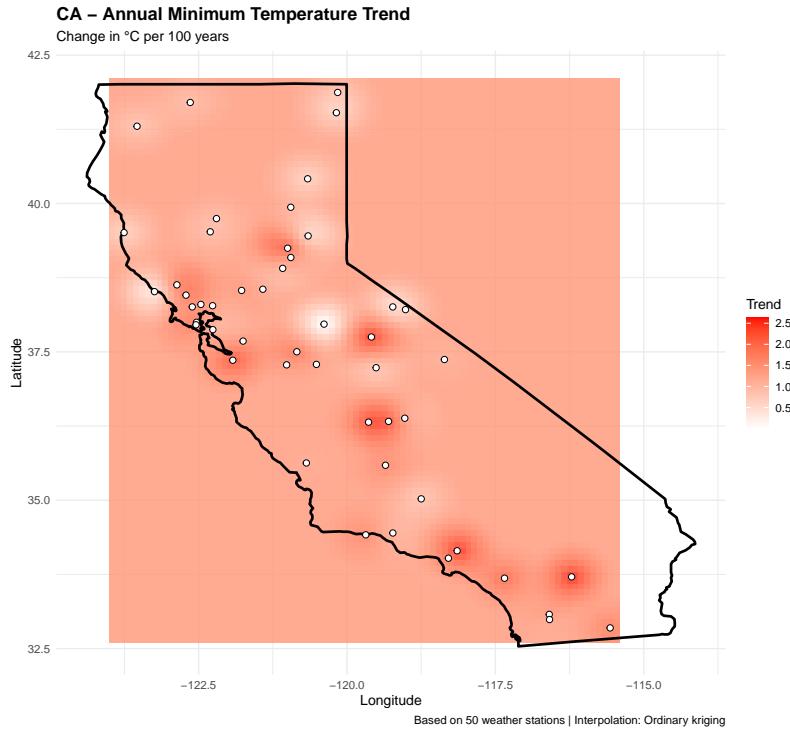
- `width, height`: Size in inches
- `dpi = 300`: Publication quality resolution
- File format determined by extension (.png, .pdf, .jpg)

7.2 Annual Minimum Temperature (TMIN)

```

## Fitting variogram for annual_trend_TMIN ...
## Performing kriging interpolation...
## [using ordinary kriging]

```



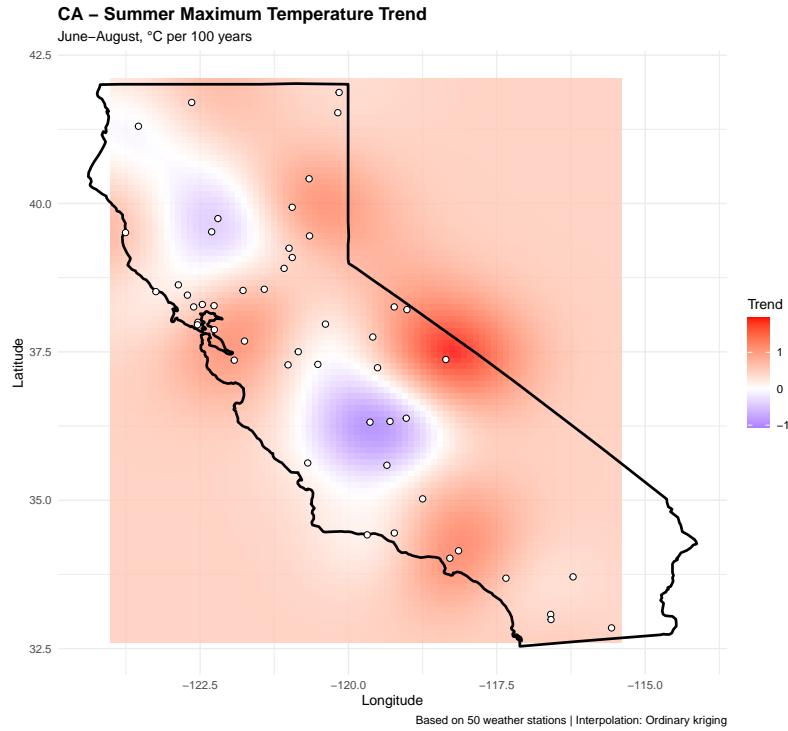
```
## [OK] Saved: Heatmap_TMIN_annual_CA.png
```

8 Seasonal Heat Maps

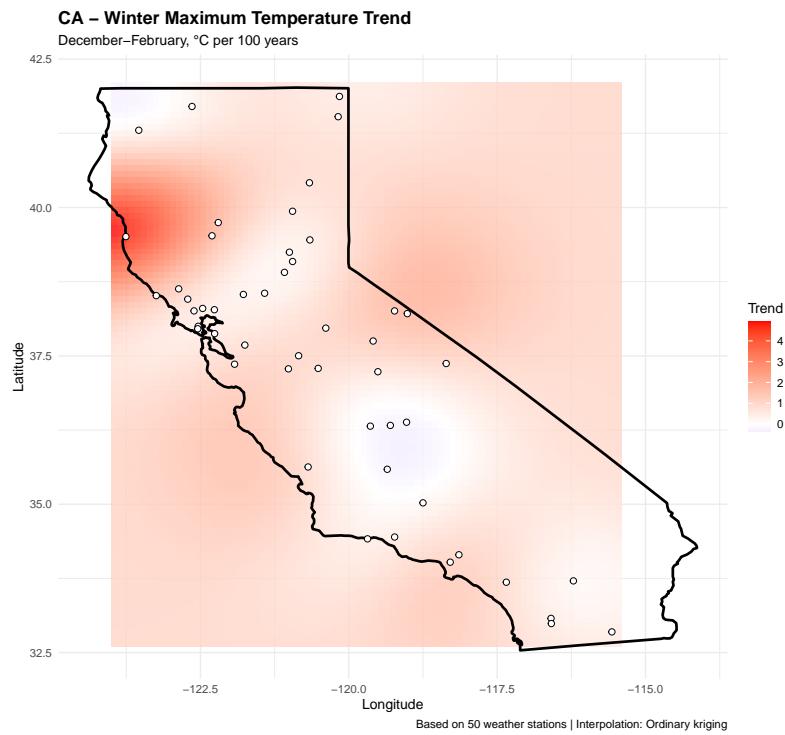
Let's compare trends across seasons.

8.1 Summer vs Winter TMAX

```
## Fitting variogram for summer_trend_TMAX ...
## Performing kriging interpolation...
## [using ordinary kriging]
```



```
## Fitting variogram for winter_trend_TMAX ...
## Performing kriging interpolation...
## [using ordinary kriging]
```

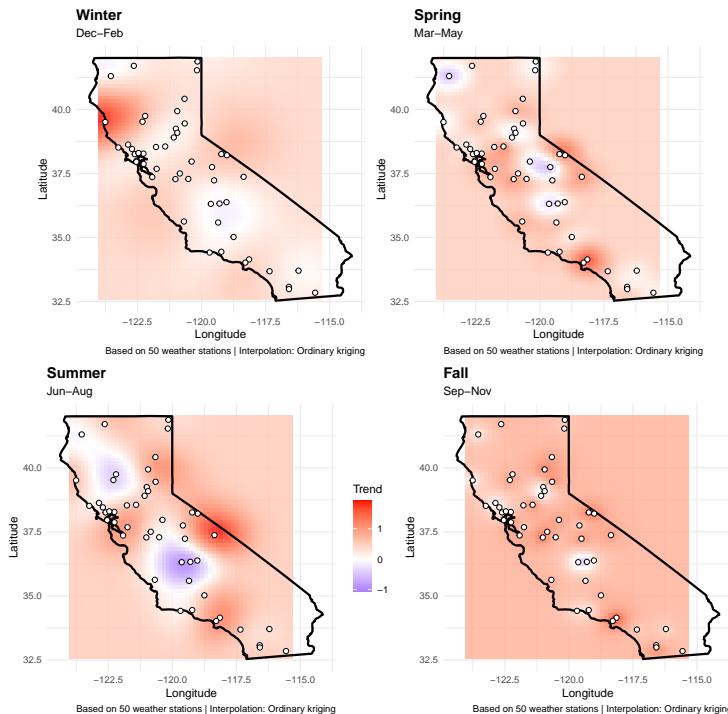


9 Learning R: Combining Plots

The `patchwork` package makes it easy to combine multiple plots.

```
## Fitting variogram for winter_trend_TMAX ...
## Performing kriging interpolation...
## [using ordinary kriging]
## Fitting variogram for spring_trend_TMAX ...
## Performing kriging interpolation...
## [using ordinary kriging]
## Fitting variogram for summer_trend_TMAX ...
## Performing kriging interpolation...
## [using ordinary kriging]
## Fitting variogram for fall_trend_TMAX ...
## Performing kriging interpolation...
## [using ordinary kriging]
```

Seasonal Maximum Temperature Trends – CA
Change in °C per 100 years by season



```
##  
## [OK] Saved: Seasonal_TMAX_comparison_CA.png
```

```
library(patchwork)

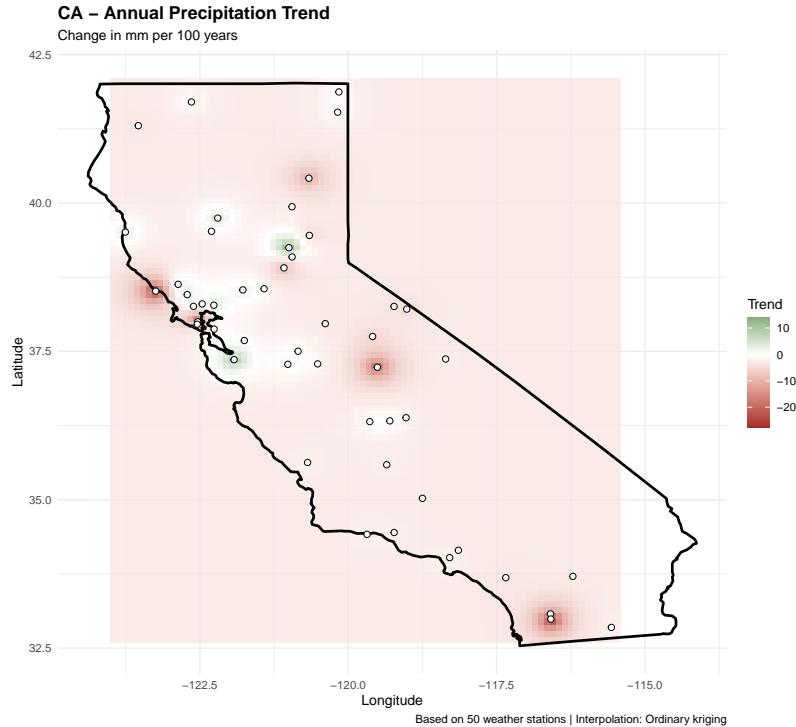
# patchwork operators:
#   |   = side by side
#   /   = stacked vertically
#   +   = add annotation

seasonal_comparison <- (winter | spring) /
  (summer | fall) +
  plot_annotation(title = "Seasonal Comparison")

print(seasonal_comparison)
```

10 Precipitation Heat Map

```
## Fitting variogram for annual_trend_PRCP ...
## Performing kriging interpolation...
## [using ordinary kriging]
```



```
## [OK] Saved: Heatmap_PRCP_annual_CA.png
```

11 Regional Summary

```
## =====
## REGIONAL SUMMARY - ANNUAL TMAX TRENDS
## =====
## # A tibble: 4 x 3
##   region      n mean_trend
##   <chr>     <int>    <dbl>
## 1 Northeast     7     1.01
## 2 Northwest    18     0.37
## 3 Southeast    18     0.38
## 4 Southwest     7     1.08
## =====
```

12 Export Summary

```
## =====
##          EXPORTED HEAT MAPS
## =====
## Total figures created: 6
## -----
## * Heatmap_PRCP_annual_CA.png
## * Heatmap_Summer_TMAX_CA.png
## * Heatmap_TMAX_annual_CA.png
## * Heatmap_TMIN_annual_CA.png
## * Heatmap_Winter_TMAX_CA.png
## * Seasonal_TMAX_comparison_CA.png
## -----
## Location: Figures/
## Resolution: 300 dpi (publication quality)
## =====
```

13 Interpreting Your Maps

When examining heat maps, consider:

1. Spatial Patterns

- Are there distinct regional differences?
- Where are the hotspots (strongest warming)?
- Do coastal vs. inland areas differ?

2. Seasonal Variation

- Which season shows strongest trends?
- Do patterns differ by season?

3. Temperature vs. Precipitation

- Do patterns align?
- Are warming areas also drying/wetting?

14 Lab 3 Summary

14.1 What You Accomplished

- Created interpolated heat maps using kriging
- Visualized annual and seasonal temperature trends

- Mapped precipitation changes
- Identified regional climate hotspots
- Generated 6 publication-quality figures

14.2 R Concepts Learned

1. **Spatial Data:** sf and sp objects
2. **Kriging:** Variograms, interpolation
3. **ggplot2:** Layers, scales, themes
4. **patchwork:** Combining plots
5. **ggsave:** Exporting figures

14.3 Key Results for CA

- Mean TMAX trend: **0.56 C/century**
- Spatial range: **-1.68 to 2.59 C/century**

14.4 Using These Maps in Your Video

1. Start with annual TMAX (overview)
2. Show seasonal variation for nuance
3. Zoom into specific hotspots
4. Compare temperature and precipitation
5. Connect to community impacts

You now have everything needed to create a compelling climate narrative video!