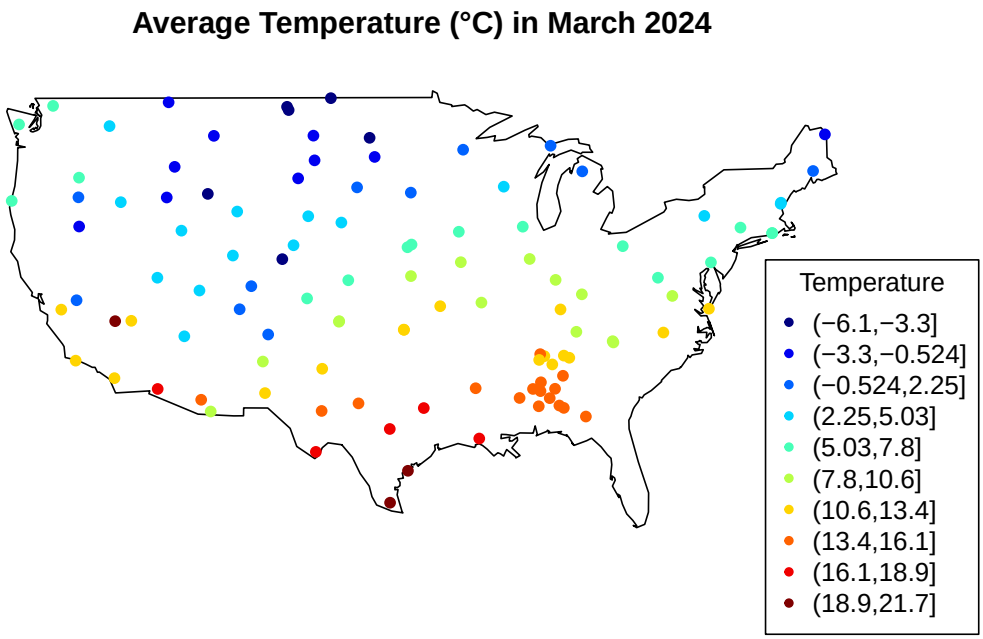
vignette

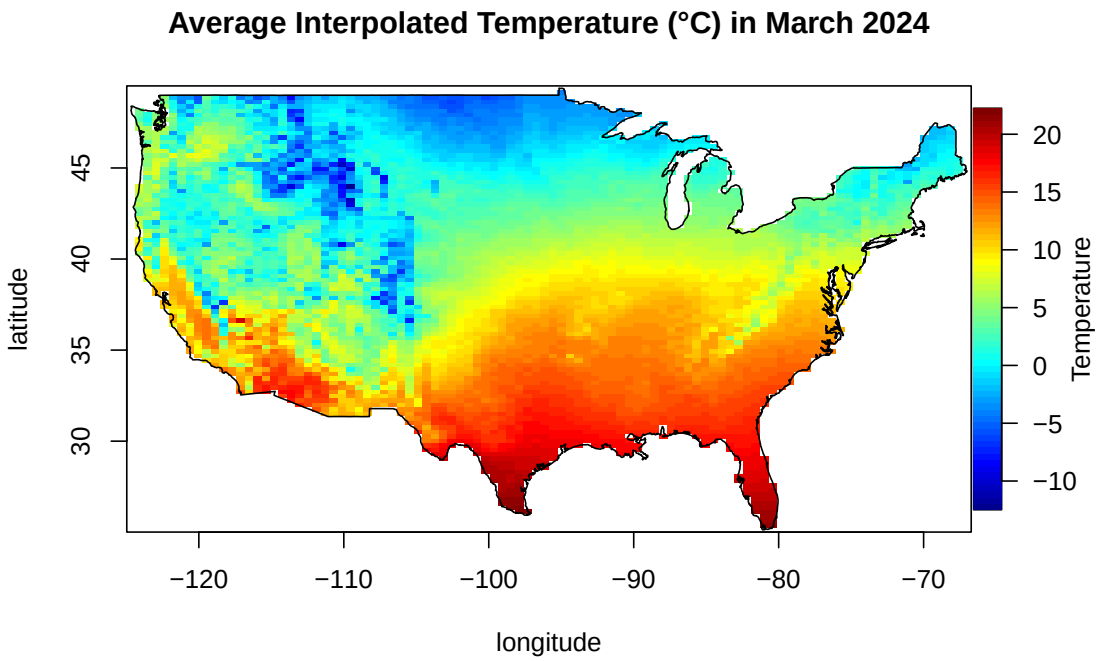
```
library(USweather)
```

```
# map of the average temperature of stations in March 2024 vs the interpolated data map
non_contig <- c("AK",
                "HI",
                "NL",
                "PE",
                "NS",
                "NB",
                "QC",
                "ON",
                "MB",
                "SK",
                "AB",
                "BC",
                "YT",
                "NT",
                "NU")
contig_stations <- station_info[!station_info$state %in% non_contig, ]

march_2024_data <- daily_weather |> dplyr:::filter(LST_DATE >= "2024-03-01",
                                                   LST_DATE < "2024-04-01",
                                                   !state %in% non_contig) |>
  dplyr:::group_by(`station name`, LONGITUDE, LATITUDE) |>
  dplyr:::summarise(avg_temp = mean(T_DAILY_AVG))

colmap <- colorRampPalette(
  c(
    "#00007F",
    "blue",
    "#007FFF",
    "cyan",
    "#7FFF7F",
    "yellow",
    "#FF7F00",
    "red",
    "#7F0000"
  )
)

maps::map("usa")
points(
  march_2024_data$LONGITUDE,
  march_2024_data$LATITUDE,
  pch = 16,
  col =  colmap(10)[cut(march_2024_data$avg_temp, 10)]
```

```
)
legend(
  x = -72,
  y = 40,
  title = "Temperature",
  legend = levels(cut(march_2024_data$avg_temp, 10)),
  col = colmap(10),
  pch = 20,
  xpd = TRUE
)
title("Average Temperature (°C) in March 2024")

grid <- create_grid(resolution_X = 100, resolution_Y = 100)
```

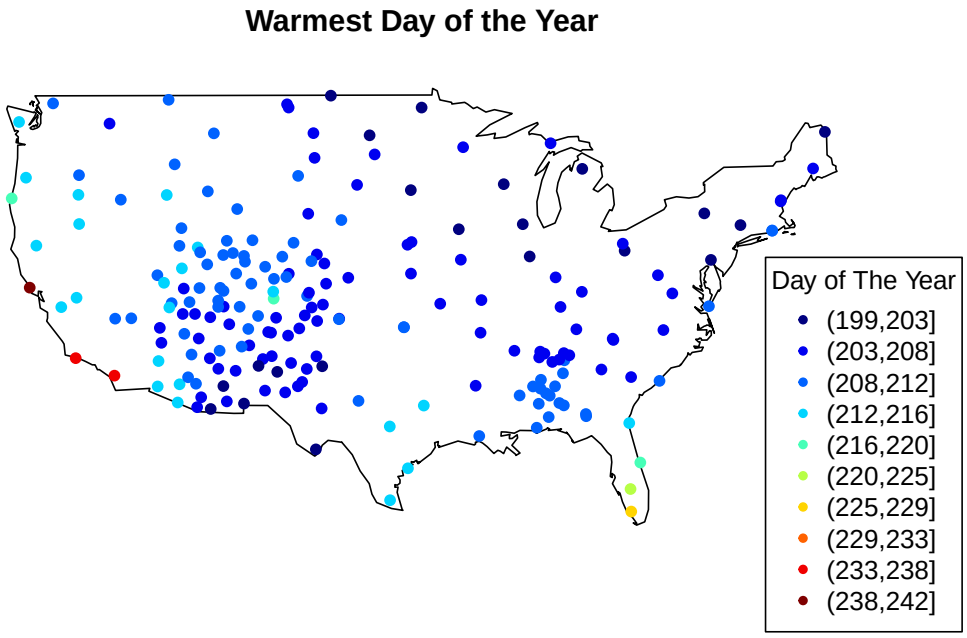



```
interp_data = interpolate_data(
  march_2024_data$avg_temp,
  march_2024_data$LONGITUDE,
  march_2024_data$LATITUDE,
  gridpoints = grid,
  use_elev = T
)
#> 17 observations removed due to missingness or Inf
#> Assuming columns 1 and 2 of locs are (longitude,latidue) in degrees
plot_interpolations(interp_data)
title("Average Interpolated Temperature (°C) in March 2024")
mtext("Temperature", side = 4, line = 3)
```



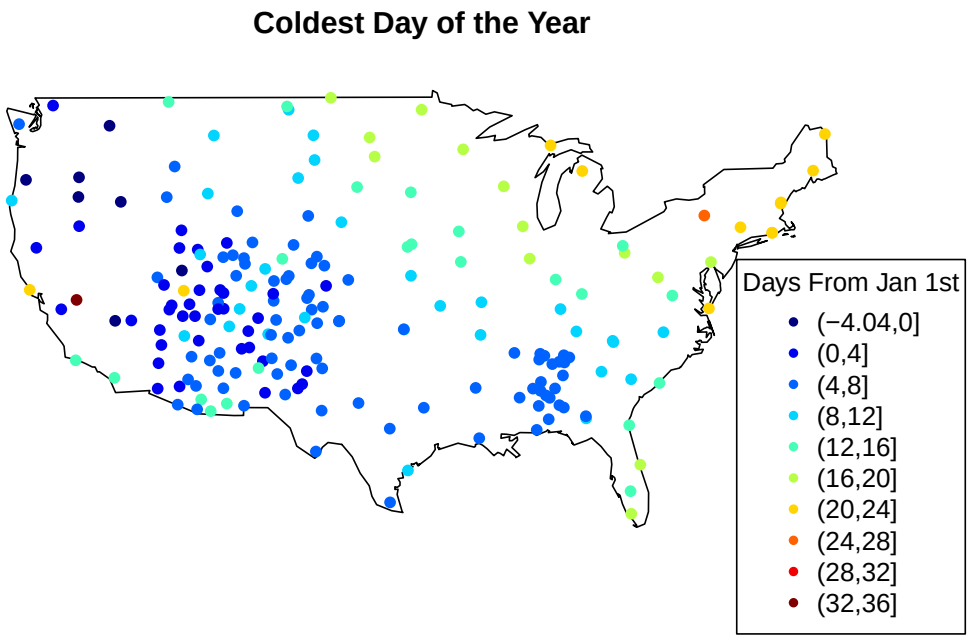

```r
num_stations <- nrow(contig_stations)
stations_high_day <- rep(NA, times = num_stations)
stations_low_day <- rep(NA, times = num_stations)

i <- 1
for (station_id in contig_stations$WBANNO) {
  yearly_estimates = get_yearly_cycle(station_id)
  min_row <- which.min(yearly_estimates$avg_temp)
  max_row <- which.max(yearly_estimates$avg_temp)
  stations_high_day[i] <- yearly_estimates[max_row, "day_of_year"]
  stations_low_day[i] <- yearly_estimates[min_row, "day_of_year"]
  i <- i + 1
}

colmap <- colorRampPalette(
  c(
    "#00007F",
    "blue",
    "#007FFF",
    "cyan",
    "#7FFF7F",
    "yellow",
    "#FF7F00",
    "red",
    "#7F0000"
  )
)
days_from_jan1 <- ifelse(stations_low_day > 100, stations_low_day - 365, stations_low_day)

maps::map("usa")
points(
```

```
  contig_stations$LONGITUDE,
  contig_stations$LATITUDE,
  pch = 16,
  col =  colmap(10)[cut(stations_high_day, 10)]
)
legend(
  x = -72,
  y = 40,
  title = "Day of The Year",
  legend = levels(cut(stations_high_day, 10)),
  col = colmap(10),
  pch = 20,
  xpd = TRUE
)
title("Warmest Day of the Year")
```

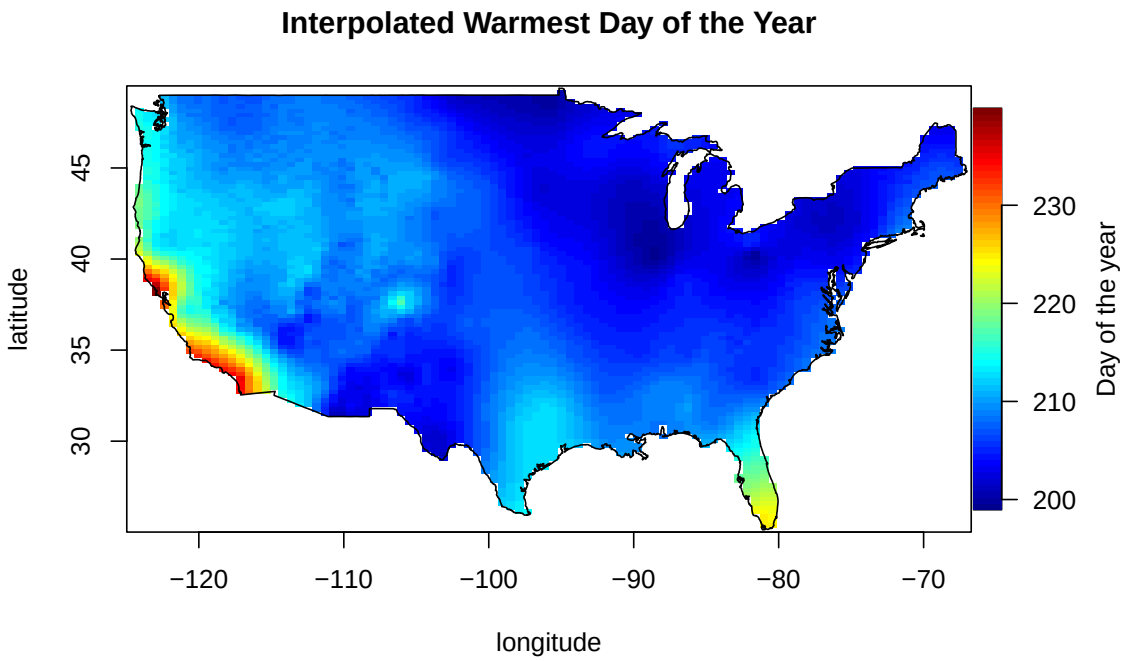



```
maps::map("usa")
points(
  contig_stations$LONGITUDE,
  contig_stations$LATITUDE,
  pch = 16,
  col =  colmap(10)[cut(days_from_jan1, 10)]
)
legend(
  x = -74,
  y = 40,
  title = "Days From Jan 1st",
  legend = levels(cut(days_from_jan1, 10)),
  col = colmap(10),
  pch = 20,
```

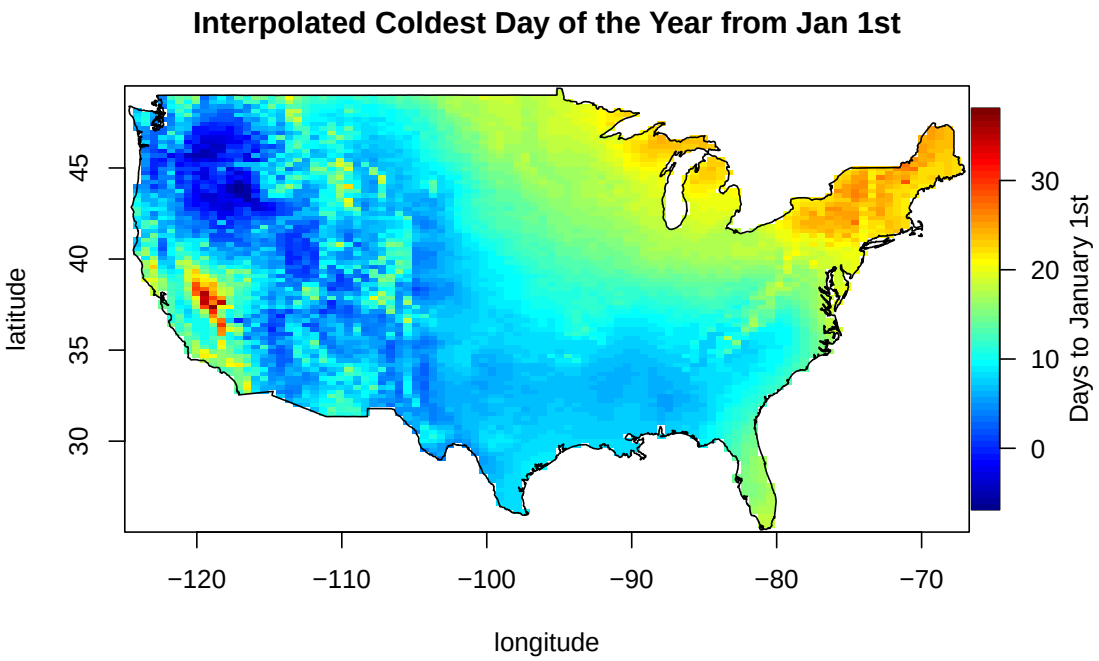
```
  xpd = TRUE
)
title("Coldest Day of the Year")
```




```
high_day_interp_data <- interpolate_data(
  stations_high_day,
  contig_stations$LONGITUDE,
  contig_stations$LATITUDE,
  gridpoints = grid,
  use_elev=T
)
#> 1 observations removed due to missingness or Inf
#> Assuming columns 1 and 2 of locs are (longitude,latidue) in degrees
plot_interpolations(high_day_interp_data)
title("Interpolated Warmest Day of the Year")
mtext("Day of the year", side = 4, line = 3.8)
```




```
low_day_interp_data <- interpolate_data(days_from_jan1,
                                        contig_stations$LONGITUDE,
                                        contig_stations$LATITUDE,
                                        gridpoints = grid,
                                        use_elev=T)
#> 1 observations removed due to missingness or Inf
#> Assuming columns 1 and 2 of locs are (longitude,latidue) in degrees
plot_interpolations(low_day_interp_data)
title("Interpolated Coldest Day of the Year from Jan 1st")
mtext("Days to January 1st", side = 4, line = 3)
```



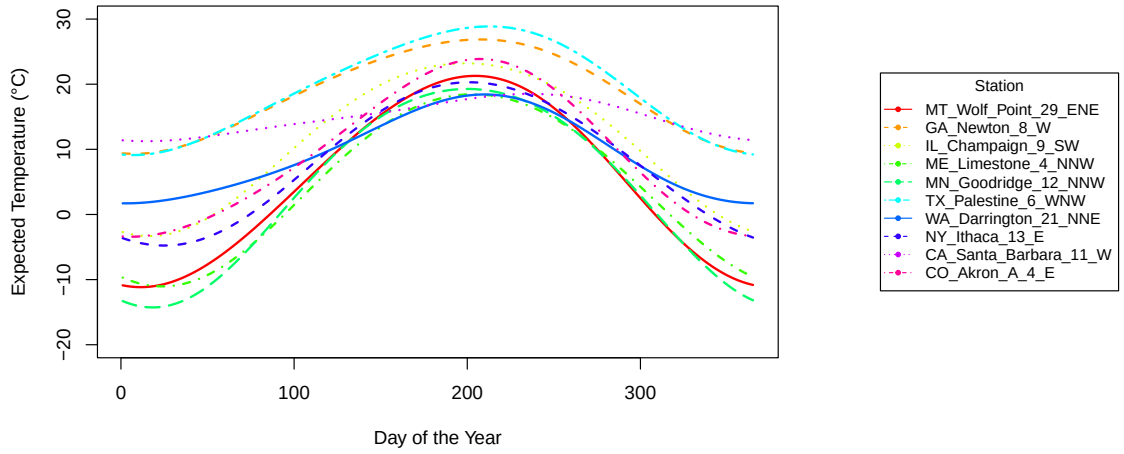
To estimate the warmest and coldest day of the year for each station, we first estimate the yearly temperature cycle for the stations. For each station, we create a ordinary least squares regression based on historical station data which optimizes to predict the daily average temperature for each day of they year using a model with the covariates: $sin(\frac{2\pi * dayofY}{yearlength})$, $cos(\frac{2\pi * dayofY}{yearlength})$, $sin(\frac{4\pi * dayofY}{yearlength})$, and $cos(\frac{4\pi * dayofY}{yearlength})$. These parameters are used to use represent days of the year as a cycle, representing January 1st and December 31st as similar days for weather as an assumption. The linear regression also assumes that each datapoint follows the formula $y_i = x_i * b + \epsilon_i$, where y_i is the average temperature on a day of the year for a station, x_i is vector with 1 (for the intercept term) and $sin(\frac{2\pi * dayofY}{yearlength})$, $cos(\frac{2\pi * dayofY}{yearlength})$, $sin(\frac{4\pi * dayofY}{yearlength})$, and $cos(\frac{4\pi * dayofY}{yearlength})$ as entries, b is a vector of coefficients for each entry in x_i, and ϵ_i is an error distributed normally with mean 0 and variance σ^2, independent from other errors. The optimization finds the b vector that results in the lowest sum of squares: $\sum((y - \hat{y})^2)$. This can be solved both numerically and with a closed-form solution.

Then, to find the coldest and warmest days of the year for each station, we take the days with the minimum and maximum temperature respectively. However, to plot the coldest day of the year, we find the days from January 1st to ensure that days near the end and start of the year are probably encoded as similar dates due to the cyclic nature of the year.

The warmest day of the year is much later in places that tend to be warmer such as CA or FL, while the coldest day of the year is earlier the further you get inland.

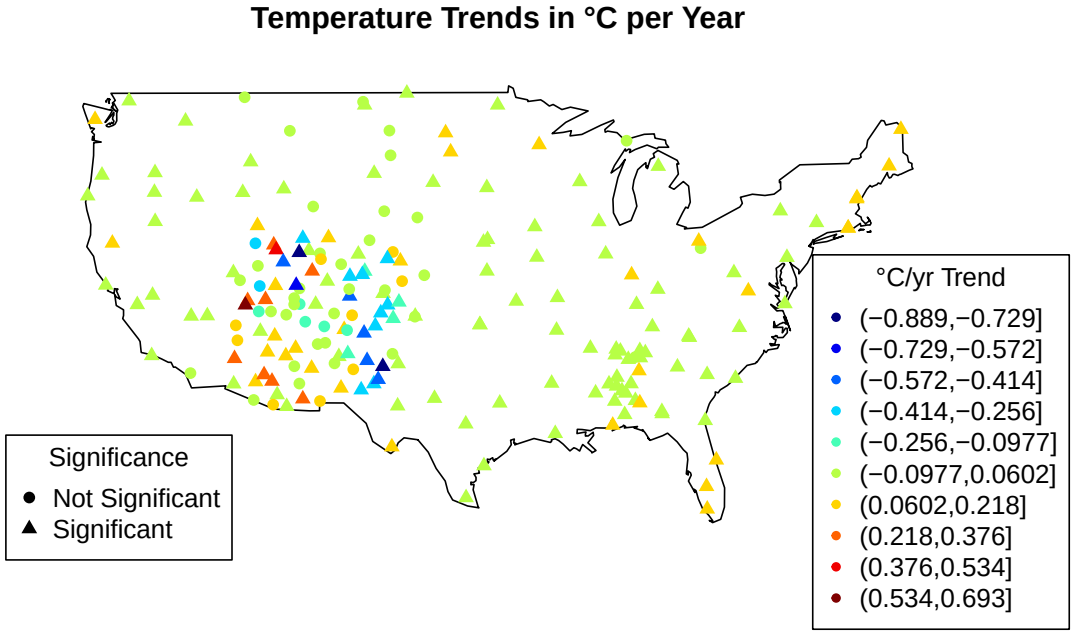
```
diverse_stations_ids <- sort(c(63828, 94060, 4994, 64758,
                               53152, 94092, 53968, 94645,
                               54808, 4223))
diverse_stations <- station_info[station_info$WBANNO %in% diverse_stations_ids, ]

yearly_cycles <- rep(NA, times = 10)
par(mar = c(4, 5, 3, 20), xpd = TRUE)

plot(
  1,
  xlab = "Day of the Year",
  ylab = "Expected Temperature (°C)",
```

```
  xlim = c(1, 365),
  ylim = c(-20, 30),
  type = 'n'
)
i <- 1
for (station_id in diverse_stations$WBANNO) {
  yearly_cycle <- get_yearly_cycle(station_id)
  points(
    x = yearly_cycle$day_of_year,
    y = yearly_cycle$avg_temp,
    type = "l",
    col = rainbow(10)[i],
    lwd = 2,
    lty = i
  )
  i = i + 1
}
par(cex = 0.8)
legend(
  x = "right",
  inset = c(-0.5, 0),
  title = "Station",
  legend = diverse_stations$`station name`,
  col = rainbow(10),
  lty = 1:10,
  pch = 20
)
```

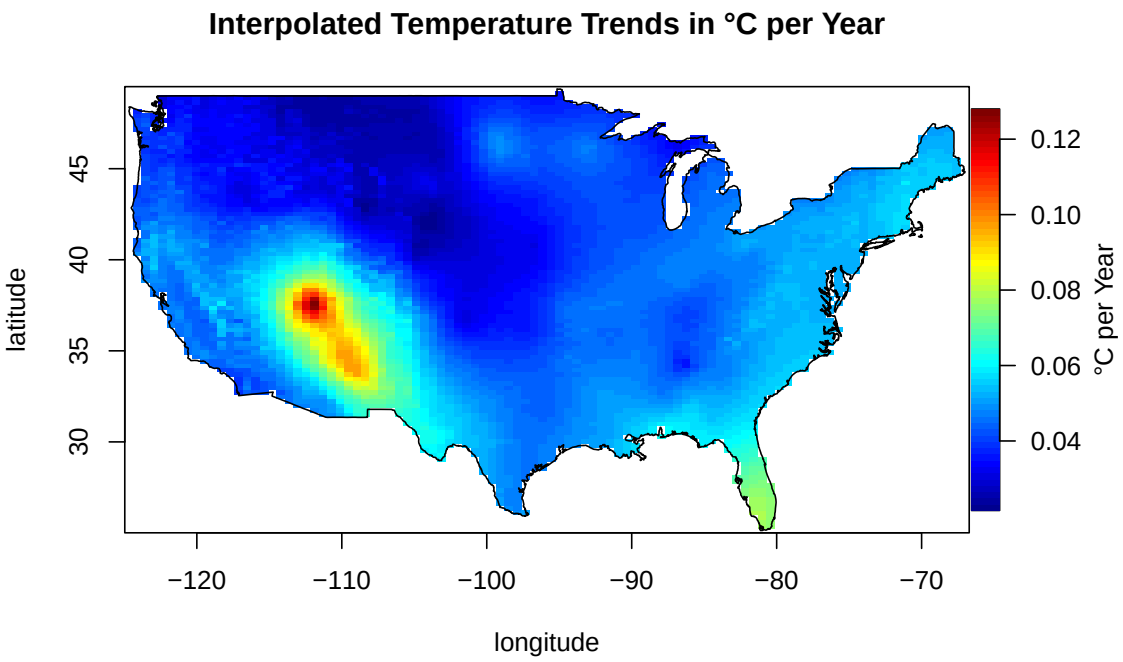



```
trend_coefs <- rep(NA, length = nrow(contig_stations))
standard_errors <- rep(NA, length = nrow(contig_stations))
is_sig <- rep(F, length = nrow(contig_stations))
i <- 1
for (station_id in contig_stations$WBANNO) {
  station_trend = temperature_trend(station_id)
  trend_coefs[i] = station_trend$coefficients["years_elapsed", "Estimate"]
  standard_errors[i] = station_trend$coefficients["years_elapsed", "Std. Error"]
```

```
  is_sig[i] = station_trend$coefficients["years_elapsed", "Pr(>|t|)"] <= 0.05
  i = i + 1
}

maps::map("usa")
points(
  contig_stations$LONGITUDE,
  contig_stations$LATITUDE,
  pch = 16 + is_sig,
  col =  colmap(10)[cut(trend_coefs, 10)]
)
legend(
  x = -74,
  y = 40,
  title = "°C/yr Trend",
  legend = levels(cut(trend_coefs, 10)),
  col = colmap(10),
  pch = 20,
  xpd = TRUE
)
legend(
  x = -130,
  y = 30,
  title = "Significance",
  legend = c("Not Significant", "Significant"),
  col = "black",
  pch = c(16, 17),
  xpd = TRUE
)
title("Temperature Trends in °C per Year")
```



```r
low_se_indices = order(standard_errors)[1:as.integer(length(standard_errors) * 2 /
                                                     3)]

trend_interp_data <- interpolate_data(trend_coefs[low_se_indices],
                                      contig_stations$LONGITUDE[low_se_indices],
                                      contig_stations$LATITUDE[low_se_indices],
                                      gridpoints = grid,
                                      use_elev=T)
#> 1 observations removed due to missingness or Inf
#> Assuming columns 1 and 2 of locs are (longitude,latidue) in degrees
plot_interpolations(trend_interp_data)
title("Interpolated Temperature Trends in °C per Year")
mtext("°C per Year", side = 4, line = 3.8)
```



For each station, a least squares regression was fit on the daily average temperature with the covariate years_elapsed, which represents the years elapsed since the start of 2000. $sin(2\pi * years\_elapsed)$, $cos(2\pi * years\_elapsed)$, $sin(4\pi * years\_elapsed)$, and $cos(4\pi * years\_elapsed)$ were added as well to the model's covariates to ignore influence of cyclic temperature patterns such as seasons. We did this to analyze only the year to year trends in weather as opposed to seasonal trend. Then, we used the coeffecient for the years_elapsed term to estimate the linear temperature trend over the years for each station.

Weather stations experiencing statistically significant changes in temperature per year are indicated with a triangle, as opposed to a circle, on the map. The method to determine statistical significance was a t-test. For each weather station in the contiguous US, this test was conducted with the null hypothesis being that there is no linear yearly temperature trend and the alternative hypothesis being that there is a linear yearly temperature trend. Each weather station then had a T statistic computed, this statistic is defined as $\frac{b_{years\_elapsed}}{SE_{b_{years\_elapsed}}}$, where $b_{years\_elapsed}$ is the station's average temperature trend per year coefficient in the linear model, $SE_{b_{years\_elapsed}}$) is the standard error of the coefficient. This T statistic is proven to be t distributed with (sample_size - na_samples - parameters) degrees of freedom under the null hypothesis. If this test statistic is beyond the middle $(1 - \alpha)\%$ of this t distribution, we reject the null hypothesis and conclude that the temperature trend is significant over time since the null hypothesis is very unlikely to see

given the data. In this case, we use a 95% confidence level and see that most of the station have a statistically significant weather trend over time.

```
# according to https://www.weather.gov/media/slc/
# ClimateBook/Annual%20Average%20Temperature%20By%20Year.pdf
# the National Weather Service
years = 2004:2023
last_20_avg_F <-
  c(
    52.1,
    53.4,
    53.8,
    53.8,
    51.9,
    52.1,
    52.7,
    51.8,
    56.6,
    53.3,
    55.6,
    56.3,
    56.2,
    56.1,
    56.2,
    53.6,
    55.7,
    56.3,
    55.9,
    55.6
  )
last_20_avg_C <- (last_20_avg_F - 32) / 1.8
gov_cycle_lm <- lm(last_20_avg_C ~
                   years)
data_avg_change <- round(mean(trend_coefs[low_se_indices]), 2)
gov_avg_change <- round(summary(gov_cycle_lm)$coefficients["years", "Estimate"], 2)
print(paste("Weather data average trend:", data_avg_change))
#> [1] "Weather data average trend: 0.05"
print(paste("Government data average trend:", gov_avg_change))
#> [1] "Government data average trend: 0.11"
```

According to the National Weather Service data for the average US temperature over the last 20 years, the average change in temperature has been 0.11 degrees Celsius per year. Our data collection and analysis shows that the average change in temperature has been 0.05 degrees Celsius per year. The two estimates are close and may differ due to different locations for the collection of data. However, they both show a positive trend in the temperature in recent years, potentially due to human global warming,