Lindsey’s Climate Farmers Challenge

The work involves the use and analysis of gridded data (usually remote sensing or model products), including land cover, climate and soil. You will need to download and visualize relationships between these over a chosen region.

Load required packages

# List of packages to load  
packages\_today <- c("tidyverse","ecmwfr","ggspatial","sf","rnaturalearth")  
  
# Load the packages  
lapply(packages\_today, library, character.only = TRUE)

## Warning: package 'tidyverse' was built under R version 4.3.2

## Warning: package 'ggplot2' was built under R version 4.3.2

## Warning: package 'tibble' was built under R version 4.3.2

## Warning: package 'tidyr' was built under R version 4.3.2

## Warning: package 'readr' was built under R version 4.3.2

## Warning: package 'purrr' was built under R version 4.3.2

## Warning: package 'dplyr' was built under R version 4.3.2

## Warning: package 'stringr' was built under R version 4.3.2

## Warning: package 'forcats' was built under R version 4.3.2

## Warning: package 'lubridate' was built under R version 4.3.2

## ── Attaching core tidyverse packages ──────────────────────── tidyverse 2.0.0 ──  
## ✔ dplyr 1.1.3 ✔ readr 2.1.4  
## ✔ forcats 1.0.0 ✔ stringr 1.5.0  
## ✔ ggplot2 3.4.4 ✔ tibble 3.2.1  
## ✔ lubridate 1.9.3 ✔ tidyr 1.3.0  
## ✔ purrr 1.0.2   
## ── Conflicts ────────────────────────────────────────── tidyverse\_conflicts() ──  
## ✖ dplyr::filter() masks stats::filter()  
## ✖ dplyr::lag() masks stats::lag()  
## ℹ Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors

## Warning: package 'ecmwfr' was built under R version 4.3.2

## Warning: package 'ggspatial' was built under R version 4.3.2

## Warning: package 'sf' was built under R version 4.3.2

## Linking to GEOS 3.11.2, GDAL 3.7.2, PROJ 9.3.0; sf\_use\_s2() is TRUE

## Warning: package 'rnaturalearth' was built under R version 4.3.2

## Support for Spatial objects (`sp`) will be deprecated in {rnaturalearth} and will be removed in a future release of the package. Please use `sf` objects with {rnaturalearth}. For example: `ne\_download(returnclass = 'sf')`

## [[1]]  
## [1] "lubridate" "forcats" "stringr" "dplyr" "purrr" "readr"   
## [7] "tidyr" "tibble" "ggplot2" "tidyverse" "stats" "graphics"   
## [13] "grDevices" "utils" "datasets" "methods" "base"   
##   
## [[2]]  
## [1] "ecmwfr" "lubridate" "forcats" "stringr" "dplyr" "purrr"   
## [7] "readr" "tidyr" "tibble" "ggplot2" "tidyverse" "stats"   
## [13] "graphics" "grDevices" "utils" "datasets" "methods" "base"   
##   
## [[3]]  
## [1] "ggspatial" "ecmwfr" "lubridate" "forcats" "stringr" "dplyr"   
## [7] "purrr" "readr" "tidyr" "tibble" "ggplot2" "tidyverse"  
## [13] "stats" "graphics" "grDevices" "utils" "datasets" "methods"   
## [19] "base"   
##   
## [[4]]  
## [1] "sf" "ggspatial" "ecmwfr" "lubridate" "forcats" "stringr"   
## [7] "dplyr" "purrr" "readr" "tidyr" "tibble" "ggplot2"   
## [13] "tidyverse" "stats" "graphics" "grDevices" "utils" "datasets"   
## [19] "methods" "base"   
##   
## [[5]]  
## [1] "rnaturalearth" "sf" "ggspatial" "ecmwfr"   
## [5] "lubridate" "forcats" "stringr" "dplyr"   
## [9] "purrr" "readr" "tidyr" "tibble"   
## [13] "ggplot2" "tidyverse" "stats" "graphics"   
## [17] "grDevices" "utils" "datasets" "methods"   
## [21] "base"

setwd("C:/Users/linds/Documents/Climate Farmers Challenge - Code/CF-Challenge")

***Step 1: Region Selection***

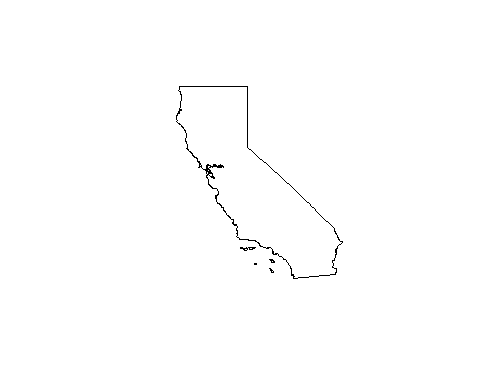
*Decide on a specific region to work with. This region should be large enough to include various land use types but small enough to keep computation times reasonable. A country or region within a country for example. The region can be defined using simple longitude and latitude limits or using a geospatial file (e.g. shape file or geojson). Use this region to filter downloaded data in the next steps.*

First, I use the packages sf and rnaturalearth to access shape files of country and regional boundaries. I will work with the state of California, USA.

# Get the natural earth data for U.S. states  
california\_sf <- ne\_states(country = "united states of america", returnclass = "sf") %>%   
 filter(name == "California") %>% st\_as\_sf()

I confirm the correct geometry of the shape file and write to the computer, encoding with “UTF-8”, as in the original file.

#Use base R to view state outline  
plot(california\_sf$geometry)



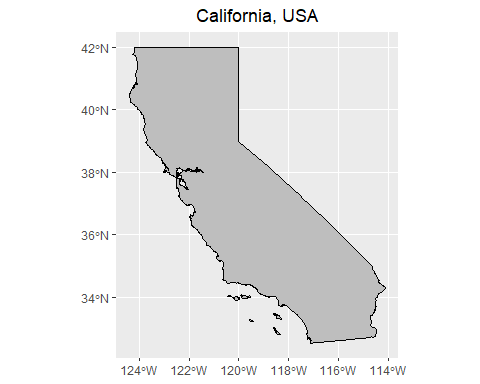
#Save shapefile  
#st\_write(california\_sf, "california\_sf.shp", driver = "ESRI Shapefile", encoding ="UTF-8")

I read back and plot the saved shape file to confirm correct writing to the drive.

#Check file saved correctly by reading in shape file and plotting geometry  
#test\_shp<-st\_read("california\_sf.shp")  
#plot(test\_shp$geometry)

Finally, I plot on coordinates with ggplot2 to confirm the correct geographic position and begin building a graph for later visualisation.

#Generate graph on coordinates to confirm position  
ggplot(data = california\_sf) +  
 geom\_sf() +  
 ggtitle("California, USA") +  
 theme(plot.title = element\_text(hjust = 0.5)) +  
 #xlab("") + ylab("") +  
 geom\_sf(color = "black", fill = "grey")



***Step 2: Data Acquisition***

*Download data for your region for: ● Monthly evapotranspiration, temperature, and precipitation covering the years 2000 to 2022 from (ERA5-Land):* [*https://cds.climate.copernicus.eu/#!/home*](https://cds.climate.copernicus.eu/#!/home) *● Land cover classification maps for the year 2020 from Land Cover Classes (Gridded Map)::* [*https://cds.climate.copernicus.eu/#!/home*](https://cds.climate.copernicus.eu/#!/home) *● Soil organic carbon (SOC) stock data:* [*https://soilgrids.org/*](https://soilgrids.org/) *If there are any questions about what exact variables should be used, use your own judgment to make a choice.*

Comments on CDS functionality and data requests: <https://cran.r-project.org/web/packages/ecmwfr/vignettes/cds_vignette.html>

Ideally, I would have downloaded this data using the package ‘ecmwfr’. First adding the keychain. Instead, for simplicity in completing the activity, I downloaded the data directly from the website using the built-in data navigator

lapply(c("ecmwfr","keyring"), library, character.only = TRUE)

## Warning: package 'keyring' was built under R version 4.3.2

## [[1]]  
## [1] "rnaturalearth" "sf" "ggspatial" "ecmwfr"   
## [5] "lubridate" "forcats" "stringr" "dplyr"   
## [9] "purrr" "readr" "tidyr" "tibble"   
## [13] "ggplot2" "tidyverse" "stats" "graphics"   
## [17] "grDevices" "utils" "datasets" "methods"   
## [21] "base"   
##   
## [[2]]  
## [1] "keyring" "rnaturalearth" "sf" "ggspatial"   
## [5] "ecmwfr" "lubridate" "forcats" "stringr"   
## [9] "dplyr" "purrr" "readr" "tidyr"   
## [13] "tibble" "ggplot2" "tidyverse" "stats"   
## [17] "graphics" "grDevices" "utils" "datasets"   
## [21] "methods" "base"

ecmwfr::wf\_set\_key(user = "269199", key = "a107d4dc-ed19-46dc-ad85-390e61b50920", service = "cds")

## User 269199 for cds service added successfully in keychain

Data Acquisition

● Monthly evapotranspiration, temperature, and precipitation covering the years 2000 to 2022 from (ERA5-Land): <https://cds.climate.copernicus.eu/#!/home>

Examine file with the raster package:

I chose to download total evaporation, soil temperature layer 1, and total precipitation at 12:00. Midday measurements will capture the transpiration component of evapotranspiration. During the default 0:00 measurements, the stomata of C3 plants are closed; thus no transpiration takes places.

Comments on use of midday measurements: <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8739081/>

Shallow soils (layer 1) contain the organic horizon and are most dynamic in response to ambient temperature and precipitation.

I wrote a function to extract the data by climate variables, defining a brick for each one in the global environment. The new named brick files should be: stl1\_brick, e\_brick, tp\_brick

lapply(c("raster","ncdf4"), library, character.only = TRUE)

## Warning: package 'raster' was built under R version 4.3.2

## Loading required package: sp

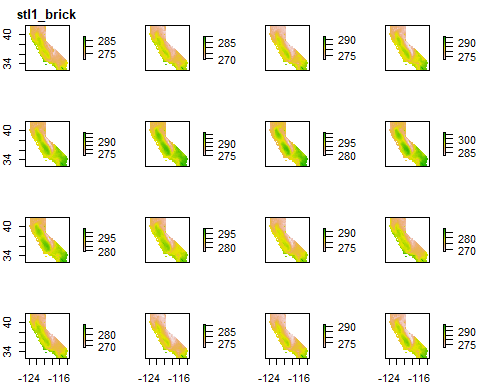
## Warning: package 'sp' was built under R version 4.3.2

##   
## Attaching package: 'raster'

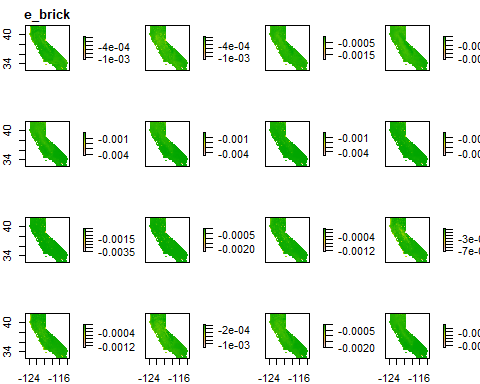
## The following object is masked from 'package:dplyr':  
##   
## select

## [[1]]  
## [1] "raster" "sp" "keyring" "rnaturalearth"  
## [5] "sf" "ggspatial" "ecmwfr" "lubridate"   
## [9] "forcats" "stringr" "dplyr" "purrr"   
## [13] "readr" "tidyr" "tibble" "ggplot2"   
## [17] "tidyverse" "stats" "graphics" "grDevices"   
## [21] "utils" "datasets" "methods" "base"   
##   
## [[2]]  
## [1] "ncdf4" "raster" "sp" "keyring"   
## [5] "rnaturalearth" "sf" "ggspatial" "ecmwfr"   
## [9] "lubridate" "forcats" "stringr" "dplyr"   
## [13] "purrr" "readr" "tidyr" "tibble"   
## [17] "ggplot2" "tidyverse" "stats" "graphics"   
## [21] "grDevices" "utils" "datasets" "methods"   
## [25] "base"

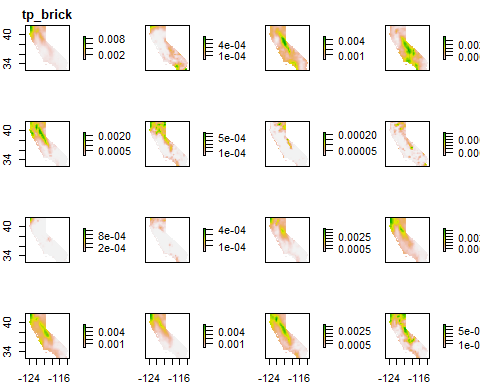
#read .nc file and convert to a brick - specify a variable  
#varname: stl1, e, tp  
  
nc\_file\_path <- "temp\_evap\_prec.nc"  
variable\_name <- "stl1"  
  
read\_var <- function(nc\_file\_path, variable\_name) {  
  
 var\_name <- deparse(substitute(variable\_name)) #unevaluated argument name, converted to character   
   
 clean\_var\_name <- gsub("\"", "", var\_name) #remove double quotations  
   
 # Read the NetCDF file for the specified variable  
 #Use the cleaned variable name in the assign function  
 assign(paste0(clean\_var\_name, "\_brick"), brick(nc\_file\_path, varname = variable\_name), envir = .GlobalEnv)  
  
 #crop to CA and plot  
 var\_cropped <- crop(get(paste0(clean\_var\_name, "\_brick")), extent(california\_sf))  
 var\_masked <- mask(var\_cropped, california\_sf)  
 plot(var\_masked, main = paste0(clean\_var\_name, "\_brick"))  
}  
  
read\_var("temp\_evap\_prec.nc","stl1")



read\_var("temp\_evap\_prec.nc","e")



read\_var("temp\_evap\_prec.nc","tp")



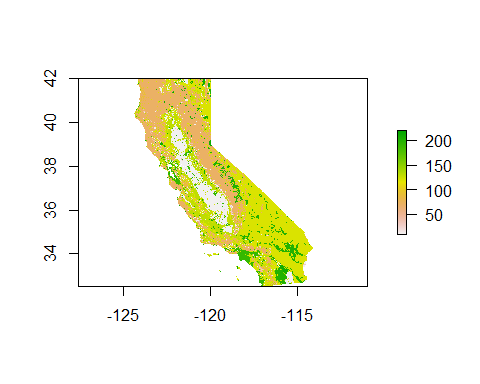
*● Land cover classification maps for the year 2020 from Land Cover Classes (Gridded Map)::* [*https://cds.climate.copernicus.eu/#!/home*](https://cds.climate.copernicus.eu/#!/home)

Look at land cover classes from 2020

landcover <- raster("landcover.nc")

## Warning in .varName(nc, varname, warn = warn): varname used is: lccs\_class  
## If that is not correct, you can set it to one of: lccs\_class, processed\_flag, current\_pixel\_state, observation\_count, change\_count

#crop to CA and plot  
var\_cropped <- crop(landcover, extent(california\_sf))  
cal\_cover <- mask(var\_cropped, california\_sf)  
plot(cal\_cover)

 Interpret the land cover data. IPCC Classes on page 15:

<https://datastore.copernicus-climate.eu/documents/satellite-land-cover/D5.3.1_PUGS_ICDR_LC_v2.1.x_PRODUCTS_v1.1.pdf>

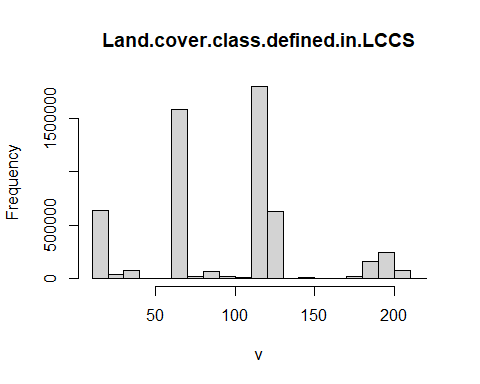
The most common classes are:

10 - Rainfed cropland 60 - Forest, Tree cover, broadleaved, deciduous, closed to open (> 15%) 110 - Grassland, Mosaic herbaceous cover (>50%) / tree and shrub (<50%) 120 - Shrubland

library(sp) #Load package for managing spatial data  
unique(cal\_cover$Land.cover.class.defined.in.LCCS)

## [1] 10 11 30 40 60 70 80 90 100 110 120 130 150 160 180 190 200 210 220

hist(cal\_cover$Land.cover.class.defined.in.LCCS)



For now, I am leaving out the soil carbon data due to time constraints. I may be able to return later to this task.

***Step 3: Data Integration*** *Reproject the different rasters to match the one with lowest resolution, thus allowing joint analysis.*

From this step forward, I will only work with the soil data brick ‘stl1\_brick’ (shallow soil temperature). This allows me to show an example of the basic spatial data processing steps I could use here. Once this process is optimised, I would write a function to carry out the same steps on the other bricks. I could also combine the bricks into a stack and loop a function over the bricks in the stack.

I used the raster package to check the resolution of the land cover raster and the soil temperature brick.

#Confirm resolution of each data set  
  
res(cal\_cover)

## [1] 0.002777778 0.002777778

proj4string(cal\_cover)

## [1] "+proj=longlat +datum=WGS84 +no\_defs"

res(stl1\_brick)

## [1] 0.1 0.1

proj4string(stl1\_brick)

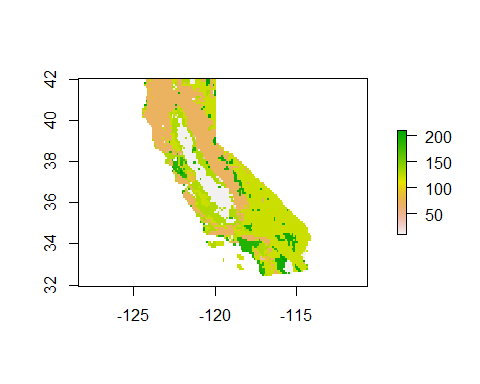
## [1] "+proj=longlat +datum=WGS84 +no\_defs"

Now I will reproject the land cover data to the lower resolution of the ERA5 climate data. The ‘resample’ function from the ‘raster’ package estimates a new value for the lower resolution data, based on a defined method. I chose ‘nearest neighbor’, which is suitable for preserving the categorical data of land cover classes.

# Resample the higher resolution raster to the resolution of the lower resolution raster  
cal\_cover\_res <- resample(cal\_cover, stl1\_brick, method = "ngb")  
res(cal\_cover\_res)

## [1] 0.1 0.1

plot(cal\_cover\_res)



unique(cal\_cover\_res)

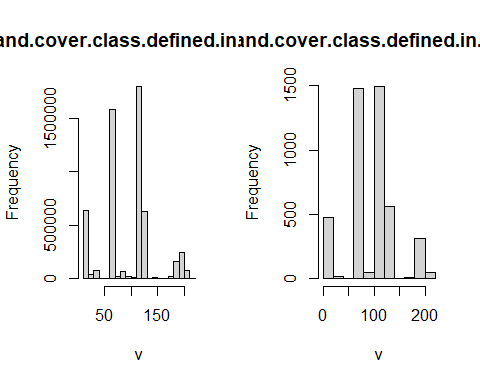
## [1] 10 11 30 40 70 80 90 110 120 130 160 180 190 200 210

Graph the high- and low-resolution histograms of land cover classes to check distribution in both projections. Note that a few rare land cover classes were lost in resampling, but the main categories are retained:

10 - Rainfed cropland 60 - Forest, Tree cover, broadleaved, deciduous, closed to open (> 15%) 110 - Grassland, Mosaic herbaceous cover (>50%) / tree and shrub (<50%) 120 - Shrubland

Unique values of land cover class are: [1] 10 11 30 40 70 80 90 110 120 130 160 180 190 200 210

par(mfrow=c(1,2))  
hist(cal\_cover$Land.cover.class.defined.in.LCCS)  
hist(cal\_cover\_res$Land.cover.class.defined.in.LCCS)



par(mfrow=c(1,1))

***Step 4: Analysis and Visualization*** *Visualize the time series of climate and soil variables in the format of your choice, aggregated separately for different land cover classes.*

Due to time constraints, I am only providing a basic time series visualisation of the soil temperature data, aggregated by land cover class. As mentioned above, this could be further written as a function to efficiently analyses other bricks in the same fasion or to loop across the bricks in a stack.

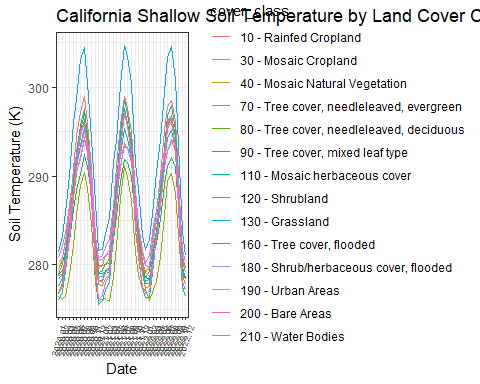
#head(cal\_cover\_res)  
#head(stl1\_brick)  
  
  
# Convert the brick to a data frame  
  
stl1\_df <- rasterToPoints(stl1\_brick) %>% as.data.frame()  
cover\_df <- rasterToPoints(cal\_cover\_res) %>% as.data.frame()  
  
#Join the data frames bases on x,y coordinates (lat,lon) so that the land cover and soil temperature data coorespond spatially.  
  
full\_df <- full\_join(cover\_df, stl1\_df, by = c("x","y")) %>% na.omit() %>%   
 rename(cover\_class = "Land.cover.class.defined.in.LCCS") %>%  
 mutate(cover\_class = as.factor(cover\_class))  
  
stl1\_summ <- full\_df[3:39.] %>%  
 gather(2:37,key="date",value="value") %>%  
 mutate(cover\_class = recode(cover\_class,  
 "10" = "10 - Rainfed Cropland",  
 "11" = "10 - Rainfed Cropland",  
 "30" = "30 - Mosaic Cropland",  
 "40" = "40 - Mosaic Natural Vegetation",  
 "70" = "70 - Tree cover, needleleaved, evergreen",  
 "80" = "80 - Tree cover, needleleaved, deciduous",  
 "90" = "90 - Tree cover, mixed leaf type",  
 "110" = "110 - Mosaic herbaceous cover",  
 "120" = "120 - Shrubland", "130" = "130 - Grassland",  
 "160" = "160 - Tree cover, flooded",  
 "180" = "180 - Shrub/herbaceous cover, flooded",  
 "190" = "190 - Urban Areas", "200" = "200 - Bare Areas", "210" = "210 - Water Bodies")) %>%  
 mutate(date = substr(as.character(date), start = 2, stop = nchar(as.character(date)) - 12)) %>%  
 mutate(date = as.factor(date)) %>%  
 group\_by(cover\_class, date) %>%   
 summarise(mn.val = mean(value), se = sd(value)/sqrt(length(value))) %>%   
 as.data.frame()

## `summarise()` has grouped output by 'cover\_class'. You can override using the  
## `.groups` argument.

stl1\_summ

## cover\_class date mn.val se  
## 1 10 - Rainfed Cropland 2020.01 279.5419 0.06416343  
## 2 10 - Rainfed Cropland 2020.02 280.7352 0.08281712  
## 3 10 - Rainfed Cropland 2020.03 282.7083 0.09833367  
## 4 10 - Rainfed Cropland 2020.04 285.9315 0.11014201  
## 5 10 - Rainfed Cropland 2020.05 290.8992 0.13491417  
## 6 10 - Rainfed Cropland 2020.06 294.4858 0.13505885  
## 7 10 - Rainfed Cropland 2020.07 297.1305 0.16037578  
## 8 10 - Rainfed Cropland 2020.08 298.9098 0.15299433  
## 9 10 - Rainfed Cropland 2020.09 295.8662 0.12686699  
## 10 10 - Rainfed Cropland 2020.10 290.9002 0.10584744  
## 11 10 - Rainfed Cropland 2020.11 282.7922 0.09311227  
## 12 10 - Rainfed Cropland 2020.12 279.6464 0.07262831  
## 13 10 - Rainfed Cropland 2021.01 279.9876 0.07122144  
## 14 10 - Rainfed Cropland 2021.02 281.0523 0.08881309  
## 15 10 - Rainfed Cropland 2021.03 281.6119 0.10026480  
## 16 10 - Rainfed Cropland 2021.04 286.6164 0.13260561  
## 17 10 - Rainfed Cropland 2021.05 291.0912 0.12805371  
## 18 10 - Rainfed Cropland 2021.06 295.7965 0.14609125  
## 19 10 - Rainfed Cropland 2021.07 298.9562 0.17333275  
## 20 10 - Rainfed Cropland 2021.08 297.7373 0.16338849  
## 21 10 - Rainfed Cropland 2021.09 295.0416 0.14741132  
## 22 10 - Rainfed Cropland 2021.10 288.1242 0.09730945  
## 23 10 - Rainfed Cropland 2021.11 283.9972 0.09859380  
## 24 10 - Rainfed Cropland 2021.12 280.5274 0.06662540  
## 25 10 - Rainfed Cropland 2022.01 279.1970 0.06657201  
## 26 10 - Rainfed Cropland 2022.02 279.8872 0.08696064  
## 27 10 - Rainfed Cropland 2022.03 283.6669 0.10080704  
## 28 10 - Rainfed Cropland 2022.04 286.0280 0.13299076  
## 29 10 - Rainfed Cropland 2022.05 290.0847 0.13795270  
## 30 10 - Rainfed Cropland 2022.06 295.0807 0.14953563  
## 31 10 - Rainfed Cropland 2022.07 297.7671 0.17271636  
## 32 10 - Rainfed Cropland 2022.08 298.5172 0.16966775  
## 33 10 - Rainfed Cropland 2022.09 296.0834 0.13877599  
## 34 10 - Rainfed Cropland 2022.10 290.1583 0.11545133  
## 35 10 - Rainfed Cropland 2022.11 280.8593 0.07767463  
## 36 10 - Rainfed Cropland 2022.12 279.5872 0.05470532  
## 37 30 - Mosaic Cropland 2020.01 276.7805 0.26486336  
## 38 30 - Mosaic Cropland 2020.02 277.9916 0.41965857  
## 39 30 - Mosaic Cropland 2020.03 280.1862 0.35780099  
## 40 30 - Mosaic Cropland 2020.04 282.8984 0.33639003  
## 41 30 - Mosaic Cropland 2020.05 287.4085 0.53058998  
## 42 30 - Mosaic Cropland 2020.06 291.5060 0.63634411  
## 43 30 - Mosaic Cropland 2020.07 294.4955 0.59721891  
## 44 30 - Mosaic Cropland 2020.08 296.3681 0.63197350  
## 45 30 - Mosaic Cropland 2020.09 293.6067 0.65236626  
## 46 30 - Mosaic Cropland 2020.10 288.7471 0.71913442  
## 47 30 - Mosaic Cropland 2020.11 280.8699 0.36978798  
## 48 30 - Mosaic Cropland 2020.12 277.8012 0.39625700  
## 49 30 - Mosaic Cropland 2021.01 277.7094 0.28770981  
## 50 30 - Mosaic Cropland 2021.02 278.4555 0.29681575  
## 51 30 - Mosaic Cropland 2021.03 278.8227 0.43790575  
## 52 30 - Mosaic Cropland 2021.04 283.3552 0.60003251  
## 53 30 - Mosaic Cropland 2021.05 287.7997 0.63486298  
## 54 30 - Mosaic Cropland 2021.06 293.6402 0.56330169  
## 55 30 - Mosaic Cropland 2021.07 297.5476 0.48765533  
## 56 30 - Mosaic Cropland 2021.08 295.9224 0.58104370  
## 57 30 - Mosaic Cropland 2021.09 292.9983 0.65854348  
## 58 30 - Mosaic Cropland 2021.10 285.6207 0.57132894  
## 59 30 - Mosaic Cropland 2021.11 281.7915 0.30708687  
## 60 30 - Mosaic Cropland 2021.12 279.0314 0.20525046  
## 61 30 - Mosaic Cropland 2022.01 277.3441 0.34395562  
## 62 30 - Mosaic Cropland 2022.02 277.5466 0.48938981  
## 63 30 - Mosaic Cropland 2022.03 280.6653 0.46764639  
## 64 30 - Mosaic Cropland 2022.04 282.7790 0.43127437  
## 65 30 - Mosaic Cropland 2022.05 286.8987 0.63847583  
## 66 30 - Mosaic Cropland 2022.06 292.1850 0.67504618  
## 67 30 - Mosaic Cropland 2022.07 295.8460 0.57371402  
## 68 30 - Mosaic Cropland 2022.08 296.8496 0.53887241  
## 69 30 - Mosaic Cropland 2022.09 294.3161 0.73224938  
## 70 30 - Mosaic Cropland 2022.10 288.0485 0.76654767  
## 71 30 - Mosaic Cropland 2022.11 278.9600 0.41183883  
## 72 30 - Mosaic Cropland 2022.12 277.8402 0.39068931  
## 73 40 - Mosaic Natural Vegetation 2020.01 279.6606 0.24634292  
## 74 40 - Mosaic Natural Vegetation 2020.02 280.3243 0.29973760  
## 75 40 - Mosaic Natural Vegetation 2020.03 281.2480 0.35152023  
## 76 40 - Mosaic Natural Vegetation 2020.04 284.0855 0.29234205  
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## 395 180 - Shrub/herbaceous cover, flooded 2022.11 281.6045 0.70799824  
## 396 180 - Shrub/herbaceous cover, flooded 2022.12 280.3315 0.47046277  
## 397 190 - Urban Areas 2020.01 280.2970 0.10286414  
## 398 190 - Urban Areas 2020.02 280.8240 0.09830608  
## 399 190 - Urban Areas 2020.03 282.5668 0.10738901  
## 400 190 - Urban Areas 2020.04 285.0275 0.09629035  
## 401 190 - Urban Areas 2020.05 288.3811 0.12471354  
## 402 190 - Urban Areas 2020.06 290.5564 0.15969946  
## 403 190 - Urban Areas 2020.07 291.8563 0.20615461  
## 404 190 - Urban Areas 2020.08 294.0851 0.20756741  
## 405 190 - Urban Areas 2020.09 292.5990 0.14927370  
## 406 190 - Urban Areas 2020.10 289.6209 0.11131137  
## 407 190 - Urban Areas 2020.11 283.1743 0.12750868  
## 408 190 - Urban Areas 2020.12 280.5151 0.12965248  
## 409 190 - Urban Areas 2021.01 280.5850 0.10928702  
## 410 190 - Urban Areas 2021.02 281.0308 0.10257348  
## 411 190 - Urban Areas 2021.03 281.2274 0.09670409  
## 412 190 - Urban Areas 2021.04 285.0023 0.12223230  
## 413 190 - Urban Areas 2021.05 287.8454 0.14595409  
## 414 190 - Urban Areas 2021.06 290.9459 0.19641423  
## 415 190 - Urban Areas 2021.07 293.5388 0.26722856  
## 416 190 - Urban Areas 2021.08 293.0648 0.22368592  
## 417 190 - Urban Areas 2021.09 291.5721 0.17626933  
## 418 190 - Urban Areas 2021.10 286.9572 0.07801542  
## 419 190 - Urban Areas 2021.11 284.4522 0.10770079  
## 420 190 - Urban Areas 2021.12 281.3235 0.09577042  
## 421 190 - Urban Areas 2022.01 279.9786 0.11492922  
## 422 190 - Urban Areas 2022.02 279.8801 0.11181325  
## 423 190 - Urban Areas 2022.03 282.9456 0.09564732  
## 424 190 - Urban Areas 2022.04 285.0626 0.13612234  
## 425 190 - Urban Areas 2022.05 287.3791 0.13556141  
## 426 190 - Urban Areas 2022.06 291.1068 0.17726101  
## 427 190 - Urban Areas 2022.07 292.7536 0.23164233  
## 428 190 - Urban Areas 2022.08 294.0816 0.24027917  
## 429 190 - Urban Areas 2022.09 293.4404 0.19810733  
## 430 190 - Urban Areas 2022.10 288.8824 0.14291799  
## 431 190 - Urban Areas 2022.11 281.3953 0.12758169  
## 432 190 - Urban Areas 2022.12 280.3947 0.11420758  
## 433 200 - Bare Areas 2020.01 276.6730 0.20641728  
## 434 200 - Bare Areas 2020.02 277.6575 0.27982580  
## 435 200 - Bare Areas 2020.03 279.8223 0.39062209  
## 436 200 - Bare Areas 2020.04 282.9110 0.52577094  
## 437 200 - Bare Areas 2020.05 287.6652 0.67568693  
## 438 200 - Bare Areas 2020.06 291.0168 0.61731627  
## 439 200 - Bare Areas 2020.07 294.6681 0.58206254  
## 440 200 - Bare Areas 2020.08 296.0523 0.59037530  
## 441 200 - Bare Areas 2020.09 292.5545 0.52391976  
## 442 200 - Bare Areas 2020.10 287.0265 0.48110152  
## 443 200 - Bare Areas 2020.11 279.9292 0.38944455  
## 444 200 - Bare Areas 2020.12 276.0993 0.25844223  
## 445 200 - Bare Areas 2021.01 276.5616 0.26873976  
## 446 200 - Bare Areas 2021.02 277.8737 0.31163447  
## 447 200 - Bare Areas 2021.03 278.8385 0.36541725  
## 448 200 - Bare Areas 2021.04 283.3936 0.56655577  
## 449 200 - Bare Areas 2021.05 286.5607 0.62045885  
## 450 200 - Bare Areas 2021.06 292.9133 0.61391160  
## 451 200 - Bare Areas 2021.07 297.2243 0.61533892  
## 452 200 - Bare Areas 2021.08 295.5838 0.59620060  
## 453 200 - Bare Areas 2021.09 292.3910 0.55382950  
## 454 200 - Bare Areas 2021.10 283.8661 0.44461217  
## 455 200 - Bare Areas 2021.11 281.1805 0.43120459  
## 456 200 - Bare Areas 2021.12 277.5209 0.28746702  
## 457 200 - Bare Areas 2022.01 276.8195 0.22692854  
## 458 200 - Bare Areas 2022.02 277.0470 0.26280245  
## 459 200 - Bare Areas 2022.03 280.2832 0.42138041  
## 460 200 - Bare Areas 2022.04 283.3079 0.55542688  
## 461 200 - Bare Areas 2022.05 286.4373 0.60959674  
## 462 200 - Bare Areas 2022.06 291.7211 0.62793547  
## 463 200 - Bare Areas 2022.07 296.1198 0.58191248  
## 464 200 - Bare Areas 2022.08 296.5360 0.63533691  
## 465 200 - Bare Areas 2022.09 292.7414 0.56718051  
## 466 200 - Bare Areas 2022.10 286.3188 0.52516005  
## 467 200 - Bare Areas 2022.11 278.1015 0.26269381  
## 468 200 - Bare Areas 2022.12 277.2891 0.18508747  
## 469 210 - Water Bodies 2020.01 278.7929 0.71805424  
## 470 210 - Water Bodies 2020.02 278.9019 0.91573406  
## 471 210 - Water Bodies 2020.03 280.2941 1.01686409  
## 472 210 - Water Bodies 2020.04 283.6854 1.07931821  
## 473 210 - Water Bodies 2020.05 288.1209 1.18131239  
## 474 210 - Water Bodies 2020.06 291.5038 1.03461255  
## 475 210 - Water Bodies 2020.07 294.9584 0.96236777  
## 476 210 - Water Bodies 2020.08 296.0438 0.97073009  
## 477 210 - Water Bodies 2020.09 293.3357 0.98619184  
## 478 210 - Water Bodies 2020.10 288.4166 1.06720082  
## 479 210 - Water Bodies 2020.11 281.6286 0.98083862  
## 480 210 - Water Bodies 2020.12 278.2697 0.82609154  
## 481 210 - Water Bodies 2021.01 278.1693 0.81123840  
## 482 210 - Water Bodies 2021.02 279.1209 0.92135365  
## 483 210 - Water Bodies 2021.03 279.5130 1.00554840  
## 484 210 - Water Bodies 2021.04 283.5844 1.17317657  
## 485 210 - Water Bodies 2021.05 287.5686 1.09252614  
## 486 210 - Water Bodies 2021.06 293.2881 0.98248653  
## 487 210 - Water Bodies 2021.07 296.9261 0.92452055  
## 488 210 - Water Bodies 2021.08 295.6477 0.96773827  
## 489 210 - Water Bodies 2021.09 292.6647 1.04397970  
## 490 210 - Water Bodies 2021.10 285.9006 0.97835902  
## 491 210 - Water Bodies 2021.11 282.4465 1.06224887  
## 492 210 - Water Bodies 2021.12 279.5464 0.77608070  
## 493 210 - Water Bodies 2022.01 279.1333 0.70205924  
## 494 210 - Water Bodies 2022.02 278.7263 0.86524363  
## 495 210 - Water Bodies 2022.03 280.3247 1.13431381  
## 496 210 - Water Bodies 2022.04 283.1282 1.21302368  
## 497 210 - Water Bodies 2022.05 286.5235 1.18232349  
## 498 210 - Water Bodies 2022.06 291.4026 1.11747381  
## 499 210 - Water Bodies 2022.07 295.3578 0.97398557  
## 500 210 - Water Bodies 2022.08 296.1869 0.99616535  
## 501 210 - Water Bodies 2022.09 293.2772 0.98829516  
## 502 210 - Water Bodies 2022.10 288.0346 1.05556212  
## 503 210 - Water Bodies 2022.11 281.0153 0.77434137  
## 504 210 - Water Bodies 2022.12 279.6879 0.64383089

# Plot the time series using ggplot2  
stl1\_plot <- ggplot(data=stl1\_summ, aes(x=date, y=mn.val, group = cover\_class)) +   
 geom\_line(aes(color=cover\_class), linewidth=.3, position = position\_dodge(width=0)) +  
 #geom\_errorbar(aes(ymin=mn.val-se,ymax=mn.val+se, color = cover\_class), size=.3, width=.3, position = position\_dodge(width=0)) +  
 ylab(expression("Soil Temperature (K)")) +  
 xlab("Date") + theme\_bw() +  
 ggtitle("California Shallow Soil Temperature by Land Cover Class") +  
 theme(axis.text.x = element\_text(angle = 70, vjust = 1, hjust = 1, size = 7))  
  
stl1\_plot



***Step 5: Sampling Design*** *Imagine you wanted to detect changes in SOC in the region in response to farm management practices or some other factor. so you need a sampling plan. Based on the SOC data you obtained, determine the number of samples that would need to be taken in the region in order to have a 95% confidence interval equal or less than 10% of the mean value. Assume a Gaussian distribution.*

Due to time constraints, I did not calculate this minimum required sample size from the SOC data. This would be possible to calculate from the formula for sample size, assuming a Gaussian (normal) distribution. According the the central limit theorem, the mean distribution of a sample will tend toward normality, as long as the sample size is high enough; therefore, the assumption of a Gaussian distribution is appropriate for large spatial data sets.

sample size = (Z^2 x sd2)/(E2)

Z = The Z-score for the 95% confidence interval sd = Estimated standard deviation, derived from the sample E = The desired margin of error

Alternatively, I will calculate the required samples size required for the same error parameters, but for data from soil temperature (stl1\_brick) at a given time (May 2022).

# Given error parameters  
conf\_int <- 0.95 # 95% confidence interval  
Z <- qnorm((1 + conf\_int) / 2) # Z-score for the given confidence level  
margin\_of\_error <- 0.10 # Desired margin of error - 10% of the mean  
  
# Estimate standard deviation  
est\_sd <- sd(as.vector(stl1\_brick$X2022.05.01.12.00.00), na.rm = TRUE)  
  
# Calculate required sample size  
sample\_size <- (Z^2 \* est\_sd^2) / (margin\_of\_error^2)  
  
# Round up to the nearest integer  
sample\_size <- ceiling(sample\_size)  
  
# Print the result  
print(sample\_size)

## [1] 9982