ESM232 A2 function application

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1. The function

```
#This is our function which models annual yield anomalies based research conducted by Lobell et
 al., 2006. More details, including variables and parameters, are in the R script.
source("R/almond_yield_anomaly.R")
```

2. Data wrangling

This subsetting process requires the following column formatting:

1. variable "month" with values January-December indicated as 1-12
2. variable "year"
3. variable "precip" with values of precipitation in mm
4. variable "temp" with values for of temperature in degrees C

```
# Read in climate data.
clim <- read.table("clim.txt")

# We need to subset the precipitation data for the January precipitation parameter.
# First, filter for January data (month == 1).
precip <- clim %>%
  filter(month == 1)

# Then, group the precipitation data by year and then sum to create annual January rainfall tota
ls.
jan_precip_sum <- precip %>%
  group_by(year) %>%
  summarize(
    jan_precip_sum = sum(precip)
  )

# Next we need to subset the temperature data for the Feburary temperature parameter.
# First, filter for February.
temp <- clim %>%
  filter(month == 2)

# Then, group by year and find the average value each year.
feb_temp_min <- temp %>%
  group_by(year) %>%
  summarize(
    feb_tmin = mean(tmin_c)
  )
```

3. Function application

```
# Data subsetting is complete.
# Now time to generate our outputs (annual yield anomaly in ton/acre).

# Generate vector of years
yset <- jan_precip_sum$year

# Generate empty holding list to store yield anomalies for each year using yset vector generate
d.
yieldanoms<- NaN*(yset)

# Loop through years and store yield anomaly outputs in yieldanoms vector.
for(j in 1:length(yieldanoms)){
  yieldanoms[j]<-almond_yield_anomaly(feb_temp_min[j,2],
                         jan_precip_sum[j,2])
                         }

#Next convert the results to a df to use ggplot. First list to a vector.
yieldanoms_vector <- unlist(yieldanoms)

#Next to a dataframe.
yieldanoms_df<- data.frame(yset, yieldanoms_vector) %>%
  rename(year = yset,
         yield_anomaly = yieldanoms_vector) %>%
  merge(feb_temp_min, by = "year") %>%
  merge(jan_precip_sum, by = "year") %>%
  rename(jan_precip = jan_precip_sum)
```

4. Result plots

For simplicity, we will not include the codes related to plot and table generation in the final report. All data used in Section 4 came from `yieldanoms_df` . Feel free to access to our full Rmd codes here (https://github.com/Ruoyu-Wang108/ESM232-A2/blob/main/MB-NE-RW-ESM232-A2.Rmd).

4.1 The historic yield anomalies

First we wanted to plot the historic yield anomalies as output by the Lobell et al. function.

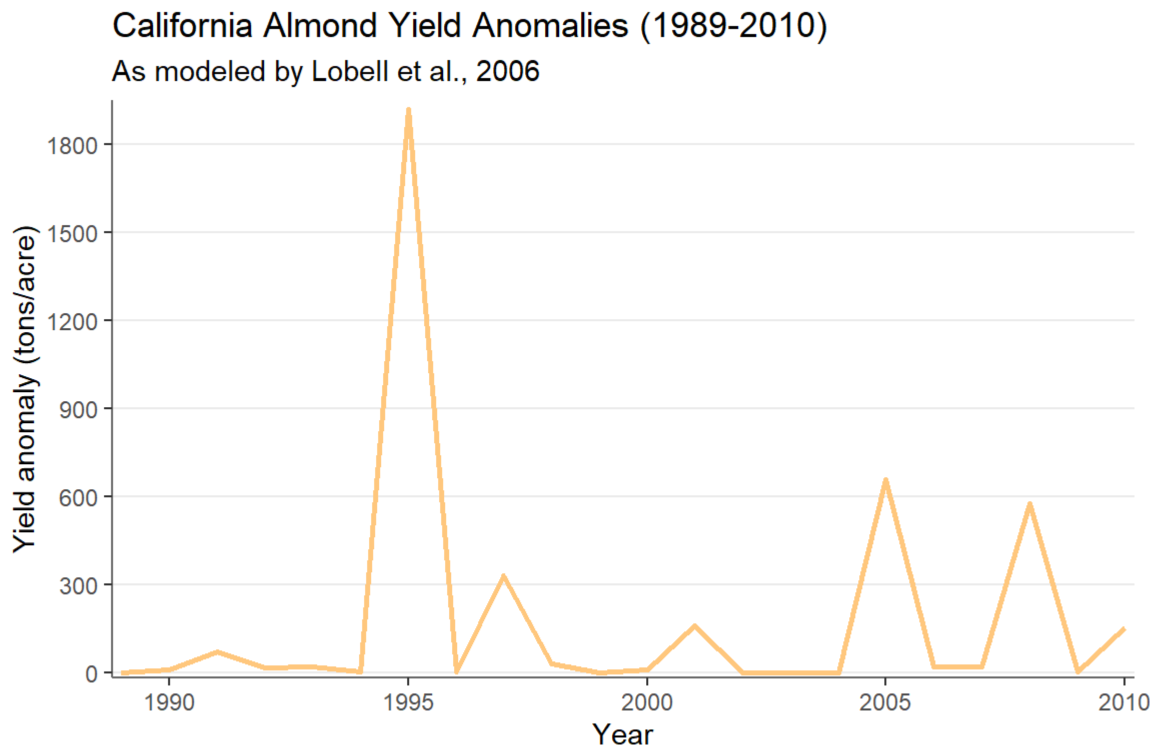

Figure 1. *California almond yield anomalies from 1989-2010 modeled using the statistical model developed by Lobell et al., 2006.*

4.2 The precipitation trend

Next to plot the precipitation.

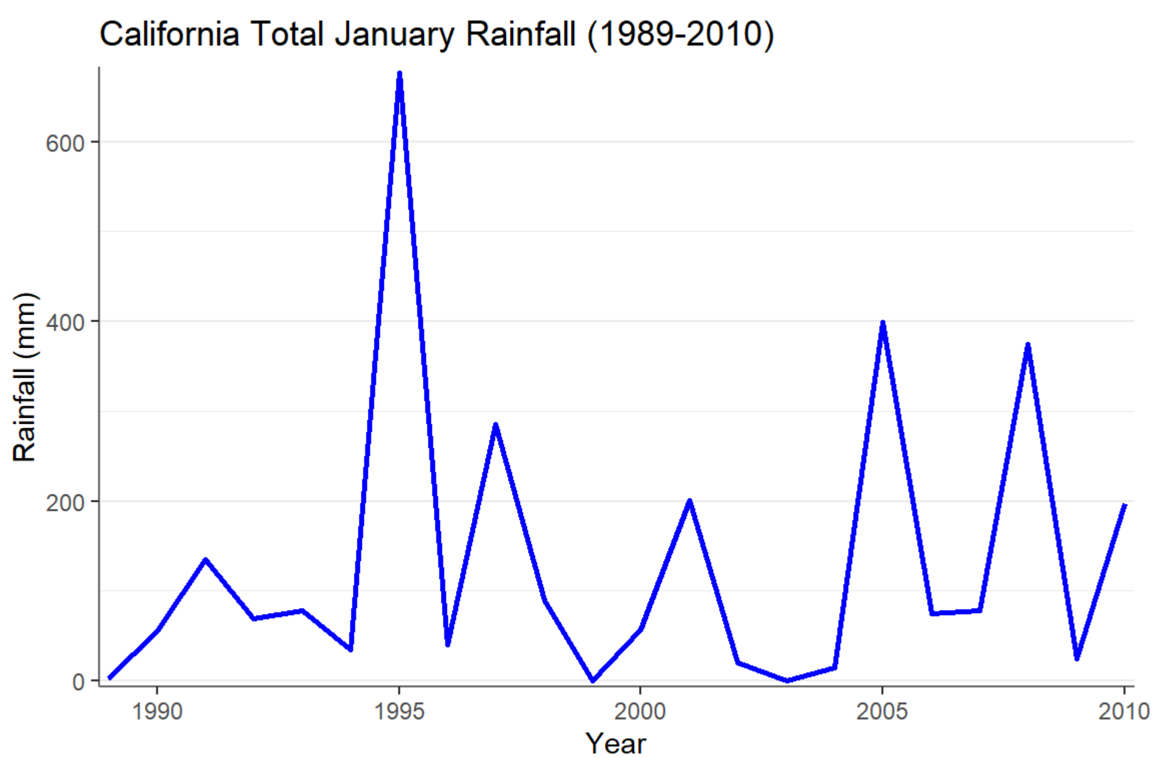

Figure 2. *The sum of total precipitation in January 1989-2010*

4.3 The temperature trend

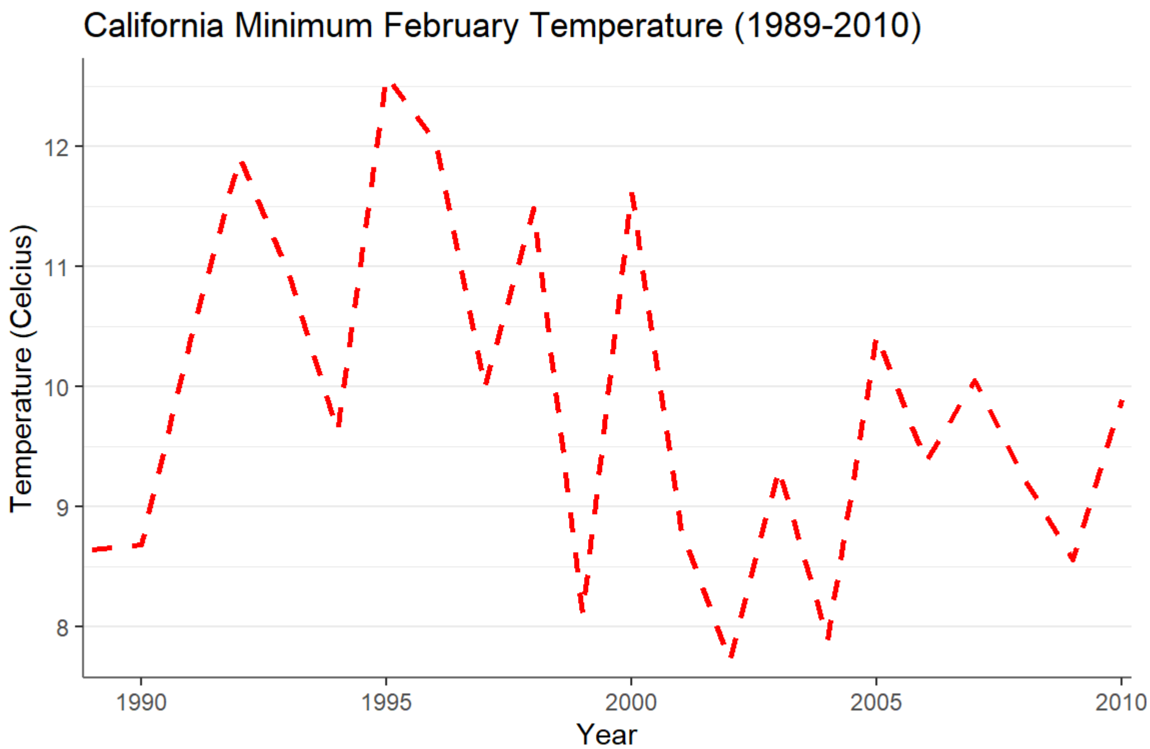

Figure 3. *The average of minimum observed temperatures in February 1989-2010*

4.4 Observations

Using the function developed by Lobell et al. to model historical almond yield anomalies reveals two important trends. First, January rainfalls seem to be the strongest predictor for almond yields, even though this crop is irrigated and therefore yield anomaly projections determined in Lobell et al. were not as impacted by the uncertainty in precipitation projections. In years where there was more than 200mm of rain the January before harvest, there was an increase in yield (Figs. 1, 2). This is especially apparent in the 1995, 2005, and 2008 harvests. Second, as outlined in the function, lower February minimum temperatures have a negative impact on yields. Throughout the years examined in this application of the function, cold temperatures only twice coincided with low January rainfalls enough to result in a negative yield anomaly (a yield below the 23-year average that the function was developed around). This occurred in 2003 and 2004 and both times resulted in less than 0.1 tons/acre of yield loss (Figs. 1, 3). Since Lobell et al. last tested the function against 2003 data, it would be interesting to see if the function continues to accurately reflect yield anomalies as rainfall and temperature patterns continue to shift as a result of climate change.

Citation:

Lobell, D.B., Field, C.B., Nicholas Cahill, K., Bonfils, C. (2006). Impacts of future climate change on California perennial crop yields: Model projections with climate and crop uncertainties. Agric, 141(2): 208-218.

5. Appendix - Result table

All data in this table came from `yieldanoms_df`.

Almond yield anormalies (outputs) and inputs used in model

Year	Yield Anomaly (tons/acre)	Mean Minimum Temperature in February (Celcius)	Total Precipitation in January (mm)

Almond yield anormalies (outputs) and inputs used in model

1989	−0.36	8.64	2.80
1990	9.29	8.68	55.81
1991	68.91	10.39	135.34
1992	15.43	11.91	69.64
1993	20.21	10.94	77.90
1994	2.48	9.62	34.80
1995	1,919.98	12.59	676.51
1996	3.58	12.04	40.25
1997	329.69	9.99	285.30
1998	27.86	11.48	89.76
1999	−0.14	8.10	0.00
2000	9.60	11.61	57.32
2001	159.51	8.82	201.04
2002	0.25	7.72	20.34
2003	−0.26	9.31	0.00
2004	−0.24	7.89	14.48
2005	656.37	10.42	399.03
2006	18.63	9.37	74.93
2007	20.20	10.05	77.72
2008	576.28	9.24	374.40
2009	0.74	8.56	24.89
2010	153.77	9.89	197.61