

Assignment 4: Almond Model

EDS 230 - Modeling Environmental Systems

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GitHub Repository: <https://github.com/jwonyk/EDS-230-HW-ALMOND-YIELD-PROFIT>

Introduction

Much of the climate change impacts literature has focused on major annual crops, with comparatively less attention given to perennial crops that play an important role in agricultural systems. Lobell et al. (2006) developed a statistical modeling framework to evaluate the sensitivity of several California perennial crops, including almonds, to changes in temperature and precipitation. Their model relates seasonal climate variables to crop yields and is intended to provide a baseline representation of climate-driven yield responses, while accounting for neither elevated CO₂ concentrations nor farmers' adaptive management.

Building on this framework, this project implements a simplified version of the almond yield anomaly model described by Lobell et al. (2006) using daily climate data. The yield anomaly estimates are then integrated into a stylized profit model to explore how climate-driven yield variability may translate into economic outcomes. An informal sensitivity analysis is conducted to examine how the modeled almond profit responds to uncertainty in key climate and economic parameters.

Step 1: Load Libraries

```
# Load packages used throughout the workflow
library(tidyverse)
library(here)
library(knitr)
library(kableExtra)
```

Step 2: Load Climate Data

```
# Read the daily climate time series
climate <- read.table(here("data", "clim.txt"), header = TRUE)
```

Step 3: Clean and Prepare Climate Data for Analysis

We want to isolate the minimum temperature values in February and calculate the total precipitation for January. These are values specified in the paper specifically for almond yield.

```
# Aggregate daily climate into annual predictors required by the yield anomaly model

# This model only pulls minimum temperature from February (Celsius)
tmin_feb <- climate %>%
  group_by(year) %>%
  filter(month == 2) %>%
  summarize(tmin_c = min(tmin_c)) %>%
  pull(tmin_c)

# This model only pulls precipitation from January (mm)
precip_jan <- climate %>%
  group_by(year) %>%
  filter(month == 1) %>%
  summarize(precip = sum(precip)) %>%
  pull(precip)
```

Step 4: Build Model

We can begin building our model! We will write a function that calculates almond yield based on climate parameters and will return a vector of estimated yields.

We will source our model from a separate R file that includes the model itself and associated documentation.

```
# Source yield anomaly model and profit/NPV helper functions
source(here("R", "almond_yield.R"))
source(here("R", "revenue_npv.R"))
source(here("R", "cost_npv.R"))
source(here("R", "yield_profit.R"))
```

To ensure our model is written properly, we can run a simple test with 0 values and expect a value of 0.28.

```
# Quick sanity check
test <- almond_yield(0, 0)
paste0("Does our model pass the 0 sensitivity test? ",
       test == 0.28)
```

```
[1] "Does our model pass the 0 sensitivity test? TRUE"
```

Step 5: Run Model

Now that we have passed the test, we can run our model using our climate vectors and check our results against the expected values.

- Maximum = 1920 tons/acre
- Minimum = -0.027 tons/acre
- Mean = 182 tons/acre

```
# Run the almond model on annual predictor vectors
model <- almond_yield(tmin_feb = tmin_feb,
                     precip_jan = precip_jan)
```

```
# Create summary table outputs for the report
summary_stats <- data.frame(
  Metric = c("Maximum Annual Yield Anomaly",
             "Minimum Annual Yield Anomaly",
             "Mean Annual Yield Anomaly"),
  "Yield Annual Anomaly (Ton/Acre)" =
    c(round(max(model), 0),
      round(min(model), 3),
      round(mean(model), 0)),
  check.names = FALSE)

summary_stats
```

	Metric	Yield Annual Anomaly (Ton/Acre)
1	Maximum Annual Yield Anomaly	1920.000
2	Minimum Annual Yield Anomaly	-0.027
3	Mean Annual Yield Anomaly	182.000

Step 6: Incorporate Profit Model into Yield

To link the yield anomaly model with the profit model, we first construct a table of annual climate predictors. Daily climate observations are aggregated to produce one row per year containing the February minimum temperature and January total precipitation. This table serves as the common input for both the yield and profit models.

```
# Create a table containing minimum temperature from February &
tmin_feb_tbl <- climate %>%
  group_by(year) %>%
  filter(month == 2) %>%
  summarise(tmin_c = min(tmin_c))

# Create a table containing precipitation sum in January
precip_jan_tbl <- climate %>%
  group_by(year) %>%
  filter(month == 1) %>%
  summarise(precip = sum(precip))

# Combined table with temperature and precipitation values per year
combined_temp_precip <- tmin_feb_tbl %>%
  left_join(precip_jan_tbl)
```

Joining with `by = join_by(year)`

Step 7: Demonstration of Modeling with Wrapper

Using the annual climate predictor table, we run the yield-profit workflow. The profit model internally calls the almond yield anomaly function to compute climate-driven yield anomalies, which are then used to calculate annual revenue, costs, and profit. This step demonstrates how yield and profit models are linked within a single modeling framework.

```
# Demonstrate workflow (yield anomaly to profit)
testing_profit <- yield_profit(combined_temp_precip, price = 2100,
                               cost = 1500, discount = 0.12)

# Check the rows
head(testing_profit)
```

	scen	yield	year	revenue	revenue_npv	cost_npv	profit
1	1	0.04321564	1989	90.75284	90.75284	1500.0000	-1409.247

2	2	9.67477539	1990	20317.02832	18140.20386	1339.2857	16800.918
3	3	69.31641316	1991	145564.46764	116043.10239	1195.7908	114847.312
4	4	15.82346139	1992	33229.26892	23651.93727	1067.6704	22584.267
5	5	20.49451926	1993	43038.49045	27351.73875	953.2771	26398.462
6	6	2.85987364	1994	6005.73464	3407.81512	851.1403	2556.675

Step 8: Informal Sensitivity Analysis (2 parameters)

To evaluate how uncertainty in economic assumptions affects modeled almond profit, we conduct an informal sensitivity analysis. We generate random samples of almond price and production cost from specified distributions. These sampled values represent plausible variability in economic conditions and are used as inputs to the profit model.

```
# Set seed for randomization
set.seed(42)

# Give a enough sample for the pattern
n_sample <- 300

# Sample two parameter (price and cost)
price_sample <- rnorm(n_sample, mean = 2100, sd = 250)
cost_sample <- rnorm(n_sample, mean = 1500, sd = 200)

# Create a table with variation for price and cost
params <- data.frame(samp = 1:n_sample,
                     price = price_sample,
                     cost = cost_sample)
```

Step 9: Run Simulations

For each sampled combination of price and cost, the yield-profit model is re-run, and the mean annual profit is calculated. The resulting simulations yield a set of profit outcomes that characterize the sensitivity of the modeled almond profit to variations in key economic parameters. These results are summarized and visualized to highlight dominant patterns and trade-offs.

```
# For each sampled price and cost, recompute yield-driven profit
# and store mean annual profit
sensitivity_results <- data.frame()
sensitivity_plot <- data.frame(matrix(ncol = n_sample,
                                     nrow = length(combined_temp_precip$year)))
```

```

sensitivity_plot$year <- combined_temp_precip$year

for (i in 1:n_sample) {

  # Run profit model for each sampled parameter set
  output <- yield_profit(combined_temp_precip,
                        price = params$price[i],
                        cost  = params$cost[i],
                        discount = 0.12)

  # Store mean annual profit for this scenario
  sensitivity_results <- rbind(sensitivity_results,
                              data.frame(
                                samp = i,
                                price = params$price[i],
                                cost  = params$cost[i],
                                mean_profit = mean(output$profit, na.rm = TRUE)))

  # Store all sensitivity results per year
  sensitivity_plot[, i] <- output$profit

}

head(sensitivity_results)

```

	samp	price	cost	mean_profit
1	1	2442.740	1499.076	159958.3
2	2	1958.825	1652.048	128094.9
3	3	2190.782	1507.798	143395.7
4	4	2258.216	1647.014	147773.4
5	5	2201.067	1470.705	144086.1
6	6	2073.469	1488.423	135693.2

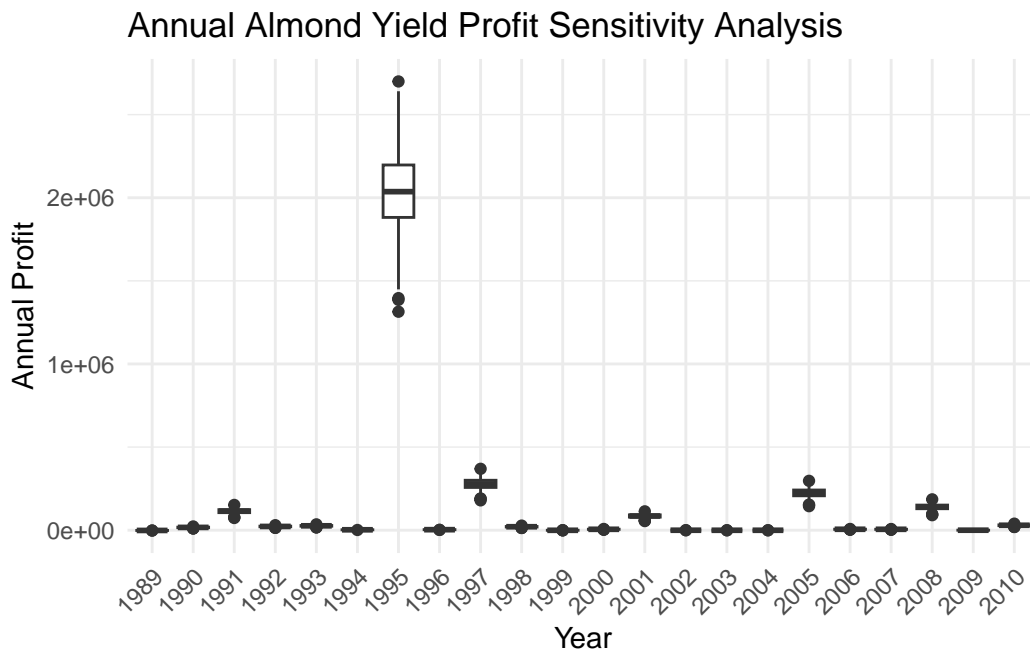
This following box plot shows the variation in Almond profit based on randomly sampling cost and price given our dataset's average for both variables and a standard deviation of 200 for cost and 250 for price.

```

# Create box plot with randomly sampled cost and price based on mean
# and standard deviation
plot_all <- sensitivity_plot %>% pivot_longer(cols = -c(year))
ggplot(plot_all, aes(x = as.factor(year), y = value)) +

```

```
geom_boxplot() +
labs(x = "Year",
     y = "Annual Profit",
     title = "Annual Almond Yield Profit Sensitivity Analysis") +
theme_minimal() +
theme(axis.text.x = element_text(angle = 45,
                                   vjust = 1,
                                   hjust = 1))
```



This following box plot shows the variation in Almond profit based on randomly sampling cost and price given our dataset's average for both variables and a standard deviation of 200 for cost and 250 for price. It excludes 1995 since it was abnormally large and hides other box plots

```
# Remove 1995
plot_wo_1995 <- sensitivity_plot %>%
  filter(year != 1995) %>%
  pivot_longer(cols = -c(year))

# Create boxplot with randomly sampled cost and price based on mean
# and standard deviation excluding 1995
ggplot(plot_wo_1995, aes(x = as.factor(year), y = value)) +
  geom_boxplot() +
  labs(x = "Year",
```

```

y = "Annual Profit",
title = "Annual Almond Yield Profit Sensitivity Analysis",
subtitle = "Without 1995") +
theme_minimal() +
theme(axis.text.x = element_text(angle = 45,
                                   vjust = 1,
                                   hjust = 1))

```

