# Checkpoint # 2

Group #3

2024-11-24

#### Research Question

Considering climate factors and chemical factors in agriculture, construction of which continent and what crop type would bring more economic impact?

#### Hypothesis

Null Hypothesis: There is no significant difference in economic impact across different continents and crop types based on climate factors (average temperature, precipitation, extreme weather events), chemical factors (fertilizer use, pesticide use) and crop yield.

Alternative Hypothesis: Economic impact significantly differs across continents and crop types due to variations in climate factors and chemical inputs.

#### Libraries

```
library(dplyr)
##
##
           : 'dplyr'
## The following objects are masked from 'package:stats':
##
##
      filter, lag
## The following objects are masked from 'package:base':
##
##
      intersect, setdiff, setequal, union
library(ggplot2)
library(tidyverse)
## -- Attaching core tidyverse packages ----- tidyverse 2.0.0 --
## v forcats
              1.0.0
                        v stringr
                                    1.5.1
## v lubridate 1.9.3
                        v tibble
                                    3.2.1
## v purrr
              1.0.2
                        v tidyr
                                    1.3.1
## v readr
              2.1.5
```

```
## -- Conflicts -----
                                              -----ctidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()
                      masks stats::lag()
## i Use the conflicted package (<a href="http://conflicted.r-lib.org/">http://conflicted.r-lib.org/</a>) to force all conflicts to become error
library(modelr)
library(boot)
library(randomForest)
## Warning:
               'randomForest' R 4.4.2
## randomForest 4.7-1.2
## Type rfNews() to see new features/changes/bug fixes.
##
            : 'randomForest'
## The following object is masked from 'package:ggplot2':
##
##
       margin
##
## The following object is masked from 'package:dplyr':
##
##
       combine
library(agricolae)
```

### Import Dataset

```
data <- read.csv("climate_change_impact_on_agriculture_2024.csv")</pre>
```

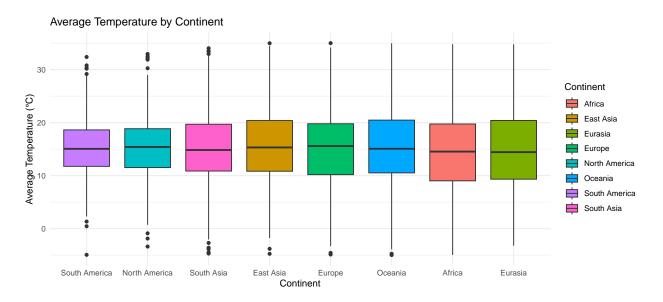
### Preparation and cleaning the data (Juhyun Lee)

```
aggregated_data <- data %>%
  group_by(Year, Continent, Crop_Type) %>%
  summarize(
   avg_crop_yield =
      mean(Crop_Yield_MT_per_HA, na.rm = TRUE),
   avg_extreme_weather_events =
     mean(Extreme_Weather_Events, na.rm= TRUE),
   avg temp c =
     mean(Average_Temperature_C, na.rm = TRUE),
   avg_total_precipitation_mm =
     mean(Total_Precipitation_mm, na.rm = TRUE),
   avg_co2_emissions_mt =
      mean(CO2_Emissions_MT, na.rm =TRUE),
   avg_pesticide_use_kg_per_ha =
      mean(Pesticide_Use_KG_per_HA, na.rm=TRUE),
   avg_fertilizer_use_kg_per_ha =
     mean(Fertilizer_Use_KG_per_HA, na.rm =TRUE),
   avg_soil_health_index =
     mean(Soil_Health_Index, na.rm=TRUE),
   avg_economic_impact_million_usd =
      mean(Economic_Impact_Million_USD, na.rm = TRUE)
  ) %>%
  ungroup()
## `summarise()` has grouped output by 'Year', 'Continent'. You can override using
## the `.groups` argument.
data <- data %>%
 left_join(aggregated_data, by = c("Year", "Continent"))
## Warning in left_join(., aggregated_data, by = c("Year", "Continent")): Detected an unexpected many-t
## i Row 1 of `x` matches multiple rows in `y`.
## i Row 592 of `y` matches multiple rows in `x`.
## i If a many-to-many relationship is expected, set `relationship =
     "many-to-many" to silence this warning.
data_constracted <- data %>%
 select(-c(6:9, 12:14, 16))
```

#### EDA by continent (Daehee Cho, Donghyun Park)

Average\_Temperature by Year

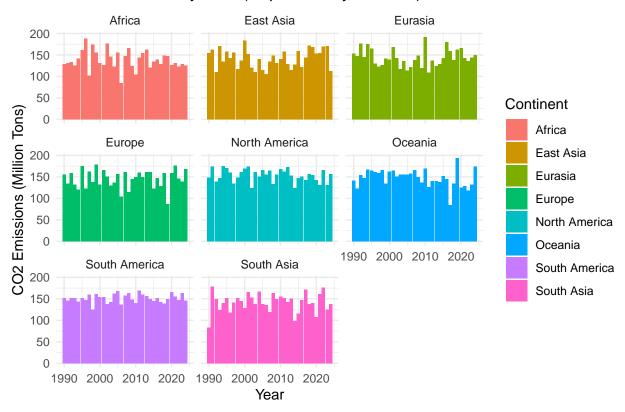
```
) +
theme_minimal()
```



#### CO<sub>2</sub> Emissions by Year

```
## Warning in geom_histogram(stat = "identity"): Ignoring unknown parameters:
## `binwidth`, `bins`, and `pad`
```

## CO2 Emissions by Year (Separated by Content)



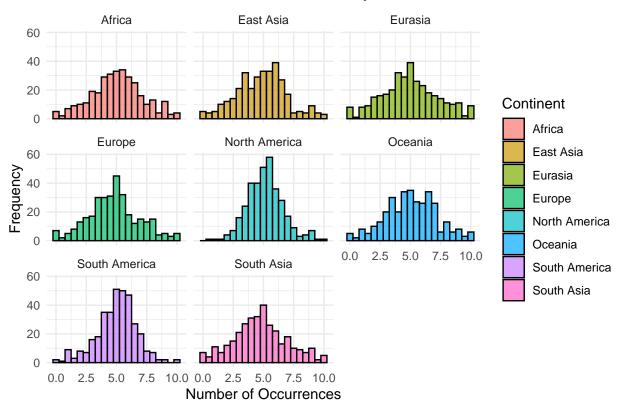
```
co2_stability <- aggregated_data %>%
  group_by(Continent) %>%
  summarize(
    variance = var(avg_co2_emissions_mt, na.rm = TRUE),
    std_dev1 = sd(avg_co2_emissions_mt, na.rm = TRUE),
    mean_co2 = mean(avg_co2_emissions_mt, na.rm = TRUE),
    cv = std_dev1 / mean_co2
)

print(co2_stability)
```

```
## # A tibble: 8 x 5
##
     Continent
                    variance std_dev1 mean_co2
                                 <dbl>
##
     <chr>>
                       <dbl>
                                          <dbl> <dbl>
                        32.1
                                 5.67
## 1 Africa
                                           14.9 0.380
## 2 East Asia
                        32.8
                                 5.73
                                           15.0 0.381
                        39.7
                                 6.30
## 3 Eurasia
                                           15.1 0.418
                                 5.67
## 4 Europe
                        32.1
                                           15.6 0.363
## 5 North America
                        18.2
                                 4.27
                                           15.4 0.277
## 6 Oceania
                        33.4
                                 5.78
                                           15.3 0.376
## 7 South America
                        14.7
                                 3.83
                                           15.1 0.254
## 8 South Asia
                        34.7
                                 5.89
                                           15.1 0.390
```

#### Extreme weather by year

# Distribution of Extreme Weather Events by Continent



```
variance_std <- aggregated_data %>%
  group_by(Continent) %>%
  summarize(
    variance = var(avg_extreme_weather_events, na.rm = TRUE),
    std_dev = sd(avg_extreme_weather_events, na.rm = TRUE)
)

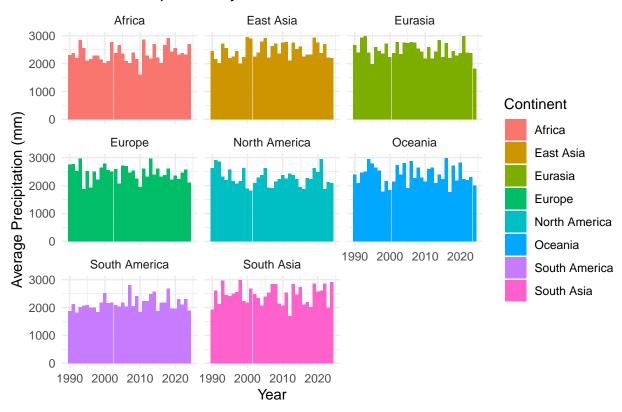
# Print the results
print(variance_std)
```

## # A tibble: 8 x 3

```
{\tt Continent} \qquad {\tt variance \ std\_dev}
##
               <chr>
##
                   4.44
## 1 Africa
                           2.11
## 2 East Asia
                   4.15 2.04
                         2.28
                   5.18
## 3 Eurasia
## 4 Europe
                   4.34 2.08
## 5 North America 2.15 1.47
## 6 Oceania
                   4.36 2.09
## 7 South America 2.65 1.63
## 8 South Asia 4.73 2.17
```

#### Precipitation vs Year

### Annual Precipitation by Year and Continent



```
precipitation_stability <- aggregated_data %>%
  group_by(Continent) %>%
  summarize(
    variance = var(avg_total_precipitation_mm, na.rm = TRUE),
    std_dev = sd(avg_total_precipitation_mm, na.rm = TRUE),
    mean_precipitation = mean(avg_total_precipitation_mm, na.rm = TRUE),
    cv = std_dev / mean_precipitation
)

print(precipitation_stability)
```

```
## # A tibble: 8 x 5
##
     Continent
                    variance std_dev mean_precipitation
##
     <chr>
                       <dbl>
                               <dbl>
                                                    <dbl> <dbl>
## 1 Africa
                     256601.
                                507.
                                                    1577. 0.321
## 2 East Asia
                     290171.
                                                    1669. 0.323
                                539.
## 3 Eurasia
                     301941.
                                549.
                                                    1583. 0.347
## 4 Europe
                     318203.
                                564.
                                                    1646. 0.343
## 5 North America
                    152401.
                                390.
                                                    1645. 0.237
## 6 Oceania
                     287098.
                                536.
                                                    1601. 0.335
## 7 South America
                    135801.
                                 369.
                                                    1552. 0.237
## 8 South Asia
                     302928.
                                                    1648. 0.334
                                550.
```

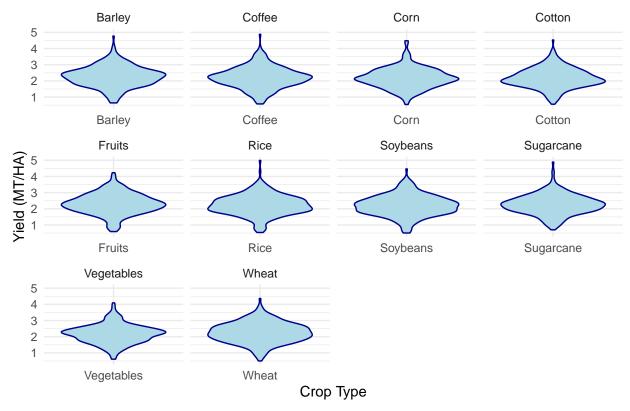
# EDA by Crop type (Sumin Chun, Janghee Cho)

```
crop_types <- unique(aggregated_data$Crop_Type)</pre>
```

#### Crop type vs yield

```
ggplot(aggregated_data, aes(x = Crop_Type, y = avg_crop_yield)) +
  geom_violin(fill = "lightblue", color = "darkblue") +
  facet_wrap(~ Crop_Type, scales = "free_x") +
  labs(
    title = "Yield Distribution by Crop Type",
    x = "Crop Type",
    y = "Yield (MT/HA)"
  ) +
  theme_minimal()
```

# Yield Distribution by Crop Type



- 1. Hypothesis H0: All the mean of average crop yield from different crop types are the same. Ha: At least one of them is different.
  - 2. alpha = 0.05
  - 3. Test = ANOVA Test

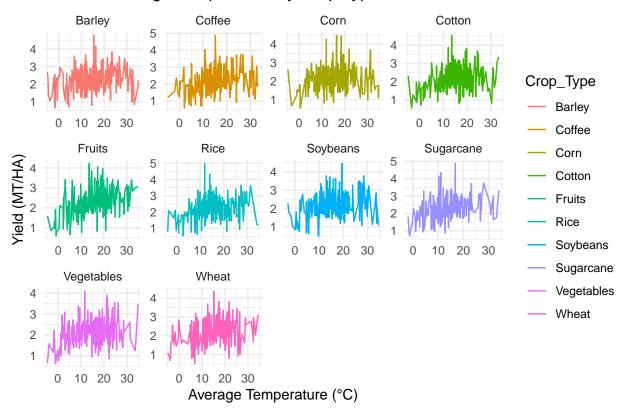
```
anova_result <- aov(avg_crop_yield ~ Crop_Type, data = aggregated_data)
summary(anova_result)</pre>
```

```
## Df Sum Sq Mean Sq F value Pr(>F)
## Crop_Type 9 5.4 0.6041 1.543 0.127
## Residuals 2670 1045.4 0.3915
```

- 4. Critical Region p-value >= alpha : Do not reject H0. p-value < alpha : Reject H0.
- 5. Conclusion Since the p-value is larger than alpha, we do not reject the hypothesis. So this plot does not have significant difference.

#### Average Temperature vs Yield

### Yield vs Average Temperature by Crop Type



```
slopes_resilience <- aggregated_data %>%
  group_by(Crop_Type) %>%
summarize(
   slope = coef(lm(avg_crop_yield ~ avg_temp_c, data = cur_data()))[2],
   intercept = coef(lm(avg_crop_yield ~ avg_temp_c, data = cur_data()))[1],
) %>%
arrange(abs(slope))
```

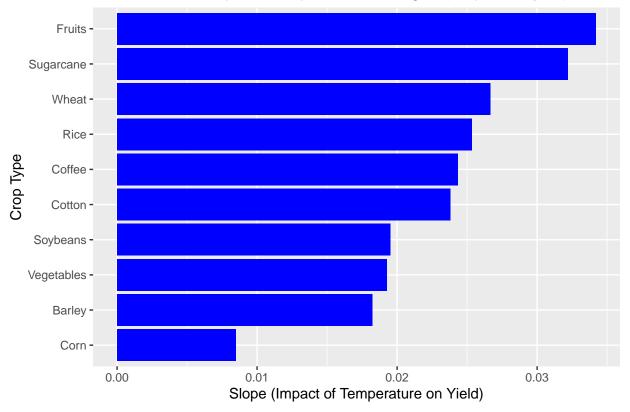
```
## Warning: There was 1 warning in `summarize()`.
## i In argument: `slope = coef(lm(avg_crop_yield ~ avg_temp_c, data =
## cur_data()))[2]`.
## i In group 1: `Crop_Type = "Barley"`.
## Caused by warning:
## ! `cur_data()` was deprecated in dplyr 1.1.0.
## i Please use `pick()` instead.
```

```
# Print
print(slopes_resilience)
```

```
## # A tibble: 10 x 3
##
                    slope intercept
      Crop_Type
##
      <chr>
                    <dbl>
                              <dbl>
    1 Corn
                 0.00850
                               2.04
##
   2 Barley
                 0.0182
                               2.02
    3 Vegetables 0.0193
                               1.88
```

```
## 4 Soybeans
                0.0195
                             1.90
##
  5 Cotton
                0.0238
                             1.82
                0.0243
                             1.84
  6 Coffee
                0.0253
                             1.85
## 7 Rice
   8 Wheat
                0.0266
                             1.84
## 9 Sugarcane 0.0322
                             1.80
## 10 Fruits
                0.0342
                             1.77
```

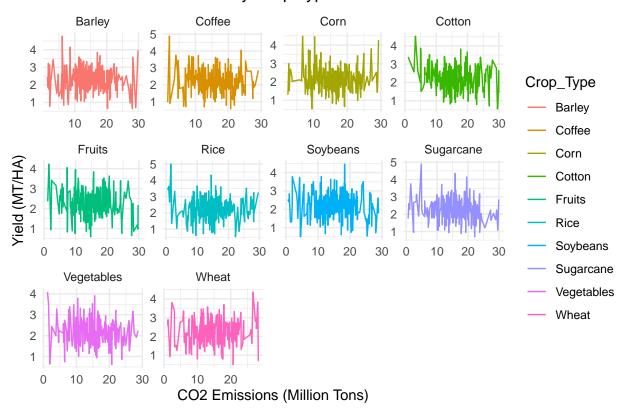
# Resilience of Crops to Temperature Changes (Slope Analysis)



#### CO<sub>2</sub> Emissions vs Yield

```
facet_wrap(~ Crop_Type, scales = "free") +
labs(
  title = "Yield vs CO Emissions by Crop Type",
  x = "CO Emissions (Million Tons)",
  y = "Yield (MT/HA)"
) +
theme_minimal()
```

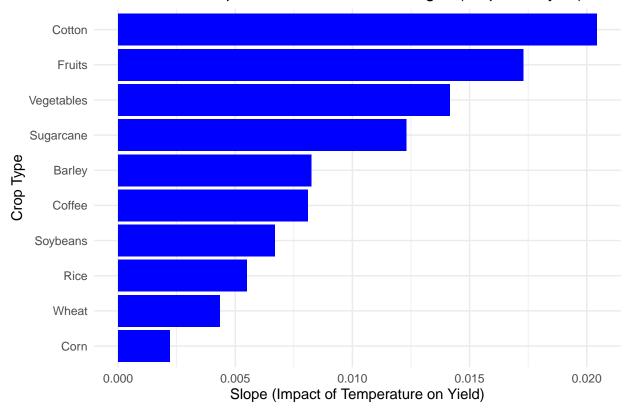
# Yield vs CO2 Emissions by Crop Type



```
## # A tibble: 10 x 3
## Crop_Type slope intercept
## <chr> <dbl> <dbl>
## 1 Cotton 0.0204 2.50
```

```
## 2 Fruits
                0.0173
                             2.57
## 3 Vegetables 0.0142
                             2.39
## 4 Sugarcane 0.0123
                             2.45
## 5 Barley
                0.00825
                             2.40
   6 Coffee
##
                0.00810
                             2.33
##
  7 Soybeans
                0.00670
                             2.30
   8 Rice
                0.00549
                             2.32
                0.00433
## 9 Wheat
                             2.19
## 10 Corn
                0.00221
                             2.21
```

# Resilience of Crops to CO2 Emission Changes (Slope Analysis)

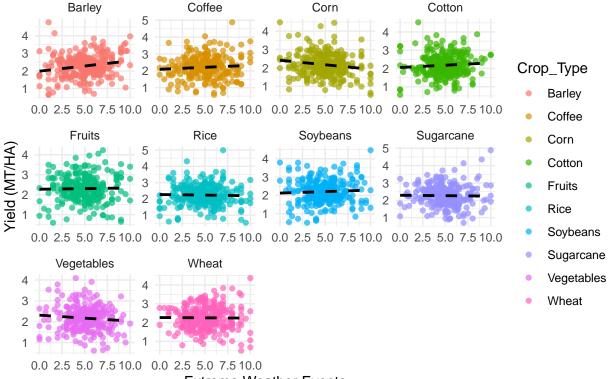


#### Extreme Weather events vs Yield

```
## Warning: Using `size` aesthetic for lines was deprecated in ggplot2 3.4.0.
## i Please use `linewidth` instead.
## This warning is displayed once every 8 hours.
## Call `lifecycle::last_lifecycle_warnings()` to see where this warning was
## generated.
```

# ## `geom\_smooth()` using formula = 'y ~ x'

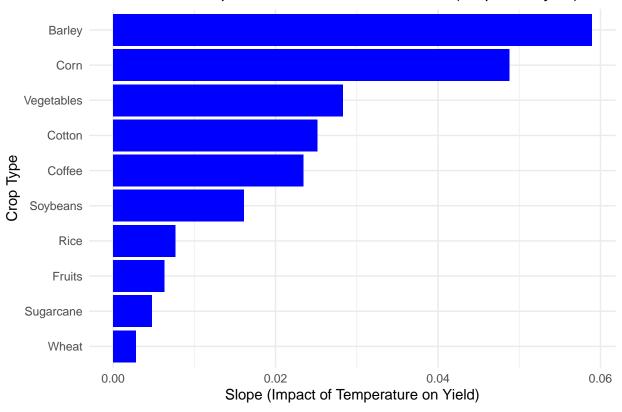
# Yield vs Extreme Weather Events by Crop Type



**Extreme Weather Events** 

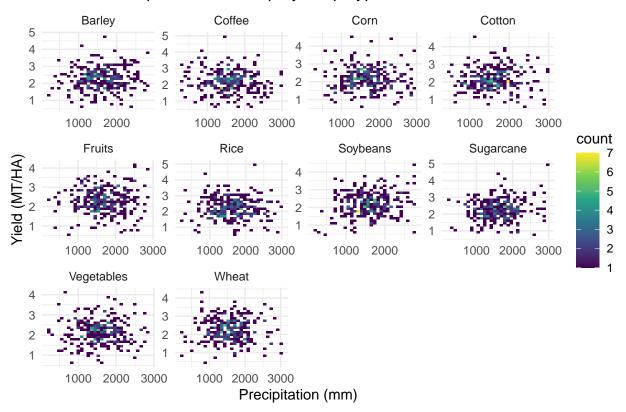
```
slopes_resilience2 <- aggregated_data %>%
  group_by(Crop_Type) %>%
  summarize(
   slope = abs(coef(lm(avg_crop_yield ~ avg_extreme_weather_events, data = cur_data()))[2]),
   intercept = coef(lm(avg_crop_yield ~ avg_extreme_weather_events, data = cur_data()))[1],
  arrange(slope)
# Print
print(slopes_resilience2)
## # A tibble: 10 x 3
##
     Crop_Type
                  slope intercept
##
      <chr>
                  <dbl>
                             <dbl>
## 1 Wheat
                0.00278
                              2.27
## 2 Sugarcane 0.00477
                              2.29
## 3 Fruits
                0.00629
                              2.27
## 4 Rice
                0.00765
                              2.27
## 5 Soybeans 0.0161
                              2.12
## 6 Coffee
                0.0234
                              2.09
## 7 Cotton
                0.0251
                              2.06
## 8 Vegetables 0.0283
                              2.31
## 9 Corn
                              2.42
                0.0488
## 10 Barley
                0.0589
                              1.99
ggplot(slopes_resilience2, aes(x = reorder(Crop_Type, abs(slope)),
                               y = slope, fill = slope > 0)) +
  geom_bar(stat = "identity", show.legend = FALSE) +
  coord_flip() +
  scale_fill_manual(values = c("blue", "red")) +
 labs(
   title = "Resilience of Crops to Extreme weather events (Slope Analysis)",
   x = "Crop Type",
   y = "Slope (Impact of Temperature on Yield)"
 ) +
  theme_minimal()
```

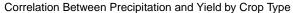
# Resilience of Crops to Extreme weather events (Slope Analysis)

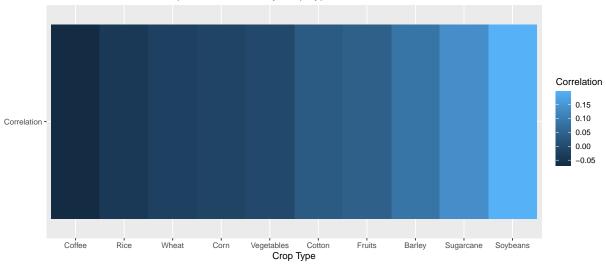


### Precipitation vs Yield

# Yield vs Precipitation Heatmap by Crop Type







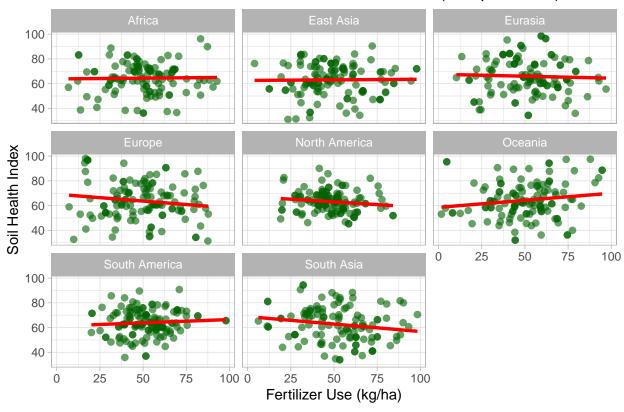
### Modeling (Joonsoo Choi)

#### Fertilizer and Soil Health Index

• continent

## `geom\_smooth()` using formula = 'y ~ x'

# Continent-wise Fertilizer Use vs Soil Health Index (Sampled Data)

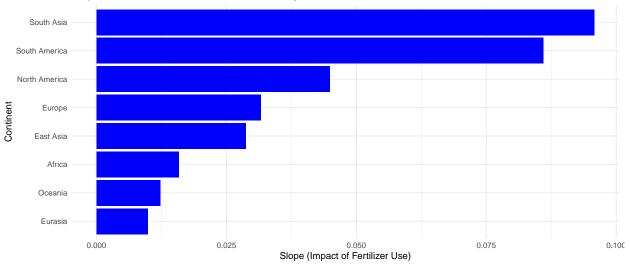


#### • Slope 1

```
## # A tibble: 8 x 3
##
     Continent
                     slope p_value
     <chr>
                              <dbl>
##
                     <dbl>
## 1 Eurasia
                   0.00990 0.813
## 2 Oceania
                   0.0123
                             0.756
                   0.0159
                             0.692
## 3 Africa
## 4 East Asia
                   0.0287
                             0.459
## 5 Europe
                   0.0316
                             0.432
## 6 North America 0.0449
                             0.247
## 7 South America 0.0860
                             0.0299
## 8 South Asia
                   0.0958
                             0.0108
```

• Slope

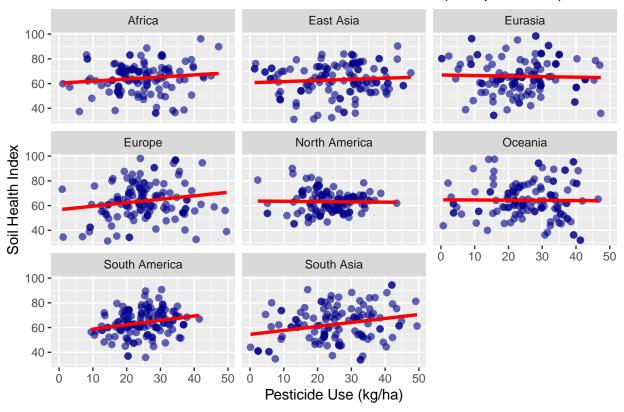
#### Slope of Fertilizer Use vs Soil Health Index by Continent



#### Pesticide Use and Soil health index

## `geom\_smooth()` using formula = 'y ~ x'

## Continent-wise Pesticide Use vs Soil Health Index (Sampled Data)

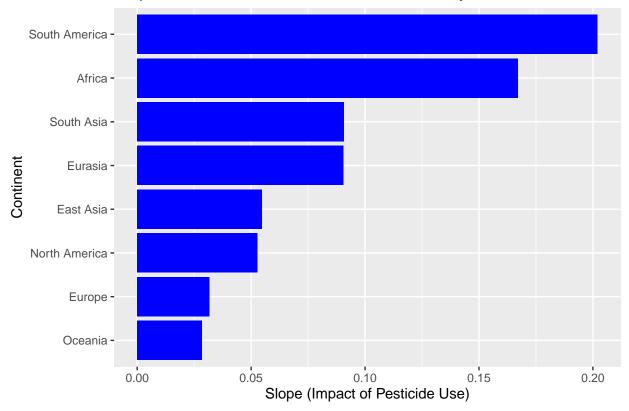


#### • Slope 2

```
## # A tibble: 8 x 3
##
     Continent
                    slope p_value
##
     <chr>
                    <dbl>
                            <dbl>
## 1 Oceania
                   0.0285
                          0.716
## 2 Europe
                   0.0318
                          0.695
## 3 North America 0.0528
                           0.451
## 4 East Asia
                   0.0548
                           0.461
## 5 Eurasia
                   0.0905
                           0.279
## 6 South Asia
                   0.0908 0.210
## 7 Africa
                   0.167
                           0.0214
## 8 South America 0.202
                           0.0109
```

• Slope visualization

# Slope of Pesticide Use vs Soil Health Index by Continent



#### Yield ~ Soil Health Index (Seunghoon Oh)

• Model 3

```
model_Crop_Yield_MT_per_HA_Soil_Health_Index <-</pre>
  lm(avg_crop_yield ~ avg_soil_health_index, data = aggregated_data)
# Summary of the model
summary(model_Crop_Yield_MT_per_HA_Soil_Health_Index)
##
## Call:
## lm(formula = avg_crop_yield ~ avg_soil_health_index, data = aggregated_data)
## Residuals:
##
                                   30
       Min
                 1Q Median
## -1.71725 -0.40170 -0.01418 0.38650 2.77571
##
## Coefficients:
                          Estimate Std. Error t value Pr(>|t|)
##
                         2.2653045 0.0625331
                                                36.23
## (Intercept)
                                                        <2e-16 ***
## avg_soil_health_index -0.0005859 0.0009449
                                               -0.62
                                                         0.535
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Residual standard error: 0.6264 on 2678 degrees of freedom
## Multiple R-squared: 0.0001435, Adjusted R-squared: -0.0002298
## F-statistic: 0.3845 on 1 and 2678 DF, p-value: 0.5353
  • Very low R-squared value.
```

```
# Rename 'avg_soil_health_index' to 'Soil_Health'
data1 <- aggregated_data %>%
   rename(Soil_Health = avg_soil_health_index)
```

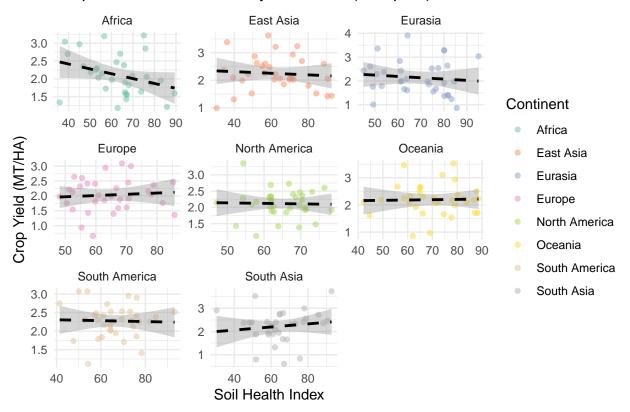
• Continent

```
sampled_data_by_continent <- data1 %>%
group_by(Continent) %>%
sample_frac(0.1) %>%
ungroup()

ggplot(sampled_data_by_continent, aes(x = Soil_Health, y = avg_crop_yield)) +
geom_point(size = 1.5, alpha = 0.5, aes(color = Continent)) +
geom_smooth(method = "lm", se = TRUE, color = "black", linetype = "dashed") +
labs(
    title = "Crop Yield vs Soil Health by Continent (Sampled)",
    x = "Soil Health Index",
    y = "Crop Yield (MT/HA)"
) +
scale_color_brewer(palette = "Set2") +
theme_minimal() +
facet_wrap(~ Continent, scales = "free") # Facet by Country
```

```
## `geom_smooth()` using formula = 'y ~ x'
```

### Crop Yield vs Soil Health by Continent (Sampled)



• Slope

```
continent_slopes <- data1 %>%
  group_by(Continent) %>%
  summarize(
    slope = coef(lm(avg_crop_yield ~ Soil_Health, data = cur_data()))[2],
    intercept = coef(lm(avg_crop_yield ~ Soil_Health, data = cur_data()))[1]
) %>%
  arrange(desc(slope)) # Sort by slope in descending order

# Print the results
print(continent_slopes)
```

```
## # A tibble: 8 x 3
##
     Continent
                        slope intercept
##
     <chr>
                        <dbl>
                                   <dbl>
## 1 Europe
                     0.00246
                                   2.01
                     0.00103
                                   2.20
## 2 South Asia
## 3 Eurasia
                     0.000860
                                   2.15
## 4 Africa
                     0.000210
                                   2.24
## 5 East Asia
                    -0.00143
                                   2.34
## 6 North America -0.00212
                                   2.35
                    -0.00381
                                   2.48
## 7 Oceania
                                   2.50
## 8 South America -0.00387
```

#### • Crop Type

```
sampled_data_by_continent <- data1 %>%
  group_by(Crop_Type) %>%
  sample_frac(0.1) %>%
  ungroup()

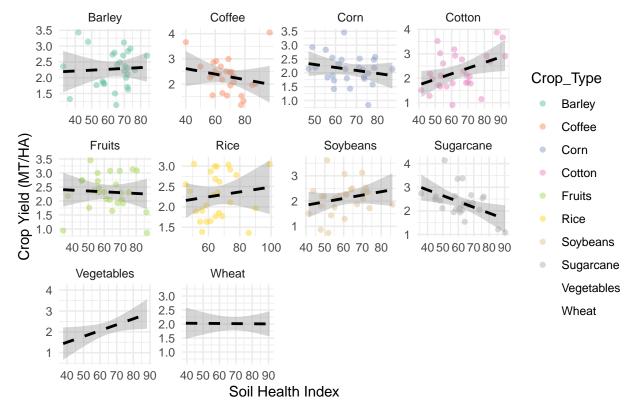
ggplot(sampled_data_by_continent, aes(x = Soil_Health, y = avg_crop_yield)) +
  geom_point(size = 1.5, alpha = 0.5, aes(color = Crop_Type)) +
  geom_smooth(method = "lm", se = TRUE, color = "black", linetype = "dashed") +
  labs(
    title = "Crop Yield vs Soil Health by Crop Type (Sampled)",
    x = "Soil Health Index",
    y = "Crop Yield (MT/HA)"
  ) +
  scale_color_brewer(palette = "Set2") +
  theme_minimal() +
  facet_wrap(~ Crop_Type, scales = "free") # Facet by Country
```

```
## `geom_smooth()` using formula = 'y ~ x'
```

## Warning in RColorBrewer::brewer.pal(n, pal): n too large, allowed maximum for palette Set2 is 8
## Returning the palette you asked for with that many colors

## Warning: Removed 53 rows containing missing values or values outside the scale range
## (`geom\_point()`).

# Crop Yield vs Soil Health by Crop Type (Sampled)



\* Slope

```
crop_type_slopes <- data1 %>%
  group_by(Crop_Type) %>%
  summarize(
    slope = abs(coef(lm(avg_crop_yield ~ Soil_Health, data = cur_data()))[2]),
    intercept = coef(lm(avg_crop_yield ~ Soil_Health, data = cur_data()))[1]
) %>%
  arrange(slope)

# Print the results
print(crop_type_slopes)
```

```
## # A tibble: 10 x 3
##
     Crop_Type
                    slope intercept
                              <dbl>
##
     <chr>
                    dbl>
## 1 Cotton
                0.0000348
                               2.18
                0.000260
                               2.32
## 2 Fruits
## 3 Soybeans
                0.000670
                               2.25
## 4 Rice
                0.00109
                               2.16
## 5 Barley
                0.00121
                               2.20
## 6 Wheat
                0.00139
                               2.16
## 7 Vegetables 0.00173
                               2.06
## 8 Coffee
                0.00180
                               2.33
## 9 Corn
                0.00490
                               2.49
## 10 Sugarcane 0.00523
                               2.61
```

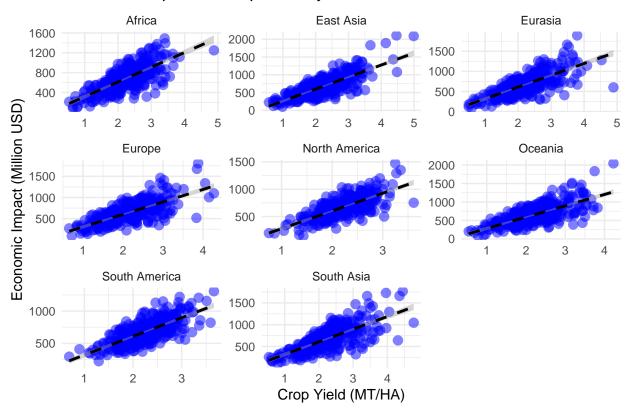
#### Visualization

• Continent

```
ggplot(data1, aes(x = avg_crop_yield, y = avg_economic_impact_million_usd)) +
  geom_point(size = 3, alpha = 0.5, color = "blue") +
  geom_smooth(method = "lm", se = TRUE, color = "black", linetype = "dashed") +
  labs(
    title = "Economic Impact vs Crop Yield by Continent",
    x = "Crop Yield (MT/HA)",
    y = "Economic Impact (Million USD)"
  ) +
  theme_minimal() +
  facet_wrap(~ Continent, scales = "free")
```

```
## `geom_smooth()` using formula = 'y ~ x'
```

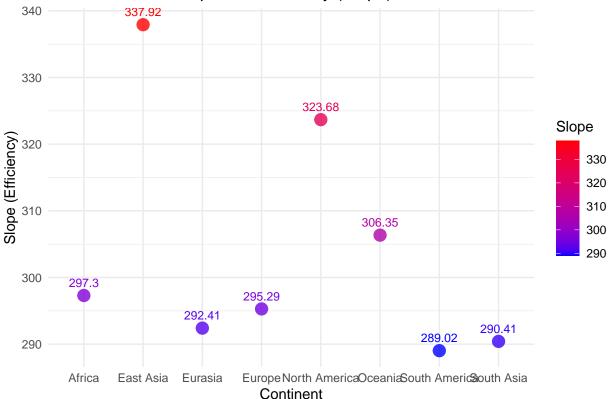
## **Economic Impact vs Crop Yield by Continent**



```
## # A tibble: 8 x 3
##
     Continent
                    Slope Intercept
##
     <chr>
                    <dbl>
                              <dbl>
## 1 East Asia
                     338.
                              -76.7
## 2 North America
                     324.
                              -44.9
## 3 Oceania
                     306.
                             -22.6
## 4 Africa
                     297.
                              17.4
## 5 Europe
                     295.
                               9.30
## 6 Eurasia
                     292.
                               25.5
## 7 South Asia
                     290.
                               25.3
## 8 South America
                     289.
                              30.8
```

```
ggplot(continent_slopes, aes(x = Continent, y = Slope, color = Slope)) +
  geom_point(size = 4, alpha = 0.8) +
  geom_text(aes(label = round(Slope, 2)), vjust = -1, size = 3) +
  labs(
    title = "Continent-wise Crop Yield Efficiency (Slope)",
    x = "Continent",
    y = "Slope (Efficiency)"
  ) +
  scale_color_gradient(low = "blue", high = "red") +
  theme_minimal()
```

# Continent-wise Crop Yield Efficiency (Slope)

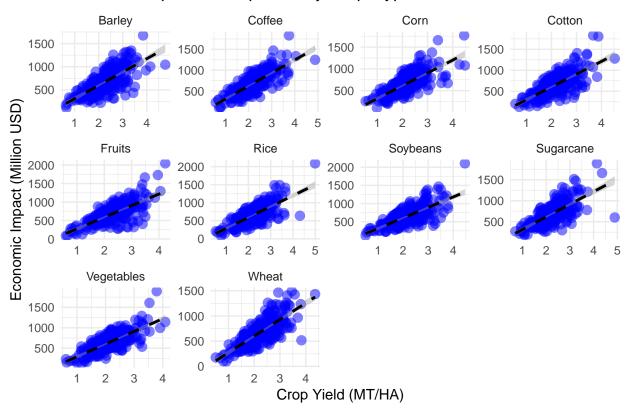


#### • Crop\_Type

```
ggplot(data1, aes(x = avg_crop_yield, y = avg_economic_impact_million_usd)) +
  geom_point(size = 3, alpha = 0.5, color = "blue") +
  geom_smooth(method = "lm", se = TRUE, color = "black", linetype = "dashed") +
  labs(
    title = "Economic Impact vs Crop Yield by Crop_Type",
    x = "Crop Yield (MT/HA)",
    y = "Economic Impact (Million USD)"
  ) +
  theme_minimal() +
  facet_wrap(~ Crop_Type, scales = "free")
```

```
## `geom_smooth()` using formula = 'y ~ x'
```

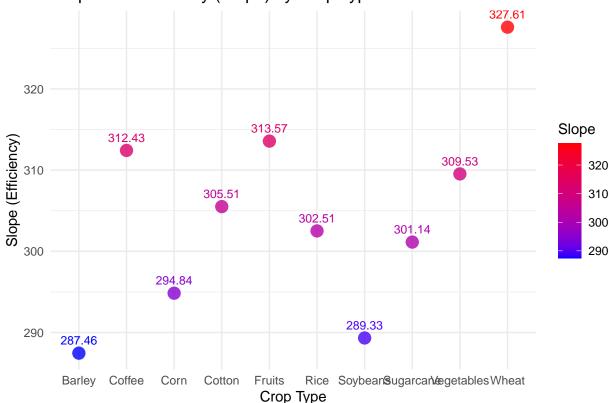
# Economic Impact vs Crop Yield by Crop\_Type



```
##
   # A tibble: 10 x 3
##
      Crop_Type
                  Slope Intercept
                             <dbl>
##
      <chr>
                  <dbl>
    1 Wheat
                   328.
                            -54.2
##
    2 Fruits
                   314.
                            -38.8
##
    3 Coffee
                             -4.16
##
                   312.
    4 Vegetables
                   310.
                            -17.1
##
##
    5 Cotton
                   306.
                             -9.65
                   303.
                            -11.6
##
    6 Rice
    7 Sugarcane
                   301.
                             12.1
##
    8 Corn
                   295.
                             22.4
##
    9 Soybeans
                   289.
                             25.3
## 10 Barley
                   287.
                             23.3
```

```
ggplot(crop_type_slopes, aes(x = Crop_Type, y = Slope, color = Slope)) +
  geom_point(size = 4, alpha = 0.8) +
  geom_text(aes(label = round(Slope, 2)), vjust = -1, size = 3) +
  labs(
    title = "Crop Yield Efficiency (Slope) by Crop Type",
    x = "Crop Type",
    y = "Slope (Efficiency)"
  ) +
  scale_color_gradient(low = "blue", high = "red") +
  theme_minimal()
```

# Crop Yield Efficiency (Slope) by Crop Type



## Prediction Analytics (Juhyun Lee)

```
set.seed(10000)
train_df <- aggregated_data %>% sample_frac(0.7)
test_df <- anti_join(aggregated_data, train_df)</pre>
```

```
## Joining with `by = join_by(Year, Continent, Crop_Type, avg_crop_yield,
## avg_extreme_weather_events, avg_temp_c, avg_total_precipitation_mm,
## avg_co2_emissions_mt, avg_pesticide_use_kg_per_ha,
## avg_fertilizer_use_kg_per_ha, avg_soil_health_index,
## avg_economic_impact_million_usd)`
```

```
train_df %>%
  summarize(
    total = n(),
    missing = sum(is.na(avg_crop_yield)),
    fraction_missing = missing / total
## # A tibble: 1 x 3
    total missing fraction_missing
                       <dbl>
   <int> <int>
## 1 1876
train_df <- train_df %>%
  mutate(avg_crop_yield = if_else(is.na(avg_crop_yield),
                                  mean(avg_crop_yield, na.rm = TRUE),
                                  avg_crop_yield))
crop_yield
rf_model <- randomForest(</pre>
  avg_crop_yield ~ avg_temp_c + avg_extreme_weather_events +
    avg_total_precipitation_mm + Continent + Crop_Type,
  data = train_df,
  ntree = 100,
  mtry = 2,
  importance = TRUE
)
print(rf_model)
##
## Call:
##
   randomForest(formula = avg_crop_yield ~ avg_temp_c + avg_extreme_weather_events +
                                                                                            avg_total_pr
##
                  Type of random forest: regression
                        Number of trees: 100
##
## No. of variables tried at each split: 2
##
##
             Mean of squared residuals: 0.3826241
##
                       % Var explained: 2.4
test_df <- test_df %>%
  mutate(
    predicted_yield = predict(rf_model, newdata = test_df)
  )
mae <- mean(abs(test_df$predicted_yield - test_df$avg_crop_yield))</pre>
print(paste("Mean Absolute Error:", mae))
```

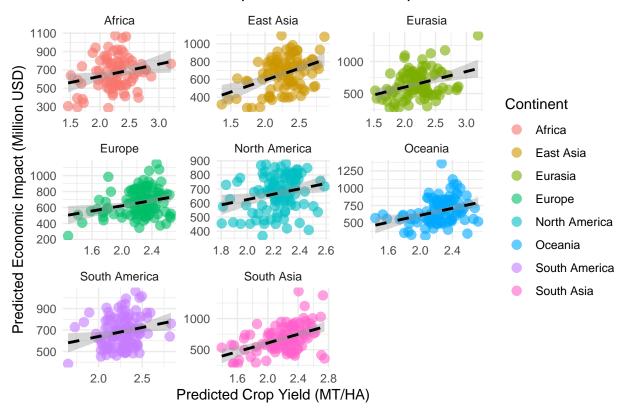
## [1] "Mean Absolute Error: 0.470680760607547"

```
head(test_df %>%
  select(Continent, Crop_Type, avg_crop_yield, predicted_yield) %>%
  arrange(predicted_yield))
## # A tibble: 6 x 4
##
     Continent Crop_Type avg_crop_yield predicted_yield
     <chr>
                <chr>>
                                   <dbl>
##
## 1 Europe
                Cotton
                                   0.855
                                                    1.28
## 2 East Asia Fruits
                                  1.30
                                                    1.37
## 3 South Asia Rice
                                   1.84
                                                    1.39
## 4 Europe
               Sugarcane
                                                     1.41
                                   1.82
## 5 Oceania
                Sugarcane
                                  1.84
                                                    1.44
## 6 Africa
                Soybeans
                                 0.72
                                                    1.46
economic_impact
rf model1 <- randomForest(</pre>
  avg_economic_impact_million_usd ~ avg_temp_c + avg_extreme_weather_events +
    avg_total_precipitation_mm + Continent + Crop_Type + avg_crop_yield,
  data = train_df,
  ntree = 100,
  mtry = 2,
  importance = TRUE
print(rf_model1)
##
## Call:
   randomForest(formula = avg_economic_impact_million_usd ~ avg_temp_c + avg_extreme_weather_even
                  Type of random forest: regression
##
##
                        Number of trees: 100
## No. of variables tried at each split: 2
##
##
             Mean of squared residuals: 34589.74
##
                       % Var explained: 48.76
test_df <- test_df %>%
  mutate(
    predicted_economic_impact = predict(rf_model1, newdata = test_df)
mae <- mean(abs(test_df$predicted_economic_impact -</pre>
                  test_df$avg_economic_impact_million_usd))
print(paste("Mean Absolute Error:", mae))
## [1] "Mean Absolute Error: 139.108089454045"
```

```
head(test_df %>%
  select(Year,Continent, Crop_Type, avg_economic_impact_million_usd,
         predicted_economic_impact) %>%
  arrange(predicted_economic_impact))
## # A tibble: 6 x 5
##
     Year Continent Crop_Type avg_economic_impact_milli~1 predicted_economic_i~2
##
     <int> <chr>
                      <chr>>
                                                       <dbl>
                                                                              <dbl>
## 1 1992 Europe
                      Cotton
                                                        353.
                                                                               244.
## 2 2009 South Asia Corn
                                                        258.
                                                                               273.
## 3 1992 South Asia Sugarcane
                                                        358.
                                                                               274.
## 4 2002 Eurasia
                     Vegetables
                                                                               275.
                                                        188.
## 5 2023 South Asia Vegetables
                                                        151.
                                                                               276.
## 6 2002 East Asia Coffee
                                                        226.
                                                                               278.
## # i abbreviated names: 1: avg_economic_impact_million_usd,
## # 2: predicted economic impact
ggplot(test_df, aes(x = predicted_yield, y = predicted_economic_impact,
                    color = Continent)) +
  geom_point(size = 3, alpha = 0.6) +
  geom_smooth(method = "lm", se = TRUE, color = "black", linetype = "dashed") +
 labs(
   title = "Predicted Economic Impact vs Predicted Crop Yield",
    x = "Predicted Crop Yield (MT/HA)",
   y = "Predicted Economic Impact (Million USD)",
    color = "Continent"
  ) +
  theme_minimal()+
  facet_wrap(~ Continent, scales = "free")
```

```
## `geom_smooth()` using formula = 'y ~ x'
```

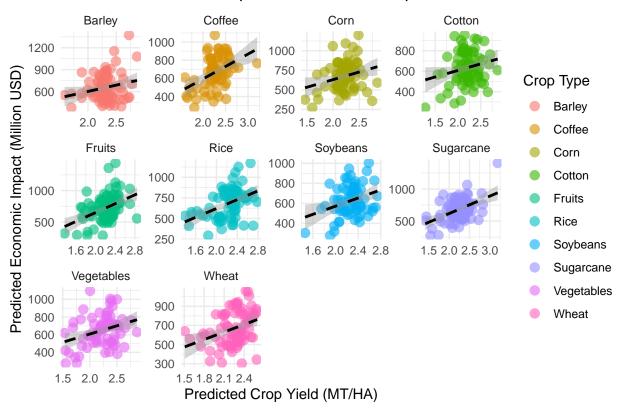
## Predicted Economic Impact vs Predicted Crop Yield



```
## # A tibble: 8 x 3
     Continent
                    slope intercept
##
     <chr>
                    <dbl>
                               <dbl>
## 1 Africa
                     134.
                               361.
                     266.
                                59.7
## 2 East Asia
                     244.
                               112.
## 3 Eurasia
## 4 Europe
                               295.
                     163.
## 5 North America
                     191.
                               243.
## 6 Oceania
                     255.
                                98.3
## 7 South America
                     169.
                               302.
                     350.
                               -92.6
## 8 South Asia
```

## `geom\_smooth()` using formula = 'y ~ x'

### Predicted Economic Impact vs Predicted Crop Yield



### print(slope\_intercept\_crop)

```
## # A tibble: 10 x 3
##
     Crop_Type slope intercept
##
     <chr>
              <dbl>
                       <db1>
## 1 Cotton
              128.
                       351.
## 2 Barley
               173.
                       256.
## 3 Corn
               196.
                       240.
## 4 Vegetables 186.
                       236.
## 5 Soybeans
               204.
                      164.
                      84.4
## 6 Rice
               268.
## 7 Wheat
               263.
                       79.4
## 8 Sugarcane 272.
                      72.9
               273.
## 9 Coffee
                      47.9
## 10 Fruits
               353.
                       -56.3
```