

Strawberry

Haochen Li

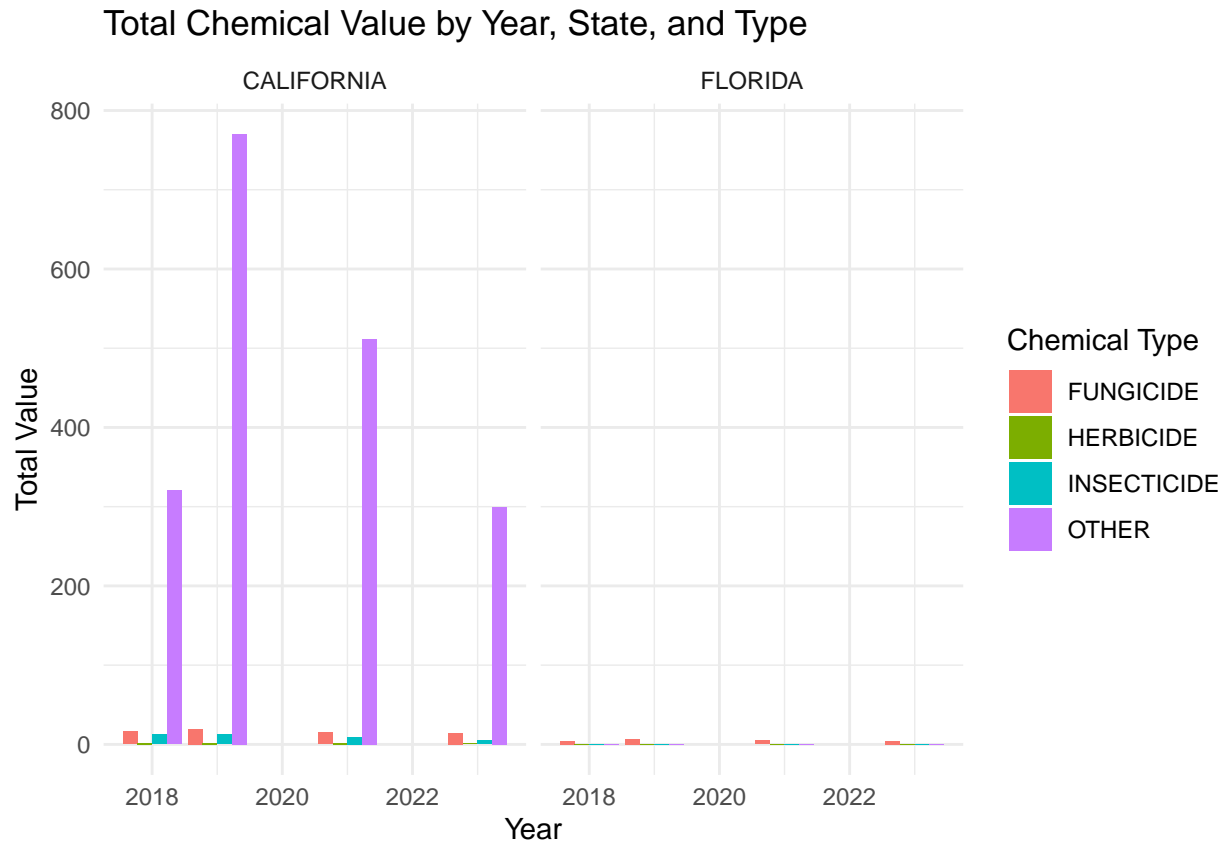
2024-11-18

Strawberries are one of the most widely cultivated and consumed fruits in the United States, cherished for their nutritional value and taste. However, their cultivation often involves significant chemical inputs, including fertilizers and pesticides, to maintain high yields and manage pests. This study aims to investigate the toxicity and chemical usage in strawberry production across different states, with a particular focus on California, the largest strawberry-producing state in the country. By analyzing chemical usage data, this research seeks to identify patterns, regional differences, and potential implications for environmental and human health. Insights from this analysis can inform sustainable agricultural practices and policy decisions for reducing the environmental footprint of strawberry cultivation while maintaining productivity.

```
grouped_data <- subset_data %>%  
  group_by(Year, State, type) %>%  
  summarise(Total_Value = sum(Value, na.rm = TRUE))
```

```
## 'summarise()' has grouped output by 'Year', 'State'. You can override using the  
## '.groups' argument.
```

```
# Create a ggplot to visualize the total Value by Year, State, and Type  
ggplot(grouped_data, aes(x = Year, y = Total_Value, fill = type)) +  
  geom_bar(stat = "identity", position = "dodge") +  
  facet_wrap(~ State) +  
  labs(title = "Total Chemical Value by Year, State, and Type",  
        x = "Year",  
        y = "Total Value",  
        fill = "Chemical Type") +  
  theme_minimal()
```



The graph shows total chemical usage by year and type in California and Florida.

California dominates with significantly higher chemical usage, particularly in the “Other” category, which peaks in 2020 and 2022. Fungicides, herbicides, and insecticides contribute minimally.

Florida’s usage is much lower overall, with “Other” chemicals still being the largest category, though at much smaller values.

The high prevalence of “Other” chemicals in California suggests a need for further investigation into their specific components and impact.

```
subset_data$Value <- as.numeric(subset_data$Value)

filtered_other <- subset_data %>%
  filter(type != "OTHER")

# Group the filtered data by Year, State, and Type, and summarize the Value column
filtered_other <- filtered_other %>%
  group_by(Year, State, type) %>%
  summarise(Total_Value = sum(Value, na.rm = TRUE))

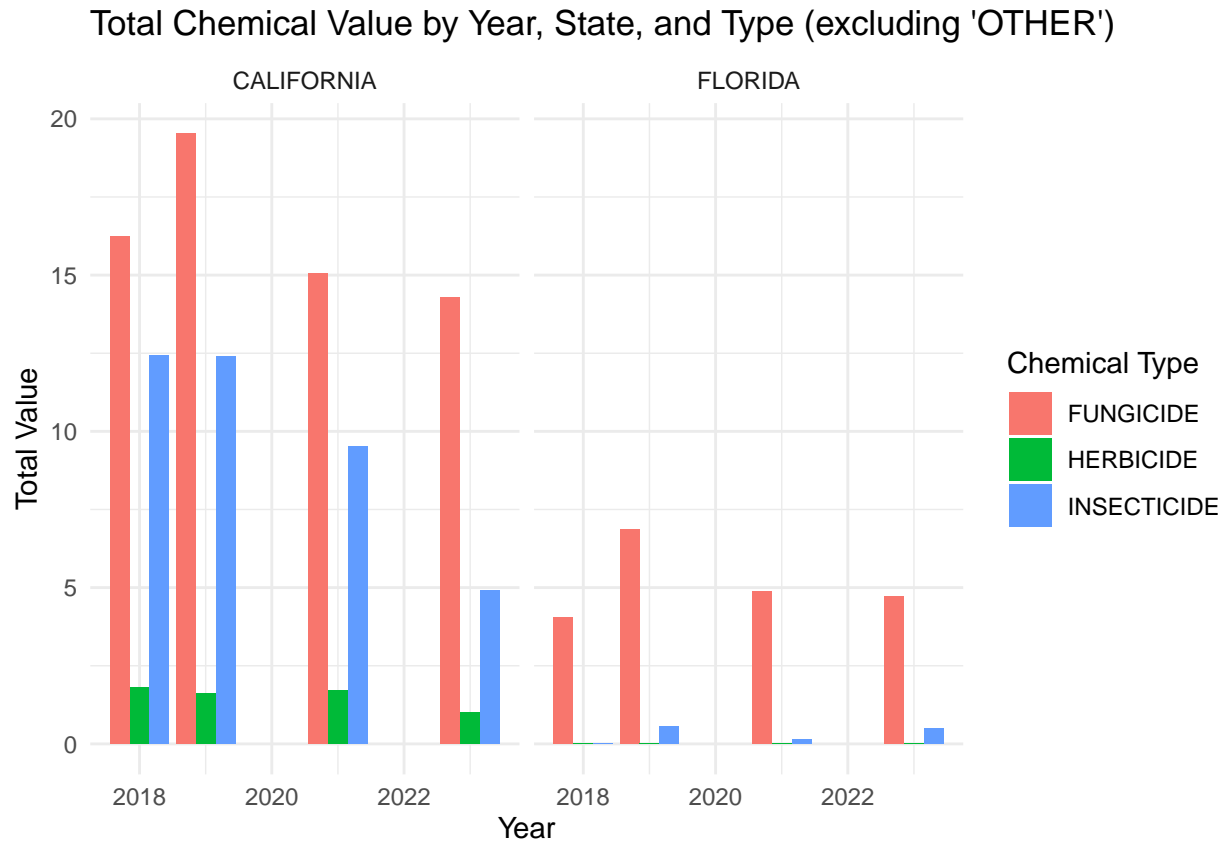
## 'summarise()' has grouped output by 'Year', 'State'. You can override using the
## '.groups' argument.

# Create a ggplot to visualize the total Value by Year, State, and Type (excluding "OTHER")
ggplot(filtered_other, aes(x = Year, y = Total_Value, fill = type)) +
  geom_bar(stat = "identity", position = "dodge") +
```

```

facet_wrap(~ State) +
labs(title = "Total Chemical Value by Year, State, and Type (excluding 'OTHER')",
     x = "Year",
     y = "Total Value",
     fill = "Chemical Type") +
theme_minimal()

```



Key Observations: California Dominates:

Fungicides (red) are the most widely used chemical type across all years in California. Insecticides (blue) are the second most prominent type, with noticeable usage across 2018, 2020, and 2022.

Herbicides (green) have minimal usage compared to fungicides and insecticides. Florida's Chemical Usage:

Fungicides dominate in Florida but on a much smaller scale compared to California. Insecticides and herbicides are rarely used.

Yearly Trends:

California shows consistent fungicide usage, peaking in 2018 and 2022. Florida exhibits lower, consistent fungicide use with no significant trends. Implications:

Fungicides are critical in both states, especially in California, where they form the bulk of chemical usage.

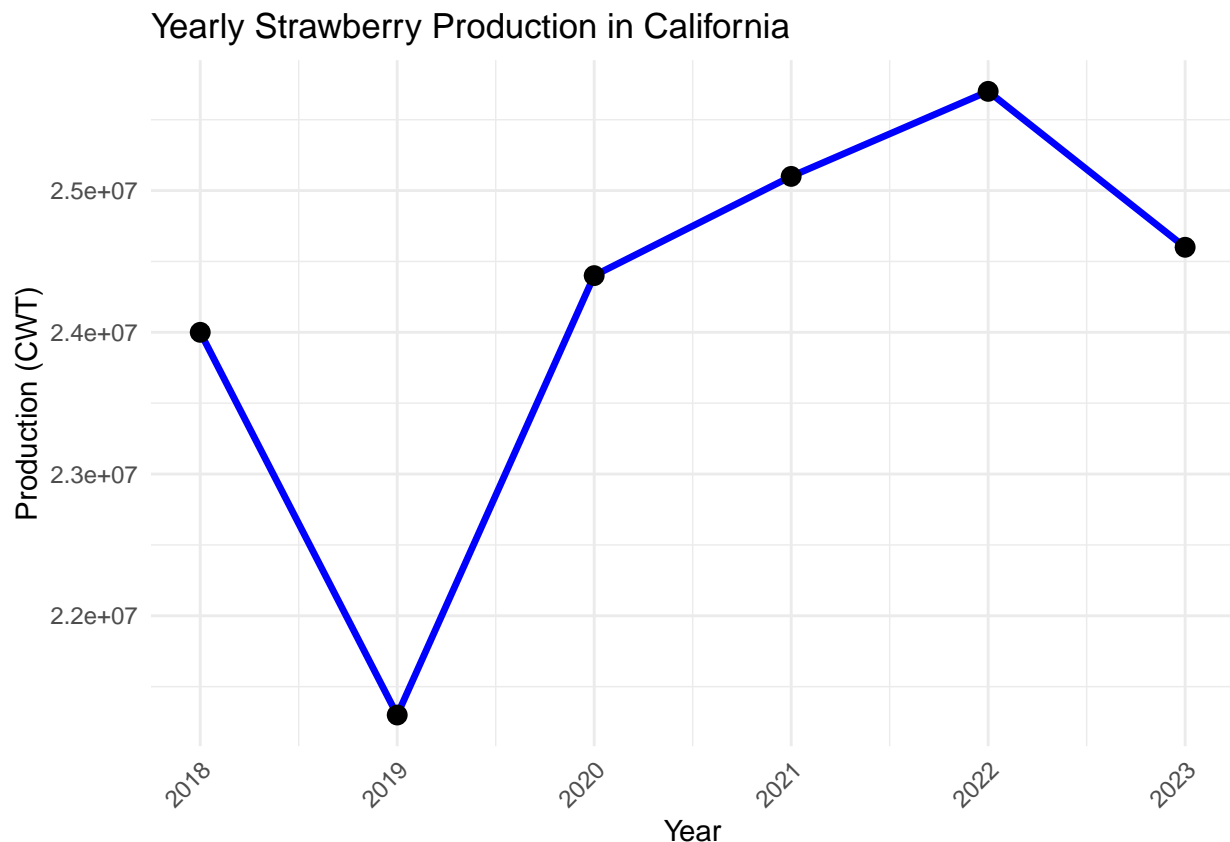
Minimal herbicide usage indicates reliance on other methods for weed control. The graph highlights California's larger agricultural chemical footprint compared to Florida.

Production

```
california_production_data <- survey_d_total %>%
  filter(State == "CALIFORNIA" & product_price == "PRODUCTION" & measure == "CWT" & Period == "YEAR")

ggplot(california_production_data, aes(x = Year, y = as.numeric(gsub(",", "", Value)))) +
  geom_line(group = 1, color = "blue", size = 1.2) + # Line plot
  geom_point(size = 3) + # Points on the plot
  labs(title = "Yearly Strawberry Production in California",
       x = "Year",
       y = "Production (CWT)") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```

```
## 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.
```



The graph depicts the yearly strawberry production in California from 2018 to 2023, measured in CWT (hundredweight). Production starts at approximately 24 million CWT in 2018, drops sharply in 2019 to around 22 million CWT, then steadily increases from 2020 to 2022, peaking at about 25.5 million CWT. In 2023, production slightly declines, falling back to around 24.5 million CWT.

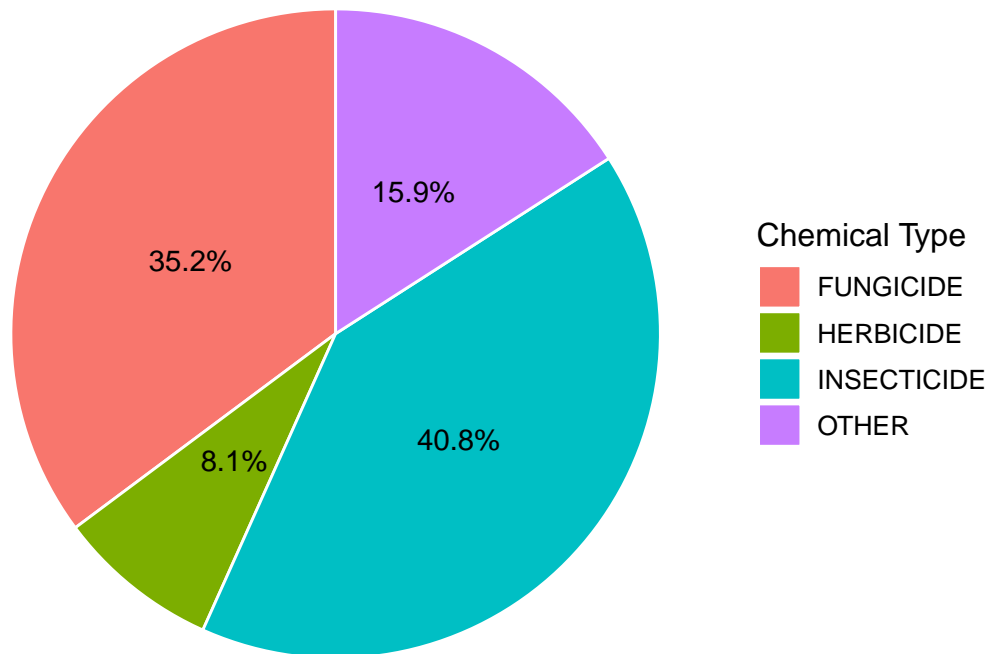
The significant dip in 2019 could indicate challenges such as adverse weather conditions, pest outbreaks, or market disruptions. The consistent growth from 2020 to 2022 reflects recovery, possibly due to improved

agricultural practices, favorable climate, or increased demand. However, the slight decline in 2023 suggests potential new pressures on production, such as resource limitations or environmental factors.

```
type_proportion <- subset_data %>%
  filter(State == "CALIFORNIA") %>%
  group_by(type) %>%
  summarise(count = n()) %>%
  mutate(proportion = (count / sum(count)) * 100)

# Plotting the pie chart
ggplot(type_proportion, aes(x = "", y = proportion, fill = type)) +
  geom_bar(stat = "identity", width = 1, color = "white") +
  coord_polar("y", start = 0) +
  labs(title = "Proportion of Each Chemical Type", fill = "Chemical Type") +
  geom_text(aes(label = paste0(round(proportion, 1), "%")),
            position = position_stack(vjust = 0.5)) +
  theme_void() +
  theme(legend.title = element_text(size = 12),
        legend.text = element_text(size = 10),
        plot.title = element_text(hjust = 0.5, size = 15))
```

Proportion of Each Chemical Type



The pie chart shows that insecticides account for the largest share of chemical usage at 40.8%, followed by fungicides at 35.2%. Herbicides (8.1%) and “Other” chemicals (15.9%) have comparatively smaller proportions, highlighting a focus on pest and disease control in chemical applications.

```

fungicides_data <- subset(subset_data, type == "FUNGICIDE")

# Summing up the 'Value' column for each fungicide
fungicide_usage <- aggregate(Value ~ chem_name, data = fungicides_data, sum)

# Sorting by usage in descending order
most_used_fungicides <- fungicide_usage[order(-fungicide_usage$Value), ]

# Selecting the top 3 most-used fungicides
top_fungicides <- head(most_used_fungicides, 3)
print(top_fungicides)

```

```

##      chem_name  Value
## 38      SULFUR 17.771
## 41      THIRAM 16.846
## 5       CAPTAN 14.965

```

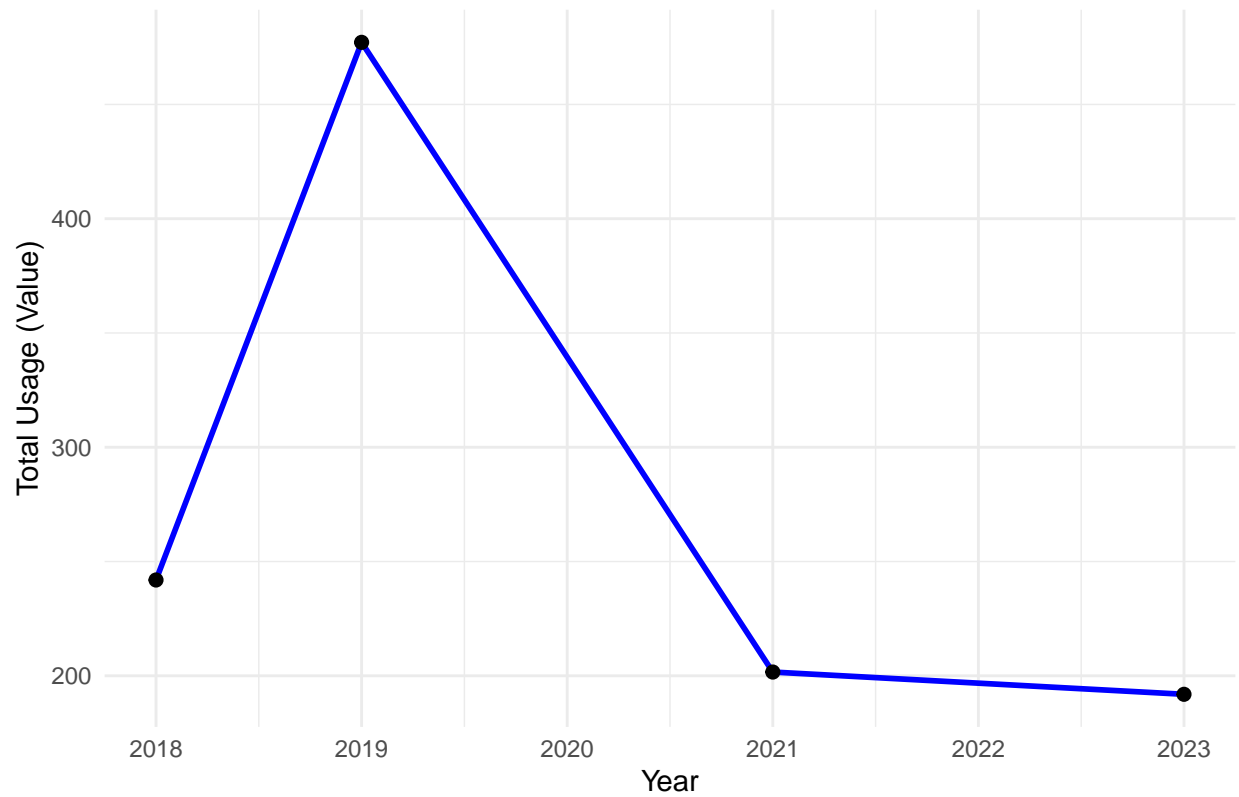
```

california_yearly <- dangerous_chemicals %>%
  group_by(Year) %>%
  summarize(Total_Usage = sum(Value, na.rm = TRUE))

# Line plot for yearly usage
ggplot(california_yearly, aes(x = Year, y = Total_Usage)) +
  geom_line(color = "blue", size = 1) +
  geom_point(size = 2) +
  labs(title = "Yearly Pesticide Usage in California",
       x = "Year",
       y = "Total Usage (Value)") +
  theme_minimal()

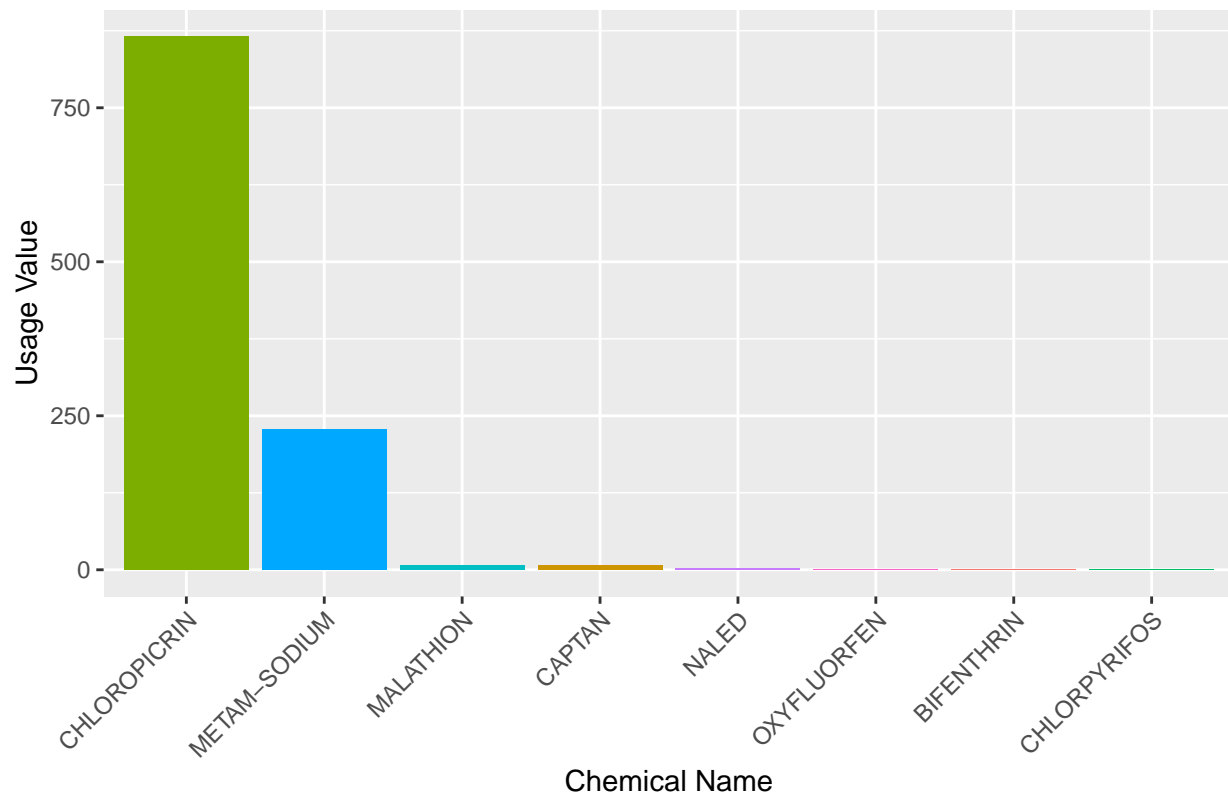
```

Yearly Pesticide Usage in California



```
# Create a bar chart of the most used dangerous chemicals
ggplot(dangerous_chemicals, aes(x = reorder(chem_name, -Value), y = Value, fill = chem_name)) +
  geom_bar(stat = "identity") +
  labs(title = "Chemicals Requiring Extra Attention", x = "Chemical Name", y = "Usage Value") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  theme(legend.position = "none")
```

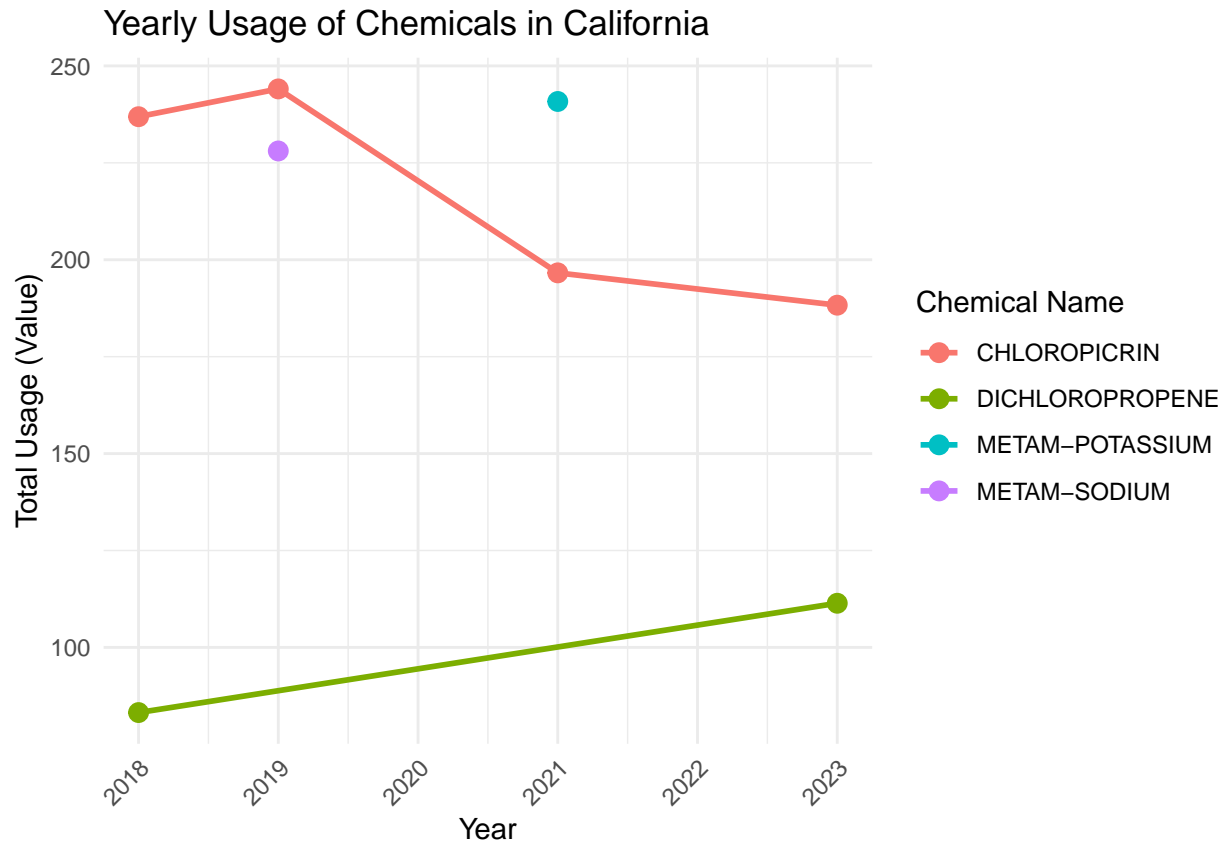
Chemicals Requiring Extra Attention



```
california_data <- subset(subset_data, State == "CALIFORNIA")

top_two_chemicals <- california_data %>%
  group_by(Year, chem_name) %>%
  summarize(Total_Usage = sum(Value, na.rm = TRUE), .groups = "drop") %>%
  group_by(Year) %>%
  slice_max(order_by = Total_Usage, n = 2)

ggplot(top_two_chemicals, aes(x = Year, y = Total_Usage, color = chem_name, group = chem_name)) +
  geom_line(size = 1) +
  geom_point(size = 3) +
  labs(title = "Yearly Usage of Chemicals in California",
       x = "Year",
       y = "Total Usage (Value)",
       color = "Chemical Name") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```

The graph shows the yearly usage of four chemicals in California between 2018 and 2023. CHLOROPICRIN was the most used chemical at the start, but its usage steadily declined over time. DICHLOROPROPENE usage, on the other hand, gradually increased each year. METAM-POTASSIUM saw a significant jump in usage in 2023, while METAM-SODIUM was only used in 2019 and 2020. The trends suggest changing preferences or regulations in chemical use over the years.

The chemicals in the graph, like CHLOROPICRIN and DICHLOROPROPENE, are widely used in farming to control pests and diseases, helping to increase crop production. However, they can be harmful to us and the environment. For example, CHLOROPICRIN can irritate our lungs and contribute to air pollution, while DICHLOROPROPENE can contaminate groundwater and may pose cancer risks. It's important to ask if using more of these chemicals really leads to higher production or if there's a point where it causes more harm than good. By looking at the trends, we can start to understand whether these chemicals are being used responsibly and how they might affect not just farming, but also our health and the world around us.