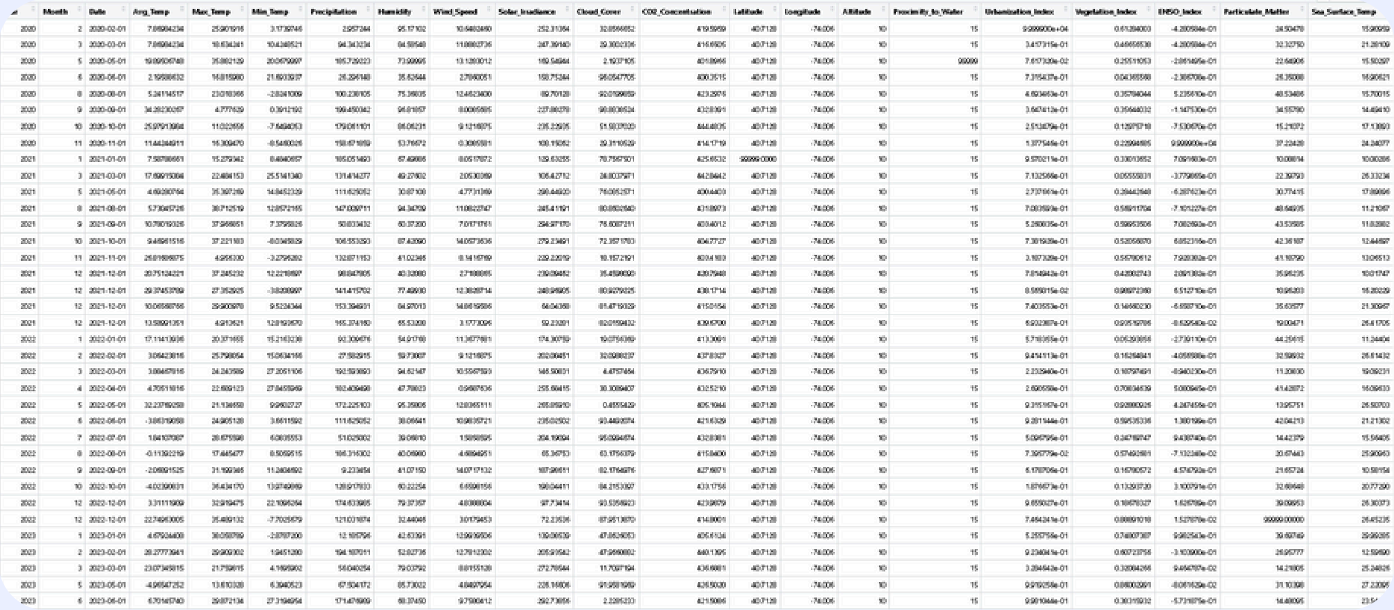
TRACKING THE SHIFT: GLOBAL CLIMATE PATTERNS & ENVIRONMENTAL IMPACT

Data Overview

This report utilizes a comprehensive dataset spanning nearly five years (January 2020 – May 2024), aimed at analyzing global climate dynamics. Unlike standard meteorological datasets, this collection integrates traditional weather metrics (such as temperature, precipitation, and humidity) with critical environmental and geographical indicators. By combining atmospheric data with urbanization indices, CO2 concentrations, and particulate matter levels, the dataset provides a holistic view of the interaction between human activity and climate patterns across various global coordinates and altitudes.

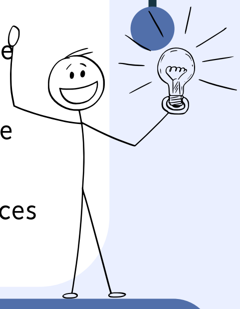


Data Dictionary

1. Temporal & Spatial Metadata

Variables identifying the time and location of observations, essential for time-series and geospatial analysis.

- Year (Integer): Represents the year of data collection, ranging from 2020 to 2024. This variable is essential for performing annual trend analysis.
- Month (Integer): Represents the month of the year (1–12). It is useful for identifying seasonality and monthly weather patterns.
- Date (Date, YYYY-MM-DD): Represents the full date, specifically the first day of each month. It serves as the main axis for time-series analysis.
- Latitude (Float, Degrees): The geographic coordinate specifying the north-south position of the location.
- Longitude (Float, Degrees): The geographic coordinate specifying the east-west position of the location.
- Altitude (Float, Meters): The height of the location above sea level, which significantly influences local temperature and atmospheric pressure.



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2. Temperature Variables

Avg_Temp (Float, °C): The average air temperature measured at a height of 2 meters during the month. Expected range: -50°C to +60°C.

Max_Temp (Float, °C): The highest temperature recorded during the specific month.

Min_Temp (Float, °C): The lowest temperature recorded during the specific month.

3. Precipitation & Humidity

Precipitation (Float, mm): The total accumulated rainfall or snowfall in millimeters for the month.

Humidity (Float, %): The relative humidity percentage, indicating the amount of water vapor in the air relative to the maximum possible saturation.

4. Wind & Solar Variables

Wind_Speed (Float, m/s): The average speed of near-surface air movement measured in meters per second.

Solar_Irradiance (Float, W/m^2): The power of solar energy reaching the Earth's surface, measured in watts per square meter.

Cloud_Cover (Float, %): The percentage of the sky obscured by clouds.

5. Greenhouse Gases

CO2_Concentration (Float, ppm): The concentration of Carbon Dioxide in the atmosphere, measured in parts per million. This is a key indicator for studying global warming.

6. Environmental & Urban Indicators

Proximity_to_Water (Float, km): The distance in kilometers to the nearest major body of water (ocean, sea, or large lake).

Urbanization_Index (Float, 0.0–1.0): A normalized index representing the level of urban development, where higher values indicate more urbanized areas.

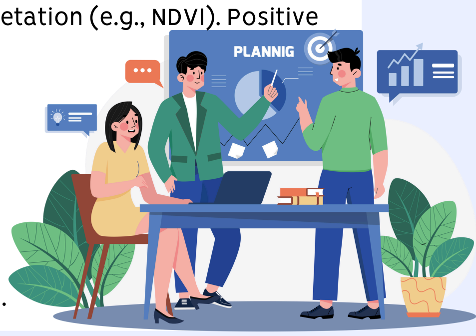
Vegetation_Index (Float, -1.0 to +1.0): An index representing the density of green vegetation (e.g., NDVI). Positive values indicate healthier/denser vegetation.

7. Advanced Climate Indicators

ENSO_Index (Float, -2.0 to +2.0): The El Niño Southern Oscillation index, used to monitor ocean-climate interactions (El Niño and La Niña phases).

Particulate_Matter (Float, µg/m^3): The concentration of air pollutants (PM10 / PM2.5) measured in micrograms per cubic meter.

Sea_Surface_Temp (Float, °C): The temperature of the water at the ocean's surface.



Data Cleaning & Preprocessing

To ensure high data quality and analytical accuracy, a comprehensive preprocessing pipeline was implemented using the R programming language (specifically tidyverse and zoo packages). The process addressed structural inconsistencies, missing values, and logical anomalies through the following stages:

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3.1. Standardizing Data Structure (Renaming & Typing)

Renaming: Original column names were translated and standardized into concise English identifiers. This ensures compatibility with visualization libraries and mathematical functions.

Type Casting: All numerical features (Temperature, Wind Speed, etc.) were explicitly converted to numeric types, while temporal features (Year, Month) were cast to integer. This step prevents execution errors during statistical aggregation.

3.2. Temporal Feature Engineering

Since climate data depends heavily on time progression, a unified Date object was constructed by combining the Year and Month columns (assigning the 1st day of each month).

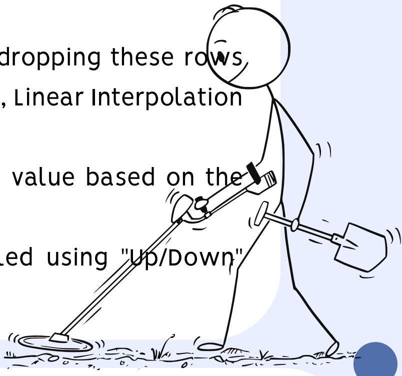
Purpose: This created a continuous time-series index, enabling accurate plotting of trends over the 53-month period.

3.3. Handling Missing Values (Imputation Strategy)

An analysis of the dataset revealed missing values across several columns. Instead of dropping these rows (which would lead to data loss) or filling them with a static mean (which distorts trends), Linear Interpolation was applied using the na.approx function from the zoo package.

Justification: Climate data is continuous by nature. Interpolation estimates the missing value based on the point before and after it, preserving the natural fluctuation of weather patterns.

Edge Cases: Any remaining gaps at the very beginning or end of the series were filled using "Up/Down" propagation.



3.4. Deduplication

The dataset was scanned for identical duplicate rows.

Outcome: Duplicate records were identified and removed to ensure that each data point represents a unique observation, preventing bias in ئstatistical calculations.

3.5. Logical Consistency & Outlier Treatment

To maintain scientific validity, the dataset was examined for physically implausible measurements. Several domain-based correction rules were applied:

Precipitation and Wind Speed:

Negative values are not physically meaningful and were therefore corrected to zero. In rare instances where negative wind speed appeared (likely due to sensor polarity issues), the absolute value was taken to preserve magnitude information.

Humidity and Cloud Cover:

Since these variables represent percentages, all values were constrained within the 0–100% range. Any measurement outside this domain was clipped to the nearest valid boundary.

Outlier Detection:

Extreme values were identified using the Interquartile Range (IQR) method. Outliers were replaced with the median to reduce distortion while maintaining the central tendency of the dataset.

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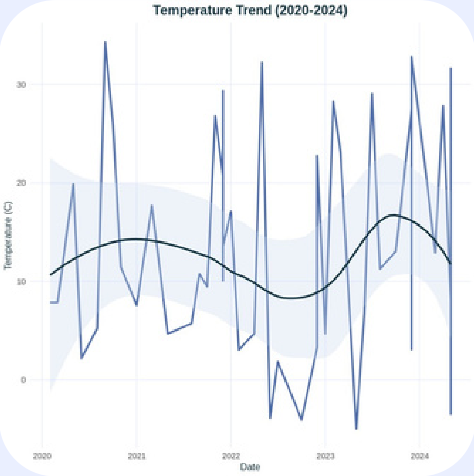
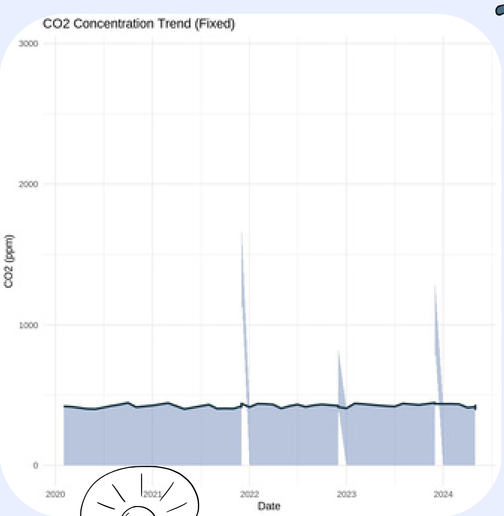
Data Visualization & Exploratory Analysis

Exploratory Data Analysis (EDA)

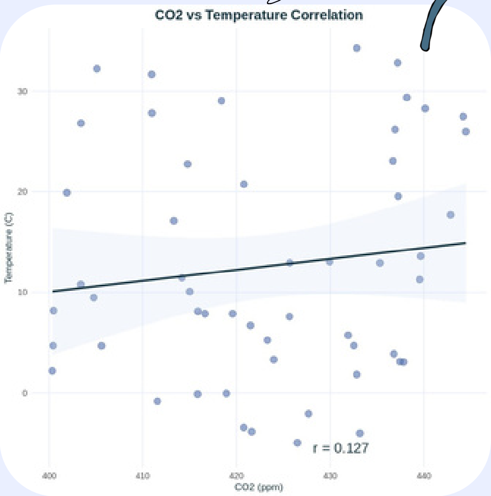
Range: –5°C to 35°C (40°C difference)
Overall Average: 13°C
Highest Average: 16°C (2023)
Lowest Average: 9°C (End of 2022)
Seasonal Fluctuations: ±15°C annually
Trend: Fluctuating with no clear upward/downward pattern





⚠ Warning: Data contains 3 outliers that were ignored
Normal Range: 408–425 ppm
Average: ~ 420 ppm
Fluctuations: ±5 ppm seasonally
Trend: Slight increase (+2–3 ppm from 2020 to 2024)
Conclusion: CO_2 concentration is relatively stable with a very slight increase – consistent with the trend.

Bivariate Correlation Analysis



Correlation Coefficient: r = 0.127
⚠ Interpretation: Very weak positive correlation (almost non-existent)
Data:
CO_2: 400–445 ppm
Temperature: –5 to 34°C
Number of Observations: 41 points
Result: Only 12.7% of the change in temperature is explained by CO_2 change. The remaining change (87.3%) is due to other factors:
✓ Seasonal fluctuations
✓ Humidity and Wind
✓ Geographical location
✓ Solar Irradiance
Conclusion: In this short-term monthly data, The effect of CO_2 on temperature is unclear. The real effect of CO_2 appears over the long term (decades).

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Distribution Analysis

Distribution Type: Bimodal (Two peaks)

Data Distribution:

Cold (-5 to 5°C): 22% of data

Moderate (5-15°C): 43% (The most)

Warm (15-25°C): 17%

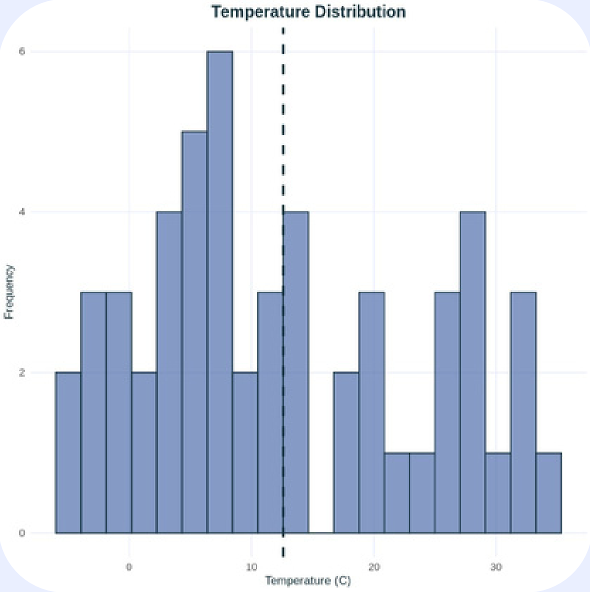
Hot (25-35°C): 18%

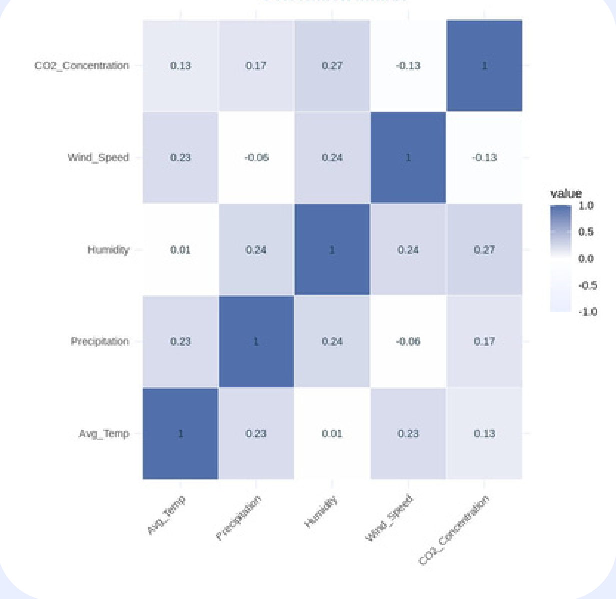
🌡️ The Two Peaks:

Winter Peak: ~7.5°C

Summer Peak: ~27.5°C

Conclusion: The distribution shows two clear seasons (Winter and Summer) With a greater concentration in the moderate region (5-15°C).





	Avg_Temp	Precipitation	Humidity	Wind_Speed	CO2_Concentration
CO2_Concentration	0.13	0.17	0.27	-0.13	1
Wind_Speed	0.23	-0.06	0.24	1	-0.13
Humidity	0.01	0.24	1	0.24	0.27
Precipitation	0.23	1	0.24	-0.06	0.17
Avg_Temp	1	0.23	0.01	0.23	0.13

Correlation Matrix

Strongest Correlations:

Humidity ↔ CO2: 0.27 (Weak positive)

Humidity ↔ Precipitation: 0.24

Humidity ↔ Wind_Speed: 0.24

Avg_Temp ↔ Precipitation: 0.23

Avg_Temp ↔ Wind_Speed: 0.23

⚠ General Conclusion:

✓ All correlations are very weak (<0.3)

✓ Variables are relatively independent of each other

✓ CO_2 has no clear effect on other variables

✓ Reason: Short-term data + strong seasonal fluctuations

Interpretation: In short-term monthly data (4.5 years), Seasonal fluctuations are much stronger than relationships between variables, Therefore, correlations are weak and do not reflect true long-term relationships.

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Monthly Seasonality Analysis

Monthly Average Temperature (2020–2024):

Hottest Month: December (19.5°C)

❄ Coldest Month: June (1.7°C)

Difference: 17.8°C

Annual Average: ~11.0°C

🌡 Month Distribution:

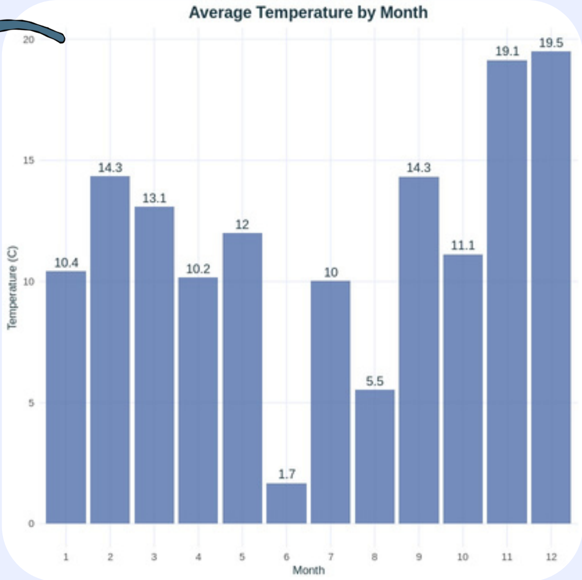
- Cold (< 10°C): 2 months
- Moderate (10–15°C): 8 months
- Warm (> 15°C): 2 months

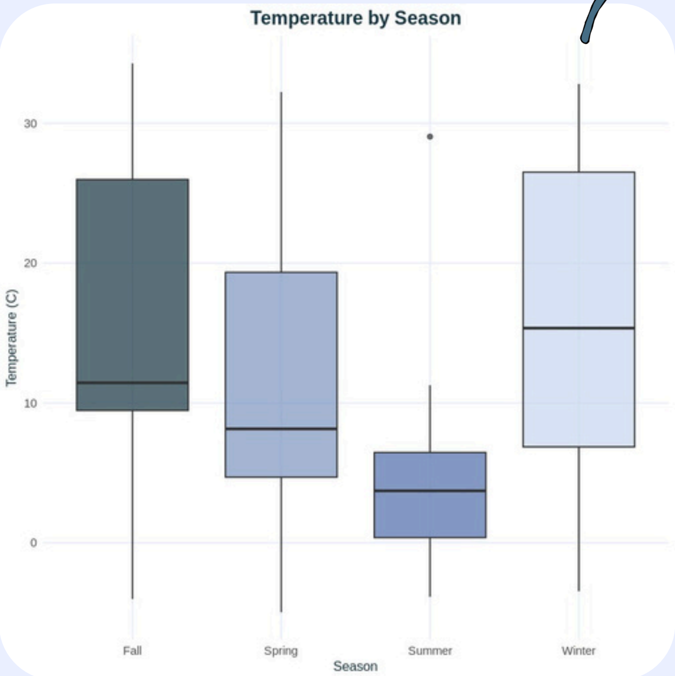
Seasonal Pattern:

⚠ Pattern is inverted (unconventional):

- Winter (Dec–Feb): 14.7°C (Warm)
- Summer (Jun–Aug): 5.7°C (Cold)
- Spring: 11.8°C (Moderate)
- Fall: 14.8°C (Warm Moderate)

Conclusion: Most months are moderate (10–15°C) With two extremes: June is very cold, December is warm. The pattern indicates a Southern Hemisphere region or unconventional data.





Correlation Matrix

Temperature Analysis by Season (Box Plot):

🌡 Median for each season:

1. Winter: 15.5°C The Warmest!
2. Fall: 11.5°C
3. Spring: 8.0°C
4. Summer: 4.0°C ❄ The Coldest!

Variability (IQR):

- Winter: 20°C (Most variable)
- Fall: 17°C
- Spring: 14.5°C
- Summer: 6°C (Most stable)

Ranges:

- Winter: –3 to 33°C
- Fall: –3 to 34°C
- Spring: –5 to 32°C
- Summer: –3 to 11°C (+ outlier value 29.5°C)

⚠ Important Notes:

✓ Pattern is inverted (Winter is warmer than Summer)

✓ Indicates a Southern Hemisphere location

✓ Very high variability in all seasons

✓ Summer is the most stable despite being the coldest

Conclusion: Data shows a Southern Hemisphere climate With high fluctuations in all seasons Winter (Dec–Feb) is warm Summer (Jun–Aug) is cold

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Descriptive Statistics

Average Climate Variables (2020–2024):

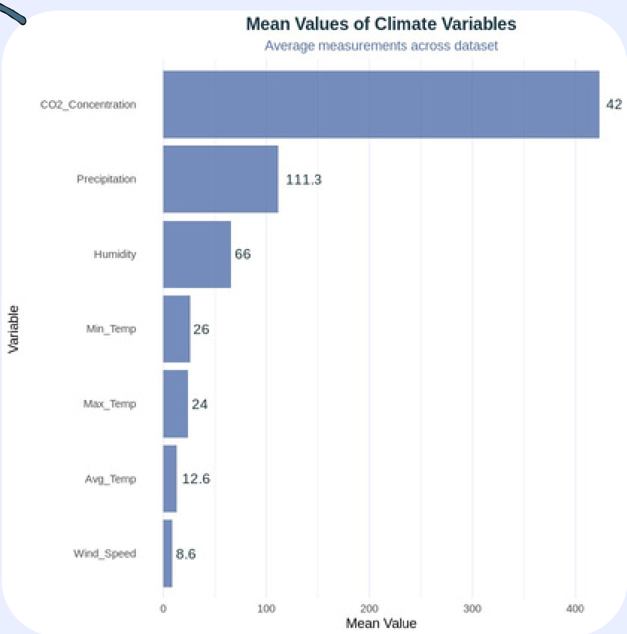
🌡️ Temperature:

- Average: 12.6°C
- Max: 24°C
- Min: 26°C

Weather: • Humidity: 66% • Precipitation: 111.3 mm/month • Wind: 8.6 m/s (~31 km/h)

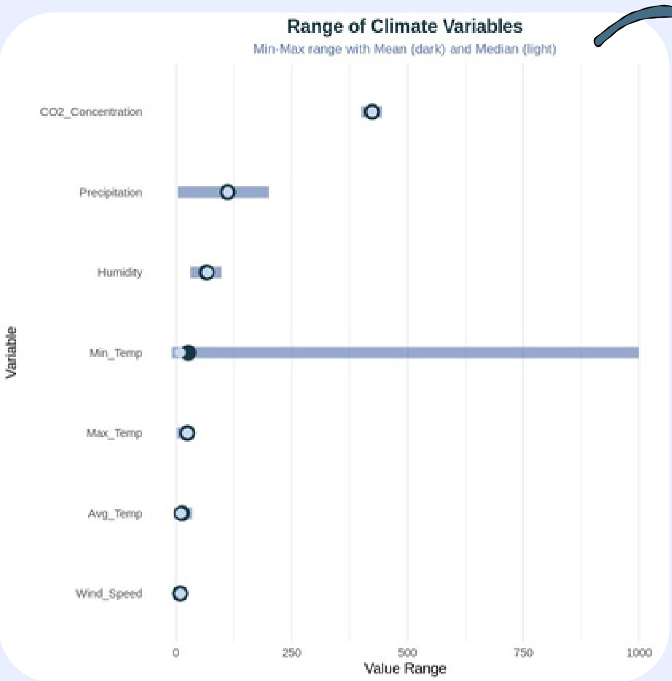
CO2: 423 ppm (Global Level)

All values are logical and reflect a moderate climate.



Mean Values of Climate Variables

Average measurements across dataset



Range of Climate Variables

Min-Max range with Mean (dark) and Median (light)

Range & Variability Analysis

Climate Variable Ranges:

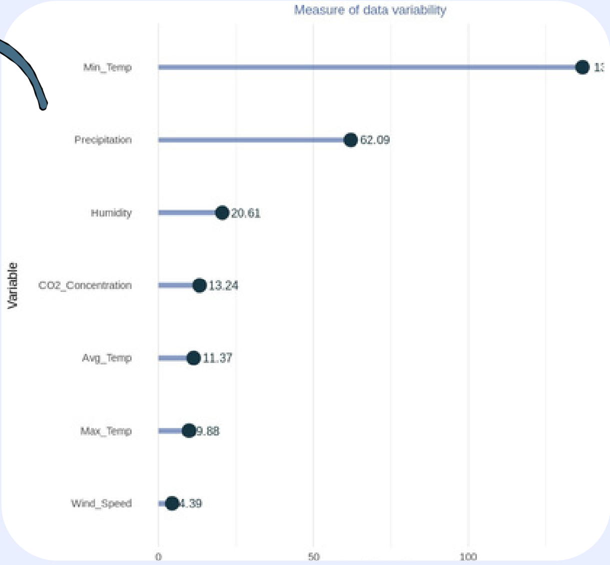
🌡️ Largest Variance: • Min_Temp: 0–1000 (Outlier – needs review)

- Precipitation: 0–250 mm

Low Variance (Stable):

- CO2: 400–450 ppm
- Humidity: 40–90%
- Wind_Speed: 5–15 m/s
- Temperature: Narrow ranges

Conclusion: Most variables are stable with Mean ≈ Median



Measure of data variability

Descriptive Statistics

Average Climate Variables (2020–2024):

🌡️ Temperature:

- Average: 12.6°C
- Max: 24°C
- Min: 26°C

Weather: • Humidity: 66% • Precipitation: 111.3 mm/month • Wind: 8.6 m/s (~31 km/h)

CO2: 423 ppm (Global Level)

All values are logical and reflect a moderate climate.

TRACKING THE SHIFT: GLOBAL CLIMATE PATTERNS & ENVIRONMENTAL IMPACT

Comprehensive Statistical

Highest Numerical Values:

- CO2: 400–450 ppm (Highest)
- Precipitation: 0–250 mm
- Humidity: 40–90%

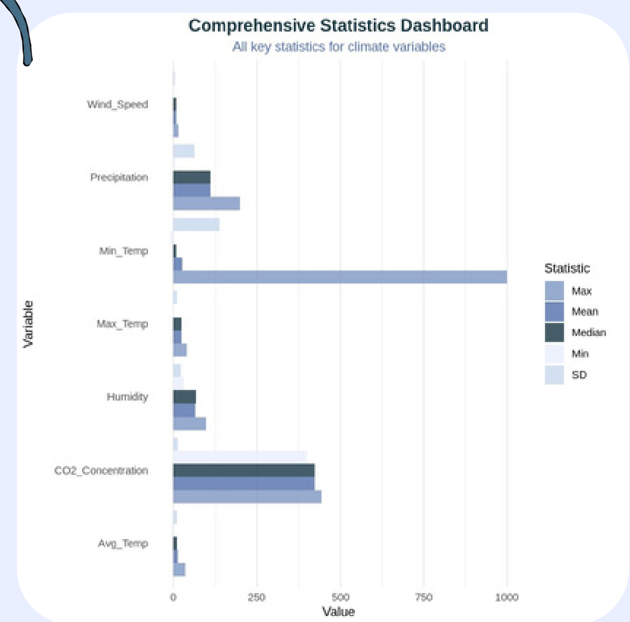
Most Stable (Low SD):

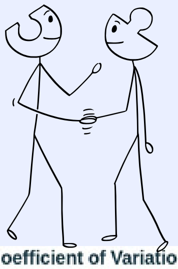
- Wind_Speed
- Max_Temp
- Avg_Temp

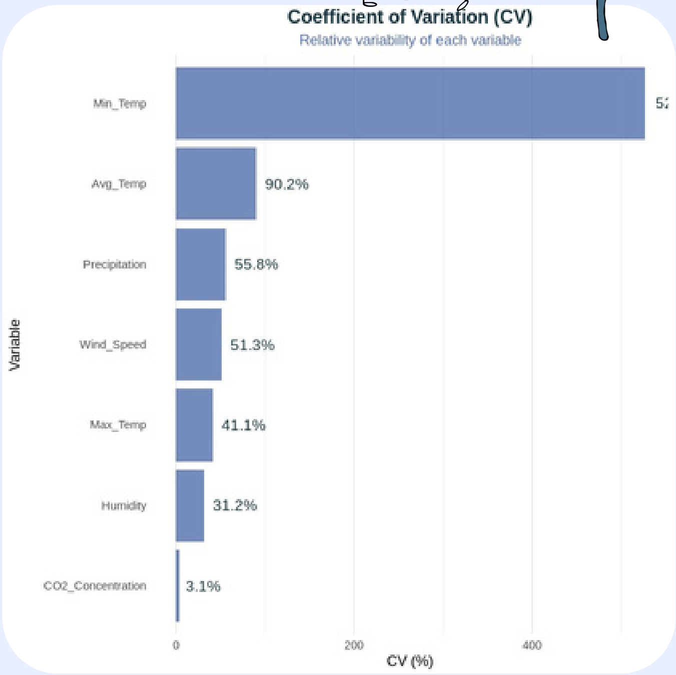
⚠ Most Volatile:

- Precipitation (Normal)
- Min_Temp (Outlier – needs correction)

Mean ≈ Median = Balanced Distribution ✓







Stability Analysis

Coefficient of Variation (CV):

Relative Variance= (SD ÷ Mean) × 100

Most Stable:

- CO2: 3.1% (Almost constant)
- Humidity: 31.2%
- Max_Temp: 41.1%

Moderate Variance:

- Wind_Speed: 51.3% · Precipitation: 55.8%

High Variance: · Avg_Temp: 90.2% (Seasonal)

Outlier: · Min_Temp: 520%+ (Needs correction)

The lower the CV = the higher the stability

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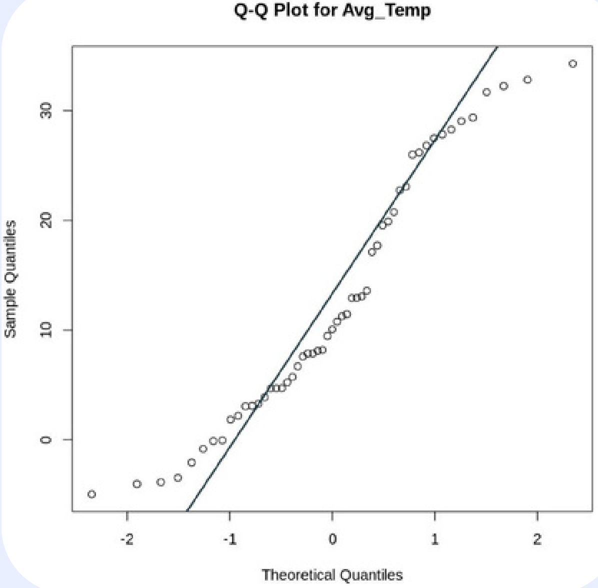
One-Factor Analysis

Q-Q Plot for Avg_Temp

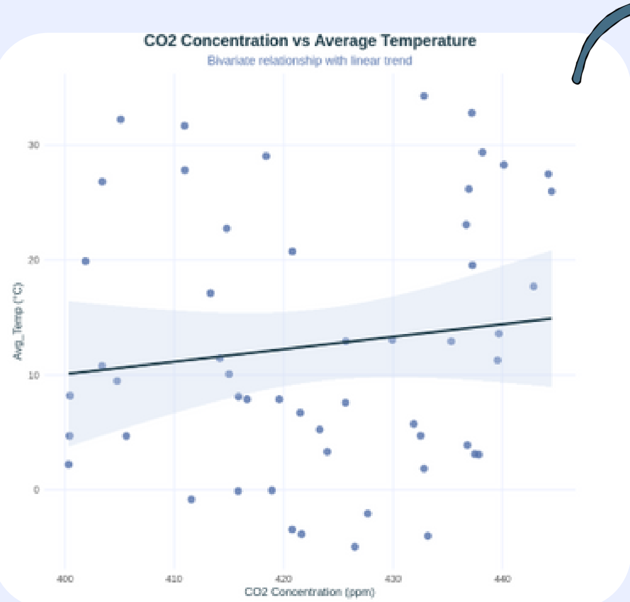
Line vs points:
In a perfect normal distribution, all points would lie close to the straight line; here, many points curve away from the line, especially at both tails.

Tails behavior:
Points at the lower and upper ends are clearly below/above the line, indicating heavier or lighter tails than a normal distribution and possible skewness.

Conclusion:
The Q-Q plot visually confirms the Shapiro-Wilk result: Avg_Temp does not follow a perfect normal distribution and shows strong deviations, likely due to seasonal temperature patterns.



Two-Factor Analysis



Bivariate: CO2 vs Avg_Temp

Type:
Bivariate relationship between one predictor (CO2 concentration) and one response (average temperature).

Direction (trend):
The regression line is slightly upward, meaning higher CO2 values are associated with slightly higher Avg_Temp on average.

Strength (scatter):
Points are widely scattered around the line, so the linear relationship is weak; CO2 alone explains only a small part of the variation in Avg_Temp.

Practical reading:
CO2 and Avg_Temp move in the same direction overall (positive relationship), but temperature is also strongly affected by other factors (seasonality, location, etc.), so this BI plot shows weak but positive association rather than a strong predictive link.

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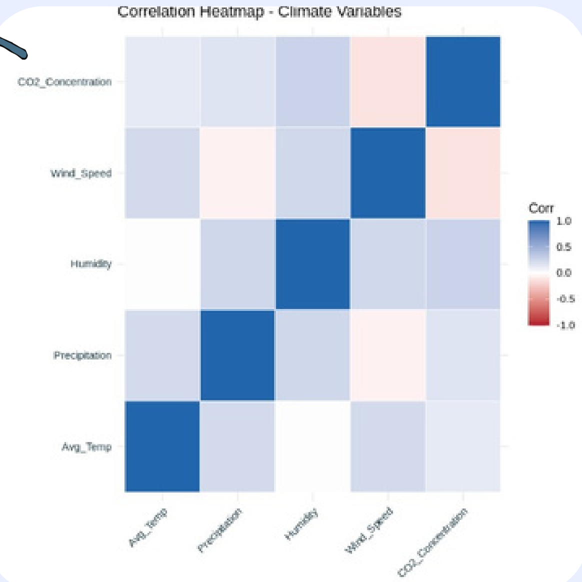
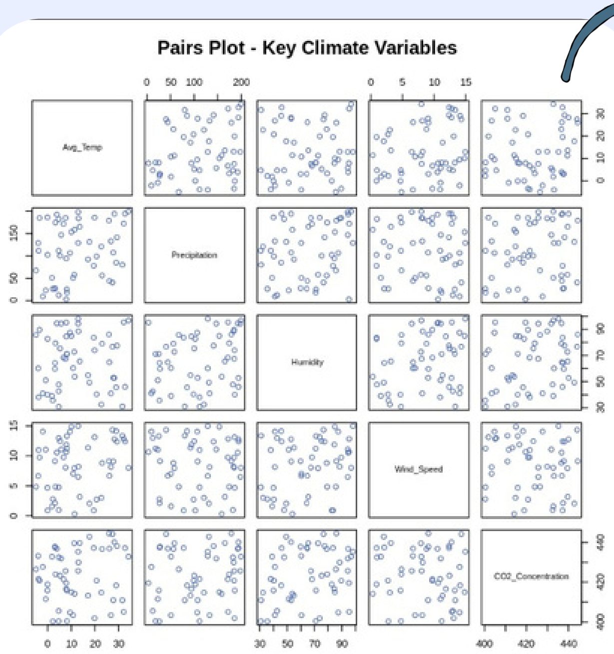
Correlation Heatmap

Climate Variables (Multivariate)

Purpose (Multi):
This heatmap shows all pairwise correlations between several climate variables at the same time (Avg_Temp, Precipitation, Humidity, Wind_Speed, CO2_Concentration).
Darker blue squares = stronger positive relationship, lighter/whitish = weak or near zero, reddish = negative.
Main patterns:
Strong blue on the diagonal is each variable with itself (correlation = 1).
Some pairs like Precipitation–Humidity and Wind_Speed with itself on diagonal appear darker, meaning stronger positive linkage between those variables.
Many off-diagonal cells are pale (close to white), meaning weak correlations, so no single variable fully explains the others.
Why this is Multivariate:
Instead of looking at one pair (BI) like CO2 vs Avg_Temp, the heatmap summarizes the structure of relationships among all variables together, giving a global multivariate view of the climate system





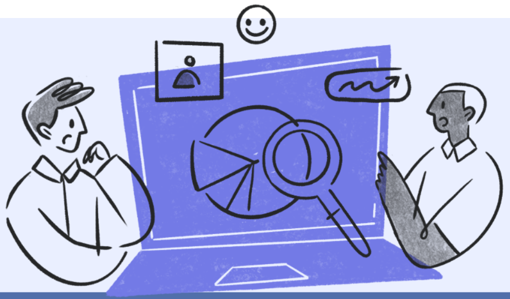
Multi-Factor Analysis

Pairs Plot – Key Climate Variables (Multivariate)

What it shows:
This grid displays a scatter plot for every pair of variables (Avg_Temp, Precipitation, Humidity, Wind_Speed, CO2_Concentration), so each small box is one bivariate relationship, and together they form a multivariate overview.

Main pattern:
Most panels show points widely scattered without a clear line, meaning linear relationships between pairs of variables are generally weak, with no single strong predictor–response pair dominating the system.

Why it is Multivariate:
Instead of focusing on one or two variables, the pairs plot lets you check all pairwise interactions at once, helping to see which relationships might be interesting (more structured clouds) and which look almost random, as part of your multivariate EDA.



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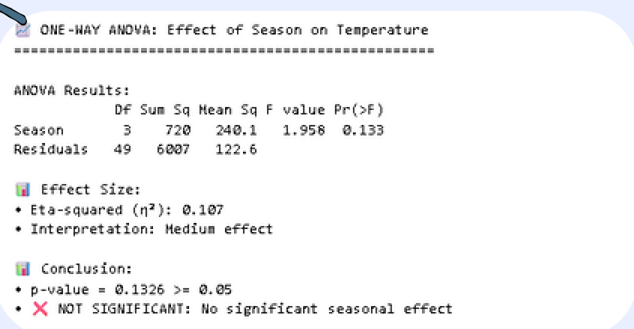
One-Way ANOVA

Objective: To test if Season significantly impacts Avg_Temp.

Results:

- F-statistic: 1.958
- P-value: 0.133 (Greater than 0.05)
- Conclusion: Not Significant. The analysis fails to reject the null hypothesis.

Key Insight: The Box Plot reveals extreme volatility within individual seasons (especially Winter). This high internal variance overshadows the differences between seasonal means, indicating a highly unpredictable climate regardless of the season.



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📈 ONE-WAY ANOVA: Effect of Season on Temperature
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ANOVA Results:
            Df Sum Sq Mean Sq F value Pr(>F)
Season       3    720   240.1   1.958  0.133
Residuals   49   6007   122.6

📊 Effect Size:
• Eta-squared (η²): 0.107
• Interpretation: Medium effect

📊 Conclusion:
• p-value = 0.1326 >= 0.05
• ❌ NOT SIGNIFICANT: No significant seasonal effect
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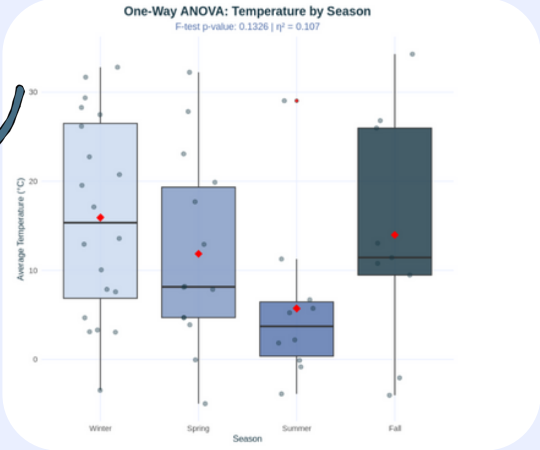

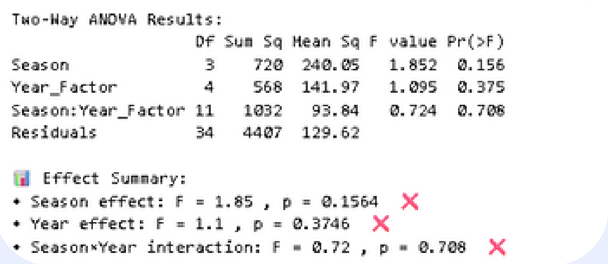

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📈 TWO-WAY ANOVA: Season × Year Interaction
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Two-Way ANOVA Results:
                   Df Sum Sq Mean Sq F value Pr(>F)
Season              3    720  240.05   1.852  0.156
Year_Factor         4    568  141.97   1.095  0.375
Season:Year_Factor 11   1032   93.84   0.724  0.708
Residuals          34   4407  129.62

📊 Effect Summary:
• Season effect: F = 1.85 , p = 0.1564  ❌
• Year effect: F = 1.1 , p = 0.3746  ❌
• Season×Year interaction: F = 0.72 , p = 0.708  ❌
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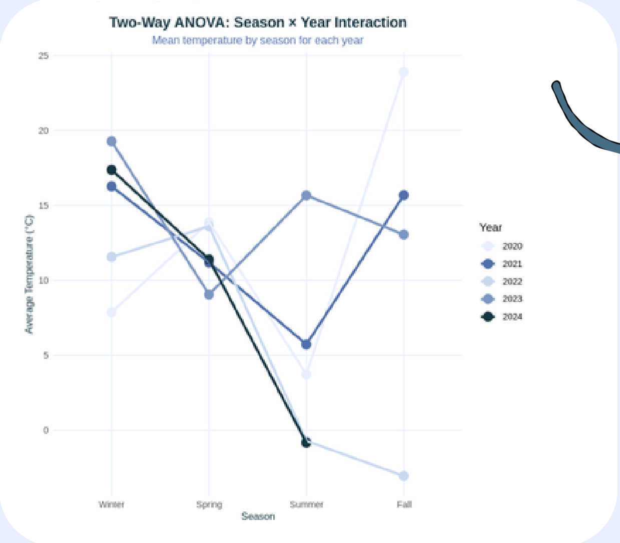

Two-Way ANOVA

To ensure the reliability of the ANOVA test, the following assumptions were verified:

- Normality (Shapiro-Wilk Test):
  - $p\text{-value} = 0.1892$ (> 0.05).
  - Result: The residuals follow a normal distribution (Assumption Met).
- Homogeneity of Variances (Levene's Test):
  - $p\text{-value} = 0.5252$ (> 0.05).
  - Result: The variance across different seasons is equal (Assumption Met).

Conclusion: Since both key assumptions are met, the ANOVA result (indicating no significant seasonal difference) is statistically valid and reliable.

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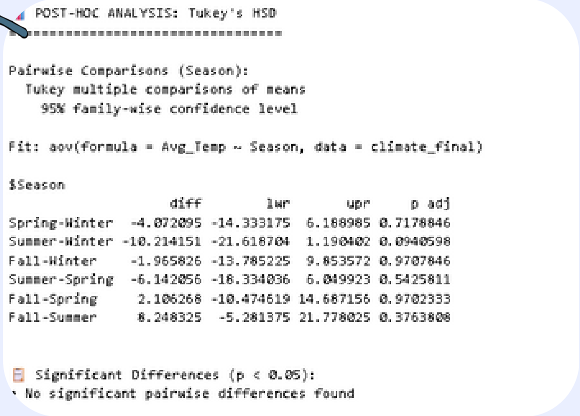
Post-hoc Analysis (Tukey's HSD)

Objective: To test if Season significantly impacts Avg_Temp.

Results:

- F-statistic: 1.958
- P-value: 0.133 (Greater than 0.05)
- Conclusion: Not Significant. The analysis fails to reject the null hypothesis.

Key Insight: The Box Plot reveals extreme volatility within individual seasons (especially Winter). This high internal variance overshadows the differences between seasonal means, indicating a highly unpredictable climate regardless of the season.



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📊 POST-HOC ANALYSIS: Tukey's HSD
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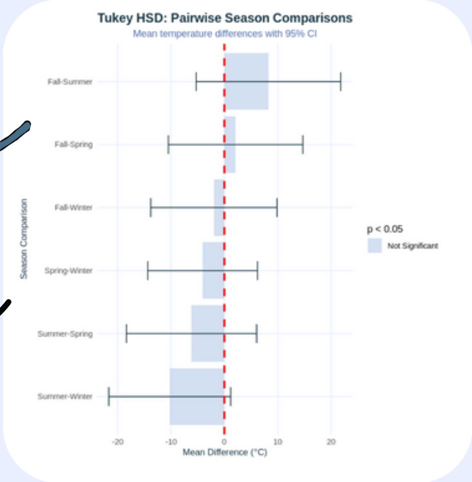
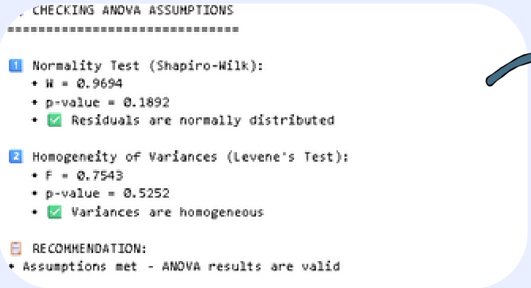
Pairwise Comparisons (Season):
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = Avg_Temp ~ Season, data = climate_final)

$Season
                    diff        lwr       upr     p adj
Spring-Winter  -4.072095 -14.333175  6.188985 0.7178846
Summer-Winter -10.214151 -21.618704  1.190402 0.0940598
Fall-Winter    -1.965826 -13.785225  9.853572 0.9707846
Summer-Spring  -6.142056 -18.334036  6.049923 0.5425811
Fall-Spring     2.106268 -10.474619 14.687156 0.9702333
Fall-Summer     8.248325  -5.281375 21.778025 0.3763808


📋 Significant Differences (p < 0.05):
• No significant pairwise differences found
```



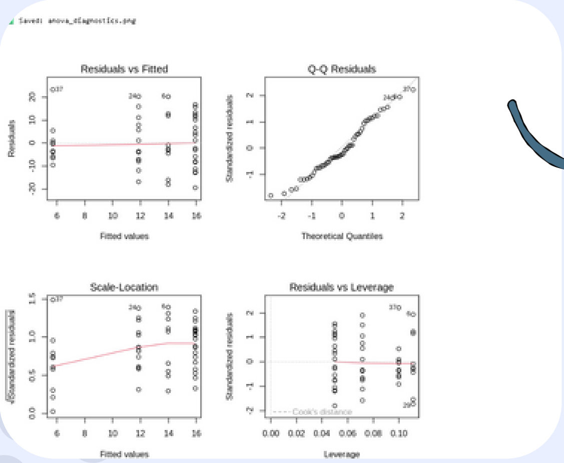


```
CHECKING ANOVA ASSUMPTIONS
==============================

1️⃣ Normality Test (Shapiro-Wilk):
   • W = 0.9694
   • p-value = 0.1892
   • ✅ Residuals are normally distributed

2️⃣ Homogeneity of Variances (Levene's Test):
   • F = 0.7543
   • p-value = 0.5252
   • ✅ Variances are homogeneous

📋 RECOMMENDATION:
• Assumptions met - ANOVA results are valid
```



```
Saved: anova_diagnostics.png
```

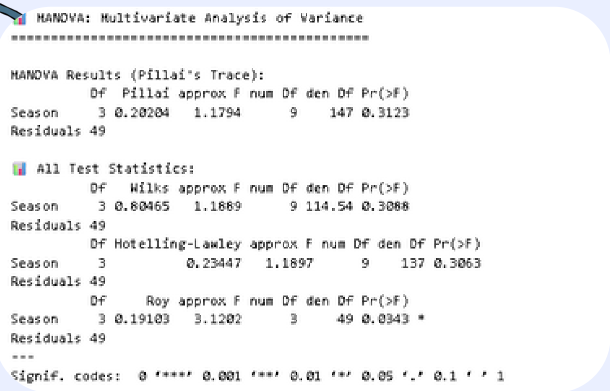
Validation of Statistical Assumptions

To ensure the reliability of the ANOVA test, the following assumptions were verified:

- Normality (Shapiro-Wilk Test):
  - $p\text{-value} = 0.1892$ (> 0.05).
  - Result: The residuals follow a normal distribution (Assumption Met).
- Homogeneity of Variances (Levene's Test):
  - $p\text{-value} = 0.5252$ (> 0.05).
  - Result: The variance across different seasons is equal (Assumption Met).

Conclusion: Since both key assumptions are met, the ANOVA result (indicating no significant seasonal difference) is statistically valid and reliable.

TRACKING THE SHIFT: GLOBAL CLIMATE PATTERNS & ENVIRONMENTAL IMPACT



```
MANOVA: Multivariate Analysis of Variance
==============================================

MANOVA Results (Pillai's Trace):
          Df  Pillai approx F num Df den Df Pr(>F)
Season     3 0.20204   1.1794      9    147 0.3123
Residuals 49

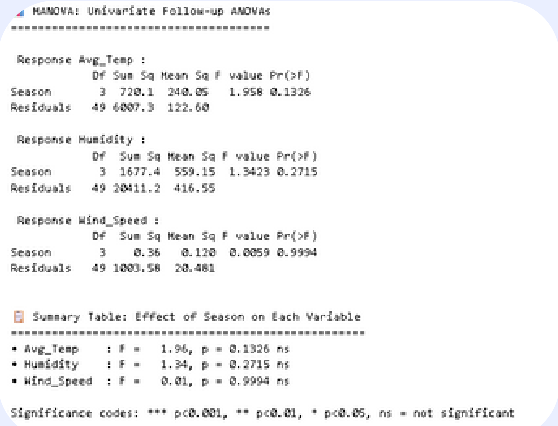
All Test Statistics:
          Df   Wilks approx F num Df den Df Pr(>F)
Season     3 0.80465   1.1869      9 114.54 0.3088
Residuals 49
          Df Hotelling-Lawley approx F num Df den Df Pr(>F)
Season     3          0.23447   1.1897      9    137 0.3063
Residuals 49
          Df     Roy approx F num Df den Df Pr(>F)
Season     3 0.19103   3.1202      3     49 0.0343 *
Residuals 49
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Multivariate Analysis (MANOVA)

Objective: To determine if Season has a significant effect on the combined atmospheric profile (Temperature + Humidity + Wind Speed) simultaneously.

Multivariate Test Results:

- Pillai's Trace (Most Robust): $p\text{-value} = 0.3123$ (> 0.05) $\rightarrow$ Not Significant.
- Wilks' Lambda: $p\text{-value} = 0.3088$ (> 0.05) $\rightarrow$ Not Significant.
- Roy's Largest Root: $p\text{-value} = 0.0343$ (< 0.05) $\rightarrow$ Significant (Outlier).
- Interpretation: While Roy's test suggests a potential difference, Pillai's Trace is the primary statistic for this data type. Since Pillai's test is not significant, we conclude that the overall climate profile does not fundamentally shift between seasons.



```
MANOVA: Univariate Follow-up ANOVAs
========================================

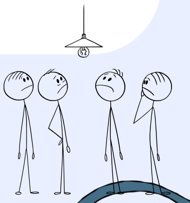
 Response Avg_Temp :
            Df Sum Sq Mean Sq F value Pr(>F)
Season       3  720.1  240.05   1.958 0.1326
Residuals   49 6007.3  122.60

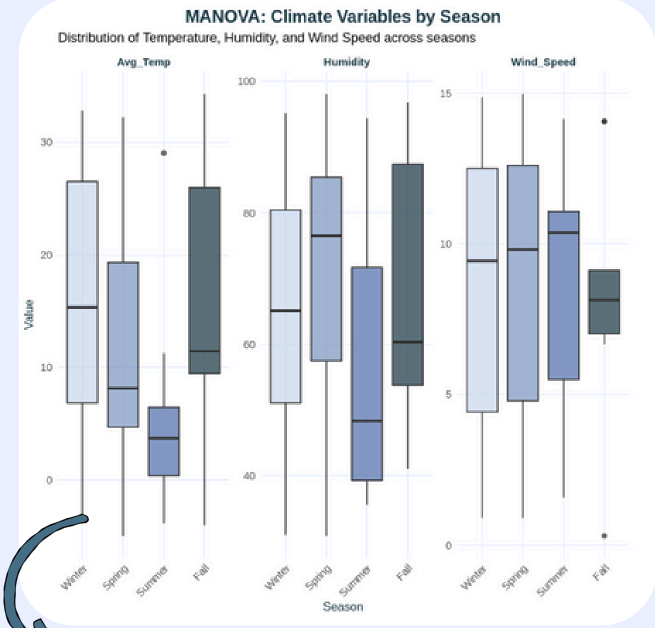
 Response Humidity :
            Df  Sum Sq Mean Sq F value Pr(>F)
Season       3  1677.4  559.15  1.3423 0.2715
Residuals   49 20411.2  416.55

 Response Wind_Speed :
            Df  Sum Sq Mean Sq F value Pr(>F)
Season       3    0.36   0.120  0.0059 0.9994
Residuals   49 1003.58  20.481


Summary Table: Effect of Season on Each Variable
=======================================================
• Avg_Temp    : F =   1.96, p = 0.1326 ns
• Humidity    : F =   1.34, p = 0.2715 ns
• Wind_Speed  : F =   0.01, p = 0.9994 ns

Significance codes: *** p<0.001, ** p<0.01, * p<0.05, ns = not significant
```





MANOVA: Climate Variables by Season

Distribution of Temperature, Humidity, and Wind Speed across seasons

Univariate Follow-up (Individual Variables):

- Avg_Temp: $p = 0.1326$ (NS)
- Humidity: $p = 0.2715$ (NS)
- Wind_Speed: $p = 0.9994$ (NS - Extremely random)
- Conclusion:

The analysis confirms that Seasonality does not significantly drive the climate variables in this dataset, neither individually nor as a combined group. The weather metrics (especially Wind Speed) appear to fluctuate independently of the traditional seasonal cycle.

Visual Analysis (MANOVA)

This visualization visually confirms why the statistical tests found no significant differences:

High Overlap: All three metrics display extensive overlapping ranges between seasons, making them statistically indistinguishable.

Temperature: The extreme vertical spread (variance) in Winter and Fall overshadows any mean differences.

Wind Speed: The medians are nearly identical across all seasons, explaining the perfect p-value of 0.99.

Conclusion: The internal variability within each season is far greater than the differences between the seasons.

TRACKING THE SHIFT: GLOBAL CLIMATE PATTERNS & ENVIRONMENTAL IMPACT

Standardized Seasonal Deviations (Heatmap)

Objective: To compare the relative intensity of climate variables across seasons using Z-scores (deviation from the global average).

- Key Observations:
- Inverted Pattern Confirmed: Summer shows strong negative deviations for Temperature (−1.39) and Humidity (−1.35), confirming it is the coldest and driest season. Conversely, Winter shows a positive Temperature deviation (+0.92).
- Wind Dynamics: Wind speed behaves inversely to other variables; it peaks in Summer (+0.96) and drops significantly in Fall (−1.32).
- Spring Anomaly: Spring is characterized by a distinct spike in Humidity (+1.01).

Conclusion: The standardized data clearly illustrates an "inverted" climate profile (Cold Summer / Warm Winter), strongly suggesting a Southern Hemisphere location.