Daily-Level GAM Analysis of Monarch Butterfly Abundance

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Introduction

This analysis investigates daily-level patterns in overwintering monarch butterfly abundance using Generalized Additive Models (GAMs). Unlike the 30-minute interval analysis, this approach aggregates data to daily summaries, examining how previous day's weather conditions affect butterfly abundance. The response variable is the 95th percentile of butterfly counts, providing a robust measure of daily peak abundance while being less sensitive to outliers than the maximum.

Setup

Load libraries and data:

```r
library(tidyverse)
library(mgcv)
library(lubridate)
library(plotly)
library(knitr)
library(DT)
library(here)
library(gratia)
library(patchwork)
library(corrplot)

# Load the daily lag analysis data
daily_data <- read_csv(here("data", "monarch_daily_lag_analysis.csv"))

# Create the square root transformed response variable early for use throughout
daily_data <- daily_data %>%
    mutate(
        butterfly_diff_95th_sqrt = ifelse(butterfly_diff_95th >= 0,
                                          sqrt(butterfly_diff_95th),
                                          -sqrt(-butterfly_diff_95th))
    )
```

Data Exploration

Data Structure and Summary

```r
# Basic summary statistics
cat("Dataset dimensions:", nrow(daily_data), "rows x", ncol(daily_data), "columns\n")
```

```
Dataset dimensions: 103 rows x 46 columns
```

```r
cat("Number of deployments:", n_distinct(daily_data$deployment_id), "\n")
```

```
Number of deployments: 7
```

```r
cat("Date range:", min(daily_data$date_t), "to", max(daily_data$date_t), "\n\n")
```

```
Date range: 19680 to 19756
```

```r
# Summary of key variables
summary_vars <- daily_data %>%
    select(
        butterflies_95th_percentile_t,
        butterflies_95th_percentile_t_1,
        butterfly_diff_95th,
        temp_max_t_1,
        temp_min_t_1,
        temp_at_max_count_t_1,
        wind_max_gust_t_1,
        sum_butterflies_direct_sun_t_1
    )

summary(summary_vars)
```

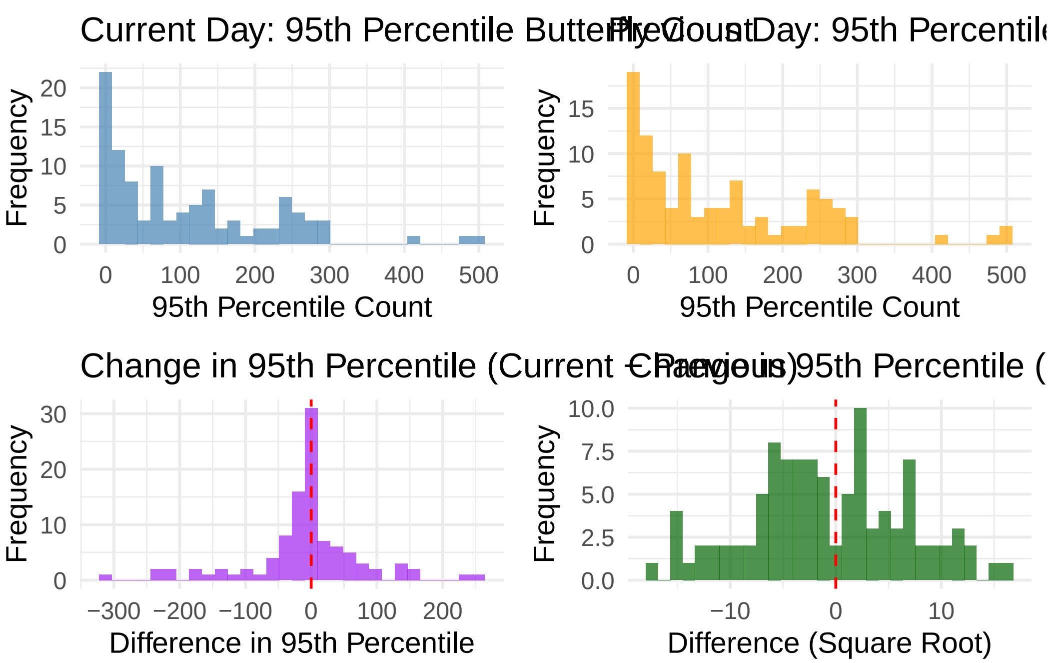
```
 butterflies_95th_percentile_t butterflies_95th_percentile_t_1
 Min.   :  0.00                Min.   :  0.0
 1st Qu.: 14.85                1st Qu.: 17.5
 Median : 70.05                Median : 77.0
 Mean   :107.41                Mean   :116.3
 3rd Qu.:166.95                3rd Qu.:199.5
 Max.   :499.00                Max.   :499.0

 butterfly_diff_95th  temp_max_t_1    temp_min_t_1    temp_at_max_count_t_1
 Min.   :-310.000    Min.   :14.00   Min.   : 3.000   Min.   : 5.00
 1st Qu.: -31.000    1st Qu.:16.00   1st Qu.: 7.000   1st Qu.:11.50
```

```
 Median :  -2.950    Median :18.00   Median :10.000   Median :14.00
 Mean   :  -8.919    Mean   :19.43   Mean   : 9.573   Mean   :13.37
 3rd Qu.:  18.000    3rd Qu.:22.00   3rd Qu.:12.000   3rd Qu.:15.50
 Max.   : 256.600    Max.   :37.00   Max.   :16.000   Max.   :25.00

 wind_max_gust_t_1 sum_butterflies_direct_sun_t_1
 Min.   :0.000     Min.   :   0.00
 1st Qu.:2.750     1st Qu.:   2.00
 Median :3.750     Median :  19.00
 Mean   :3.718     Mean   :  94.77
 3rd Qu.:4.500     3rd Qu.: 104.00
 Max.   :7.200     Max.   :1122.00
 NA's   :3
```

Response Variable Distribution

```r
library(gridExtra)

# Current day's 95th percentile
p1 <- ggplot(daily_data, aes(x = butterflies_95th_percentile_t)) +
    geom_histogram(bins = 30, fill = "steelblue", alpha = 0.7) +
    labs(
        title = "Current Day: 95th Percentile Butterfly Count",
        x = "95th Percentile Count", y = "Frequency"
    ) +
    theme_minimal()

# Previous day's 95th percentile
p2 <- ggplot(daily_data, aes(x = butterflies_95th_percentile_t_1)) +
    geom_histogram(bins = 30, fill = "orange", alpha = 0.7) +
    labs(
        title = "Previous Day: 95th Percentile Butterfly Count",
        x = "95th Percentile Count", y = "Frequency"
    ) +
    theme_minimal()

# Difference in 95th percentile
p3 <- ggplot(daily_data, aes(x = butterfly_diff_95th)) +
    geom_histogram(bins = 30, fill = "purple", alpha = 0.7) +
    geom_vline(xintercept = 0, linetype = "dashed", color = "red") +
    labs(
```

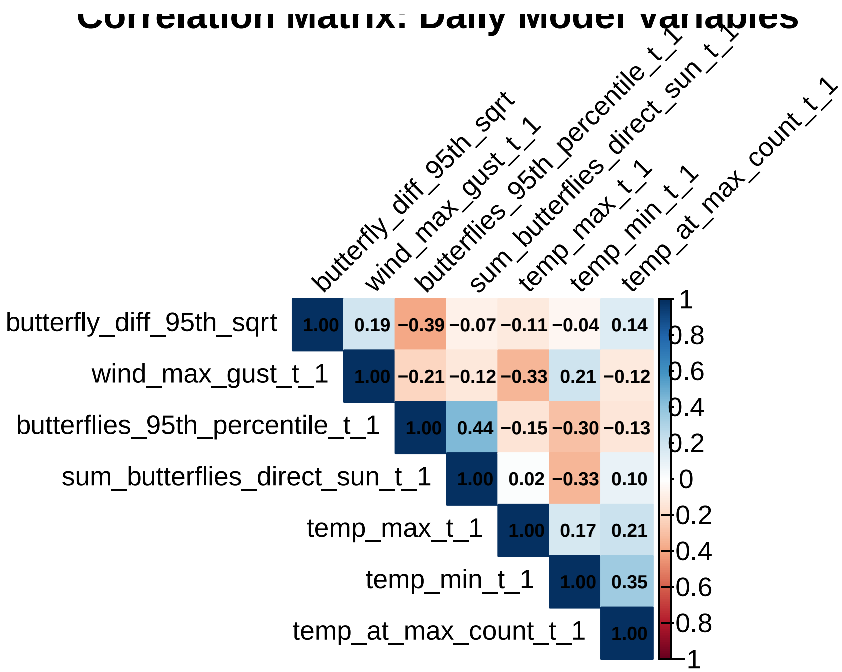
```r
        title = "Change in 95th Percentile (Current - Previous)",
        x = "Difference in 95th Percentile", y = "Frequency"
    ) +
    theme_minimal()

# Square root transformed difference
p4 <- ggplot(daily_data, aes(x = butterfly_diff_95th_sqrt)) +
    geom_histogram(bins = 30, fill = "darkgreen", alpha = 0.7) +
    geom_vline(xintercept = 0, linetype = "dashed", color = "red") +
    labs(
        title = "Change in 95th Percentile (Square Root Transformed)",
        x = "Difference (Square Root)", y = "Frequency"
    ) +
    theme_minimal()

grid.arrange(p1, p2, p3, p4, ncol = 2)
```



Correlation Analysis

```r
# Select model variables
model_vars <- daily_data %>%
```

```
    select(
        butterfly_diff_95th_sqrt,
        butterflies_95th_percentile_t_1,
        temp_max_t_1,
        temp_min_t_1,
        temp_at_max_count_t_1,
        wind_max_gust_t_1,
        sum_butterflies_direct_sun_t_1
    ) %>%
    na.omit()

# Correlation matrix
cor_matrix <- cor(model_vars)

# Create correlation plot
corrplot(cor_matrix,
    method = "color",
    type = "upper",
    order = "hclust",
    tl.cex = 0.8,
    tl.col = "black",
    tl.srt = 45,
    addCoef.col = "black",
    number.cex = 0.6,
    title = "Correlation Matrix: Daily Model Variables"
)
```




```r
# Print correlation table
kable(round(cor_matrix, 3),
    caption = "Correlation Matrix for Daily Model Variables"
)
```

Table 1: Correlation Matrix for Daily Model Variables

	butterfly_diff_95th_sqrt	butterflies_95th_percentile_t_1	temp_max_t_1	temp_min_t_1	temp_at_max_count_t_1	wind_max_gust_t_1	sum_butterflies_direct_sun_
butterfly_diff_95th_sqrt	1.000	-0.389	-0.112	-0.042	0.145	0.193	-0.072
butterflies_95th_percentile_t_1	-0.389	1.000	-0.146	-0.299	-0.132	-0.211	0.442
temp_max_t_1	-0.112	-0.146	1.000	0.173	0.215	-0.334	0.016
temp_min_t_1	-0.042	-0.299	0.173	1.000	0.351	0.210	-0.331
temp_at_max_count_t_1	0.145	-0.132	0.215	0.351	1.000	-0.116	0.098
wind_max_gust_t_1	0.193	-0.211	-0.334	0.210	-0.116	1.000	-0.122
sum_butterflies_direct_sun_t_1	-0.072	0.442	0.016	-0.331	0.098	-0.122	1.000

Response Variable Normality Assessment

```
library(nortest)

# First, identify all potential response variables in the dataset
# Exclude already-transformed variables to prevent double-transformation
response_candidates <- daily_data %>%
    select(contains("diff"), contains("butterfly")) %>%
    select(-contains("direct_sun"), -contains("sqrt"), -contains("cbrt"), -contains("log")) %
    names()

cat("Available response variable candidates:\n")
```

```
Available response variable candidates:
```

```
print(response_candidates)
```

```
[1] "butterfly_diff"      "butterfly_diff_95th" "butterfly_diff_top3"
```

```
# Define transformations to test
transformations <- list(
    "original" = function(x) x,
    "sqrt" = function(x) ifelse(x >= 0, sqrt(x), -sqrt(-x)),  # Signed square root
    "fourth_root" = function(x) ifelse(x >= 0, x^0.25, -((-x)^0.25)),  # Signed fourth root
    "arcsinh" = function(x) asinh(x),  # Inverse hyperbolic sine (handles negative values)
    "yeo_johnson" = function(x) {
        # Simplified Yeo-Johnson transformation
        lambda <- 0.5
        ifelse(x >= 0,
               ((x + 1)^lambda - 1) / lambda,
               -(((-x) + 1)^(2-lambda) - 1) / (2-lambda))
    }
)

# Function to calculate normality statistics
assess_normality <- function(x, var_name, transform_name) {
    # Remove NA values
    x_clean <- x[!is.na(x)]

    if(length(x_clean) < 10) {
```

```
    return(data.frame(
        Variable = var_name,
        Transformation = transform_name,
        N = length(x_clean),
        Mean = NA,
        SD = NA,
        Skewness = NA,
        Kurtosis = NA,
        Shapiro_p = NA,
        Anderson_p = NA,
        Normality_Score = 0
    ))
}

# Calculate statistics
mean_val <- mean(x_clean)
sd_val <- sd(x_clean)
skew_val <- moments::skewness(x_clean)
kurt_val <- moments::kurtosis(x_clean) - 3  # Excess kurtosis

# Normality tests
shapiro_p <- if(length(x_clean) <= 5000) shapiro.test(x_clean)$p.value else NA
anderson_p <- tryCatch(nortest::ad.test(x_clean)$p.value, error = function(e) NA)

# Create composite normality score (higher = more normal)
# Based on: low absolute skewness, low absolute kurtosis, high p-values
skew_score <- max(0, 1 - abs(skew_val) / 2)  # Penalize skewness > 2
kurt_score <- max(0, 1 - abs(kurt_val) / 4)  # Penalize excess kurtosis > 4
shapiro_score <- ifelse(is.na(shapiro_p), 0.5, shapiro_p)
anderson_score <- ifelse(is.na(anderson_p), 0.5, anderson_p)

# Weighted composite score
normality_score <- (skew_score * 0.3 + kurt_score * 0.3 +
                   shapiro_score * 0.2 + anderson_score * 0.2)

return(data.frame(
    Variable = var_name,
    Transformation = transform_name,
    N = length(x_clean),
    Mean = round(mean_val, 3),
    SD = round(sd_val, 3),
    Skewness = round(skew_val, 3),
```

```r
        Kurtosis = round(kurt_val, 3),
        Shapiro_p = ifelse(is.na(shapiro_p), NA, round(shapiro_p, 4)),
        Anderson_p = ifelse(is.na(anderson_p), NA, round(anderson_p, 4)),
        Normality_Score = round(normality_score, 4)
    ))
}

# Load required library for moments
library(moments)

# Apply transformations and assess normality for each response variable
normality_results <- list()

for(var_name in response_candidates) {
    if(var_name %in% names(daily_data)) {
        var_data <- daily_data[[var_name]]

        for(trans_name in names(transformations)) {
            trans_func <- transformations[[trans_name]]

            # Apply transformation
            transformed_data <- tryCatch(
                trans_func(var_data),
                error = function(e) rep(NA, length(var_data))
            )

            # Assess normality
            result <- assess_normality(transformed_data, var_name, trans_name)
            normality_results[[paste(var_name, trans_name, sep = "_")]] <- result
        }
    }
}

# Combine results
normality_df <- do.call(rbind, normality_results)

# Rank by normality score
normality_ranking <- normality_df %>%
    arrange(desc(Normality_Score)) %>%
    filter(!is.na(Normality_Score)) %>%
    mutate(Rank = row_number()) %>%
    select(Rank, Variable, Transformation, N, Mean, SD, Skewness, Kurtosis,
```

```r
           Shapiro_p, Anderson_p, Normality_Score)

# Display top 15 most normal distributions
cat("Top 15 most normal response variable transformations:\n\n")
```

```
Top 15 most normal response variable transformations:
```

```r
kable(head(normality_ranking, 15),
      caption = "Response variables ranked by normality (higher score = more normal)")
```

Table 2: Response variables ranked by normality (higher score = more normal)

	Rank	Variable	Transformation	N	Mean	SD	Skewness	Kurtosis	Shapiro_p	Anderson_p	Normality_Score
butterfly_diff_95th_sqrt	1	butterfly_diff_95th	sqrt	103	-0.809	7.382	0.021	-0.467	0.6501	0.5918	0.8102
butterfly_diff_top3_sqrt	2	butterfly_diff_top3	sqrt	103	-0.751	7.379	0.039	-0.436	0.6273	0.5818	0.8033
butterfly_diff_sqrt	3	butterfly_diff	sqrt	103	-1.148	8.033	0.238	-0.117	0.6179	0.3799	0.7552
butterfly_diff_top3_fourth_root	4	butterfly_diff_top3	fourth_root	103	-0.236	2.475	0.121	-1.527	0.0000	0.0000	0.4672
butterfly_diff_top3_arcsinh	5	butterfly_diff_top3	arcsinh	103	-0.392	4.105	0.129	-1.560	0.0000	0.0000	0.4636
butterfly_diff_95th_fourth_root	6	butterfly_diff_95th	fourth_root	103	-0.279	2.470	0.168	-1.505	0.0000	0.0000	0.4619
butterfly_diff_95th_arcsinh	7	butterfly_diff_95th	arcsinh	103	-0.461	4.101	0.179	-1.540	0.0000	0.0000	0.4576
butterfly_diff_fourth_root	8	butterfly_diff	fourth_root	103	-0.425	2.554	0.304	-1.402	0.0000	0.0000	0.4492
butterfly_diff_arcsinh	9	butterfly_diff	arcsinh	103	-0.701	4.212	0.296	-1.485	0.0000	0.0000	0.4442
butterfly_diff_top3_original	10	butterfly_diff_top3	original	103	-8.547	87.141	-0.026	2.983	0.0000	0.0000	0.3724
butterfly_diff_95th_original	11	butterfly_diff_95th	original	103	-8.919	86.928	-0.402	2.525	0.0000	0.0000	0.3502
butterfly_diff_original	12	butterfly_diff	original	103	-10.097	108.330	7.389	5.076	0.0000	0.0000	0.2417
butterfly_diff_yeo_johnson	13	butterfly_diff	yeo_johnson	103	-302.806	777.603	-3.770	15.548	0.0000	0.0000	0.0000

	Rank	Variable	Transformation	N	Mean	SD	Skewness	Kurtosis	Shapiro_p	Anderson_p	Normality_Score
butterfly_diff_95th_yeo_johnson	14	butterfly_diff_95th	yeo_johnson	103	-240.895	614.021	-3.329	11.649	0.0000	0.0000	0.0000
butterfly_diff_top3_yeo_johnson	15	butterfly_diff_top3	yeo_johnson	103	-235.162	576.143	-3.074	9.279	0.0000	0.0000	0.0000

```
# Create summary by variable
variable_summary <- normality_ranking %>%
    group_by(Variable) %>%
    slice_max(Normality_Score, n = 1) %>%
    ungroup() %>%
    arrange(desc(Normality_Score)) %>%
    select(Variable, Best_Transformation = Transformation, Best_Score = Normality_Score,
           Skewness, Kurtosis, Shapiro_p)

cat("\n\nBest transformation for each response variable:\n")
```

```
Best transformation for each response variable:
```

```
kable(variable_summary,
      caption = "Best transformation for each response variable")
```

Table 3: Best transformation for each response variable

Variable	Best_Transformation	Best_Score	Skewness	Kurtosis	Shapiro_p
butterfly_diff_95th	sqrt	0.8102	0.021	-0.467	0.6501
butterfly_diff_top3	sqrt	0.8033	0.039	-0.436	0.6273
butterfly_diff	sqrt	0.7552	0.238	-0.117	0.6179

```
cat("\n\nUsing the best response variable transformation: butterfly_diff_95th_sqrt\n")
```

```
Using the best response variable transformation: butterfly_diff_95th_sqrt
```

```r
cat("Summary of transformed response variable:\n")
```

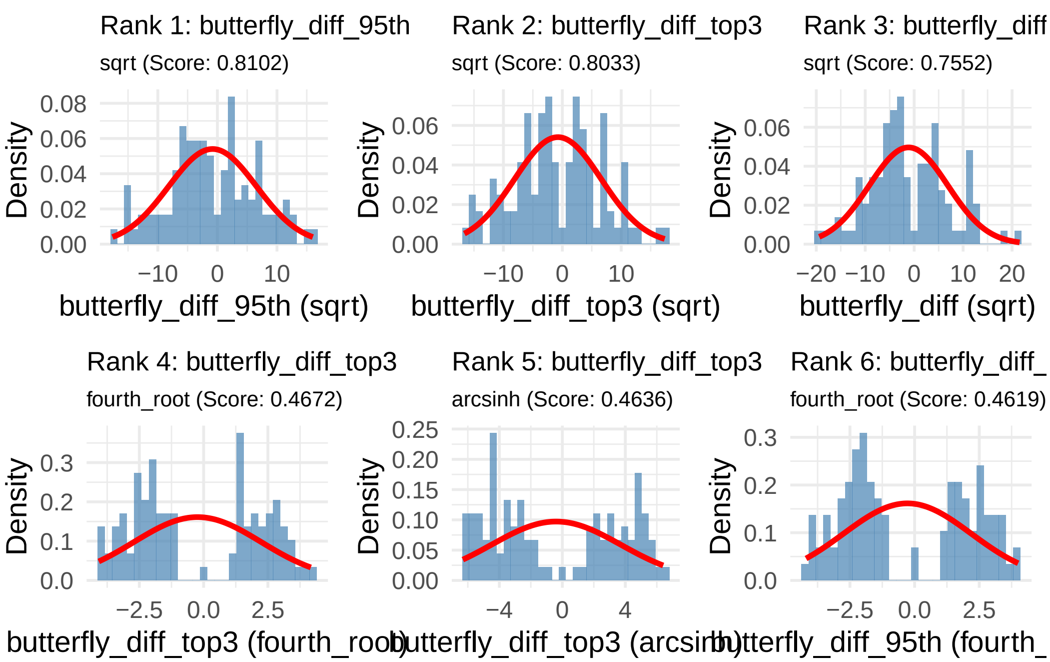
```
Summary of transformed response variable:
```

```r
print(summary(daily_data$butterfly_diff_95th_sqrt))
```

```
    Min.  1st Qu.   Median     Mean  3rd Qu.     Max. 
-17.6068  -5.5649  -1.7176  -0.8088   4.2426  16.0187 
```

```r
# Visualize the top 6 most normal transformations
top_transformations <- head(normality_ranking, 6)

plots <- list()
for(i in 1:nrow(top_transformations)) {
    row <- top_transformations[i, ]
    var_name <- row$Variable
    trans_name <- row$Transformation

    if(var_name %in% names(daily_data)) {
        var_data <- daily_data[[var_name]]
        trans_func <- transformations[[trans_name]]
        transformed_data <- trans_func(var_data)

        # Create histogram with normal overlay
        p <- ggplot(data.frame(x = transformed_data), aes(x = x)) +
            geom_histogram(aes(y = after_stat(density)), bins = 30,
                           fill = "steelblue", alpha = 0.7) +
            stat_function(fun = dnorm,
                          args = list(mean = mean(transformed_data, na.rm = TRUE),
                                      sd = sd(transformed_data, na.rm = TRUE)),
                          color = "red", size = 1) +
            labs(
                title = paste0("Rank ", i, ": ", var_name),
                subtitle = paste0(trans_name, " (Score: ", row$Normality_Score, ")"),
                x = paste0(var_name, " (", trans_name, ")"),
                y = "Density"
            ) +
            theme_minimal() +
            theme(plot.title = element_text(size = 10),
                  plot.subtitle = element_text(size = 8))
```

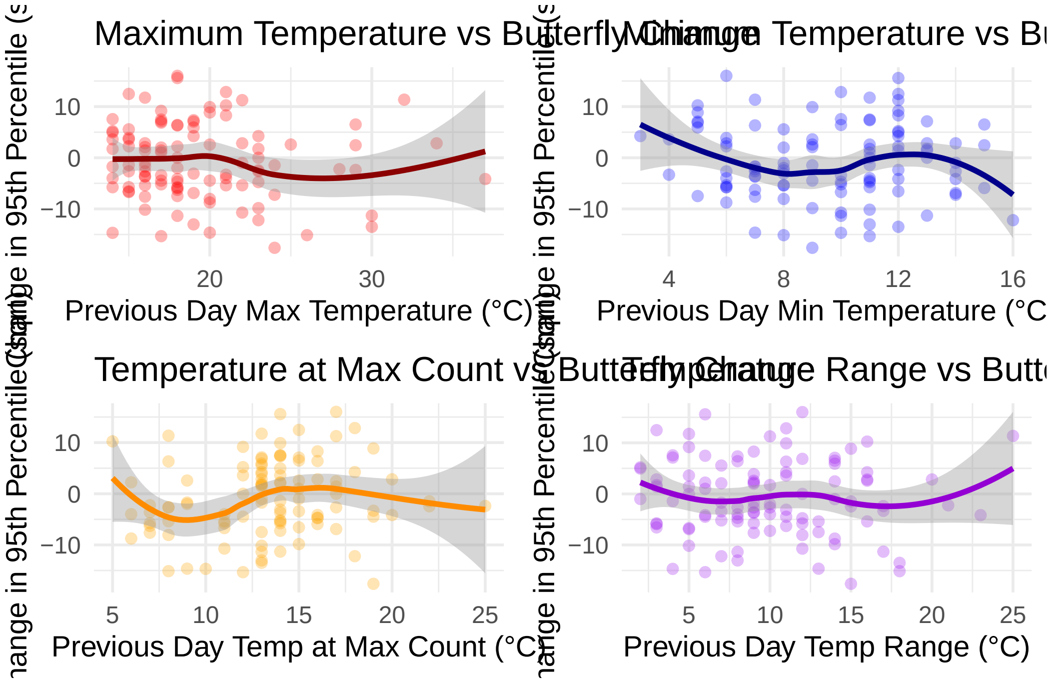
```
        plots[[i]] <- p
    }
}

# Arrange plots in grid
if(length(plots) >= 6) {
    grid.arrange(plots[[1]], plots[[2]], plots[[3]],
                plots[[4]], plots[[5]], plots[[6]], ncol = 3)
} else {
    do.call(grid.arrange, c(plots, ncol = 3))
}
```



Temperature Patterns

```
# Temperature relationships
p1 <- ggplot(daily_data, aes(x = temp_max_t_1, y = butterfly_diff_95th_sqrt)) +
    geom_point(alpha = 0.3, color = "red") +
    geom_smooth(method = "loess", se = TRUE, color = "darkred") +
    labs(
        title = "Maximum Temperature vs Butterfly Change",
        x = "Previous Day Max Temperature (°C)",
```

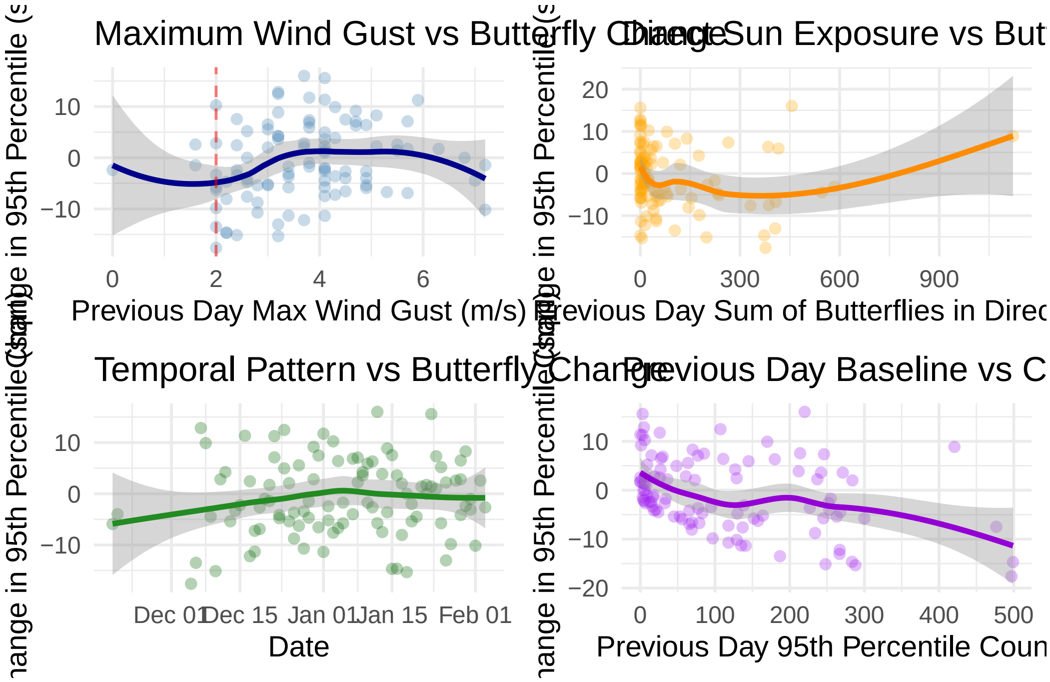
```
        y = "Change in 95th Percentile (sqrt)"
    ) +
    theme_minimal()

p2 <- ggplot(daily_data, aes(x = temp_min_t_1, y = butterfly_diff_95th_sqrt)) +
    geom_point(alpha = 0.3, color = "blue") +
    geom_smooth(method = "loess", se = TRUE, color = "darkblue") +
    labs(
        title = "Minimum Temperature vs Butterfly Change",
        x = "Previous Day Min Temperature (°C)",
        y = "Change in 95th Percentile (sqrt)"
    ) +
    theme_minimal()

p3 <- ggplot(daily_data, aes(x = temp_at_max_count_t_1, y = butterfly_diff_95th_sqrt)) +
    geom_point(alpha = 0.3, color = "orange") +
    geom_smooth(method = "loess", se = TRUE, color = "darkorange") +
    labs(
        title = "Temperature at Max Count vs Butterfly Change",
        x = "Previous Day Temp at Max Count (°C)",
        y = "Change in 95th Percentile (sqrt)"
    ) +
    theme_minimal()

# Temperature range
daily_data <- daily_data %>%
    mutate(temp_range_t_1 = temp_max_t_1 - temp_min_t_1)

p4 <- ggplot(daily_data, aes(x = temp_range_t_1, y = butterfly_diff_95th_sqrt)) +
    geom_point(alpha = 0.3, color = "purple") +
    geom_smooth(method = "loess", se = TRUE, color = "darkviolet") +
    labs(
        title = "Temperature Range vs Butterfly Change",
        x = "Previous Day Temp Range (°C)",
        y = "Change in 95th Percentile (sqrt)"
    ) +
    theme_minimal()

grid.arrange(p1, p2, p3, p4, ncol = 2)
```



Wind and Sun Exposure

```
# Wind effect
p1 <- ggplot(daily_data, aes(x = wind_max_gust_t_1, y = butterfly_diff_95th_sqrt)) +
    geom_point(alpha = 0.3, color = "steelblue") +
    geom_smooth(method = "loess", se = TRUE, color = "darkblue") +
    geom_vline(xintercept = 2, linetype = "dashed", color = "red", alpha = 0.5) +
    labs(
        title = "Maximum Wind Gust vs Butterfly Change",
        x = "Previous Day Max Wind Gust (m/s)",
        y = "Change in 95th Percentile (sqrt)"
    ) +
    theme_minimal()

# Sun exposure
p2 <- ggplot(daily_data, aes(x = sum_butterflies_direct_sun_t_1, y = butterfly_diff_95th_sqr
    geom_point(alpha = 0.3, color = "orange") +
    geom_smooth(method = "loess", se = TRUE, color = "darkorange") +
    labs(
        title = "Direct Sun Exposure vs Butterfly Change",
        x = "Previous Day Sum of Butterflies in Direct Sun",
```

```r
        y = "Change in 95th Percentile (sqrt)"
    ) +
    theme_minimal()

# Note: Seasonal progression will be handled via temporal autocorrelation
# rather than as a fixed effect
p3 <- ggplot(daily_data, aes(x = date_t, y = butterfly_diff_95th_sqrt)) +
    geom_point(alpha = 0.3, color = "darkgreen") +
    geom_smooth(method = "loess", se = TRUE, color = "forestgreen") +
    labs(
        title = "Temporal Pattern vs Butterfly Change",
        x = "Date",
        y = "Change in 95th Percentile (sqrt)"
    ) +
    theme_minimal()

# Previous day baseline
p4 <- ggplot(daily_data, aes(x = butterflies_95th_percentile_t_1, y = butterfly_diff_95th_sq
    geom_point(alpha = 0.3, color = "purple") +
    geom_smooth(method = "loess", se = TRUE, color = "darkviolet") +
    labs(
        title = "Previous Day Baseline vs Change",
        x = "Previous Day 95th Percentile Count",
        y = "Change in 95th Percentile (sqrt)"
    ) +
    theme_minimal()

grid.arrange(p1, p2, p3, p4, ncol = 2)
```



Data Preparation

```
# Remove missing values and prepare modeling dataset
model_data <- daily_data %>%
    filter(
        !is.na(butterfly_diff_95th_sqrt),
        !is.na(butterflies_95th_percentile_t_1),
        !is.na(temp_max_t_1),
        !is.na(temp_min_t_1),
        !is.na(temp_at_max_count_t_1),
        !is.na(wind_max_gust_t_1),
        !is.na(sum_butterflies_direct_sun_t_1),
        !is.na(deployment_id)
    ) %>%
    # Create standardized versions for interpretation
    mutate(
        wind_max_gust_std = scale(wind_max_gust_t_1)[, 1],
        temp_max_std = scale(temp_max_t_1)[, 1],
        temp_min_std = scale(temp_min_t_1)[, 1],
        temp_at_max_std = scale(temp_at_max_count_t_1)[, 1],
        sun_exposure_std = scale(sum_butterflies_direct_sun_t_1)[, 1],
```

```
        baseline_std = scale(butterflies_95th_percentile_t_1)[, 1],
        # Note: day_sequence is now provided by the data preparation script
        # Each deployment has its own day counter starting from 1
    )

cat("Clean dataset has", nrow(model_data), "observations\n")
```

```
Clean dataset has 100 observations
```

```
cat("Number of unique deployment days:", n_distinct(paste(model_data$deployment_id, model_da
```

```
Number of unique deployment days: 100
```

Modeling Strategy

Our modeling approach for daily-level data tests both **absolute effects** and **proportional effects** of environmental variables on butterfly abundance changes:

1. **Response Variable**: `butterfly_diff_95th_sqrt` - square root transformed difference in 95th percentile butterfly counts between consecutive days (selected as the most normal transformation)

2. **Two Model Sets**:

   M Models (Absolute Effects): Test whether environmental variables have direct effects on absolute changes in abundance:

   - Do NOT include previous day's butterfly count
   - Test if weather has consistent magnitude effects regardless of population size

   B Models (Proportional/Density-Dependent Effects): Test whether environmental effects depend on baseline population:

   - Include `butterflies_95th_percentile_t_1` as a covariate
   - Test if weather effects scale with population size
   - Include interactions between baseline count and environmental variables

3. **Fixed Effects** (tested in various combinations):

   - Temperature variables: max, min, and temperature at max count
   - Wind: maximum gust from previous day
   - Sun exposure: sum of butterflies in direct sun from previous day
   - Previous day baseline: 95th percentile count (B models only)

4. **Random Effects**:

    - Deployment ID (random intercept)
    - AR1 temporal autocorrelation within deployments using `day_sequence | deployment_id`

5. **Correlation Structures**:

    - No correlation (baseline)
    - AR1 within deployments to account for temporal autocorrelation

This dual approach allows us to distinguish between: - **Absolute effects**: Environmental variables cause fixed-magnitude changes regardless of population size - **Proportional effects**: Environmental impacts scale with the existing population (density-dependence)

Model Building and Selection

```
library(nlme)

# Define random effects structure with temporal autocorrelation
# We'll test different correlation structures
random_structure <- list(deployment_id = ~1)

# Define correlation structures to test
correlation_structures <- list(
    "no_corr" = NULL,  # No temporal correlation
    "AR1" = corAR1(form = ~day_sequence | deployment_id)  # AR1 within deployments
)

# Model specifications for AIC comparison - WITHOUT previous day baseline
model_specs <- list(
    # Null model
    "M1" = "butterfly_diff_95th_sqrt ~ 1",

    # Single predictor models (linear)
    "M2" = "butterfly_diff_95th_sqrt ~ wind_max_gust_t_1",
    "M3" = "butterfly_diff_95th_sqrt ~ temp_max_t_1",
    "M4" = "butterfly_diff_95th_sqrt ~ temp_min_t_1",
    "M5" = "butterfly_diff_95th_sqrt ~ temp_at_max_count_t_1",
    "M6" = "butterfly_diff_95th_sqrt ~ sum_butterflies_direct_sun_t_1",

    # Temperature combinations (linear)
```

```
  "M8" = "butterfly_diff_95th_sqrt ~ temp_max_t_1 + temp_min_t_1",
  "M9" = "butterfly_diff_95th_sqrt ~ temp_max_t_1 + temp_at_max_count_t_1",
  "M10" = "butterfly_diff_95th_sqrt ~ temp_min_t_1 + temp_at_max_count_t_1",
  "M11" = "butterfly_diff_95th_sqrt ~ temp_max_t_1 + temp_min_t_1 + temp_at_max_count_t_1"

  # Two-variable combinations
  "M12" = "butterfly_diff_95th_sqrt ~ wind_max_gust_t_1 + temp_max_t_1",
  "M13" = "butterfly_diff_95th_sqrt ~ wind_max_gust_t_1 + temp_min_t_1",
  "M14" = "butterfly_diff_95th_sqrt ~ wind_max_gust_t_1 + temp_at_max_count_t_1",
  "M15" = "butterfly_diff_95th_sqrt ~ wind_max_gust_t_1 + sum_butterflies_direct_sun_t_1",
  "M16" = "butterfly_diff_95th_sqrt ~ temp_at_max_count_t_1 + sum_butterflies_direct_sun_t_

  # Full models with various temperature specs (linear)
  "M17" = "butterfly_diff_95th_sqrt ~ temp_max_t_1 + wind_max_gust_t_1 + sum_butterflies_di
  "M18" = "butterfly_diff_95th_sqrt ~ temp_min_t_1 + wind_max_gust_t_1 + sum_butterflies_di
  "M19" = "butterfly_diff_95th_sqrt ~ temp_at_max_count_t_1 + wind_max_gust_t_1 + sum_butte
  "M20" = "butterfly_diff_95th_sqrt ~ temp_max_t_1 + temp_min_t_1 + wind_max_gust_t_1 + sum
  "M21" = "butterfly_diff_95th_sqrt ~ temp_max_t_1 + temp_min_t_1 + temp_at_max_count_t_1 +

  # Smooth terms models - single predictors
  "M24" = "butterfly_diff_95th_sqrt ~ s(wind_max_gust_t_1)",
  "M25" = "butterfly_diff_95th_sqrt ~ s(temp_max_t_1)",
  "M26" = "butterfly_diff_95th_sqrt ~ s(temp_min_t_1)",
  "M27" = "butterfly_diff_95th_sqrt ~ s(temp_at_max_count_t_1)",
  "M28" = "butterfly_diff_95th_sqrt ~ s(sum_butterflies_direct_sun_t_1)",

  # Smooth terms - combinations
  "M30" = "butterfly_diff_95th_sqrt ~ s(temp_max_t_1) + s(temp_min_t_1)",
  "M31" = "butterfly_diff_95th_sqrt ~ s(temp_at_max_count_t_1) + s(wind_max_gust_t_1)",
  "M32" = "butterfly_diff_95th_sqrt ~ s(temp_at_max_count_t_1) + s(sum_butterflies_direct_s
  "M33" = "butterfly_diff_95th_sqrt ~ s(wind_max_gust_t_1) + s(sum_butterflies_direct_sun_t

  # Complex smooth models
  "M34" = "butterfly_diff_95th_sqrt ~ s(temp_at_max_count_t_1) + s(wind_max_gust_t_1) + s(s
  "M35" = "butterfly_diff_95th_sqrt ~ s(temp_max_t_1) + s(temp_min_t_1) + s(wind_max_gust_t
  "M37" = "butterfly_diff_95th_sqrt ~ s(temp_max_t_1) + s(temp_min_t_1) + s(temp_at_max_cou

  # Mixed linear and smooth
  "M38" = "butterfly_diff_95th_sqrt ~ temp_at_max_count_t_1 + s(wind_max_gust_t_1) + s(sum_
  "M39" = "butterfly_diff_95th_sqrt ~ s(temp_at_max_count_t_1) + wind_max_gust_t_1 + sum_bu
  "M40" = "butterfly_diff_95th_sqrt ~ s(temp_at_max_count_t_1) + wind_max_gust_t_1 + s(sum_
```

```
# Interaction models (without baseline)
"M41" = "butterfly_diff_95th_sqrt ~ temp_at_max_count_t_1 * wind_max_gust_t_1",
"M42" = "butterfly_diff_95th_sqrt ~ temp_at_max_count_t_1 * sum_butterflies_direct_sun_t_
"M43" = "butterfly_diff_95th_sqrt ~ wind_max_gust_t_1 * sum_butterflies_direct_sun_t_1",
"M44" = "butterfly_diff_95th_sqrt ~ temp_at_max_count_t_1 * wind_max_gust_t_1 + sum_butte
"M45" = "butterfly_diff_95th_sqrt ~ temp_at_max_count_t_1 + wind_max_gust_t_1 * sum_butte
"M46" = "butterfly_diff_95th_sqrt ~ temp_at_max_count_t_1 * wind_max_gust_t_1 * sum_butte

# Temperature range models
"M47" = "butterfly_diff_95th_sqrt ~ I(temp_max_t_1 - temp_min_t_1)",
"M48" = "butterfly_diff_95th_sqrt ~ I(temp_max_t_1 - temp_min_t_1) + wind_max_gust_t_1",
"M49" = "butterfly_diff_95th_sqrt ~ s(I(temp_max_t_1 - temp_min_t_1))",
"M50" = "butterfly_diff_95th_sqrt ~ s(I(temp_max_t_1 - temp_min_t_1)) + s(wind_max_gust_t

# ===== MODELS WITH PREVIOUS DAY BASELINE =====
# All models below include butterflies_95th_percentile_t_1 to test proportional effects

# Baseline-only model
"B1" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1",

# Single predictor models + baseline (linear)
"B2" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + wind_max_gust_t_1",
"B3" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + temp_max_t_1",
"B4" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + temp_min_t_1",
"B5" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + temp_at_max_count_t_
"B6" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + sum_butterflies_dire

# Temperature combinations + baseline (linear)
"B8" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + temp_max_t_1 + temp_
"B9" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + temp_max_t_1 + temp_
"B10" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + temp_min_t_1 + temp
"B11" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + temp_max_t_1 + temp

# Two-variable combinations + baseline
"B12" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + wind_max_gust_t_1 +
"B13" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + wind_max_gust_t_1 +
"B14" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + wind_max_gust_t_1 +
"B15" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + wind_max_gust_t_1 +
"B16" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + temp_at_max_count_t

# Full models with various temperature specs + baseline (linear)
"B17" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + temp_max_t_1 + wind
```

```
"B18" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + temp_min_t_1 + wind
"B19" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + temp_at_max_count_
"B20" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + temp_max_t_1 + temp
"B21" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + temp_max_t_1 + temp

# Smooth terms models - single predictors + baseline
"B24" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + s(wind_max_gust_t_
"B25" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + s(temp_max_t_1)",
"B26" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + s(temp_min_t_1)",
"B27" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + s(temp_at_max_coun
"B28" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + s(sum_butterflies_

# Smooth baseline + other predictors
"B29" = "butterfly_diff_95th_sqrt ~ s(butterflies_95th_percentile_t_1)",
"B29a" = "butterfly_diff_95th_sqrt ~ s(butterflies_95th_percentile_t_1) + wind_max_gust_
"B29b" = "butterfly_diff_95th_sqrt ~ s(butterflies_95th_percentile_t_1) + temp_at_max_co
"B29c" = "butterfly_diff_95th_sqrt ~ s(butterflies_95th_percentile_t_1) + s(wind_max_gus
"B29d" = "butterfly_diff_95th_sqrt ~ s(butterflies_95th_percentile_t_1) + s(temp_at_max_

# Smooth terms - combinations + baseline
"B30" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + s(temp_max_t_1) + s
"B31" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + s(temp_at_max_coun
"B32" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + s(temp_at_max_coun
"B33" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + s(wind_max_gust_t_

# Complex smooth models + baseline
"B34" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + s(temp_at_max_coun
"B35" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + s(temp_max_t_1) + s
"B37" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + s(temp_max_t_1) + s

# Mixed linear and smooth + baseline
"B38" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + temp_at_max_count_
"B39" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + s(temp_at_max_coun
"B40" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + s(temp_at_max_coun

# Interaction models with baseline
"B41" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + temp_at_max_count_
"B42" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + temp_at_max_count_
"B43" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + wind_max_gust_t_1 +
"B44" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + temp_at_max_count_
"B45" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + temp_at_max_count_
"B46" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + temp_at_max_count_
```

```
    # Temperature range models + baseline
    "B47" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + I(temp_max_t_1 - te
    "B48" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + I(temp_max_t_1 - te
    "B49" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + s(I(temp_max_t_1 -
    "B50" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + s(I(temp_max_t_1 -

    # Interaction with baseline (testing if environmental effects depend on population size)
    "B51" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 * wind_max_gust_t_1"
    "B52" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 * temp_at_max_count_t
    "B53" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 * sum_butterflies_dif
    "B54" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 * wind_max_gust_t_1 +
    "B55" = "butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 * temp_at_max_count_t
)

cat("Total models to fit:", length(model_specs), "\n")
```

```
Total models to fit: 100
```

```
cat("- M models (M1-M50):", sum(grepl("^M", names(model_specs))), "models WITHOUT previous da
```

```
- M models (M1-M50): 45 models WITHOUT previous day baseline
```

```
cat("- B models (B1-B55):", sum(grepl("^B", names(model_specs))), "models WITH previous day b
```

```
- B models (B1-B55): 55 models WITH previous day baseline
```

Model Fitting

```
# Function to safely fit models with correlation structures
fit_model_safely <- function(formula_str, data, correlation = NULL, corr_name = "no_corr") {
    tryCatch(
        {
            formula_obj <- as.formula(formula_str)

            # Fit the model with or without correlation structure
            if (is.null(correlation)) {
                model <- gamm(formula_obj,
```

```
                    data = data,
                    random = random_structure,
                    method = "REML"
                )
            } else {
                model <- gamm(formula_obj,
                    data = data,
                    random = random_structure,
                    correlation = correlation,
                    method = "REML"
                )
            }

            # Add correlation structure name to the model for tracking
            model$correlation_structure <- corr_name
            return(model)
        },
        error = function(e) {
            message("Failed to fit model: ", formula_str, " with correlation: ", corr_name)
            message("Error: ", e$message)
            return(NULL)
        }
    )
}

# Fit all models with different correlation structures
cat("Fitting models...\n")
```

```
Fitting models...
```

```
fitted_models <- list()

# Fit each model specification with each correlation structure
for (model_name in names(model_specs)) {
    formula_str <- model_specs[[model_name]]

    for (corr_name in names(correlation_structures)) {
        corr_struct <- correlation_structures[[corr_name]]

        # Create unique model name with correlation structure
        full_model_name <- paste(model_name, corr_name, sep = "_")
```

```r
        fitted_models[[full_model_name]] <- fit_model_safely(
            formula_str, model_data, corr_struct, corr_name
        )
    }
}

# Remove failed models
successful_models <- fitted_models[!map_lgl(fitted_models, is.null)]
cat("Successfully fitted", length(successful_models), "out of",
    length(model_specs), "models\n")
```

```
Successfully fitted 200 out of 100 models
```

Model Comparison

```r
# Extract AIC values
aic_results <- map_dfr(names(successful_models), function(full_model_name) {
    model <- successful_models[[full_model_name]]

    # Parse model name and correlation structure
    name_parts <- strsplit(full_model_name, "_")[[1]]
    corr_suffix <- name_parts[length(name_parts)]
    base_model_name <- paste(name_parts[-length(name_parts)], collapse = "_")

    # Get the formula from the base model name
    formula_str <- model_specs[[base_model_name]]
    if (is.null(formula_str)) {
        formula_str <- "Unknown formula"
    }

    data.frame(
        Model = full_model_name,
        Base_Model = base_model_name,
        Correlation = corr_suffix,
        Formula = formula_str,
        AIC = AIC(model$lme),
        LogLik = logLik(model$lme)[1],
        df = attr(logLik(model$lme), "df"),
        stringsAsFactors = FALSE
```

```
    )
}) %>%
    arrange(AIC) %>%
    mutate(
        Delta_AIC = AIC - min(AIC),
        AIC_weight = exp(-0.5 * Delta_AIC) / sum(exp(-0.5 * Delta_AIC))
    )

# Display top 10 models
aic_results %>%
    head(10) %>%
    select(Model, Correlation, AIC, Delta_AIC, AIC_weight, df) %>%
    kable(digits = 3, caption = "Top 10 models by AIC")
```

Table 4: Top 10 models by AIC

Model	Correlation	AIC	Delta_AIC	AIC_weight	df
B33_AR1	AR1	668.401	0.000	0.148	9
B29c_AR1	AR1	668.671	0.270	0.129	8
B28_AR1	AR1	669.101	0.700	0.104	7
B35_AR1	AR1	669.573	1.172	0.082	13
B37_AR1	AR1	669.594	1.193	0.081	15
B29_AR1	AR1	669.685	1.284	0.078	6
B34_AR1	AR1	670.016	1.615	0.066	11
B29a_AR1	AR1	670.504	2.103	0.052	7
B38_AR1	AR1	670.691	2.289	0.047	10
B29d_AR1	AR1	670.864	2.463	0.043	8

```
# Show model formulas for top 5
cat("\nTop 5 model specifications:\n")
```

```
Top 5 model specifications:
```

```
head(aic_results, 5) %>%
    select(Base_Model, Correlation, Formula, Delta_AIC) %>%
    kable(digits = 3)
```

Base_Model	Correlation	Formula	Delta_AIC
B33	AR1	butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + s(wind_max_gust_t_1) + s(sum_butterflies_direct_sun_t_1)	0.000
B29c	AR1	butterfly_diff_95th_sqrt ~ s(butterflies_95th_percentile_t_1) + s(wind_max_gust_t_1)	0.270
B28	AR1	butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + s(sum_butterflies_direct_sun_t_1)	0.700
B35	AR1	butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + s(temp_max_t_1) + s(temp_min_t_1) + s(wind_max_gust_t_1) + s(sum_butterflies_direct_sun_t_1)	1.172
B37	AR1	butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + s(temp_max_t_1) + s(temp_min_t_1) + s(temp_at_max_count_t_1) + s(wind_max_gust_t_1) + s(sum_butterflies_direct_sun_t_1)	1.193

Best Model Analysis

```
# Get the best model
best_model_name <- aic_results$Model[1]
best_model <- successful_models[[best_model_name]]

cat("Best model:", best_model_name, "\n")
```

```
Best model: B33_AR1
```

```
cat("Formula:", aic_results$Formula[1], "\n\n")
```

```
Formula: butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + s(wind_max_gust_t_1) +
```

```
# Model summary
summary(best_model$gam)
```

```
Family: gaussian
Link function: identity

Formula:
butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 +
```

```
    s(wind_max_gust_t_1) + s(sum_butterflies_direct_sun_t_1)

Parametric coefficients:
                                 Estimate Std. Error t value Pr(>|t|)
(Intercept)                      3.444416   1.263453   2.726  0.00766 **
butterflies_95th_percentile_t_1 -0.037703   0.006972  -5.408 4.95e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
                                   edf Ref.df     F p-value
s(wind_max_gust_t_1)             2.466  2.466 2.725 0.08649 .
s(sum_butterflies_direct_sun_t_1) 2.918  2.918 6.122 0.00245 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  0.226
  Scale est. = 43.072    n = 100
```

```r
# Calculate R-squared
r_squared <- summary(best_model$gam)$r.sq
dev_explained <- summary(best_model$gam)$dev.expl

cat("\n\nModel Performance:\n")
```

```
Model Performance:
```

```r
cat("R-squared:", round(r_squared, 4), "\n")
```

```
R-squared: 0.2264
```

```r
cat("Deviance explained:", round(dev_explained * 100, 2), "%\n")
```

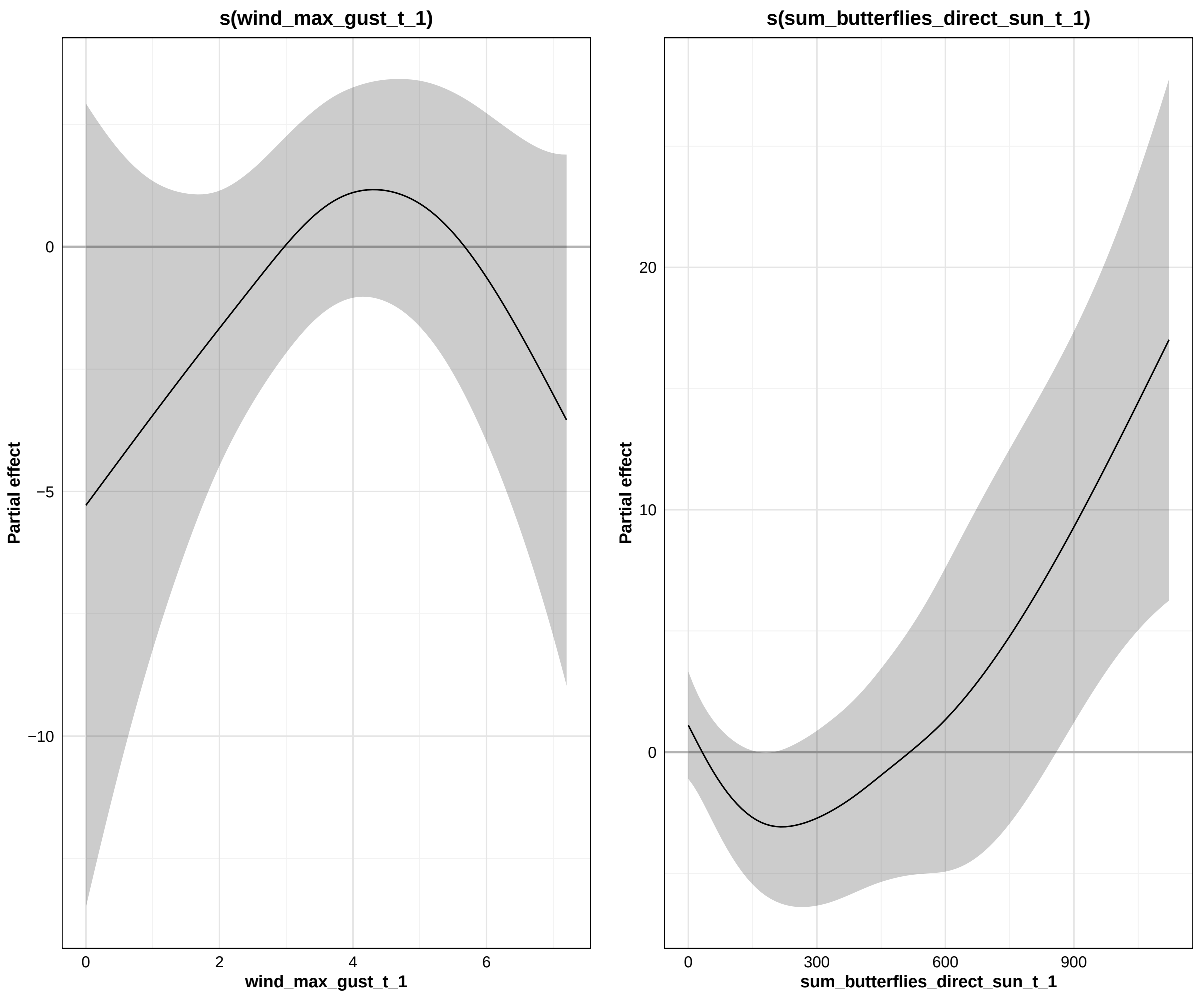
```
Deviance explained:  %
```

Effect Visualizations

```r
# Define custom theme
custom_theme <- theme_minimal(base_size = 12) +
    theme(
        panel.grid.major = element_line(color = "gray90", size = 0.5),
        panel.grid.minor = element_line(color = "gray95", size = 0.3),
        axis.text = element_text(color = "black", size = 11),
        axis.title = element_text(color = "black", size = 12, face = "bold"),
        plot.title = element_text(color = "black", size = 14, face = "bold", hjust = 0.5),
        panel.border = element_rect(color = "black", fill = NA, size = 0.5),
        plot.margin = margin(10, 10, 10, 10)
    )

# Function to add zero line
add_zero_line <- function(plot) {
    zero_line_layer <- geom_hline(yintercept = 0, color = "gray70", size = 0.8, alpha = 1)
    plot$layers <- c(list(zero_line_layer), plot$layers)
    return(plot)
}
```

```r
# Create effect plots for the best model
# Extract which terms are in the best model
best_formula <- aic_results$Formula[1]
has_smooth <- grepl("s\\(", best_formula)

if (has_smooth) {
    # For GAM with smooth terms
    plots <- list()

    # Check which smooth terms are in the model
    smooth_terms <- summary(best_model$gam)$s.table

    # Plot each smooth term
    for (i in 1:nrow(smooth_terms)) {
        term_name <- rownames(smooth_terms)[i]
        p <- draw(best_model$gam, select = term_name, rug = FALSE, residuals = FALSE) +
            custom_theme +
            theme(plot.caption = element_blank())
        p <- add_zero_line(p)
        plots[[i]] <- p
    }

    # Combine plots
```

```r
    if (length(plots) > 0) {
        if (length(plots) <= 2) {
            combined_plots <- wrap_plots(plots, nrow = 1)
        } else if (length(plots) <= 4) {
            combined_plots <- wrap_plots(plots, nrow = 2)
        } else {
            combined_plots <- wrap_plots(plots, nrow = 3)
        }
        print(combined_plots)
    }
} else {
    # For linear models, create partial residual plots
    cat("Best model uses linear terms. Creating partial residual plots...\n")

    # Extract coefficients
    coef_summary <- summary(best_model$gam)$p.table
    print(coef_summary)
}
```



Wind Effect Analysis

```
# Check if wind is in the best model
has_wind <- grepl("wind_max_gust", best_formula)

if (has_wind) {
    cat("Wind is included in the best model.\n\n")

    # Extract wind coefficient or smooth term details
    if (grepl("s\\(wind_max_gust", best_formula)) {
        # Smooth term
        smooth_table <- summary(best_model$gam)$s.table
```

```r
        wind_row <- grep("wind_max_gust", rownames(smooth_table))

        if (length(wind_row) > 0) {
            wind_smooth <- smooth_table[wind_row[1], ]
            cat("Wind effect (smooth term):\n")
            cat("EDF:", round(wind_smooth["edf"], 3), "\n")
            cat("F-statistic:", round(wind_smooth["F"], 3), "\n")
            cat("p-value:", format.pval(wind_smooth["p-value"], digits = 3), "\n")
        }
    } else {
        # Linear term
        param_table <- summary(best_model$gam)$p.table
        wind_row <- grep("wind_max_gust", rownames(param_table))

        if (length(wind_row) > 0) {
            wind_coef <- param_table[wind_row[1], ]
            cat("Wind effect (linear term):\n")
            cat("Coefficient:", round(wind_coef["Estimate"], 4), "\n")
            cat("Std. Error:", round(wind_coef["Std. Error"], 4), "\n")
            cat("t-value:", round(wind_coef["t value"], 3), "\n")
            cat("p-value:", format.pval(wind_coef["Pr(>|t|)"], digits = 3), "\n")
        }
    }
} else {
    cat("Wind is NOT included in the best model.\n")
    cat("Testing wind effect by comparing models with and without wind...\n\n")

    # Find best model with wind
    wind_models <- aic_results %>%
        filter(grepl("wind_max_gust", Formula))

    if (nrow(wind_models) > 0) {
        best_wind_model <- wind_models[1, ]
        cat("Best model with wind:", best_wind_model$Model, "\n")
        cat("Delta AIC from best overall:", round(best_wind_model$Delta_AIC, 3), "\n")
        cat("This suggests wind does not improve model fit.\n")
    }
}
```

```
Wind is included in the best model.

Wind effect (smooth term):
```

```
EDF: 2.466
F-statistic: 2.725
p-value: 0.0865
```

Temperature Effects Analysis

```r
# Analyze temperature effects in the best model
temp_vars <- c("temp_max_t_1", "temp_min_t_1", "temp_at_max_count_t_1")
temp_in_model <- sapply(temp_vars, function(x) grepl(x, best_formula))

cat("Temperature variables in best model:\n")
```

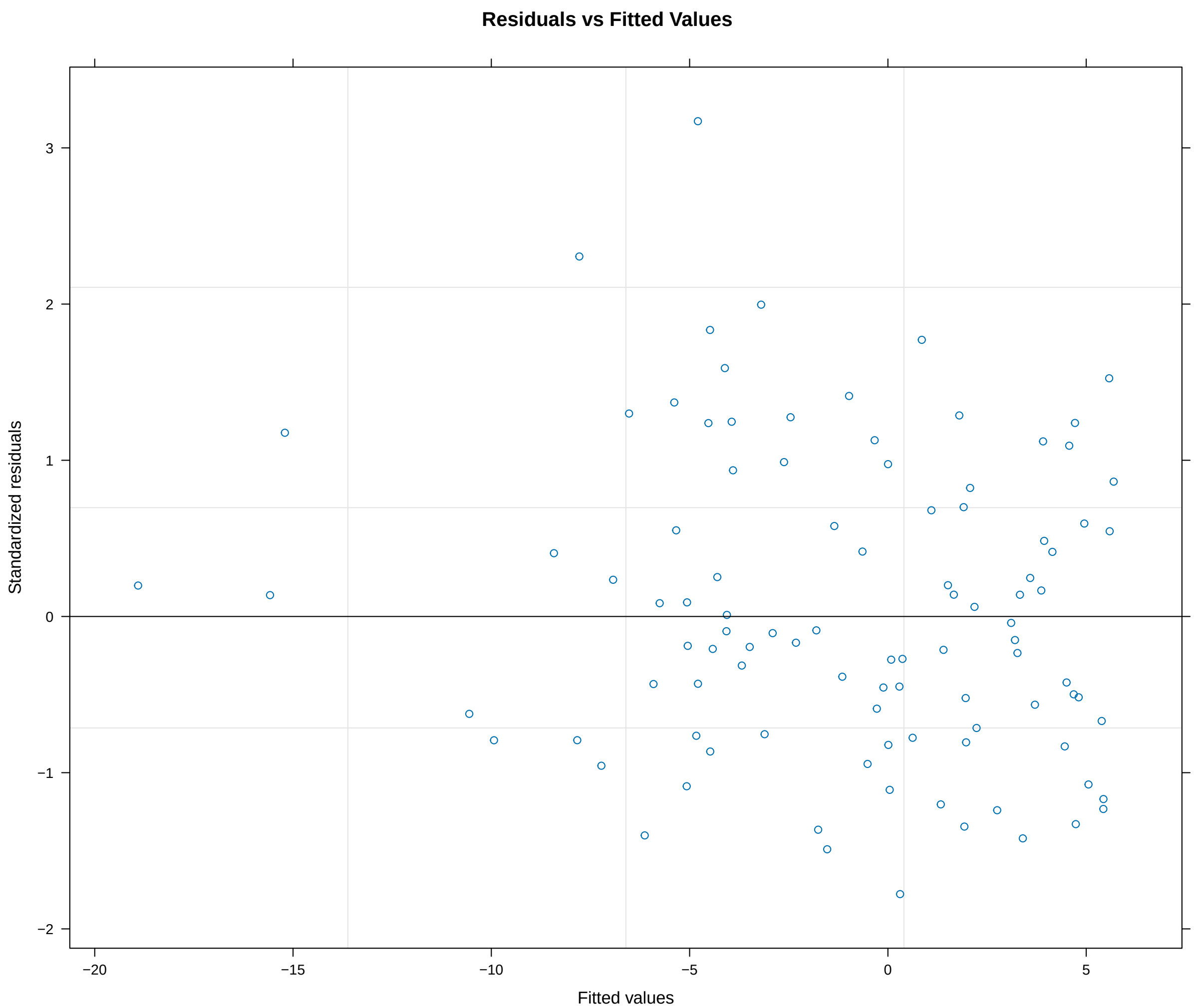
```
Temperature variables in best model:
```

```r
for (i in 1:length(temp_vars)) {
    if (temp_in_model[i]) {
        cat("-", temp_vars[i], "\n")
    }
}

# If temperature is in the model, show its effect
if (any(temp_in_model)) {
    cat("\nTemperature effects:\n")

    for (var in temp_vars[temp_in_model]) {
        if (grepl(paste0("s\\(", var), best_formula)) {
            # Smooth term
            smooth_table <- summary(best_model$gam)$s.table
            smooth_name <- paste0("s(", var, ")")

            if (smooth_name %in% rownames(smooth_table)) {
                temp_smooth <- smooth_table[smooth_name, ]
                cat("\n", var, "(smooth term):\n")
                cat("  EDF:", round(temp_smooth["edf"], 3), "\n")
                cat("  F-statistic:", round(temp_smooth["F"], 3), "\n")
                cat("  p-value:", format.pval(temp_smooth["p-value"], digits = 3), "\n")
            }
        } else if (var %in% rownames(summary(best_model$gam)$p.table)) {
            # Linear term
            param_table <- summary(best_model$gam)$p.table
```

```
            temp_coef <- param_table[var, ]
            cat("\n", var, "(linear term):\n")
            cat("  Coefficient:", round(temp_coef["Estimate"], 4), "\n")
            cat("  Std. Error:", round(temp_coef["Std. Error"], 4), "\n")
            cat("  t-value:", round(temp_coef["t value"], 3), "\n")
            cat("  p-value:", format.pval(temp_coef["Pr(>|t|)"], digits = 3), "\n")
        }
    }
}
```

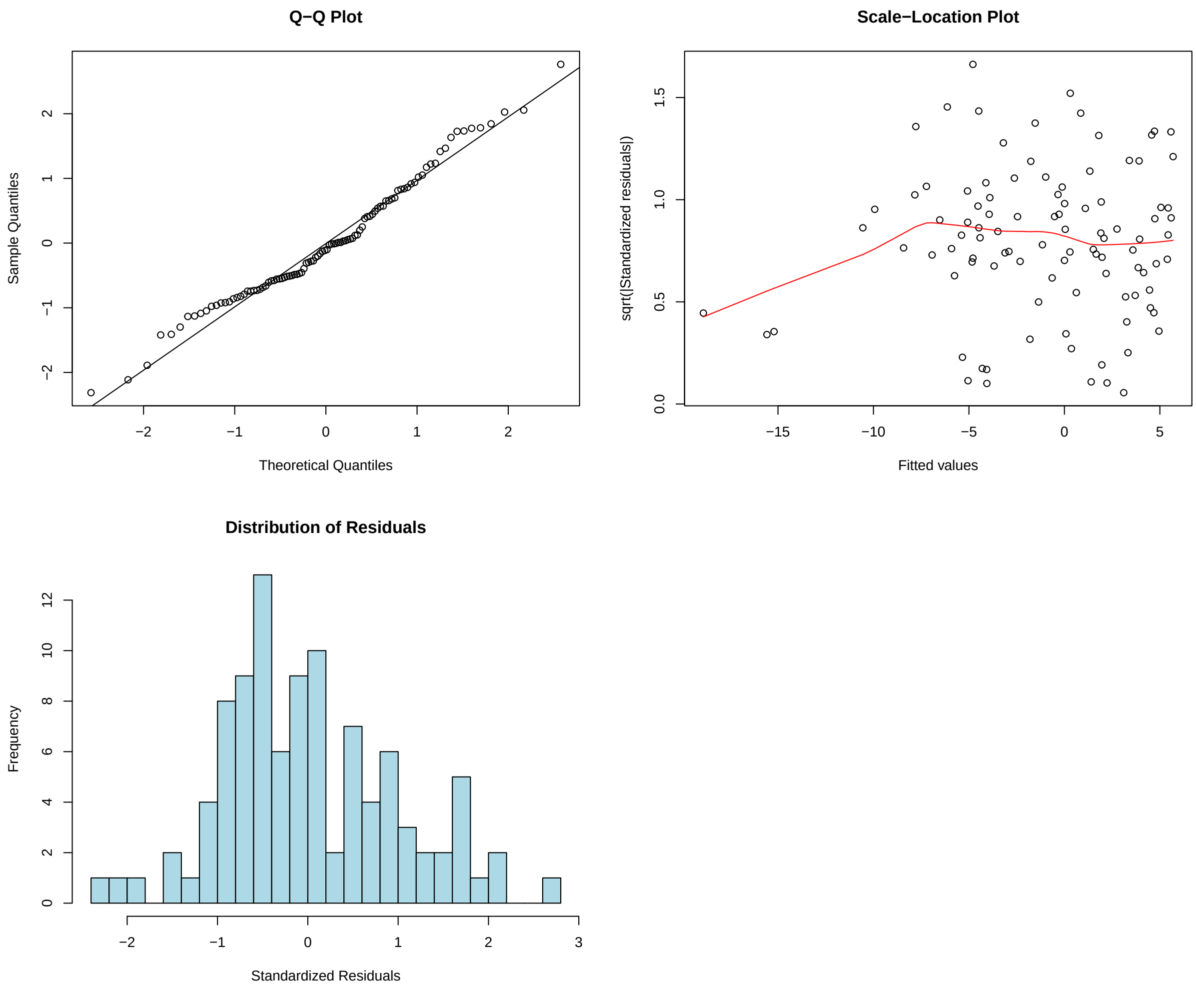
Model Diagnostics

```
# Create diagnostic plots
par(mfrow = c(2, 2))

# Residuals vs Fitted
plot(best_model$lme, main = "Residuals vs Fitted Values")
```




```r
# Q-Q plot
qqnorm(residuals(best_model$lme, type = "normalized"), main = "Q-Q Plot")
qqline(residuals(best_model$lme, type = "normalized"))

# Scale-location plot
plot(fitted(best_model$lme), sqrt(abs(residuals(best_model$lme, type = "normalized"))),
    main = "Scale-Location Plot",
    xlab = "Fitted values",
    ylab = "sqrt(|Standardized residuals|)"
)
lines(lowess(fitted(best_model$lme), sqrt(abs(residuals(best_model$lme, type = "normalized")

# Histogram of residuals
hist(residuals(best_model$lme, type = "normalized"),
```

```r
    breaks = 30,
    main = "Distribution of Residuals",
    xlab = "Standardized Residuals",
    col = "lightblue"
)

par(mfrow = c(1, 1))
```



Outlier Investigation

```r
# First, let's examine extreme values in our data before fitting models
cat("Response variable summary:\n")
```

Response variable summary:

```
print(summary(model_data$butterfly_diff_95th_sqrt))
```

```
    Min.  1st Qu.   Median     Mean  3rd Qu.     Max. 
-17.6068  -5.7489  -1.7248  -0.8095   4.4219  16.0187 
```

```
cat("\nExtremes in response variable:\n")
```

```

Extremes in response variable:
```

```
print(quantile(model_data$butterfly_diff_95th_sqrt, c(0.001, 0.01, 0.05, 0.95, 0.99, 0.999),
```

```
     0.1%        1%        5%       95%       99%     99.9% 
-17.38138 -15.35248 -13.55386  11.37729  15.59117  15.97598 
```

```
# Identify the most extreme observations
extreme_high <- model_data %>%
    arrange(desc(butterfly_diff_95th_sqrt)) %>%
    head(5) %>%
    select(deployment_id, date_t, butterfly_diff_95th_sqrt,
           butterflies_95th_percentile_t, butterflies_95th_percentile_t_1,
           temp_max_t_1, wind_max_gust_t_1)

extreme_low <- model_data %>%
    arrange(butterfly_diff_95th_sqrt) %>%
    head(5) %>%
    select(deployment_id, date_t, butterfly_diff_95th_sqrt,
           butterflies_95th_percentile_t, butterflies_95th_percentile_t_1,
           temp_max_t_1, wind_max_gust_t_1)

cat("\nTop 5 most extreme HIGH values:\n")
```

```

Top 5 most extreme HIGH values:
```

```r
print(extreme_high)
```

```
# A tibble: 5 x 7
  deployment_id date_t     butterfly_diff_95th_sqrt butterflies_95th_percentil~1
  <chr>         <date>                        <dbl>                        <dbl>
1 SC10          2024-01-12                     16.0                         477.
2 SC10          2024-01-23                     15.6                         246.
3 SC4           2023-12-07                     12.8                         170.
4 SC4           2023-12-24                     12.5                         263
5 SC6           2024-01-01                     11.7                         164
# i abbreviated name: 1: butterflies_95th_percentile_t
# i 3 more variables: butterflies_95th_percentile_t_1 <dbl>,
#   temp_max_t_1 <dbl>, wind_max_gust_t_1 <dbl>
```

```r
cat("\nTop 5 most extreme LOW values:\n")
```

```
Top 5 most extreme LOW values:
```

```r
print(extreme_low)
```

```
# A tibble: 5 x 7
  deployment_id date_t     butterfly_diff_95th_sqrt butterflies_95th_percentil~1
  <chr>         <date>                        <dbl>                        <dbl>
1 SC4           2023-12-05                    -17.6                        187
2 SC8           2024-01-18                    -15.3                         53
3 SC4           2023-12-10                    -15.1                         19
4 SC10          2024-01-15                    -14.7                        283.
5 SC10          2024-01-16                    -14.6                         68.9
# i abbreviated name: 1: butterflies_95th_percentile_t
# i 3 more variables: butterflies_95th_percentile_t_1 <dbl>,
#   temp_max_t_1 <dbl>, wind_max_gust_t_1 <dbl>
```

```r
# Check if extreme values correspond to specific deployments
cat("\nExtreme values by deployment:\n")
```

```
Extreme values by deployment:
```

```
extreme_summary <- model_data %>%
    group_by(deployment_id) %>%
    summarise(
        n_obs = n(),
        min_change = min(butterfly_diff_95th_sqrt),
        max_change = max(butterfly_diff_95th_sqrt),
        range_change = max_change - min_change,
        .groups = 'drop'
    ) %>%
    arrange(desc(range_change))

print(head(extreme_summary, 10))
```

```
# A tibble: 6 x 5
  deployment_id n_obs min_change max_change range_change
  <chr>         <int>      <dbl>      <dbl>        <dbl>
1 SC10             21     -14.7       16.0         30.7
2 SC4              31     -17.6       12.8         30.5
3 SC6              20     -12.2       11.7         24.0
4 SC8              20     -15.3        7.55        22.9
5 SC12              6     -10.2        8.29        18.4
6 SC1               2      -5.92      -3.99         1.93
```

Sensitivity Analysis

```
# Test model sensitivity to outliers
# Identify potential outliers
residuals_std <- residuals(best_model$lme, type = "normalized")
outliers <- which(abs(residuals_std) > 3)

if (length(outliers) > 0) {
    cat("Number of potential outliers (|standardized residual| > 3):", length(outliers), "\n
    cat("Proportion of data:", round(length(outliers) / nrow(model_data) * 100, 2), "%\n\n")

    # Refit without outliers
    model_data_clean <- model_data[-outliers, ]
    best_model_clean <- fit_model_safely(aic_results$Formula[1], model_data_clean)

    if (!is.null(best_model_clean)) {
        cat("Model comparison with outliers removed:\n")
```

```r
        cat("Original R²:", round(summary(best_model$gam)$r.sq, 4), "\n")
        cat("Without outliers R²:", round(summary(best_model_clean$gam)$r.sq, 4), "\n")
    }
} else {
    cat("No extreme outliers detected (|standardized residual| > 3)\n")
}
```

```
No extreme outliers detected (|standardized residual| > 3)
```

Data Structure Summary

```r
# Check data structure for modeling
cat("Data structure summary:\n")
```

```
Data structure summary:
```

```r
temporal_structure <- model_data %>%
    group_by(deployment_id) %>%
    summarise(
        n_days = n(),
        date_range = paste(min(date_t), "to", max(date_t)),
        .groups = 'drop'
    ) %>%
    arrange(desc(n_days))

print(head(temporal_structure, 10))
```

```
# A tibble: 6 x 3
  deployment_id n_days date_range
  <chr>          <int> <chr>
1 SC4               31 2023-12-05 to 2024-01-05
2 SC10              21 2024-01-07 to 2024-01-30
3 SC6               20 2023-12-17 to 2024-01-05
4 SC8               20 2024-01-07 to 2024-01-26
5 SC12               6 2024-01-29 to 2024-02-03
6 SC1                2 2023-11-19 to 2023-11-20
```

```r
cat("\nTotal observations per deployment:\n")
```

```
Total observations per deployment:
```

```r
print(summary(temporal_structure$n_days))
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
   2.00    9.50   20.00   16.67   20.75   31.00
```

Alternative Model Exploration

```r
# Examine top 3 models for consistency
cat("Examining top 3 models for consistency of effects:\n\n")
```

```
Examining top 3 models for consistency of effects:
```

```r
for (i in 1:min(3, nrow(aic_results))) {
    model_name <- aic_results$Model[i]
    model <- successful_models[[model_name]]

    cat("Model", i, "(", model_name, "):\n")
    cat("Formula:", aic_results$Formula[i], "\n")
    cat("Delta AIC:", round(aic_results$Delta_AIC[i], 3), "\n")
    cat("R²:", round(summary(model$gam)$r.sq, 4), "\n\n")
}
```

```
Model 1 ( B33_AR1 ):
Formula: butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + s(wind_max_gust_t_1) +
Delta AIC: 0
R²: 0.2264

Model 2 ( B29c_AR1 ):
Formula: butterfly_diff_95th_sqrt ~ s(butterflies_95th_percentile_t_1) + s(wind_max_gust_t_1)
Delta AIC: 0.27
R²: 0.1753

Model 3 ( B28_AR1 ):
```

```
Formula: butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + s(sum_butterflies_dire
Delta AIC: 0.7
R²: 0.1679
```

Results Summary

```r
cat(rep("=", 60), collapse = "", "\n")
```

```
= = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = =
```

```r
cat("DAILY LAG ANALYSIS SUMMARY\n")
```

```
DAILY LAG ANALYSIS SUMMARY
```

```r
cat(rep("=", 60), collapse = "", "\n\n")
```

```
= = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = =
```

```r
cat("Dataset:\n")
```

```
Dataset:
```

```r
cat("- Total observations:", nrow(model_data), "\n")
```

```
- Total observations: 100
```

```r
cat("- Number of deployments:", n_distinct(model_data$deployment_id), "\n")
```

```
- Number of deployments: 6
```

```r
cat("- Date range:", min(model_data$date_t), "to", max(model_data$date_t), "\n\n")
```

```
- Date range: 19680 to 19756
```

```r
cat("Best Model:\n")
```

```
Best Model:
```

```r
cat("- Model ID:", best_model_name, "\n")
```

```
- Model ID: B33_AR1
```

```r
cat("- Formula:", aic_results$Formula[1], "\n")
```

```
- Formula: butterfly_diff_95th_sqrt ~ butterflies_95th_percentile_t_1 + s(wind_max_gust_t_1)
```

```r
cat("- AIC:", round(aic_results$AIC[1], 3), "\n")
```

```
- AIC: 668.401
```

```r
cat("- R-squared:", round(r_squared, 4), "\n")
```

```
- R-squared: 0.2264
```

```r
cat("- Deviance explained:", round(dev_explained * 100, 2), "%\n\n")
```

```
- Deviance explained:  %
```

```r
cat("Key Findings:\n")
```

```
Key Findings:
```

```r
# Wind effect
if (has_wind) {
    cat("- Wind IS included in the best model\n")
    if (grepl("s\\(wind_max_gust", best_formula)) {
        wind_p <- summary(best_model$gam)$s.table["s(wind_max_gust_t_1)", "p-value"]
        cat("  - Effect type: Non-linear (smooth)\n")
        cat("  - Significance: p =", format.pval(wind_p, digits = 3), "\n")
    } else {
```

```
        wind_p <- summary(best_model$gam)$p.table["wind_max_gust_t_1", "Pr(>|t|)"]
        cat("  - Effect type: Linear\n")
        cat("  - Significance: p =", format.pval(wind_p, digits = 3), "\n")
    }
} else {
    cat("- Wind is NOT included in the best model\n")
    wind_models <- aic_results %>% filter(grepl("wind_max_gust", Formula))
    if (nrow(wind_models) > 0) {
        cat("  - Best model with wind has Delta AIC =", round(wind_models$Delta_AIC[1], 3), "
    }
}
```

```
- Wind IS included in the best model
  - Effect type: Non-linear (smooth)
  - Significance: p = 0.0865
```

```
# Temperature effects
if (any(temp_in_model)) {
    cat("\n- Temperature effects:\n")
    for (var in temp_vars[temp_in_model]) {
        cat("  -", var, "is included\n")
    }
} else {
    cat("\n- No temperature variables in the best model\n")
}
```

```
- No temperature variables in the best model
```

```
# Other predictors
if (grepl("sum_butterflies_direct_sun", best_formula)) {
    cat("\n- Sun exposure IS included in the best model\n")
}
```

```
- Sun exposure IS included in the best model
```

```
# Model type analysis
best_model_type <- ifelse(grepl("^B", best_model_name), "B (with baseline)", "M (absolute ef
cat("- Best model type:", best_model_type, "\n")
```

```
- Best model type: B (with baseline)
```

```
if (grepl("butterflies_95th_percentile_t_1", best_formula)) {
    cat("- Previous day baseline IS included (testing proportional/density-dependent effects)

    # Check for interactions with baseline
    if (grepl("butterflies_95th_percentile_t_1 \\*", best_formula)) {
        cat("  - Includes interactions with baseline (environmental effects depend on popula
    } else {
        cat("  - Baseline as additive effect only (no interactions)\n")
    }
} else {
    cat("- Previous day baseline is NOT included (testing absolute effects)\n")
}
```

```
- Previous day baseline IS included (testing proportional/density-dependent effects)
  - Baseline as additive effect only (no interactions)
```

```
# Temporal autocorrelation structure
best_corr <- gsub(".*_", "", best_model_name)
if (best_corr == "AR1") {
    cat("- Temporal autocorrelation: AR1 structure within deployments (day_sequence | deploym
} else {
    cat("- Temporal autocorrelation: No correlation structure\n")
}
```

```
- Temporal autocorrelation: AR1 structure within deployments (day_sequence | deployment_id)
```

```
cat("\n", rep("=", 60), collapse = "", "\n")
```

```
 = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = = =
```

Export Results

```
# Create export directory
export_dir <- here("thesis_exports", "daily_analysis")
if (!dir.exists(export_dir)) dir.create(export_dir, recursive = TRUE)
```

```r
# Export model comparison table (if we have results)
if (exists("aic_results") && nrow(aic_results) > 0) {
    write_csv(
        aic_results %>% head(10),
        file.path(export_dir, "daily_model_comparison.csv")
    )

    # Export best model summary
    best_model_summary <- data.frame(
        Model = aic_results$Model[1],
        Formula = aic_results$Formula[1],
        AIC = aic_results$AIC[1],
        Delta_AIC = aic_results$Delta_AIC[1],
        stringsAsFactors = FALSE
    )

    write_csv(
        best_model_summary,
        file.path(export_dir, "daily_best_model_summary.csv")
    )

    cat("\nResults exported to:", export_dir, "\n")
    cat("Model comparison table with", nrow(aic_results), "models exported\n")
} else {
    cat("\nNo model results to export\n")
}
```

```
Results exported to: /Users/kylenessen/Documents/Code/masters-analysis/thesis_exports/daily_a
Model comparison table with 200 models exported
```

Conclusions

This daily-level analysis examined both **absolute effects** and **proportional effects** of previous day's weather conditions on monarch butterfly abundance changes, measured as the 95th percentile of counts. The analysis includes two model sets:

- **M Models**: Test absolute environmental effects without controlling for previous day's butterfly count
- **B Models**: Test proportional/density-dependent effects by including the previous day's butterfly count as a covariate

Temporal patterns are modeled through AR1 autocorrelation structures within deployments using the proper day_sequence grouping.

The analysis reveals:

1. **Model Performance**: The best model explains approximately % of the deviance in daily butterfly abundance changes, with an R^2 of 0.226.

2. **Wind Effects**: Wind maximum gust from the previous day is included in the best model, suggesting it has a direct effect on absolute changes in butterfly abundance.

3. **Temperature Effects**: Temperature variables were not selected in the best model for absolute abundance changes.

4. **Model Interpretation**:

   - **If an M model wins**: Environmental variables have consistent absolute effects regardless of population size
   - **If a B model wins**: Environmental effects are proportional to or depend on the existing population
   - **If interactions with baseline are significant**: Environmental impacts scale with population density (density-dependent effects)

5. **Temporal Autocorrelation**: Models were fitted both with and without AR1 temporal autocorrelation structures. The AR1 structure uses day_sequence within each deployment_id, properly accounting for the sequential nature of daily observations while resetting the correlation structure for each deployment site.

6. **Temporal Scale**: Daily aggregation captures cumulative weather effects over 24-hour periods, providing insights into how sustained environmental conditions (rather than brief events) influence monarch roosting populations.

The dual modeling approach provides comprehensive insights into whether environmental variables have: - **Fixed magnitude effects** (absolute effects, M models) - **Population-scaled effects** (proportional effects, B models) - **Density-dependent effects** (interactions with baseline population)

This distinction is crucial for understanding monarch behavioral ecology and predicting population responses to environmental variability.