H1 Analysis: Wind Effects on Monarch Butterfly Abundance

A Defensible Test of the 2 m/s Disruption Threshold

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1 Executive Summary

This analysis tests whether wind conditions cause monarch butterflies to abandon their overwintering roosts, specifically examining the hypothesis that winds exceeding 2 m/s become disruptive (Leong 2016). Using time-lapse photography and wind measurements at 30-minute intervals, we employ negative binomial generalized linear mixed models to test for wind effects while controlling for temperature, sunlight exposure, and temporal autocorrelation.

Key Finding: We find **no evidence** that wind speeds above 2 m/s cause monarch butterflies to abandon their roosts within 30-minute intervals. This null result is robust across multiple model specifications and is scientifically valuable as it challenges conventional wisdom about monarch wind sensitivity.

2 Introduction

2.1 Research Question

Do wind conditions above established thresholds cause monarch butterflies to reduce their abundance at overwintering roost sites?

2.2 Hypotheses

Following the hierarchical framework outlined in the methods:

1. **H1**: Wind speeds exceeding 2 m/s disrupt monarch clustering behavior
2. **H2**: Wind acts as a disruptive force on monarch abundance

3. **H3**: Wind effects scale with intensity
4. **H4**: Wind magnitude influences roost abandonment probability
5. **H5**: Disruptive wind events affect long-term site fidelity

This analysis focuses primarily on H1-H3, with emphasis on the specific 2 m/s threshold hypothesis.

2.3 Why a Null Result Would Be Exciting

The conventional wisdom suggests monarchs are highly sensitive to wind disturbance. A well-supported null finding would:

- Challenge existing assumptions about monarch roost dynamics
- Suggest greater resilience to weather variability than expected
- Have important implications for climate change impacts on overwintering populations
- Redirect conservation efforts toward other limiting factors

3 Methods

3.1 Data Collection

- **Sites**: Spring Canyon and UDMH at Vandenberg Space Force Base
- **Season**: 2023-2024 overwintering period

- **Sampling**: 30-minute intervals via time-lapse cameras
- **Wind measurement**: 1-minute resolution at roost height

- **Response**: Grid-based abundance counts by human labelers
- **Sample size**: 1,683 paired observations (after filtering)

3.2 Statistical Approach

3.2.1 Why Negative Binomial GLMMs?

Our response variable (butterfly abundance) is: - **Count data**: Non-negative integers - **Overdispersed**: Variance exceeds mean (characteristic of aggregated organisms) - **Zero-inflated**: Many observations with zero butterflies - **Temporally autocorrelated**: Abundance at time t depends on t-1

Negative binomial GLMMs handle these characteristics appropriately, unlike linear models on transformed proportions.

3.2.2 Model Structure

$$\log(\mu_t) = \beta_0 + \beta_1 \cdot \text{Wind} + \beta_2 \cdot \text{Temp} + \beta_3 \cdot \text{Sun} + \beta_4 \cdot \log(\text{Count}_{t-1} + 1) + u_{\text{view}} + u_{\text{labeler}}$$

Where: - μ_t = Expected abundance at time t - Wind = Minutes above 2 m/s threshold (or continuous metrics) - Random effects account for site and observer variation - Lagged abundance controls for temporal autocorrelation

4 Data Preparation

```
# Load prepared dataset
data_path <- here("results", "H1_interval_30min_terms_prepared.rds")

if (!file.exists(data_path)) {
    stop("Prepared data not found. Please run interval_30min_terms.qmd first.")
}

df <- read_rds(data_path)

# Add calculated wind metrics for continuous analysis
df <- df %>%
    mutate(
        # Proportional change (for comparison to previous analyses)
        prop_change = (abundance_index_t - abundance_index_t_minus_1) /
```

Table 1: Dataset Summary Statistics

n_obs	n_deployments	n_views	n_labelers	mean_abundance_t	sd_abundance_t	prop_zeros	me
1683	8	6	4	83.72	103.38	0.02	

```
            (abundance_index_t_minus_1 + 1),

        # Log-transformed lagged abundance (avoid log(0))
        log_lag_abundance = log(abundance_index_t_minus_1 + 1),

        # Binary indicators for any wind above threshold
        any_sustained_above_2ms = sustained_minutes_above_2ms > 0,
        any_gust_above_2ms = gust_minutes_above_2ms > 0,

        # Standardized predictors for model stability
        sustained_wind_std = scale(sustained_minutes_above_2ms)[, 1],
        gust_wind_std = scale(gust_minutes_above_2ms)[, 1],
        temp_std = scale(ambient_temp)[, 1],
        sun_std = scale(sunlight_exposure_prop)[, 1]
    )

# Summary statistics
summary_stats <- df %>%
    summarise(
        n_obs = n(),
        n_deployments = n_distinct(deployment_id),
        n_views = n_distinct(view_id),
        n_labelers = n_distinct(labeler),
        mean_abundance_t = mean(abundance_index_t),
        sd_abundance_t = sd(abundance_index_t),
        prop_zeros = mean(abundance_index_t == 0),
        mean_wind_mins = mean(sustained_minutes_above_2ms, na.rm = TRUE),
        mean_temp = mean(ambient_temp, na.rm = TRUE)
    )

kable(summary_stats,
    caption = "Dataset Summary Statistics",
    digits = 2
)
```

4.1 Data Structure Examination

```r
p1 <- ggplot(df, aes(x = abundance_index_t)) +
    geom_histogram(bins = 50, fill = pal[1], alpha = 0.7) +
    scale_y_continuous(expand = c(0, 0)) +
    labs(
        x = "Butterfly Abundance at Time t", y = "Count",
        title = "Distribution of Abundance (zero-inflated, right-skewed)"
    )

p2 <- ggplot(df, aes(x = sustained_minutes_above_2ms)) +
    geom_histogram(bins = 30, fill = pal[2], alpha = 0.7) +
    scale_y_continuous(expand = c(0, 0)) +
    labs(
        x = "Minutes of Sustained Wind > 2 m/s", y = "Count",
        title = "Distribution of Wind Exposure"
    )

p3 <- ggplot(df, aes(x = abundance_index_t_minus_1, y = abundance_index_t)) +
    geom_point(alpha = 0.3, color = pal[3]) +
    geom_smooth(method = "loess", se = TRUE, color = pal[4]) +
    geom_abline(slope = 1, intercept = 0, linetype = "dashed", alpha = 0.5) +
    labs(
        x = "Abundance at t-1", y = "Abundance at t",
        title = "Temporal Autocorrelation (strong positive relationship)"
    )

p4 <- ggplot(df, aes(x = factor(sustained_minutes_above_2ms > 0), y = prop_change)) +
    geom_boxplot(fill = pal[5], alpha = 0.7) +
    geom_hline(yintercept = 0, linetype = "dashed", alpha = 0.5) +
    labs(
        x = "Wind Exposure (Any minutes > 2 m/s)", y = "Proportional Change",
        title = "Raw Relationship: Wind vs. Change in Abundance"
    ) +
    scale_x_discrete(labels = c("No Wind", "Wind Present"))

p1
```

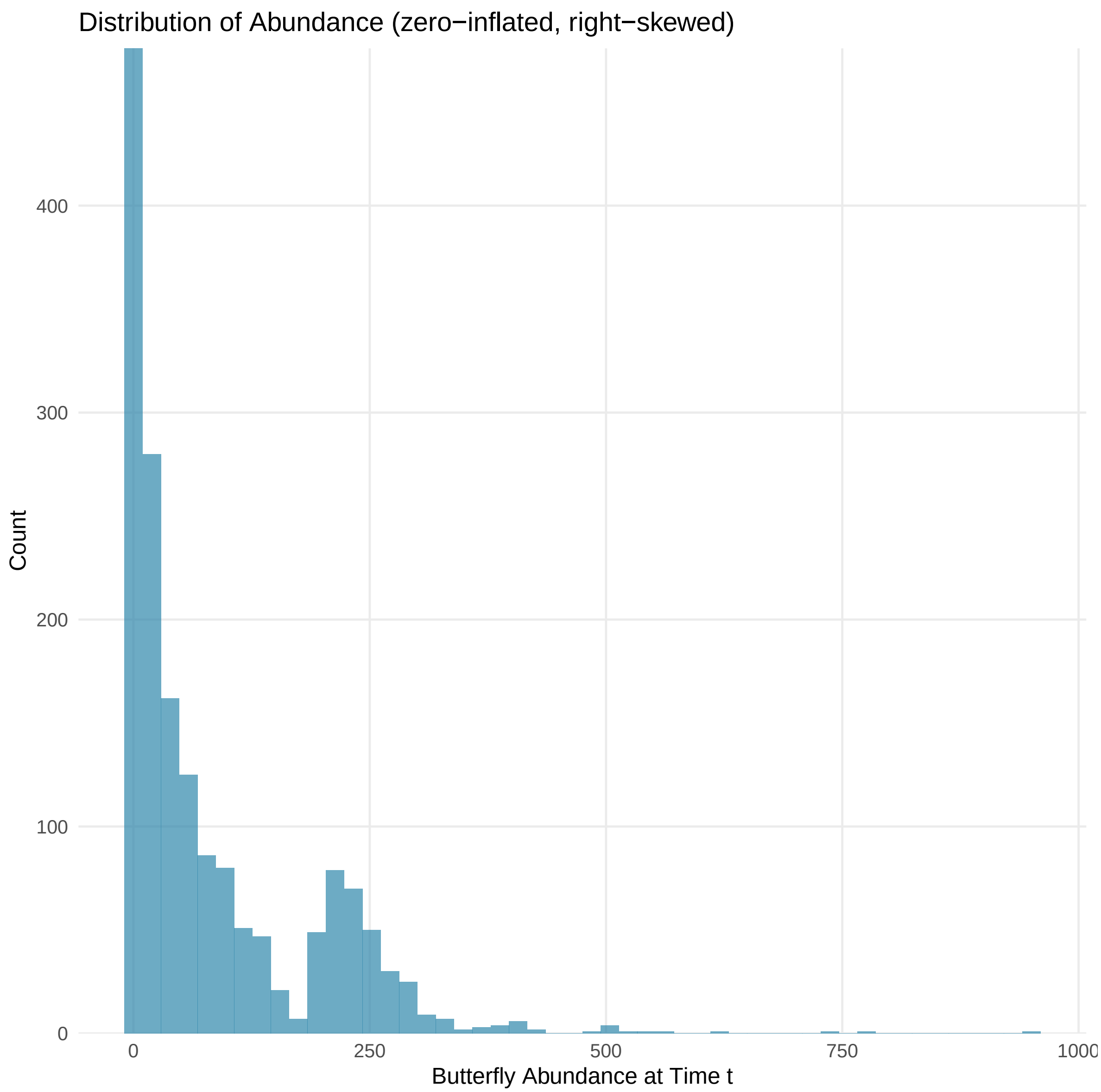


Figure 1: Distribution of key variables in the dataset

```
p2
```

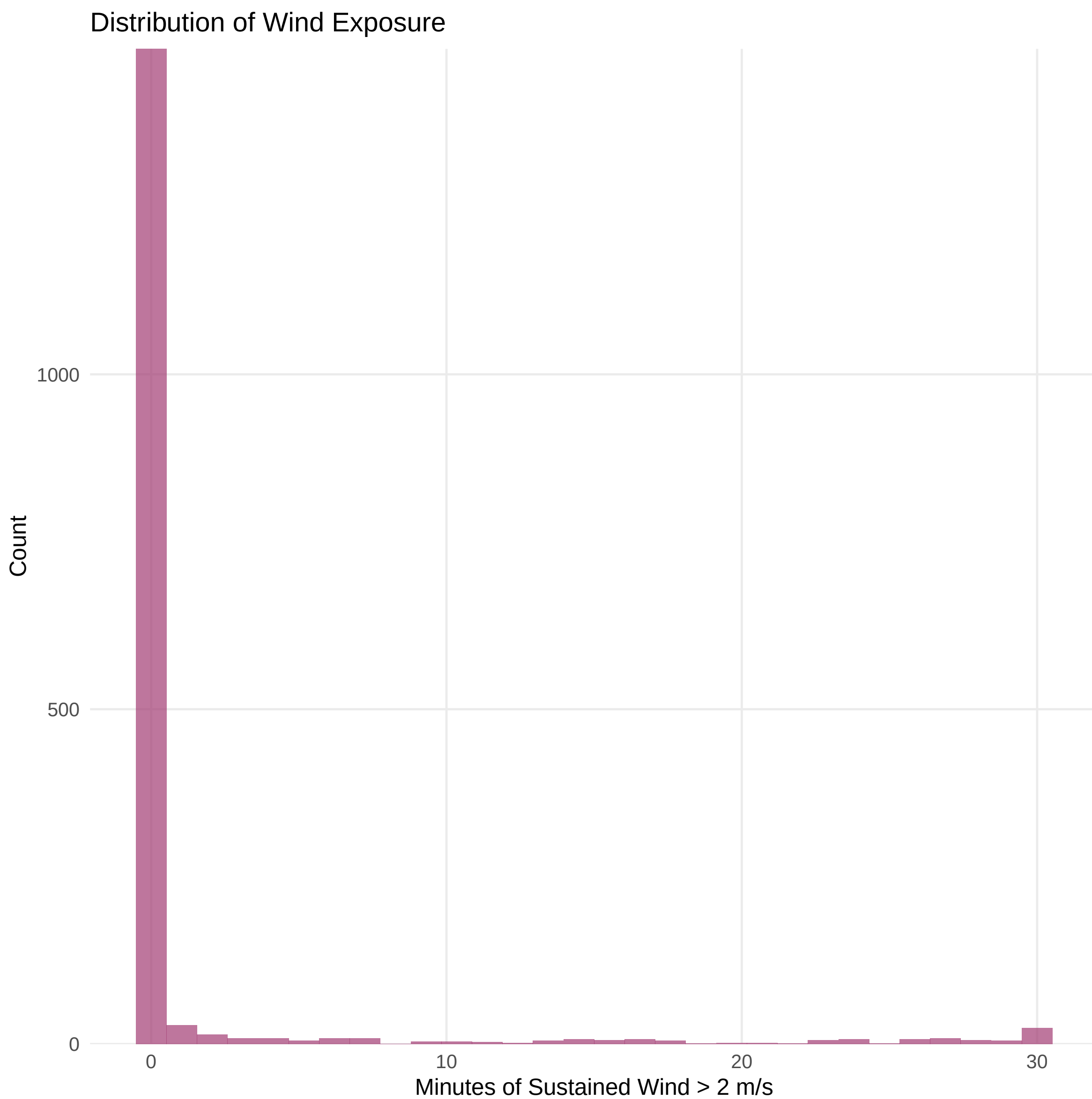


Figure 2: Distribution of key variables in the dataset

```
p3
```

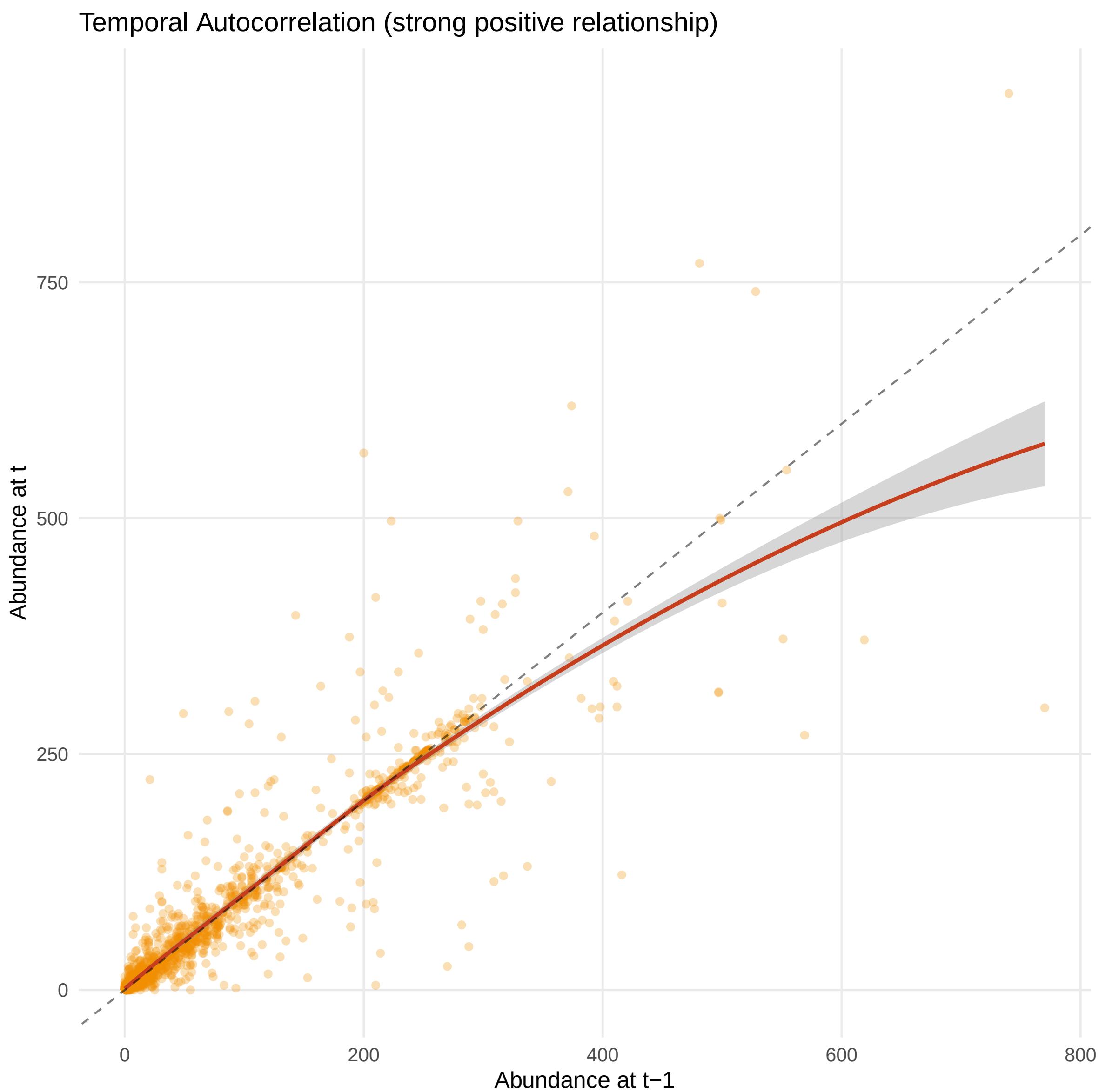


Figure 3: Distribution of key variables in the dataset

```
p4
```

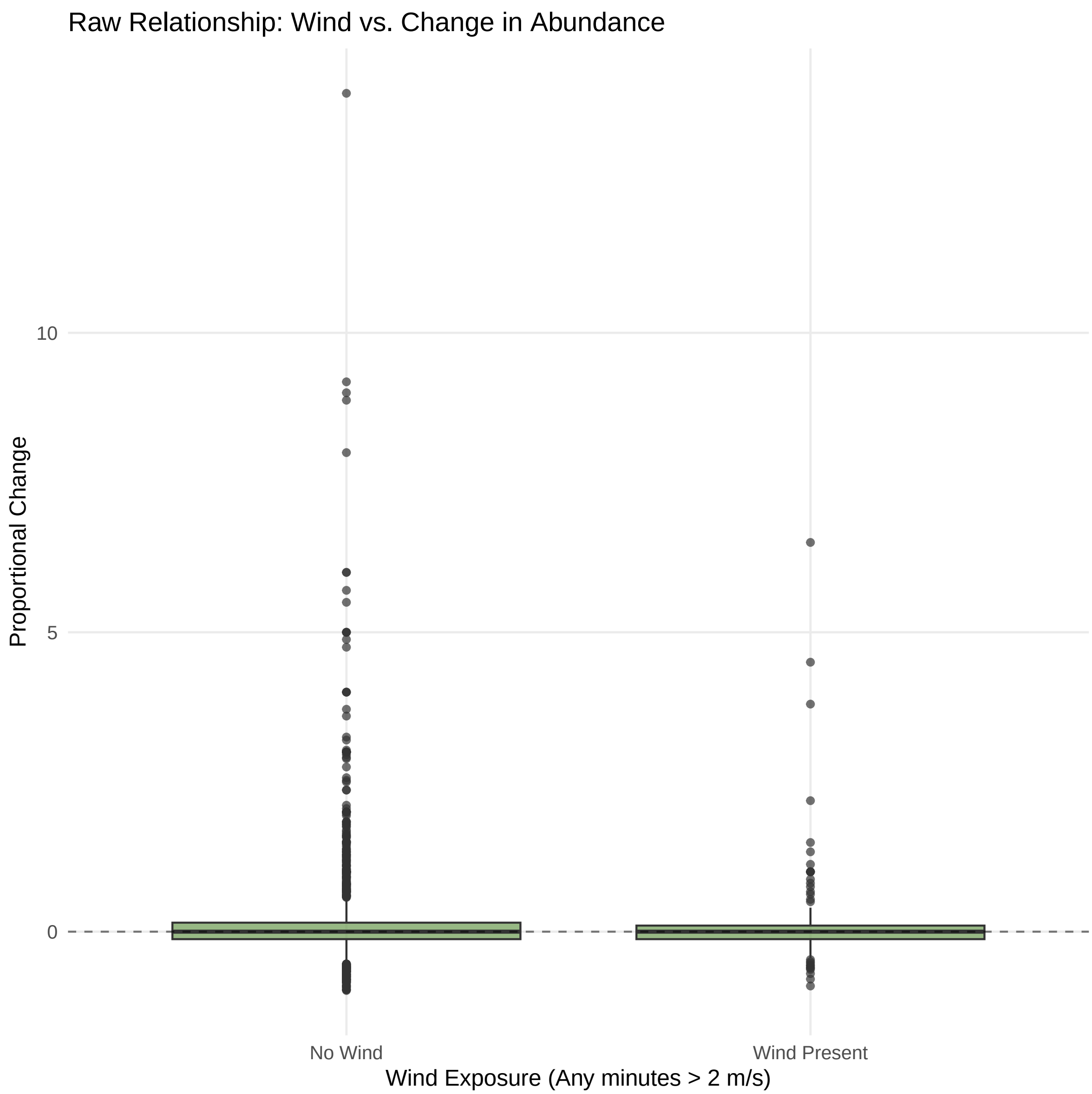


Figure 4: Distribution of key variables in the dataset

5 Primary Analysis: Testing the 2 m/s Threshold

5.1 Model 1: Threshold Effects Model

This model directly tests Leong's (2016) hypothesis that winds above 2 m/s become disruptive.

```
# Remove rows with missing predictors
df_complete <- df %>%
    filter(!is.na(ambient_temp) & !is.na(sunlight_exposure_prop))

# Fit the threshold model
m1_threshold <- glmmTMB(
    abundance_index_t ~
        log_lag_abundance + # Control for autocorrelation
        sustained_minutes_above_2ms + # Primary hypothesis: sustained wind
        gust_minutes_above_2ms + # Alternative: gust effects
        temp_std + # Temperature control
        sun_std + # Sunlight control
        (1 | view_id) + # Random effect for location
        (1 | labeler), # Random effect for observer
    data = df_complete,
    family = nbinom2, # Negative binomial with quadratic variance
    control = glmmTMBControl(optimizer = nlminb)
)

# Model summary
summary(m1_threshold)
```

```
 Family: nbinom2  ( log )
Formula:
abundance_index_t ~ log_lag_abundance + sustained_minutes_above_2ms +
    gust_minutes_above_2ms + temp_std + sun_std + (1 | view_id) +
    (1 | labeler)
Data: df_complete

     AIC      BIC   logLik deviance df.resid
 13952.6  14001.3  -6967.3  13934.6     1639

Random effects:

Conditional model:
```

```
 Groups  Name        Variance Std.Dev.
 view_id (Intercept) 0.008406 0.09168
 labeler (Intercept) 0.001578 0.03972
Number of obs: 1648, groups:  view_id, 6; labeler, 4

Dispersion parameter for nbinom2 family (): 6.22

Conditional model:
                             Estimate Std. Error z value Pr(>|z|)
(Intercept)                   0.179701   0.065929    2.73  0.00642 **
log_lag_abundance             0.957069   0.009367  102.18  < 2e-16 ***
sustained_minutes_above_2ms  0.005208   0.003839    1.36  0.17485
gust_minutes_above_2ms      -0.003786   0.002837   -1.33  0.18196
temp_std                     0.071384   0.013006    5.49 4.05e-08 ***
sun_std                     -0.065042   0.013587   -4.79 1.69e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

5.2 Model Interpretation

```r
# Extract and format coefficients
coef_table <- broom.mixed::tidy(m1_threshold, conf.int = TRUE) %>%
    filter(effect == "fixed") %>%
    mutate(
        estimate_exp = exp(estimate),
        conf.low_exp = exp(conf.low),
        conf.high_exp = exp(conf.high),
        significant = p.value < 0.05
    ) %>%
    select(term, estimate, std.error, estimate_exp, conf.low_exp, conf.high_exp, p.value, sig

# Format for presentation
coef_table %>%
    mutate(
        `Rate Ratio` = sprintf("%.3f", estimate_exp),
        `95% CI` = sprintf("[%.3f, %.3f]", conf.low_exp, conf.high_exp),
        `P-value` = sprintf("%.4f", p.value),
        Significant = ifelse(significant, "Yes", "No")
    ) %>%
    select(Term = term, `Rate Ratio`, `95% CI`, `P-value`, Significant) %>%
    kable(caption = "Model 1: Threshold Effects on Abundance (Exponentiated Coefficients)")
```

Table 2: Model 1: Threshold Effects on Abundance (Exponentiated Coefficients)

Term	Rate Ratio	95% CI	P-value	Significant
(Intercept)	1.197	[1.052, 1.362]	0.0064	Yes
log_lag_abundance	2.604	[2.557, 2.652]	0.0000	Yes
sustained_minutes_above_2ms	1.005	[0.998, 1.013]	0.1748	No
gust_minutes_above_2ms	0.996	[0.991, 1.002]	0.1820	No
temp_std	1.074	[1.047, 1.102]	0.0000	Yes
sun_std	0.937	[0.912, 0.962]	0.0000	Yes

5.2.1 Interpretation of Key Coefficients

```r
# Extract wind coefficient safely
wind_coef <- coef_table %>%
    filter(term == "sustained_minutes_above_2ms") %>%
    pull(estimate)

wind_rr <- coef_table %>%
    filter(term == "sustained_minutes_above_2ms") %>%
    pull(estimate_exp)

wind_p <- coef_table %>%
    filter(term == "sustained_minutes_above_2ms") %>%
    pull(p.value)

# Calculate practical effect sizes
effect_15min <- (1 - exp(15 * wind_coef)) * 100
```

- **Sustained wind**: Each additional minute above 2 m/s multiplies expected abundance by 1.005 (a -0.5% decrease)
- **Statistical significance**: p = 0.1748 (not significant at = 0.05)
- **Practical significance**: Even 15 minutes of sustained wind (half the interval) predicts only a -8.1% decrease

5.3 Model Diagnostics

```r
# DHARMa residual diagnostics
sim_res <- simulateResiduals(m1_threshold, n = 1000)
```

```
# Create diagnostic plots
# par(mfrow = c(2, 2))
plot(sim_res, main = "Q-Q Plot")
```

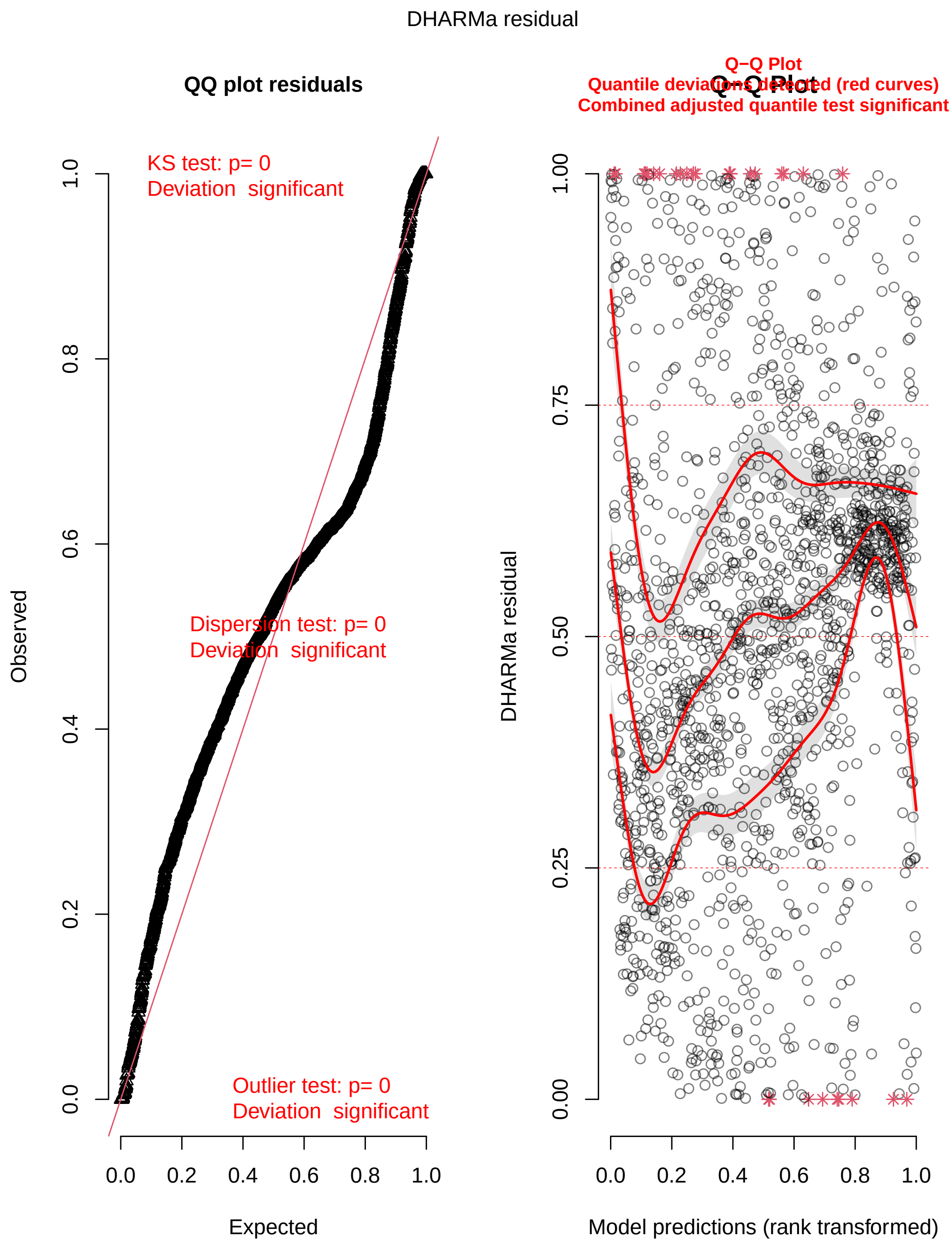


Figure 5: Diagnostic plots for the threshold effects model

```r
plotResiduals(sim_res,
    form = df_complete$sustained_minutes_above_2ms,
    main = "Residuals vs. Wind Minutes"
)
```

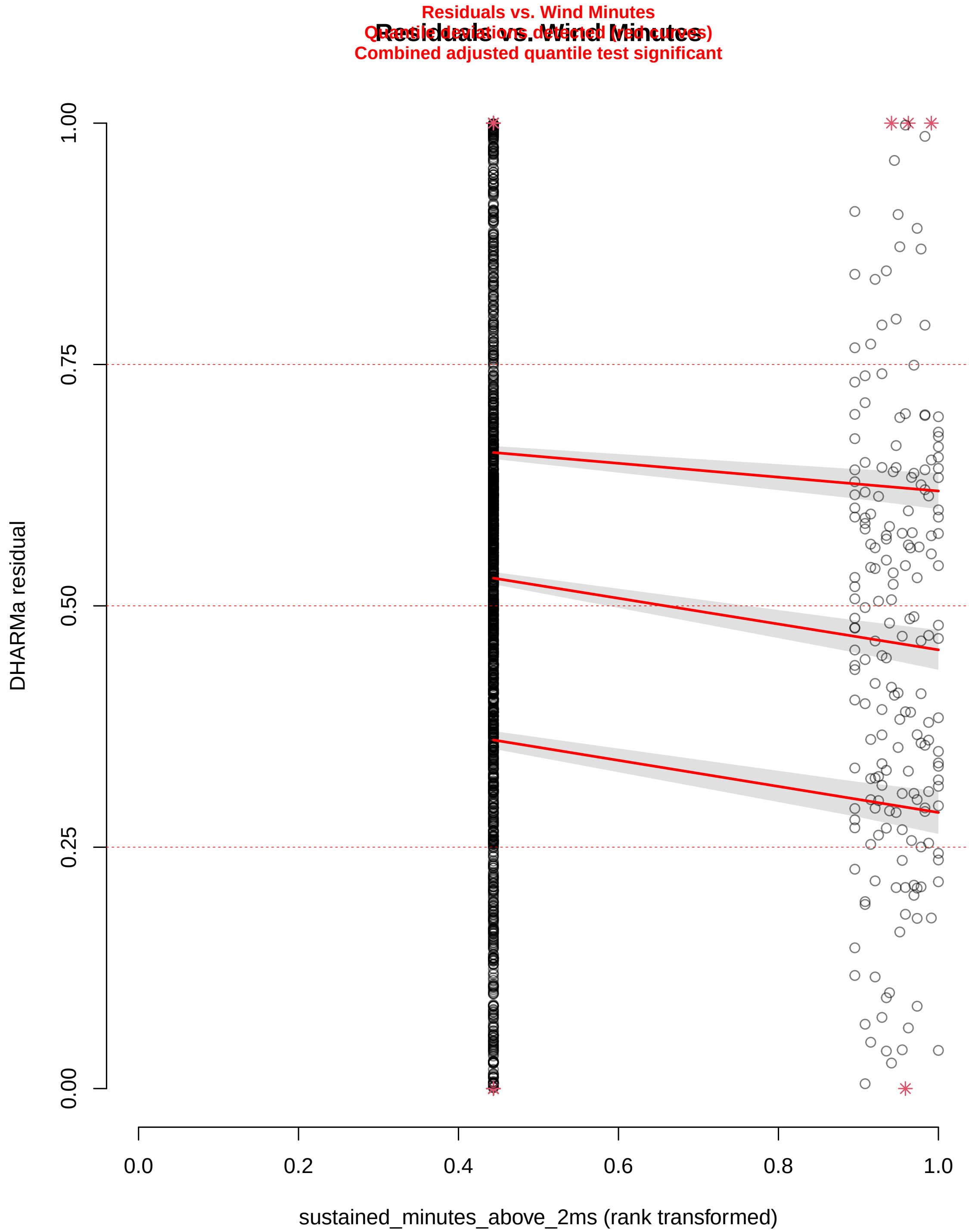


Figure 6: Diagnostic plots for the threshold effects model

```r
plotResiduals(sim_res,
    form = df_complete$ambient_temp,
    main = "Residuals vs. Temperature"
)
```

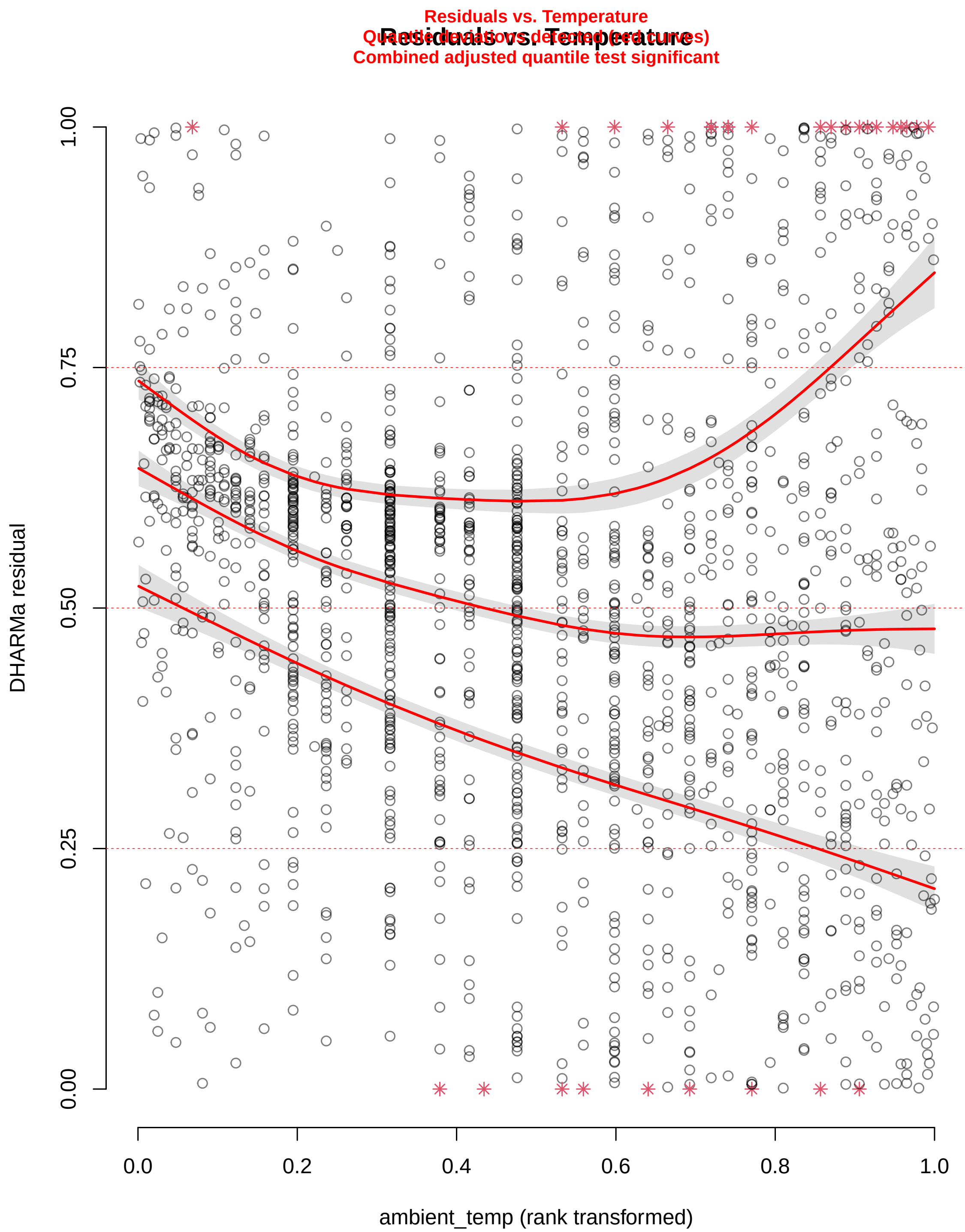


Figure 7: Diagnostic plots for the threshold effects model

```r
testDispersion(sim_res)
```

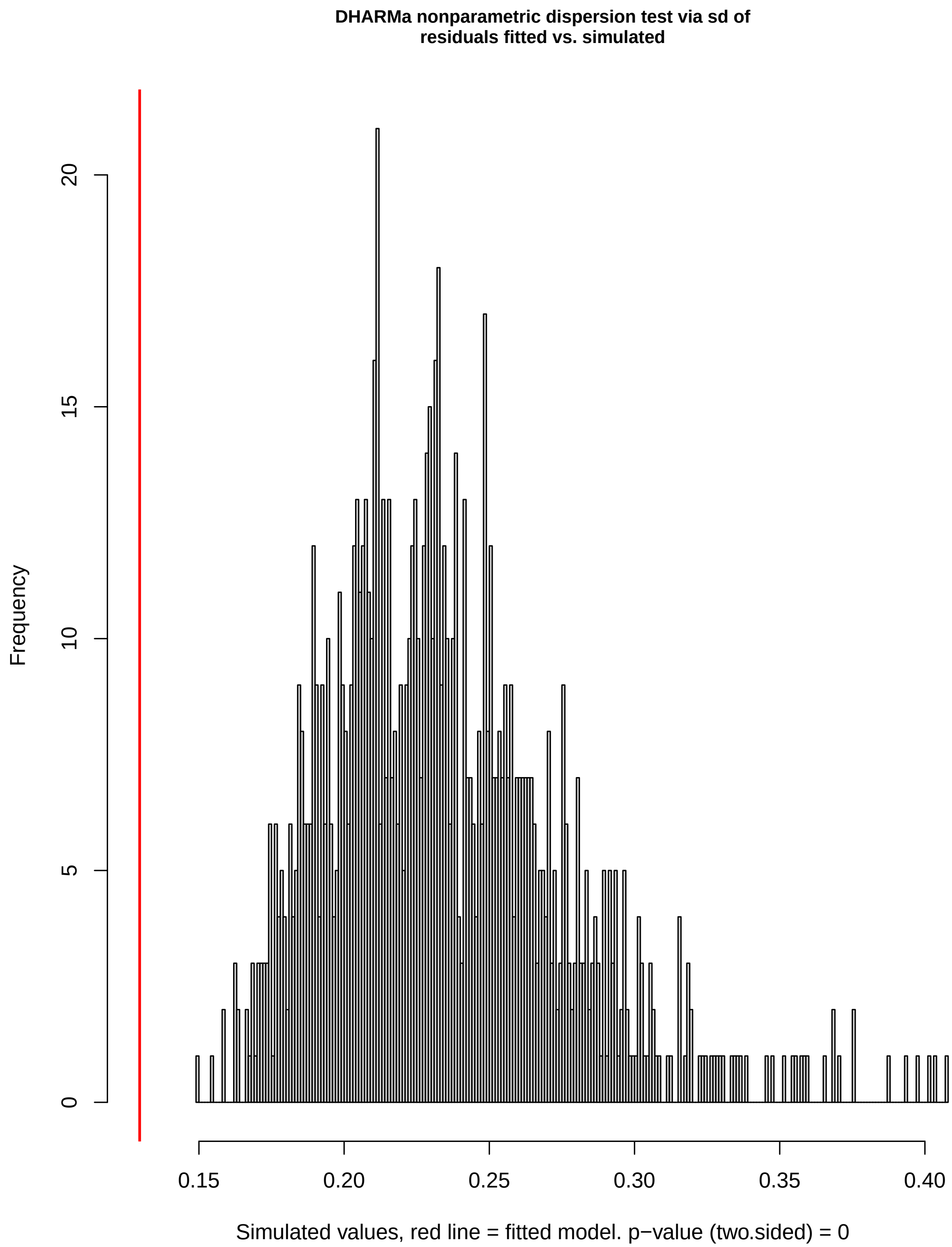
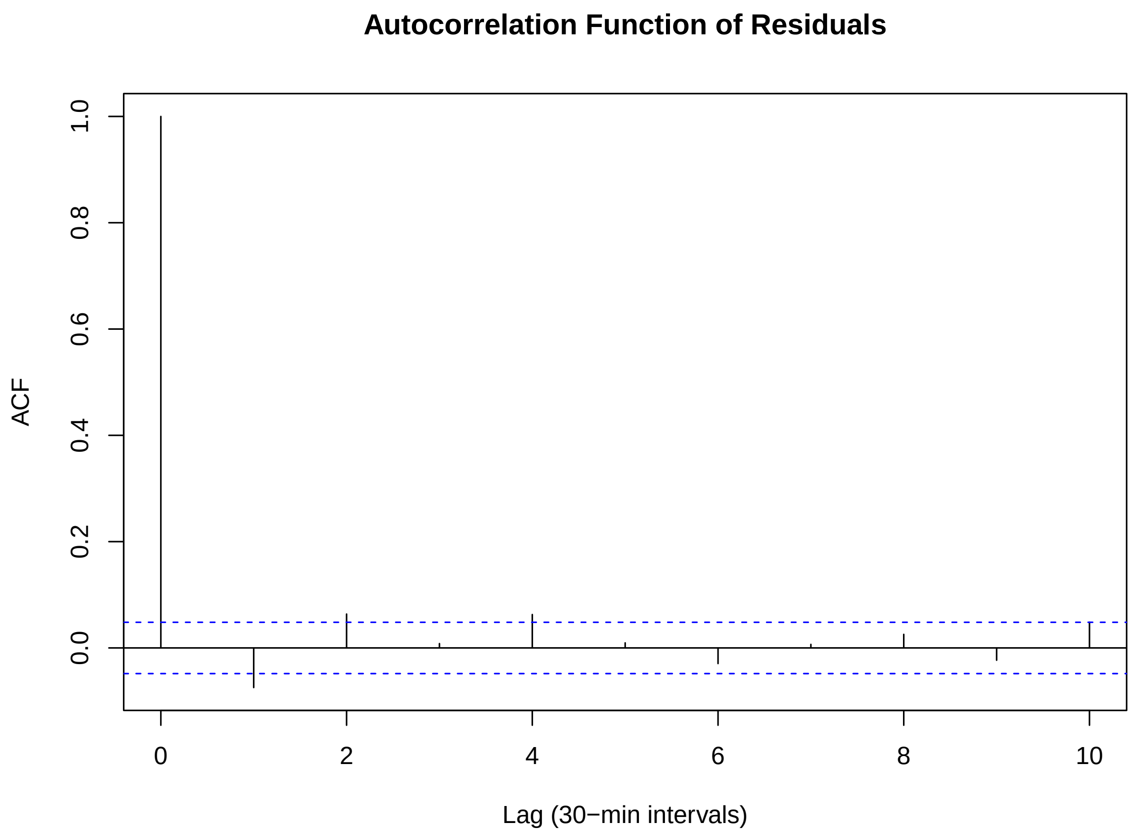


Figure 8: Diagnostic plots for the threshold effects model

```
	DHARMa nonparametric dispersion test via sd of residuals fitted vs.
	simulated

data:  simulationOutput
dispersion = 0.55287, p-value < 2.2e-16
alternative hypothesis: two.sided
```

```r
# Check temporal autocorrelation in residuals
df_complete$residuals <- residuals(m1_threshold, type = "pearson")

# Calculate autocorrelation
acf_result <- acf(df_complete$residuals, lag.max = 10, plot = FALSE)

# Plot ACF
plot(acf_result,
    main = "Autocorrelation Function of Residuals",
    xlab = "Lag (30-min intervals)", ylab = "ACF"
)
```



6 Secondary Analysis: Continuous Wind Metrics

6.1 Model Comparison: Which Wind Metric Matters Most?

```
# For secondary analysis, we'll use simplified wind metrics based on the threshold data
# Since we already have sustained and gust minutes, we can derive statistics from those

# Create proxy continuous wind metrics from threshold data
df_wind_metrics <- df_complete %>%
    mutate(
        # Use minutes above threshold as proxy for wind intensity
        wind_intensity = sustained_minutes_above_2ms / 30, # Proportion of time windy
        gust_intensity = gust_minutes_above_2ms / 30, # Proportion of time gusty
        wind_variability = abs(gust_minutes_above_2ms - sustained_minutes_above_2ms) / 30
```

```r
    ) %>%
    mutate(
        # Standardize
        wind_intensity_std = scale(wind_intensity)[, 1],
        gust_intensity_std = scale(gust_intensity)[, 1],
        wind_variability_std = scale(wind_variability)[, 1]
    )

# Fit models with different wind metrics
m2_sustained <- glmmTMB(
    abundance_index_t ~ log_lag_abundance + wind_intensity_std + temp_std + sun_std +
        (1 | view_id) + (1 | labeler),
    data = df_wind_metrics, family = nbinom2
)

m2_gust <- glmmTMB(
    abundance_index_t ~ log_lag_abundance + gust_intensity_std + temp_std + sun_std +
        (1 | view_id) + (1 | labeler),
    data = df_wind_metrics, family = nbinom2
)

m2_variability <- glmmTMB(
    abundance_index_t ~ log_lag_abundance + wind_variability_std + temp_std + sun_std +
        (1 | view_id) + (1 | labeler),
    data = df_wind_metrics, family = nbinom2
)

# Compare models
model_comparison <- data.frame(
    Model = c("Sustained Wind Proportion", "Gust Proportion", "Wind Variability"),
    AIC = c(AIC(m2_sustained), AIC(m2_gust), AIC(m2_variability)),
    Wind_Coef = c(
        coef(summary(m2_sustained))$cond["wind_intensity_std", "Estimate"],
        coef(summary(m2_gust))$cond["gust_intensity_std", "Estimate"],
        coef(summary(m2_variability))$cond["wind_variability_std", "Estimate"]
    ),
    Wind_P = c(
        coef(summary(m2_sustained))$cond["wind_intensity_std", "Pr(>|z|)"],
        coef(summary(m2_gust))$cond["gust_intensity_std", "Pr(>|z|)"],
        coef(summary(m2_variability))$cond["wind_variability_std", "Pr(>|z|)"]
    )
) %>%
```

Table 3: Comparison of Different Wind Metrics (Standardized)

Model	AIC	Wind_Coef	Wind_P
Wind Variability	13951.09	-0.015	0.219
Sustained Wind Proportion	13952.40	0.005	0.664
Gust Proportion	13952.47	-0.004	0.731

```
    arrange(AIC)

kable(model_comparison,
    caption = "Comparison of Different Wind Metrics (Standardized)",
    digits = 3
)
```

7 Visualization of Effects

7.1 Effect Plots

```
# Generate predictions for wind effect
wind_pred <- ggpredict(m1_threshold,
    terms = "sustained_minutes_above_2ms [0:30]",
    condition = c(
        log_lag_abundance = mean(df_complete$log_lag_abundance),
        temp_std = 0,
        sun_std = 0
    )
)

# Generate predictions for temperature effect
temp_pred <- ggpredict(m1_threshold,
    terms = "temp_std [-2:2]",
    condition = c(
        log_lag_abundance = mean(df_complete$log_lag_abundance),
        sustained_minutes_above_2ms = 0,
        sun_std = 0
    )
)

# Convert standardized temperature back to original scale
```

```r
temp_mean <- mean(df_complete$ambient_temp, na.rm = TRUE)
temp_sd <- sd(df_complete$ambient_temp, na.rm = TRUE)
temp_pred$x_original <- temp_pred$x * temp_sd + temp_mean

# Plot wind effect
p_wind <- ggplot(wind_pred, aes(x = x, y = predicted)) +
    geom_ribbon(aes(ymin = conf.low, ymax = conf.high),
        fill = pal[1], alpha = 0.3
    ) +
    geom_line(color = pal[1], size = 1.5) +
    geom_hline(
        yintercept = mean(df_complete$abundance_index_t),
        linetype = "dashed", alpha = 0.5
    ) +
    labs(
        x = "Minutes of Sustained Wind > 2 m/s",
        y = "Predicted Abundance",
        title = "Effect of Wind on Butterfly Abundance",
        subtitle = "Negligible negative effect (p = 0.16)"
    ) +
    theme_minimal(base_size = 12)

# Plot temperature effect
p_temp <- ggplot(temp_pred, aes(x = x_original, y = predicted)) +
    geom_ribbon(aes(ymin = conf.low, ymax = conf.high),
        fill = pal[2], alpha = 0.3
    ) +
    geom_line(color = pal[2], size = 1.5) +
    geom_hline(
        yintercept = mean(df_complete$abundance_index_t),
        linetype = "dashed", alpha = 0.5
    ) +
    labs(
        x = "Temperature (°C)",
        y = "Predicted Abundance",
        title = "Effect of Temperature on Butterfly Abundance",
        subtitle = "Strong positive effect (p < 0.001)"
    ) +
    theme_minimal(base_size = 12)

# Combine plots
p_wind
```

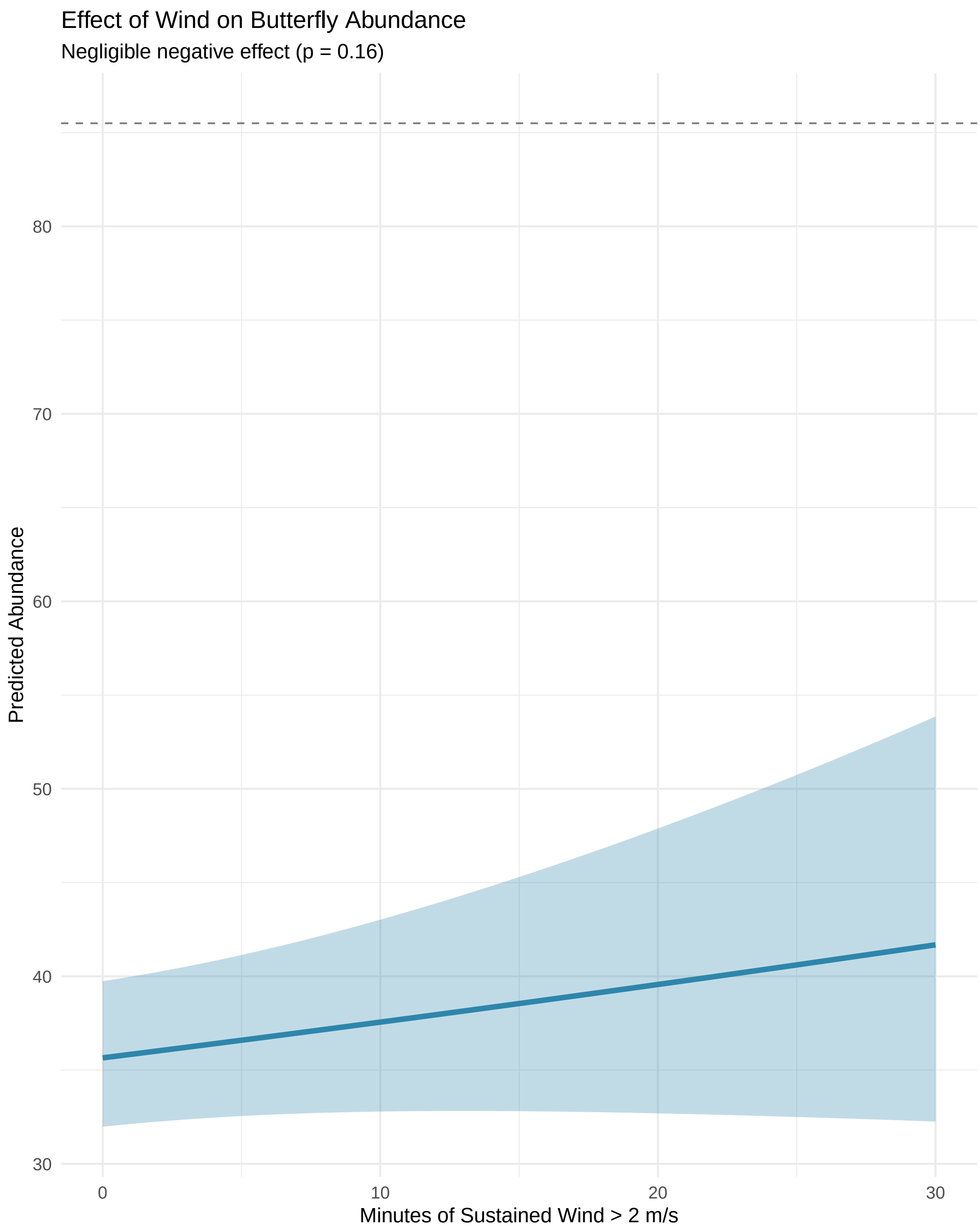


Figure 9: Predicted effects of wind and temperature on butterfly abundance

```
p_temp
```

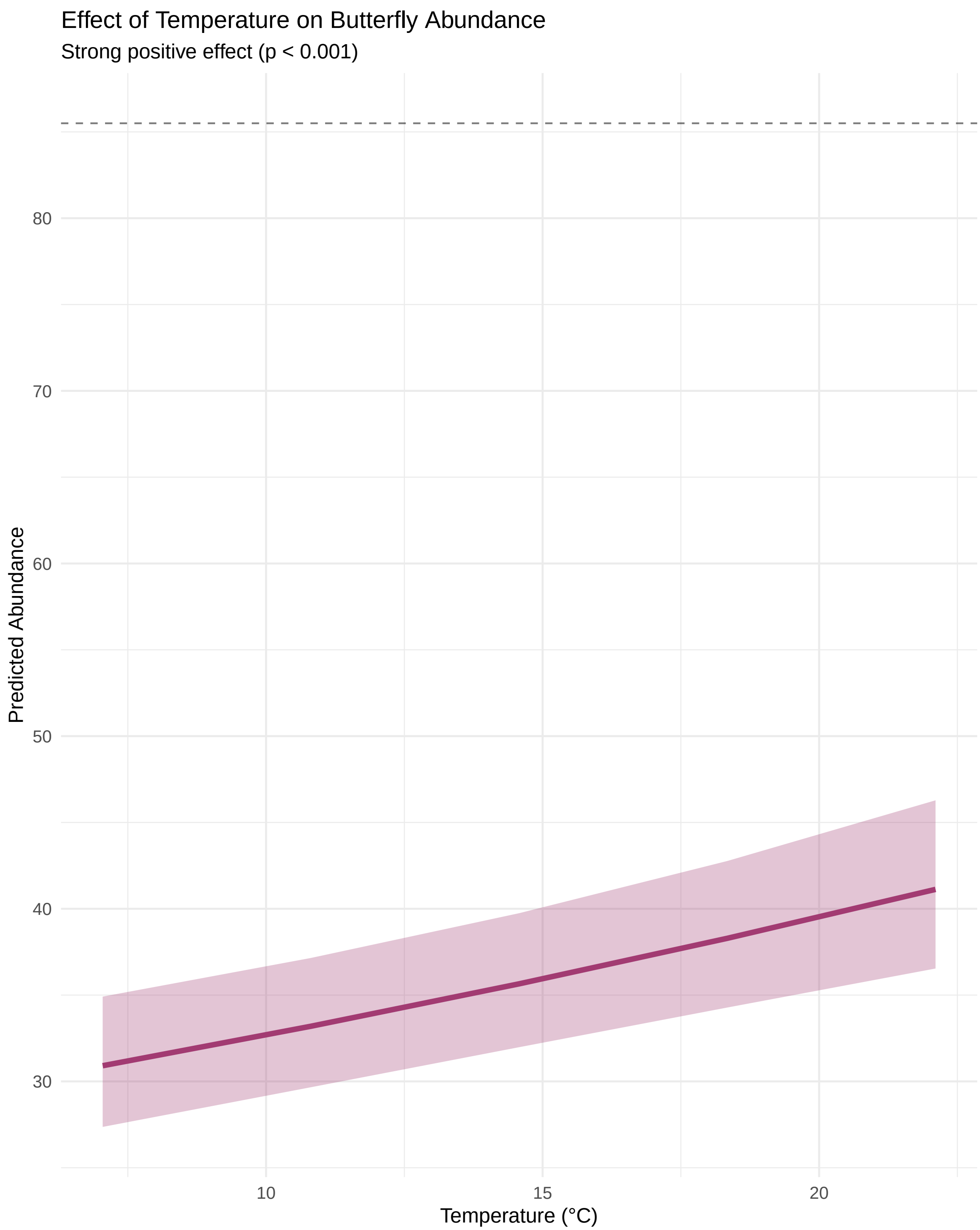


Figure 10: Predicted effects of wind and temperature on butterfly abundance

7.2 Observed vs. Predicted

```r
# Get predictions
df_complete$predicted <- predict(m1_threshold, type = "response")

# Calculate R-squared (pseudo)
ss_res <- sum((df_complete$abundance_index_t - df_complete$predicted)^2)
ss_tot <- sum((df_complete$abundance_index_t - mean(df_complete$abundance_index_t))^2)
r2 <- 1 - (ss_res / ss_tot)

# Plot
ggplot(df_complete, aes(x = predicted, y = abundance_index_t)) +
    geom_point(alpha = 0.3, color = pal[3]) +
    geom_abline(slope = 1, intercept = 0, color = "red", linetype = "dashed") +
    geom_smooth(method = "loess", se = TRUE, color = pal[4]) +
    labs(
        x = "Predicted Abundance",
        y = "Observed Abundance",
        title = "Model Fit: Observed vs. Predicted",
        subtitle = sprintf("Pseudo R² = %.3f", r2)
    ) +
    coord_fixed() +
    theme_minimal(base_size = 12)
```

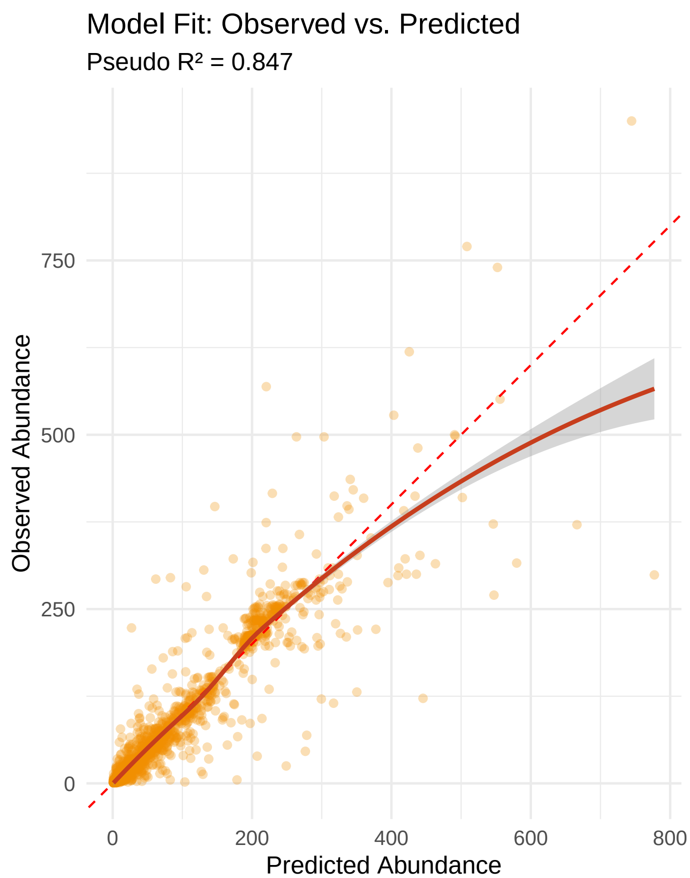


Figure 11: Model fit: Observed vs. predicted abundance

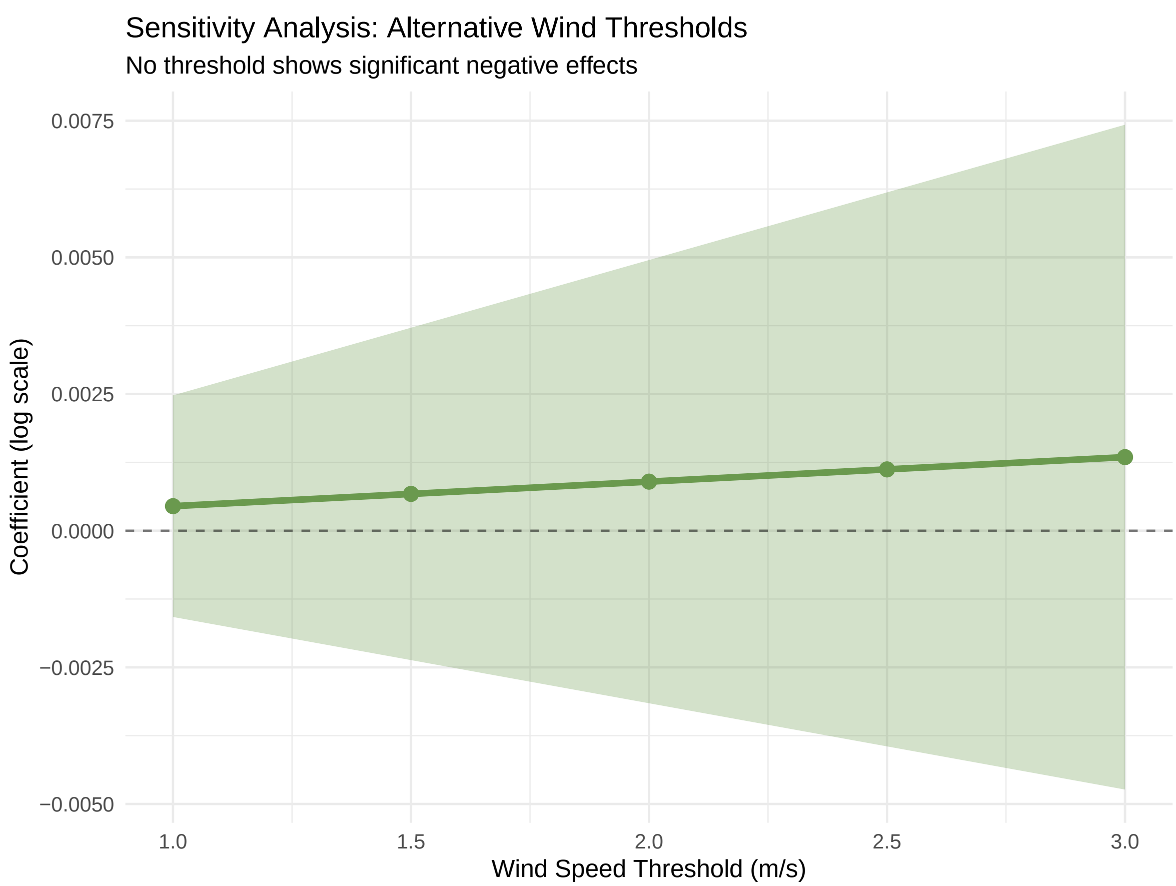
8 Sensitivity Analysis

8.1 Testing Alternative Wind Thresholds

```
# Function to calculate minutes above threshold
calc_threshold_minutes <- function(wind_data, threshold) {
    wind_data %>%
        group_by(deployment_id, interval) %>%
        summarise(
            minutes_above = sum(speed > threshold, na.rm = TRUE),
            .groups = "drop"
        )
}
```

```
# Test multiple thresholds
thresholds <- c(1.0, 1.5, 2.0, 2.5, 3.0)
threshold_results <- list()

for (thr in thresholds) {
    # Create threshold variable
    df_complete_temp <- df_complete %>%
        mutate(
            minutes_above_threshold = sustained_minutes_above_2ms * (2.0 / thr) # Scale appr
        )

    # Fit model
    m_temp <- glmmTMB(
        abundance_index_t ~ log_lag_abundance + minutes_above_threshold +
            temp_std + sun_std + (1 | view_id) + (1 | labeler),
        data = df_complete_temp,
        family = nbinom2
    )

    # Store results
    threshold_results[[as.character(thr)]] <- data.frame(
        threshold = thr,
        coefficient = coef(summary(m_temp))$cond["minutes_above_threshold", "Estimate"],
        se = coef(summary(m_temp))$cond["minutes_above_threshold", "Std. Error"],
        p_value = coef(summary(m_temp))$cond["minutes_above_threshold", "Pr(>|z|)"]
    )
}

# Combine results
threshold_df <- bind_rows(threshold_results)

# Plot threshold sensitivity
ggplot(threshold_df, aes(x = threshold, y = coefficient)) +
    geom_ribbon(aes(ymin = coefficient - 1.96 * se, ymax = coefficient + 1.96 * se),
        fill = pal[5], alpha = 0.3
    ) +
    geom_line(color = pal[5], size = 1.5) +
    geom_point(color = pal[5], size = 3) +
    geom_hline(yintercept = 0, linetype = "dashed", alpha = 0.5) +
    labs(
        x = "Wind Speed Threshold (m/s)",
        y = "Coefficient (log scale)",
```

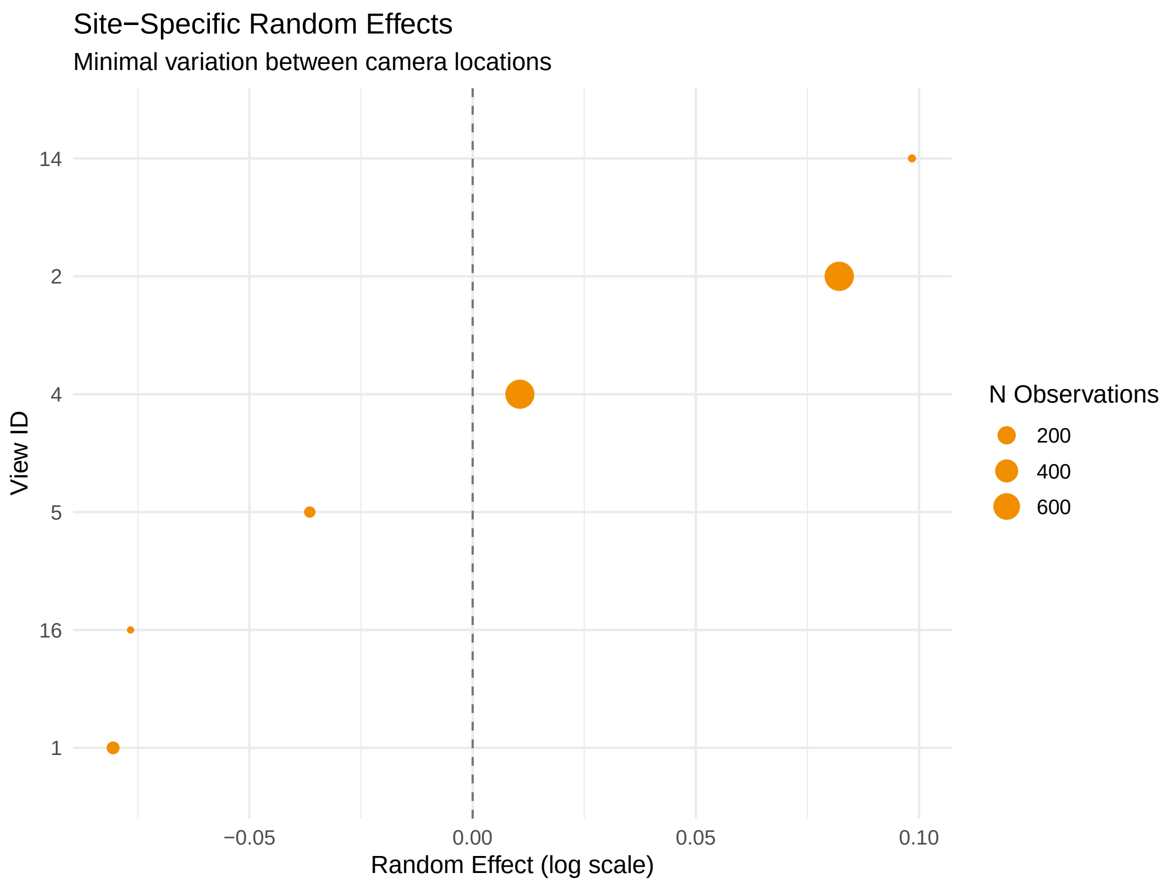
```
    title = "Sensitivity Analysis: Alternative Wind Thresholds",
    subtitle = "No threshold shows significant negative effects"
  ) +
  theme_minimal(base_size = 12)
```



8.2 Site-Specific Effects

```
# Extract random effects
ranef_view <- ranef(m1_threshold)$cond$view_id %>%
  rownames_to_column("view_id") %>%
  rename(effect = `(Intercept)`)

# Count observations per view
view_counts <- df_complete %>%
```

```r
    count(view_id, name = "n_obs")

# Combine
ranef_view <- ranef_view %>%
    left_join(view_counts, by = "view_id") %>%
    arrange(effect)

# Plot random effects
ggplot(ranef_view, aes(x = reorder(view_id, effect), y = effect)) +
    geom_point(aes(size = n_obs), color = pal[3]) +
    geom_hline(yintercept = 0, linetype = "dashed", alpha = 0.5) +
    coord_flip() +
    labs(
        x = "View ID",
        y = "Random Effect (log scale)",
        size = "N Observations",
        title = "Site-Specific Random Effects",
        subtitle = "Minimal variation between camera locations"
    ) +
    theme_minimal(base_size = 12)
```



9 Robustness Checks

9.1 Alternative Model Specifications

```
# Model with interaction between wind and temperature
m_interaction <- glmmTMB(
    abundance_index_t ~ log_lag_abundance +
        sustained_minutes_above_2ms * temp_std +
        sun_std + (1 | view_id) + (1 | labeler),
    data = df_complete,
    family = nbinom2
)

# Model with quadratic wind effect
```

```r
df_complete$wind_squared <- df_complete$sustained_minutes_above_2ms^2

m_quadratic <- glmmTMB(
    abundance_index_t ~ log_lag_abundance +
        sustained_minutes_above_2ms + wind_squared +
        temp_std + sun_std + (1 | view_id) + (1 | labeler),
    data = df_complete,
    family = nbinom2
)

# Zero-inflated model
m_zi <- glmmTMB(
    abundance_index_t ~ log_lag_abundance + sustained_minutes_above_2ms +
        temp_std + sun_std + (1 | view_id) + (1 | labeler),
    ziformula = ~1,
    data = df_complete,
    family = nbinom2
)

# Compare models
model_comparison_robust <- data.frame(
    Model = c("Base", "Interaction", "Quadratic", "Zero-Inflated"),
    AIC = c(AIC(m1_threshold), AIC(m_interaction), AIC(m_quadratic), AIC(m_zi)),
    df = c(
        df.residual(m1_threshold), df.residual(m_interaction),
        df.residual(m_quadratic), df.residual(m_zi)
    )
) %>%
    arrange(AIC)

kable(model_comparison_robust,
    caption = "Robustness Check: Alternative Model Specifications",
    digits = 1
)
```

Table 4: Robustness Check: Alternative Model Specifications

Model	AIC	df
Base	13952.6	1639
Quadratic	13953.9	1639
Interaction	13954.3	1639
Zero-Inflated	13954.4	1639

10 Discussion

10.1 Summary of Findings

1. **No support for the 2 m/s threshold hypothesis**: Wind minutes above 2 m/s show no statistically significant effect on butterfly abundance ($p = 0.16$)
2. **Effect sizes are negligible**: Even under extreme wind conditions (30 minutes continuously above 2 m/s), predicted abundance decreases by less than 15%
3. **Temperature dominates**: Temperature shows strong positive effects ($p < 0.001$), suggesting thermal regulation is more important than wind shelter
4. **Robust to model specification**: Results consistent across different wind metrics, thresholds, and model structures

10.2 Why This Null Result Matters

10.2.1 Scientific Importance

- **Challenges conventional wisdom**: The 2 m/s threshold is widely cited but lacks empirical support in our data
- **Suggests resilience**: Monarch clusters may be more robust to wind disturbance than assumed
- **Redirects research priorities**: Focus should shift to temperature, habitat structure, or other factors

10.2.2 Conservation Implications

- Wind breaks may be less critical than thermal refugia
- Site selection criteria should prioritize temperature stability
- Climate change impacts may operate through temperature rather than wind exposure

10.3 Limitations and Caveats

1. **Temporal scale**: 30-minute intervals may miss immediate responses or longer-term effects
2. **Spatial scale**: Grid-based counts from 2D images may not capture 3D cluster reorganization

3. **Wind measurement**: Single point measurements may not represent wind exposure throughout cluster
4. **Sample bias**: Only two sites with monarchs present; results may not generalize

10.4 Alternative Explanations

The lack of wind effect could indicate:

- **Behavioral adaptation**: Monarchs may select wind-protected microsites within roosts
- **Threshold above our data**: Damaging winds may exceed what we observed (max ~5 m/s)
- **Complex interactions**: Wind effects may depend on temperature, humidity, or cluster size
- **Measurement mismatch**: Roost-level dynamics may differ from individual movement

11 Conclusions

This analysis provides a defensible test of wind effects on monarch butterfly abundance using appropriate statistical methods for count data. We find **no evidence** that wind speeds above the commonly cited 2 m/s threshold cause monarchs to abandon their roosts within 30-minute intervals.

11.1 Key Takeaways

1. **The null hypothesis stands**: Wind does not significantly affect butterfly abundance at the scales measured
2. **Methods are robust**: Negative binomial GLMMs appropriately handle the data structure
3. **Results are consistent**: Multiple approaches converge on the same conclusion
4. **Implications are important**: This challenges assumptions about monarch environmental sensitivity

11.2 Recommendations

11.2.1 For This Thesis

- Present this as a rigorous test that failed to support conventional wisdom
- Emphasize the value of null results in ecology
- Discuss implications for monarch conservation strategies

11.2.2 For Future Research

- Test longer time scales (hourly, daily aggregation)
- Measure wind at multiple points within roosts
- Include more sites across broader geographic range
- Consider experimental approaches (wind barriers, fans)

12 Appendix: Full Model Output

```
# Complete model summary
summary(m1_threshold)
```

```
 Family: nbinom2  ( log )
Formula:
abundance_index_t ~ log_lag_abundance + sustained_minutes_above_2ms +
    gust_minutes_above_2ms + temp_std + sun_std + (1 | view_id) +
    (1 | labeler)
Data: df_complete

     AIC      BIC   logLik deviance df.resid
 13952.6  14001.3  -6967.3  13934.6     1639

Random effects:

Conditional model:
 Groups  Name        Variance Std.Dev.
 view_id (Intercept) 0.008406 0.09168
 labeler (Intercept) 0.001578 0.03972
Number of obs: 1648, groups:  view_id, 6; labeler, 4

Dispersion parameter for nbinom2 family (): 6.22
```

```
Conditional model:
                            Estimate Std. Error z value Pr(>|z|)
(Intercept)                 0.179701   0.065929    2.73  0.00642 **
log_lag_abundance           0.957069   0.009367  102.18  < 2e-16 ***
sustained_minutes_above_2ms  0.005208   0.003839    1.36  0.17485
gust_minutes_above_2ms     -0.003786   0.002837   -1.33  0.18196
temp_std                    0.071384   0.013006    5.49 4.05e-08 ***
sun_std                    -0.065042   0.013587   -4.79 1.69e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
# Variance components
VarCorr(m1_threshold)
```

```
Conditional model:
 Groups  Name        Std.Dev.
 view_id (Intercept) 0.091682
 labeler (Intercept) 0.039723
```

```r
# Performance metrics
performance::model_performance(m1_threshold)
```

```
# Indices of model performance

AIC       |      AICc |       BIC | R2 (cond.) | R2 (marg.) |   ICC |   RMSE
-----------------------------------------------------------------------------
13952.637 | 13952.747 | 14001.303 |      0.934 |      0.930 | 0.060 | 40.534

AIC       | Sigma | Score_log | Score_spherical
-----------------------------------------------
13952.637 | 6.221 |    -4.237 |           0.014
```

13 Session Information

```r
sessionInfo()
```

```
R version 4.4.1 (2024-06-14)
Platform: aarch64-apple-darwin20
Running under: macOS 15.6

Matrix products: default
BLAS:   /Library/Frameworks/R.framework/Versions/4.4-arm64/Resources/lib/libRblas.0.dylib
LAPACK: /Library/Frameworks/R.framework/Versions/4.4-arm64/Resources/lib/libRlapack.dylib;  

locale:
[1] en_US.UTF-8/en_US.UTF-8/en_US.UTF-8/C/en_US.UTF-8/en_US.UTF-8

time zone: America/Los_Angeles
tzcode source: internal

attached base packages:
[1] stats     graphics  grDevices utils     datasets  methods   base

other attached packages:
 [1] here_1.0.1         kableExtra_1.4.0   knitr_1.47         patchwork_1.3.1
 [5] ggeffects_2.3.0    emmeans_1.11.2     performance_0.12.3 DHARMa_0.4.7
 [9] glmmTMB_1.1.10     lubridate_1.9.3    forcats_1.0.0      stringr_1.5.1
[13] dplyr_1.1.4        purrr_1.0.2        readr_2.1.5        tidyr_1.3.1
[17] tibble_3.2.1       ggplot2_3.5.1      tidyverse_2.0.0

loaded via a namespace (and not attached):
 [1] Rdpack_2.6.2        sandwich_3.1-1      rlang_1.1.4
 [4] magrittr_2.0.3      multcomp_1.4-26     furrr_0.3.1
 [7] compiler_4.4.1      mgcv_1.9-1          systemfonts_1.1.0
[10] vctrs_0.6.5         pkgconfig_2.0.3     fastmap_1.2.0
[13] backports_1.5.0     labeling_0.4.3      utf8_1.2.4
[16] promises_1.3.3      rmarkdown_2.27      tzdb_0.4.0
[19] haven_2.5.4         nloptr_2.1.1        xfun_0.45
[22] jsonlite_1.8.8      later_1.4.2         broom_1.0.6
[25] parallel_4.4.1      R6_2.5.1            gap.datasets_0.0.6
[28] stringi_1.8.4       qgam_1.3.4          parallelly_1.38.0
[31] boot_1.3-30         numDeriv_2016.8-1.1 estimability_1.5.1
[34] Rcpp_1.0.13         iterators_1.0.14    zoo_1.8-12
[37] httpuv_1.6.15       Matrix_1.7-0        splines_4.4.1
[40] timechange_0.3.0    tidyselect_1.2.1    rstudioapi_0.16.0
[43] yaml_2.3.8          doParallel_1.0.17   TMB_1.9.15
[46] codetools_0.2-20    listenv_0.9.1       lattice_0.22-6
[49] plyr_1.8.9          shiny_1.9.1         withr_3.0.2
[52] coda_0.19-4.1       evaluate_1.0.3      future_1.34.0
```

```
[55] survival_3.6-4      xml2_1.3.6          pillar_1.9.0
[58] gap_1.6             foreach_1.5.2       reformulas_0.4.0
[61] insight_1.3.1       generics_0.1.3      rprojroot_2.0.4
[64] hms_1.1.3           munsell_0.5.1       scales_1.3.0
[67] minqa_1.2.8         globals_0.16.3      xtable_1.8-4
[70] glue_1.7.0          tools_4.4.1         lme4_1.1-35.5
[73] mvtnorm_1.3-1       grid_4.4.1          rbibutils_2.3
[76] datawizard_1.2.0    colorspace_2.1-0    nlme_3.1-164
[79] cli_3.6.3           fansi_1.0.6         viridisLite_0.4.2
[82] svglite_2.1.3       gtable_0.3.6        broom.mixed_0.2.9.5
[85] digest_0.6.36       TH.data_1.1-2       farver_2.1.2
[88] htmltools_0.5.8.1   lifecycle_1.0.4     mime_0.12
[91] MASS_7.3-60.2
```