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Effects of Climate Change on Butterfly Species Richness/Abundance

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ABSTRACT

Butterflies are ideal model organisms to study ecological responses to environmental change, yet long-term population responses to climatic variation remain understudied. This study seeks to assess the impacts of climatic variation on butterfly populations at Porton Down, Wiltshire, United Kingdom, between 1994 and 2013. Butterfly abundance data from the Environmental Change Network were analyzed for five butterfly species: Common blue, Dark green fritillary, Green hairstreak, Small heath, and Meadow brown. Climate data (daily maximum, minimum, mean, and minimum grass temperatures; total rainfall) were obtained from Boscombe Down. Trends were analyzed visually, and Pearson correlation with linear regression assessed species-climate relationships. All five species declined between 1994 and 2013, with the Green hairstreak most threatened. Rainfall increased while temperature trends varied seasonally: daily maximum temperature increased in cold months but decreased in warm months; daily minimum and minimum grass temperatures increased in warm months but decreased in cold months. Small Heath ($r = 0.48$, $p < 0.001$) and Meadow brown ($r = 0.45$, $p < 0.001$) showed significant positive correlations with daily mean temperature. Small Heath ($r = 0.32$, $p = 0.002$), Meadow brown ($r = 0.34$, $p = 0.005$), and Green hairstreak ($r = -0.32$, $p = 0.05$) showed significant correlations with minimum grass temperature. Rainfall correlations were negative but non-significant for all species. Temperature affects butterfly species differently according to life history traits, with pupal-overwintering species most vulnerable to changing minimum temperatures. If current trends continue, butterfly abundance is expected to decline further.

INTRODUCTION

Climate change stands as one of the major drivers of the global biodiversity crisis (Maxwell *et al.,* 2016). The surge in global temperatures, driven by greenhouse gas emissions, is affecting the behavior, lifespan, and population dynamics of species worldwide (Bonifacino *et al.,* 2022). Across Europe, considerable changes in climatic conditions have been observed, such as increased summer temperature and dryness (Rödder *et al.,* 2021; Seneviratne *et al.,* 2006). These changes cause drive modifications in species community composition, distribution patterns, and ecological interaction, with many species exhibiting polewards range shifts (Rödder *et al.,* 2021) such as the speckled wood butterfly (Pararge aegeria), which has established populations north of its historical range (Parmesan *et al.,* 1999).

Butterflies are particularly sensitive to environmental changes, due to their ectothermic nature, narrow habitat requirement and specific host plant relationships for development (Yuki, 2025). They are popular, easily identified with a relatively shorter life cycle, making them ideal model organisms to study ecological responses to environmental change (Kasiske *et al.,* 2025). Recent research demonstrates that shifts in species distribution result from a complex interplay among climate change, land-use practices, and species-specific traits that influence their ability to adapt, spread, and settle in new environments (Franzén *et al.,* 2020; Hill *et al.,* 2021; Warren *et al.,* 2021). Beyond their scientific value, butterflies provide crucial ecosystem services, about 85% of crops require insects for pollination, positioning them at billions of pounds in economic value (Manpreet, 2024).

Butterfly development follows complete metamorphosis, which includes four stages: egg, larva (caterpillar), pupa (chrysalis), and adult (Samanta, 2021). They possess an important life history trait called voltinism, which is defined as the number of generations produced per year (Lindestad *et al.,* 2020). Univoltine butterflies produce one generation per year, while bivoltine butterflies produce two generations per year (Plazio & Nowicki, 2021). Overwintering stages in species also impact their vulnerability in relation to seasonal climatic conditions (Rich *et al.,* 2025).

Climate change affects how butterfly responds through various mechanisms. Temperature influences growth rates, behavior, reproductive success, and phenology (Shan *et al.,* 2024; Vickery, 2008). Warmer spring temperatures may result in earlier emergence, while multivoltine may exploit this lengthier period of activity to produce additional broods, leading to growth in population (Henry *et al.,* 2022). Studies have reported a phenological shift across multiple butterfly taxa over time, such as spring emergence advancing approximately three times faster than that of herbaceous plants (Parmesan, 2007; Zografou *et al.,* 2021). Conversely, butterflies exhibit weaker phenological responses than their potential nectar food plants, suggesting potential for phenological mismatches (Kharouba & Vellend, 2015). The sensitivity

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of butterflies to climate extremes varies across their life cycle, particularly eggs, larvae, and pupae, which makes them more vulnerable in comparison to mobile adults (McDermott Long *et al.,* 2017; Shan *et al.,* 2024).

Butterflies are among the most threatened wildlife groups in the United Kingdom (UK) due to habitat modification, land use change, and climate change. Semi-natural grasslands continue to be modified by increasing population, urbanization, changing agricultural policies, and economic pressures (Van Swaay *et al.,* 2010). Butterfly abundance has decreased by 76% since 1976, with 26% of species now at risk of extinction (Manpreet, 2024). Species responses to warming are divergent: warm-weather species such as the comma (Polygonia c-album) and holly blue (Celastrina argiolus) are spreading northwards, while cold-weather species, including the northern brown argus (Aricia Artaxerxes) and grizzled skipper (Pyrgus malvae), are declining(Hill, 2017; Pidcock, 2017). Some montane species are experiencing local extinction as a consequence of climate change (Hill, 2022). While numerous studies have documented climate-driven range shifts and phenological changes in UK butterflies, few have examined how species with different voltinism strategies respond to local climatic variables over multi-decadal timescales (Ashe-Jepson *et al.,* 2022; Martay *et al.,* 2017; WESTGARTH-SMITH *et al.,* 2012; Wynne *et al.,* 2003).

This study examines butterfly populations at Porton Down, Wiltshire, a site of special scientific interest representing the largest preserved tract of semi-natural chalk grassland in the United Kingdom (UKECN, 2019). Located in Southern England, this site supports diverse calcareous grassland habitats and is part of the UK Environmental Change Network (ECN) monitoring programme (Council, 2007; JNCC, 2015). Long-term butterfly monitoring data collected between 1994 and 2013 provide an opportunity to assess population responses to climatic variation over two decades. Five butterfly species were selected for detailed analysis based on data completeness and contrasting life histories: Common blue (Polyommatus icarus): a variable-brooded lycaenid found in a variety of grassland habitats; dark green fritillary (Argynnis aglaja): a single-brooded species found in coastal and chalk grassland; green hairstreak (Callophrys rubi): a single-brooded specie that uniquely overwinters in the chrysalis stage instead of larva; small heath (Coenonympha pamphilus): a double-brooded species representing the smallest of the 'brown' butterflies; meadow brown (Maniola jurtina): a single-brooded species that is the most ubiquitous and abundant butterflies in the UK. This selection permits comparison between single- and double- brooded species, and between larval and pupal overwintering strategies.

This study seeks to assess the impacts of climatic variation on butterfly populations at Porton Down by: (i) analyzing trends in temperature, rainfall and butterfly abundance between 1994 and 2013; (ii) evaluating relationships between climatic variables and species abundance using correlation and regression analysis; and (iii) comparing climate responses among species with different life history traits to identify the most vulnerable species.

MATERIALS AND METHODS

Study Site

This study was conducted at Porton Down, Wiltshire, in southern England (latitude 51.13°N, longitude 1.67°W). It is situated at 126 m above sea level and has the largest preserved tract of semi-natural chalk grassland in the United Kingdom (UKECN, 2019). The landscape is characterized by a mixture of slope, hilly, and lowland topography (100 to 150 m above sea level). The soil and geology of the site are made up of basic clay and calc-schists, providing calcareous soils, home to species-rich grassland communities (JNCC, 2015). Porton Down is designated as a site of special scientific interest (SSSI), participating in the UK Environmental Change Network (ECN) monitoring programme (Council, 2007). The site supports a large area of mixed scrub, qualifying as an important breeding ground for protected bird species such as the stone curlew (Burhinus oedicnemus).

Butterfly Data Collection

The butterfly abundance data were sourced from the Environmental Change Network (ECN) program (http://data.ecn.ac.uk), a consortium of UK government departments and agencies established to monitor the causes and consequences of environmental change. The national Butterfly Monitoring Scheme (BMS) methodology (Pollard & Yates, 1993) was adopted to collect data from the Porton Down field site between 1994 and 2013.

Observations were recorded along a fixed transect divided into 15 sections, each corresponding to the major habitat types existing on the study site. Trained observers walk the transect weekly between 1st April and 29th September annually; this chosen period is established to be the peak butterfly activity observed across the United Kingdom. Butterfly counts were recorded within an imaginary box measuring 5m high, 5m wide, and 5m in front of the observer. The number of butterflies seen flying through this box was recorded for species and counted. Since the observer was moving continuously along the transect, the possibility of counting the individuals twice was eliminated. These observations were conducted under specific climatic conditions for consistent detectability. The walks were strategically scheduled in adherence to BMS protocol when:

- The temperature was between 13 and 17 °C. If sunshine is below 60%, or
- Temperature is above 17 °C under any condition, provided it is not raining.

According to Pollard & Yates (1993), periods of strong wind, heavy clouds, or precipitation impact butterfly activity and observer visibility. Hence, observations were not conducted during these weather conditions.

Climate Data Collection

Climate data was acquired from the Met Office Meteorological Service Synoptic network (https://www.metoffice.gov.uk/) from 1995 to 2013. Since the Porton Down weather station was decommissioned, the data was sourced from the Boscombe Down (latitude 51.16°N, longitude 1.75°W) weather station, which is 5 miles north of Porton Down and at an equivalent elevation of 126m above sea level, similar to the study site.

Climate data was collected across five variables for analysis, including daily maximum temperature (°C), daily minimum temperature(°C), daily mean temperature(°C), minimum grass temperature(°C), and total Rainfall (mm). This daily data was used to estimate the monthly mean of each climatic variable, e.g., maximum, minimum, mean, and minimum grass temperature, and the sum of rainfall to estimate monthly and annual totals. For both warm (April-September) and cold (October-March) months, seasonal means were calculated corresponding to the butterfly flight period an overwintering period for respective seasons.

Despite being at the same elevation as the Porton Down site and the nearest long-term monitoring station, the Boscombe Down station may encounter microclimatic differences; the results were cautiously interpreted, addressing these limitations.

Specie Selection

The criteria for selecting the butterflies were as follows: (i) available and consistent data throughout the study period; (ii) no missing data exceeding 50% of annual records; (iii) representation of both single and double-brooded species to allow the comparison of life history. Selected species and their ecological characteristics are summarized in Table 1 below.

Detailed natural history accounts for each species are available in the published literature (Eeles, 2024; Nikon, 2011; 2013; 2014; Pinder, 2024) (Eeles, 2024a, 2024b, 2024c; Nikon, 2011a, 2011b, 2011c; Pinder, 2024a, 2024b, 2024c).

Table 1: Ecological characteristics of the five butterfly species selected for this study

Species	Scientific Name	Brood Type	Overwintering Stage	Flight Period	Habitat Association
Common blue	Polyommatus icarus	Variable (1-3)	Larva	May–September	Grassland, downland, heathland
Dark green fritillary	Argynnis aglaja	Single	Larva	June–August	Chalk grassland, coastal grassland
Green hairstreak	Callophrys rubi	Single	Pupa	May–June	Chalk grassland, heathland, woodland clearings
Small heath	Coenonympha pamphilus	Double	Larva	May–September	Grassland, heathland, meadows
Meadow brown	Maniola jurtina	Single	Larva	June–September	Ubiquitous in grassland habitats

Data Processing

All data were imported into spreadsheet software (Microsoft Excel) for initial organization and quality checking. Butterfly data were sorted by species, date, and transect section. Climate data were sorted by date and variable type.

Butterfly data processing followed these steps:

1. Weekly counts for each species were extracted for the period 1994–2013.
2. Total abundance scores were calculated by the sum of weekly counts of each species during the study period (1994-2013).
3. Species richness was calculated as the total number of species recorded within each year.
4. Flight periods were determined by identifying the first and last observation dates for each species annually.

Climate data processing followed these steps:

1. Daily measurements were quality-checked for missing values and outliers.
2. Daily values were averaged to produce monthly means for temperature variables.
3. Daily rainfall was summed to produce monthly totals.
4. Monthly values were averaged to produce seasonal means (warm months: April–September; cold months: October–March).
5. Monthly rainfall was summed to produce annual totals.

Species with missing annual records were excluded from correlation analyses for those specific years. No data imputation was performed; all analyses were conducted on an available case basis. Moreover, climate data contained no missing values for the study period.

Statistical Analysis

All statistical analyses were conducted in R version 4.4.0 (R Core Team, 2024) using the following packages: ggplot2 (version 3.4.0) for data visualization, dplyr (version 1.1.0) for data manipulation, and the base R stats package for correlation and regression analyses. Complete R code is provided in the Appendix.

Normality of the data was assessed using the Shapiro-Wilk test (Uhm & Yi, 2023) for each species' abundance data and each climatic variable. When the data were not normally distributed ($p < 0.05$), a log-normal distribution was applied, followed by re-testing for normality. This allows for the use of parametric tests (Leydesdorff & Bensman, 2006). Pearson's correlation coefficient was used to measure the strength and direction of linear association between butterfly abundance and climatic variables. The reason for using Pearson's method included since the data were measured on interval scales, exhibited normality, contained no significant outliers, fulfilling the assumptions of linearity and homoscedasticity (Schober *et al.,* 2018; Sreedevi, 2022).

Statistical significance was assessed at $\alpha = 0.05$ for all tests. Results with $p < 0.05$ were considered statistically significant. The F-statistic and associated p-value were reported for each regression model to assess overall model fit.

Ethical Consideration

No ethical approval was required for this observational study using publicly available data. The research complied with institutional and national guidelines for ecological research.

Data Availability

Butterfly abundance data are publicly available through the Environmental Change Network Data Portal (http://data.ecn.ac.uk). Climate data are available from the Met Office (https://www.metoffice.gov.uk). Complete R code for all statistical analyses and figure generation is provided in the Appendix.

RESULTS AND DISCUSSIONS

Species Abundance and Richness

Total abundance and species richness. Total butterfly abundance for the five study species showed a declining trend at Porton Down between 1994 and 2013 (Figure 1). The earlier years of the study period, i.e., 1996, 1997, and 1998, recorded higher butterfly abundance than the latter years. The years 2003 and 2006 experienced temporary increases before the declining trend resumed. Although the overall trend shows a decline, 2013 showed an increase in total butterfly abundance compared to the immediately preceding years. The total abundance of butterflies of the five species varied considerably across the study period.

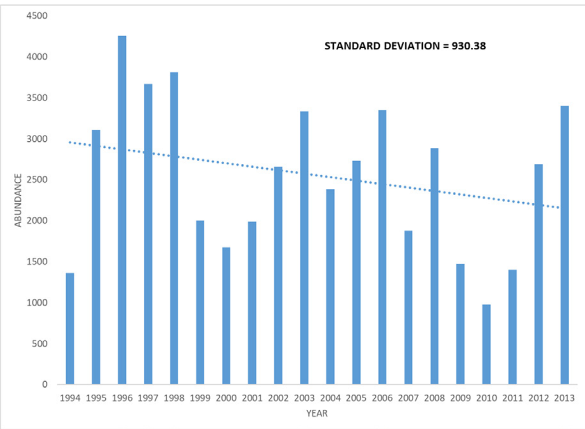

Figure 1: Butterfly species total abundance (1994 to 2013)

Butterfly species richness also exhibited a declining trend between 1994 and 2013 (Figure 2). Defined as the total number of species recorded within each year, species richness was recorded as higher in earlier years and lower in later years.

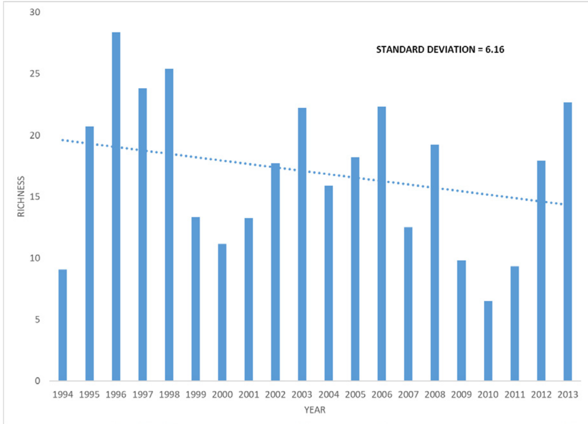

Figure 2: Butterfly species richness (1994 to 2013)

Individual Species Trend. Each of the five butterfly species showed differing abundance patterns over the period of study, though a general declining trend was observed across all species.

Small heath (Coenonympha pamphillus) abundance increased between 1994 and 1996, reaching its highest levels in the early study period (Figure 3). Therefore, the species exhibited a declining trend between 1996 and 2013. Within this period of decline, abundance was comparatively higher in year 2003, 2004, and 2013. A major decline occurred in four years: 2000, 2001, 2002, and 2007.

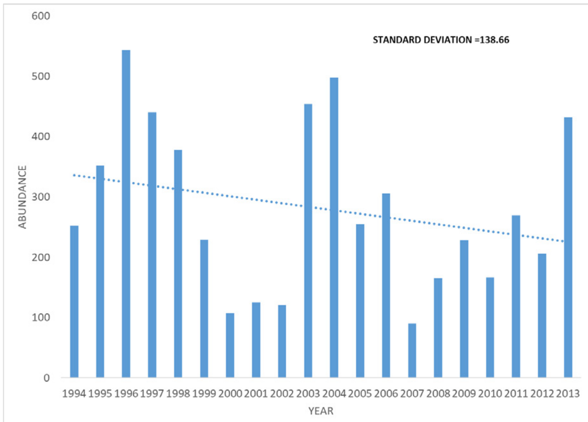

Figure 3: Small health (Coenonympha pamphillus) abundance at Porton Down, 1994 to 2013

Green hairstreak (Callophrys rubi) abundance declined markedly between 1994 and 2013 (Figure 4). Only a few years recorded abundance approached those of 1994. However, the species was mostly absent or very low in number in multiple years, earning a threatened position among those studied at Porton Down.

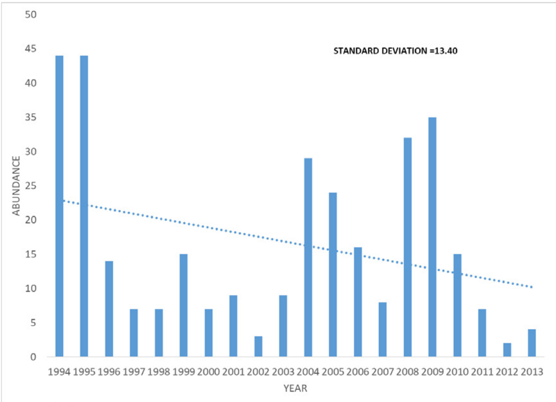

Figure 4: Green hairstreak (Callophrys rubi) abundance at Porton Down, 1994 to 2013

Dark green fritillary Argynnis aglaja) Abundance declined between 1995 and 2012 (Figure 5). A notable spike in abundance in 2013, which recorded the highest abundance for this species across the entire study period.

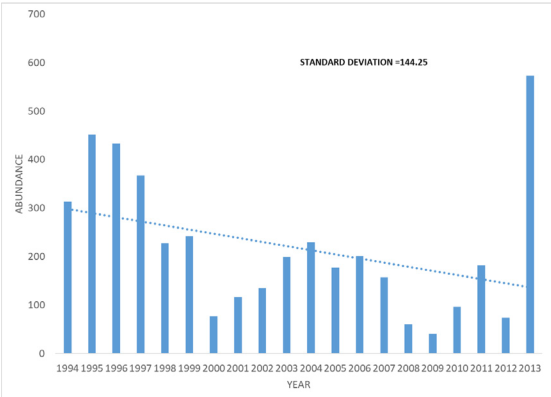

Figure 5: Dark green fritillary Argynnis aglaja) abundance at Porton Down, 1994 to 2013

Meadow brown (Maniola jurtina) abundance increased between 1994 and 1998, when the peak abundance was recorded (Figure 6). Followed by a declining trend between 1998 and 2013. However, Meadow brown maintained the highest abundance of all five species across the study period, aligning with earlier reports of this species being the most ubiquitous in UK grasslands.

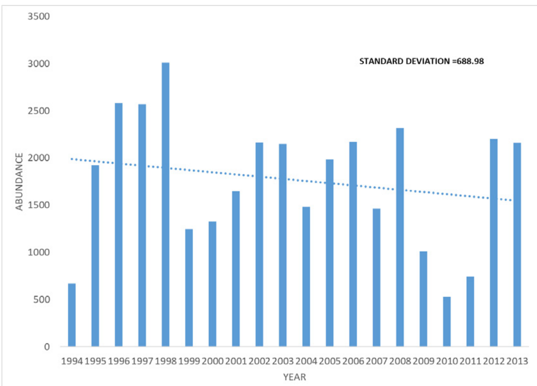

Figure 6: Meadow brown (Maniola jurtina) abundance at Porton Down, 1994 to 2013

Common blue (Polyommatus icarus) abundance increased between 1994 and 1996, then demonstrated a declining trend between 1996 and 2013 (Figure 7). Only a few years in the latter half of the study period recorded higher abundance.

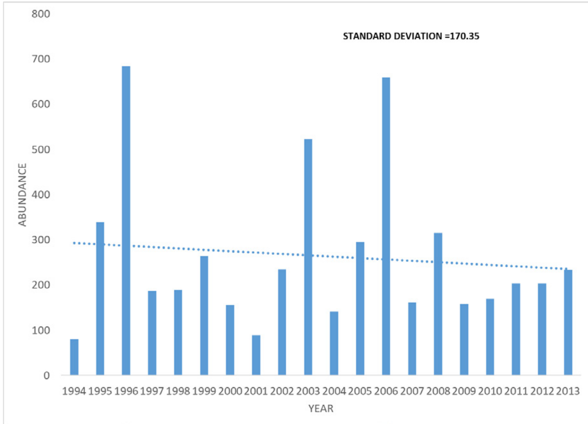

Figure 7: Common blue (Polyommatus icarus) abundance at Porton Down, 1994 to 2013

Species Flight Periods. The five butterfly species showed variations in emergence and disappearance period (Table 1). Flight times ranged from May to September, with species-specific differences in the duration and timing of adult activity.

Table 2: Adult butterfly species flight periods at Porton Down, based on weekly transect observations 1994-2013

Butterfly Species	Emergence Month	Disappearance Month
Small heath	May - June	September
Green hairstreak	May	June
Dark green fritillary	June	August
Meadow brown	June – July	September
Common blue	May	September

Temperature and Rainfall Trends

Temperature Trends. Daily maximum temperature demonstrated a contrast between seasons at Porton Down between 1995 and 2013 (Figure 8). During warm months (April – September), average daily maximum temperature exhibited a slightly declining trend over the study period. During cold months (October – March), the average daily maximum temperature showed a very slight upward trend. The cold months demonstrated higher variations than the warm months throughout the study period.

The patterns for daily minimum temperature varied between seasons (Figure 9). During the warm months (April – September), average daily minimum temperature showed no visible trend between 1995 and 2013. During cold months (October – March), the average daily minimum temperature displayed a slight declining trend over the study period.

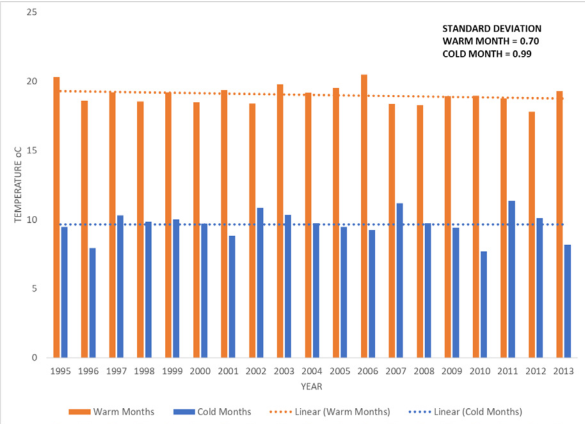

Figure 8: Average daily maximum temperature at Boscombe Down, 1995 – 2013, for cold months (October – March), and warm months (April – September)

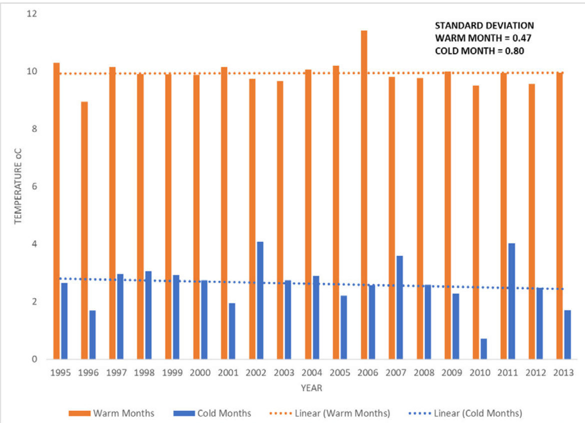

Figure 9: Average daily minimum temperature at Boscombe Down, 1995 – 2013, for cold months (October – March), and warm months (April – September)

Daily mean temperature showed a slight declining trend for both warm months (April – September) and cold months (October – March) between 1995 and 2013 (Figure 10). Temperature variation was greater during the cold months.

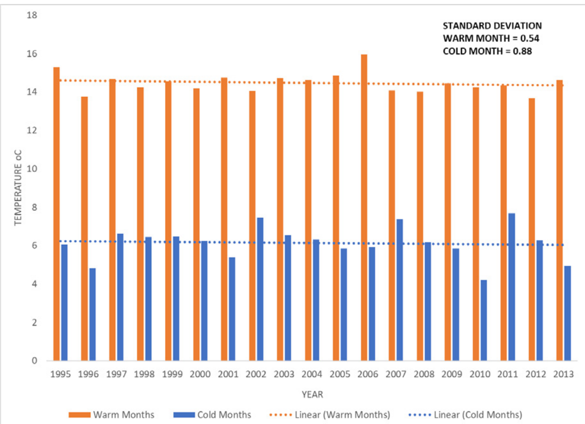

Figure 10: Average daily mean temperature at Boscombe Down, 1995 – 2013, for cold months (October – March), and warm months (April – September)

Minimum grass temperature showed opposing trends between the seasons (Figure 11). During warm months (April – September), average minimum grass temperature exhibited an upward trend between 1995 and 2013. During cold months (October – March), the average minimum grass temperature displayed a declining trend over the same period.

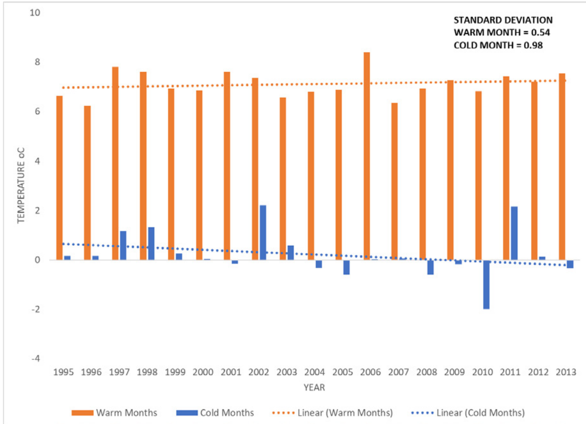

Figure 11: Average minimum grass temperature at Boscombe Down, 1995 – 2013, for cold months (October – March), and warm months (April – September)

Rainfall Trends. Total annual rainfall showed an increasing precipitation trend at Porton Down between 1995 and 2013 (Figure 12). The year 2000 recorded the highest total amount of yearly rainfall across the study period, while 2005 recorded the lowest total yearly rainfall.

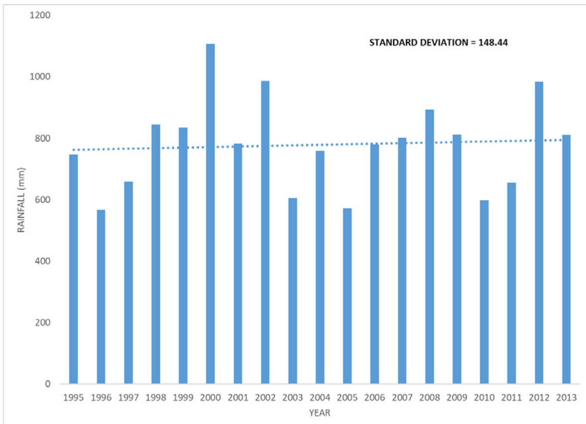

Figure 12: Total annual rainfall at Boscombe Down, 1995 – 2013

Correlation and Regression Analysis

Pearson correlation and linear regression analyses were conducted to examine the associations between butterfly species abundance and three climatic factors: daily mean temperature, minimum grass temperature, and total rainfall. Correlation strength was interpreted as weak ($|r| < 0.3$), moderate ($0.3 \leq |r| < 0.7$), or strong ($|r| \geq 0.7$) following Schober *et al.* (2018).

Daily Mean Temperature. Two species, i.e., Small Heath and Meadow brown, demonstrated a significant positive relationship with daily mean temperature (both moderate strength, $p < 0.001$). The other three species, i.e., Common blue, Dark green fritillary, and Green hairstreak, exhibited weak and non-significant correlations (Table 3).

Table 3: Correlation and regression of daily mean temperature with butterfly species

Butterfly Species	r value	T-statistics	df	p-value	F-statistics	Regression Equation
Common blue	0.17	1.61	91	0.11	2.59	y = 5.81x - 32.39
Dark green fritillary	0.22	1.68	54	0.10	2.81	y = 16.06x - 187
Green hairstreak	-0.05	-0.30	38	0.77	0.09	y = -0.16x + 9.4
Small heath	0.48	5.09	87	2.06E-06	25.90	y = 17.76x - 212.4
Meadow brown	0.45	4.13	66	0.0001	17.05	y

Minimum Grass Temperature. Three species showed significant correlations with minimum grass temperature (Table 4). Meadow brown and Small Heath demonstrated weak positive relationships ($p = 0.005$ and $p = 0.002$, respectively). Greed hairstreak showed a weak negative correlation ($p = 0.05$), making it distinct from other candidates. This negative association may be attributed to Green hairstreak's overwintering strategy as a pupa rather than larva (Frohawk, 1924). Common blue and Dark green fritillary showed no significant correlation.\
Total Rainfall. All five species showed a weak negative relationship with monthly total rainfall, but none reached statistical significance (all $p > 0.05$; Table 5).

Table 4: Correlation and regression of daily minimum grass temperature with butterfly species

Butterfly Species	r value	T-statistics	df	p-value	F-statistics	Regression Equation
Common blue	0.07	0.62	91	0.54	0.38	y = 2.16x + 39.48
Dark green fritillary	-0.002	-0.01	54	0.99	0.0001	y = -0.11x + 74.84
Green hairstreak	-0.32	-2.05	38	0.05	4.20	y = -1.13x + 14.55
Small heath	0.32	3.16	87	0.002	9.98	y = 11.21x + -26.6
Meadow brown	0.34	2.93	66	0.005	8.58	y = 120.28x - 493.79

Table 5: Correlation and regression of monthly total rainfall with butterfly species

Butterfly Species	r value	T-statistics	df	p-value	F-statistics	Regression Equation
Common blue	-0.19	-1.83	91	0.07	3.34	y = -10.78x + 78.18
Dark green fritillary	-0.23	-1.71	54	0.09	2.92	y = -20.1x + 116.28
Green hairstreak	-0.24	-1.55	38	0.13	2.39	y = -1.43x + 9.92
Small heath	-0.14	-1.29	87	0.20	1.65	y = -7.94x + 76.59
Meadow brown	-0.14	-1.17	66	0.24	1.36	y = -71.32x + 656.5

Discussion

This study assessed the impacts of climatic variation on butterfly populations at Porton Down. The findings revealed a decline in the total butterfly abundance and species richness at the site of study across 1994 and 2013. Green hairstreak demonstrated a significant decline in comparison to other species studied. There was a deviation recorded in local temperature against the pattern established nationally, particularly the cooling during the arid months. Furthermore, while Small Heath and Meadow brown significantly correlated with temperature positively, Green Hairstreak negatively correlated with the minimum grass temperature. Rainfall had no significant relationships with any species.

The increase in the total rainfall at Porton Down peaked in 2000. These findings align with similar observations conducted across the country, reporting that 1991-2020 was 8% wetter than 1961-1990, with an increased intensity of rainfall recorded over the recent decade. Seasonal divergence in temperature trends is also noteworthy. Daily maximum temperature increased slightly during colder months but decreased during warm months. While daily minimum temperature and minimum grass temperatures increased during warm months but decreased during cold months. These local findings diverge from the commonly observed UK-wide warming (Perry, 2006), which may be subject to Porton Down's complex topography. Slope, hilly, and lowland terrains exhibit microclimatic heterogeneity via cold air drainage or shelter effects.

Our findings identified declining abundance of all five species, which is in line with national trends demonstrating an 80% decline of butterflies across the UK since 1970 (Fox *et al.,* 2023). Among the five species, this decline was severely evident in the green hairstreak, as it was almost absent in multiple years. Its vulnerability may be rooted in its single-brooded life history and a longer pupal overwintering period (approximately ten months), which exposes this species to a critical environmental risk compared to other species. Flight periods differed, likely due to voltinism expressed by the species studied. Longer activity periods (May – September) were recorded among double-brooded Small Heath and variable-brooded Common blue, unlike single-brooded species. Another factor impacting the Green hairstreak's ability to confront adverse weather conditions might be the brief (May - June) flight window.

This study noted that though not statistically significant, weak negative correlations between all five species and rainfall, which contradicts studies conducted in different sites across the UK that report positive rainfall-abundance relationships. However, non-significance does not take away the effect. An intense spell of rain may drown eggs and larvae, impacting the adult abundance in the community in future flight seasons, a lagged effect not captured by same-year correlations.

The significant positive correlations observed in small heath and Meadow brown with daily mean and minimum grass temperature are an important finding. It reflects with broader literature demonstrates that warmer temperatures increase butterfly activity, reproductive success, and population size (Bristow *et al.,* 2024; Kral-O'Brien *et al.,* 2021). Warmer temperatures also improve male mate-finding success, which is often restricted during cooler temperatures, particularly for small heath (Wickman, 1985). The decline in warm-month temperature might reflect the reduced reproductive rates in these species in the context of Porton Down.

A notable finding was the green hairstreak's significant negative correlation with minimum grass temperature, which is more likely a result of its pupal overwintering strategy. The exposure to near-surface temperature for pupae developing closer to the soil surface may be detrimental. Warmer winter conditions, which impact diapause, increase metabolic rates, deplete energy reserves, or advance emergence even before a host plant is available (McDermott Long *et al.,* 2017). The increase observed in warm-month minimum grass temperature might emerge as a disadvantage for this species, while benefiting larval-overwintering species. No temperature relationships were observed in the common blue and dark green fritillary in the adult stage. Despite this, the effect of temperature in the earlier stage could not be overlooked. Since the typical development of common blue larval is dependent on temperature and host presence (Burghardt *et al.,* 2001). However, Dark green fritillary might be impacted by inter temperature despite its adult form exhibiting no associations (McDermott Long *et al.,* 2017).

This study outlines some conservation implications. Initially, Green hairstreak must be made a priority. Conserving microhabitats should be prioritized by the management to lessen the impact of extreme minimum temperatures, for example, south-facing slopes with dense vegetation cover. For small heath and Meadow brown, it is essential to maintain habitat connectivity, which facilitates range shifts in case of regional warming. While rainfall effects were non-significant, the predicted increases in winter flooding (Kendon *et al.,* 2022) require proper drainage and protective measures to safeguard larval host plants.

Given these insights, this study possesses several limitations. The distance between Porton Down and Boscombe Down (8 km) subjects the collected climatic data to be a true representative of the microclimatic conditions true to the topography of the Porton Down site. Missing data from some species may affect the statistical power of the analysis. Furthermore, the 20-year study period may not be sufficient to establish long-term climatic cycles and subsequent statistical associations, helpful in determining causations. It is essential to extend the monitoring period beyond 2013 to establish if the weather conditions persisted. Future autecological research must focus green hairstreak to understand the impact of temperature, particularly concerning the exceedingly long pupal stage.

CONCLUSION

This study demonstrates that butterfly populations at Porton Down declined between 1994 and 2013, with Green hairstreak emerging as the most threatened species. Temperature variables showed significant relationships with Small Heath, Meadow brown, and Green Hairstreak, while rainfall did not, suggesting temperature is a more immediate driver of abundance at this site. The contrasting responses among species highlight the importance of life history traits, particularly the overwintering stage. Species overwintering as pupae (Green hairstreak) face greater risks from changing minimum temperatures than those overwintering as larvae. These findings underscore the value of long-term monitoring programs and the need for species-specific conservation strategies in an era of climate change. Future management should prioritize protecting microhabitats that buffer against extreme temperatures, particularly for the most vulnerable species.

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Appendix

R Code For All Statistical Analyses and Figure Generation

Load data library(readr) data = read.csv("FinalProject/Data/Butterfly1.csv") data

#INVESTIGATING The relationship between Small Heath and Daily Mean Temp.

Check normality of Daily Mean Temp. using Shapiro-Wilk test

#Null Hypothesis: Daily Mean Temp data conforms to a normal distribution

shapiro.test(data$Daily.Mean.Temp)

Shapiro-Wilk normality test

data: data$Daily.Mean.Temp, W = 0.98707, p-value = 0.4876

p-value > 0.05, The Daily Mean Temp is normal. Accept the null hypthesis

Check normality of Small Heath using Shapiro-Wilk test

#Null Hypothesis: Small Heath data conforms to a normal distribution

shapiro.test(data$Small.Heath)

Shapiro-Wilk normality test

data: data$Small.Heath, W = 0.74748, p-value = 4.547e-11

p-value < 0.05, The data is not normal. I Reject null hypothesis

#Check if the log transform is normal #Null Hypothesis: log transform is normal shapiro.test(log(data$Small.Heath))

Shapiro-Wilk normality test

data: log(data$Small.Heath), W = 0.97927, p-value =

0.1657
# p-value > 0.05, Log transform is normal. Accept the null hypthesis
# Check for missing values sum(is.na(data$Small.Heath)) sum(is.na(data$Daily.Mean.Temp))
# Calculate the correlation between Small Heath and Daily Mean Temp correlation <- cor(data$Small.Heath, data$Daily.Mean.Temp, use = "complete.obs", method="pearson") correlation
# r 0.4789285
# Perform linear regression analysis model <- lm(Small.Heath ~ Daily.Mean.Temp, data = data)
# Plot the regression line library(ggplot2)
ggplot(data, aes(x = Daily.Mean.Temp, y = Small.Heath)) + geom_point() + geom_smooth(method = "lm", col = "red") + ggtitle("Regression of Small Heath on Daily Mean Temp") + xlab("Daily Mean Temp") + ylab("Small Heath")
# Display the model coefficients
coef(model)
#(Intercept) Daily.Mean.Temp
# -212.40258 17.75726
intercept <- coef(lm_model)[1] slope <- coef(lm_model)[2]
# Create the equation of the line as a string line_eq <- paste0("y = ", round(slope, 2), "x + ", round(intercept, 2)) line_eq
#y = 17.76x + -212.4
#INVESTIGATING The relationship between Small Heath and Min Grass Temp.
Check normality of Min Grass Temp. using Shapiro-Wilk test
#Null Hypothesis: Min. Grass Temp data conforms to a normal distribution
shapiro.test(data$Min.Grass.Temp)
# Shapiro-Wilk normality test
# data: data$Min.Grass.Temp, W = 0.97766, p-value = 0.1075
# p-value > 0.05, Min Grass Temp. is normal. Accept the null hypthesis
# Previous analysis has confirmed that Small Heath is normal
# Calculate the correlation between Small Heath and Min Grass Temp correlation <- cor(data$Small.Heath, data$Min.Grass.Temp, use = "complete.obs",
method="pearson")
correlation
# r 0.3207651
# Perform linear regression analysis model <- lm(Small.Heath ~ Min.Grass.Temp, data = data)
# Plot the regression line
ggplot(data, aes(x = Min.Grass.Temp, y = Small.Heath)) + geom_point() + geom_smooth(method = "lm", col = "blue") + ggtitle("Regression of Small Heath on Min. Grass Temp") + xlab("Min Grass Temp") + ylab("Small Heath")
# Display the model coefficients coef(model)
# (Intercept) Min.Grass.Temp # -26.59701 11.20970
intercept <- coef(model)[1] slope <- coef(model)[2]
# Create the equation of the line as a string line_eq <- paste0("y = ", round(slope, 2), "x + ", round(intercept, 2)) line_eq
#y = 11.21x + -26.6
#INVESTIGATING The relationship between Small Heath and Total Rainfall.
Check normality of Tot Rain data using Shapiro-Wilk test
#Null Hypothesis: Tot Rain data conforms to a normal distribution
shapiro.test(data$Tot.Rain)
# Shapiro-Wilk normality test
# data: data$Tot.Rain, W = 0.94507, p-value = 0.0006221
# p-value < 0.05, Tot. Rainfall is not normal. Reject the null hypthesis
#Check if the log transform is normal #Null Hypothesis: log transform is normal shapiro.test(log(data$Tot.Rain))
# Shapiro-Wilk normality test
# data: log(data$Tot.Rain), W = 0.97107, p-value = 0.03507
# p-value > 0.05, Log transform is normal. Accept the null hypthesis
# Calculate the correlation between Small Heath and Total Rainfall correlation <- cor(data$Small.Heath, data$Tot.Rain, use = "complete.obs",
method="pearson") correlation
# Correlation: -0.1365501
# Perform linear regression analysis model <- lm(Small.Heath ~ Tot.Rain, data = data)
# Plot the regression line
ggplot(data, aes(x = Tot.Rain, y = Small.Heath)) + geom_point() +
geom_smooth(method = "lm", col = "blue") + ggtitle("Regression of Small Heath on Total Rain") + xlab("Tot. Rain") + ylab("Small Heath")
# Display the model coefficients coef(model)
# (Intercept) Tot.Rain # 76.589111 -7.938456
intercept <- coef(model)[1] slope <- coef(model)[2]
# Create the equation of the line as a string line_eq <- paste0("y = ", round(slope, 2), "x + ", round(intercept, 2)) line_eq
y = -7.94x + 76.59
#INVESTIGATING The relationship between Green Hairstreak and Daily Mean Temp.
Previous analysis has shown that Daily Mean Temp is normal
Check normality of Green Hairstreak using Shapiro-Wilk test
#Null Hypothesis: Green Hairstreak data conforms to a normal distribution
shapiro.test(data$Green.hairstreak)
# Shapiro-Wilk normality test
# data: data$Green.hairstreak, W = 0.81854, p-value = 1.69e-05
# p-value < 0.05, The data is not normal. I Reject null hypothesis
#Check if the log transform is normal #Null Hypothesis:

log transform is normal shapiro.test(log(data$Green.hairstreak))
Shapiro-Wilk normality test
data: log(data$Green.hairstreak), W = 0.89374, p-value = 0.001263
p-value < 0.05, Log transform is not normal. Reject the null hypthesis
Check for missing values sum(is.na(data$Green.hairstreak))
54 Values are missing indicating Green Hairstreak is rear
Calculate the correlation between Green Hairstreak and Daily Mean Temp correlation <- cor(data$Green.hairstreak, data$Daily.Mean.Temp, use = "complete.obs", method="pearson") correlation
#r -0.04803815
Perform linear regression analysis model <- lm(Green.hairstreak ~ Daily.Mean.Temp, data = data) model
Plot the regression line library(ggplot2)
ggplot(data, aes(x = Daily.Mean.Temp, y = Green.hairstreak)) +
geom_point() + geom_smooth(method = "lm", col = "red") + ggtitle("Regression of Green Hairstreak on Daily Mean Temp") + xlab("Daily Mean Temp") + ylab("Green Hairstreak")
# Display the model coefficients coef(model)
#(Intercept) Daily.Mean.Temp
# 9.3973056 -0.1567583
intercept <- coef(model)[1] slope <- coef(model)[2]
# Create the equation of the line as a string line_eq <- paste0("y = ", round(slope, 2), "x + ", round(intercept, 2)) line_eq
#y = -0.16x + 9.4
#INVESTIGATING The relationship between Green Hairstreak and Min Grass Temp.
Previous analysis has confirmed that Min Grass Temp is normal
Previous analysis has confirmed that Green Hairstreak is not normal
Calculate the correlation between Green Hairstreak and Min Grass Temp correlation <- cor(data$Green.hairstreak, data$Min.Grass.Temp, use = "complete.obs", method="pearson")
correlation
#r -0.3155703
# Perform linear regression analysis model <- lm(Green.hairstreak ~ Min.Grass.Temp, data = data)
# Plot the regression line
ggplot(data, aes(x = Min.Grass.Temp, y = Green.hairstreak)) + geom_point() + geom_smooth(method = "lm", col = "blue") + ggtitle("Regression of Green Hairstreak on Min. Grass Temp") + xlab("Min Grass Temp") + ylab("Green Hairstreak")
# Display the model coefficients coef(model)
# (Intercept) Min.Grass.Temp # 14.551313 -1.129179
intercept <- coef(model)[1] slope <- coef(model)[2]
# Create the equation of the line as a string line_eq <- paste0("y = ", round(slope, 2), "x + ", round(intercept, 2)) line_eq
#y = -1.13x + 14.55
#INVESTIGATING The relationship between Green Hairstreak and Total Rainfall. # Previous analysis has confirmed that Total is a normal
# Previous analysis has confirmed that Green Hairstreak is not normal
# Calculate the correlation between Green Hairstreak and Total Rainfall correlation <- cor(data$Green.hairstreak, data$Tot.Rain, use = "complete.obs", method="pearson") correlation
# Correlation: -0.2433072
# Perform linear regression analysis model <- lm(Green.hairstreak ~ Tot.Rain, data = data)
# Plot the regression line
ggplot(data, aes(x = Tot.Rain, y = Green.hairstreak)) + geom_point() + geom_smooth(method = "lm", col = "blue") + ggtitle("Regression of Green Hairstreak on Total Rain") + xlab("Tot. Rain") + ylab("Green Hairstreak")
# Display the model coefficients coef(model)
# (Intercept) Tot.Rain # 9.915297 -1.431607 intercept <- coef(model)[1] slope <- coef(model)[2]
# Create the equation of the line as a string
line_eq <- paste0("y = ", round(slope, 2), "x + ", round(intercept, 2)) line_eq
#y = -1.43x + 9.92
#INVESTIGATING The relationship between Dark green fritillary and Daily Mean Temp.
Previous analysis has shown that Daily Mean Temp is normal
Check normality of Dark green fritillary using Shapiro-Wilk test
#Null Hypothesis: Green Hairstreak data conforms to a normal distribution
shapiro.test(data$Dark.green.fritillary)
# Shapiro-Wilk normality test
# data: data$Dark.green.fritillary, W = 0.67198, p-value = 6.532e-10
# p-value < 0.05, The data is not normal. I Reject null hypothesis
#Check if the log transform is normal #Null Hypothesis: log transform is normal shapiro.test(log(data$Dark.green.fritillary))
# Shapiro-Wilk normality test
# data: log(data$Dark.green.fritillary), W = 0.96872, p-value = 0.1535
# p-value > 0.05, Log transform is normal. Accept the null hypthesis
# Check for missing values
sum(is.na(data$Dark.green.fritillary))
# 38 Values are missing indicating Dark green fritillary is rear
# Calculate the correlation between Dark green fritillary and Daily Mean Temp correlation <- cor(data$Dark.green.fritillary, data$Daily.Mean.Temp, use = "complete.obs",
method="pearson") correlation

#r 0.2226102
# Perform linear regression analysis model <- lm(Dark.green.fritillary ~ Daily.Mean.Temp, data = data) model
# Plot the regression line.
ggplot(data, aes(x = Daily.Mean.Temp, y = Dark.green.fritillary)) + geom_point() + geom_smooth(method = "lm", col = "red") + ggtitle("Regression of Dark green fritillary on Daily Mean Temp") + xlab("Daily Mean Temp") + ylab("Dark Green Fritillary")
# Display the model coefficients coef(model)
#(Intercept) Daily.Mean.Temp
# -187.00107 16.06459
intercept <- coef(model)[1] slope <- coef(model)[2]
# Create the equation of the line as a string line_eq <- paste0("y = ", round(slope, 2), "x + ", round(intercept, 2)) line_eq
#y = 16.06x + -187
#INVESTIGATING The relationship between Dark green fritillary and Min Grass Temp.
Previous analysis has confirmed that Min Grass Temp is normal
Previous analysis has confirmed that Dark green fritillary is normal
Calculate the correlation between Dark green fritillary and Min Grass Temp correlation <- cor(data$Dark.green.fritillary, data$Min.Grass.Temp, use = "complete.obs", method="pearson") correlation
#r -0.001595415
Perform linear regression analysis model <- lm(Dark.green.fritillary ~ Min.Grass.Temp, data = data)
model
# Plot the regression line
ggplot(data, aes(x = Min.Grass.Temp, y = Dark.green.fritillary)) + geom_point() + geom_smooth(method = "lm", col = "blue") + ggtitle("Regression of Dark green fritillary on Min. Grass Temp") + xlab("Min Grass Temp") + ylab("Dark.green.fritillary")
# Display the model coefficients coef(model)
# (Intercept) Min.Grass.Temp # 74.8439536 -0.1128981
intercept <- coef(model)[1] slope <- coef(model)[2]
# Create the equation of the line as a string line_eq <- paste0("y = ", round(slope, 2), "x + ", round(intercept, 2)) line_eq
#y = -0.11x + 74.84
#INVESTIGATING The relationship between Dark green fritillary and Total Rainfall.
# Previous analysis has confirmed that Total is a normal
# Previous analysis has confirmed that Dark green fritillary is normal
# Calculate the correlation between Dark green fritillary and Total Rainfall.
correlation <- cor(data$Dark.green.fritillary, data$Tot.Rain, use = "complete.obs", method="pearson") correlation
# Correlation: -0.2267309
# Perform linear regression analysis model <- lm(Dark.green.fritillary ~ Tot.Rain, data = data) # Plot the regression line
ggplot(data, aes(x = Tot.Rain, y = Dark.green.fritillary)) + geom_point() + geom_smooth(method = "lm", col = "blue") + ggtitle("Regression of Dark Green Fritillary on Total Rain") + xlab("Tot. Rain") + ylab("Dark Green Fritillary")
# Display the model coefficients coef(model)
# (Intercept) Tot.Rain # 116.27541 -20.10451
intercept <- coef(model)[1] slope <- coef(model)[2]
# Create the equation of the line as a string line_eq <- paste0("y = ", round(slope, 2), "x + ", round(intercept, 2)) line_eq
#y = -20.1x + 116.28
#INVESTIGATING The relationship between Meadow Brown and Daily Mean Temp.
Previous analysis has shown that Daily Mean Temp is normal
Check normality of Meadow Brown using Shapiro-Wilk test
#Null Hypothesis: Meadow Brown data conforms to a normal distribution
shapiro.test(data$Meadow.brown)
# Shapiro-Wilk normality test
# data: data$Meadow.brown, W = 0.78579, p-value = 1.443e-08
# p-value < 0.05, The data is not normal. I Reject null hypothesis
#Check if the log transform is normal #Null Hypothesis: log transform is normal shapiro.test(log(data$Meadow.brown))
# Shapiro-Wilk normality test
# data: log(data$Meadow.brown), W = 0.86632, p-value = 3.027e-06
# p-value < 0.05, Log transform is not normal. Reject the null hypthesis
# Check for missing values
sum(is.na(data$Meadow.brown))
# 26 Values are missing in data$Meadow.brown
# Calculate the correlation between Meadow Brown and Daily Mean Temp correlation <- cor(data$Meadow.brown, data$Daily.Mean.Temp, use = "complete.obs", method="spearman") correlation
#r 0.4597471
# Perform linear regression analysis model <- lm(Meadow.brown ~ Daily.Mean.Temp, data = data) model
# Plot the regression line
ggplot(data, aes(x = Daily.Mean.Temp, y = Meadow.brown)) + geom_point() + geom_smooth(method = "lm", col = "red") + ggtitle("Regression of Meadow Brown on Daily Mean Temp") + xlab("Daily Mean Temp") + ylab("Meadow Brown")
# Display the model coefficients coef(model)
#(Intercept) Daily.Mean.Temp
# -2312.7098 176.4777
intercept <- coef(model)[1] slope <- coef(model)[2]
# Create the equation of the line as a string line_eq <- paste0("y = ", round(slope, 2), "x + ", round(intercept, 2)) line_eq
#y = 176.48x + -2312.71

#INVESTIGATING The relationship between Meadow Brown and Min Grass Temp.
Previous analysis has confirmed that Min Grass Temp is normal
Previous analysis has confirmed that Meadow Brown is not normal
Calculate the correlation between Meadow Brown and Min Grass Temp correlation <- cor(data$Meadow.brown, data$Min.Grass.Temp, use = "complete.obs", method="spearman")
correlation
# 0.3329484
# Perform linear regression analysis model <- lm(Meadow.brown ~ Min.Grass.Temp, data = data) model
# Plot the regression line
ggplot(data, aes(x = Min.Grass.Temp, y = Meadow.brown)) + geom_point() + geom_smooth(method = "lm", col = "blue") + ggtitle("Regression of Meadow Brown on Min. Grass Temp") + xlab("Min Grass Temp") + ylab("Meadow Brown")
# Display the model coefficients coef(model)
# (Intercept) Min.Grass.Temp # -493.7861 120.2759
intercept <- coef(model)[1] slope <- coef(model)[2]
# Create the equation of the line as a string line_eq <- paste0("y = ", round(slope, 2), "x + ", round(intercept, 2)) line_eq
#y = 120.28x + -493.79
#INVESTIGATING The relationship between Meadow Brown and Total Rainfall.
# Previous analysis has confirmed that Total is a normal
# Previous analysis has confirmed that Meadow Brown is not normal
# Calculate the correlation between between Meadow Brown and Total Rainfall correlation <- cor(data$Meadow.brown, data$Tot.Rain, use = "complete.obs", method="spearman") correlation
# Correlation: -0.09145224
# Perform linear regression analysis model <- lm(Meadow.brown ~ Tot.Rain, data = data) model
# Plot the regression line
ggplot(data, aes(x = Tot.Rain, y = Meadow.brown)) + geom_point() + geom_smooth(method = "lm", col = "blue") + ggtitle("Regression of Meadow Brown on Total Rain") + xlab("Tot. Rain") + ylab("Meadow Brown")
# Display the model coefficients coef(model)
# (Intercept) Tot.Rain # 656.50440 -71.31602
intercept <- coef(model)[1] slope <- coef(model)[2]
# Create the equation of the line as a string line_eq <- paste0("y = ", round(slope, 2), "x + ", round(intercept, 2)) line_eq
#y = -71.32x + 656.5
#INVESTIGATING The relationship between Common Blue and Daily Mean Temp.
Previous analysis has shown that Daily Mean Temp is normal
Check normality of Dark green fritillary using Shapiro-Wilk test
#Null Hypothesis: Green Hairstreak data conforms to a normal distribution
shapiro.test(data$Common.blue)
# Shapiro-Wilk normality test
# data: data$Common.blue, W = 0.69857, p-value = 1.599e-12
# p-value < 0.05, The data is not normal. I Reject null hypothesis
#Check if the log transform is normal #Null Hypothesis: log transform is normal shapiro.test(log(data$Common.blue))
Shapiro-Wilk normality test
data: log(data$Common.blue), W = 0.96766, p-value = 0.02084
p-value < 0.05, Log transform is not normal. Accept the null hypthesis
Check for missing values sum(is.na(data$Common.blue))
1 Value is missing from common blue
Calculate the correlation between Common and Daily Mean Temp correlation <- cor(data$Common.blue, data$Daily.Mean.Temp, use = "complete.obs", method="spearman") correlation
#r 0.1324767
# Perform linear regression analysis model <- lm(Common.blue ~ Daily.Mean.Temp, data = data) model
# Plot the regression line
ggplot(data, aes(x = Daily.Mean.Temp, y = Common.blue)) + geom_point() + geom_smooth(method = "lm", col = "red") + ggtitle("Regression of Dark Common Blue on Daily Mean Temp") + xlab("Daily Mean Temp") + ylab("Common Blue")
# Display the model coefficients coef(model)
#(Intercept) Daily.Mean.Temp
# -32.394006 5.809047
intercept <- coef(model)[1] slope <- coef(model)[2]
# Create the equation of the line as a string line_eq <- paste0("y = ", round(slope, 2), "x + ", round(intercept, 2)) line_eq
#y = 5.81x + -32.39
#INVESTIGATING The relationship between Common Blue and Min Grass Temp.
Previous analysis has confirmed that Min Grass Temp is normal
Previous analysis has confirmed that Common Blue distribution is normal
Calculate the correlation between Commmon Blue and Min Grass Temp correlation <- cor(data$Common.blue, data$Min.Grass.Temp, use = "complete.obs", method="spearman") correlation
#r 0.03786143
Perform linear regression analysis model <- lm(Common.blue ~ Min.Grass.Temp, data = data) model
Plot the regression line
ggplot(data, aes(x = Min.Grass.Temp, y = Common.blue)) + geom_point() + geom_smooth(method = "lm", col = "blue") + ggtitle("Regression of Common

Blue on Min. Grass Temp") + xlab("Min Grass Temp") + ylab("Common Blue")
# Display the model coefficients coef(model)
# (Intercept) Min.Grass.Temp # 39.483713 2.163383
intercept <- coef(model)[1] slope <- coef(model)[2]
# Create the equation of the line as a string line_eq <- paste0("y = ", round(slope, 2), "x + ", round(intercept, 2)) line_eq
#y = 2.16x + 39.48
#INVESTIGATING The relationship between Dark green fritillary and Total Rainfall.
# Previous analysis has confirmed that Total is a normal
# Previous analysis has confirmed that Common Blue is not normal
# Calculate the correlation between Common Blue and Total Rainfall.
correlation <- cor(data$Common.blue, data$Tot.Rain, use = "complete.obs", method="spearman") correlation
# Correlation: -0.130372
# Perform linear regression analysis
model <- lm(Common.blue ~ Tot.Rain, data = data) model
# Plot the regression line
ggplot(data, aes(x = Tot.Rain, y = Common.blue)) + geom_point() + geom_smooth(method = "lm", col = "blue") + ggtitle("Regression of Common Blue on Total Rain") + xlab("Tot. Rain") +
ylab("Common Blue")
# Display the model coefficients coef(model)
# (Intercept) Tot.Rain # 78.1763 -10.7837 intercept <- coef(model)[1] slope <- coef(model)[2]
# Create the equation of the line as a string line_eq <- paste0("y = ", round(slope, 2), "x + ", round(intercept, 2)) line_eq
#y = -10.78x + 78.18