

## REPORT

# Long-term decline in montane insects under warming summers

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## Abstract

Widespread declines in the abundance of insects portend ill-fated futures for their host ecosystems, all of which require their services to function. For many such reports, human activities have directly altered the land or water of these ecosystems, raising questions about how insects in less impacted environments are faring. I quantified the abundance of flying insects during 15 seasons spanning 2004–2024 on a relatively unscathed, subalpine meadow in Colorado, where weather data have been recorded for 38 years. I discovered that insect abundance declined an average of 6.6% annually, yielding a 72.4% decline over this 20-year period. According to model selection following information theoretic analysis of 59 combinations of weather-related factors, a seasonal increase in insect abundance changed to a seasonal decline as the previous summer's temperatures increased. This resulted in a long-term decline associated with increasing summer temperatures, particularly daily lows, which have increased 0.8°C per decade. However, other factors, such as ecological succession and atmospheric elevation in nitrogen and carbon, are also plausible drivers. In a relatively pristine ecosystem, insects are declining precipitously, auguring poorly for this and other such ecosystems that depend on insects in food webs and for pollination, pest control, and nutrient cycling.

## KEYWORDS

arthropods, climate change, ecosystem services, high elevation, mountain, subalpine

## INTRODUCTION

Insects have a unique, if inauspicious, position in the biodiversity crisis due to the ecological services they provide and to their vulnerability to environmental change. Insects are necessary for terrestrial and fresh-water ecosystems to function (Schowalter et al., 2018). Through pollination, they propagate flowering plants (Ollerton et al., 2011), and through decomposition, they recycle nutrients (Yang & Gratton, 2014). As both consumers and prey (Morse, 1971), they fill essential roles in many food webs (Mattson & Addy, 1975). It is of concern,

therefore, when insects decline; loss of their services can lead to ecological ruin (Harvey et al., 2022).

Several recent studies report significant insect declines across a variety of human-altered ecosystems, particularly in North America and Europe. For example, from 2015 to 2019, mayflies declined 84% during their annual emergence in Lake Erie, and from 2012 to 2019, their abundance along the upper Mississippi River declined by 52% (Stepanian et al., 2020). Across agricultural landscapes in Germany, total insect biomass declined by more than 75% over less than 30 years (Hallmann et al., 2017). Most such studies report on ecosystems that

have been directly impacted by humans or are surrounded by impacted areas (Forister et al., 2023), raising questions about insect declines and their drivers in more natural areas (Eggleton, 2020; Wagner et al., 2021).

Climate change (Harvey et al., 2022; Menéndez, 2007; Wagner et al., 2021) is among several potential drivers of insect decline (Sánchez-Bayo & Wyckhuys, 2019), particularly at high elevations (Hodkinson, 2005) and high latitudes, where it is inordinately rapid and where other human impacts tend to be reduced due to remoteness (Forister et al., 2018; Halsch et al., 2021; Janzen & Hallwachs, 2021; Wagner et al., 2021). Although insect mobility facilitates dispersal (Warren et al., 2001) and their rapid generation times enable adaptation (Menéndez, 2007) (but see Kingsolver & Buckley, 2018), their small size and ectothermy render them vulnerable to temperature change (Mirth et al., 2021). And, although mountains offer refuge from climate change (McCain & Garfinkel, 2021), the highest elevations are inescapable islands.

I quantified flying insect abundance over a 20-year period on a remote, subalpine meadow in the Colorado Rocky Mountains, USA. The site has undergone virtually no land- or water-use change during this period and has a weather station operating for the past 38 years, enabling a long-term assessment of weather precisely at the location where insects were sampled.

## MATERIALS AND METHODS

Field crew members and I sampled flying insects on a 15-ha wet meadow at Molas Pass, Colorado, USA (37.746° N, 107.691° W, elevation 3200 m). Typical for the North American subalpine, flora was a patchy distribution of willow shrubs (*Salix glaucus* and *Salix wolfii*) and open areas of Nebraska sedge (*Carex nebrascensis*). The meadow is flanked by hillsides of mature Engelmann spruce (*Picea engelmannii*), yielding alpine peaks approaching 4000 m in elevation.

Adjacent to the largest wilderness area in Colorado, the site is remote, with the only human development within several kilometers being a two-lane, paved road and two semi-primitive campgrounds, neither of which have significantly changed over the 20 years of sampling. The nearest town, of about 600 permanent residents, is 7 km away and 400 m lower in elevation. There has been almost no change in human development, no obvious change in road traffic, and no wildfires, except for the 416/Burro Complex fires of the 2018 summer, which burned ca. 22,000 ha centered ca. 33 km south-southwest of the study site. In 2015, wastewater from an abandoned mine spilled into another watershed ca. 18 km northeast

of the study site. In short, it is not obvious that, during the period of sampling, the area experienced any forms of environmental change, other than those associated with atmospheric change (e.g., rising carbon and nitrogen levels, climate change) and ecological succession.

During each of 15 summers spanning a 20-year period (2005–2013, 2015–2016, and 2021–2024), we collected insects using six traps (Sockman, 2009). Each consisted of a yellow, rectangular, plastic tub approximately 35 × 25 × 20 cm (L × W × D) that rested in a plywood frame elevated approximately 1 m above-ground on four threaded rods. At the start of each year's field season, we positioned each of the traps in each of the same six locations, spaced 100–400 m from one another. We filled each tub three-fourths full with water and added ca. 30-mL liquid detergent. We collected insects into vials containing 70% ethanol always in 7-day intervals at midday. After each collection, we replenished emptied traps with new water and detergent. The first trap-setting was always by June 5 (+0–3 days), and the last was always at least July 10 (+0–3 days), resulting in at least five 7-day sampling periods from early June to mid-July each season. After a season, we filtered the insects from the ethanol and counted them, using a tally counter. Although we did not classify them in detail, most were Diptera and Hemiptera, with some Hymenoptera and other orders. Nearly all were flying insects, as expected based on trap design.

A USDA weather station (37.749° N, 107.689° W) was located on the north side of the study site 250–700 m from traps. I accessed (<https://wcc.sc.egov.usda.gov/nwcc/site?sitenum=632&state=co>) the water content of snowpack (in millimeters) at midnight; precipitation accumulation (in millimeters); and minimum, mean, and maximum temperature (in degrees Celsius) for each day from August 7, 1986 to July 24, 2024. I removed values that were obvious recording errors and generated summaries (below) that could be relevant to the abundance of subalpine insects either directly or through habitat green-up.

I summarized within-season weather by calculating the mean daily temperature-minimum, -maximum, and -mean and the cumulative precipitation for each of the 1, 2, and 3 weeks immediately preceding each sampling date. Of all dates with weather data, 4% had at least one missing or obviously incorrect value. For the dates on which I statistically associated a weather measure with an insect count, 0.5% had at least one such value. For these dates, I determined the means without them; counts were at least 6, 12, and 18 for each of the respective time periods specified above. For missing precipitation values (assuming the counts above), I calculated a mean daily precipitation accumulation using the

non-missing days and applied it to the missing days, before summing all days in the range. I interpolated missing temperature-maxima as  $\text{mean} + (\text{mean} - \text{minimum})$  and missing temperature-minima as  $\text{mean} - (\text{maximum} - \text{mean})$ . To predict the values of several missing temperature measures in July 2005, I used the equation for regressing all available daily June and July 2005 temperature data (separately for minima, means, and maxima) from the weather station on the same daily data from a temperature logger (Onset Computer, Bourne, Massachusetts, USA) I had deployed a few hundred meters away.

I also generated the following between-season weather summaries: peak snow water content; first ordinal date with no snow; duration of snow melt (date of peak snow—first date of no snow); cumulative precipitation over the summer (June 1 to August 31) and fall (September 1 to October 31); mean daily temperature-minima, -maxima, and -means of May, summer, and fall; and first fall date of persisting (until spring melt) snow. I summarized the May, summer, and fall values only when there were at least 24, 78, and 48 values, respectively. Although winter and early spring snow can have long-term consequences on habitat green-up (Jonas et al., 2008), I assumed that between-year variation in winter and early spring temperature was not relevant to insect count, as temperatures then for this highly seasonal, subalpine climate were well below activity and development thresholds, and snowpack was always present and often deep.

I used principal components analyses to reduce the number of correlated weather summaries in my analyses described below. The within-season temperature summaries (mean daily temperature-minimum, -maximum, and -mean for each of 1, 2, and 3 weeks preceding each sampling date) were highly correlated with each other (Appendix S1: Table S1). Although within-season precipitation summaries (cumulative precipitation for each of 1, 2, and 3 weeks preceding each sampling date) were also highly correlated with one another, precipitation summaries were not consistently correlated with temperature summaries. Thus, for each of the sampling dates, I reduced within-season weather summaries to two predictors, corresponding to the first-axis factor scores from a principal components analysis on the nine within-season temperature summaries and the first-axis factor scores from another principal components analysis on the three within-season precipitation summaries (Appendix S1: Table S2). I also included the sampling period analyzed as a continuous (hereafter sampling period) and, separately, as a categorical variable, yielding four within-season predictors for each sampling date.

For the springs, the three snow summaries and the three temperature summaries were mostly correlated with each other (Appendix S1: Table S1). For the summers, the three temperature summaries were all correlated with each other. However, summer cumulative precipitation was correlated with only the mean daily temperature-maximum for the summer. For the falls, the three temperature summaries, cumulative precipitation, and the first date of persisting snow were nearly all correlated with each other. Thus, using the first-axis factor scores from each of four principal components analyses, I reduced between-season weather summaries to four predictors for analyses below. Variables for the four principal components analyses were (1) peak snow water content, first ordinal date with no snow, duration of snow melt, and the three May temperature summaries all for the same year as the insect count and, separately, (2) all for the previous year; (3) the three summer temperature summaries of the previous year (hereafter, previous summer temperature); and (4) the previous fall's snow, precipitation, and three temperature measures (Appendix S1: Table S2). To these, I added year and cumulative precipitation of the previous summer, for a total of six between-season predictors for analyses below.

## Analysis

Statistical analyses were primarily mixed-effects linear models, in which the insect count of one trap on one date— $\log_{10}$ -transformed to normalize residuals—was the response and each of the six observations (corresponding to each of the six traps) on one date was nested within the random intercept sampling period, itself nested within the random intercept year. Year was also a random coefficient for any fixed effect that varied within a year (Schielzeth & Forstmeier, 2009). For each model, I specified an autoregressive residual error structure to adjust coefficients and standard errors for serial autocorrelation. All models included an intercept, and analyses were conducted using Stata version 15.1 for Mac (StataCorp, College Station, TX, USA). To avoid overparameterization, I limited individual models to a maximum of two predictors plus their interaction, with one a within-season variable and the other a between-season variable. I also ran all the two-predictor models but without an interaction term, a model for each single predictor, and a null model with only an intercept, yielding a total of 59 models.

I calculated Akaike's information criterion (AIC) (Burnham & Anderson, 2002) for each model in order to determine the most efficient predictor(s) of insect count,

each model's weight, and the cumulative weights of each predictor. To estimate model fit, I squared the coefficient of correlation between response and fitted values from each model. 2005 and 2006 showed outlying counts, but Cook's Distances following elimination of each year (2005: 0.20; 2006: 0.56) and both years (0.55) did not suggest excessive influence of either year on the top model. Nor did they support excessive influence of any individual observation from any year (all  $<0.21$ ).

AIC results best supported the relationship between insect count and the interaction between sampling period and previous summer temperature (see [Results](#)), and thus, in order to determine whether summer temperature showed long-term, monotonic trends characteristic of climate change, I used linear regressions to examine how summer temperature and each of the individual weather variables used to calculate it varied over the 20 years of sampling and over the 38 years of available weather data. For each regression, a Breusch–Godfrey test failed to reject the null hypothesis of no autocorrelation of the residuals (each  $p > 0.1$ ).

## RESULTS

All models'  $R^2$  values ranged from 0.44 to 0.49 (Appendix S1: Table S3), a similarity presumably due to the influence of a random effects structure that varied little between models. The model with the highest AIC-based efficiency was discernable from all others by a  $\Delta\text{AIC} > 4.08$  and had a weighting of 86.0%. It included the predictors sampling period (coef.  $\pm$  SEM =  $0.045 \pm 0.012$ ;  $z = 3.63$ ,  $p < 0.001$ ), with a cumulative variable weighting of 99.87%; previous summer temperature (coef.  $\pm$  SEM =  $-0.023 \pm 0.049$ ;  $z = 0.48$ ,  $p > 0.2$ ), with a cumulative variable weighting of 86.07%; their interaction (coef.  $\pm$  SEM =  $-0.041 \pm 0.009$ ;  $z = -6.18$ ,  $p < 0.001$ ); and an intercept (coef.  $\pm$  SEM =  $1.857 \pm 0.065$ ;  $z = 6.81$ ,  $p < 0.001$ ) (Appendix S1: Tables S3 and S4). The second best model had a weighting of 11.2% and included the predictors sampling period (coef.  $\pm$  SEM =  $14.664 \pm 4.02$ ;  $z = 3.65$ ,  $p < 0.001$ ); year (coef.  $\pm$  SEM =  $-0.001 \pm 0.009$ ;  $z = -0.06$ ,  $p > 0.2$ ), with a cumulative variable weighting of 11.44%; their interaction (coef.  $\pm$  SEM =  $-0.007 \pm 0.002$ ;  $z = -3.64$ ,  $p < 0.001$ ); and an intercept (coef.  $\pm$  SEM =  $2.999 \pm 18.710$ ;  $z = 0.16$ ,  $p > 0.2$ ). With a summed weight of 97%, these two models exceeded the 95% confidence set (Symonds & Moussalli, 2010), and no other had a weighting more than 2.0%.

To summarize these top two models, insect abundance declined with previous summer temperature and

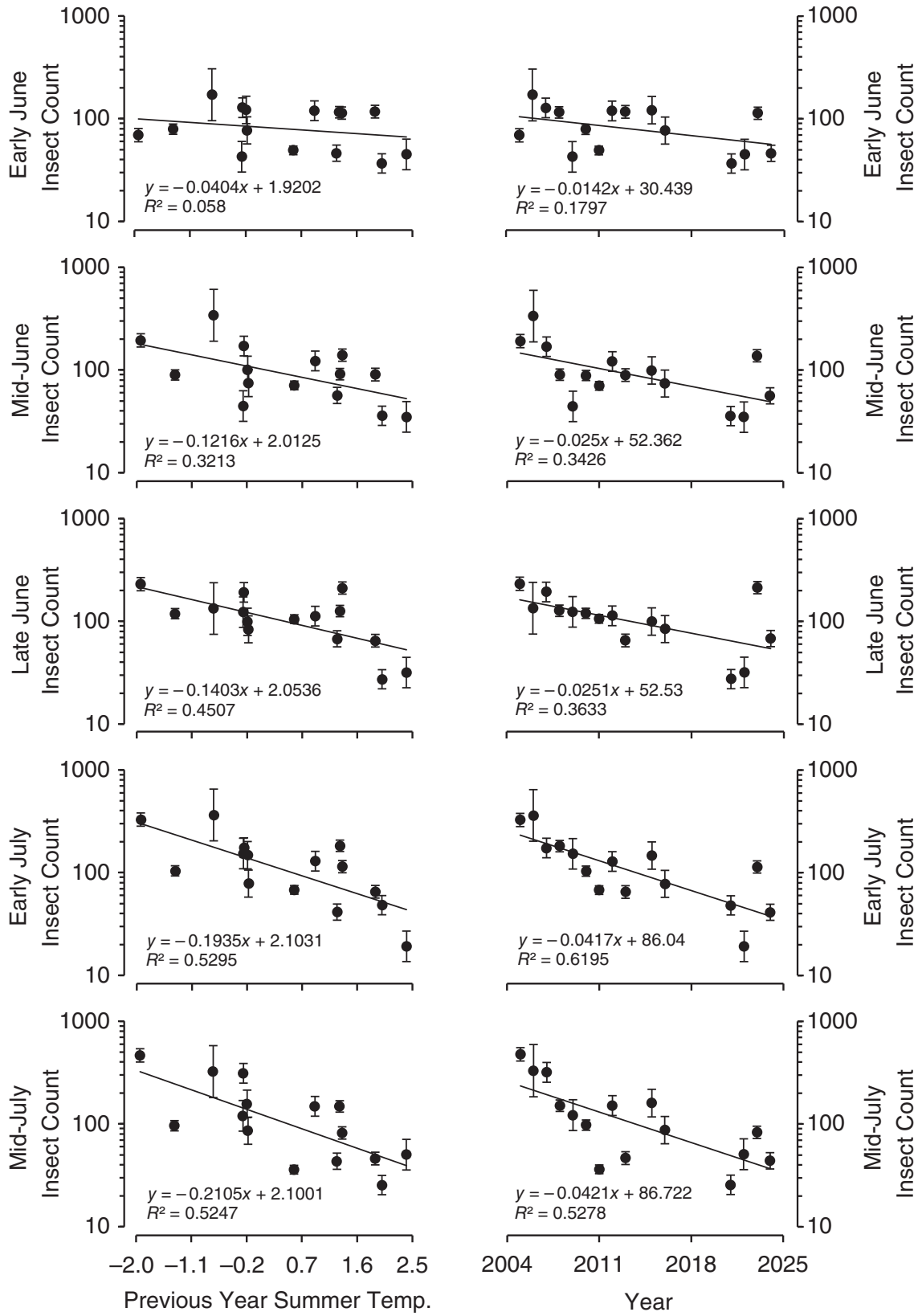
with year, primarily for later-season samples (Figure 1). It increased with sampling period but only in early years or when the previous summer temperature was low; otherwise, it declined (Figure 2). Stated differently, as previous summer temperature or year increased, the effect of sampling period declined, leading to an overall decline in insect abundance.

Summer temperature and the three weather summaries from which it was derived—summer mean daily minimum, mean, and maximum—have each increased over the 20 years of insect sampling, and all but summer mean daily maximum have increased over the 38 years of weather data (Figure 3). Summer mean daily-minimum temperature has increased  $0.8^\circ\text{C}$  per decade over the 38-year period of weather data. Possibly because of its relationship with the previous summer temperature and this long-term rise in summer temperature, the abundance of flying insects declined over the 20-year period of the study (Figures 1 and 2). Specifically, year interacted with sampling period (see statistics above) to yield a 72.4% reduction in insect count over the recent 20 years (2005–2024), averaging a 6.6% annual rate of decline.

## DISCUSSION

Flying insects at a montane site in Colorado have declined in abundance by 72.4% over the past 20 years. Extrapolation of the study's 6.6% mean annual decline to 27 years (83% decline) suggests that, in this relatively pristine ecosystem, they are faring no better than those in a more human-altered agricultural landscape of a seminal German study, which reported an 82% decline in the biomass of midsummer flying insects over 27 years (Hallmann et al., 2017). Although human changes to land or water are unlikely drivers in the present study, no cause of this decline can be known with high certainty due to the study's observational nature and limits of collected data. However, plausible drivers include the effects of ecological succession, elevated nitrogen, and elevated carbon on the dilution of nutrition (Welti et al., 2020), none of which I assessed.

Among plausible drivers that I did assess, all of which were weather-related, an information theoretic approach best supported the role of the previous summer temperature. That role involved a lag, in that elevated summer temperatures 1 year were associated with reduced insect abundance the following year (Figures 1 and 2). Other than the lag, this finding is consistent with another reporting rising temperature minima as a driver of declines in montane butterflies (Halsch et al., 2021). Future studies would benefit from



**FIGURE 1** Change in insect count (mean ± SEM of six traps) with the previous year's summer temperature score (Temp.) from a principal components analysis (left panels) and with year (right panels) for each of 5 week-long sampling periods (row).

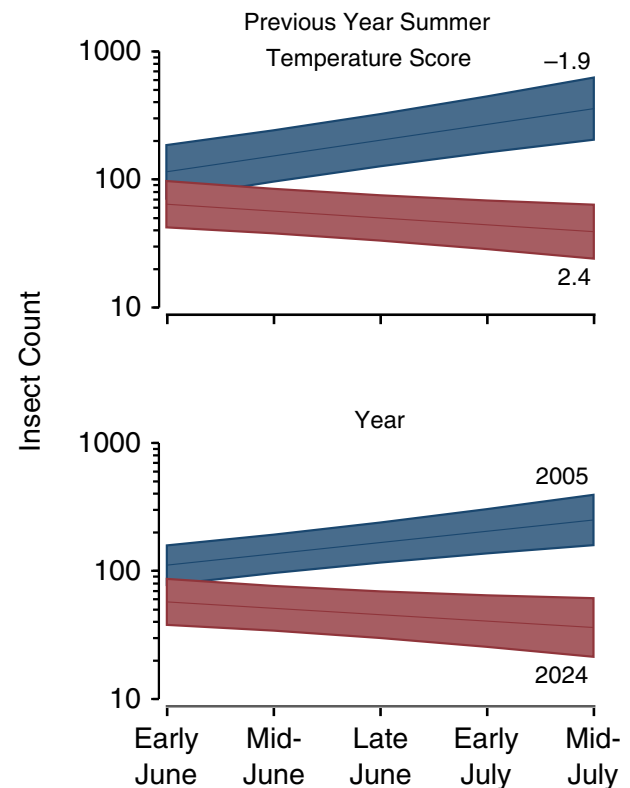
classification of the insects to at least the order or family level to better understand any taxonomic concentrations of these declines.

Summer lows at this location have increased by ca. 0.8°C per decade over nearly four decades (Figure 3), which is more rapid than global averages but parallels warming in polar systems (Bekryaev et al., 2010; Serreze & Francis, 2006), and thus, to the extent that this climate change could be a driver of this insect decline, these findings serve as a warning for high-elevation and high-latitude ecosystems alike. Nevertheless, because of AIC limitations (Symonds & Moussalli, 2010) and the correlational nature of the weather results, other means of predicting insect counts, some of which may interact with weather, could better explain the decline. In fact, even interactions involving multiple within-season and between-season weather predictors may better explain insect abundance. However, I did not investigate such interactions. Also, I investigated only insects susceptible to my particular form of capture, and thus, results here do not imply similar changes here for insects as a whole or even other insect communities.

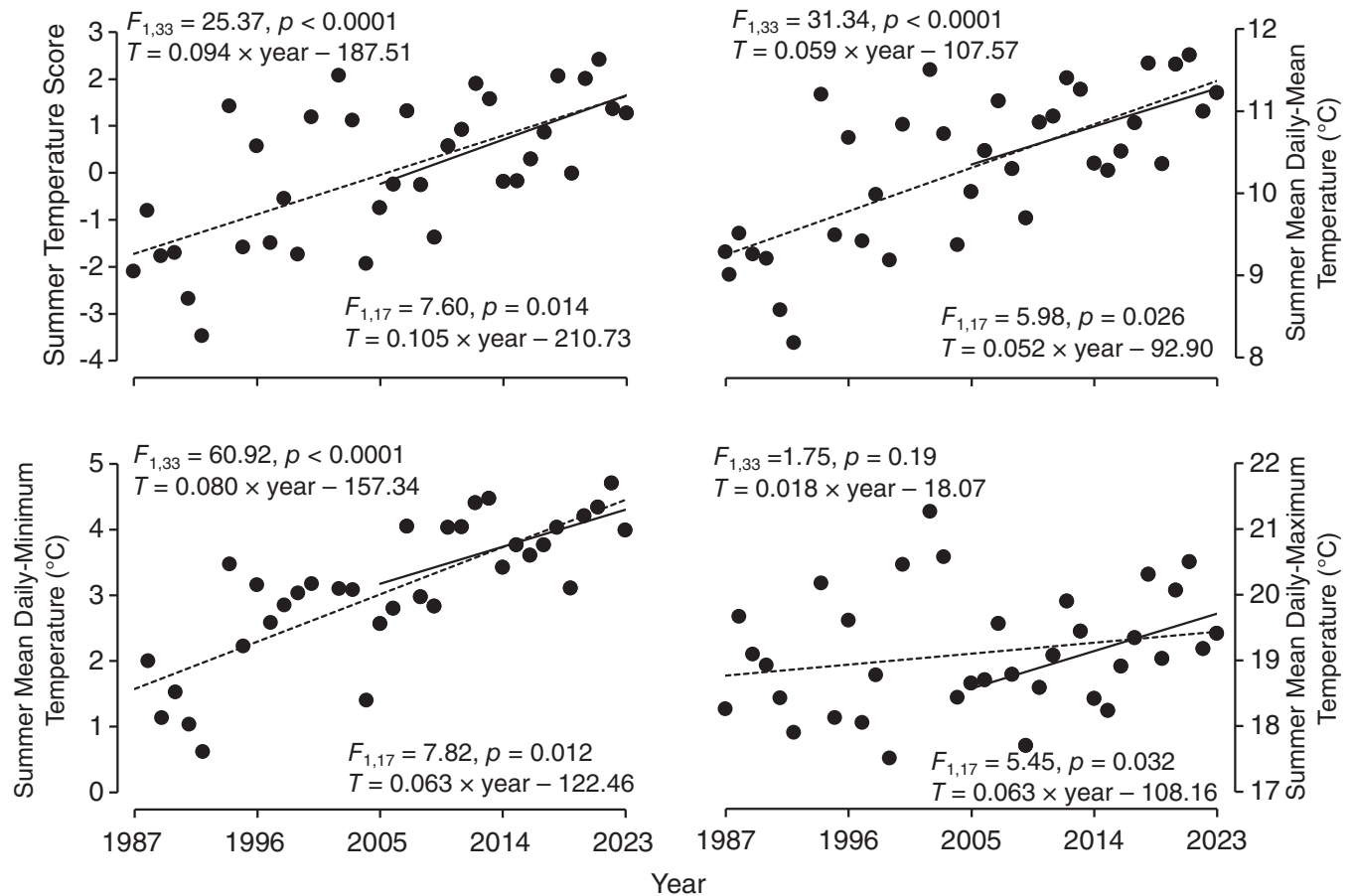
Because temperature tends to drop with increasing elevation and latitude, insects elsewhere are responding to climate warming with elevational and latitudinal distributional shifts (McCain & Garfinkel, 2021). Insects formerly at Molas Pass may have moved to higher elevations, but, because abundance declined, comparable shifts from lower elevation did not appear to occur perhaps due to elevational rarefaction (McCain & Garfinkel, 2021) or to the possibility that warming is not having this effect in this area. It is also worth noting that because sampling never occurred earlier than June, I cannot rule out the possibility that a phenological advance explains what otherwise appears as a decline in abundance. Still, if I missed an early-season peak, I would have expected one or more springtime weather summaries to play a role in predicting abundance, but that was not the case. Also, according to regressions of abundance on year (Figure 1), high counts from 2005 to 2016 (all in early July) are higher than those from 2017 to 2024 (all in mid-June), suggesting that a phenological shift cannot explain the decline entirely.

Insects are essential for the functioning of most terrestrial and freshwater ecosystems (Schowalter et al., 2018) and can sometimes have complex effects in food webs. Indeed, at the location of this study, their abundance as prey may affect time and energy budgets and thus behavioral performances in omnivorous birds (Sockman, 2009). In high-elevation, montane ecosystems such as that of this study, many insects require specific traits such as cold tolerance, UV resilience, rapid

reproduction and development, respiratory efficiency, wind resistance, and the ability to use unique floral components of the habitat (Dillon et al., 2006; Hodkinson, 2005). Further, the role of insect pollinators in restricting plant diversity can increase with elevation (Pellissier et al., 2010), as can the effects of pollinator limitations on plants (Totland, 2001). Thus, in addition to the loss of pollination and other services expected from the substantial long-term decline in flying insects shown here, the potential for replacement of those services may be challenged by an ecosystem that requires a high degree of local adaptation. Ecosystem services, food-web effects, and the extent of local adaptation may vary taxonomically, and thus understanding the classification of these insects would be of considerable value. Mountains are host to disproportionately high numbers of locally adapted endemic species, including insects (Dirnböck et al., 2011; Myers et al., 2000). And thus, the status of mountains as biodiversity hotspots may be in jeopardy if the declines shown here reflect trends broadly.



**FIGURE 2** Seasonal change in insect count at the minimum and maximum previous year's summer temperature score from a principal components analysis (top panel) and first and last study year (bottom panel). Lines and shaded 95% confidence bands are from margins estimates from statistical analyses in the text at the low and high recorded values for the previous year's summer temperature score and for year.



**FIGURE 3** Long-term change in the summer temperature score from a principal components analysis (top left panel) and in each of the three variables (as labeled for each of the other three panels) used to calculate temperature score. For each panel, the dotted line and upper linear regression statistics refer to all data, and the solid line and lower linear regression statistics refer to data used in this study’s analysis of insect counts.

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**CONFLICT OF INTEREST STATEMENT**

The author declares no conflicts of interest.

**DATA AVAILABILITY STATEMENT**

Data and code (Sockman, 2025) are available in Figshare at <https://doi.org/10.6084/m9.figshare.29553026.v1>.

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## SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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Appendix S1

Keith W. Sockman

Long-term decline in montane insects under warming summers

*Ecology*

**Table S1. Correlation coefficients (below diagonal) and P values (above diagonal) of weather summaries\* at Molas Pass, Colorado for each of four time periods.**

Within-season

	Tmin_1wk	Tmean_1wk	Tmax_1wk	Tmin_2wk	Tmean_2wk	Tmax_2wk	Tmin_3wk	Tmean_3wk	Tmax_3wk	Precip_1wk	Precip_2wk	Precip_3wk
Tmin_1wk		< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	0.062	0.125	0.435
Tmean_1wk	0.823		< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	0.001	0.003	0.001
Tmax_1wk	0.666	0.933		< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
Tmin_2wk	0.926	0.756	0.609		< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	0.007	0.021	0.225
Tmean_2wk	0.841	0.900	0.827	0.885		< 0.001	< 0.001	< 0.001	< 0.001	0.762	0.093	0.010
Tmax_2wk	0.728	0.849	0.878	0.754	0.944		< 0.001	< 0.001	< 0.001	0.560	0.019	0.001
Tmin_3wk	0.873	0.707	0.571	0.960	0.841	0.715		< 0.001	< 0.001	0.013	0.011	0.159
Tmean_3wk	0.813	0.812	0.734	0.887	0.944	0.879	0.916		< 0.001	0.510	0.884	0.078
Tmax_3wk	0.711	0.773	0.785	0.779	0.901	0.933	0.807	0.952		0.750	0.478	0.014
Precip_1wk	0.137	-0.235	-0.270	0.198	-0.023	-0.043	0.182	0.049	0.024		< 0.001	< 0.001
Precip_2wk	0.113	-0.216	-0.262	0.170	-0.125	-0.173	0.186	-0.011	-0.053	0.796		< 0.001
Precip_3wk	0.058	-0.238	-0.280	0.090	-0.190	-0.237	0.104	-0.132	-0.181	0.678	0.883	

Spring

	Sno_pk	Sno_0	Sno_mlt	Tmin_may	Tmean_may	Tmax_may
Sno_pk		< 0.001	0.331	0.087	0.106	0.389
Sno_0	0.693		0.002	< 0.001	< 0.001	0.002
Sno_mlt	0.162	0.482		0.076	0.006	0.013
Tmin_may	-0.285	-0.549	-0.296		< 0.001	< 0.001
Tmean_may	-0.270	-0.649	-0.445	0.869		< 0.001
Tmax_may	-0.146	-0.489	-0.407	0.628	0.863	

Summer

	Tmin_sum	Tmean_sum	Tmax_sum	Precip_sum
Tmin_sum		< 0.001	0.009	0.862
Tmean_sum	0.891		< 0.001	0.073
Tmax_sum	0.438	0.742		0.015
Precip_sum	-0.031	-0.307	-0.410	

Fall

	Tmin_fall	Tmean_fall	Tmax_fall	Precip_fall	Sno_first
Tmin_fall		< 0.001	0.027	0.047	0.568
Tmean_fall	0.898		< 0.001	< 0.001	0.050
Tmax_fall	0.370	0.695		< 0.001	0.003
Precip_fall	-0.334	-0.573	-0.634		0.049
Sno_first	0.099	0.330	0.481	-0.325	

\*Definitions for weather summaries on other page.

**Table S2. Eigenvectors for first-component (proportion-of-variance-explained in parentheses) weather summaries\* in principal components analyses on correlation matrices.**

Within-season temperature summaries for five analyses, corresponding to each of five seasonal periods of insect collection

Weather Summary*	Eigenvector Early June (0.83)	Eigenvector Mid-June (0.82)	Eigenvector Late June (0.77)	Eigenvector Early July (0.72)	Eigenvector Mid-July (0.62)
Tmin_1wk	0.32	0.31	0.33	0.31	0.32
Tmean_1wk	0.35	0.33	0.33	0.34	0.30
Tmax_1wk	0.31	0.30	0.29	0.29	0.26
Tmin_2wk	0.33	0.33	0.34	0.33	0.33
Tmean_2wk	0.36	0.36	0.37	0.38	0.40
Tmax_2wk	0.34	0.34	0.33	0.34	0.33
Tmin_3wk	0.31	0.33	0.33	0.32	0.31
Tmean_3wk	0.34	0.35	0.36	0.37	0.39
Tmax_3wk	0.33	0.34	0.32	0.33	0.34

Within-season precipitation summaries for five analyses, corresponding to each of five seasonal periods of insect collection

Weather Summary*	Eigenvector Early June (0.83)	Eigenvector Mid-June (0.82)	Eigenvector Late June (0.77)	Eigenvector Early July (0.72)	Eigenvector Mid-July (0.62)
Precip_1wk	0.57	0.55	0.55	0.55	0.54
Precip_2wk	0.60	0.60	0.60	0.60	0.62
Precip_3wk	0.57	0.58	0.59	0.58	0.57

**Spring weather**

Weather Summary*	Eigenvector (0.59)
Sno_pk	-0.27
Sno_0	-0.31
Sno_mlt	-0.44
Tmin_may	0.43
Tmean_may	0.50
Tmax_may	0.44

**Summer temperature**

Weather Summary*	Eigenvector (0.80)
Tmin_sum	0.57
Tmean_sum	0.64
Tmax_sum	0.52

**Fall weather**

Weather Summary*	Eigenvector (0.6)
Tmin_fall	0.43
Tmean_fall	0.54
Tmax_fall	0.49
Precip_fall	-0.44
Sno_first	0.31

\*Definitions for weather summaries on other page.

**Table S3. AIC results and fit (R-Squared) for statistical models predicting aerial insect abundance at Molas Pass, Colorado.**

Model Rank	Within-Yr Predictor*	Between-Yr Predictor*	Interaction Term Present?	Delta AIC	Weight	R-Squared
1	Prd	SumT	yes	0	0.8596	0.4427
2	Prd	Y	yes	4.0805	0.1117	0.4404
3	Prd	Fall	yes	7.4999	0.0202	0.4453
4	Prd	SumP	no	12.9227	0.0013	0.4482
5	Prd	Y	no	13.0295	0.0013	0.4482
6	prd	Y	yes	13.2822	0.0011	0.4388
7	Prd		no	13.5819	0.0010	0.4475
8	Prd	SumT	no	14.4485	0.0006	0.4461
9	Prd	Fall	no	14.8822	0.0005	0.4446
10	Prd	Sprng	no	15.005	0.0005	0.4482
11	Prd	Sprng	yes	15.2353	0.0004	0.4487
12	Prd	SumP	yes	15.2821	0.0004	0.4487
13	prd	SumT	no	15.3823	0.0004	0.4611
14	Prd	SYSprng	no	15.5434	0.0004	0.4475
15	Prd	SYSprng	yes	17.4698	0.0001	0.4475
16	T	Y	yes	18.7033	0.0001	0.4539
17		Y	no	19.1446	0.0001	0.4680
18	T	Y	no	19.1779	0.0001	0.4547
19	T	SumT	yes	19.7182	0.0000	0.4521
20	T	SumT	no	19.8805	0.0000	0.4538
21	prd	Fall	yes	20.3916	0.0000	0.4426
22		SumT	no	20.6113	0.0000	0.4679
23	T	Fall	yes	22.5648	0.0000	0.4554
24	P	Y	no	22.7136	0.0000	0.4671
25		Fall	no	23.6937	0.0000	0.4687
26	P	SumT	no	23.7195	0.0000	0.4671
27	prd	Y	no	23.9181	0.0000	0.4613
28	P	Y	yes	24.2216	0.0000	0.4660
29	prd	Sprng	no	24.8305	0.0000	0.4621
30	prd	SYSprng	no	24.8873	0.0000	0.4621
31	T	Fall	no	25.3073	0.0000	0.4577
32	P	Fall	yes	25.3763	0.0000	0.4631
33	P	SumT	yes	25.4418	0.0000	0.4658
34	P	Fall	no	26.2097	0.0000	0.4671
35			no	28.1174	0.0000	0.4689
36	prd	Fall	no	28.4674	0.0000	0.4620
37	T		no	29.4775	0.0000	0.4580
38		Sprng	no	30.0604	0.0000	0.4689
39		SumP	no	30.0898	0.0000	0.4689
40		SYSprng	no	30.1173	0.0000	0.4689
41	T	SumP	no	31.1258	0.0000	0.4573
42	P		no	31.1742	0.0000	0.4679
43	T	Sprng	no	31.3627	0.0000	0.4578
44	T	SYSprng	no	31.4615	0.0000	0.4579
45	T	Sprng	yes	32.484	0.0000	0.4589
46	T	SumP	yes	32.7337	0.0000	0.4562
47	prd		no	32.8874	0.0000	0.4621
48	T	SYSprng	yes	33.0965	0.0000	0.4580
49	P	Sprng	no	33.1025	0.0000	0.4680
50	P	SumP	no	33.1498	0.0000	0.4680
51	P	SYSprng	no	33.1666	0.0000	0.4679
52	P	Sprng	yes	34.5101	0.0000	0.4674
53	P	SumP	yes	34.8066	0.0000	0.4671
54	P	SYSprng	yes	34.8076	0.0000	0.4673
55	prd	SumP	no	34.8599	0.0000	0.4621
56	prd	SumP	yes	35.4642	0.0000	0.4537
57	prd	Sprng	yes	39.0793	0.0000	0.4571
58	prd	SYSprng	yes	40.506	0.0000	0.4595
59	prd	SumT	yes	55.0905	0.0000	0.4941

\*Definitions for predictors on other page.

**Table S4. Ranking of each predictor\* of aerial insect abundance at Molas Pass, Colorado, based on cumulative model weightings.**

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Rank	Predictor*	Cumulative Weight (%)
1	Prd	99.87
2	SumT	86.07
3	Y	11.44
4	SumP	0.18
5	prd	0.09
6	Spring	0.09
7	SYSpring	0.05
8	T	0.02
9	P	0.00
10	Fall	0.00

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\*Definitions for predictors on other page.

## **\*Definitions of Weather Summaries and Analysis Predictors:**

Tmin_1wk	mean daily temperature-minimum for the 1 wk immediately preceding the sampling date
Tmean_1wk	mean daily temperature-mean for the 1 wk immediately preceding the sampling date
Tmax_1wk	mean daily temperature-maximum for the 1 wk immediately preceding the sampling date
Tmin_2wk	mean daily temperature-minimum for the 2 wk immediately preceding the sampling date
Tmean_2wk	mean daily temperature-mean for the 2 wk immediately preceding the sampling date
Tmax_2wk	mean daily temperature-maximum for the 2 wk immediately preceding the sampling date
Tmin_3wk	mean daily temperature-minimum for the 3 wk immediately preceding the sampling date
Tmean_3wk	mean daily temperature-mean for the 3 wk immediately preceding the sampling date
Tmax_3wk	mean daily temperature-maximum for the 3 wk immediately preceding the sampling date
Precip_1wk	Cumulative precipitation for the 1 wk immediately preceding the sampling date
Precip_2wk	Cumulative precipitation for the 2 wk immediately preceding the sampling date
Precip_3wk	Cumulative precipitation for the 3 wk immediately preceding the sampling date
Sno_pk	peak snow water-content
Sno_0	first ordinal date with no snow
Sno_mlt	duration of snow melt
Tmin_may	Mean daily temperature minimum for May
Tmean_may	Mean daily temperature mean for May
Tmax_may	Mean daily temperature maximum for May
Tmin_sum	Mean daily temperature minimum for the summer
Tmean_sum	Mean daily temperature mean for the summer
Tmax_sum	Mean daily temperature maximum for the summer
Precip_sum	Cumulative precipitation for the summer
Tmin_fall	Mean daily temperature minimum for the fall
Tmean_fall	Mean daily temperature mean for the fall
Tmax_fall	Mean daily temperature maximum for the fall
Precip_fall	Cumulative precipitation for the fall
Sno_first	first fall date of persisting snow
Fall	first-axis factor score from PCA on previous year's fall weather measures
P	first-axis factor score from PCA on period-specific precipitation measures
Prd	insect weekly sampling period (1-5)
prd	insect weekly sampling period (1-5, categorical)
Sprng	first-axis factor score from PCA on previous year's spring weather measures
SumP	previous year's cumulative summer precipitation
SumT	first-axis factor score from PCA on previous year's summer temperature measures
SYSprng	first-axis factor score from PCA on same year's spring weather measures
T	first-axis factor score from PCA on period-specific temperature measures
Y	year (2005-2024)