# Global effects of land-use and climate change interactions on local insect biodiversity

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## Summary Paragraph (200 words, fully referenced)

*2-3 sentences of basic-level introduction to the field; a brief account of the background and rationale of the work; a statement of the main conclusions (introduced by the phrase 'Here we show' or its equivalent); and finally, 2-3 sentences putting the main findings into general context so it is clear how the results described in the paper have moved the field forwards.* [*Example*](https://www.nature.com/documents/nature-summary-paragraph.pdf)*.*

* 1-2 sentences basic intro to the field

Recent studies suggest that insects have experienced large-scale declines in biodiversity (Hallmann et al., 2017; Lister & Garcia, 2018; Sánchez-Bayo & Wyckhuys, 2019; van Strien, van Swaay, van Strien-van Liempt, Poot, & WallisDeVries, 2019). Since insects perform a number of essential ecosystem functions (Yang & Gratton, 2014), losses in insect diversity would have severe consequences for human well-being as well as for wider biodiversity.

* 2-3 sentences more detailed background

Considerable progress has been made in understanding the global responses of biodiversity to major drivers such as land use and climate change (e.g. (Bartlett, Newbold, Purves, Tittensor, & Harfoot, 2016; Jetz, Wilcove, & Dobson, 2007; Kehoe et al., 2015; Newbold et al., 2015)), however, much of this research is based on the response of vertebrates. Those recent studies that do assess trends in insect biodiversity and their drivers are limited in that they have been undertaken at local (Lister & Garcia, 2018) or national scales (Powney et al., 2019; van Strien et al., 2019), and often focus on a single taxa (e.g. (Soroye, Newbold, & Kerr, 2020)).

* 1 sentence – gap

To date, there has not been a global study of change in insect biodiversity in response to both land use and climate change or considered the interactions between these two major drivers.

* 1 sentence – main result – *here we show*

Here, we show that both insect species richness and abundance are reduced in response to climate change globally, with greater declines in intensely used agriculture.

* 2-3 sentences what the results show

The detrimental effect of climate change, assessed as a standardised climate anomaly, on biodiversity in agricultural areas was high [between XX and XX% declines]. However, the availability of nearby natural habitat surrounding agricultural areas buffered against the negative impact of climate change, but only in areas of low use-intensity.

* 1-2 sentences to put the results in context

Our results support the narrative of large-scale declines in insect biodiversity and highlight the need for insect conservation if valuable ecosystem services are to be maintained into the future. The ability of nearby natural habitat to buffer negative climate responses in agricultural systems suggests a way to conserve biodiversity in human-dominated landscapes.

* 2-3 sentence broader perspective (optional)

Since many locations globally have already experienced high climate anomalies, strong climate-driven declines in insect biodiversity have likely already taken place, highlighting the need for urgent action.

**Summary word count: 299 (with Nature style references)**

## Main text

*The typical length of an article with 3-4 modest display items (figures and tables) is 2000-2500 words (summary paragraph plus body text). Sections are separated with subheadings to aid navigation. Subheadings may be up to 40 characters (including spaces).*

**Current total word count (with Nature style references):**

Increasing evidence shows that many insect populations have undergone declines in recent decades (Hallmann et al., 2017; Klink et al., 2020; Outhwaite, Gregory, Chandler, Collen, & Isaac, 2020; Powney et al., 2019; Soroye et al., 2020; van Strien et al., 2019). With observations including a 75% decline in the biomass of flying insects in Germany (Hallmann et al., 2017), a 67% decline in the distribution of butterflies in the Netherlands (van Strien et al., 2019), a third of UK pollinators having declined in occupancy (Powney et al., 2019) and a 9% average decline in insect abundance per decade globally (Klink et al., 2020). Some positive change has been shown, for example positive trends of freshwater insects in temperate regions (Klink et al., 2020; Outhwaite et al., 2020), however, the body of evidence shows that large-scale declines of insects are potentially greater than previously recognised, putting the spotlight on changes in insect biodiversity. Due to the role insects play in a number of key ecosystem functions and services, from pollination and pest control, to soil quality regulation and decomposition (Yang & Gratton, 2014), this decline is of great concern for both biodiversity conservation and human well-being.

Although recent studies have shown the magnitude of trends in insect biodiversity, there is currently little understanding of the global drivers of insect declines or the potential for interactions between large-scale drivers such as land use and climate change. There is increasing evidence that land-use, land-use intensity and climate change interact to shape biodiversity more generally (Betts et al., 2017; Frishkoff, Gabot, Sandler, Marte, & Mahler, 2019; Frishkoff, Hadly, & Daily, 2015; Frishkoff et al., 2016; Hendershot et al., 2020; Mantyka-pringle, Martin, & Rhodes, 2012; Merckx et al., 2018; Northrup, Rivers, Yang, & Betts, 2019; Oliver et al., 2017; Oliver & Morecroft, 2014; Peters et al., 2019), yet interactions at the global scale are not well understood, particularly for insects.

To address this gap, we analysed global data on local insect biodiversity from the PREDICTS database (Hudson et al., 2014, 2017, 2016) alongside information on land use, land-use intensity and climate change to determine how the interactions of these drivers affect insect total abundance and species richness. To assess the impact of climate change, we determine a standardised climate anomaly metric. This metric is based on the difference between local present day and past temperature estimates which are then standardised to account for historical temperature variability. A similar metric based on maximum temperatures was also tested. We present models of insect total abundance and insect richness response to land use, land-use intensity and climate change and their interactions, based on XXX records of insects from XXX sites from across the world (Fig. 1a). We then examine the ability of nearby natural habitat to buffer negative responses of insects to climate change, offering a potential mitigation strategy to reduce future impacts of climate change on insect biodiversity, potentially safeguarding those ecosystem services provided by insects.

## Insect response to land-use intensity

Insect total abundance declines with increasing land-use intensity, with the greatest declines in high intensity agriculture (Fig. 1). Here, agricultural land uses in PREDICTS (cropland, plantation, pasture) have been combined according to their use intensity into two groupings: low-intensity agriculture and high-intensity agriculture (see Methods for details). These classifications are based on the levels of pesticide usage and likelihood of monoculture associated with each PREDICTS land use and use-intensity combination. In high-intensity agriculture, insect total abundance was reduced by about 35% and species richness by XX% compared to levels in primary vegetation, whereas in low-intensity agriculture there was a 16% and XX% reduction respectively (Fig. 1). This loss of insect biodiversity in agricultural systems will likely reduce the provisioning of ecosystem services essential to agriculture such as pollination and pest control (Grab et al., 2019; Rusch et al., 2016). The greater declines in more intensively used systems will likely have an impact on the resilience of agricultural systems to future shocks [REF].

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| ***Figure 1: Locations of sites and responses of insect species richness and total abundance to land use.***  *a. Location of PREDICTS sites that include insect data. b. Response of insect species richness to land use. c. Response of insect total abundance to land use. Error bars show the 95% confidence intervals. PV, primary vegetation; SV, secondary vegetation; AG.Low, low-intensity agriculture; AG.Hi, high-intensity agriculture; URB, urban.* |

## Insect response to climate change

To assess the impacts of climate change and its interaction with the land use and use intensity, we modelled the response of insect richness and abundance within four major land use and intensity-based classes (primary vegetation, secondary vegetation, low-intensity agriculture and high-intensity agriculture) to climate change. Climate change was estimated as a standardised climate anomaly (SCA) based on past and present temperature values from the Climatic Research Unit Time Series (CRU TS) dataset version 4.03 (Harris, Osborn, Jones, & Lister, 2020). The standardised climate anomaly was calculated as the difference between the grand mean of the mean monthly temperatures of the 12 months preceding the end sample date for each unique sampling location and the mean monthly temperature of the same location, averaged across every month from 1901 to 1905. The climate anomaly was then standardised by dividing it by the standard deviation of the mean monthly temperatures between 1901 and 1905 at the site. This standardisation removes the effect of the variability of temperatures in temperate regions, where species tend to experience a broader range of temperatures in these locations in comparison to the more stable temperatures experienced in the tropics. This standardising by historical variability makes it possible to observe those regions where present-day temperatures exceed this variability.

The effect of this standardisation is evident when absolute and standardised warming is compared (Fig. 2). Considering absolute warming, temperate regions have experienced the greatest magnitude of change in temperature relative to the baseline, whereas under the standardised anomaly, the tropics have experienced the most relative warming. Warming tends to be well below one standard deviation of temperature variation in temperate regions, meaning that temperatures stay within ‘normal’ bounds and communities are much less likely to experience novel temperatures. In contrast, warming in tropical areas has often exceeded one standard deviation of temperature variation (Fig. 2), here communities are being pushed towards novel temperature maximums. Many regions have already experienced changes in climate that exceed historic variability.

Biodiversity responses to the standardised climate anomaly were much steeper in human dominated land uses (Fig. 2c). Models predicted that warming equivalent to 1 standard deviation of baseline temperature variation (0 to 1 SCA) would lead to a 52% decline in insect abundance and XX% in species richness (Extended Data Figure ?) in high-intensity agriculture compared to areas of primary vegetation that have not experienced a changing climate. Over the same range, low-intensity agriculture experienced a 28% decline in insect abundance and XX% in species richness (Extended Data Figure ?), while biodiversity in primary and secondary vegetation did not experience declines due to climate change.

There is growing evidence that temperature change relative to historical variability is a key driver of biodiversity loss (Bonebrake and Deutsch, 2012; Mora et al., 2013; Soroye, Newbold and Kerr, 2020; Trisos, Merow and Pigot, 2020). Our study builds on this, by linking this standardised temperature change to land use and land-use intensity. As agricultural landscapes have a reduced availability of microclimates (González del Pliego et al., 2016) and higher local temperatures than neighbouring primary vegetation (Senior et al., 2017), novel temperature environments for insect species may emerge faster within agricultural and intensely used landscapes than in natural habitat, explaining the steeper rates of decline with climate change seen here. This is supported by work showing that insects depend on thermoregulatory behaviour to access thermally buffered microhabitats (e.g. shade) to survive the warmest parts of the year (Sunday et al., 2014). As land-use change reduces the availability of these buffered microhabitats (González del Pliego et al., 2016), climate change interactions with land use are likely worse in more intensified landscapes. If species don’t have access to microhabitats in high-intensity landscapes, they may be unable to survive climate warming and associated extreme temperature environments (Sunday et al., 2014; Suggitt et al., 2018).

It was possible that the responses observed here were being driven by communities in the tropics being more sensitive to land-use change. To test this…

This is the first study to explicitly link land use and climate change interactions with insect biodiversity declines at the global scale. A recent meta-analysis by van Klink *et al.,* (2020) describing global insect declines was unable to find a link between local temperature changes and insect declines, this may be because they did not consider the potential for land use and climate interactions, or because temperature change was not standardised to historical variability, as it was here.

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| ***Figure 2: Response of insect abundance across land uses to the standardised climate anomaly.*** *Reference…. Lines…. Shaded areas… 95% of anomaly range.* |

## Buffering effect of natural habitat

Recent evidence has shown that landscapes with more natural habitat can protect against the detrimental effects of climate change, by reducing or reversing the associated rate of biodiversity decline (Northrup et al., 2019, Betts et al., 2018), or resisting climate induced shifts in community composition (Hendershot et al., 2020). However, work so far has considered birds only and was regional in scope. There is a need to test these patterns at the global scale, and to test whether they apply to insects. To do this, we used a global gridded dataset of estimates of fractional cover of natural habitat at a XX by XX resolution (Hoskins et al. 2016) to assess whether biodiversity declines associated with climate change were buffered in sites that have a greater proportion of natural habitat in the surrounding landscape.

We found that natural habitat buffers against the detrimental impacts of climate change, but only in low-intensity agriculture (Fig. 3). This buffering effect was highest when there was a greater fractional cover of natural habitat surrounding the site. For example, in low-intensity agriculture surrounded by a high fractional cover of natural habitat (70%) insect abundance declined by XX% compared to declines of XX% when only 20% natural habitat were present. In contrast, high-intensity agriculture experienced abundance declines in response to climate change regardless of the fractional cover of natural habitat available. A similar pattern was observed for changes in species richness (Extended Data Figure ?).

If biodiversity change in agricultural systems can be mitigated by the presence of nearby natural habitat, it is likely that benefits for agricultural production, through the greater provision and resilience of ecosystem services, as well as for conservation will be possible. These findings promote the idea that to maintain biodiversity within agricultural systems, a land sharing (rather than land sparing) approach would be more beneficial. This is supported by work undertaken at local scales [REFS]. As the global demand for food increases, it is likely that the expansion of agricultural systems will continue. This could further reduce the availability of natural habitat within production areas, exacerbating the associated negative impacts of biodiversity loss, if options such as land sharing within agricultural systems are not implemented.

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| ***Figure 3: The response of total abundance to climate change across sites with differing levels of nearby natural habitat.*** *Each panel presents responses within that land use-intensity class, with a line and associated 95% confidence intervals for each set percentage of nearby natural habitat.* *The reference point for modelled responses was Primary vegetation sites with a standardised climate anomaly value of 0 and 100% nearby natural habitat.* |

## Future change in insect diversity

* These analyses based on years in recent past
* Climate change continued, with some areas experiencing even greater anomalies (2018 map), add in some values as examples?
* Our analyses indicate that serious declines in insect diversity have occurred as a result.
* With warming set to continue, areas affected by climate change exceeding 1 SCA will expand (2070 map)
* Clearly, changes need to be made to the way land is managed so that insect diversity can continue to be supported in agricultural systems.

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| ***Figure 4: Maps of the standardised climate anomaly for the years 2018 and 2070.*** |

As with any correlative study, this study cannot directly identify the mechanisms behind the strong relationships with the standardised anomalies. Future work that directly measures different aspects of microclimate between land uses and use-intensities in locations undergoing different rates of climate change could identify mechanistic relationships underlying land use and climate interactions. This study also did not include other aspects of climate, such as precipitation; studies that include more climate variables and finer scale land use/use-intensity data might be able to identify more accurately which parts of the globe are most at risk from the detrimental impacts of climate and land-use change interactions. The median sample date of PREDICTS is also 2005, indicating that significantly greater warming and negative impacts on insect diversity may have taken place since that we have not detected here.

* Testing of results using different baselines for the anomaly…

## Conclusions

Recent studies have shown the ongoing declines of insects across scales. Here, we start to uncover the global-scale drivers of these declines by assessing the effect of land use, land-use intensity, climate change and their interactions. Insect total abundance was XX% lower in high intensity agriculture than in primary vegetation, highlighting the detrimental effects of agricultural production, with less severe declines in low-intensity agriculture. Climate change reduced insect diveristy in agricultural systems, with the greatest impact in high-intensity agriculture, likely due to the hotter and drier systems created as a result of the combination of drivers. Importantly, we show that this negative impact can be buffered against to some degree depending on the availability of nearby natural habitat, but only for low-intensity agricultural sites. Insect biodiversity is essential for many ecosystem functions and services, including key services for agriculture. Ensuring these services remain available in agricultural landscapes will benefit both people and nature. The ability of natural habitat availability to buffer against the negative impacts of climate change in low-intensity agriculture, presents a management option that can be put in place to prevent further declines in the future, or restore biodiversity into certain areas.

Maintaining biodiversity into the future is key since climate change and land use change impacts are likely to continue or increase as the global demand for food increases. The fact that many regions of the world have already experienced 1 standard deviation of climate warming compared to historic variability, with species experiencing novel high temperatures as a result, is concerning. Aiming to reduce future warming, whilst putting measures in place to mitigate the impacts on biodiversity where possible should be an immediate goal for the global community.

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## Tables

## Figure Legends

## Methods

### Biodiversity data - PREDICTS

The PREDICTS database is an aggregation of spatial comparisons of local biodiversity across land uses from across the terrestrial regions of the world (Hudson et al., 2017, 2016). These samples are taken from both published and other sources and include measures of species abundance, presence/absence and richness for a wide range of taxa. The most recent release includes data from 666 studies with measures of biodiversity from across land uses and across land-use intensities. The data within PREDICTS are organised hierarchically: Studies contain data that were collected using the same methodology from one or more than one spatial Blocks. Within these Blocks, data may then be collected from various Sites which have an associated geographical coordinates (Hudson et al., 2014).

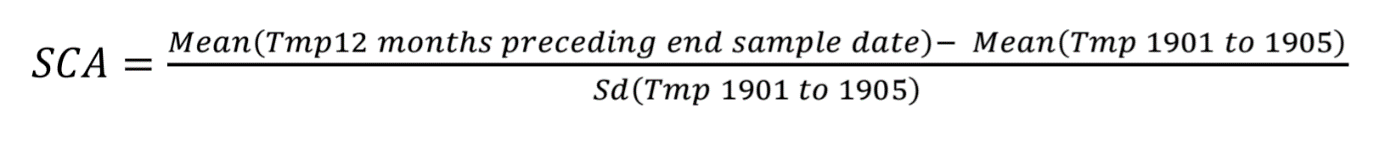
For this study, we used the data for insects only, by subsetting the PREDICTS database by class = “Insecta”. Within-sample species richness was calculated as the total number of species sampled at a site, while total abundance was the sum of all abundance measurements at a site where available. Where samples needed to be corrected for sampling effort, sampling effort was scaled for each study so that the highest sampling effort had a value of 1. The abundance measurements were then divided by this measure of relative sampling effort. Here, we assume that recording effort scales linearly with sampling effort (Newbold et al., 2015). The abundance values in our PREDICTS insect subset were highly skewed, to reduce the impact of this skew on our analysis abundance values were scaled. Within each study, abundance values were scaled between 0 and 1 where the highest abundance value was set to 1 and remaining values rescaled relative to the maximum value.

The PREDICTS database has 8 land use classifications based on the predominant land use (as described by the authors of the original study) at the site location: primary vegetation, young secondary vegetation, intermediate secondary vegetation, mature secondary vegetation, cropland, pasture, plantation forest and urban which are further sub-divided into three use intensities: minimal, light and intense. For this study, sites were pooled into four land use/use intensity classes based on combinations of these original PREDICTS classifications so that there were enough sites to investigate interactions between land use, use intensity, climate change and the amount of landscape natural habitat. These classifications were: primary vegetation, secondary vegetation, low-intensity agriculture and high-intensity agriculture. For the agricultural sites (including Cropland, Pasture and Plantation), PREDICTS definitions that had high pesticide input were deemed high-intensity agriculture, if pesticide input was uncertain, sites that were in monoculture were deemed high-intensity agriculture. If the site was unlikely to have significant inputs of pesticides and was not in monoculture, then it was deemed low-intensity agriculture (See Supplementary Table 1 for PREDICTS definitions and reclassification). The factors were chosen because both pesticide input and monoculture are relevant aspects of use-intensity that are extremely likely to influence insect biodiversity.

### Climate anomaly data

The standardised climate anomaly metric was based on mean annual temperatures and their standard deviation. Local climate estimates were obtained from the Climatic Research Unit Time Series (CRU TS) v4.03 (Harris et al., 2020). This dataset provides mean daily temperature for every month since 1901 (12 measurements per year). The climate anomaly was calculated as the difference between the grand mean of the mean monthly temperature of the 12 months preceding the end sample date of the PREDICTs data and the mean monthly temperature of the same location averaged across every month from 1901 to 1905. The climate anomaly was then standardised by dividing it by the standard deviation of the mean monthly temperatures between 1901 and 1905 (Equation 1). For reference, places with a SCA of 1 have experienced warming since 1901 equal to the standard deviation of mean monthly temperatures of 1901 to 1905, indicating considerable forcing towards novel temperatures for any given location.

**Equation 1:** Calculation of Standardised Climate Anomaly from CRU V4.03. Tmp = Mean Daily Temperature (In CRU dataset one measurement for each month since 1901)



(1)

Where *Tmp1…12* are the mean monthly temperature estimates for either the 12 months preceding the sample date (*t-12*) or for all months in the years 1901 to 1905.

Similarly, the Standardised climate anomaly based on maximum monthly temperatures was determined ….

(2)

### Percentage Natural Habitat data

Percentage natural habitat estimates were obtained from an openly available dataset (Hoskins et al., 2016). This dataset has global maps of fractional cover for primary and secondary vegetation at 30 arc-seconds resolution (1 x 1km at the equator) for the year 2005 and was derived by statistically downscaling the land-use data. The median sample year for insect sites in PREDICTS is also 2005, reducing the likelihood of large differences in percentage natural habitat between the time the PREDICTS sample was collected and the value used in the analysis. To calculate the fractional cover of primary and secondary vegetation (natural habitat) around each sampling location in PREDICTS a circular buffer, with a radius of 5km, was created around the coordinates of each sampling location using the *buffer* function in the *raster* R package(Hijmans, 2018) version 3.0-12. This buffer was used to crop the primary and secondary vegetation layers and the mean fractional cover of primary and secondary vegetation from all grid cells within the buffer was extracted. Finally, the proportion primary and proportion secondary were summed to calculate the proportion of natural habitat surrounding each sampling location.

### Statistical analysis

Generalized linear mixed effects models were constructed for insect abundance following the methods of Zuur et al., (2010) for data exploration. Mixed effects models were constructed using the *lme4* R package version 1.1-21 (Bates, Maechler, Bolker, & Walker, 2015). Random effects were needed to account for the hierarchical structure of the PREDICTs database. Total abundance values were log(x+1) transformed to allow construction of linear mixed models. Poisson models for total abundance values in PREDICTS could not be constructed because not all data in PREDICTS are true count data, for example many total abundance values in PREDICTS are density data. The fixed effect terms were the standardised climate anomaly, land-use class and the proportion of natural habitat in the 5km buffer. Random effects terms used were the identity of the study from which the data were taken (accounting for between study differences in sampling) and the spatial block within the study which the site was nested within (accounting for geographic variation within a study). These random effect structures are consistent with other studies using the PREDICTS database (Newbold et al., 2015)

We made models for species richness and scaled abundance with only three combinations of fixed effect structures testing three explicit hypotheses:

1. (~Land): Intensification of agricultural landscapes reduces insect biodiversity

2. (~Land \* Standardized Climate Anomaly): Declines due to climate change will be steeper in landscapes that have experienced more human intensification

3. (~ Land \* Standardised Climate Anomaly \* Percentage Natural habitat): Natural habitat Can buffer against the detrimental effects of climate change on insects.

To minimize the effect of collinearity, predictor variables were rescaled and centered before constructing models by subtracting the mean of the predictor and dividing by the standard deviation. We then checked for collinearity by calculating variance inflation factors for each parameter in the models. We checked for spatial autocorrelation in the residuals of models using a permutation test for Moran’s I using the R package spdep version 1.1-3 (Bivand and Wong, 2018). This was done for all residuals, as well as for residuals grouped by study.

Species richness if we want this

#### Model 1…land use and use intensity

#### Model 2… LU + UI + climate + percNH + interactions

Model checking – *sentence in methods, plots etc in supplementary.*

* QQPlots
* Residuals Vs fitted
* Residuals by land use and Residuals against Climate anomaly (homogeneity of variance)
* Variance inflation factors, correlation of fixed effects collinearity

### Testing different baselines

* *Add in info here when available on the testing of different baseline times and length.*

## Data availability statement

## Code availability statement

The code required to rerun the analyses presented here is available on Github (*add URL*).

## Methods references

## Acknowledgements

## Author contributions

## Supplementary Material

## Competing interest declaration

There are no competing interests.

## Additional information