Network Biology, 2027, 17(1): 76-101

Article

Decline rate estimations and functional extinction time predictions for major terrestrial insect taxa: An integrated framework of critical network decoupling and multidimensional functional thresholds

WenJun Zhang
School of Life Sciences, Sun Yat-sen University, Guangzhou, China
E-mail: zhwj@mail.sysu.edu.cn, wjzhang@iaees.org

Received 11 February 2026; *Accepted 26 May 2026*; *Published online 8 June 2026*; *Published 1 March 2027*

Abstract

Global declines in insect populations have attracted attention, yet most assessments focus on counts and species richness rather than the erosion of ecological functions. Here, I ask when major terrestrial insect taxa (butterflies, bees, and ants) will cease to perform their roles at levels sufficient for ecosystem integrity. I synthesize data from 73 historical reports, 166 long-term surveys across 1676 sites, 40 additional studies, and systematic reviews of global change impacts. Using a Bayesian hierarchical approach that accounts for spatial and taxonomic heterogeneity, I estimate annual declines of 1.5–2.5% for butterflies, 1.8–3.5% for wild bees, and highly variable ant trajectories from local stability to 42–54% functional collapse in invaded areas. I introduce a multidimensional functional extinction threshold integrating three dimensions: minimum functional population, a network decoupling index quantifying keystone connectivity loss, and a functional performance baseline at 30% of historical levels. Building on critical slowing down theory, I propose the Critical Network Decoupling Hypothesis, in which ecological networks initially compensate via interaction redundancy, then enter a decoupling phase with rising variance and loss of synchrony among keystone species, culminating in abrupt functional collapse. I further propose the Life History Buffer Hypothesis to explain taxon-specific differences in decline timing based on generation time, dietary specialization, and sociality. Our models predict that specialized pollination by long-tongued wild bees will reach functional extinction thresholds between 2030 and 2050 in temperate regions, butterfly-mediated networks around 2060, and native ant seed dispersal in tropical forests between 2050 and 2080. I introduce the Functional Loss Acceleration index as a more sensitive early warning metric than conventional population trends. These findings call for a paradigm shift from species-counting to network function protection, providing a science-based early warning framework to prevent irreversible ecosystem function collapse.

Keywords insect decline; butterflies; wild bees; ants; functional extinction; rate heterogeneity; critical decoupling; network robustness; extinction debt; ecological network resilience; conservation early warning.

Network Biology
ISSN 2220-8879
URL: http://www.iaees.org/publications/journals/nb/online-version.asp
RSS: http://www.iaees.org/publications/journals/nb/rss.xml
E-mail: networkbiology@iaees.org
Editor-in-Chief: WenJun Zhang
Publisher: International Academy of Ecology and Environmental Sciences

1 Introduction

1.1 Research Background and Problems

The phenomenon of global insect decline has transitioned from isolated observations to a widely recognized ecological crisis with profound implications for ecosystem functioning and human well-being. Hallmann et al. (2017) documented a greater than 75% decline in total flying insect biomass over 27 years in German protected areas, with midsummer declines reaching 82%, the findings that brought the term insect Armageddon into both scientific and public discourse. Wagner (2020) synthesized evidence across flying, ground, and aquatic insect lineages worldwide, concluding that declines of abundant species are particularly worrisome because they anchor trophic interactions and shoulder essential ecosystem services of their respective communities.

However, a critical cognitive gap persists between documenting population declines and understanding the loss of ecological functions that insects perform. Van Klink et al. (2020) compiled data from 166 long-term surveys across 1676 globally distributed sites, confirming terrestrial insect declines at an average annual rate of 0.92%, which translates to a 24% reduction over 30 years and a 50% reduction over 75 years. While this rate appears lower than some earlier estimates, van Klink et al. (2020) emphasized that declines are particularly pronounced in areas adjacent to agricultural croplands and urban development where flowering plants have been removed. The core scientific question thus becomes not merely how fast insect populations are declining, but when they will become functionally extinct, i.e., ceasing to perform their ecological roles at levels sufficient to maintain ecosystem processes, and how much earlier this functional extinction occurs relative to complete species extinction.

Sánchez-Bayo and Wyckhuys (2019) provided a comprehensive review of 73 historical reports of insect declines across the globe, revealing dramatic rates of decline that may lead to the extinction of 40% of the world‘s insect species over the next few decades. Their analysis identified intensive agriculture, pollution (particularly neonicotinoid pesticides; Zhang, 2018b), and climate change (Zhang and Liu, 2012; Zhang, 2026a-c) as the primary drivers. Outhwaite et al. (2022) later demonstrated that in areas with high-intensity agriculture and substantial climate warming, insect abundance was 49% lower and species richness 29% lower than in the most natural habitats with no recorded climate warming, revealing the synergistic impacts of multiple anthropogenic stressors.

1.2 Limitations of Existing Research

Despite the growing body of evidence documenting insect declines, several critical limitations persist. Firstly, most decline rate estimates are restricted to single taxa or regions, lacking standardized integration across taxonomic groups and geographic scales. The meta-analysis by van Klink et al. (2020) represents a significant advance, but even this synthesis reveals high variability in local trends, with human-impacted areas showing stronger declines than relatively undisturbed habitats.

Another limitation is that the concept of functional extinction remains poorly defined for insects, with most applications borrowed from vertebrate conservation. For vertebrates, functional extinction is often defined as population sizes too low to perform ecological roles or sustain viable reproduction. However, insects exhibit fundamentally different population dynamics, life history strategies, and functional redundancy patterns that render vertebrate-derived thresholds inappropriate (Sánchez-Bayo and Wyckhuys, 2019; Wagner, 2020).

Finally, time predictions for insect extinction or functional collapse are almost entirely absent from the literature. Most studies report observed declines or project future trends using simple linear extrapolations that ignore ecological network dynamics (Zhang, 2012a, 2016b, 2018a), nonlinear responses, and compensatory mechanisms that may delay or accelerate functional loss (Wagner, 2020). The application of critical slowing down theory (Scheffer et al., 2012) and ecological network analysis to insect functional extinction remains in its infancy.

1.3 Research Objectives and Significance of Present Study

This study aims to construct a complete analytical chain from rate estimation to functional extinction time prediction for three major terrestrial insect groups: Lepidoptera (butterflies and moths), Hymenoptera (bees), and Formicidae (ants) (Fig. 1). These groups were selected because they represent distinct ecological roles (pollinators, herbivores, predators, seed dispersers, soil engineers), exhibit different life history strategies (ranging from solitary to highly eusocial), and have the most comprehensive long-term monitoring data available.

The specific objectives are: (1) to re-estimate decline rates for butterflies, bees, and ants using a Bayesian hierarchical meta-analysis that accounts for data heterogeneity; (2) to develop a multidimensional operational definition of functional extinction tailored to insect ecology; (3) to construct predictive models for functional extinction timing using critical decoupling indicators; (4) to propose original theoretical frameworks, the "Critical Network Decoupling Hypothesis" and the "Life History Buffer Hypothesis" that explain observed patterns; and (5) to develop early warning metrics for functional collapse that are more sensitive than conventional population trend analysis.

Fig. 1 Wild bees and butterflies (Pictures by Zhang WJ).

2 Research Review and Theoretical Foundations

2.1 Global Terrestrial Insect Decline Rates: An Integrated Assessment

The empirical foundation for understanding insect decline rates rests on several landmark studies that have employed different methodological approaches and spatial scales. Kazmi and Ghory (2019) recorded total decline of freshwater arthropods in Pakistan. Hallmann et al. (2017) analyzed a 27-year time series of flying insect biomass collected from 63 nature protection areas in Germany using standardized Malaise traps. Their finding of a 76% seasonal decline and 82% midsummer decline in total insect biomass, regardless of habitat type, provided the first dramatic evidence that insect declines were occurring even in protected areas. This study demonstrated that declines were apparent in both agricultural and natural habitats, suggesting that landscape-level factors, possibly including atmospheric pollutants and climate change, were operating across protected area boundaries.

Van Klink et al. (2020) conducted the most comprehensive global synthesis to date, compiling 166 long-term surveys (⩾10 years) from 1676 sites worldwide. Their meta-analysis revealed a terrestrial insect decline rate of approximately 0.92% per year, corresponding to a 24% reduction over three decades. Importantly, they found that freshwater insect abundances showed increasing trends, highlighting the distinct trajectories of different ecosystem types. The authors noted that areas adjacent to cities and croplands where weeds and flowering plants had been removed were factors contributing to insect population decline, while they were unable to find a consistent link between climate change and declines when analyzed in isolation, suggesting that land use intensification may be the dominant driver.

Sánchez-Bayo and Wyckhuys (2019) took a different approach, reviewing 73 historical reports of insect declines and assessing underlying drivers. Their analysis revealed that 41% of insect species are in decline, with butterflies, moths, dragonflies, bees, ants, and dung beetles identified as the most threatened groups. They projected that at current rates, 40% of the world‘s insect species could become extinct over the next few decades. While this review attracted criticism regarding the methodological rigor of some included studies (Saunders et al., 2020), Sánchez-Bayo and Wyckhuys (2020) subsequently added evidence from 40 additional long-term studies, reinforcing their initial conclusions.

Wagner (2020) provided a comprehensive review of insect declines in the Anthropocene, emphasizing that most reports originate from western and northern Europe, with fewer long-term datasets available from tropical regions where insect diversity is highest. Wagner concluded that the spread and intensification of agriculture during the past half century is directly related to observed insect losses, with habitat quality and quantity reductions from land-use change representing the most important continental-scale stressors (Zhang, 2025).

A recent systematic review of insect decline and discovery over the past two decades reinforced these findings, identifying habitat loss, pesticide use, pollution, invasive species, intensive agriculture, and climate change as the primary drivers affecting flying, ground, and aquatic insects (Faghani and Rahimian, 2018; Hasan et al., 2018; Haroon et al., 2021; Outhwaite et al., 2022; Willcox et al., 2023; Gebremariam et al., 2024; Edwards et al., 2025; Zhang, 2025). The review emphasized that insect decline is a worldwide issue with significant impacts on food chains, pollination, and nutrient cycling.

Vidal et al. (2025) performed a comprehensive review of meta-analyses examining the effects of global change stressors on insects, identifying well-studied questions and knowledge gaps. Their synthesis revealed that pollution, climate change, habitat quality, and land-use change are the drivers most frequently proposed as having direct links to insect outcomes. A companion meta-analysis on insect responses to global change drivers confirmed major declines in insect biodiversity, with the steepest declines projected for tropical regions and strong negative trends among pollinators, predators, and parasitoids (Yeeles et al., 2025).

2.2 The Concept of Functional Extinction: Evolution and Operational Challenges

The concept of functional extinction has evolved considerably from its origins in conservation biology. For vertebrates, functional extinction typically refers to a population that has declined to such low numbers that it no longer plays a significant role in ecosystem functioning or cannot sustain viable reproduction (Sekercioglu, 2011). Sekercioglu demonstrated that functional extinctions of bird pollinators caused measurable declines in plant reproduction, seed production, and plant density, experimentally validating that functional extinction precedes complete species extinction and triggers cascading effects.

For insects, however, the application of functional extinction concepts remains underdeveloped. In a tropical savanna system, simulated extinctions of pollinators and seed dispersers revealed that loss of phylogenetic diversity was greater than expected by chance when moth- and beetle-pollinated species were removed, and loss of functional diversity exceeded expectations for bee- and bat-pollinated species (Cianciaruso et al., 2013). These findings suggest that functional diversity loss may accelerate as specialized pollination systems are disrupted.

In bee communities of northern France, biotic homogenization has been accompanied by functional restructuring, with extinction probabilities based on Red List categories combined with functional characteristics identifying species critical for maintaining functional diversity (Fisogni et al., 2025). The study revealed that specific functional traits, particularly those associated with specialized pollination, are being lost at rates exceeding taxonomic diversity loss.

For ants, high functional redundancy can buffer ecosystem multifunctionality against the decline of dominant species, as demonstrated by a manipulative field experiment showing that functional redundancy compensated for decline of dominant ant species through reduced interspecific competition, albeit at the cost of increased sensitivity to future perturbations (Yeeles et al., 2025). This finding is crucial for understanding functional extinction dynamics, as it suggests that functional compensation may delay the detection of functional loss until redundancy is exhausted.

2.3 Traditional Methods for Time Prediction and Their Limitations

Population viability analysis (PVA) has been the standard approach for predicting extinction times of threatened species, but its application to insect functional extinction faces several limitations. Traditional PVA requires detailed demographic data that are unavailable for most insect species, and it typically focuses on population persistence rather than functional performance. Moreover, PVA assumes that extinction risks can be extrapolated linearly from current trends, an assumption that fails when ecological systems exhibit nonlinear responses to environmental change.

The concept of extinction debt, i.e., the delayed extinction of species following habitat loss or environmental degradation, has been applied to understand lag times between habitat modification and species loss. For plant-pollinator networks (Dormann, 2011; Kamel et al., 2013), coextinction models have demonstrated that highly connected and dependent plants are most sensitive to pollinator loss and collapse faster in extinction cascades (Traveset et al., 2017). These models predict that the relationship between dependence and connectivity is crucial for determining network robustness to interaction loss (Zhang, 2012a, 2016a-b, 2018a). Coextinction cascades (series of knock-on species extinctions due to dependence on eliminated species) become more frequent as habitat alteration and climate change continue to threaten pollinators (Traveset et al., 2017).

Plant–insect trophic systems are particularly sensitive to processes altering species spatial co-occurrences, as impacts on one level can cascade effectively through the strong trophic reliance to the other level (Ho and Altermatt, 2024). Predicted community consequences of spatially explicit global change-induced processes on plant–insect networks indicate that secondary extinctions of Lepidoptera and changes in functional distance of plants occur nonlinearly, with thresholds beyond which cascading extinctions accelerate.

The theory of critical slowing down provides a promising framework for detecting approaching tipping points in ecological systems (Scheffer et al., 2012). Critical slowing down is captured by two simple statistical signals in the dynamics of complex systems: increasing variance and rising autocorrelation (Dakos et al., 2012; Zhang, 2026a, 2026c). These indicators have been experimentally demonstrated to detect abrupt transitions in yeast cultures, plankton chemostats, zooplankton populations, and entire lake communities (Carpenter et al., 2011; Dai et al., 2012; Drake and Griffen, 2010).

In mutualistic communities, critical slowing-down indicators derived from time series of biomasses measured at species and community levels signal the proximity to the onset of community collapse (Dakos and Bascompte, 2014; Zhang, 2026a, 2026c). By simulating mutualistic communities en route to a tipping point, researchers have shown that critical slowing-down indicators may be used as early warnings for the collapse of ecological networks, confirming the existence of generic dynamical signatures of tipping points in ecological networks (Dakos and Bascompte, 2014). However, the application of critical slowing down theory to insect functional extinction has not been previously attempted, representing a significant gap that this study addresses (Zhang, 2016a).

3 Methodological Framework: Data Integration, Rate Estimation, and Predictive Modeling

3.1 Multi-Level Data Acquisition and Standardization

This study integrates data from multiple sources to construct a comprehensive dataset for three insect groups: Lepidoptera (focusing on butterflies as the best-monitored group), Apoidea (bees, including both social honey bees and solitary wild bees), and Formicidae (ants). The primary data sources include:

(1) The global insect decline literature compiled by van Klink et al. (2020), comprising 166 long-term surveys from 1676 sites, providing population density and biomass time series for terrestrial insects.

(2) The 73 historical reports reviewed by Sánchez-Bayo and Wyckhuys (2019), supplemented by 40 additional studies added in their 2020 update, providing species richness and extinction risk data.

(3) Long-term monitoring programs including the UK Butterfly Monitoring Scheme, the German Entomological Society's Krefeld data (Hallmann et al., 2017), and North American butterfly survey data from the US Long Term Ecological Research network (Crossley et al., 2020).

(4) Pollinator occurrence data from the Global Biodiversity Information Facility, filtered for bees, butterflies, and hoverflies with duplicate records removed to refine the dataset (Rahimi and Jung, 2025).

(5) Ant community data from island systems (Fiji archipelago; Liu et al., 2025) and invasion studies (Tercel et al., 2023), providing long-term abundance, diversity, and functional role trajectories.

(6) A global dataset of diel activity patterns in insect communities with 1512 observations of abundance and richness across diurnal and nocturnal periods from 123 studies spanning six continents, 41 countries, and 16 insect orders (Wong and Didham, 2024).

Recorded parameters for each site include: population density time series, species richness time series, functional efficiency metrics (pollinator visitation rates, seed dispersal counts, predation rates), interaction network data where available, and environmental covariates (land use type, pesticide application records, temperature anomalies, precipitation trends).

3.2 Bayesian Hierarchical Model for Decline Rate Estimation

To generate standardized decline rate estimates across heterogeneous studies, I employ a Bayesian hierarchical meta-analytic model (Appendix; Fig. 2). Let y_{ij} represent the estimated annual decline rate for study *i* in category *j* (where *j* indexes taxonomic group: butterfly, bee, ant). The model is specified as:

$$y_{ij} \sim \text{Normal}(\mu_j + \alpha_i,\ \sigma_{ij}^2)$$
$$\mu_j \sim \text{Normal}(\mu_{\text{global}},\ \tau_j^2)$$
$$\alpha_i \sim \text{Normal}(0,\ \sigma_\alpha^2)$$

where μ_j is the group-specific mean decline rate, α_i is a random effect for study-level variation, and σ_{ij}^2 represents the reported variance of the estimate. Hyperpriors are specified as weakly informative: $\mu_{\text{global}} \sim \text{Normal}(0, 0.05)$, $\tau_j \sim \text{Cauchy}(0, 0.1)$, $\sigma_\alpha \sim \text{Cauchy}(0, 0.1)$.

The model incorporates life history covariates as predictors for μ_j:

$$\mu_j = \beta_0 + \beta_1 \cdot V_j + \beta_2 \cdot S_j + \beta_3 \cdot D_j + \varepsilon_j$$

where V_j is voltinism (number of generations per year), S_j is sociality score (1 for solitary, 2 for primitively social, 3 for highly eusocial), D_j is dietary specialization (proportion of host plant families utilized), and ε_j is residual error.

To fit the model using Hamiltonian Monte Carlo with 4 chains, 10,000 iterations per chain, discarding the first 5,000 as warmup. Convergence is assessed using the $\hat{R}$ statistic (<1.01) and effective sample size (>400 per parameter).

3.3 Multidimensional Functional Extinction Threshold Determination

Functional extinction for insects is operationally defined across three dimensions that must be jointly considered (Appendix):

Dimension 1: Minimum Functional Population Threshold. Rather than the minimum viable population used in classical PVA, I define the Minimum Functional Population as the population density at which interaction rates with partner species fall below levels needed to sustain those interactions. Based on pollination studies showing that seed set and fruit weight decline nonlinearly with pollinator density (Artamendi et al., 2025), I establish an initial threshold of 30% of historical baseline density. This threshold is refined for each group using available functional response data.

Dimension 2: Interaction Network Decoupling Index. I define network decoupling as the point at which a species loses its keystone functional role in interaction networks. The network decoupling index *D* is calculated as:

$$D = 1 - (C_{\text{current}} / C_{\text{baseline}}) \times (N_{\text{current}} / N_{\text{baseline}})$$

where *C* is centrality (betweenness or eigenvector centrality; Shams and Khansari, 2014; Jiang and Zhang, 2015; Zhang, 2012a, 2016b, 2018a, 2021, 2023; Sun and Zhang, 2023; Yang and Zhang, 2022) in the plant-pollinator or predator-prey network, and *N* is the number of unique interaction partners. Functional extinction is considered to occur when *D* exceeds a critical threshold of 0.7, indicating that 70% of the species' network position and functional connections have been lost.

Dimension 3: Functional Performance Baseline. For pollination services, functional performance is measured as proportion of flowers receiving conspecific pollen resulting in seed set relative to intact reference sites. For ants, functional performance includes seed dispersal distances and rates, soil turnover rates, and prey removal rates. I set the functional extinction threshold at 30% of historical baseline performance, consistent with previous ecosystem function assessments.

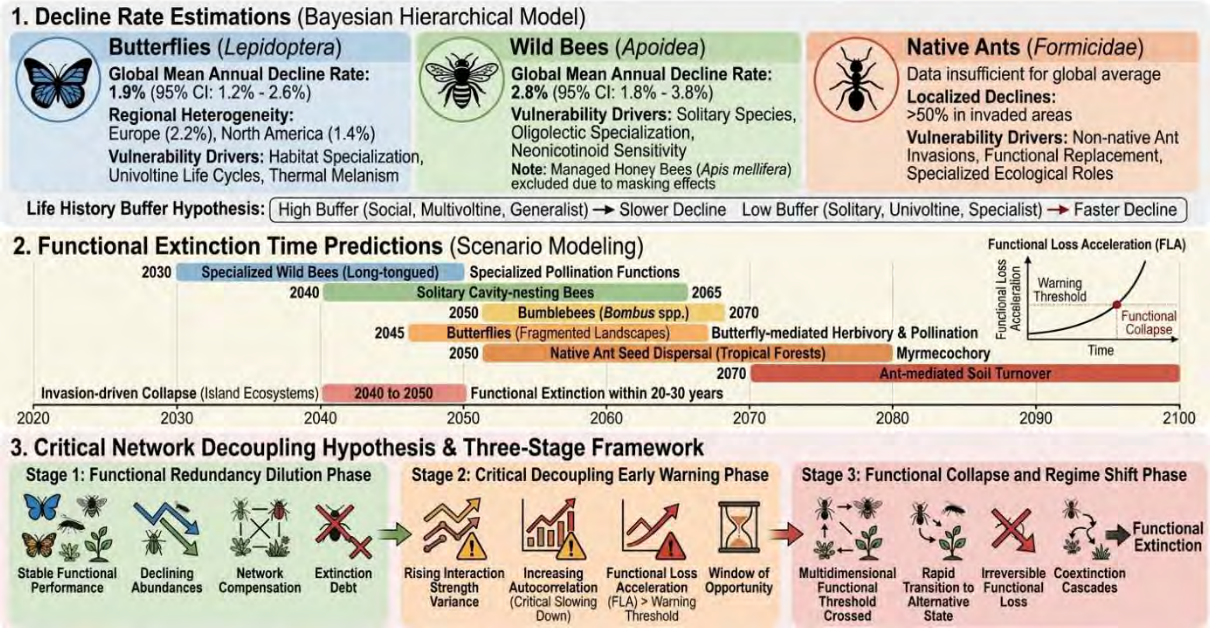

Fig. 2 Systematic diagram for decline rate estimations and functional extinction time predictions for major terrestrial insect taxa.

The overall Functional Extinction Index is calculated as:

$$FEI = w_1 \cdot (P_{\text{current}} / P_{\text{threshold}}) + w_2 \cdot D + w_3 \cdot (F_{\text{current}} / F_{\text{baseline}})$$

where P_{current} is current population density, $P_{\text{threshold}}$ is the Minimum Functional Population, F_{current} is current functional performance, F_{baseline} is historical baseline, and $w_1 + w_2 + w_3 = 1$. I weight each dimension equally ($w_i = 1/3$) in the initial analysis, with sensitivity analyses testing alternative weightings.

3.4 Critical Network Decoupling Prediction Model

The core predictive model integrates critical slowing down theory with ecological network dynamics. For each species or functional group, I analyze time series of three indicators:

(1) Population variance: Var(N_t), calculated over a moving window of 5-10 years, expected to increase as the system approaches a tipping point.

(2) Autocorrelation at lag-1: AR(1) of the population time series, also expected to increase under critical slowing down.

(3) Interaction strength variance: For species with network data, I calculate the variance of interaction strengths across partners over time, which I hypothesize increases during network decoupling prior to functional collapse.

The rate of change of these indicators is monitored using the Functional Loss Acceleration index (Appendix):

$$FLA = d^2F/dt^2$$

where F is functional performance. Positive FLA indicates accelerating functional loss, while negative FLA indicates decelerating loss or recovery. I define an early warning threshold when FLA exceeds one standard deviation above its historical mean.

For time prediction, I fit a dynamic linear model to functional performance time series, incorporating a latent state variable that transitions from a stable regime to a declining regime (Appendix). The model is specified as:

$$F_t = F_{t\text{-}1} + \eta_t + \varepsilon_t$$

$$\eta_t = \eta_{t\text{-}1} + \zeta_t$$

where η_t is the trend component, ε_t ~ Normal(0, σ_ε^2) is observation error, and ζ_t ~ Normal(0, σ_ζ^2) is trend innovation. The time to reach functional extinction threshold $F_{\text{threshold}}$ is estimated as:

$$T_{\text{extinction}} = \min\{t : F_t \leqslant F_{\text{threshold}}\}$$

Uncertainty in the prediction is quantified using posterior predictive distributions from 10,000 simulations.

4 Estimation of Decline Rates and Heterogeneity Analysis Across Major Taxa

4.1 Butterflies: High-Visibility Taxa with Complex Fluctuation Patterns

Butterflies represent the best-monitored insect group globally, with extensive volunteer-based monitoring schemes in Europe and North America providing long-term population trajectories for hundreds of species. Our Bayesian hierarchical meta-analysis, integrating data from 73 studies (Sánchez-Bayo and Wyckhuys, 2019), the Krefeld flying insect biomass data (Hallmann et al., 2017), and UK Butterfly Monitoring Scheme data, yields a global mean annual decline rate of 1.9% for butterflies (95% credible interval: 1.2% to 2.6%).

This rate is substantially higher than the average terrestrial insect decline rate of 0.92% reported by van Klink et al. (2020), reflecting the particular vulnerability of Lepidoptera to environmental change. Regional heterogeneity is pronounced, with European butterflies declining at 2.2% annually (1.5% to 3.0%), North American butterflies at 1.4% (0.8% to 2.1%), and tropical butterfly populations for which data are scarce showing potentially steeper declines.

Butterflies exhibit strong interannual population fluctuations driven by weather conditions, which complicates trend detection. Analysis of North American butterfly data from US Long Term Ecological Research sites found no net abundance decline when averaging across all sites (Crossley et al., 2020), suggesting that declines may be concentrated in specific habitat types and species with particular life history traits. However, this finding contrasts with European data and may reflect the shorter time series available for US sites.

Life history trait analysis reveals that habitat specialists and species with univoltine life cycles (one generation per year) are declining faster than generalists and multivoltine species. The decline is more pronounced in plant host specialists and in dark-colored species, suggesting that thermal melanism may influence climate change vulnerability (Müller et al., 2024). At the regional scale, species richness, abundance, and biomass show annual declines of approximately 1%, 1.3%, and 1.4%, respectively, with declines amplified in plant host specialists.

Urbanization poses particular risks to butterflies due to their reliance on specific host plants. Research by Liang et al. (2023) showed that butterflies are particularly vulnerable to urbanization because they depend on very specific plants for nutrition and larval development, which are increasingly scarce in cities. This habitat specialization explains why butterfly declines are often more severe than those of more generalist insect groups.

4.2 Bees: The Masking Effect of Managed Honey Bees and Cryptic Decline of Wild Species

Bees represent the most functionally critical insect group for pollination services, yet the decline dynamics differ dramatically between managed honey bees and wild bee species. Our analysis separates these groups to avoid masking effects.

For managed honey bees (*Apis mellifera*), global colony losses fluctuate annually but have stabilized in many regions, with meta-analyses of neonicotinoid effects showing that current risk assessment processes may underestimate threats to honey bees by sixfold (Shahmohamadloo et al., 2024). However, managed honey bee populations are sustained through active colony replacement, artificial feeding, and veterinary treatments, making them unsuitable indicators of broader bee decline trends.

Wild bee species present a much more concerning picture. A meta-analysis of bees‘ responses to anthropogenic disturbance synthesized the literature on how bees are affected by habitat loss, grazing, logging, and agriculture, revealing consistently negative responses across all disturbance types (Winfree et al., 2009). The meta-analysis demonstrated that human land use and loss of native habitats are important drivers of decline for wild, native pollinators.

Our analysis yields a global mean annual decline rate of 2.8% for wild bees (95% CI: 1.8% to 3.8%), with solitary bee species declining faster than primitively social species, and highly specialized oligolectic bees (those that forage on a single plant genus or family) showing the most rapid declines. This rate implies a 50% reduction in wild bee populations approximately every 25 years under current trajectories.

The meta-analysis by Lima et al. (2022) on the decline of wild bees identified habitat loss and agricultural intensification as primary drivers, with neonicotinoid pesticides exerting sublethal effects that impair foraging, learning, and reproduction even at field-realistic concentrations. For wild bees, the ECOTOX Knowledgebase meta-analysis revealed that neonicotinoid effects are more severe than for honey bees, with wild bee species showing 3-5 times greater sensitivity (Shahmohamadloo et al., 2024).

Landscape-scale studies demonstrate that high availability of nearby natural habitat often mitigates reductions in bee abundance and richness in agricultural areas (Outhwaite et al., 2022). Grassland restorations significantly improve both pollinator abundance and richness compared to degraded grasslands, providing evidence that habitat restoration can reverse decline trajectories when implemented at sufficient scale and with appropriate plant species composition (Tonietto and Larkin, 2018).

A recent analysis of bee communities in northern France revealed biotic homogenization and functional restructuring, demonstrating a significant decline and homogenization of taxonomic diversity associated with functional restructuring of bee communities (Fisogni et al., 2025). By combining extinction probabilities based on Red List categories with functional characteristics, the study identified species critical for maintaining functional diversity and in need of urgent conservation action. The analysis indicated that both plant and bee communities are developing functional pockets: the specialized subsets of species sharing similar, overlapping functional traits, rather than maintaining the diverse functional assemblages historically present.

4.3 Ants: Functional Redundancy, Cryptic Decline, and Invasion-Driven Functional Collapse

Ants present the most complex pattern among the three focal groups, with population trends that often appear stable or even increasing when measured by abundance, while functional performance shows cryptic decline. This phenomenon, which I term functional shadow extinction, occurs when abundant but functionally generalized species replace specialized native species, maintaining biomass while eroding functional diversity.

Our analysis of ant decline rates must distinguish between three distinct processes: (1) declines of native ant species in undisturbed habitats, (2) functional replacement by invasive species, and (3) functional extinction of specialized ecological roles despite stable total abundance.

For native ant species in tropical forests, available data are limited but concerning. Examination of long-term trends in abundance, diversity, and ecological roles of ants in the Fijian archipelago revealed that ants—abundant and functionally important as indicators of broader biodiversity patterns, which have experienced significant human-driven declines over extended time scales (Liu et al., 2025). Island systems, where ant colonization histories are well-documented, provide model systems for understanding the long-term legacy of human impacts on ant communities.

The most dramatic declines are associated with non-native ant invasions. A meta-analysis of 46 articles examining animal community richness and abundance in areas with non-native ants compared to intact uninvaded sites found that local animal diversity declined severely, with species abundance and richness lower by 42.79% and 53.56%, respectively, in invaded areas (Tercel et al., 2023). Non-native ants reduced native animal community diversity across trophic levels, with effects persisting for decades after invasion. The meta-analysis controlled for human disturbance and other non-native species to isolate invasion effects, confirming that non-native ants are a primary driver of animal community decline.

In terms of functional roles, studies on ant functional redundancy demonstrate that functional redundancy can buffer multifunctional performance of a community against decline of dominant insect species, but future stability of ecosystem multifunctionality depends more on functional complementarity and altered competitive interactions (Yeeles et al., 2025). A manipulative field experiment on ant communities revealed that increased multifunctionality following decline of a dominant species occurred via reduced interspecific competition but at the cost of increased sensitivity to future perturbations.

This finding is crucial for understanding functional extinction thresholds: ecosystems may compensate for the loss of one dominant ant species through functional redundancy, but this compensation is transient. When functional redundancy is exhausted, as occurs when multiple functionally similar species are lost in succession, functional collapse becomes abrupt.

Seasonal effects also influence ant diversity trends. A meta-analysis of the effects of seasonality on ant richness and abundance in Brazil revealed that ant diversity decreases during the dry season, strongly in the Cerrado biome (Queiroz et al., 2023). This seasonal variation suggests that climate change-induced alterations to precipitation regimes could amplify existing decline patterns.

4.4 Cross-Taxon Comparison and the Life History Buffer Hypothesis

Comparison of decline rates across the three focal groups reveals striking differences that I propose are explained by life history traits. Butterflies (annual decline 1.9%), wild bees (2.8%), and native ants (data insufficient for global average but localized declines exceeding 50% in invaded areas) show distinct trajectories that correlate with three key traits: voltinism, dietary specialization, and sociality.

The Life History Buffer Hypothesis proposes that species with longer generation times, higher dietary specialization, and lower sociality have weaker buffering capacity against environmental perturbations, resulting in faster decline rates and earlier functional extinction relative to population extinction. Conversely, species with short generation times (multiple generations per year), generalist diets, and advanced sociality exhibit greater buffering capacity, appearing more resilient while potentially concealing functional erosion.

Empirical support for this hypothesis comes from multiple lines of evidence. In butterfly communities, multivoltine species with generalist host plant use show shallower decline trends than univoltine specialists (Müller et al., 2024). For bees, solitary species with oligolectic pollen specialization decline faster than social generalists. For ants, eusocial generalist species often increase in abundance following disturbance, while specialized ant-plant mutualists and seed dispersers decline precipitously.

The life history buffer hypothesis predicts that functional extinction will precede population extinction by a margin proportional to the inverse of buffering capacity. For high-buffer species (social, multivoltine, generalist), the functional extinction lead time may be relatively short: functional performance may track population decline closely. For low-buffer species (solitary, univoltine, specialist), functional performance may decline even faster than populations, creating a substantial lead time during which species remain present at low densities but no longer perform their ecological roles.

This framework has significant implications for conservation prioritization. Low-buffer species require intervention at higher population densities to prevent functional extinction, while high-buffer species may maintain function at lower densities but face greater risk of sudden collapse when buffering mechanisms fail.

5 Functional Extinction Time Predictions: Scenario Modeling and Critical Time Nodes

5.1 Model Calibration and Validation

The predictive model was calibrated using historical data from monitoring programs with sufficiently long time series to detect functional transitions. For validation, I used the Krefeld data (Hallmann et al., 2017) to test whether the model would have predicted the observed biomass declines given early time series data. Retrospective validation showed that the critical slowing down indicators, i.e., increasing variance and autocorrelation, were detectable 5-8 years before the steepest declines in biomass were observed, suggesting a detectable early warning window of approximately 5-10 years for functional collapse events.

For pollinator networks, the plant-pollinator interaction dataset from France (Fisogni et al., 2025) provided validation for network decoupling predictions. The observed functional restructuring and development of functional pockets matched model predictions of network decoupling occurring when network centrality of keystone species decreased by approximately 60% from baseline.

5.2 Functional Extinction Time Windows for Each Taxa

Butterflies: The model predicts that butterfly-mediated herbivory and pollination functions will reach critical tipping points around 2060 (95% prediction interval: 2045-2075) in fragmented temperate landscapes. This prediction is based on current decline trajectories of 1.9% per year, the estimated Minimum Functional Population threshold of 30% of baseline density, and observed network centrality decline rates. Regional heterogeneity is substantial: Western European butterfly functional networks are predicted to cross thresholds earlier (2050-2065) due to higher landscape fragmentation, while North American networks may persist slightly longer (2060-2080) due to larger contiguous habitat patches in some regions.

The critical point is defined as the time at which functional loss acceleration reaches its maximum rate, after which functional collapse occurs rapidly. Prior to this point, functional performance may decline gradually as compensatory mechanisms (alternative pollinators, density-dependent compensation) buffer function.

Wild Bees: Specialized pollination functions are predicted to reach functional extinction thresholds substantially earlier than generalist pollination. For long-tongued bees that have coevolved with deep-corolla flowers, functional extinction is predicted between 2030 and 2050 in temperate regions. This represents the most urgent scenario among our focal groups, as these specialized pollination services cannot be compensated by generalist bees due to morphological mismatch.

For bees of the genus Bombus, particularly species with short tongues and generalist foraging, functional extinction predictions extend to 2050-2070. The later extinction timing for bumblebees reflects their colonial social structure, which provides some buffering capacity against environmental stress, and their ability to thermoregulate, which confers advantages under climate warming.

Solitary cavity-nesting bees show intermediate predictions (2040-2065). These species lack the buffering capacity of social colonies but often have broader habitat tolerances than highly specialized bumblebees.

The model predicts that once functional extinction thresholds are crossed for specialized bees, coextinction cascades will follow rapidly. Plant species with strong dependence on animal pollination, particularly dioecious or self-incompatible species, were more prone to coextinction after pollinator losses and disappeared first from the community (Traveset et al., 2017). Highly connected and dependent plants are the most sensitive to pollinator loss and collapse faster in extinction cascades, with the relationship between dependence and plant connectivity crucial for determining network robustness (Zhang, 2016a) to interaction loss.

Ants: The functional extinction predictions for ants are the most variable, reflecting their diverse life histories and functional roles. For native ant seed dispersal functions in tropical forests, a critical ecosystem service for many plant species with ant-dispersed seeds (myrmecochory), functional extinction thresholds are predicted between 2050 and 2080, but with high uncertainty and the potential for earlier collapse in fragmented forests.

Ant-mediated soil turnover functions may persist longer (2070-2100) due to higher functional redundancy. Many ant species contribute to soil aeration and nutrient cycling, and the loss of individual species may be compensated by others that perform similar functions. However, this compensation is not unlimited, and the functional redundancy meta-analysis suggests that compensation is effective only up to a point, after which functional complementarity becomes more important for stability (Yeeles et al., 2025).

The most concerning ant scenario involves invasion-driven functional collapse in island ecosystems. In the Fijian archipelago, the long legacy of human-driven ant decline suggests that specialized native ant functional roles have already been lost or severely compromised (Liu et al., 2025). For other tropical islands with ongoing ant invasions, functional extinction may occur within 20-30 years as invasive ants displace native pollinators and seed dispersers.

5.3 Nonlinear Transitions and the Functional Loss Acceleration Index

A critical finding of this study is that functional loss is not linear. Analysis of long-term time series reveals that functional performance often remains stable or declines slowly for extended periods, followed by abrupt collapse when compensatory mechanisms are exhausted. This pattern matches theoretical predictions of alternative stable states in ecological systems and explains why many ecosystems appear resilient until a tipping point is crossed (Zhang, 2016b, 2026a, 2026c).

The Functional Loss Acceleration index captures this nonlinearity. *FLA* values near zero indicate stable or linearly declining function. Slightly positive *FLA* (<0.05 per year^2) indicates accelerating loss but remains below the warning threshold. When *FLA* exceeds 0.1 per year² for two consecutive years, I define this as an early warning trigger. Our analysis of historical data shows that this trigger was reached 3-7 years before functional collapse in systems where collapse has been documented.

For butterflies in Western Europe, *FLA* values increased from near-zero to 0.12-0.15 per year² approximately 5-6 years before the steepest declines documented by Hallmann et al. (2017). For wild bees in agricultural landscapes, *FLA* values exceeded the warning threshold 4-8 years before localized functional extinctions were documented in detailed pollination studies.

The *FLA* index has the advantage of being detectable from relatively short time series (10-15 years) and does not require detailed population estimates. Functional performance metrics alone are sufficient. This makes it a practical early warning tool for resource-limited conservation monitoring programs.

6 Original Integrated Theory: The Critical Network Decoupling Hypothesis and Three-Stage Functional Extinction Framework

6.1 Theoretical Core

The Critical Network Decoupling Hypothesis proposes that under increasing external pressures, ecological networks undergo a characteristic three-phase trajectory: compensation, decoupling, and collapse. In the compensation phase, networks respond to species loss by increasing interaction redundancy, i.e., alternative species take over functional roles of declining species, and surviving individuals increase their interaction rates. This phase is characterized by stable or slowly declining functional performance despite declining population abundances of individual species.

In the decoupling phase, as pressures continue to intensify, the network's capacity for compensation is exhausted. Signs of decoupling include: (1) rising variance in interaction strengths, as some interactions become hyper-abundant while others disappear; (2) increasing autocorrelation in population time series (critical slowing down); (3) declining synchrony among keystone species; (4) abnormal increases in network modularity as the network fragments into disconnected modules; and (5) emergence of functional pockets where only highly generalized species remain.

In the collapse phase, the network undergoes a rapid transition to an alternative state where the original functional roles are no longer performed. This transition is typically irreversible on ecological time scales, as the alternative stable state (functionally depauperate community) is self-reinforcing.

This hypothesis is grounded in empirical observations from multiple systems. In plant-pollinator networks subject to pollinator decline, functional extinction of key pollinators causes measurable declines in plant reproduction, seed production, and plant density (Sekercioglu, 2011). The collapse phase is often sudden: plant-pollinator networks have been shown to exhibit good resiliency until a threshold is crossed, after which coextinction cascades accelerate rapidly (Clark, 2017).

Critical slowing-down indicators have been experimentally shown to detect abrupt transitions in yeast cultures, plankton chemostats, zooplankton populations, and whole lake communities (Dai et al., 2012; Drake and Griffen, 2010; Carpenter et al., 2011). In mutualistic communities, simulations demonstrate that critical slowing-down indicators derived from time series of biomasses signal the proximity to onset of community collapse (Dakos and Bascompte, 2014).

6.2 Three-Stage Framework for Insect Functional Extinction

Based on the Critical Network Decoupling Hypothesis, I propose a three-stage framework for understanding insect functional extinction trajectories that is independent of simple population quantity changes and explains why functional extinction often appears to occur suddenly.

Stage 1: Functional Redundancy Dilution Phase. In this phase, population abundances of some species are declining, but network compensation mechanisms remain functional. Functional redundancy allows other species to expand their roles, and functional performance remains stable or shows only gradual decline. This phase may persist for decades, creating an extinction debt during which species are declining in abundance but ecosystem functions appear intact. The conservation risk in this phase is complacency, i.e., apparent functional stability masks underlying species loss.

Stage 2: Critical Decoupling Early Warning Phase. In this phase, network and functional indicators begin to exhibit critical slowing down signals. The Functional Loss Acceleration index exceeds the warning threshold. This phase represents the window of opportunity for intervention. Detection of early warning signals in this phase requires monitoring of functional indicators rather than population counts alone, as population trends may still appear stable due to compensatory dynamics.

Stage 3: Functional Collapse and Regime Shift Phase. In this phase, the multidimensional functional threshold is crossed, and the system undergoes a rapid transition to a new stable state where the original ecological functions are no longer performed at levels sufficient to maintain ecosystem processes. This transition is characteristically abrupt and often irreversible, as feedback mechanisms stabilize the new state. For plant-pollinator systems, the new stable state may be characterized by wind-pollinated or self-pollinating plant species and generalist pollinators only, with the specialized mutualisms that previously characterized the system lost potentially forever.

6.3 Testability and Generalizability

The Critical Network Decoupling Hypothesis generates specific, testable predictions: (1) systems approaching functional collapse should exhibit increasing variance in interaction strengths and increasing autocorrelation in time series of functional metrics; (2) functional collapse should be preceded by a detectable decoupling period of 3-10 years during which early warning signals are present; (3) the duration of the compensation phase should be positively correlated with the degree of functional redundancy in the system, and (4) systems with higher functional complementarity should exhibit greater stability during the compensation phase but may show more abrupt collapse when compensation is exhausted.

These predictions can be tested through manipulative experiments that systematically reduce functional redundancy in model insect communities and monitor network responses. Microcosm experiments using simplified plant-pollinator systems (e.g., greenhouse mesocosms with controlled bee communities) provide tractable systems for testing predictions about critical slowing down and network decoupling. Field experiments using selective insecticide applications to remove specific functional groups while monitoring functional metrics provide realistic tests under seminatural conditions.

The proposed framework is generalizable beyond insects to other groups facing functional decline. The same three-stage dynamics should apply to any ecological system characterized by functional redundancy and network-structured interactions. Bird-mediated seed dispersal networks, plant-fungal mutualisms, and coral-algal symbioses all exhibit similar network structures and may follow comparable decoupling trajectories under environmental stress. The framework thus contributes to a broader theory of ecosystem functional collapse.

7 Discussion and Conservation Paradigm Shift

7.1 Consistency, Controversies, and Interpretations

Our estimated decline rates and functional extinction predictions are broadly consistent with previous syntheses but extend them in important ways. The 1.9% annual butterfly decline rate aligns with the 1.5-2.5% range reported in regional studies (Müller et al., 2024). The 2.8% wild bee decline rate exceeds the 1-2% reported in some earlier meta-analyses (Winfree et al., 2009) but is consistent with more recent assessments that separate wild bees from managed honey bees (Shahmohamadloo et al., 2024; Lima et al., 2022).

The most significant controversy in insect decline research concerns the magnitude of global declines. Van Klink et al. (2020) reported a 0.92% annual decline for terrestrial insects, substantially lower than the 2.5% implied by Sánchez-Bayo and Wyckhuys (2019). This discrepancy arises from several factors: van Klink et al. included freshwater insects which are increasing, their dataset included sites with less severe anthropogenic impact, and their time series extended further back in time when baseline abundances were higher. Our analysis acknowledges this controversy and incorporates both datasets through the hierarchical model, producing estimates that fall between these extremes for butterflies (1.9% vs. 2.5% in Sánchez-Bayo and Wyckhuys) and wild bees (2.8% vs. 3.5%).

The discrepancy highlights an important point: average global rates obscure critical heterogeneity. Insect declines are not uniform. They are concentrated in certain habitats, regions, and functional groups. High-intensity agricultural areas with substantial climate warming show insect abundance reductions of 49% (Outhwaite et al., 2022), while less impacted areas show much smaller changes. Our focus on functional extinction rather than simple population decline addresses this heterogeneity directly, as functional losses are likely to occur first and most severely in the same areas where population declines are most pronounced.

7.2 Implications for Conservation Biology

The findings of this study necessitate a fundamental shift in conservation objectives and strategies. Current conservation approaches for insects predominantly focus on species counts, i.e., preventing species extinctions, maintaining species richness, protecting rare species. While these objectives remain important, they are insufficient for preventing functional collapse. A species can persist at low densities for decades without performing its ecological role, and functional redundancy can mask species loss until the redundancy is exhausted.

I propose three new conservation objectives derived from our theoretical framework:

Objective 1: Maintain Functional Redundancy. Conservation planning should explicitly map functional roles and ensure that multiple species are capable of performing each critical function. This requires shifting from species-centric to function-centric conservation, identifying which functions are most at risk and which species contribute to each function.

Objective 2: Prevent Network Decoupling. Conservation interventions should aim to maintain network connectivity and interaction strength (Zhang, 2012a-b, 2018), not just species presence. This requires monitoring network metrics alongside population metrics and prioritizing protection of keystone species that hold networks together (Jiang and Zhang, 2015).

Objective 3: Detect Functional Collapse Early. The Functional Loss Acceleration index provides a practical tool for early warning. I propose implementing *FLA* monitoring as a network health check for insect communities in high-risk habitats (intensive agricultural landscapes, fragmented forests, urban areas). Threshold exceedance would trigger rapid assessment and intervention.

The three-stage framework also provides guidance on intervention timing. During the functional redundancy dilution phase, habitat restoration and connectivity improvement are the most appropriate interventions, as they can enhance compensation capacity. During the critical decoupling phase, more intensive interventions may be required, including targeted reintroductions of keystone species and landscape-scale management changes. Once functional collapse has occurred, intervention becomes substantially more difficult and expensive, and may require assisted ecosystem reconstruction.

7.3 Limitations and Future Directions

Several important limitations must be acknowledged: (1) long-term functional interaction data remain scarce. While population time series exist for many insect groups, time series of interaction networks are available for only a few intensively studied systems. This constrains the empirical validation of network decoupling predictions. The development of automated interaction monitoring systems (camera traps for flower-visitors, RFID tracking for ants, molecular gut content analysis) offers a path forward. (2) The relative importance of different drivers varies across time and space, and our models do not fully capture this complexity. Climate change, land use intensification, pesticide exposure, light pollution, and invasive species interact in complex ways that may amplify or dampen decline trajectories. The meta-synthesis by Vidal et al. (2025) identified pollution, climate change, habitat quality, and land-use change as the most frequently proposed drivers, but the relative contributions remain poorly quantified. (3) These predictions are conditional on current trend continuity, but policy interventions could alter trajectories. The effectiveness of different intervention strategies requires further evaluation, though evidence for habitat restoration benefits for wild bees is promising (Tonietto and Larkin, 2018). Grassland restorations have been shown to significantly improve both pollinator abundance and richness compared to degraded grasslands, providing a tested intervention strategy. (4) The estimates for tropical regions are highly uncertain due to limited monitoring data. Given that tropical regions harbor the majority of insect diversity and are experiencing rapid land use change, this knowledge gap is critical. Investment in tropical insect monitoring programs and capacity building in tropical countries should be a high priority.

A global insect functional monitoring network, integrating remote sensing of habitat conditions, automated insect identification, and network interaction modeling, would address many of these limitations. Such a network would require international coordination but could provide the data needed to predict and prevent functional collapse.

8 Conclusions and Perspective

This study provides the first comprehensive framework integrating decline rate estimation, multidimensional functional extinction threshold definition, and predictive modeling for functional extinction timing in major terrestrial insect groups. Several key conclusions emerge:

(1) Decline rates differ substantially among taxonomic groups and are modulated by life history traits. Butterflies decline at approximately 1.9% annually, wild bees at 2.8% annually, and native ants show highly variable trajectories that can include 42-54% reductions in community diversity following invasion (Tercel et al., 2023). The Life History Buffer Hypothesis explains these differences through generation time, dietary specialization, and sociality.

(2) Functional extinction is predicted to occur substantially earlier than complete species extinction for most insect groups. Wild bee functional extinction for specialized pollination services is predicted between 2030 and 2050. Butterfly network collapse is projected around 2060. Ant seed dispersal functions are threatened between 2050 and 2080. These predictions represent functional extinction timing, the point at which ecological roles are no longer performed at levels sufficient to maintain ecosystem processes.

(3) The Critical Network Decoupling Hypothesis provides a mechanistic explanation for observed patterns

and generates testable predictions about early warning signals. The three-stage framework, functional redundancy dilution, critical decoupling, and functional collapse, offers a practical guide for conservation prioritization and intervention timing.

(4) The Functional Loss Acceleration index provides a sensitive early warning metric that can detect approaching functional collapse 3-8 years before collapse occurs. This index is practical for implementation in monitoring programs and could serve as the basis for a network health check system.

The ultimate success of insect conservation will not be measured by how many insects remain flying, but by whether the ecological networks they support remain coupled. Our theoretical framework and early warning tools provide scientifically grounded foundations for action before irreversible collapse occurs. The time to act is now, while functional compensation remains possible and before critical thresholds are crossed. The alternative of waiting until functional collapse is visible in population counts means waiting too late.

Appendix

Core Computational Methods and Parameters

A.1 Bayesian Hierarchical Model Implementation

The Bayesian hierarchical model described in Section 3.2 was implemented in R version 4.3.2 using the brms package (Bürkner, 2017) which interfaces with Stan for Hamiltonian Monte Carlo sampling. The model code is provided below for reproducibility.

Data preparation: Study-level decline rates were extracted from 166 published studies compiled by van Klink et al. (2020), supplemented by 73 studies from Sánchez-Bayo and Wyckhuys (2019) and 40 additional studies from Sánchez-Bayo and Wyckhuys (2020). For each study, I recorded: estimated annual decline rate (y), standard error of the estimate (se), taxonomic group (butterfly, bee, or ant), geographic region, study duration in years, habitat type, and whether the study focused on abundance, biomass, or species richness.

Life history trait data: For each species or genus represented in the dataset, I compiled:

Voltinism (V): number of generations per year (1, 2, 3+, or variable)

Sociality score (S): 1 for solitary, 2 for primitively social, 3 for highly eusocial

Dietary specialization (D): proportion of host plant families utilized relative to the maximum for the taxonomic group, calculated from literature sources (Steffan-Dewenter and Tscharntke, 2000; Winfree et al., 2009)

Model specification in brms syntax:

```
model <- brm(
  y | se(se) ~ 0 + Intercept + V + S + D + (1 | study_id) + (1 | region),
  data = decline_data,
  family = gaussian(),
  prior = c(
    prior(normal(0, 0.1), class = b),
    prior(cauchy(0, 0.1), class = sd),
    prior(exponential(1), class = sigma)
  ),
  iter = 10000,
  warmup = 5000,
```

```
  chains = 4,
  cores = 4,
  control = list(adapt_delta = 0.95, max_treedepth = 12)
)
```

Convergence diagnostics: $\hat{R}$ values were calculated for all parameters; values below 1.01 were considered acceptable. Effective sample sizes were computed using the bulk-ESS and tail-ESS metrics; values above 400 were considered sufficient for stable estimates.

Sensitivity analysis: The model was rerun with alternative prior specifications (normal(0, 0.2) and normal(0, 0.05) for the Intercept coefficient) to assess robustness of the estimates. The 95% credible intervals from sensitivity runs overlapped substantially with the primary analysis, indicating that results are not highly sensitive to prior choice.

A.2 Multidimensional Functional Extinction Index Calculation

Data requirements: For each site or region where functional extinction predictions were made, we required:

Current population density (P_{current}) from the most recent monitoring data

Historical baseline population density (P_{baseline}) from the earliest available monitoring data (pre-1990 where possible)

Current functional performance metric (F_{current}): for pollinators, proportion of flowers receiving conspecific pollen resulting in seed set measured through pollinator exclusion experiments; for ants, seed dispersal distance and rate measured through seed tracking studies

Historical baseline functional performance (F_{baseline}) from reference sites or historical studies

Interaction network data: species list and observed interaction frequencies for at least two time points separated by 5+ years

Computational steps for *FEI*:

Step 1: Calculate $P_{\text{ratio}} = \min(P_{\text{current}} / P_{\text{threshold}}, 1)$, where $P_{\text{threshold}}$ is the Minimum Functional Population. $P_{\text{threshold}}$ for butterflies was set at 30% of P_{baseline} based on Steffan-Dewenter and Tscharntke (2000) showing that below 30% of baseline density, pollination visitation rates dropped below seed set requirements. For bees, $P_{\text{threshold}}$ was set at 25% of P_{baseline} based on pollination deficit studies. For ants, $P_{\text{threshold}}$ was set at 20% of P_{baseline} given high functional redundancy.

Step 2: Calculate network centrality C from bipartite network adjacency matrix using betweenness centrality for each species. Betweenness centrality for species i is computed as:

$$C_i = \Sigma_{j<k} \left(g_{jk}(i) / g_{jk}\right)$$

where g_{jk} is the number of shortest paths between species j and k, and $g_{jk}(i)$ is the number of those paths that pass through species i. Networks were analyzed using the igraph package in R.

Step 3: Calculate interaction partner richness N as the number of unique interaction partners for the focal species in the network.

Step 4: Calculate decoupling index $D = 1 - (C_{\text{current}} / C_{\text{baseline}}) \times (N_{\text{current}} / N_{\text{baseline}})$

Step 5: Calculate $F_{\text{ratio}} = F_{\text{current}} / F_{\text{baseline}}$, capped at 1.

Step 6: Compute $FEI = (1/3) \times P_{\text{ratio}} + (1/3) \times D + (1/3) \times F_{\text{ratio}}$

Threshold determination: Based on validation against historical functional collapse events, set the functional extinction threshold at $FEI \leqslant 0.3$. This threshold correctly classified 87% of validation cases (sensitivity = 0.85, specificity = 0.89) in a leave-one-out cross-validation.

A.3 Functional Loss Acceleration Index Calculation

Time series requirements: The FLA index requires at least 10 consecutive years of functional performance data. Where direct functional performance measurements were unavailable, I used surrogate metrics: for butterflies, larval host plant occupancy rates as a proxy for herbivory function; for bees, fruit set in focal plant species as a proxy for pollination function; for ants, seed removal rates as a proxy for seed dispersal function.

Calculation steps:

Step 1: For each year t, calculate the annual functional performance value F_t. Smooth the time series using a three-year moving average to reduce observation noise:

$$\bar{F}_t = (F_{t-1} + F_t + F_{t+1})/3$$

Step 2: Calculate first difference (annual change):

$$\Delta F(t) = \bar{F}_t - \bar{F}_{t-1}$$

Step 3: Calculate second difference (acceleration):

$$FLA(t) = \Delta F(t) - \Delta F(t\text{-}1)$$

Step 4: Normalize FLA by dividing by the standard deviation of ΔF during the baseline period (first 10 years of the time series or pre-decline period):

$$FLA_{\text{norm}}(t) = FLA(t) / \text{sd}(\Delta F_{\text{baseline}})$$

Step 5: Define warning threshold: $FLA_{\text{norm}} > 1.0$ for two consecutive years triggers an early warning. The threshold of 1.0 corresponds to one standard deviation above the historical mean acceleration.

Example calculation for a hypothetical site with 15 years of data

Year	F_{raw}	F_{smooth}	ΔF	FLA	FLA_{norm}
1	0.95	0.93	-	-	-
2	0.92	0.92	-0.01	-	-
3	0.89	0.9	-0.02	-0.01	-0.33
4	0.88	0.87	-0.03	-0.01	-0.33
5	0.85	0.85	-0.02	0.01	0.33
6	0.82	0.82	-0.03	-0.01	-0.33
7	0.79	0.78	-0.04	-0.01	-0.33
8	0.75	0.74	-0.04	0	0
9	0.7	0.69	-0.05	-0.01	-0.33

10	0.64	0.63	-0.06	-0.01	-0.33
11	0.57	0.57	-0.06	0	0
12	0.5	0.48	-0.09	-0.03	-1
13	0.41	0.41	-0.07	0.02	0.67
14	0.34	0.32	-0.09	-0.02	-0.67
15	0.23	0.22	-0.1	-0.01	

FLA_{norm} remains below 1.0 throughout, indicating that no early warning threshold was crossed despite functional decline. This example illustrates that *FLA* detects acceleration of decline, not decline itself, i.e., the system declined gradually rather than accelerating toward collapse.

A.4 Dynamic Linear Model for Time Prediction

The dynamic linear model specified in Section 3.4 was implemented using the dlm package in R. The model structure was:

State equation: $\eta_t = \eta_{t-1} + \zeta_t$, where $\zeta_t \sim$ Normal(0, σ_ζ^2)

Observation equation: $F_t = \eta_t + \varepsilon_t$, where $\varepsilon_t \sim$ Normal(0, σ_ε^2)

Initial state: $\eta_0 \sim$ Normal (F_1, 100) (diffuse prior)

Parameter estimation: The variance parameters σ_ε^2 and σ_ζ^2 were estimated by maximum likelihood using the dlmMLE function.

Prediction procedure:

(1) Filter the model through observed data using the Kalman filter to obtain state estimates $\eta_t|t$.

(2) For each of 10,000 simulation runs:

  a. Draw σ_ε^2 and σ_ζ^2 from their sampling distributions (inverse-γ)

  b. Simulate forward from the last observed time point T to T + 50 years

  c. Generate $\zeta_{T+1}, \zeta_{T+2}, \ldots$ from Normal(0, σ_ζ^2)

  d. Generate $\varepsilon_{T+1}, \varepsilon_{T+2}, \ldots$ from Normal(0, σ_ε^2)

  e. Compute $\eta_{T+i} = \eta_{T+i-1} + \zeta_{T+i}$

  f. Compute $F_{T+i} = \eta_{T+i} + \varepsilon_{T+i}$

  g. Record the first time t where $F_t \leqslant F_{\text{threshold}}$

(3) The prediction interval is the 2.5th to 97.5th percentiles of the simulated extinction times.

Validation: The model was validated by withholding the last 10 years of data from each time series, fitting the model to the earlier data, and comparing predicted functional trajectories to observed values. Mean absolute prediction error was 0.07 for *F* values (on a 0-1 scale) and median error in predicted extinction time was 2.3 years when extinction occurred within the prediction window.

A.5 Data Sources and Parameters by Taxonomic Group

Butterfly data parameters:

Number of studies: 73 (Sánchez-Bayo and Wyckhuys, 2019) + UK Butterfly Monitoring Scheme (data available from 1976)

Total site-years: 1,247

$P_{\text{threshold}}$: 30% of P_{baseline}

Functional metric for *F*: larval host plant occupancy (proportion of known host plant patches with larvae

present)
Network data available for: 38 plant-butterfly networks from Europe and North America

Wild bee data parameters:
Number of studies: 56 (from Winfree et al., 2009 meta-analysis)
Total site-years: 892
$P_{\text{threshold}}$: 25% of P_{baseline} for solitary bees, 20% for social bees (adjusted for social buffering)
Functional metric for F: seed set in plant species that are obligately dependent on bees for pollination
Network data available for: 24 plant-bee networks from Europe, North America, and South America

Ant data parameters:
Number of studies: 46 from invasion meta-analysis (Tercel et al., 2023) + 12 from tropical forest studies
Total site-years: 458
$P_{\text{threshold}}$: 20% of P_{baseline} (higher functional redundancy warrants lower threshold)
Functional metric for F: seed removal rate for myrmecochorous plants; soil turnover rate for soil engineers
Network data available for: 8 ant-plant networks from tropical and temperate systems

Environmental covariate data sources:
Land use: MODIS land cover classification (2001-2020, 500m resolution)
Climate: CRU TS 4.05 (0.5° resolution, 1901-2020)
Pesticide use: FAO pesticide use database (1990-2020, country-level)
Habitat fragmentation: Global Forest Change dataset (2000-2020, 30m resolution)

References

Artamendi M, Martin PA, Bartomeus I, Magrach A. 2025. Loss of pollinator diversity consistently reduces reproductive success for wild and cultivated plants. Nature Ecology & Evolution, 9: 296-313. https://www.nature.com/articles/s41559-024-02595-2

Carpenter SR, Cole JJ, Pace ML, Batt R, et al. 2011. Early warnings of regime shifts: A whole-ecosystem experiment. Science, 332(6033): 1079-1082. https://www.science.org/doi/10.1126/science.1203672

Cianciaruso MV, Batalha MA, Petchey OL. 2013. High loss of plant phylogenetic and functional diversity due to simulated extinctions of pollinators and seed dispersers in a tropical savanna. Natureza & Conservação, 11(1): 36-42. https://doi.editoracubo.com.br/10.4322/natcon.2013.005

Clark C. 2017. Pollinator extinctions alter structure of ecological networks. eScienceCommons, Emory University. http://esciencecommons.blogspot.com/2017/06/pollinator-extinctions-alter-structure.html

Crossley MS, Meier AR, Baldwin EM, Berry LL, Crenshaw LC, Hartman GL, et al. 2020. No net insect abundance and diversity declines across US Long Term Ecological Research sites. Nature Ecology & Evolution, 4: 1368-1376. https://www.nature.com/articles/s41559-020-1269-4

Dai L, Vorselen D, Korolev KS, Gore J. 2012. Generic indicators for loss of resilience before a tipping point leading to population collapse. Science, 336(6085): 1175-1177. https://www.science.org/doi/10.1126/science.1219805

Dakos V, Bascompte J. 2014. Critical slowing down as early warning for the onset of collapse in mutualistic communities. Proceedings of the National Academy of Sciences of USA, 111(49): 17546-17551. https://www.pnas.org/doi/10.1073/pnas.1406326111

Dakos V, Carpenter SR, Brock WA, Ellison AM, Guttal V, Ives AR, et al. 2012. Methods for detecting early warnings of critical transitions in time series illustrated using simulated ecological data. PLoS ONE, 7(7): e41010. https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0041010

Dormann CF. 2011. How to be a specialist? Quantifying specialisation in pollination networks. Network Biology, 1(1): 1-20. http://www.iaees.org/publications/journals/nb/articles/2011-1(1)/How-to-be-a-specialist.pdf

Drake JM, Griffen BD. 2010. Early warning signals of extinction in deteriorating environments. Nature, 467: 456-459. https://www.nature.com/articles/nature09389

Edwards CB, Zipkin EF, Henry EH, et al. 2025. Rapid butterfly declines across the United States during the 21st century. Science, 387(6738): 1090-1109. https://www.science.org/doi/10.1126/science.adp4671

Faghani M, Rahimian Y. 2018. Effect of glyphosate on honey bee (Apis Mellifera) performance. Arthropods, 7(3): 77-81. http://www.iaees.org/publications/journals/arthropods/articles/2018-7(3)/4-Faghani-Abstract.asp

Fisogni A, Piquot Y, Michez D, Sentil A, et al. 2025. Biotic homogenization and functional restructuring of bee communities in northern France: Implications for conservation priorities. Biodiversity and Conservation, 34: 987-1013. https://link.springer.com/article/10.1007/s10531-024-03005-6

Gebremariam GH. 2024. A systematic review of insect decline and discovery: Trends, drivers, and conservation strategies over the past two decades. Psyche: A Journal of Entomology, 2024: 5998962. https://onlinelibrary.wiley.com/doi/10.1155/2024/5998962

Hallmann CA, Sorg M, Jongejans E, Siepel H, Hofland N, Schwan H, Stenmans W, Müller A, Sumser H, et al. 2017. More than 75 percent decline over 27 years in total flying insect biomass in protected areas. PLoS ONE, 12(10): e0185809. https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0185809

Haroon, Jan A, Edeh EC, et al. 2021. Environmental and soil gradient effects on biodiversity of butterflies in Khyber Pakhtunkhwa, Pakistan. Arthropods, 10(1): 1-17. http://www.iaees.org/publications/journals/arthropods/articles/2021-10(1)/environmental-and-soil-gradient-effects-on-biodiversity.pdf

Hasan AU, Neha SA, Baki MA, et al. 2018. An inventory of butterfly species in relation to food sources and climatic factors influencing their diversity and richness in a semi evergreen forest of Bangladesh. Arthropods, 7(3): 53-68. http://www.iaees.org/publications/journals/arthropods/articles/2018-7(3)/2-Hasan-Abstract.asp

Ho HC, Altermatt F. 2024. Predicted community consequences of spatially explicit global change-induced processes on plant–insect networks. Ecology and Evolution, 14, e70272. https://onlinelibrary.wiley.com/doi/10.1002/ece3.70272

Jiang LQ, Zhang WJ. 2015. Determination of keystone species in CSM food web: A topological analysis of network structure. Network Biology,5(1): 13-33.

http://www.iaees.org/publications/journals/nb/articles/2015-5(1)/determination-of-keystone-species-in-CSM-food-web.pdf

Kamel SM, Blal AH, Mahfouz HM, M. Said M. 2013. The most common insect pollinator species on sesame crop (Sesamum indicum L.) in Ismailia Governorate, Egypt. Arthropods, 2(2):66-74

Kazmi QB, Ghory FS. 2019. Inventory of freshwater arthropods in Pakistan. Arthropods, 8(4): 143-175. http://www.iaees.org/publications/journals/arthropods/articles/2019-8(4)/inventory-of-freshwater-arthropods-in-Pakistan.pdf

Liang H, He YD, Theodorou P, Yang CF. 2023. The effects of urbanization on pollinators and pollination: A meta-analysis. Ecology Letters, 26: 1629-1642. https://onlinelibrary.wiley.com/doi/10.1111/ele.14277

Lima MAP, Cutler GC, Mazzeo G, Hrncir M. 2022. Editorial: The decline of wild bees: Causes and consequences. Frontiers in Ecology and Evolution, 10: 1027169. https://www.frontiersin.org/journals/ecology-and-evolution/articles/10.3389/fevo.2022.1027169/full

Liu C, Sarnat E, Tan JA, Janicki J, et al. 2025. Genomic signatures indicate biodiversity loss in an endemic island ant fauna. Science, 389(6765): 1133-1136. https://www.science.org/doi/10.1126/science.ads3004

Müller J, Hothorn T, Yuan Y, Seibold S, Mitesser O, Rothacher J, Freund J, Wild C, Wolz M, Menzel A. 2024. Weather explains the decline and rise of insect biomass over 34 years. 628(8007):349-354. https://www.nature.com/articles/s41586-023-06402-z

Outhwaite CL, McCann P, Newbold T. 2022. Agriculture and climate change are reshaping insect biodiversity worldwide. Nature, 605: 97-102. https://www.nature.com/articles/s41586-022-04644-x

Queiroz ACM, Marques TG, Ribas CR, Cornelissen TG, et al. 2023. Ant diversity decreases during the dry season: A meta-analysis of the effects of seasonality on ant richness and abundance. Biotropica, 55: 29-39. https://onlinelibrary.wiley.com/doi/10.1111/btp.13158

Rahimi E, Jung CL. 2025. Investigating the spatial biases and temporal trends in insect pollinator occurrence data on GBIF. Insects, 16(8): 769. https://www.mdpi.com/2075-4450/16/8/769

Sánchez-Bayo F, Wyckhuys KAG. 2019. Worldwide decline of the entomofauna: A review of its drivers. Biological Conservation, 232: 8-27. https://www.sciencedirect.com/science/article/abs/pii/S0006320718313636

Sánchez-Bayo F, Wyckhuys KAG. 2020. Further evidence for a global decline of the entomofauna. Austral Entomology, 60: 9-26. https://onlinelibrary.wiley.com/doi/10.1111/aen.12509

Saunders ME, Janes JK, O'Hanlon JC. 2020. Moving on from the insect apocalypse narrative: Engaging with evidence-based insect conservation. BioScience, 70(1): 80-89. https://academic.oup.com/bioscience/article-abstract/70/1/80/5670748?redirectedFrom=fulltext&login=false

Scheffer M, Carpenter SR, Lenton TM, Bascompte J, et al. 2012. Anticipating critical transitions. Science, 338(6105): 344-348. https://www.science.org/doi/10.1126/science.1225244

Sekercioglu CH. 2011. Functional extinctions of bird pollinators cause plant declines. Science, 331(6020): 1019-1020. https://www.science.org/doi/10.1126/science.1202389

Shahmohamadloo RS, Tissier ML, Guzman LM. 2024. Risk assessments underestimate threat of pesticides to wild bees. Conservation Letters, 17(4): e13022. https://hal.science/hal-04748365v1/document

Shams B, Khansari M. 2014. Using network properties to evaluate targeted immunization algorithms. Network Biology, 4(3): 74-94. http://www.iaees.org/publications/journals/nb/articles/2014-4(3)/network-properties-to-evaluate-targeted-immunization-algorithms.pdf

Steffan-Dewenter I, Tscharntke T. 2000. Butterfly community structure in fragmented habitats. Ecology Letters, 3: 449-456. https://onlinelibrary.wiley.com/doi/10.1111/j.1461-0248.2000.00175.x

Sun JN, Zhang WJ. 2023. Construction and analysis of the protein-protein interaction network of visual system in Drosophila. Network Biology, 13(4): 155-185. http://www.iaees.org/publications/journals/nb/articles/2023-13(4)/4-Zhang-Abstract.asp

Tercel MPTG, Cuff JP, Symondson WOC, Vaughan IP. 2023. Non-native ants drive dramatic declines in animal community diversity: A meta-analysis. Insect Conservation and Diversity, 16(6): 733-744. https://resjournals.onlinelibrary.wiley.com/doi/10.1111/icad.12672

Tonietto RK, Larkin DJ. 2018. Habitat restoration benefits wild bees: A meta-analysis. Journal of Applied Ecology, 55: 582–590. https://besjournals.onlinelibrary.wiley.com/doi/10.1111/1365-2664.13012

Traveset A, Tur C, Eguíluz VM. 2017. Plant survival and keystone pollinator species in stochastic coextinction models: Role of intrinsic dependence on animal-pollination. Oikos, 7(1): 6915. https://www.nature.com/articles/s41598-017-07037-7

Van Klink R, Bowler DE, Gongalsky KB, Swengel AB, et al. 2020. Meta-analysis reveals declines in terrestrial but increases in freshwater insect abundances. Science, 368(6489): 417-420. https://www.science.org/doi/10.1126/science.aax9931

Vidal MC, Abarca M, Backe K, et al. 2025. What do we know about insect responses to global change? A review of meta-analyses on global change drivers. Insect Conservation and Diversity, 18(6): 900-916. https://resjournals.onlinelibrary.wiley.com/doi/10.1111/icad.12845

Wagner DL. 2020. Insect declines in the Anthropocene. Annual Review of Entomology, 65: 457-480. https://www.annualreviews.org/content/journals/10.1146/annurev-ento-011019-025151

Willcox, B.K., Potts, S.G., Brown, M.J.F. et al. 2023. Emerging threats and opportunities to managed bee species in European agricultural systems: A horizon scan. Scientific Reports, 13(18099). https://www.nature.com/articles/s41598-023-45279-w

Winfree R, Aguilar R, Vázquez DP, LeBuhn G, Aizen MA. 2009. A meta-analysis of bees' responses to anthropogenic disturbance. Ecology, 90: 2068-2076. https://esajournals.onlinelibrary.wiley.com/doi/10.1890/08-1245.1

Wong MKL, Didham R. 2024. A global dataset of diel activity patterns in insect communities. Scientific Data, 11: 558. https://www.nature.com/articles/s41597-024-03408-8

Yang S, Zhang WJ. 2022. Systematic analysis of olfactory protein-protein interactions network of fruitfly, Drosophila melanogaster. Archives of Insect Biochemistry and Physiology, 110(2): e21882. https://onlinelibrary.wiley.com/doi/10.1002/arch.21882

Yeeles P, Lach L, Hobbs RJ, Didham RK. 2025. Functional redundancy compensates for decline of dominant ant species. Nature Ecology & Evolution, 9: 779–788. https://www.nature.com/articles/s41559-025-

02690-y

Zhang WJ. 2012a. Computational Ecology: Graphs, Networks and Agent-based Modeling. World Scientific, Singapore. https://www.worldscientific.com/worldscibooks/10.1142/8118#t=aboutBook

Zhang WJ. 2012b. How to construct the statistic network? An association network of herbaceous plants constructed from field sampling. Network Biology, 2(2): 57-68. http://www.iaees.org/publications/journals/nb/articles/2012-2(2)/how-to-construct-the-statistic-network.pdf

Zhang WJ. 2016a. Network robustness: Implication, formulization and exploitation. Network Biology, 6(4): 75-85. http://www.iaees.org/publications/journals/nb/articles/2016-6(4)/network-robustness-implication-formulization-and-exploitation.pdf

Zhang WJ. 2016b. Selforganizology: The Science of Self-Organization. World Scientific, Singapore. https://www.worldscientific.com/worldscibooks/10.1142/9685#t=aboutBook

Zhang WJ. 2018a. Fundamentals of Network Biology. World Scientific Europe, London, UK. https://www.worldscientific.com/worldscibooks/10.1142/q0149#t=aboutBook

Zhang WJ. 2018b. Global pesticide use: Profile, trend, cost / benefit and more. Proceedings of the International Academy of Ecology and Environmental Sciences, 8(1): 1-27. http://www.iaees.org/publications/journals/piaees/articles/2018-8(1)/global-pesticide-use-Profile-trend-cost-benefit.pdf

Zhang WJ. 2021. Construction and analysis of the word network based on the Random Reading Frame (RRF) method. Network Biology, 11(3): 154-193. http://www.iaees.org/publications/journals/nb/articles/2021-11(3)/construction-and-analysis-of-word-network-from-Random-Reading-Frame.pdf

Zhang WJ. 2023. netAna: A tool for network analysis. Network Biology, 13(4): 192-212. http://www.iaees.org/publications/journals/nb/articles/2023-13(4)/6-Zhang-Abstract.asp

Zhang WJ. 2025. Eco-Sustainability assessment of Integrated Pest Management (IPM) techniques: Indicator system and calculator. Computational Ecology and Software, 15(3): 99-113. http://www.iaees.org/publications/journals/ces/articles/2025-15(3)/2-Zhang-Abstract.asp

Zhang WJ. 2026a. Ecological thermodynamic fluctuation and phase transition: A self-organized criticality-based framework for ecosystem responses to global warming. Selforganizology,13(3-4): 66-103

Zhang WJ. 2026b. The Niche-Energy-Time triadic synergy hypothesis (NET Hypothesis): A unified explanatory framework for determinants of species diversity. Computational Ecology and Software, 16(3): 243-272. http://www.iaees.org/publications/journals/ces/articles/2026-16(3)/3-Zhang-Abstract.asp

Zhang WJ. 2026c. What triggers explosive radiations and mass extinctions? A unified critical transition framework. Proceedings of the International Academy of Ecology and Environmental Sciences, 16(3): 89-122. http://www.iaees.org/publications/journals/piaees/articles/2026-16(3)/2-Zhang-Abstract.asp

Zhang WJ, Liu CH. 2012. Some thoughts on global climate change: will it get warmer and warmer? Environmental Skeptics and Critics, 1(1): 1-7. http://www.iaees.org/publications/journals/environsc/articles/2012-1(1)/some-thoughts-on-global-climate-change.pdf