Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

From oceans to forests, biodiversity powers climate-regulating services

Emma Moffett

emma.moffett@kcl.ac.uk

King's College London, Department of Geography, 30 Bush House, North East Wing, Aldwych, London, WC2B 4BG, UK https://orcid.org/0000-0001-9891-6217

Joel Gayford

The Georgina Mace Centre for the Living Planet, Department of Life Sciences, Silwood Park Campus, Imperial College London, Ascot, Berkshire UK SL5 7PY

Lexi Chen

The Georgina Mace Centre for the Living Planet, Department of Life Sciences, Silwood Park Campus, Imperial College London, Ascot, Berkshire UK SL5 7PY

Yuming Shi

The Georgina Mace Centre for the Living Planet, Department of Life Sciences, Silwood Park Campus, Imperial College London, Ascot, Berkshire UK SL5 7PY

Lucy Somekh

The Georgina Mace Centre for the Living Planet, Department of Life Sciences, Silwood Park Campus, Imperial College London, Ascot, Berkshire UK SL5 7PY https://orcid.org/0009-0002-6317-7076

Olivia Morris

The Georgina Mace Centre for the Living Planet, Department of Life Sciences, Silwood Park Campus, Imperial College London, Ascot, Berkshire UK SL5 7PY

Nicole Stasik

The Georgina Mace Centre for the Living Planet, Department of Life Sciences, Silwood Park Campus, Imperial College London, Ascot, Berkshire UK SL5 7PY

Andy Purvis

Natural History Museum https://orcid.org/0000-0002-8609-6204

Guy Woodward

Imperial College https://orcid.org/0000-0001-6158-2559

Will Pearse

Imperial College London

Biological Sciences - Article

Keywords:

Posted Date: January 14th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-8562138/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: There is **NO** Competing Interest.

Version of Record: A version of this preprint was published at Nature Ecology & Evolution on October 6th, 2026. See the published version at https://doi.org/10.1038/s41559-026-03200-4.

From oceans to forests, biodiversity powers climate-regulating services

Abstract

Biodiversity loss threatens the ecosystem services on which humanity depends, yet the functional forms and context-dependency of biodiversity-ecosystem service relationships remain poorly quantified. Here, we analyse an unprecedentedly large biodiversity-ecosystem service compilation, comprising 423 studies, to determine how biodiversity affects ecosystem service delivery. We show that regulating services such as water quality and pollination often exhibit linear relationships, suggesting an additive role for diversity. While biodiversity enhances most services, our effect-size analysis shows that oceanic 'blue carbon' sequestration is exceptionally sensitive, revealing how critical marine biodiversity is for climate mitigation. Conversely, services like hazard regulation appear relatively insensitive to biodiversity, instead depending on a few functionally unique foundational species whose persistence nonetheless is interdependent on the wider community. Our new synthesis enables the forecasting of impacts and highlights how ecosystem services might be used to address future problems ahead of time. For instance, we forecast that biodiversity loss will reduce food security in countries experiencing population growth and intensive development, due to a loss of natural protection from pests. Our findings provide the largest global synthesis of BES relationships to date, offering a novel quantitative framework that integrates empirical synthesis with predictive modelling and provides mechanistic insight and actionable guidance.

Main

Ecological research highlights the close relationship between biodiversity and a wide range of critical ecosystem services (ES), from pollination to carbon sequestration[1–4]. Anthropogenic pressures (*e.g.*, land-use change, introduction of exotic species) have driven an unprecedented number of species, estimated at 1 million, towards extinction, threatening ecosystem services[4–8]. While global policies aim to halt this decline[9,10], effective action requires a quantitative and synthetic understanding of the relationship between biodiversity and ES (BES), which is currently lacking.

While the consequence of biodiversity declines on ecosystem functioning is well-established, the functional form and scalability of BES relationships remain a fundamental challenge. BES relationships are often classified simplistically as linear or saturating, with no clear consensus on the scalability of data to real-world ecosystems and global patterns of

BES[1,11]. Whether these relationships are typically linear, implying all species including rare and/or pollution-sensitive taxa contribute equally to ES, or saturating, suggesting widespread functional redundancy, is poorly resolved at a global scale[11–13]. For a limited set of processes, such as primary production in plant communities, mechanistic explanations of biodiversity effects, such as selection, complementarity, or portfolio effects are relatively well studied[14–16]. However, our understanding of the generality of the qualitative (linear vs. saturating) and quantitative relationship between biodiversity and ES is limited as it is unclear if these mechanisms apply to the full range of ecosystem services.

Foundational BES research has often focused on ecosystems that are particularly amenable to experimental manipulation, such as small-scale experimental plots in grasslands. Although recent studies have expanded the scope of BES research across a wider range of ecosystems and spatial scales, a comprehensive global synthesis (*i.e.*, across ecosystem types and regions) is still lacking[3,17]. Here we present a new global database of 423 studies of BES, more than twice as large as the next largest database[18], representing a major expansion in ecological, methodological, and geographical diversity (**Fig. 1**). This database combines experimental and observational evidence across terrestrial, freshwater, marine, and estuarine systems, enabling, for the first time, a consistent global assessment of how biodiversity measurements (species number, functional group, taxonomic group) influence multiple categories of ecosystem service. Using this framework, we evaluate the functional forms of BES relationships, quantify the sensitivities of different ES categories to biodiversity loss, identify generalised factors shaping these patterns, and model future trajectories in a key ES, food and feed, under alternative population growth and development scenarios.

Functional variation in BES relationships

While positive BES relationships are commonly described[11,19], the functional forms of these relationships remain poorly quantified across and within ES categories[20]. Across 22 categories of ES, quadratic (n = 11) and linear (n = 9) relationships were most prevalent, with only two best-described by a logarithmic model, suggesting that most ecosystem services continue to increase rather than saturate at low levels of biodiversity (**Fig. 2**). Although saturating relationships are often reported[3,21–23], we find that linear relationships are also common, with their prevalence varying among ES categories. For some services, such as Terrestrial NPP, different models performed equally well, suggesting contextual factors (*e.g.,* region, study type) modulate the form of the relationship.

Regulating services, including water quality, hazards, and pollination, were typically linear, indicating a broad equivalent role for biodiversity (*e.g.,* species number, functional group, or taxonomic group) in maintaining them. In contrast, oceanic carbon sequestration and learning and inspiration exhibited saturating relationships, indicating higher functional redundancy among species. While uneven data distribution, likely resulting from biases in the literature, across ES categories may influence these findings, the observed variation in BES relationships within well-studied ES categories suggests that some services follow linear relationships while others tend towards saturation. Any changes in biodiversity are expected to affect ecosystem services when biodiversity levels fall below the saturation point. The prevalence of linear and saturating relationships suggests that some ES peak only at the highest observed levels of biodiversity, underscoring the importance of the richest communities. However, linear trends may either reflect limited sampling of high-biodiversity systems or genuinely linear ecological responses in which linear relationships may be intrinsic to some ES types.

No ES can rise indefinitely with biodiversity, but our data suggest saturation limits have rarely been reached, implying functional redundancy may be overestimated. In other words, individual species contribute more uniquely to ecosystem functioning, and ecological uniqueness plays a key role in sustaining service delivery, consistent with the wide variation in saturation levels across ecosystems observed.

For saturating relationships, the asymptote is reached at a median of ~4 (± MAD = 2) species in freshwater, ~14 (±9) in terrestrial, and ~23 (±17) in marine ecosystems (**Extended Data Fig. 1**). Faster saturation in freshwater systems may reflect their smaller scale and higher functional redundancy, particularly as they are characterised by relatively generalist food webs, whereas the vast scale and high trophic complexity and prevalence of mutualisms and co-evolutionary interactions in marine systems, such as coral reefs, may require higher biodiversity to sustain function[1,24–27]. Marine systems may also display low species multifunctionality, meaning that individual ES can often be supported by a small subset of species, but maintaining a wide range of ES requires a high overall diversity[27]. While our data show differences in median saturation values across ecosystem types, there was a wide range of saturation values, indicating that differences in experimental design, scale, and habitat may also shape BES relationships (See *Influence of spatial grain, ecosystem type, and study type on BES trends*), warranting closer examination in future studies.

Biodiversity and ecosystem services effect sizes

The variation in functional BES forms makes it challenging to understand how ES categories respond to biodiversity. To overcome this, we use a second approach that allows us to explore relationships across forms. To our knowledge, this is the first analysis to quantify BES relationships across multiple functional forms using a standardized effect-size framework. We calculated the effect size, as the response of ES to increasing biodiversity (Fisher's Z-transformed correlation coefficient), for each dataset (**Methods**, n = 1959)[28].

Higher biodiversity enhanced most ES, from carbon capture to food production (**Fig. 3**). While the magnitude of this effect varied across ES categories (Regulation of air quality, Zr = -0.03, very weak; Oceanic carbon sequestration, Zr = 1.48, very strong), the dependence of critical regulatory services on biodiversity, until the point of saturation, is unequivocal. The imperative to foster and safeguard biodiversity is particularly acute for marine ecosystems. Oceanic carbon sequestration, which is a significant part of the global carbon cycle, exhibits by far the strongest positive response to biodiversity of any ES category[29]. This exceptional sensitivity implies that blue carbon sinks are both vulnerable to biodiversity loss and dependent on sustaining diverse communities[30,31]. Maximising the efficacy and long-term viability of blue carbon strategies will require moving beyond habitat preservation toward explicitly incorporating biodiversity as a key component[32,33].

Conversely, some services, like hazard regulation, appeared insensitive to biodiversity (**Fig. 3**). This may reflect functional uniqueness, where service provision is dominated by a few foundational species or ecosystem engineers that define the ecosystem itself. For example, sand dunes are stabilised by one or two key shrub species that create a natural barrier against flooding and erosion[34]. Here, the service is provided by the foundational species, and the system's direct performance in this role is not necessarily enhanced by the addition of other species. However, maintaining broader biodiversity may still be important for sustaining the conditions that allow these foundational species to persist and function effectively[32,33,35–37]. In systems governed by functionally unique species, maintaining ecosystem functioning may rely more on the persistence of these taxa than on biodiversity *per se*. This approach aligns with the concept of ecosystem-specific "planetary boundaries," which are thresholds of control variables that, when crossed, can lead to the collapse of ecosystem functions[38]. Identifying a *priori* which systems are shaped by uniqueness versus redundancy is a critical challenge. Our data suggest that developing a typology of species and system traits is a promising avenue for future research to guide conservation priorities. Beyond further data synthesis, progress will depend on a new generation of targeted field experiments explicitly designed to disentangle the roles of

uniqueness and redundancy in sustaining ecosystem functioning, thereby providing direct empirical tests of these theoretical predictions.

Influence of spatial grain, ecosystem type, and study type on BES trends

Effect-size analyses offer robust insights into BES relationships, but they do not fully explain variation depending on ecosystems' context. Contextual factors, such as spatial grain, ecosystem type, and study type, may influence both the strength and form of BES relationships. Understanding such patterns is essential to interpreting the generality of BES findings and improving forecasts under global change. Using a linear mixed-effect model, we tested for BES relationships with spatial grain (the scale at which biodiversity and ES were measured), ecosystem type, and study type as factors (see **Methods; Table S1**).

The influence of spatial grain on BES was highly context dependent. Biodiversity effects strengthened with increasing grain ($\beta = 210.26$, $p < 0.001$; **Table S1**), indicating that biodiversity contributions to ecosystem services become more apparent at broader spatial scales. This pattern may partly reflect a beta-diversity effect, whereby spatial turnover in species composition enhances functional complementarity across sites, amplifying aggregate ecosystem service delivery at larger grains, as predicted by spatial insurance and complementarity theories. However, this pattern varied strongly across ecosystem services. For example, biodiversity contributions to regulation of hazards and extreme events, net primary productivity, and biomass turnover all declined significantly with increasing spatial grain. This scale-dependence is consistent with forest plot studies where positive BES relationships at fine grains (*e.g.,* 20m²) can become negative at coarser grains (*e.g.,* 50m²)[39]. Averaging over larger areas likely masks the fine-scale heterogeneity and species interactions that fuel ES provision[27,39]. Consequently, failing to account for measurement scale can fundamentally alter conclusions about ecosystem stability and responses to environmental change.

Second, ecosystem type significantly influenced BES relationships and highlighted data gaps in the literature. Although our literature review was not designed to quantify ecosystem type biases *per se*, the differences we found in sampling, particularly the sparse coverage of freshwater and marine systems, are unlikely to reflect sampling artefacts alone, but rather systematic biases in research focus and accessibility, with terrestrial systems historically receiving disproportionate attention (**Extended Data Fig. 3; Table S1**). Oceanic carbon sequestration was especially underrepresented (n = 7), with far fewer datasets in our database than for terrestrial carbon sequestration (n = 154), highlighting a critical gap in current knowledge (**Fig. 3**). Overall, biodiversity effects were positive in freshwater systems ($\beta = 0.34$, *p*

= 0.01), negative in marine systems (β = –0.25, p = 0.016), and not significant in terrestrial systems (p > 0.05). However, these averages mask strong variation across ecosystem service categories. For example, biodiversity significantly enhanced biomass turnover rate in marine systems, reduced it in freshwater systems and had no effect in terrestrial systems. In contrast, for maintenance of options, biodiversity effects were consistently positive in both freshwater and marine environments. Such differences may reflect underlying ecological processes, such as higher functional redundancy, or may arise from sampling and design biases.

Finally, observational studies revealed modest but statistically stronger biodiversity effects than experiments (β = 0.03, p = 0.005), demonstrating that study type significantly shapes BES trends. This overall effect size is small relative to other predictors in our models and should be interpreted as highlighting service-specific contrasts rather than a universal shift *per se*. Biodiversity effects were pronounced in observational studies for multifunctionality (β = 0.48), pollination and dispersal of seeds and other propagules (β = 0.37), and NPP (β = 0.19). Effects were weaker for biomass turnover rate (β = –0.03) and regulation of hazards and extreme events (β = –0.13), with no detectable differences for several other services, including evapotranspiration and food and feed **(Table S1; Extended Data Fig. 2)**. These findings indicate that experiments are critical for revealing mechanisms such as complementarity, overyielding, and sampling effects, but typically operate at small scales and simplified conditions potentially underestimating cumulative or context-dependent impacts[40–43]. Observational studies capture broader spatial and temporal scales, larger biodiversity gradients (including rare and functionally unique species), and interactions among multiple biotic and abiotic factors.

Future progress will rely on combining global syntheses with coordinated, cross-system experiments that explicitly test how biodiversity scales through space, time, and function. Priorities include creating hybrid experimental and observational networks that embed manipulations within long-term monitoring frameworks (*e.g.,* plots scale manipulations on reef patches and survey data collected at both local and regional scales), hierarchical sampling designs to quantify α-, β-, and γ-diversity contributions to service delivery, and standardised experimentation across ecosystem types to get closer to elucidate mechanisms, generalities, and context-dependant differences.

Predicting BES relationships

In the effect size analysis above, we demonstrate that multiple ES, including carbon sequestration, biomass turnover rates, and food and feed provision, exhibit significant sensitivity to biodiversity loss. Using these data, we predict future shifts in global BES relationships.

Existing literature is geographically biased toward developed countries (**Fig. 1A**), underrepresenting regions critical for global food production, like South America and Africa[44]. To address this gap, we developed a novel heuristic modelling framework that, for the first time, links global BES relationships with projected climate and land-use change. By integrating climate projections from the Intergovernmental Panel on Climate Change (IPCC)[45], biodiversity forecasts under projected changes in land use (Biodiversity Intactness Index; BII[46]), and our BES database. This framework enables spatially explicit projections of future shifts in ES provision and identifies regions where biodiversity loss may most severely compromise ecosystem functioning.

We applied our modelling framework to a spatially and temporally explicit case study on food security and abundance, a globally critical issue. This aligns with the majority of our data being terrestrial and growing attention on agricultural sustainability[47,48]. In particular, we examined the ratio of natural enemies to pests, which is important to food and feed production as natural enemies provide 50–90% of biological pest control in crop systems[47–49]. To link our BES model with large-scale projections of biodiversity, we scaled BES data to Biodiversity Intactness Index[50] data to estimate future changes in the ratio of natural enemies to pests and the pest control services they provide. We focus on two shared Socio-economic Pathways (SSPs)[45]: SSP2, a "middle-of-the-road" trajectory reflecting continuation of current socioeconomic trends, and SSP5, a fossil-fuel-driven trajectory characterised by intensive resource exploitation.

Our projections suggest that food and feed provision is generally reduced under fossil fuel development compared to the middle-of-the-road development trajectory, though the impacts are heterogeneous (**Fig. 4A, B**) and particularly pronounced in regions experiencing rapid population growth and with low Human Development Index values (**Fig. 4C, D; Table S2**). For example, our model predicts that natural enemies exhibit declines in North America, South America, and Asia under SSP5 relative to SSP2, whereas Australasia and Africa show comparatively minor differences between scenarios. These results suggest that biodiversity loss will directly affect food production, with the greatest impacts concentrated in regions facing the highest pressure to feed expanding populations. By contrast, countries with higher human development index values are predicted to experience greater relative increases in food and feed provision, reflecting potential gains for food security. Importantly, our framework enables these regional and scenario-based differences to be quantified and compared on a common scale, providing a scientifically grounded basis for assessing biodiversity-driven changes in

ecosystem services. We release model outputs and forecasts across all 22 ES and 5 SSPs in the supplementary materials to support policy and planning.

Conclusion

Our analysis, leveraging the largest global synthesis of its kind, demonstrates that biodiversity underpins a wide range of ecosystem services, with biomass turnover, carbon sequestration, and food and feed provision showing particularly strong sensitivity to high biodiversity. Exceptional sensitivity of oceanic carbon sequestration underscores the urgency of marine conservation. By combining this synthesis with a heuristic modelling framework, we predict how biodiversity loss may alter key ecosystem services under future climate and land-use scenarios, identifying regions and services most at risk. Distinguishing between functional redundancy and functionally unique species, we show that conservation priorities must balance maintaining overall diversity with safeguarding irreplaceable foundational taxa. Contextual factors, including study type, ecosystem type, and spatial grain, modulate biodiversity effects, highlighting the importance of context-dependent patterns. Integrating global syntheses with targeted cross-system experiments, standardized trait and service metrics, and hierarchical sampling will be essential to resolve mechanisms and improve predictions of ecosystem service provision under global change.

Acknowledgements

We express gratitude to the numerous researchers whose dedicated efforts and invaluable contributions were fundamental to this synthesis. We release details of all these studies in supplementary table 4 and apologise that we cannot cite in the main text them due to citation constraints. We would also like to acknowledge the vital financial support provided by The Hitachi Global Foundation, which made this research possible. WDP and the Pearse lab are supported by Singapore Green Finance Centre (Nature-Related Financial Risks in Southeast Asia), the Alan Turing Institute (FA.04), and UKRI BB/Y008766/1, NE/X00547X/1, and NE/X013022/1. We thank Tim Newbold for comments on an early version of this manuscript.

Author Contributions

E.R.M, W.D.P., and G.W. designed the project and this study; E.R.M. created the data-collection protocols and database; E.R.M., L.C., Y.S., L.S., and N.S. contributed to data-collection; E.R.M. and J.H.G. performed the analyses; E.R.M. wrote the initial manuscript and J.H.G., L.C., Y.S., L.S., O.F.M., N.S., A.P., G.W., and W.D.P. contributed to editing the manuscript.

Competing interests

The authors declare no competing interests.

Materials & Correspondence

Materials and Correspondence to E.R.M.

Data availability

The datasets generated during and analysed during the current study have been uploaded with submission for review and will be publicly shared upon publication. The code and maps to create the food and feed model are available on Dropbox during the review period and will be archived upon publication (https://www.dropbox.com/scl/fo/kpd9dm9u08yzvupoip8ou/AAG5SDEg8TjtlioFZzyO-Pk?rlkey=f64xr3787ac8321xta2v94xfs&st=e5b9n03m&dl=0)

Data figures

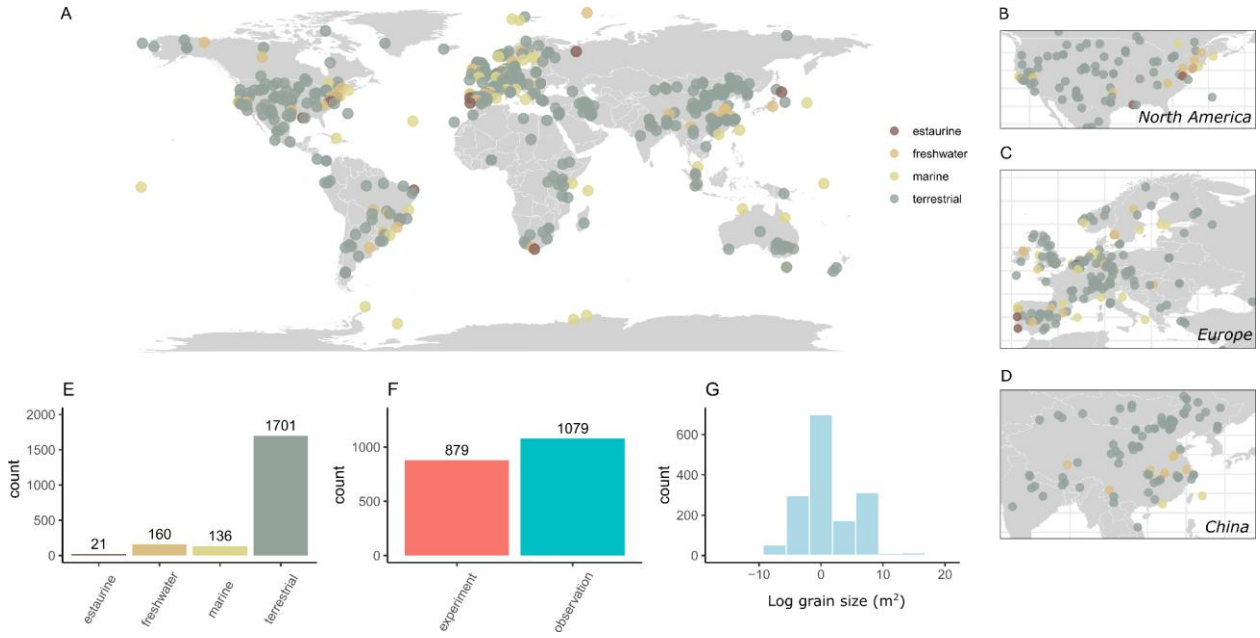


Figure 1: The type and distribution of Biodiversity-Ecosystem Service data collated worldwide. Study sites used to analyse global BES trends (A), with studies colour-coded according to ecosystem type and inserts showing North America (B), Europe (C), and China (D). BES study sites are predominantly terrestrial and located in developed countries. There are 1759 datasets from terrestrial studies compared to 183 in freshwater, 153 in marine and 23 in estuarine systems (E). There are 20% more observational (n = 1079) datasets in our database compared to experimental (n = 879) datasets (F). Grain size ranged from 0.0000007 m^2 to 260,018,758 m^2 with a median value of 1 m^2 across datasets (G).

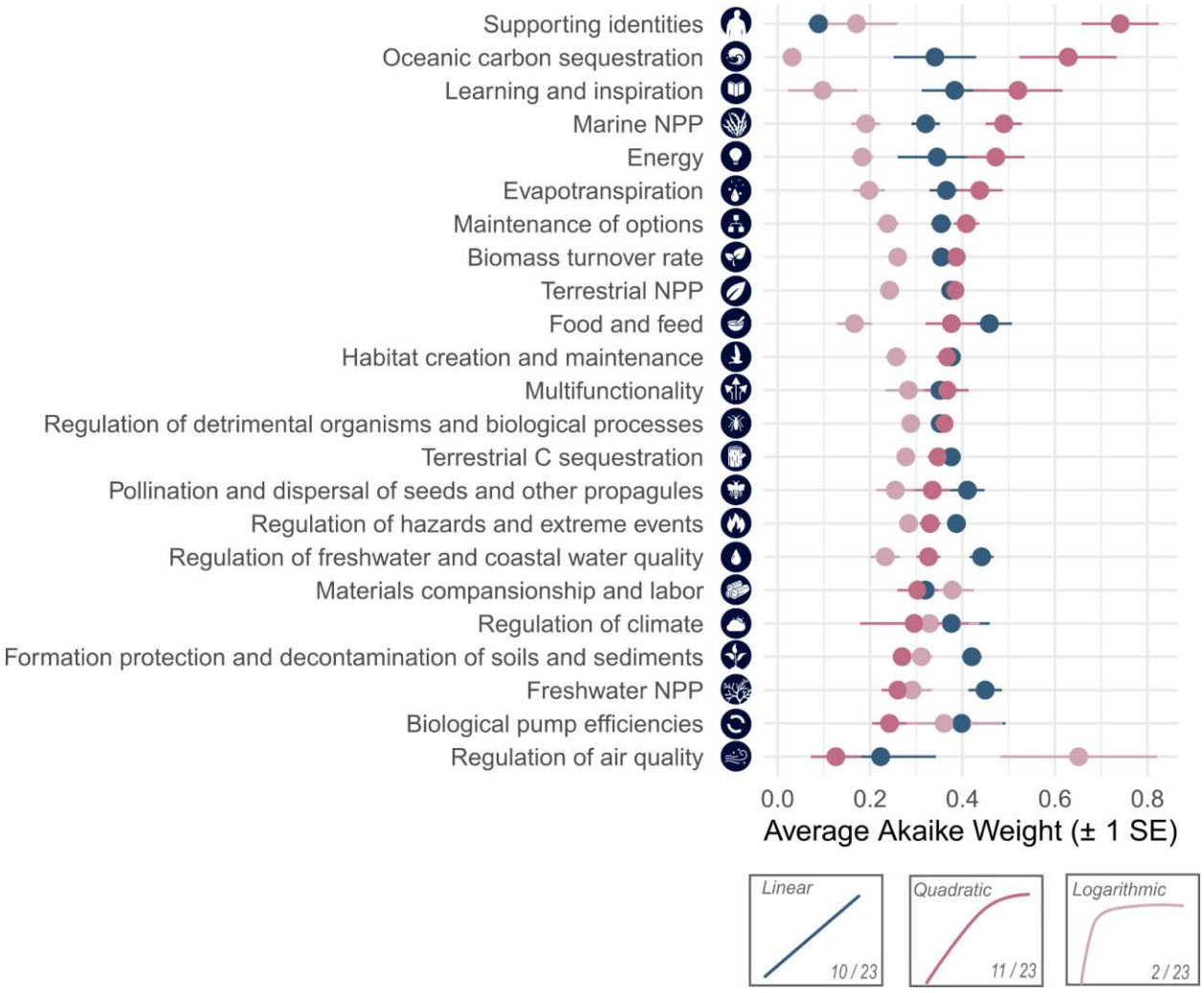


Figure 2: Linear BES relationships are almost as common as saturating (quadratic or logarithmic) ones. The relative likelihood that an ecosystem service category (rows; measured by Akaike Weights with error bars representing ± 1 SE) is fit by linear and saturating (quadratic or logarithmic) models. A high average Akaike weight value indicates a greater likelihood that the model type best fits the data than other model types. Most BES relationships show quadratic (11/23) or linear (10/23) models, whereas only two ecosystem services are best fit by a logarithmic model (2/23). We note that these results are not induced by a splitting of variance among two saturating models; we find qualitatively identical results when comparing the best-fitting saturating model with linear (46% supporting linear, 54% supporting saturating). Data are sorted by highest - lowest mean value of the quadratic model.

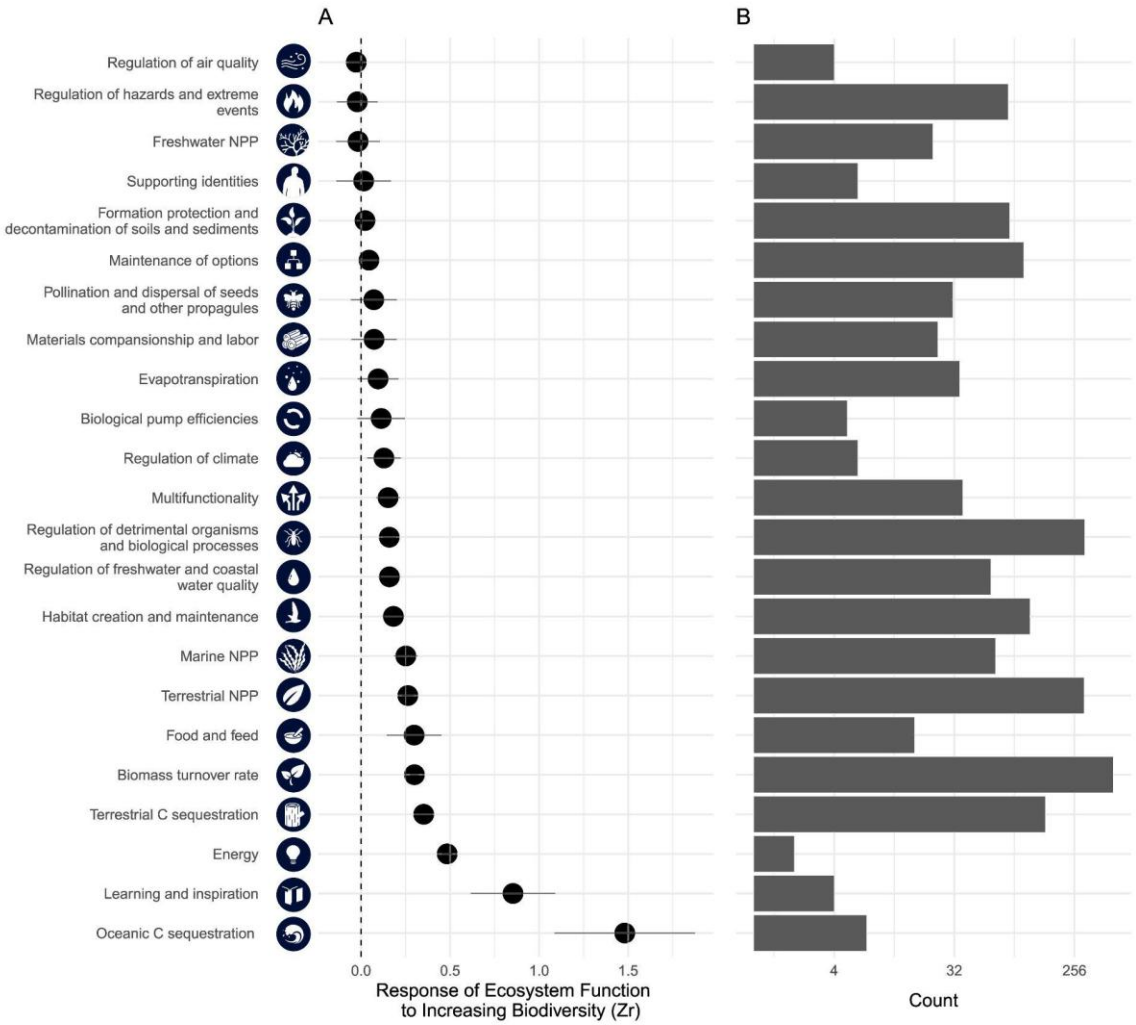


Figure 3. Comparison of biodiversity responses among ecosystem service categories, as effect size (Fisher's Z-score; Zr; Panel A) and the number of datasets used to calculate effect size (Panel B). Effect size data are average ± 1SE, calculated on datasets within each ecosystem service category, where a high effect size value indicates a stronger effect of biodiversity on ecosystem service compared to a lower value. See Figure S2 for effect sizes split by study type (experiment vs. observation). Higher biodiversity enhanced most ES, from carbon capture to food production, in particular oceanic and terrestrial carbon sequestration were strongly dependent on biodiversity. Conversely, some services, like hazard regulation, appeared insensitive to biodiversity. Notably, these effects vary by habitat type, spatial grain, and study type.

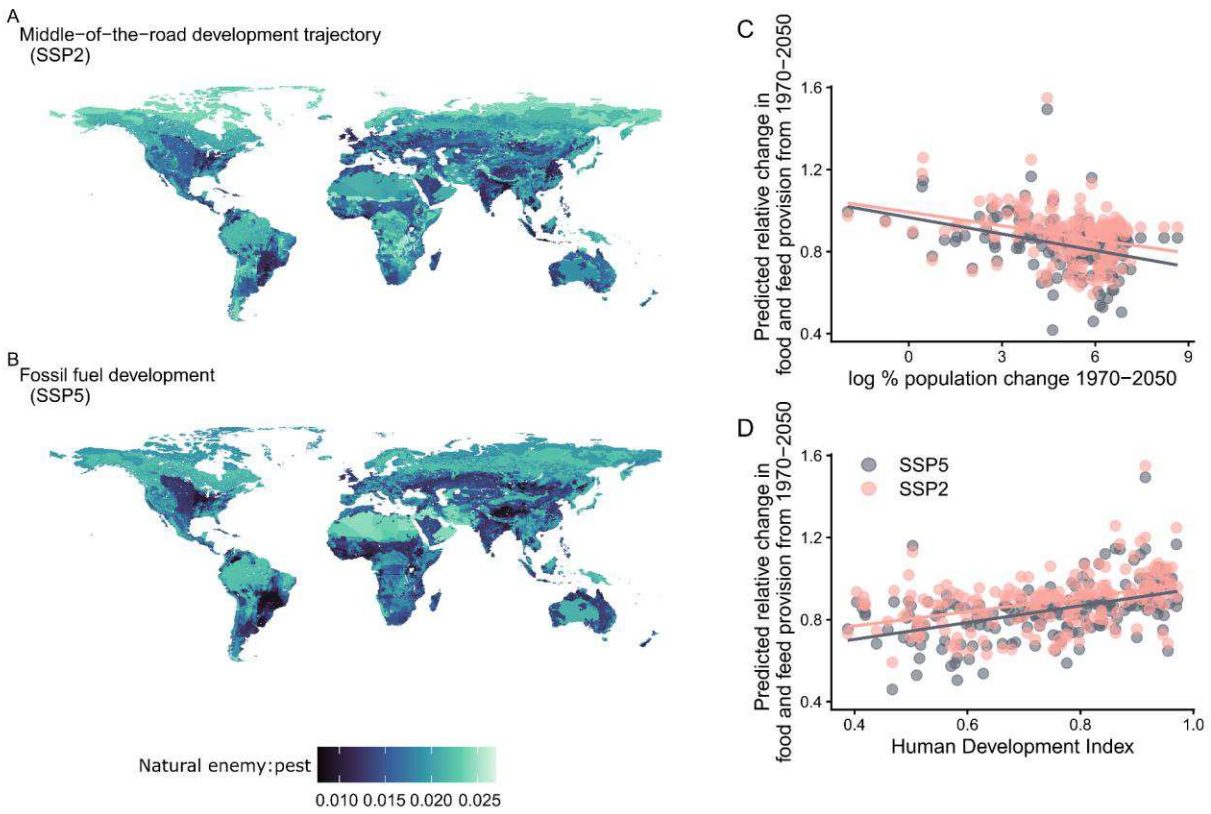
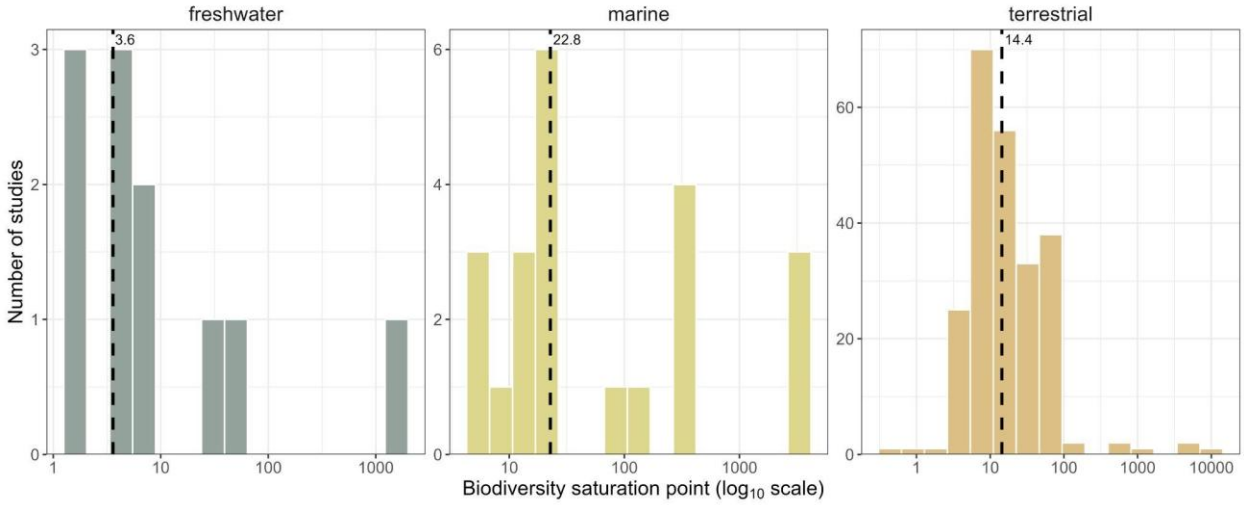
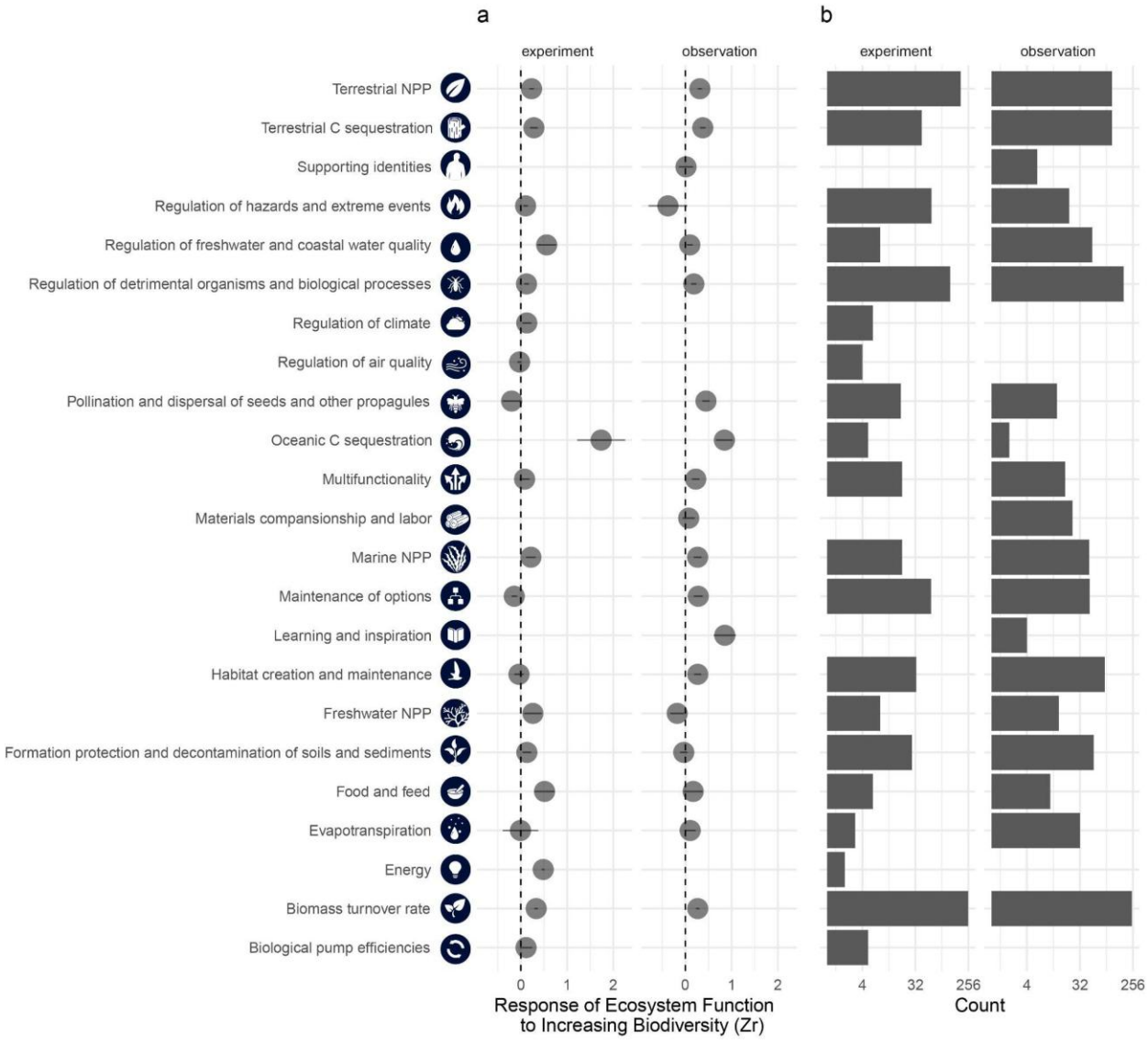


Figure 4: Forecasting ecosystem services helps in planning to meet future human demands. Here we combine our BES model with two IPCC shared socio-political climate-change scenarios (SSPs)[45] and their resulting biodiversity intactness values[46] under 'middle of the road' (A; SSP2) and 'fossil-fuel development' (B; SSP5) scenarios. While the differences between these two scenarios for biodiversity are complex, our model forecasts that under each scenario, there will be subtly different degrees of protection provided from crops by natural pathogens (A and B). A decrease in natural protection from pests would be expected to make agricultural production more difficult, and these changes will disproportionately affect countries experiencing greater population growth and with low human development index values (C, D). We found that pest protection is reduced under fossil-fuel–driven development (SSP5; $\beta = -0.0488 \pm 0.0105$, $z = -4.65$, $p < 0.001$), and we observe a disproportionately greater decline in faster-growing countries ($\beta = -0.0088 \pm 0.0021$, $z = -4.28$, $p < 0.001$; **Table S2**). Pest protection is also reduced in countries with low human development index values ($\beta = 0.176 \pm 0.038$, $z = 4.59$, $p < 0.001$) which is further exacerbated under fossil fuel development ($\beta = -0.048 \pm 0.0105$, $z = -4.59$, $p < 0.001$; **Table S3**). This case study highlights the importance of considering not only forecasting climate or biodiversity, but also ecosystem services when considering future decision-making.

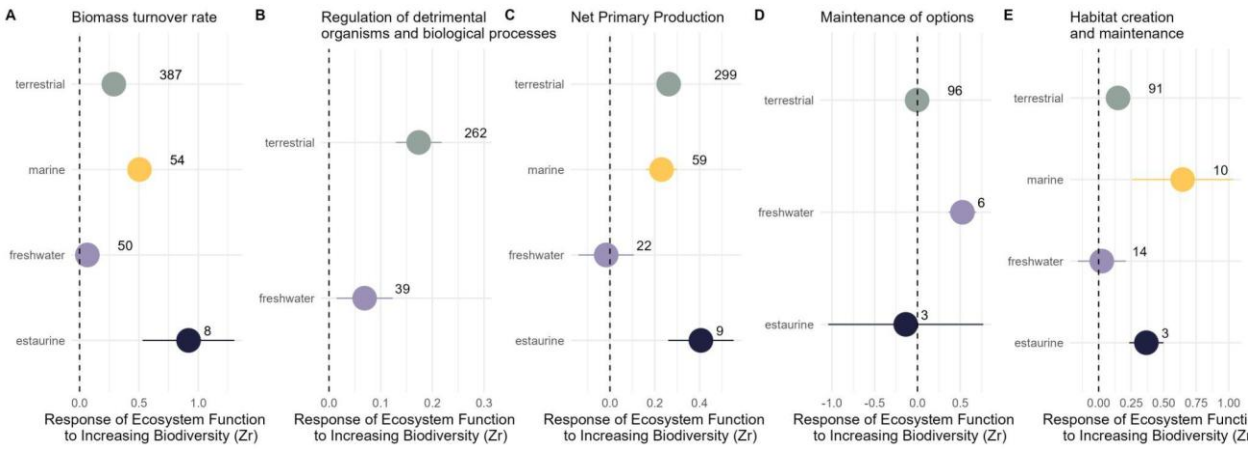
Extended data figures



Extended Data Figure 1. Biodiversity and ecosystem-service saturation points across ecosystem types. Biodiversity data are untransformed species richness (count data) only. Saturation points occur at lower median species richness in freshwater (3.6 ± 1.99) and terrestrial (14.4 ± 9) systems than in marine ecosystems (22.8 ± 16.5), where higher median values are observed. Uncertainty is expressed as median absolute deviation (MAD). Data are from datasets best predicted by quadratic and logarithmic models, as indicated by Akaike Weight values. Saturation for quadratic models was calculated when the slope reached zero, and for logarithmic models, when the slope was 10% of the initial value. The horizontal dashed line shows the median value for each ecosystem type. Large saturation values may be due to the large spatial scale the data were collected at or due to the diverse fauna at lower levels of the food web (*e.g.,* meiofauna in marine ecosystems).



Extended Data Figure 2. Comparison of biodiversity responses across ecosystem service categories, as effect size (Fisher's Z-score; Zr; Panel a) and the number of studies used to calculate effect size (Panel b). High effect size values indicate a stronger effect of biodiversity on ecosystem service compared to values. Data are split by study type.



Extended Data Figure 3: Biodiversity and ecosystem service effect sizes vary across ecosystem types. Data are shown for our database's five most common ecosystem service categories. Effect size scores (measured with Fisher's Z-score; Zr) are averaged (±1 SE) across datasets within each ecosystem service category and ecosystem type, where a high effect size value indicates a stronger effect of biodiversity on ecosystem service compared to a lower value. Dataset n values are shown beside the average effect size value. Overall, our database has high dataset n values for terrestrial studies and low n values for estuarine studies, and this was consistent across all ecosystem service categories. Datasets from marine and freshwater ecosystems were not as common as those from terrestrial studies, and for some ecosystem services (regulation of detrimental organisms and biological processes, maintenance of options), data from these ecosystem types were scarce or missing.

Methods

This study presents a comprehensive global analysis of the relationship between biodiversity and ecosystem services (BES), aiming to elucidate the impacts of biodiversity loss on critical ecological processes worldwide through the synthesis of a substantial body of existing BES research. We first investigated functional variation in BES relationships to assess the prevalence of linear versus saturating forms, the results of which underscore the consistent importance of high biodiversity levels. Subsequently, we quantified the magnitude of biodiversity's influence on various functions, with particular emphasis on vital services such as carbon sequestration. Our analysis then explored factors influencing BES trends, including spatial grain, ecosystem type, and study type, to understand their effects on BES relationships across diverse ecosystems and research methodologies. Finally, we predicted BES relationships under projected future scenarios, using IPCC climate projections and biodiversity forecasts to model potential consequences for an ecosystem service (ES) critical to human wellbeing: food provision[51]. All data analysis and statistical modelling were performed using the R programming language (R-4.4.2[52]), and the complete database is made publicly available in **x data repository.** We express gratitude to the numerous researchers whose dedicated efforts and invaluable contributions were fundamental to this global synthesis; a comprehensive list of all contributors is provided in supplementary table 4.

Stratified literature survey

We downloaded Biodiversity-Ecosystem Service (BES) literature from the Web Of Science using the following search terms: '(Ecosystem service* OR Ecosystem function* OR Ecosystem stability) AND (Biodiversity OR species richness OR species diversity)'. This search resulted in 312,291 publications. To reduce the number of papers while ensuring a representative spread of data, we used a stratified survey method. After first filtering the literature search results by ecosystem type and ecoregion, we took the 100 most relevant results from each ecosystem type and ecoregion, resulting in 3875 papers. In addition, we carried out a specific search for Biodiversity OR species richness OR species diversity and each of the top 10 most reported ES, as defined by IPBES[53], based on a Web of Science keyword search (Energy, Regulation of Climate, Food and Feed, Regulation of Air quality, Net Primary Productivity (NPP), Maintenance of options, Regulation of freshwater and coastal water quality, Biomass turnover rate, and Evapotranspiration). We added the top 100 most relevant papers for each of these ten ES categories to our literature database, meaning our stratified survey

resulted in 4875 papers (**Fig. S1)**. As our literature review method was not exhaustive, it was not designed to quantitatively measure biases in data collection across ecosystem type or ES. However, we would not expect the paper-selection processes to select certain systems over others, as data across regions and ecosystem type was explicitly considered. While most of the ES categories reported are commonly used in the biodiversity literature, some are less well known such as *Maintenance of options* which refers to the "Capacity of ecosystems, habitats, species or genotypes to keep options open to support a good quality of life" or *Biological pump efficiencies* which concerns the transport of carbon from surface water into deeper water and sediments where the residence time is much longer[53]. The abstract and keywords of each paper in our stratified survey were screened for BES data. If a paper was relevant, we extracted raw BES data where possible; if raw data were unavailable, we extracted average and standard deviation values for each condition. We used Web Plot Digitiser, in-text tables, supplementary information, or online data repositories to extract BES data. Papers whose data were unavailable were discarded (Fig S3).

From each of the papers included in our database, we collected data on environmental context (ecosystem type, location, experimental treatment, land use, GPS, spatial grain or the size of the unit of measurement, spatial extent) and any experimental manipulation (*i.e.,* temperature, biodiversity) and measurement type (experimental, observational). Land-use categories were defined by The Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES)[54]. In total, our database includes data from 545 papers.

Data analysis

Frequently, a given study would measure multiple ES, measure across different experiments within a broader study, or within sites within a wider region. To separate and distinguish among these groups so that we could assess those, while also being able to statistically control for differences among studies, we assigned studies with multiple measurements of biodiversity, ES, location, or taxon dataset numbers. We use these dataset numbers for analysis. Within each dataset, we filtered out BES data with fewer than six data points for either ES or biodiversity measurement. After filtering, our database includes 222,829 data points from 1959 unique datasets extracted from 423 unique papers (**Fig. S1**).

Data were standardised to control for different measurement units across studies using the *scale* function in R, with the standardised data used to calculate AIC scores and effect size values (see below). Rescaling our BES data allowed us to control for differences in

measurement methods and to allow for a greater conceptual understanding. First, studies use diverse metrics (*e.g.*, species richness, evenness, functional and phylogenetic diversity), as well as differing sampling effort, spatial scale, and regional species pools. This heterogeneity impedes direct comparison of raw biodiversity values, introducing both statistical noise and interpretive ambiguity in cross-system syntheses. Thus, rescaling isolates the within-study relationship between biodiversity and ES, enabling comparability across studies despite differences in biodiversity measurements and sampling design, which was critical to identifying general BES patterns across ecosystems and experimental contexts. This approach also lets us summarise and unpick how systems respond to differences in biodiversity seen within that system, be it observational or experimental, and so understand how ecosystems might be expected to respond.

To determine the form (shape) of BES relationships, we applied multiple statistical models to evaluate if relationships were linear or saturating (quadratic or logarithmic). Model selection was based on Akaike Weights, identifying the best-fitting relationship for each dataset. We calculated a single coefficient in the case of linear and logarithmic relationships, and two coefficients in the case of polynomial relationships. We calculated AIC scores for BES data fit by linear, quadratic, and logarithmic models for each dataset. Using these AIC scores, we calculated Akaike weights for each dataset to determine the relative likelihood that a model is correct compared to the other models considered. We calculated the average Akaike weight across datasets for each ES category for comparison.

We assessed saturation points of BES relationships across ecosystem types. Saturation points were defined as the biodiversity value at which the slope of the relationship reached zero for quadratic models with negative, significant curvature, or the value at which the slope declined to 10% of its initial value for logarithmic models; linear models were treated as non-saturating. Analyses were done on non-standardised data and restricted to taxonomic, count-based species richness data.

Effect size

To determine differences in biodiversity effects among ES, we calculated effect size as the response of ES to increasing biodiversity for each dataset. To calculate effect size, we used simple correlation coefficients (*r*) between biodiversity and ES, which were normalised using Fisher's z-algorithm (*Zr*; Rosenberg et al., 2000) as:

$$Zr = \frac{1}{2} ln \frac{(1+r)}{(1-r)} \quad (1)$$

Zr normalises correlation coefficients for statistical comparison and allows us to compare the average strength of BES relationships among ES categories. We use the *metafor* package (v. 4.2-0) to carry out Cochran's Q test and construct a funnel plot to test for residual heterogeneity.

Ecosystem type, study type, and spatial grain

We used a reduced linear mixed-effects model to determine the effects of ES category, ecosystem type, study type, and spatial grain on BES relationships. We explicitly included interactions between biodiversity and each of these factors to test whether the strength or direction of BES relationships depended on ecosystem function type, biome, study design, or spatial scale. Additionally, three-way interactions between biodiversity, ecosystem service type, and each factor were included to capture more complex, function-specific dependencies. We used the dataset as a random effect to control for differences across studies and this was forced to be in every model during model selection. AIC-based model selection was then used to retain the most informative effects while minimising overfitting. We did not run model averaging, as no other model was well supported by our data (ΔAICc < 4). Our final model was: *ecosystem service value ~ biodiversity value + ecosystem type + ecosystem service category + study type + spatial grain + (1 | dataset) + biodiversity value:ecosystem type + biodiversity value:ecosystem service category + biodiversity value:study type + biodiversity value:spatial grain + biodiversity value:ecosystem type:ecosystem service category + biodiversity value:ecosystem service category:study type + biodiversity value:ecosystem service category:spatial grain*. Models were run using *lme4* and *lmerTest* packages, and model selection was performed using *MuMIn* in R[55–57].

Forecast future changes to ecosystem service

To model predicted future changes to biodiversity, we used projected Biodiversity Intactness Index (BII) values from the PREDICTS project[50,58]. BII is the average abundance across a large and functionally diverse set of species relative to their reference populations, but does not consider climate change impact[46]. Specifically, we obtained rasterised (spatial resolution 0.25 degrees) predicted BII values (and country-level averaged BII values) for each of the five climate change scenarios described by the IPCC[59,60]. Climate change scenarios include: sustainable development (SSP1), middle of the road (SSP2), regional rivalry (SSP3), inequality (SSP4), and fossil fuel development (SSP5) and were taken for the following years: 1970, 2020,

2030, 2040, 2050. We chose these pathways as they represent the most realistic greenhouse gas emission trajectories under future socio-economic development[59].

There is a fundamental disconnect between how biodiversity is measured and how potential future changes to biodiversity are forecast. The latter typically comprises unitless, bounded indices (such as BII), whereas the former comprises a variety of measurements, including primary production, species abundance, and percentage cover[7,61]. These metrics vary substantially in terms of their units of measurement, spatial scale, and the range of plausible data values. To address this issue, matching the range of values of BII data (bounded from 0-1.18) and BES data, we used four different scaling procedures, so biodiversity values correspond to BII values of 0-1.18, 0.3-1.18, 0-0.6, and 0.3-0.6, respectively. These ranges were chosen to capture the full spectrum of possible values, exclude extreme low outliers, focus on low-to-moderate biodiversity, or highlight the mid-range where most sites cluster. Using multiple overlapping scales ensures that observed trends in BES relationships are robust and not an artifact of the chosen scaling procedure, allowing clear visualisation of qualitative patterns. This was achieved by applying a scaling function as follows:

$$scaled(x) = \frac{x}{x_{max}} \times (u - l) + l \quad (2)$$

Where x is an unscaled biodiversity value, u is the upper bound of the scaled data (1, 0.6, or 0.6), and l is the lower bound of the scaled data (0.3, 0, or 0.3). While this does not create exact quantitative equivalence between metrics, it ensures that trends in BES relationships can be visualised unambiguously and compared across different types of biodiversity data, allowing qualitative patterns to emerge despite the diversity of original measurements.

All non-terrestrial biodiversity and ES data were excluded, as PREDICTS contains BII values for terrestrial ecosystems only. To control for baseline differences in ES, BII data were subset by ecoregions to allow ES predictions to be made separately for each ecoregion[62]. Within our database, each BES data point was also assigned an ecoregion. Predictions for future ES values were obtained by inputting scaled BII values into BES forecast models using a posterior sampling method. As the observed BES relationships are underlain by uncertainty due to variation in experimental approaches, spatiotemporal scales, and sample sizes, we used a Monte Carlo uncertainty approach to propagate this uncertainty forward. Specifically, one hundred predictions of future ES were drawn from two normal distributions (one centred around the mean BES coefficient and the other centred around the mean intercept, both with standard error equivalent to the mean standard error of BES coefficients and intercepts respectively) for each unique combination of ES, ecoregion, year, and climate change scenario. In the case of

quadratic relationships, three normal distributions were used for posterior sampling due to the existence of a quadratic BES coefficient in addition to the linear BES coefficient term.

The predictions obtained by this procedure are, at this stage, relative and unitless. This makes inferring the scale of the predicted change in ES challenging. Consequently, we scaled predicted ES values to represent absolute values with known units as follows:

$$scaled(p_x) = \frac{p_x - p_{fmin}}{p_{fmax}}(fmax - fmin) + fmin \quad (3)$$

Where p is the predicted ES at a BII value x, and $f$min and $f$max are the raw, absolute minimum and maximum ES values. As ES values do not have the same units, $f$min and $f$max were obtained from the ES type that was most prevalent for each given ES.

To visualise ES forecasts, mean predicted ES values were generated for each unique combination of ES, ecoregion, year and climate change scenario, and mean forecasts were plotted using the R package *sf*. All these forecasts are released in **DATA REPOSITORY**.

Country-level predictions, population change, and human development index

We examined the potential for correlation between future population change or human development index (HDI) against forecasted BES relationships. We used the approach outlined in the section above (*Forecast future changes to ecosystem service)* to forecast country-level relative changes in 'food and feed' provisioning in the years 1970 and 2050 under SSP2 and SSP5 pathways. For these forecasts, country-level average BII values were used. The percentage change in population forecasted to occur between 1970 and 2050 in each country was obtained from the United Nations Department of Economic and Social Affairs Population Division[63]. Human Development Index data, which is a summary of three dimensions of human health (a long and healthy life, being knowledgeable, and having a decent standard of living) are from 2023, the most recent year available[64]. Note that any territory for which BII data were not accessible was excluded.

We assessed the influence of projected population growth between 1970 and 2050 and HDI on the total relative change in food and feed provisioning between 1970 and 2050. We used a spatial autoregressive (SAR) model to account for spatial autocorrelation between regions in both models (% population growth: Moran's I = 0.457, $p < 0.0001$; HDI: Moran's I = 0.449, $p < 0.0001$). We use the R package *spatialreg* to construct the SAR model[65].

References

1. Brose, U. & Hillebrand, H. Biodiversity and ecosystem functioning in dynamic landscapes. *Philos Trans R Soc Lond B Biol Sci* **371**, 20150267 (2016).
2. Isbell, F. *et al.* Linking the influence and dependence of people on biodiversity across scales. *NATURE* **546**, 65–72 (2017).
3. Cardinale, B. *et al.* Biodiversity loss and its impact on humanity. *NATURE* **486**, 59–67 (2012).
4. Díaz, S. *et al.* Pervasive human-driven decline of life on Earth points to the need for transformative change. *Science* **366**, eaax3100 (2019).
5. Newbold, T. *et al.* Global effects of land use on local terrestrial biodiversity. *Nature* **520**, 45–50 (2015).
6. Pereira, H. M. Global trends and scenarios for terrestrial biodiversity and ecosystem services from 1900 to 2050 | Science. *Science* **384**, 458–465.
7. Purvis, A. & Hector, A. Getting the measure of biodiversity. *Nature* **405**, 212–219 (2000).
8. Dasgupta, P. *The Economics of Biodiversity: The Dasgupta Review: Full Report*. (HM Treasury, London, 2021).
9. Joly, C. A. The Kunming-Montréal Global Biodiversity Framework. *Biota Neotrop.* **22**, e2022e001 (2023).
10. Biodiversity strategy for 2030 - European Commission. https://environment.ec.europa.eu/strategy/biodiversity-strategy-2030_en (2025).
11. Schwartz, M. W. *et al.* Linking biodiversity to ecosystem function: implications for conservation ecology. *Oecologia* **122**, 297–305 (2000).
12. Wagg, C. *et al.* Diversity and asynchrony in soil microbial communities stabilizes ecosystem functioning. *ELIFE* **10**, (2021).
13. Tilman, D., Reich, P. & Knops, J. Biodiversity and ecosystem stability in a decade-long grassland experiment. *NATURE* **441**, 629–632 (2006).

14. Tucker, C. M. *et al.* Assessing the utility of conserving evolutionary history. *Biological Reviews* **94**, 1740–1760 (2019).
15. Cadotte, M. W. Functional traits explain ecosystem function through opposing mechanisms. *Ecology Letters* **20**, 989–996 (2017).
16. Loreau, M. & Hector, A. Partitioning selection and complementarity in biodiversity experiments. *Nature* **412**, 72–76 (2001).
17. Schmid, B. *et al.* Consequences of species loss for ecosystem functioning: meta-analyses of data from biodiversity experiments. in *Biodiversity, Ecosystem Functioning, and Human Wellbeing: An Ecological and Economic Perspective* (eds Naeem, S., Bunker, D. E., Hector, A., Loreau, M. & Perrings, C.) 0 (Oxford University Press, 2009). doi:10.1093/acprof:oso/9780199547951.003.0002.
18. Ren, Y., Lü, Y., Fu, B. & Zhang, K. Biodiversity and Ecosystem Functional Enhancement by Forest Restoration: A Meta-analysis in China. *Land Degradation & Development* **28**, 2062–2073 (2017).
19. van der Plas, F. Biodiversity and ecosystem functioning in naturally assembled communities. *BIOLOGICAL REVIEWS* **94**, 1220–1245 (2019).
20. IPBES. *Global Assessment Report on Biodiversity and Ecosystem Services of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services*. https://zenodo.org/records/6417333 (2019) doi:10.5281/zenodo.6417333.
21. Hooper, D. *et al.* Effects of biodiversity on ecosystem functioning: A consensus of current knowledge. *ECOLOGICAL MONOGRAPHS* **75**, 3–35 (2005).
22. Cardinale, B., Bennett, D., Nelson, C. & Gross, K. Does productivity drive diversity or vice versa? A test of the multivariate productivity-diversity hypothesis in streams. *ECOLOGY* **90**, 1227–1241 (2009).
23. Tilman, D., Lehman, C. L. & Thomson, K. T. Plant diversity and ecosystem productivity: Theoretical considerations. *Proceedings of the National Academy of Sciences* **94**, 1857–

1861 (1997).

24. Worm, B. *et al.* Impacts of Biodiversity Loss on Ocean Ecosystem Services. *Science* **314**, 787–790 (2006).

25. Stachowicz, J. J., Bruno, J. F. & Duffy, J. E. Understanding the Effects of Marine Biodiversity on Communities and Ecosystems. *Annual Review of Ecology, Evolution, and Systematics* **38**, 739–766 (2007).

26. Daam, M. A., Teixeira, H., Lillebø, A. I. & Nogueira, A. J. A. Establishing causal links between aquatic biodiversity and ecosystem functioning: Status and research needs. *Science of The Total Environment* **656**, 1145–1156 (2019).

27. Gonzalez, A. *et al.* Scaling-up biodiversity-ecosystem functioning research. *Ecology Letters* **23**, 757–776 (2020).

28. Rosenberg, M. S., Rothstein, H. R. & Gurevitch, J. Effect Sizes: in *Handbook of Meta-analysis in Ecology and Evolution* (eds Gurevitch, J., Koricheva, J. & Mengersen, K.) 61–71 (Princeton University Press, 2013).

29. Friedlingstein, P. *et al.* Global Carbon Budget 2024. *Earth System Science Data* **17**, 965–1039 (2025).

30. Kemppinen, K. M. S. *et al.* Global reforestation and biodiversity conservation. *Conservation Biology* **34**, 1221–1228 (2020).

31. Hulvey, K. *et al.* Benefits of tree mixes in carbon plantings. *NATURE CLIMATE CHANGE* **3**, 869–874 (2013).

32. Duffy, J. E. Why biodiversity is important to the functioning of real-world ecosystems. *Frontiers in Ecology and the Environment* **7**, 437–444 (2009).

33. Klaus, V. H. *et al.* Do biodiversity-ecosystem functioning experiments inform stakeholders how to simultaneously conserve biodiversity and increase ecosystem service provisioning in grasslands? *Biological Conservation* **245**, 108552 (2020).

34. Arkema, K. K. *et al.* Coastal habitats shield people and property from sea-level rise and

storms. *Nature Clim Change* **3**, 913–918 (2013).

35. Craven, D. *et al.* Multiple facets of biodiversity drive the diversity-stability relationship. *NATURE ECOLOGY & EVOLUTION* **2**, 1579–1587 (2018).
36. Loreau, M. *et al.* Biodiversity and Ecosystem Functioning: Current Knowledge and Future Challenges. *Science* **294**, 804–808 (2001).
37. Isbell, F. *et al.* High plant diversity is needed to maintain ecosystem services. *Nature* **477**, 199–202 (2011).
38. Mace, G. M. *et al.* Approaches to defining a planetary boundary for biodiversity. *Global Environmental Change* **28**, 289–297 (2014).
39. Chisholm, R. A. *et al.* Scale-dependent relationships between tree species richness and ecosystem function in forests. *Journal of Ecology* **101**, 1214–1224 (2013).
40. Kröel-Dulay, G. *et al.* Field experiments underestimate aboveground biomass response to drought. *Nat Ecol Evol* **6**, 540–545 (2022).
41. Jochum, M. *et al.* The results of biodiversity–ecosystem functioning experiments are realistic. *Nat Ecol Evol* **4**, 1485–1494 (2020).
42. Hagan, J., Vanschoenwinkel, B. & Gamfeldt, L. We should not necessarily expect positive relationships between biodiversity and ecosystem functioning in observational field data. *ECOLOGY LETTERS* **24**, 2537–2548 (2021).
43. Eisenhauer, N. *et al.* Biodiversity–ecosystem function experiments reveal the mechanisms underlying the consequences of biodiversity change in real world ecosystems. *Journal of Vegetation Science* **27**, 1061–1070 (2016).
44. Sá, J. C. de M. *et al.* Low-carbon agriculture in South America to mitigate global climate change and advance food security. *Environment International* **98**, 102–112 (2017).
45. IPCC. *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. vol. In Press (Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA,

2021).

46. Scholes, R. J. & Biggs, R. A biodiversity intactness index. *Nature* **434**, 45–49 (2005).
47. Singh, B. K. *et al.* Climate change impacts on plant pathogens, food security and paths forward. *Nat Rev Microbiol* **21**, 640–656 (2023).
48. Muluneh, M. G. Impact of climate change on biodiversity and food security: a global perspective—a review article. *Agric & Food Secur* **10**, 36 (2021).
49. Martin, E. A., Reineking, B., Seo, B. & Steffan-Dewenter, I. Natural enemy interactions constrain pest control in complex agricultural landscapes. *Proceedings of the National Academy of Sciences* **110**, 5534–5539 (2013).
50. Hudson, L. N. *et al.* The database of the PREDICTS (Projecting Responses of Ecological Diversity In Changing Terrestrial Systems) project. *Ecology and Evolution* **7**, 145–188 (2017).
51. Godfray, H. C. J. *et al.* Food Security: The Challenge of Feeding 9 Billion People. *Science* **327**, 812–818 (2010).
52. R Development Core Team. R: A language and environment for statistical computing. R Foundation for Statistical Computing (2021).
53. Díaz, S. *et al.* Assessing nature's contributions to people. *Science* **359**, 270–272 (2018).
54. Hudson, L. N. *et al.* The PREDICTS database: a global database of how local terrestrial biodiversity responds to human impacts. *Ecology and Evolution* **4**, 4701–4735 (2014).
55. Bartoń, K. MuMIn: Multi-Model Inference. (2025).
56. Bates, D., Mächler, M., Bolker, B. & Walker, S. Fitting Linear Mixed-Effects Models Using lme4. *Journal of Statistical Software* **67**, 1–48 (2015).
57. Kuznetsova, A., Brockhoff, P. B. & Christensen, R. H. B. lmerTest Package: Tests in Linear Mixed Effects Models. *Journal of Statistical Software* **82**, 1–26 (2017).
58. Purvis, A. *et al.* Chapter Five - Modelling and Projecting the Response of Local Terrestrial Biodiversity Worldwide to Land Use and Related Pressures: The PREDICTS Project. in

Advances in Ecological Research (eds Bohan, D. A., Dumbrell, A. J., Woodward, G. & Jackson, M.) vol. 58 201–241 (Academic Press, 2018).

59. Strandsbjerg Tristan Pedersen, J. *et al.* An assessment of the performance of scenarios against historical global emissions for IPCC reports. *Global Environmental Change* **66**, 102199 (2021).
60. Phillips, H. *et al.* The Biodiversity Intactness Index - country, region and global-level summaries for the year 1970 to 2050 under various scenarios. https://doi.org/10.5519/he1eqmg1 (2021).
61. Pavoine, S. & Bonsall, M. B. Measuring biodiversity to explain community assembly: a unified approach. *Biol Rev Camb Philos Soc* **86**, 792–812 (2011).
62. Ferdaña, Z., Bruce, C. & Wyckoff, T. *Geospatial Conservation at The Nature Conservancy: 2022 Annual Report & Map Book*. http://maps.tnc.org/gis (2023).
63. United Nations, Department of Economic and Social Affairs, Population Division (2024). World Population Prospects 2024: Summary of Results. (2025).
64. UNDP (United Nations Development Programme). Human Development Report 2025. *UNDP (United Nations Development Programme)* https://report.hdr.undp.org, (2025). 63. Pebesma, E. & Bivand, R. Spatial Data Science With Applications in R. https://r-spatial.org/book/, Chapman & Hall, (2025).

Supplementary materials

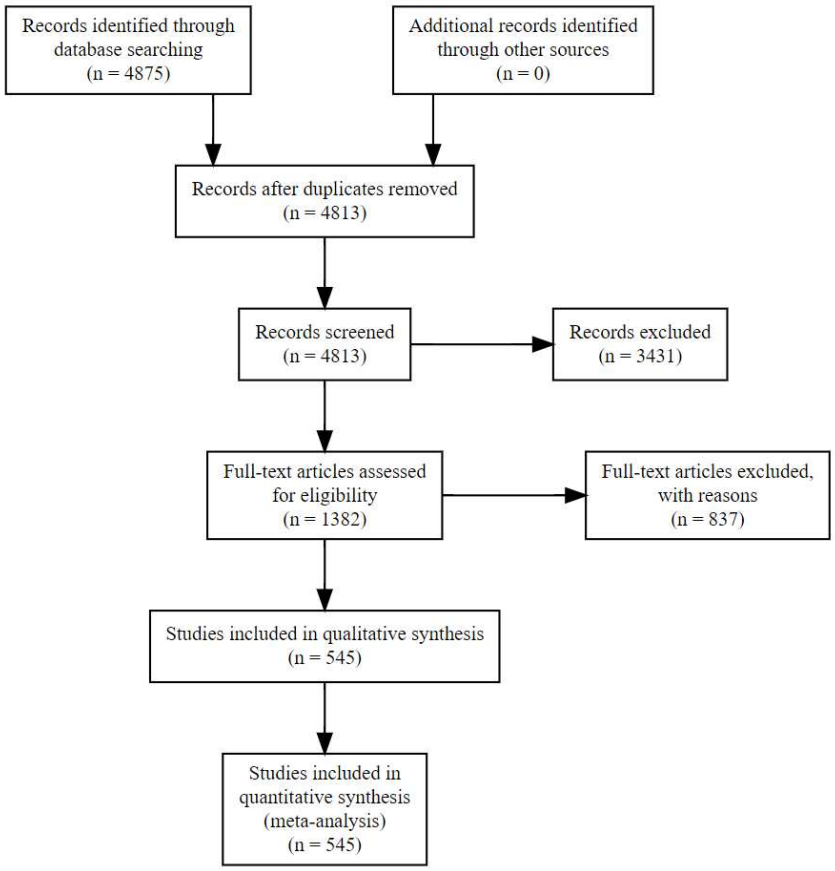


Figure S1. Summary of information used in our stratified meta-analysis. Screened papers were removed where they were not relevant to our project, were based on simulated data, were review papers, or access was denied. At the full-text stage, articles were excluded from analysis where there was no available dataset or the ecosystem services or biodiversity metrics used were unclear.

Table S1. Linear Mixed-Effects Model (*lmer*) summary describing the relationship between biodiversity and ecosystem service with interactions with ecosystem service category, ecosystem type, study type (experiment or observational), and spatial grain with a random effect of the dataset.

	Estimate (β)	Std. Error	df	t value	Pr(>|t|)
(Intercept)	0.48	0.81	2729	0.59	0.554
Biodiversity value	11.86	0.50	165802	23.56	0.000
Biome general freshwater	0.39	0.25	2299	1.57	0.116
Biome general marine	1.02	0.25	2323	4.08	0.000
Biome general terrestrial	0.54	0.23	2422	2.32	0.020
Ecosystem service metric Biomass turnover rate	0.50	0.78	2756	0.64	0.523
Ecosystem service metric Energy	0.57	0.94	2644	0.60	0.546
Ecosystem service metric Evapotranspiration	0.48	0.79	2713	0.61	0.539
Ecosystem service metric Food and feed	–0.22	0.82	2724	–0.27	0.789
Ecosystem service metric Formation protection and decontamination of soils and sediments	0.34	0.78	2755	0.43	0.664
Ecosystem service metric Habitat creation and maintenance	0.45	0.78	2751	0.58	0.562
Ecosystem service metric Learning and inspiration	–0.27	0.88	2867	–0.31	0.755
Ecosystem service metric Maintenance of options	0.94	0.78	2747	1.21	0.227
Ecosystem service metric Materials companionship and labour	0.06	0.80	2860	0.07	0.942

Ecosystem service metric Multifunctionality	0.80	0.79	2726	1.02	0.309
Ecosystem service metric NPP	0.32	0.78	2755	0.41	0.681
Ecosystem service metric Oceanic C sequestration	–1.53	0.90	3166	–1.69	0.090
Ecosystem service metric Pollination and dispersal of seeds and other propagules	0.20	0.80	2739	0.25	0.806
Ecosystem service metric Regulation of air quality	1.11	0.85	2529	1.31	0.189
Ecosystem service metric Regulation of climate	1.38	0.83	2625	1.67	0.094
Ecosystem service metric Regulation of detrimental organisms and biological processes	0.54	0.78	2755	0.70	0.485
Ecosystem service metric Regulation of freshwater and coastal water quality	–0.13	0.78	2746	–0.17	0.868
Ecosystem service metric Regulation of hazards and extreme events	–0.02	0.78	2936	–0.02	0.984
Ecosystem service metric Terrestrial C sequestration	0.55	0.78	2756	0.71	0.478
Experiment or Observation observation	-0.07	0.04	1913	-1.76	0.079
Spatial grain	–0.06	0.01	1787	–4.14	0.000
Biodiversity value: Biome general freshwater	0.34	0.13	53780	2.59	0.010
Biodiversity value: Biome general marine	–0.25	0.10	48610	–2.42	0.016
Biodiversity value: Biome general terrestrial	–0.02	0.10	46262	–0.23	0.819
Biodiversity value: Ecosystem service metric Biomass turnover rate	–17.63	2.54	41745	–6.94	0.000
Biodiversity value: Ecosystem service metric Energy	0.28	0.41	140984	0.69	0.490
Biodiversity value: Ecosystem service metric Evapotranspiration	–12.80	1.69	90650	-7.58	0.000

Biodiversity value: Ecosystem service metric Food and feed	248.33	809.04	35983	0.31	0.759
Biodiversity value: Ecosystem service metric Formation protection and decontamination of soils and sediments	14.42	24.12	28303	0.60	0.550
Biodiversity value: Ecosystem service metric Habitat creation and maintenance	–11.72	0.52	160912	–22.73	0.000
Biodiversity value: Ecosystem service metric Learning and inspiration	0.44	0.30	169108	1.46	0.145
Biodiversity value: Ecosystem service metric Maintenance of options	–11.88	0.49	168065	–24.08	0.000
Biodiversity value: Ecosystem service metric Materials companionship and labour	–0.13	0.28	168311	–0.45	0.654
Biodiversity value: Ecosystem service metric Multifunctionality	–338.03	43.08	52892	–7.85	0.000
Biodiversity value: Ecosystem service metric NPP	–11.74	0.49	168070	–23.80	0.000
Biodiversity value: Ecosystem service metric Oceanic C sequestration	0.96	0.35	169124	2.75	0.006
Biodiversity value: Ecosystem service metric Pollination and dispersal of seeds and other propagules	10.96	22.28	19308	0.49	0.623
Biodiversity value: Ecosystem service metric Regulation of air quality	–0.19	0.27	168984	–0.70	0.487
Biodiversity value: Ecosystem service metric Regulation of climate	162.79	1960.73	145768	0.08	0.934t
Biodiversity value: Ecosystem service metric Regulation of detrimental organisms and biological processes	–11.81	0.49	168082	–23.96	0.000
Biodiversity value: Ecosystem service metric Regulation of freshwater and coastal water quality	–0.22	0.26	167739	–0.85	0.395
Biodiversity value: Ecosystem service metric Regulation of hazards and extreme events	–26585.66	6109.11	15	–4.35	0.001
Biodiversity value: Ecosystem service metric Terrestrial C sequestration	-0.14	0.27	168952	–0.52	0.601

Biodiversity value: Experiment or Observation observation	0.03	0.01	164839	2.81	0.005
Biodiversity value: Spatial grain	210.26	7.46	167511	28.17	0.000
Biodiversity value: Biome general freshwater: Ecosystem service metric Biomass turnover rate	–0.64	0.16	51687	–3.89	0.000
Biodiversity value: Biome general marine: Ecosystem service metric Biomass turnover rate	0.36	0.14	48699	2.52	0.012
Biodiversity value: Biome general terrestrial: Ecosystem service metric Biomass turnover rate	–0.12	0.14	47344	–0.83	0.404
Biodiversity value: Biome general marine: Ecosystem service metric Energy	0.25	0.33	54020	0.74	0.459
Biodiversity value: Biome general freshwater: Ecosystem service metric Habitat creation and maintenance	–0.13	0.22	34116	–0.59	0.557
Biodiversity value: Biome general marine: Ecosystem service metric Habitat creation and maintenance	0.58	0.23	73773	2.53	0.011
Biodiversity value: Biome general terrestrial: Ecosystem service metric Habitat creation and maintenance	–0.11	0.15	38823	–0.72	0.472
Biodiversity value: Biome general freshwater: Ecosystem service metric Maintenance of options	0.40	0.11	80453	3.81	0.000
Biodiversity value: Biome general marine: Ecosystem service metric Maintenance of options	1.24	0.06	143477	20.55	0.000
Biodiversity value: Biome general freshwater: Ecosystem service metric NPP	–0.60	0.09	69883	–6.42	0.000
Biodiversity value: Biome general freshwater: Ecosystem service metric Regulation of detrimental organisms and biological processes	–0.34	0.09	68828	–3.71	0.000
Biodiversity value: Ecosystem service metric Biomass turnover rate: Experiment or Observation observation	–0.03	0.02	135885	–1.99	0.046

Biodiversity value: Ecosystem service metric Evapotranspiration: Experiment or Observation observation	0.05	0.15	121722	0.35	0.728
Biodiversity value: Ecosystem service metric Food and feed: Experiment or Observation observation	–0.24	0.17	26638	–1.40	0.161
Biodiversity value: Ecosystem service metric Formation protection and decontamination of soils and sediments: Experiment or Observation observation	–0.04	0.04	42188	–0.95	0.343
Biodiversity value: Ecosystem service metric Habitat creation and maintenance: Experiment or Observation observation	0.10	0.04	65882	2.58	0.010
Biodiversity value: Ecosystem service metric Maintenance of options: Experiment or Observation observation	0.13	0.02	138281	5.82	0.000
Biodiversity value: Ecosystem service metric Multifunctionality: Experiment or Observation observation	0.48	0.08	69308	5.89	0.000
Biodiversity value: Ecosystem service metric NPP: Experiment or Observation observation	0.19	0.01	153216	13.06	0.000
Biodiversity value: Ecosystem service metric Pollination and dispersal of seeds and other propagules: Experiment or Observation observation	0.37	0.09	54450	4.14	0.000
Biodiversity value: Ecosystem service metric Regulation of detrimental organisms and biological processes: Experiment or Observation observation	0.12	0.02	125804	6.55	0.000
Biodiversity value: Ecosystem service metric Regulation of hazards and extreme events: Experiment or Observation observation	–0.13	0.06	79552	–2.14	0.032
Biodiversity value: Ecosystem service metric Biomass turnover rate: Spatial grain	–319.57	45.37	41030	–7.04	0.000
Biodiversity value: Ecosystem service metric Evapotranspiration: Spatial grain	–234.20	29.94	88339	–7.82	0.000
Biodiversity value: Ecosystem service metric Food and feed: Spatial grain	4465.40	14577.67	35982	0.31	0.759

Biodiversity value: Ecosystem service metric Formation protection and decontamination of soils and sediments: Spatial grain	262.17	434.49	28301	0.60	0.546
Biodiversity value: Ecosystem service metric Habitat creation and maintenance: Spatial grain	–210.25	7.46	167511	–28.17	0.000
Biodiversity value: Ecosystem service metric Maintenance of options: Spatial grain	–206.98	7.46	167503	–27.73	0.000
Biodiversity value: Ecosystem service metric Multifunctionality: Spatial grain	–6093.07	776.30	52885	–7.85	0.000
Biodiversity value: Ecosystem service metric NPP: Spatial grain	–210.10	7.46	167511	–28.15	0.000
Biodiversity value: Ecosystem service metric Pollination and dispersal of seeds and other propagules: Spatial grain	202.15	401.35	19286	0.50	0.614
Biodiversity value: Ecosystem service metric Regulation of climate: Spatial grain	2934.71	35323.72	145769	0.08	0.934
Biodiversity value: Ecosystem service metric Regulation of detrimental organisms and biological processes: Spatial grain	–210.27	7.46	167511	–28.17	0.000
Biodiversity value: Ecosystem service metric Regulation of hazards and extreme events: Spatial grain	–478947.01	110057.63	15	–4.35	0.001

Table S2. Spatial autoregressive model (SAR) of relative change in food and feed provision from 1970 to 2050, population change from 1970 to 2050, and SSP scenario. Estimates are reported as coefficients (± SE), with SSP2 as the reference category. Population growth had a significant negative effect, and SSP5 predicted significantly lower values than SSP2. The spatial lag parameter was strong (rho = 0.596, $p < 0.001$), confirming spatial dependence.

	Estimate	SE	z	p-value
Intercept	0.413	0.048	8.55	<0.001
Population change	–0.0088	0.0021	–4.28	<0.001
SSP5 (vs SSP2)	–0.0488	0.0105	–4.65	<0.001

Spatial lag parameter: $\rho = 0.596$ (SE = 0.050, $p < 0.001$)

Model fit: AIC = –540.7, log-likelihood = 275.3, $\sigma = 0.088$.

Residual autocorrelation not detected (LM test $p = 0.99$).

Table S3. Spatial autoregressive model (SAR) of relative change in food and feed provision from 1970 to 2050, Human Development Index (HDI) value, and SSP scenario. Estimates are reported as coefficients (± SE), with SSP2 as the reference category. HDI value had a significant positive effect on food and feed provision, and SSP5 predicted significantly lower values than SSP2.

	Estimate	SE	z	p-value
Intercept	0.252	0.041	6.31	<0.001
HDI value	0.176	0.038	4.59	<0.001
SSP5 (vs SSP2)	–0.049	0.011	–4.60	<0.001

Spatial lag parameter: $\rho = 0.588$ (SE = 0.050, $p < 0.001$)

Model fit: AIC = –532.83, log-likelihood = 271.4, $\sigma = 0.088$.

Residual autocorrelation not detected (LM test $p = 0.51$).

Table S4. List of all journal articles used in this stratified meta-analysis. List is sorted by first author surname.

Please see attached file.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- readme.xlsx
- TableS4.DOIlist.xlsx
- BESDATACOMBINED.csv