Measuring biodiversity impact, change and restoration opportunity for business

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Abstract

Most pressures that cause biodiversity loss are driven by economic activity. There is significant interest from the private sector in understanding impacts and dependencies of business activity on biodiversity. However, measuring the impacts of direct and indirect business activities on biodiversity, including species, at multiple scales remains a considerable challenge. There are no currently widely applicable measures that can map species-specific responses to pressures at a high spatial resolution across a broad range of scales. Here, we describe the Species Occurrence Index, a tractable and scalable measure for quantifying business impacts on nature, based on species distribution models. Using case studies, we demonstrate the use of the metric in understanding the direct impacts of a business and sector's operations and how it can be used to guide nature positive protection and restoration actions. As private sector interest in biodiversity measures grows, so will demand for metrics that can scale between large, global scales (e.g. whole of investment portfolio, entire sectors) and local, context specific scales, while maintaining ecological realism. Our Species Occurrence Index allows businesses and sectors to estimate their total impact while also providing opportunities to deliver positive outcomes for biodiversity by ensuring businesses accurately account for and respond to their impacts on nature.

Key Words
Biodiversity footprint, species distribution model, business, biodiversity metric, impacts, species, nature related financial disclosure, ESG reporting, nature accounting

Introduction

Biodiversity is crucial for human health, society and the global economy (Hooper et al., 2012; World Economic Forum, 2020), but it is rapidly declining (Johnson et al., 2017). In 2022, the Kunming-Montreal Global Biodiversity Framework set out goals, targets and potential indicators for tracking biodiversity impacts and recovery (CBD, 2022). Following the establishment of the Global Biodiversity Framework and subsequent Nature Positive movement (Milner-Gulland, 2022), there is a strong desire for metrics that appropriately capture the 'State of Nature' and, crucially, how nature is responding to a broad range of pressures (Harrer et al., 2024). This is especially true for the private sector, which is increasingly required to understand their impacts on nature. Despite this desire, measuring the impacts of direct and indirect business activities on biodiversity, including species, at multiple scales remains a considerable challenge and many of the existing tools deriving from other applications such as policy or lifecycle analysis remain unfit for purpose (Smith et al., 2024).

There is currently a proliferation of measures being developed to describe the impacts of pressures on biodiversity. Globally-applicable, top-down measures such as changes in mean species abundance (MSA) and the potentially disappeared fraction of species (PDF) are widely used (Hawkins et al., 2024; Kuipers et al., 2025). However, these measures do not provide insight at a high spatial resolution and do not explicitly model individual species responses to pressures, leaving a gap in impact analyses that is crucial to fill if businesses are to satisfy regulatory and reputational imperatives to demonstrably conserve local species and ecosystems. There are existing metrics that are based on individual species' extinction risk, such the IUCN Red List Index and Living Planet Index (Butchart et al., 2025; Visconti et al., 2016). However, these are not sufficiently sensitive to changes over short time-scales or fine spatial scales, and are limited to species listed under the IUCN Red List. Newer metrics, such as the LIFE metric (Eyres et al., 2025), STAR (Mair et al., 2021), and estimates of species habitat provision (Giljohann et al., 2025) address this by producing spatially explicit estimates of pressure impacts on species through threat status or changes in habitat condition (Mokany et al., 2025). However, these approaches do not consider variability in the responses of individual species to specific individual pressures that might be brought by particular business activities. Spatially varying impacts of business activities caused by diverse biodiversity responses to pressures, cannot currently be captured. Taken together, there are no currently available measures that can map species-specific responses to pressures at a high spatial resolution across a broad range of scales (Burgess et al., 2024).

The risk of a species' extinction is regularly proposed as an important indicator of the state of nature (Mace et al., 2008; Stevenson et al., 2024). Extinction risk can be estimated through the development of models of population dynamics derived from abundance or count data. However, the collection and analysis of this type of data is challenging and resource intensive at the scale required to understand the likelihood of species extinctions across a broad range of taxa and spatial scales. Models of population dynamics also suffer from scaling challenges when trying to estimate model parameters, including spatial correlation in environmental stochasticity (Moilanen, 2000). Global biodiversity policy and private sector-driven frameworks are demanding high resolution measures that can provide robust estimates of individual species responses to pressures and aggregate these insights across species, space and time (Hawkins et al., 2024). The availability of suitable habitat is a dominant driver of increased extinction risk, globally (Crooks et al., 2017). Estimates of habitat availability derived from species distribution models of the likelihood of occurrence of a species in a location, relative to the distribution of pressures (Figure 1) can address this gap (Guillera-Arroita et al., 2015). By providing statistically robust estimates of species-specific habitat availability, and therefore occurrence, species distribution models can offer important insights into the state of nature but without the need for intensive, site-scale population counts.

Metrics derived from species distribution models for a wide range of taxa offer a potentially tractable and feasible approach for quantifying the footprint of a broad range of activities on biodiversity that can also be readily updated with new data from globally available databases. Here, we propose an occurrence-based species footprint metric (the Species Occurrence Index) that can be applied across a broad range of species at global and local-scales and evaluation contexts (e.g. reporting and disclosure of biodiversity impacts, status and trends) while also providing a tractable approximation of species extinction risk. We demonstrate the utility of this metric with two case studies–analysing the biodiversity footprint of a sector at a large spatial scale, and an individual entity at a local spatial-scale.

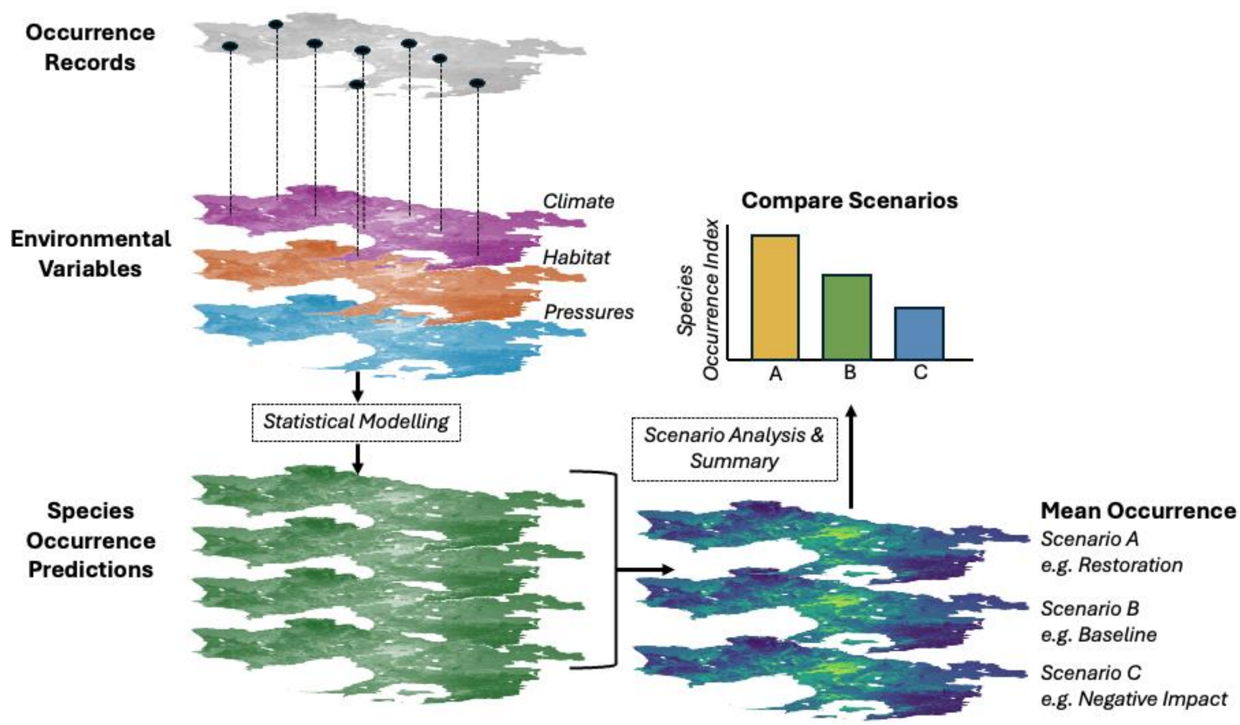

Figure 1: The *Species Occurrence Index* modelling and mapping framework is based on combining records of species' occurrences and environmental variables (e.g. climate, habitat, pressures) in a statistical modelling framework to estimate the relationship between species occurrences and the environment and therefore the prediction of species occurrences across space. These models can then be used to make predictions of species occurrences under alternative scenarios (e.g. changes in a pressure) and summarised across locations and species to allow comparison between scenarios, such as positive or negative changes from a baseline.

The Species Occurrence Index

Quantifying the biodiversity footprint of a pressure begins with building species distribution models of a representative set of species that suit the modelling objective (Figure 1). There are a wide variety of approaches for building species distribution models, including presence-only, presence-absence and abundance data (Austin, 2002).

These models are typically fit with covariates that include potential drivers of species distributions (e.g. climate, soil, habitat features) (Elith & Leathwick, 2009), but may include other variables reflecting natural or human induced disturbance or direct impacts on species such as persecution, hunting, or pollution. To understand, quantify and represent the impact of pressures in species distribution models, spatial representation of potential pressures (e.g. land-use change, pollution, water extraction) must also be included as covariates (Tulloch et al., 2015). For example, land-use class or intensity are increasingly incorporated into species distribution models as they provide a direct representation of potential habitat availability for some species (Kapitza et al., 2021; Visconti et al., 2016). In doing so, species-specific responses to variation in the intensity of individual pressures can be quantified.

Once species distribution models have been parameterised, changes in relative likelihood of species' occurrences in responses to changes in the distribution and intensity of pressures can be calculated (Figure 1). This might include forecasting changes in species occurrences under future climate or land-use scenarios (Newbold et al., 2016), or quantifying local-scale changes in species occurrences due to individual company activities (Hawkins et al., 2024).

While it is often valuable to describe and predict the likely outcome of pressures on individual species of local, legal, or cultural importance or priority, understanding and communicating the net outcomes of changes in pressures for hundreds or thousands of species individually is generally not useful due to our limited ability to report and digest large amounts of complex data. This is especially the case in the context of reporting at global and national scales where thousands or millions of individual species predictions may be relevant. Therefore, metrics that summarise impacts or changes in species distributions across many species simultaneously may be particularly useful for many applications including impact assessment or reporting on changes in biodiversity over time. Quantifying the difference in species' occurrence (which we define as the mean change in the probability or likelihood of occurrence across species due to changes in the distribution or intensity of a pressure) is a potentially useful approach to communicating overall changes in biodiversity using multiple predictions of individual species outcomes as the input. Previous studies have demonstrated the potential of this approach (Kapitza et al., 2021). Here we define a metric that formalises the process of quantifying changes in biodiversity across many species in response to spatially mapped changes in environmental or anthropogenic pressures.

For a given scenario, the mean probability of occurrence of J species under K pressures across n pixels, $\bar{p}$, can be written as:

$$SOI = \bar{p} = \frac{1}{n \cdot J \cdot K} \sum_{i=1}^{n} \sum_{j=1}^{J} \sum_{k=1}^{K} p_{ijk} \quad (1)$$

Where $p_{i,j}$ represents the probability of occurrence at pixel *i* for species *j* under pressure *k*, *n* represents the total number of pixels, *J* represents the total number of species, *K* the total number of pressures (Equation 1).

The mean probability of occurrence of species in a given footprint can then be calculated for two or more alternative scenarios, such as pre-impact ($\bar{p}^A$) and post-impact ($\bar{p}^B$), representing an impact by a change in the *k*th pressure for the *j*th species, such as those driven by company activities (Equation 2). The difference between these scenarios is the change in species occurrence index (ΔSOI) attributable to this impact. Figure 2 illustrates this with a worked example.

$$\Delta SOI = \bar{p}^B - \bar{p}^A \quad (2)$$

The change in species occurrence index in a pixel or location can therefore be interpreted as the fraction of species lost (or gained) in that pixel as a result of changing pressures or conditions. This interpretation is conceptually analogous to the broadly used potentially disappeared fraction of species used in life cycle analyses (Huijbregts et al., 2017).

Species distribution models generally aim to model species occurrence or occupancy. However, at their most basic (presence-only models) model predictions can only be interpreted as the relative likelihood of suitable habitat, rather than occurrence or occupancy (Guillera-Arroita et al., 2015). As the aim of our metric is to be widely applicable, we refer to it as the species *occurrence* index but acknowledge that a broad range of data can be used to model species distributions, which has implications for their interpretation. We feel this is appropriate given that the objective of the index is to capture changes in occurrence of a species in response to pressures.

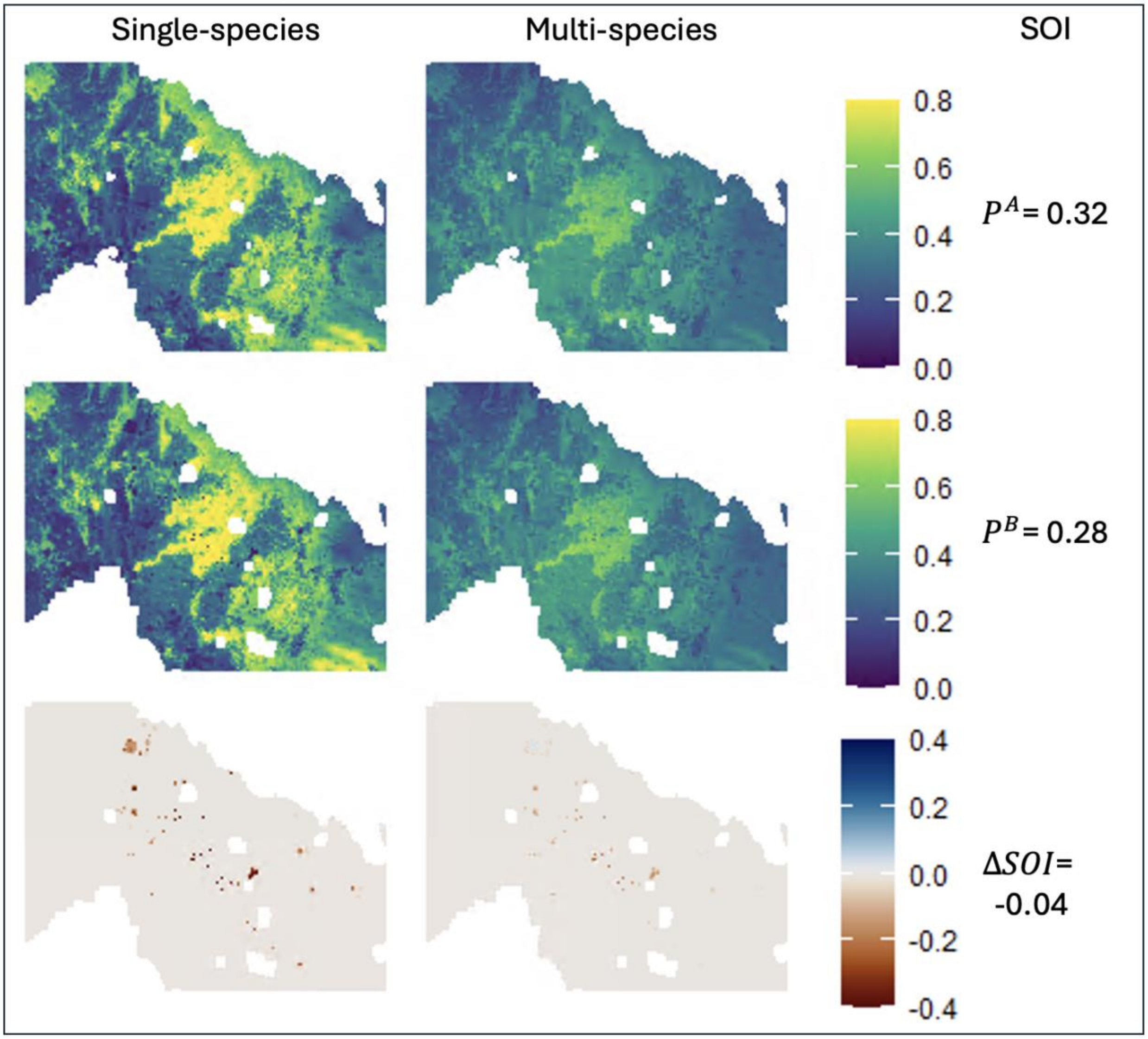

Figure 2: A demonstration of how the Species Occurrence Index can be calculated for individual species (left column) and then by aggregating changes in occurrences across individual species to understand changes across a suite of species (right column). In this example, the top row is the relative likelihood of occurrence before an impact (P^A), the middle row is after an impact (P^B), and the bottom row is the change in species occurrence index attributable to the impact calculated using Equation 2 as the difference between P^A and P^B. Each can be shown either spatially or summarised as an overall number averaged across all pixels in the area of interest (e.g. a business footprint). SOI numbers on the right relate to the multi-species maps, not the single-species maps.

Quantifying the benefits of positive action

In some instances, it may be of value to quantify the *potential* for species to exist in a given location or across large areas. Such measures would allow for the quantification of the value of restoration or other activities that may remove pressures that currently prevent species from occurring in a particular place that might otherwise be climatically, edaphically, and ecologically suitable. Such pressures could include over-exploitation or the existence of invasive predators or herbivores that render potentially usable habitat unoccupied by a single or many species. Similarly, an area may be potentially suitable for a species or suite of species but for the absence of a particular resource or habitat attribute. For example, by restoring a previously removed attribute, such as a food plant or a canopy or hollow-bearing tree, an area may become suitable for a suite of species that had previously been excluded.

Using this interpretation opens up the possibility of our index for supporting future scenario planning. For example, a biodiversity restoration potential map could be constructed in a way similar to our species occurrence footprint map, but with a shift of focus from the expected current distribution of species under current environmental or management conditions, to an anticipated future distribution of species under a given set of assumptions about future management or restoration:

For example,the mean probability of occurrence of species in a given footprint can then be calculated for a restoration or conservation action scenario by quantifying the potential species occurrence before (P^A) and after the action (P^C). In this instance, the potential impact of the action could be defined as a change in the *j*th pressure (e.g. a reduction of cleared land caused by restoration) for the *i*th species (Equation 3). The difference between these scenarios is the change in species occurrence index (ΔSOI) attributable to this action, which would likely be a positive number.

$$\Delta SPI = P^C - P^A \quad (3)$$

Case study 1: Understanding and reducing the footprint of an individual business

An important application of biodiversity footprinting approaches is an assessment of the footprint of individual businesses, based on where and how their activity and their supply chains intersect with nature (Figure 3). Based on a biodiversity footprint analysis, businesses can (i) identify business activities that are causing large or unacceptable impacts on biodiversity, (ii) prioritise which business activities to avoid or adapt to reduce or mitigate damage, and (iii) report or disclose those damages, mitigation actions, residual impacts, and restoration benefits (Forico, 2023). Robust and accurate biodiversity footprint assessments, informed by ecological knowledge and evidence are therefore essential for informing these analyses, actions and reporting as errors may lead to misinformed responses, wasted resources or accusations of greenwashing.

To illustrate the utility of the species occurrence index for understanding the biodiversity footprint and biodiversity impact mitigation opportunities for an individual company, we used the land area under management by Yarra Valley Water, a water utility company in south-eastern Australia. Yarra Valley Water has direct land management responsibilities for large tracts of land, on which a range of activities occur, including water treatment, infrastructure development and restoration activities. Therefore, for the purposes of this case study, the land under management by Yarra Valley Water can be used to estimate the companies direct impacts on nature (as distinct from their upstream or downstream supply chain impacts).

Yarra Valley Water is interested in assessing the biodiversity footprint of land management across their holdings and opportunities for positive outcomes for nature from restoration that may offset some of their impacts (Naylor et al., 2025). To demonstrate the use of our metric for these purposes, we predicted the expected change in the species occurrence index for two scenarios for Yarra Valley Water: A) spatial variation in the impacts of clearing remnant native vegetation across Yarra Valley Water's land holdings, and B) restoring a selection of cleared land to forest to compensate their supply chain impacts.

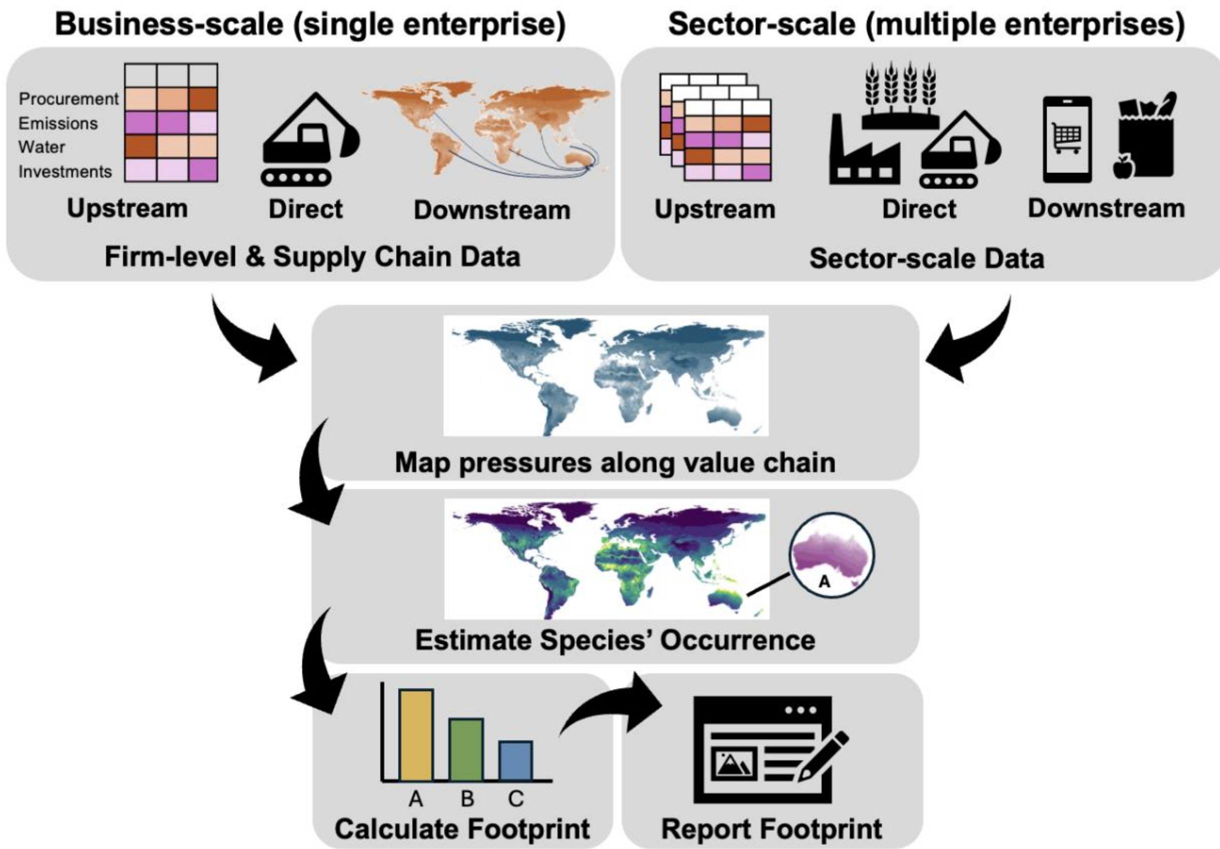

Figure 3: Quantifying the biodiversity footprint using the species occurrence index for an individual enterprise or business activity (left) and sector-scale activity (right).

Current footprint assessment

To estimate Yarra Valley Water's direct impacts on nature, we calculated the Species Occurrence Index by fitting species distribution models for 47 mammals, 250 birds and 37 reptiles across the region in which Yarra Valley operates its business (Figure 4). Species distribution models were fitted using an open source species distribution modelling workflow (Bal et al., 2026), applied to the Greater Melbourne region, Australia where Yarra Valley Water operates. See Supporting Information 1 for a description of the species distribution modelling methods used in this case study.

Because our species distribution models include land-use types as covariates (represented as fractions of the pixel that is estimated to be that land-use type), we were able to simulate these restoration and clearing scenarios by directly modifying the rasters used to predict species distributions across the region. To simulate the effects of clearing we set each pixel's 'Urban' fraction to 1. We use this approach to represent the extreme of potential changes in land uses driven by land management decisions made within the company footprint.

Within Yarra Valley Water's land holdings, there is spatial variation in the effects of clearing and restoration due to spatial variation in the distribution of species (Figure 4a, b). Mapping that variation allows identification of the specific locations where positive and negative changes in the species occurrence index are greatest. Identification of locations where changes are greatest is essential for planning where companies might first focus on avoiding or minimising impacts (e.g. avoiding clearing) or undertaking positive actions for biodiversity (e.g. implementing restoration activities) that are most cost-effective or that improve outcomes for species that are of highest importance to the business or stakeholders.

Our analysis shows that, on average, the Species Occurrence Index decreases in the habitat loss scenario (Figure 4a,c). There are also clearly divergent responses across species (Figure 4c), and those responses vary spatially. Because the analysis builds from individual species models that quantify the impact on each species of impacts or restoration actions it is possible to drill down to the change in footprint of individual species (Figure 4d). This level of granularity in responses is only possible when the analysis starts with individual species outcomes and then builds up the footprint index of overall (across species) impacts rather than estimating those impacts using a top-down model such as in the case of 'potentially disappeared fraction' (PDF:(Huijbregts et al., 2017)) or 'mean species abundance' (MSA: (Schipper et al., 2020)).

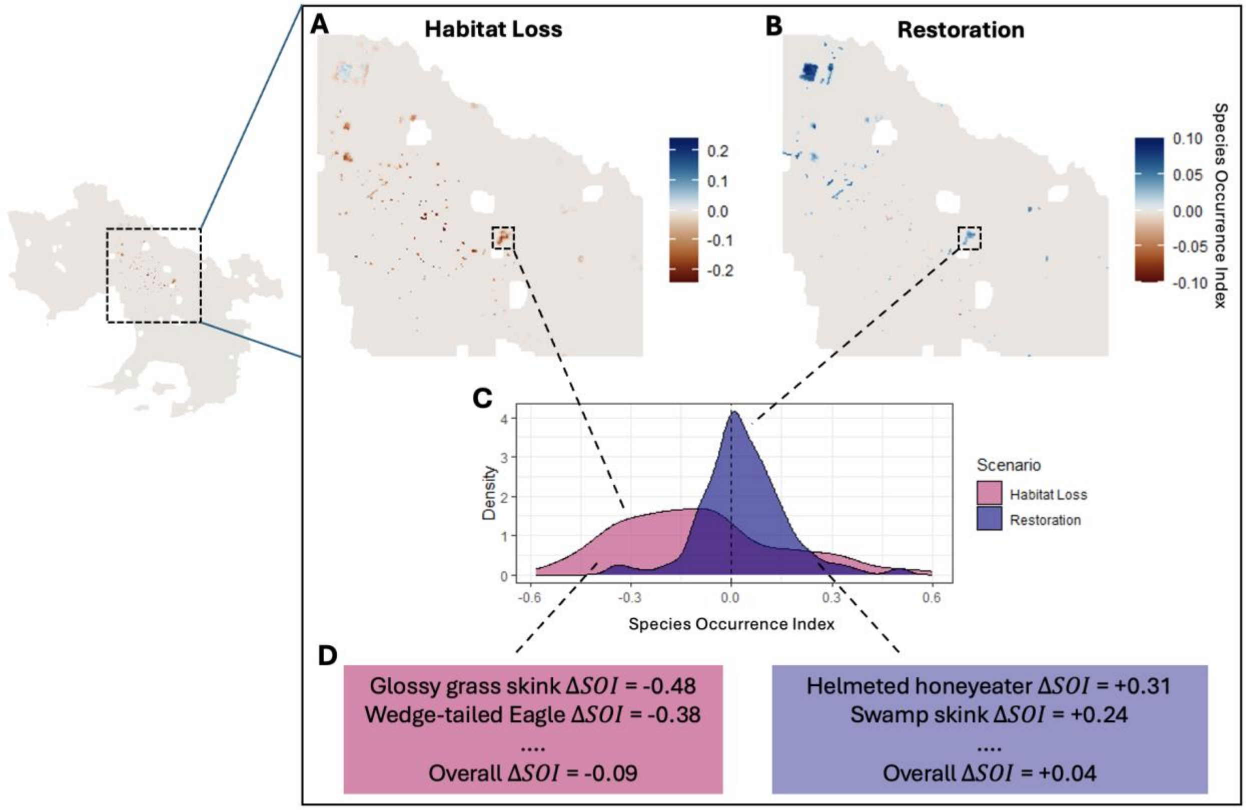

Figure 4: Spatial estimates of the change in species occurrence index across all species for a) habitat loss and b) restoration scenarios. The density plots c) show the distribution of changes and average change in species occurrence index in the inset parcel of land for each scenario. In d) change in example individual species occurrence index estimates and overall mean change in species occurrence index estimates for the inset land parcel are shown for the habitat loss scenario (left) and restoration scenario (right). Mapped colours in a) and b) represent the change in Species Occurrence Index, which is defined as the change in probability of occurrence in each pixel for either a single species, or a set of species.

Compensating supply chain impacts

To demonstrate the ability of the Species Occurrence Index to quantify the area of restoration required to offset using a locally relevant metric, we developed an approach to translate between a commonly used measure of ecosystem impacts of supply chain activity and our Species Occurrence Index.

First, to quantify the change in Species Occurrence Index attributable to the effects of restoration, we modified the land use covariates used to predict each species' distribution in our study area. Specifically, we set each pixel's 'Primary Forest' value to 1- the fraction of pixel that is urban. This materialised as an overall increase in the amount of Primary Forest land use type in most pixels within the Yarra Valley Water land holdings. We then predicted the distribution of each species to this modified covariate stack and then quantified the difference in predicted relative likelihood of occurrence for each species between the baseline predictions and the restoration predictions and summarised these predictions as the change in Species Occurrence Index (Figure 4b,c). The average benefit of restoration across all species modelled in our case study was a 0.04 mean increase in occurrence (Figure 4d).

Yarra Valley Water have previously estimated the impacts of their direct and supply chain activities using life cycle assessment, with their upstream supply chain impacts on nature estimated to be equivalent to 0.74 species.yr (Naylor et al., 2025; Wright et al., 2025), as estimated using ReCIPe (Huijbregts et al., 2017). This metric is interpreted as the potentially disappeared fraction (PDF) of species globally due to Yarra Valley Water's upstream supply chain annually.

To quantify the area of restoration required to offset Yarra Valley Water's supply chain impacts on nature, we developed an approach to translate between the estimated PDF and our estimated change in SOI attributable to restoration (see methods in Supplementary Information 2). Using this approach we estimate that an area of roughly 125 Ha per year of restoration is required to offset Yarra Valley Water's supply chain impacts on nature. Importantly, this worked example does not consider the need to target restoration in places that benefit the species impacted by Yarra Valley Water's supply chain activities, which could be distributed globally. Our spatially explicit maps of the change in SOI attributable to restoration can then be used to prioritise where restoration of Yarra Valley Water's land holdings will deliver the greatest benefit in terms of SOI, such as prioritising pixels with larger expected increases in SOI (Figure 4b).

Case study 2: Scaling up to understand the biodiversity footprint of a sector

Understanding the biodiversity footprint of specific sectors can help to pinpoint locations where a specific sector has the greatest impact, or facilitate comparison between sectors. This knowledge helps to guide businesses in identifying parts of their supply chains with the greatest biodiversity footprint, so that businesses can either move to different suppliers or engage suppliers in moving toward more biodiversity-friendly practices. In this case study, we demonstrate the application of the Species Occurrence Index for quantifying the overall biodiversity impact of a sector, while also providing guidance on specific locations that a sector might have relatively higher or lower footprint.

In this case study, we predict the species occurrence footprint of increasing the intensity of the agricultural cropping sector by increasing the fractional land use cover of cropping by 20 percentage points (i.e. 20% becomes 40%) in all pixels where cropping currently occurs in Australia. We then calculate the biodiversity footprint of this change by calculating the Species Occurrence Index as the difference between the current distribution of cropping fractional land-use cover and a scenario where the fractional land use of cropping is increased by 20 percentage points.

This example highlights that the Species Occurrence Index can be calculated at multiple spatial scales allowing whole-of-sector and location-specific analyses (Figure 5a,b). Then, the Species Occurrence Index can be disaggregated in multiple ways, including focusing specifically on threatened species or specific individual species (Figure 5c). This application highlights how the Species Occurrence iIdex could be used to understand the footprint of entire sectors, or identify specific regions or locations where the footprint of a sector is higher or lower. Sector-scale analyses have a range of applications, including potentially informing procurement decisions or certification of supply chains, where impacts on biodiversity are essential pieces of information.

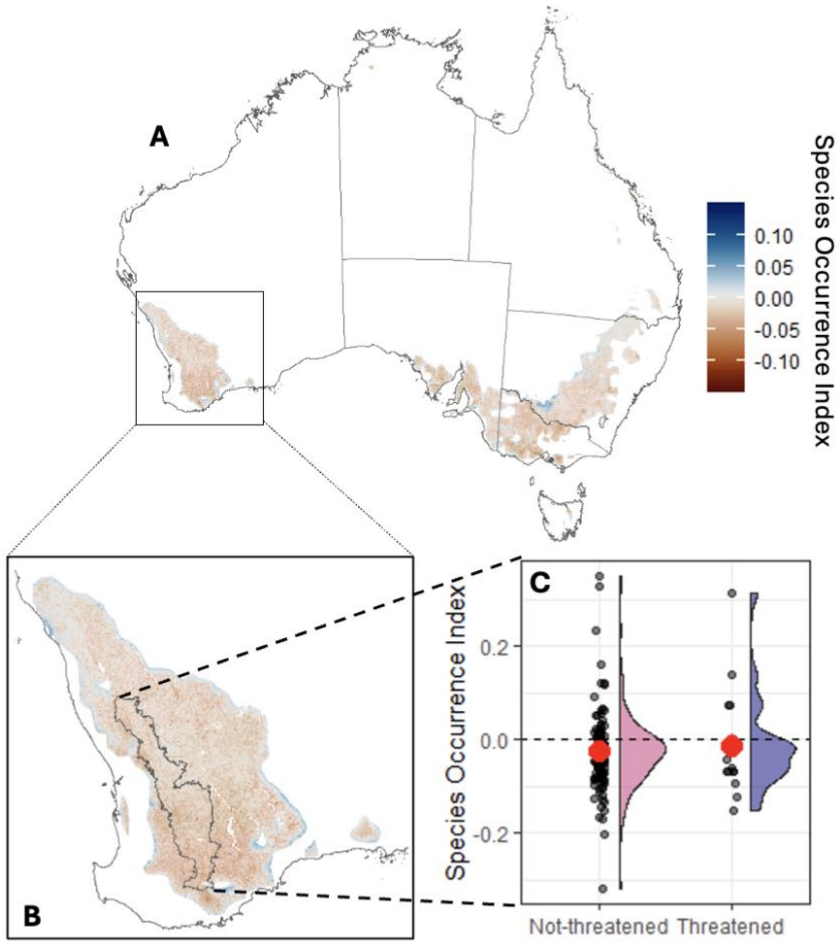

Figure 5: Spatial estimates of the change in Species Occurrence Index due to an increase in cropping fractional lands-use across all species for a) all of Australia, b) south-west western Australia (inset black lines are the Avon Wheatbelt bioregion) and c) raincloud plots of Species Occurrence Index for threatened (EPBC listed) and non-threatened species for the Avon Wheatbeld bioregion. In c) black points represent individual species changes and density plots represent the overall distribution of individual species changes. Mapped colours in a) and b) represent the change in species occurrence index (red indicating decrease, blue indicating increase), which is defined as the mean change in probability of occurrence in each pixel for either a single species, or a set of species.

Applications

In the context of nature-related disclosures and responses, the Species Occurrence Index provides a broad range of insights. At high spatial resolution, our approach allows for insights at the scale of individual land parcels and individual species. This allows businesses to identify and disclose risks related to impacts at this scale, such as impacts on individual threatened or culturally significant species or comparisons of impacts between land-parcels. Such insights are essential for identifying and disclosing regulatory, reputational and therefore financial risks associated with individual species, locations or activities. At the opposite end of the spatial scale, the Species Occurrence Index allows aggregation across many species and over many locations, from a small local business or the local operations of a larger business right through to the aggregate footprint of a globally distributed enterprise or holding that might involve multiple individual businesses across large areas that impact thousands of species. Additional considerations can also be included in the calculation of our index, such as non-equal weighting of species (e.g. by threatened status) or pixels (e.g. protected areas) when calculating the SOI, depending on the priorities and interests of users.

Whole-of-business footprint estimates can then be tracked over time to allow businesses to determine whether they are having a net positive or net negative impact on biodiversity. These estimates would also allow businesses to pinpoint within their activities where impacts could be avoided or mitigated. For example, if a company estimates its impact from its supply chain activities to be an ΔSOI of -0.4, this value can then be treated as the conservation outcomes required to be achieved in order to offset their impacts and claim becoming nature positive (notwithstanding the need for targeting conservation actions at the same species that were impacted, ensuring like for like).

Future directions

Model-based estimates of biodiversity responses to economy-related pressures are in demand globally (Hawkins et al., 2024). Each of the currently available methods have areas for improvement (Damiani et al., 2023), including the Species Occurrence Index. While readily applicable, there are several avenues for future development that will improve the utility of our species footprint metric. These areas for improvement run across all aspects of our modelling workflow, including comprehensive company data, improved modelling of the environmental pressures generated by economic activities and robust models of species responses to these pressures.

Robust consideration of biodiversity in business risk disclosure and decision-making requires local-scale information (Nedopil, 2023), only possible with metrics built from bottom-up. Essential for building bottom-up estimates of the impacts of business activity include robust, spatially-explicit data of company activities. The emerging field of spatial finance (Caldecott et al., 2022) which focuses on developing spatial datasets of economic activity holds considerable promise here. This allows company activity to be associated with location-specific environmental pressures (e.g. land-use change, pollution, water extraction). In addition to spatial data on economic activities, businesses must also start monitoring the positive and negative effects of their direct activities on species, which can then be used directly to update their species occurrence index. The outcome of this is current, context-specific information of biodiversity impacts, a standard that will likely be demanded by regulators and shareholders.

Further, our case study featured a company with a clear understanding of the location of its direct interface with biodiversity. However, further work is required by companies to understand the location of indirect impacts derived through their supply chains. Without this information, the species footprint of companies is likely to be underestimated, especially for companies with relatively less direct exposure to biodiversity. A large proportion of the impacts of economic activity on biodiversity occurs in business supply chains, rather than direct activities (Irwin &

Geschke, 2023; Moran & Kanemoto, 2017). Our demonstration of the Species Occurrence Index focuses on the direct impacts of businesses, rather than upstream or downstream supply chain impacts. Quantifying the upstream and downstream impacts of supply chains on biodiversity is an essential step in quantifying an organisation or sector's true biodiversity footprint (Crenna et al., 2020). Therefore, efforts to map the supply chains within and between sectors such as TRASE (https://trase.earth/) are essential for fully measuring an individual business' impact on biodiversity. In the interim, quantifying the species occurrence index of specific types of activities (e.g. cropping agriculture, Case Study 2) gives businesses and sectors the opportunity to measure the impact of specific pressures if there is evidence of those pressures in their supply chains.

Our approach relies on spatially explicit representations of pressures that affect species, as these are key ingredients in the species distribution models. Many pressures can be represented through maps of land-use change, but other important pressures that may be driven by company activity (e.g. pollution, invasive species) will require a more nuanced understanding of their distribution and intensity. Considerable efforts have been made in the conservation literature to understand spatial variation in a broad range of pressures on biodiversity (Tulloch et al., 2015; Venegas-Li et al., 2025). By contrast, currently available tools for business footprinting allow for only a limited consideration of pressures (e.g. land-use change) that apply generic estimates of impact across broad biodiversity indices (Balogh et al., 2025). By basing our species occurrence index on species distribution models, there is inherent flexibility to incorporate any pressure that can be spatially mapped, as well as important drivers of variation in biodiversity more broadly (e.g. climate, soils, vegetation). To be able to incorporate a broad range of pressures is an important advance on existing metrics and improved spatial models of biodiversity pressures will further facilitate this.

Conclusion

To be fit-for-purpose, biodiversity footprinting measures for businesses need to be built from the bottom-up and provide high spatial resolution, species-specific and ecologically sound estimates of impact and change. Such measures are transparent, data driven and can be readily updated with new data and information. Our Species Occurrence Index is one such measure, allowing businesses to estimate their total impact while also providing opportunities to pinpoint locations and species where risks and opportunities might differ. As interest in biodiversity measures from the private sector grows, so will demand for metrics that can scale between large, global (e.g. whole of investment portfolio, entire sectors) scales and local, context specific scales while maintaining ecological realism. Robust biodiversity metrics that can achieve this will ultimately deliver positive outcomes for biodiversity by ensuring businesses accurately account for and respond to their impacts on nature.

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Supplementary Information

1. Methods to develop species distribution models used in case studies

To demonstrate the application of our species occurrence footprint metric using case studies, we used a presence-background species distribution modelling framework developed by Bal et al. (2026)

In Case Study 1, we apply this modelling framework to a subset of mammal, bird and reptile species from the original study with ≥20 records each after data cleaning within the broader region surrounding Melbourne, Victoria, Australia. This totalled 47 mammals, 250 birds and 37 reptiles across the region. Records were obtained in March 2025, using the galah R package v2.0.2 (Westgate et al., 2024). We trained our models and predicted each species distribution within the Greater Melbourne area (see Figure 2).

We included environmental variables representing climate, land use, soil and vegetation across the study region as covariates in our distribution models. Refer to Bal et al. (2026) for methods on how covariates were processed. Covariates were resampled to 250m resolution and reprojected to GDA2020/Australian Albers (EPSG9473) and checked for multi-colinearity. Our model fitting process included the development of taxa-specific bias layers which accounted for sampling intensity, distance from roads, protected areas and water bodies. For each species, we generated 10,000 weighted-random background points using the ppmData package (Woolley & Foster, 2023) and the method developed by Bal et al. (2026).

Species distribution models were fit using a Poisson point-process-based approach, using the glmnet package (Friedman et al., 2023) and the method developed by Bal et al. (2026). Models were fit as infinitely-weighted logistic regression models with a logit link function and used lasso regularisation to penalize complex model structures to reduce the risk of overfitting to the data.

For the baseline scenario, we predicted each species' likely distribution to the 'current' set of conditions, including current land-use classes and climates across the study region. For the clearing scenario we directly modified the covariate rasters used to predict species distributions across the region. To simulate the effects of clearing within Yarra Valley Water's land holdings, we set each pixel's 'Urban' fraction to 1 in all pixels of land owned and managed by Yarra Valley Water. We then predicted each species' distribution to this new set of covariates to understand how species' likelihood of occurrence changed due to the simulated effects of clearing. The difference in each species' relative likelihood of occurrence between the baseline and clearing scenarios is therefore the predicted impact of clearing in each pixel.

To simulate the effects of restoration, we again modified the land use covariates used to predict each species' distribution in our study area. Specifically, we set each pixel's 'Primary Forest' value to 1 - the fraction of a pixel that is urban. This materialised as an overall increase in the amount of Primary Forest land use type in most pixels within the Yarra Valley Water land holdings. We then predicted each species' distribution to this new set of covariates to understand how species' likelihood of occurrence changed due to the simulated effects of restoring habitat. The difference in each species' relative likelihood of occurrence between the baseline and restoration scenarios is therefore the predicted impact of restoration in each pixel.

In Case Study 2, instead of fitting new models, we use the existing models developed by Bal et al. (2026) for each scenario. The baseline relative likelihood of occurrence for each species in this case study was again each species' distribution under current land use and climate conditions, as predicted by Bal et al. (2026). Then, to predict the relative likelihood of each species occurrence under a scenario of increasing intensity of the agricultural cropping sector, we increased the fractional land use cover of cropping by 20 percentage points (i.e. 20% becomes 40%) in all pixels where cropping currently occurs in Australia. We then proportionally reduced all other land use fractions and vegetation cover estimates (e.g. tree density) to make room for the increase in cropping. We then predicted each species' distribution under the increased cropping scenario. The difference in each species' relative likelihood of occurrence in each pixel between the baseline scenario and the cropping scenario can therefore be interpreted as the per pixel predicted impact of increasing cropping intensity.

Species included in our case study analyses were those whose models had an AUC value of ≥ 0.7 to ensure model predictions were relatively reliable. Then, to ensure our index was calculated only on species that relied on the region relevant to each case study, we only included species that had a maximum relative likelihood of occurrence of ≥0.8 within the study regions.

2. Conversion of Potentially Disappeared Fraction of Species to SOI

To demonstrate the ability of the species occurrence index to be used to quantify the area of restoration required to offset using a locally relevant metric, we developed an approach to translate between a commonly used measure of ecosystem impacts of supply chain activity and our species occurrence metric.

Yarra Valley Water have previously estimated the impacts of their direct and supply chain activities using life cycle assessment. Specifically, their upstream supply chain impacts on nature are estimated to be equivalent to 0.74 species.yr (Wright et al., 2025), as estimated using ReCIPe (Huijbregts et al., 2017). This metric is interpreted as the potentially disappeared fraction (PDF) of species globally due to Yarra Valley Water's upstream supply chain annually.

Using our framework and new metrics, we can translate between PDF and the species occurrence index to estimate the area of restoration that may be required to offset Yarra Valley Water's supply chain impacts on biodiversity.

ReCIPe metrics assume that there is an average species density across the globe of 1.48×10^{-8} species per m^2 or 0.148 species/Ha (Huijbregts et al., 2017). Our species occurrence index estimates a mean increase in occurrence probability from restoration of 0.04, which can be interpreted as 0.04 per species. Therefore, the biodiversity benefits in terms of species.yr as estimated by our SOI can be estimated to be:

$$Benefit = SOI \times species.ha$$
$$= 0.04 \times 0.148$$
$$= 0.00592\ species.ha.year$$

We can then take both the estimates of impact from Yarra Valley Water's supply chain and our estimated biodiversity benefits represented as species.yr to estimate the annual area of restoration required to offset their supply chain impacts. This can be calculated as follows:

$$Annual\ Restoration\ Area = \frac{species.yr}{species.ha.yr}$$
$$= \frac{0.74}{0.00592}$$
$$= 125\ ha\ per\ year$$

Therefore, in this worked example, the estimated annual area of restoration required to offset Yarra Valley Water's supply chain impacts is 125 hectares. Importantly, however, this example has some important assumptions that mean it should only be treated as an illustrative example of converting between area, PDF and SOI, rather than a prescriptive recommendation. ReCIPe's characterisation factors have a range of assumptions about the taxa being quantified, depending on the midpoint pressure (Huijbregts et al., 2017). For example, some characterisation factors only consider plants, others consider vertebrate species too (Huijbregts et al., 2017). By contrast, our case study species distribution models include only mammals, birds and reptiles and so our worked example here assumes that the mean benefit of restoration can be extrapolated beyond the taxa modelled. Restoration benefits can also take time to accumulate (Vesk et al., 2008), whereas our worked example here assumes benefits are realised annually.