BIODIVERSITY BUILDING BLOCKS FOR POLICY

D6.1 Biodiversity change

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Author(s): Shawn Dove, Yanina V. Sica, Maarten Trekels, Hanno Seebens

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1. Key takeaway messages

- The vast majority of Wetlands of International Importance remain beyond the reach of GBIF-enabled biodiversity-trend monitoring: verifiable, open-access biodiversity records support trend estimation across a small time window for about 60 of the world's 2,529 sites (2.4%), and full robust trend estimation for only 3 of those sites.
- The gap extends to the species that matter most: nearly half of Wetlands of International Importance where species of conservation concern are known to occur have no occurrence records for those species uploaded to GBIF, and a third of sites still lack digital boundaries.
- The bottleneck is data depth, not geographic coverage. Almost all sites with digital boundaries available have some occurrence data, but most have too little to pass sampling-completeness (Chao2) and species-accumulation-saturation (SAC) checks.
- The taxonomic and geographic breadth of open-data sufficiency is narrow, largely limited to birds in a handful of northern-European countries, with insects and plants almost entirely absent.
- Global, open-access biodiversity occurrence data are not automatically fit for local decision support. If the scale, coverage, or completeness doesn't match the question, drawing firm conclusions can easily mislead.

2. Executive summary

The Convention on Wetlands (Ramsar) commits its Contracting Parties to maintaining the 'ecological character' of more than 2,500 Wetlands of International Importance. Assessing whether this obligation is being met requires the ability to detect biodiversity change at the site level. This case study, conducted under Work Package 6 of the EU-funded B3 (Biodiversity Building Blocks for Policy) project, asks a practical question: to what extent can freely available, open-access species-occurrence data, mobilised through the Global Biodiversity Information Facility (GBIF), actually support biodiversity-trend monitoring across the global network of Wetlands of International Importance?

The analysis is tiered. Part 1 is a global data-sufficiency audit that screens every Wetland of International Importance with a usable boundary against transparent criteria for spatial precision, observation density, sampling completeness, species-accumulation saturation, and temporal decoupling of richness from effort. Part 2 applies the full suite of `b3gbi` temporal indicators to the small subset of sites that pass. Part 3 is a targeted, illustrative deep dive into invasive-species impact and establishment rates at three well-sampled sites.

The central finding is stark and policy-relevant: on current open data, the overwhelming majority of Wetlands of International Importance cannot be monitored for biodiversity trends using GBIF records. Approximately 96% of mapped sites fail at least one sufficiency criterion (sites without boundaries could not be associated with data, so fail by default). The primary reason is not only a lack of records, but a lack of depth, due to opportunistic, effort-driven sampling that never approaches taxonomic completeness. The sites that can actually be monitored by open GBIF data are few, and geographically concentrated in a few countries with high monitoring capacity. Identifying where these blind spots lie is itself a valuable, actionable output for conservation policy.

The same shortfall is visible upstream, in the data the Convention relies on. More than one third (35%) of sites still lack digital boundaries, 74% have Ramsar Information Sheets more than six years old, and 41% of sites with internationally important species listed have no GBIF records for the very species that justify their designation. Open data may be able to complement reporting of the Convention on Wetlands cost-effectively, but only once Contracting Parties close upstream gaps in site boundaries and standardised species reporting and feed their own records into the open-data commons.

3. Non-technical summary

Wetlands are among the most valuable and most threatened ecosystems on Earth. The Convention on Wetlands protects 2,529 internationally important wetlands, and the countries that sign it promise to keep these sites ecologically healthy. To know whether that promise is being kept, we need to be able to measure how the plants and animals at each site are changing over time.

This study assessed whether freely available biodiversity records, many contributed by citizen scientists and accessible online through the Global Biodiversity Information Facility (GBIF), are sufficiently complete and reliable to track these changes.We checked every Wetland of International Importance for which a map boundary exists and applied a series of quality tests to see whether the data were deep and consistent enough to reveal a genuine biodiversity trend, rather than just a reflection of how many people happened to visit and record wildlife there.

The answer is sobering. For the vast majority of designated wetlands, the open data are simply too thin to support a reliable assessment. Most sites have some records, but too few, too patchy, or too concentrated on easy-to-spot species such as birds. Only a small number of well-monitored wetlands, mostly in northern Europe, have sufficient open-access biodiversity data for reliable trend analysis. This does not mean the other wetlands are unimportant, poorly managed, or ecologically unhealthy. Some may be effectively protected and monitored through national, provincial, or local programmes, but those records may not be published through GBIF. Rather, the findings show that open data alone are currently insufficient to assess biodiversity trends at most sites. Identifying these information gaps is therefore valuable because it can help governments target data mobilisation and additional monitoring where they would have the greatest benefit.

4. List of abbreviations

B3 – Biodiversity Building Blocks for Policy
CBD - Convention on Biological Diversity
COL - Catalogue of Life
EICAT – Environmental Impact Classification for Alien Taxa
EU – European Union
GBIF – Global Biodiversity Information Facility
GIDIAS – Global Impacts Dataset of Invasive Alien Species
GRIIS – Global Register of Introduced and Invasive Species
IPBES - Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services
IUCN – International Union for Conservation of Nature
KM-GBF - Kunming-Montreal Global Biodiversity Framework
MAGV – Moving-Average Growth-Volatility

MGRS – Military Grid Reference System
RIS – Ramsar Information Sheet
RLE – Run Length Encoding
RSIS – Ramsar Sites Information Service
SAC – species-accumulation-saturation
SPR – Spatial Precision Ratio

5. Introduction

5.1. Wetlands, the Convention on Wetlands, and 'ecological character'

Despite occupying less than 1% of the Earth's surface, inland freshwaters support a disproportionately large share of global biodiversity, including around one-third of vertebrate species and diverse, often highly specialised aquatic and wetland flora (Dijkstra et al., 2014). They also underpin essential ecosystem services, including water purification, flood regulation and carbon storage (Reid et al., 2019). They are also among the most rapidly declining ecosystems on Earth. The Global Wetland Outlook 2025 estimates that some 411 million hectares of wetland, about 22% of the global total, have been lost since 1970, with ongoing losses of around 0.5% per year, and that roughly a quarter of remaining wetlands are in poor ecological condition (Secretariat of the Convention on Wetlands, 2025b). Populations of freshwater-dependent vertebrates monitored by the Living Planet Index have fallen by more than 80% on average since 1970, the steepest decline of any realm (WWF, 2024).

The Convention on Wetlands (Ramsar, 1971) is the principal intergovernmental treaty addressing this crisis. Its Contracting Parties designate Wetlands of International Importance and commit to maintaining their 'ecological character', defined as the combination of ecosystem components, processes and services that characterise the wetland at the time of designation (Secretariat of the Convention on Wetlands, 2025a). Detecting change in ecological character, and reporting it through national reports and the Ramsar Sites Information Service (RSIS, https://rsis.ramsar.org/), is a core obligation, embedded in the Strategic Plan of the Convention on Wetlands (Secretariat of the Convention on Wetlands, 2025a) and echoed in the Kunming-Montreal Global Biodiversity Framework (KM-GBF, https://www.cbd.int/gbf). In practice, however, monitoring is fragmented and uneven; reviews of national implementation find inconsistent methods, incomplete coverage and a widespread inability to compare ecological status across sites, so that change at many wetlands cannot be fully determined owing to a lack of data (Clemens et al., 2021; Kingsford et al., 2021). The problem is therefore one of verification: Contracting Parties commit to maintaining and reporting on each site's ecological character, yet for most sites there is no way to independently check whether that character is being maintained.

The Convention's reporting system also identifies which species are of conservation concern. At designation and periodically thereafter, each Contracting Party completes a Ramsar Information Sheet (RIS) through the RSIS, describing the site and listing the species whose presence relates to its international importance. These listed species are the most direct, policy-defined target for monitoring: they are the biological basis on which the site was recognised. This creates two complementary questions for any open-data assessment. First, a targeted question: are a site's own internationally important species even visible in open data? Second, a general

question: across all taxa, are the data deep and stable enough to compute reliable biodiversity trends? A site can fail the first while superficially appearing rich in the second, and vice versa, so both must be assessed. This report addresses both, alongside the more basic prerequisites, an RIS and a digital site boundary, without which neither question can be answered at all.

5.2. The biodiversity-data challenge

The difficulty of monitoring wetland biodiversity is a specific instance of a broader problem: our knowledge of where and when species occur is deeply incomplete and non-randomly biased (Hughes et al. 2021), reflecting both Wallacean and Linnean shortfalls (Hortal et al., 2015). The Global Biodiversity Information Facility (GBIF, https://gbif.org) has transformed data availability, mobilising more than three billion occurrence records from museums, herbaria, structured surveys and, increasingly, citizen-science platforms, and integrating them with the taxonomic backbone provided by the Catalogue of Life (COL, https://www.catalogueoflife.org). Since these records are aggregated from heterogeneous sources, not designed as a coordinated monitoring programme, they carry strong biases. Records are spatially skewed towards accessible and high-income regions, with taxonomic biases towards conspicuous, popular groups, most notably birds, for which sampling is far more complete than for any other taxa (Boakes et al., 2010; Hughes et al., 2021; Troudet et al., 2017).

These biases complicate the detection of real species trends. Records in GBIF conflate two very different signals: genuine ecological change, and change in how much observation effort was expended. A rise in recorded species richness at a site may reflect a real increase in biodiversity, or simply the arrival of more birdwatchers with better cameras and a mobile app (Boakes et al., 2010; La Sorte & Somveille, 2024). Uneven, unquantified effort can therefore manufacture spurious trends or mask real ones. Robust use of open data for monitoring consequently demands a careful assessment of whether the data at a given place and time are complete enough to carry an ecological signal at all, which we refer to as data sufficiency. More specifically, data sufficiency means having *sufficient* taxonomic, spatial, and temporal coverage, with a *sufficiently* even distribution, that we can attribute observed patterns to real ecological variation rather than sampling bias or noise. Established tools exist for this: non-parametric richness estimators such as Chao2 quantify how much of the true species pool has been detected, and coverage-based rarefaction quantifies sample completeness and the rate at which new species are still being discovered (Chao & Jost, 2012; Chao et al., 2014; Colwell et al., 2012). Earlier work applying such estimators to open databases established practical ‘moderate’ completeness thresholds for judging inventory adequacy (Troia & McManamay, 2016), which we adopt and adapt here.

5.3. Data cubes, `b3gbi` and the B3 workflow

The B3 project was created to make biodiversity data more usable for policy by standardising both the data and the indicators derived from them. Its central data structure is the GBIF occurrence cube: a pre-aggregated summary of records along taxonomic, temporal and spatial dimensions, produced through a GBIF service developed within the B3 project (Desmet et al., 2023). On top of cubes, the `b3gbi` R package provides automated, reproducible workflows that compute a broad suite of spatial and temporal biodiversity indicators, including species richness, Hill diversity, evenness, rarity, occupancy turnover, taxonomic distinctness and more, with integrated uncertainty estimation (Dove, 2026). Because the input data and the workflow

are FAIR, all outputs produced are similarly FAIR and auditable, which is important for effective biodiversity monitoring (Sica et al., 2024).

5.4. Monitoring invasive alien species under the Global Biodiversity Framework

Invasive alien species are one of the most important direct drivers of global biodiversity loss (IPBES, 2023). Nearly 37,000 alien species have been introduced by human activity worldwide, with some 200 newly recorded each year, and around 3,500 of these are known to have harmful effects on nature and people (IPBES, 2023). Wetlands are among the systems most severely affected: the Ramsar Convention has recognised since 1999 that invasive species pose a major threat to the ecological character of wetlands and to wetland species, and has repeatedly urged Contracting Parties to identify, monitor, control and eradicate them within their jurisdictions (Ramsar Convention, 1999, Resolution VII.14; Ramsar Convention, 2002, Resolution VIII.18). For Wetlands of International Importance, biological invasions are therefore a recognised driver of change in ecological character, and one that Contracting Parties are expected to monitor and report. This makes it a natural test of what open data can and cannot deliver.

The KM-GBF, adopted under the Convention on Biological Diversity, addresses biological invasions in Target 6, which commits Parties to reducing the rate of introduction and establishment of invasive alien species by at least 50% by 2030 and to minimising their impacts (CBD, 2022, Decision 15/4). The target thus measures two aspects, namely how fast new alien species establish, and how much damage those already present cause. Progress is tracked through a headline indicator on the rate of invasive alien species establishment, “Headline Indicator 6.1”, supported by component and complementary indicators covering impact and management response (CBD, 2022, Decision 15/5). This report examines both aspects of Target 6 at three well-sampled Wetlands of International Importance.

Neither aspect is straightforward to measure from largely opportunistic occurrence records. The rate at which alien species are newly reported has risen continuously over the past two centuries, with no sign of saturation in any taxonomic group (Seebens et al., 2017). But the date of the first record is not the date of arrival. Records accumulate only when an organism is correctly identified and published, making first-record series highly sensitive to survey effort, detectability, and taxonomic expertise (Solow and Costello, 2004). As mentioned above, raw occurrence counts, conflated with effort, can mask genuine ecological change. To resolve this, statistical approaches, most notably Solow and Costello (2004), separate the underlying arrival signal from time-varying search effort to estimate the true timeline of introductions.

Measuring impact requires an assessment of how each species interacts with the new environment and the resident species where it establishes. The IUCN Environmental Impact Classification for Alien Taxa (EICAT) supplies the standard vocabulary, classifying alien taxa into five categories from Minimal Concern to Massive according to the level of biological organisation affected and the severity and reversibility of the effect (Blackburn et al., 2014; IUCN, 2020). Published assessments remain scattered, but the Global Impacts Dataset of Invasive Alien Species (GIDIAS), compiled for the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) invasive alien species assessment, brings together more than 22,000 impact records for 3,353 species from over 6,700 sources and scores them on a four-level magnitude scale that follows EICAT in condensed form, distinguishing effects on individual performance, population declines, and local or global

extinctions (Bacher et al., 2025). Combining such scores with occurrence records yields an impact indicator, but it also inherits the effort problem. An indicator that sums impact-weighted records will rise whenever recording rises, whether or not invasion pressure has changed. At the same time, recorded impacts are spatially explicit and context dependent: the same species may have markedly different impacts across locations, even within the same country. EICAT scores therefore need to be combined in ways that appropriately integrate multiple impact measures while retaining either a robust overall signal or locally relevant interpretation (Yahaya et al., 2026).

Measuring impact or estimating establishment also requires a reference list of which recorded species are considered alien in a given country. The Global Register of Introduced and Invasive Species (GRIIS) provides national checklists for this purpose (Pagad et al., 2022), and because it is published through GBIF it can be matched to occurrence records using the same taxonomic backbone, the COL, keeping the whole calculation within the open infrastructure already described.

5.5. Aims and structure of this case study

This case study applies B3 tools to all Wetlands of International Importance (the Ramsar network) to answer three policy-relevant questions posed in the M30 milestone (Dove, 2025a): (1) what is the current state of open-access biodiversity-data sufficiency across Wetlands of International Importance, and which regions are best and worst served; (2) to what degree can the `b3gbi` workflow quantify biodiversity trends in sites where data suffice; and (3) how can these outputs inform and streamline national reporting, including on invasive and threatened species? The assessment begins by establishing the basic availability of open data accessible in GBIF and the coverage of internationally important (RIS-listed) species across all Wetlands of International Importance, and then proceeds through a tiered analysis of the sites where data allow.

- **Part 1:** a global data-sufficiency audit of all Wetlands of International Importance, using simple, low-requirement metrics to identify data gaps and quantify open-data monitoring capacity.
- **Part 2:** application of the full `b3gbi` temporal-indicator suite to the sites that pass, with Europe as the primary focus and the remaining global sites as context.
- **Part 3:** a targeted, illustrative deep dive into invasive-species impact and establishment rates at three well-sampled sites, addressing both aspects of GBF Target 6.

The remainder of this report describes the methods used, presents the results in full, and discusses the implications and takeaways.

6.Methods

6.1. Study system and site boundaries

The analysis covers all Wetlands of International Importance, as recorded in the RSIS (n = 2,529). Site boundaries were obtained as spatial geometries from RSIS (Secretariat of the Convention on Wetlands, n.d.) , and boundaries were available for 1,638 out of the 2,529 designated sites (65%). Site polygons were used both to compute site area and to clip occurrence data to each site. Sites lacking a digital boundary could not be analysed at all

because any related occurrence data that may be present on GBIF could not be reliably linked to them; they were therefore considered to fail data-sufficiency testing by default.

6.2. Occurrence data and cube construction

Species-occurrence data were downloaded from GBIF as continent-scale occurrence cubes. To accommodate the very small area of many wetlands, occurrences were aggregated (before downloading) to a fine 100 m Military Grid Reference System (MGRS) grid. At first, automated downloading of individual site cubes was attempted, using the `rgbif` R package (Chamberlain et al., 2026), but proved intractable due to geometry mismatches and query limits. Therefore, entire continental cubes were downloaded manually from the GBIF web interface, then individual site cubes were batch generated locally in R by aggregating occurrences from grid cells falling within or overlapping the boundaries of each Wetland of International Importance. While the cubes contain all historical occurrence data available in GBIF, analyses of data sufficiency and site trends were restricted to records from 1990 onwards to focus on the period of substantial digital recording. Cubes were ingested and validated with the `b3gbi process_cube()` function, which checks and standardises column names, removes invalid rows, aggregates monthly or daily records (if present) by year, and translates cell codes into x-y coordinates, in preparation for calculating indicators using B3 standardised workflows.

6.3. Coverage of internationally important (RIS-listed) species

In parallel with the all-taxa audit, we assessed how well open data cover the species whose presence relates to each site's international importance. Lists of these species were obtained from the Convention's database where available and, where not, extracted from the RISs, yielding species lists for 2,419 sites. For each site, the listed species and subspecies (all taxon ranks below subspecies were removed) were matched against the occurrence records available in its GBIF cube to quantify the proportion of listed species with at least one open record (per-site coverage). The analysis was summarised across the network, mapped geographically, and tracked over time to determine the share of sites with at least one matching record per year since 1971 (the year the Convention on Wetlands was signed). We also recorded two basic prerequisites for any such assessment: whether a site had a digital boundary, and whether its RIS was current (updated within the last seven years). The results of the analysis of the coverage of RIS-listed species formed the foundation of an associated policy brief (Sica et al., 2026).

6.4. Taxonomic separation

Because detectability and recording effort differ enormously among taxa, all data-sufficiency and indicator analyses were carried out separately for each of five taxonomic groups: birds (Aves), mammals (Mammalia), herpetofauna (Amphibia and Reptilia), insects (Insecta) and plants (Plantae), in addition to the full community. A given site therefore contributes several 'site×taxon' combinations, each evaluated on its own merits, so that a site can be monitorable for birds while remaining data-deficient for plants. Any site×taxon combinations with fewer than ten records were not analysed.

6.5. Data-sufficiency framework

Each site×taxon combination was screened against five criteria and classified as data-sufficient only if it passed all five. The criteria progress from a basic check that records can be attributed to the site, through checks on sampling intensity and completeness, to a check that the richness signal is not merely tracking observation effort.

- **1. Spatial Precision Ratio (SPR).** The mean coordinate-uncertainty area, which is the radius of uncertainty around an observation expressed as an area, πr^2, with *r* being the mean coordinate uncertainty (GBIF cube field `coordinateUncertaintyInMeters`) across all observations for that site, divided by the area of the site (geodesic area of the Ramsar boundary polygon in km^2), must be ≤ 0.10. In other words, SPR is the fraction of the whole site that the typical record's positional uncertainty covers. Records that do not report uncertainty are excluded from the calculation by necessity, which can lead to underestimation; but if no records at a site report uncertainty, the site fails and is excluded from analysis. Because GBIF coordinate uncertainty is frequently kilometre-scale while many Wetlands of International Importance are small, this ratio assesses whether observations can be reliably attributed to a site. Site×taxon combinations are discarded when average positional uncertainty exceeds 10% of the site's spatial extent. Caveats worth noting are that the uncertainty reported for each aggregated cube record is a minimum, not an average; rows are not weighted by number of occurrences; records that lack uncertainty were not filtered out; and by Jensen's inequality, since the mean is taken before calculating area instead of taking the mean of the areas, there is systematic understatement if uncertainty varies across cube rows, which it typically does. The number of sites passing this check may therefore be optimistic. These caveats were recognised post-analysis and should be taken as lessons to apply a more rigorous application of the method in future studies.
- **2. Observation density.** At least 0.25 occurrences must be present per km², following the 'moderate' survey-adequacy threshold of Troia & McManamay (2016).
- **3. Chao2 completeness.** Estimated sampling completeness is the observed richness (count of unique species in the sample at year *t*) divided by the Chao2-estimated species pool. It must be ≥ 0.70 for a site×taxon combination to be deemed complete enough. Chao2 is computed from an incidence matrix of species across 100 m grid cells, treating occupied grid cells as the sampling unit and pooling years across the full time series, using the bias-corrected estimator:

$$\hat{S} = \{S_{obs} + \frac{t-1}{t}\frac{Q_1^2}{2Q_2} \; if \; Q_2 > 0 \; S_{obs} + \frac{t-1}{t}\frac{Q_1(Q_1-1)}{2} \; if \; Q_2 = 0 \,,$$

  where S_{obs} is observed richness, *t* is the total number of distinct occupied grid cells, Q_1 is the species found in exactly one cell, and Q_2 is the species found in exactly two cells. Combinations with too few occupied cells to estimate Chao2 fail this criterion.
- **4. Species-accumulation saturation (SAC slope).** The species-accumulation slope is one minus the mean annual sample coverage, with coverage being Chao's incidence estimator:

$$\hat{C} = 1 - \left(\frac{Q_1}{U}\right)\left[\frac{(t-1)Q_1}{((t-1)Q_1+2Q_2)}\right]$$

where *t* is the total number of sampling units (100 m grid cells), Q_1 is the species found in exactly one sample, Q_2 is the species found in exactly two samples, and *U* is the total number of incidences across all species. It was computed via `b3gbi`'s `completeness_ts()` function, which in turn calls the `DataInfo()` function from the `iNEXT` R package (Hsieh et al., 2022). To pass, the SAC slope must be ≤ 0.10, i.e. less than a 10% chance that the next record is a previously undetected species, indicating a saturating inventory (Chao et al., 2014; Hsieh et al., 2016).

- **5. Temporal decoupling of richness from effort.** We tested whether changes in recorded species richness reflect real biodiversity patterns rather than simply changes in how much people sampled. For each site and taxonomic group, annual species richness is compared with the annual number of occurrence records. If the two rise and fall together, the site fails this criterion because the apparent biodiversity signal is still dominated by observation effort. If they behave differently enough, the site passes, indicating that richness contains information beyond sampling intensity. A data-driven "elbow" threshold in the Jaccard-distance distribution is used to separate coupled from decoupled time series.For each site×taxon combination the annual time series of total occurrences (sum of all occurrences in the sample at year *t*) and of observed richness are compared using the Jaccard distance. The Jaccard distance is calculated as

$$d_{Jaccard} = \frac{\sum_{t=1}^{n}\left(P_t - Q_t\right)^2}{\sum_{t=1}^{n} P_t^2 + \sum_{t=1}^{n} Q_t^2 - \sum_{t=1}^{n} P_t Q_t}$$

(from Cha, 2007), where P_t and Q_t are index values from two trends *P* and *Q* at time point *t*, and *n* is the number of time points. A dynamic elbow threshold across all sites separates site×taxon combinations where the two time series remain tightly coupled (rejected) from those where richness carries information beyond effort (retained). The threshold is calculated as follows: across all site×taxon combinations, sort the Jaccard distances in ascending order, assign a rank to each sorted distance, then normalise the rank to x∈[0,1] and distance to y∈[0,1]; the "elbow" is the point of maximum perpendicular deviation from the 1:1 line ($|x-y|/\sqrt{2}$), and its distance value becomes the pass threshold. Combinations where total occurrences and recorded richness are closely coupled fail this criterion, indicating that the ecological signal of species richness is obscured by survey effort.

A sixth, spatial-Jaccard variant (comparing occurrence and richness across grid cells within a site) was implemented during development but is deliberately not used here because coordinate uncertainty routinely exceeds the 100 m grid, within-site spatial mapping is not meaningful, and the Spatial Precision Ratio already governs spatial data quality. Consequently no spatial (map-based) indicators are computed or reported; the study is restricted to temporal trends.

6.6. Saturation reliability and temporal phasing (MAGV)

Passing a data-sufficiency screen does not guarantee a stable trend over the full time frame; effort can arrive in bursts, for example when a site is 'discovered' by recorders, while assessing trends requires having sufficient data over a prolonged period of time. For each data-sufficient site×taxon combination we therefore computed an effort-stability metric on the annual total-occurrence series, the Moving-Average Growth Volatility (MAGV). Year-on-year relative

change in effort was summarised over a five-year rolling window by its mean absolute change and its volatility (rolling standard deviation), and combined into a reliability score of 1 / (1 + volatility + mean absolute change). Years scoring above 0.8 are treated as stable and years equal to or below 0.8 as unstable; run-length encoding (RLE) then identifies the longest continuous stable window. RLE is a sequence-compression method that encodes consecutive identical values as (value, length) pairs; here it is applied to the years scoring as stable and unstable to find the longest continuous run of stable years. If the longest run is at least 5 years in length, the site has a 'usable window'. Indicator trends are reported both over the full 1990-onwards series and, where a stable window of sufficient length exists, restricted to that window.

6.7. Biodiversity indicators for data-sufficient sites

For every data-sufficient site×taxon combination, the full suite of `b3gbi` temporal (time-series) indicators was computed, including observed and estimated (Hill) richness, Hill-Shannon and Hill-Simpson diversity, Pielou's and Williams evenness, abundance- and area-based rarity, occupancy turnover, taxonomic distinctness, cumulative richness, mean year of occurrence and total occurrences (see Table A2 in Annex 12.2 for formulas and references). Full definitions, formulas and per-indicator references for all calculated indicators are given in the B3 deliverable D5.1 (Dove, 2025). Bootstrapped confidence intervals were generated for the indicators that support them. For each indicator at each site we fitted a straight line (linear regression) to its annual values. The sign of that line's slope shows whether the indicator rose, fell or stayed level over the period, and we classified each series as increasing, decreasing or showing no significant change accordingly.

6.8. Invasive-impact vignette

To illustrate the specialised, species-specific analysis that becomes feasible only where open data are rich, we conducted a targeted invasive-impact assessment at three high-data Wetlands of International Importance of contrasting character, namely La Petite Camargue in France, the Severn Estuary in the United Kingdom and the Okavango Delta System in Botswana, each of which passes the data-sufficiency criteria for both its full community and its bird assemblage. The assessment combines three data sources with the `impIndicator` R package developed within B3 (Yahaya et al., 2026).

Alien and invasive status. The occurrence records were first intersected with the Global Register of Introduced and Invasive Species (GRIIS) checklists for France (Roy et al., 2026), Great Britain (Roy et al., 2026), and Botswana (Pagad et al., 2026). Species on the checklist were flagged as alien, and the subset that GRIIS records as invasive was flagged accordingly, yielding the site's alien and invasive species lists.

Impact assessments (EICAT). For each alien species, environmental-impact scores were drawn from GIDIAS (Bacher et al., 2025), which provides more than 22,000 impact records and their magnitude assessed using a simplified EICAT (Hawkins et al., 2015; IUCN, 2020). One of the simplifications concerns the impact categories: In GIDIAS the five categories of environmental impacts of EICAT categories were condensed to four: Level 0 (no impact), Level 1 (performance of native individuals affected), Level 2 (population declines), and Level 3 (local or global extinctions). Here we mapped those GIDIAS categories to EICAT categories, Level 0 was mapped to MC, Level 1 to MN, Level 2 to MO, and Level 3 combines MR and MV into a

single category, MR. Each species was assigned its maximum recorded category; alien species without a GIDIAS assessment were retained but labelled 'not assessed'. It should be noted that the EICAT were global, and therefore not useful for application to impact assessment for individual wetland sites; however, the purpose of this analysis is not to conduct impact assessments but to determine the sufficiency of the data for impact assessments.

Impact indicator. The standardised invasive-impact indicator was computed with the function `compute_impact_indicator()` from `impIndicator`, using the cumulative-mean method (by specifying the option `method = 'mean_cum'` for the function; defined in the `impIndicator` documentation). For each year this combines the occurrence records of assessed alien species with their EICAT impact scores to produce a single, category-weighted value of potential impact for the site, tracked as a time series from 1990. The indicator is first reported as computed, and then recomputed under three different effort-standardisation protocols (implemented by us, not part of the `impIndicator` package). We did not compute confidence intervals for the unstandardised results.

Effort standardisation. Because `impIndicator` lacks a built-in sampling effort correction method, we recomputed the indicator using three different approaches. The first, *size-based rarefaction*, holds recording volume constant. For each year we drew a fixed number of EICAT-assessed alien occurrence records without replacement, re-aggregated them into cube form and recomputed the indicator. This was repeated 100 times for each year, reporting the mean and the 2.5th-97.5th percentiles across draws. Cubes contain rows of aggregated occurrence counts, which we disaggregated into individual records before sampling, to ensure equal selection likelihoods for each record. The number of draws per year was set to the smallest annual total among retained years (23 records at La Petite Camargue, 34 at the Severn Estuary and 20 in the Okavango Delta), with years having fewer than twenty assessed alien records excluded as too sparse to rarefy. The year defining the draw size at each site contributed no sampling variability because sampling was without replacement. The second method, *coverage-based rarefaction*, instead holds sample completeness constant (Chao & Jost, 2012), similar to the implementation in the `iNEXT` package used for coverage-based estimation of Hill diversity values by `b3gbi`. Each year's sample coverage was estimated from the frequencies of species represented by one and two records, with target coverage equal to the lowest value among retained years. We then solved for the year-specific number of records reaching that target then calculated bootstrapped CIs as for size-based rarefaction described above. The third method, composition ratios, avoids resampling by expressing impact as a proportion within each year: the share of assessed alien records belonging to species classified as EICAT-equivalent Major or Massive (GIDIAS Level 3), and the record-weighted mean EICAT-equivalent score. This is the same strategy used by Bacher et al. (2026), which they termed 'average impact severity'. Ratios largely bypass sample-size dependence and do not require excluding any years. CIs for the annual proportions were computed as Wilson score intervals (Wilson, 1927):

$$\mathrm{CI} = \frac{(\hat{p} + \frac{z^2}{2n}) \mp z\sqrt{\frac{\hat{p}(1-\hat{p})}{n} + \frac{z^2}{4n^2}}}{1 + \frac{z^2}{n}}$$

where n is the number of assessed alien records in a given year, $\hat{p}$ is the observed proportion of assessed alien records belonging to Major-impact species in that year, and z = 1.96 is the

standard normal quantile for 95% confidence, and the minus and plus signs give the lower and upper limits respectively. Unlike the normal (Wald) approximation, the Wilson interval remains bounded within [0, 1] and retains good coverage at small sample sizes and for proportions close to zero or one (Agresti & Coull, 1998; Brown et al., 2001), properties that matter here because several annual proportions are based on very few records. Years with fewer than twenty records were flagged but not excluded, and we reported correlations both for all years and for only well-sampled years. Resampling for the rarefaction methods used set.seed so that the rarefaction can be reproduced exactly.

Scope. The vignette is deliberately illustrative because there were too few sites with the level of data sufficiency needed for a more thorough analysis. A network-wide invasive-impact analysis, and a phylogenetic-diversity treatment using `pdindicatoR` (Breugelmans et al., 2024), another R package developed within B3, remain out of scope for open data at this stage (see Discussion).

6.9. Rate of alien species establishment

Using the same three data-rich sites as for the invasive-impact assessment, we used the `b3alien` Python package (Trekels, 2026) to investigate rates of alien species establishment using the same GBIF-supplied open data. The b3alien package is another tool that was developed within B3, which enables estimation of IAS establishment rates, and aligns with FAIR data principles. Species were matched against GRIIS checklists as described in section 6.8. For each alien species, the year of first record within the site boundary was taken from the occurrence cube, and these were accumulated into an annual series of newly detected species and a cumulative discovery curve. The observed discovery series was fitted using the Solow-Costello model (Solow and Costello, 2004), which represents the number of species discovered in each year as the product of an underlying introduction process and a detection probability that varies over time, and estimates the trend in introduction rate while accounting for the lag between arrival and first record. The change in the rate of establishment per year is then the fitted parameter. The model was fit from 1991 to 2023 for the Severn Estuary and the Okavango Delta, and from 1991 to 2025 for La Petite Camargue. Note that since the series starts in 1990 and there are time lags in data availability, some already established species being recorded for the first time may influence the model slope in the early years, and data deficiency may influence it in later years. Confidence intervals (95%) were obtained by bootstrapping the model residuals over 500 iterations (however the number of bootstraps is a settable parameter and can be adjusted if necessary). Survey effort was quantified to account for effort sensitivity of the discovery time series. Since GBIF occurrence cubes generated in this use-case didn't contain the number of distinct observers per cell, the observer-based measure of effort was not available, so effort was measured as total occurrence records aggregated to a higher taxonomic rank.

6.10. Software and reproducibility

Analyses were performed in R using the `b3gbi` package for indicator calculation and the `iNEXT` package for coverage-based estimation, with spatial operations handled through the `sf` package (Pebesma, 2018) and confidence intervals calculated by the `dubicube` package, another B3 development (Langeraert & Van Daele, 2026). To estimate the rate of establishment

of alien species, the Python package `b3alien` was used. Sufficiency screening, indicator computation and summarisation are scripted and version-controlled so that the full audit is reproducible and can be re-run as new data accrue.

7. Results

7.1. Coverage of internationally important species

Before biodiversity status and trends can be assessed using open data, three prerequisites must be met: a site must have a digital boundary so that occurrences can be reliably attributed to it, and occurrence records must exist and be openly accessible. Furthermore, to determine status or trends of the internationally important species whose presence determines a site's designation, those species must be listed in an up-to-date RIS. Of 2,529 designated sites, 74% do not have an RIS sheet that has been updated within the last six years; nonetheless, 2,419 sites (96%) have at least one species listed in an RIS (Table 1), outdated or otherwise. 35% of sites have no digital boundary submitted to the Convention (Table 1), so open records cannot be reliably linked to them at all; of those that remain, almost all (1,619) have at least one record on GBIF, but only 1,425 have records covering at least one RIS-listed species, and only 135 sites have records covering at least 90% of RIS-listed species (Fig. 1). We designate this as 'near-complete GBIF coverage', but 'complete' here refers to the percentage of species with records; spatial and temporal coverage of individual species cannot be assessed based on presence-only records.

Table 1: Data availability funnel for internationally important species.

Stage in the funnel	Sites	% of designated
Designated Wetlands of International Importance	2,529	100%
With a species list in the RIS	2,419	96%
With a digital site boundary	1,638	65%
With ≥ 1 spatially verifiable GBIF occurrence	1,619	64%
With ≥ 1 spatially verifiable GBIF occurrence for at least 1 RIS-listed species	1,425	56%
With ≥ 1 spatially verifiable GBIF occurrence for at least 50% of RIS-listed species	878	35%
With ≥ 1 spatially verifiable GBIF occurrence for at least 90% of RIS-listed species	135	6%

Overall, the GBIF coverage of the species that actually justify each designation is highly incomplete, with 41% (994 sites) having zero GBIF occurrences for any RIS-listed species, and the median site having records available for a mere 26% of its RIS-listed species (Fig. 1). In other words, for the majority of Wetlands of International Importance, the specific biodiversity features on which their status depends cannot currently be tracked with open data.

This coverage is highly unequal geographically (Fig. 2). Sites with high coverage of their listed species are concentrated in Western and Northern Europe, whereas much of Central Africa, South and Southeast Asia and parts of Latin America show little or no open-data representation of their internationally important species, the same north-western skew seen in the all-taxa results below, and a clear signal of where data-mobilisation effort is most needed.

Encouragingly, coverage has improved steadily over time (Fig. 3). The share of sites with at least one GBIF record matching their listed species rose from about 10% in 1971 to roughly 45% by 2023. The trajectory is positive but slow: after five decades, more than half of the sites with listed species still have no open record of any of them, underscoring that current rates of data mobilisation remain well short of what network-wide monitoring requires.

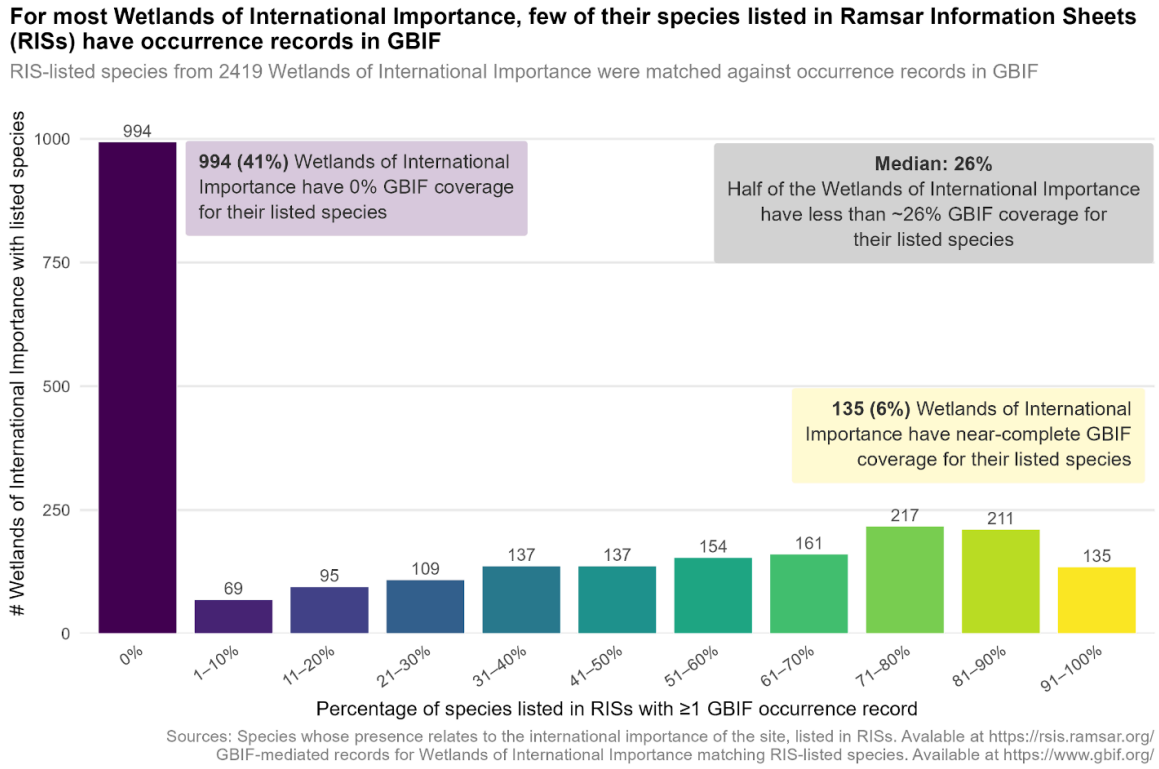

Figure 1. For most Wetlands of International Importance, few of their RIS-listed species have GBIF occurrence records. Across 2,419 sites, nearly half (994, 41%) have zero coverage; the median is 26% and only 135 (6%) are near-complete. Source: Sica et al. (2026).

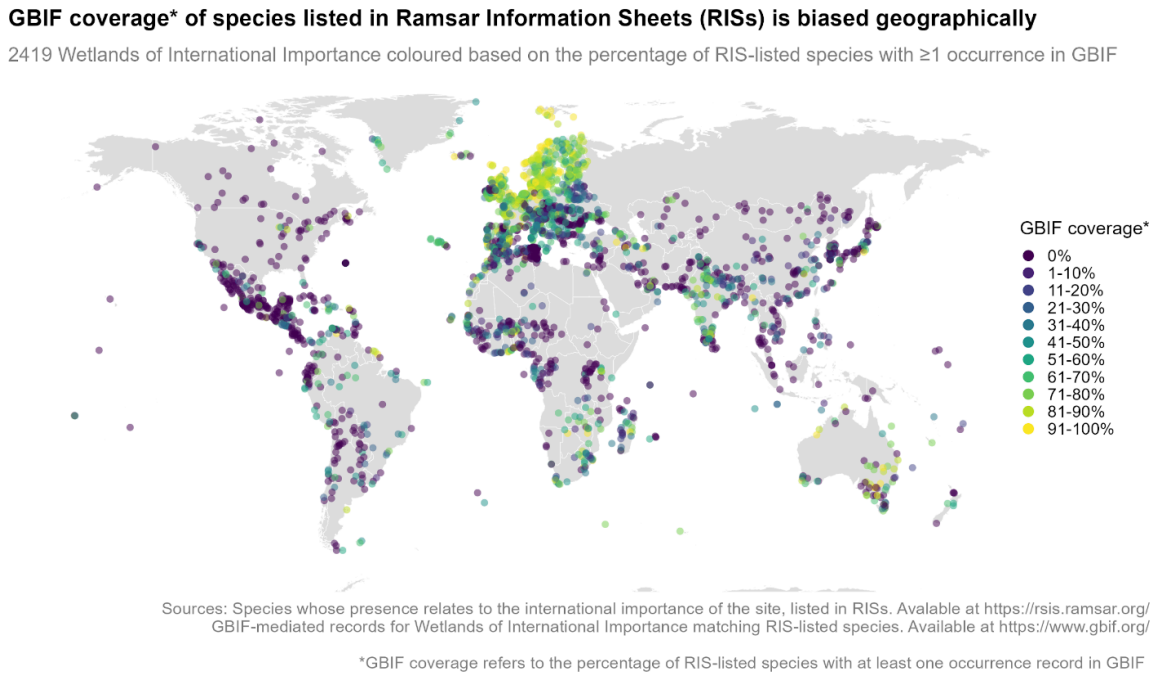

Figure 2. GBIF coverage of RIS-listed species is strongly biased geographically, concentrated in Western and Northern Europe. Each point is a site, coloured by the percentage of its RIS-listed species with at least one GBIF record. Source: Sica et al. (2026).

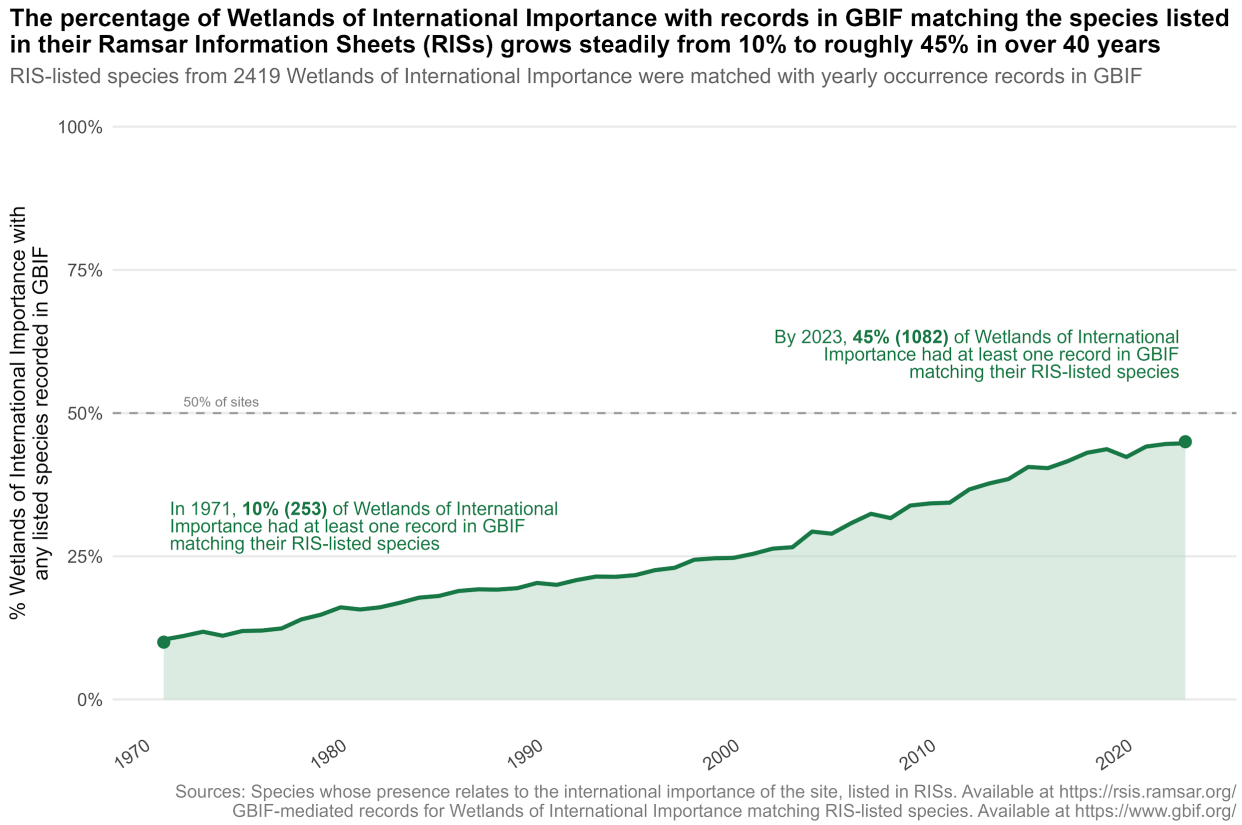

Figure 3. The share of sites with at least one GBIF record matching their RIS-listed species grew from about 10% (1971) to roughly 45% (2023), but over half still have none. Source: Sica et al. (2026).

Having established that basic availability and listed-species coverage are the first, coarse filters on open-data monitoring capacity, we now turn to the deepest filter: for the sites that do have attributable records, are those records sufficient in density, completeness, saturation and temporal stability, to compute reliable biodiversity trends?

7.2. Data sufficiency for Wetlands of International Importance (Part 1)

Across the global network of Wetlands of International Importance the capacity to monitor biodiversity trends from open data is extremely limited. Of 1,638 Wetlands of International Importance with digital boundaries, only 60 unique sites (3.7%, or 2.4% of all sites) pass all five sufficiency criteria for at least one taxonomic group, corresponding to 77 passing site×taxon combinations (Fig. 4). Equivalently, almost 98% of the entire site network is ‘open-data-invisible’: its biodiversity status and trends cannot be reliably assessed from open occurrence data. Where sites do pass, they typically do so for a single taxonomic group and over a relatively short time window.

The reason for this shortfall is not a simple absence of records. As the bottleneck cascade shows (Fig. 4), every evaluated combination passes the observation-density check (sites do have data) but most are eliminated by the completeness and saturation criteria. Sampling completeness (Chao2) removes 58% (3,930 of 6,761) of all combinations, and species-accumulation saturation (SAC slope) removes 82% of what remains (2,316 of 2,831).

The data are broadly present but overwhelmingly too shallow: occurrence data in GBIF (mostly opportunistic records) rarely reaches the point where the species list stabilises.

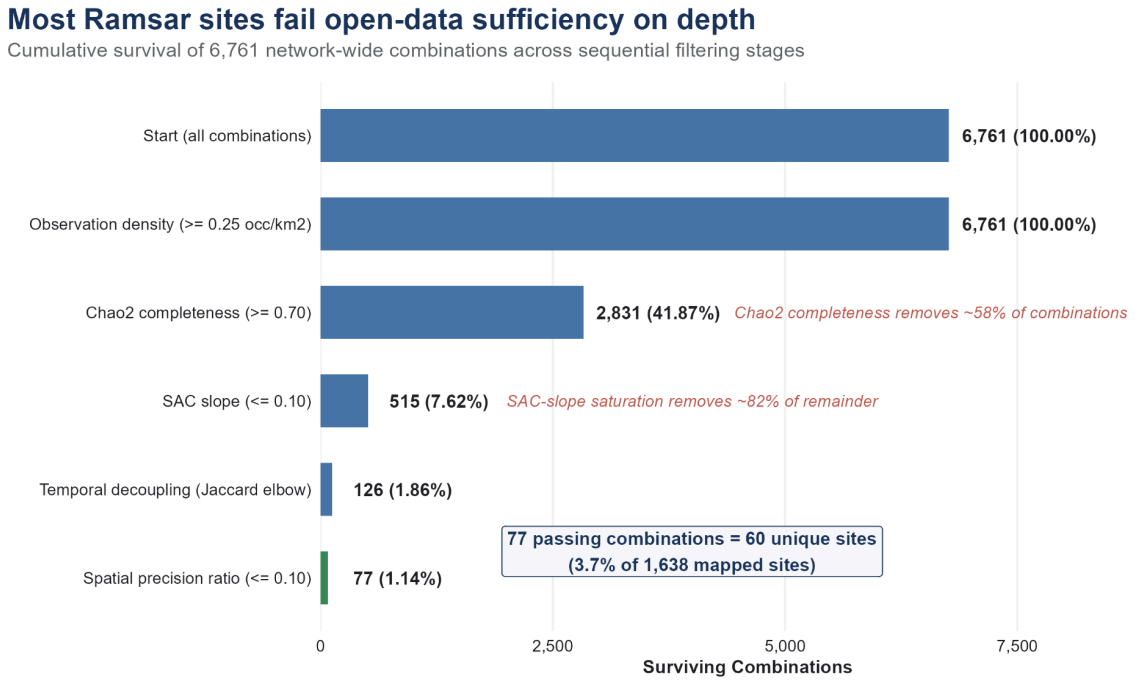

Figure 4. The data-sufficiency funnel. Of 6,761 site×taxon combinations, only 77 (60 unique sites) pass all five criteria; sampling completeness (Chao2) and species-accumulation saturation (SAC slope) account for almost all of the loss.

Open-data monitoring capacity is highly uneven geographically (Table 2). Europe accounts for the clear majority of data-sufficient sites, reflecting dense, sustained records in GBIF; Asia is almost entirely data-invisible in this open repository. However, it must be noted that Europe's dominance is partly a function of having far more designated sites with digital boundaries than any other continent; the actual percentage of passing sites for Europe (3.9%) was lower than that of Oceania (5.8%) and South America (5.1%), both of which have fewer designated sites by an order of magnitude.

Table 2: Data sufficiency by continent (unique sites passing at least one taxonomic group).

Continent	Official RSIS sites	Sites with boundaries	Passing sites	Pass rate (% of RSIS total)
Europe	1,088	943	34	3.9%
Africa	434	288	9	2.1%
South America	137	52	7	5.1%
Oceania	86	54	5	5.8%
North America	303	48	3	1.0%
Asia	481	236	2	0.4%
Global	2,529	1,638	60	2.4%

The GBIF-monitorable network is also taxonomically narrow (Table 3). Birds account for more than half (55%) of all passing combinations, and together birds and herpetofauna make up almost three-quarters (73%). Only a single insect combination and a single plant combination pass anywhere in the world, making these hyper-diverse but under-recorded groups effectively unmonitorable from open data, a critical blind spot, since these groups underpin wetland function.

Table 3: Passing site×taxon combinations by taxonomic group.

Taxonomic group	Passing combinations	Pass rate (% of RSIS global site total: 2,529)
Birds (Aves)	42	1.7%
Herpetofauna	14	0.6%
Full community	10	0.4%
Mammals	9	0.4%
Plants	1	0.04%
Insects	1	0.04%

Finally, passing sites concentrate in a small number of high-capacity countries (Table 4). The United Kingdom alone contributes more passing sites than any continent outside Europe, and a handful of northern-European and a few other well-resourced countries dominate, underlining that the 'functional Ramsar network' for open-data monitoring is, at present, a largely northern-European phenomenon.

Table 4: Countries with the highest number of data-sufficient Wetlands of International Importance.

Country	Official RSIS sites	Passing sites	Passing combinations	Pass rate (% of RSIS total)
United Kingdom	176	13	17	7.4%
France	57	5	8	8.8%
Netherlands	58	5	8	8.6%
Australia	67	5	5	7.5%
Portugal	32	5	5	15.6%
Kenya	6	3	5	50%
Argentina	24	2	3	8.3%
Spain	76	2	3	2.6%
Germany	35	2	2	5.7%
South Africa	32	2	2	6.3%
United States	41	2	2	4.9%

7.3. Biodiversity trends in data-sufficient sites (Part 2)

Monitoring reliability. Passing the static sufficiency criteria does not guarantee a temporally stable record. Applying the MAGV saturation-reliability metric to all 77 passing combinations reveals that recording effort is highly volatile even at the best-recorded sites: as shown in Fig. 5,

only 3 of the 77 (4%) contain a continuous stable window of at least five years, all bird series in north-western Europe (two Dutch sites, one UK; Panel A), and no combination sustains a reliability score above the 0.80 stability threshold across its record (median mean-reliability 0.46; maximum 0.72; Panel B). Among the small minority of sites that clear the sufficiency bar, almost none therefore offer a stretch of consistently monitored years over which a trend can be read with confidence.

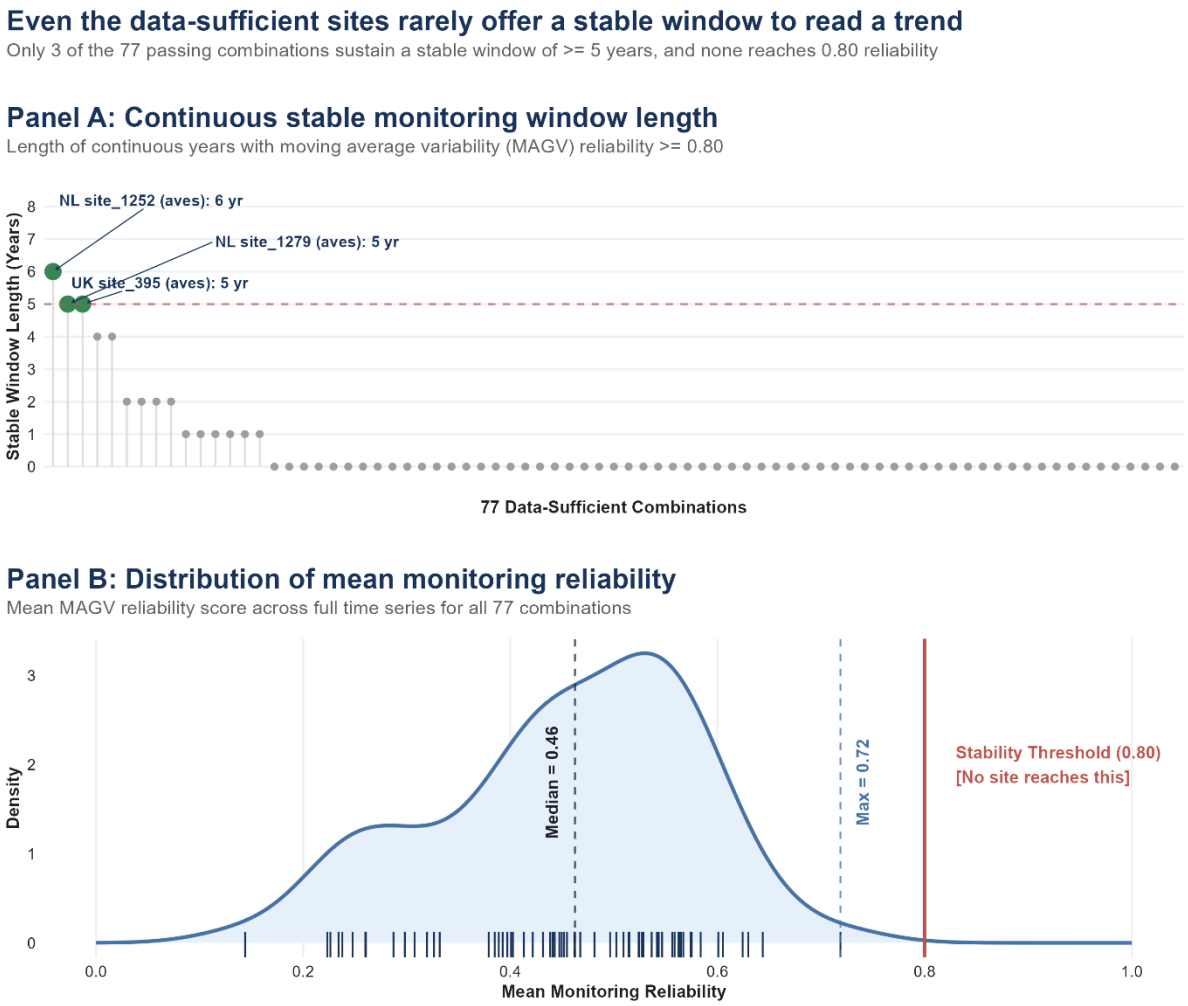

Figure 5. Monitoring-window reliability across the 77 data-sufficient combinations. Only three site×taxon combinations (all of which are European bird series) sustain a stable window of ≥ 5 years (Panel A), and no combination reaches the 0.80 reliability threshold across its record (Panel B).

With `b3gbi` indicators computed for all 77 data-sufficient combinations, a clear and cautionary pattern emerges (Table 5; Fig. 6). Indicators that scale with sampling effort rise almost universally: total occurrences, occurrence density, and cumulative and observed species richness increase at most sites, while few indicators remain stable and virtually none decline.. Taken at face value, these patterns suggest widespread biodiversity gain.

Table 5: Direction of change for key indicators across data-sufficient combinations — counts of combinations increasing / decreasing / showing no significant change, for Europe (primary) and globally. *Note that cumulative richness cannot go down, it can only rise or stay the same.

Indicator	Europe (↑ / ↓ / –)	Global (↑ / ↓ / –)
Total occurrences (effort)	37 / 0 / 5	58 / 2 / 17
Observed richness	25 / 1 / 16	32 / 3 / 42
Cumulative richness	40 / 0 / 2	65 / 0 / 12
Estimated richness (Hill q=0)	11 / 5 / 22	17 / 9 / 44
Hill-Shannon diversity (q=1)	7 / 3 / 21	11 / 6 / 41
Hill-Simpson diversity (q=2)	5 / 3 / 22	9 / 8 / 41
Pielou's evenness	12 / 3 / 12	13 / 4 / 16
Williams evenness	7 / 5 / 15	7 / 6 / 20
Abundance-based rarity	33 / 2 / 7	51 / 3 / 23
Occupancy turnover	0 / 12 / 13	0 / 20 / 32
Taxonomic distinctness	24 / 2 / 12	32 / 4 / 34

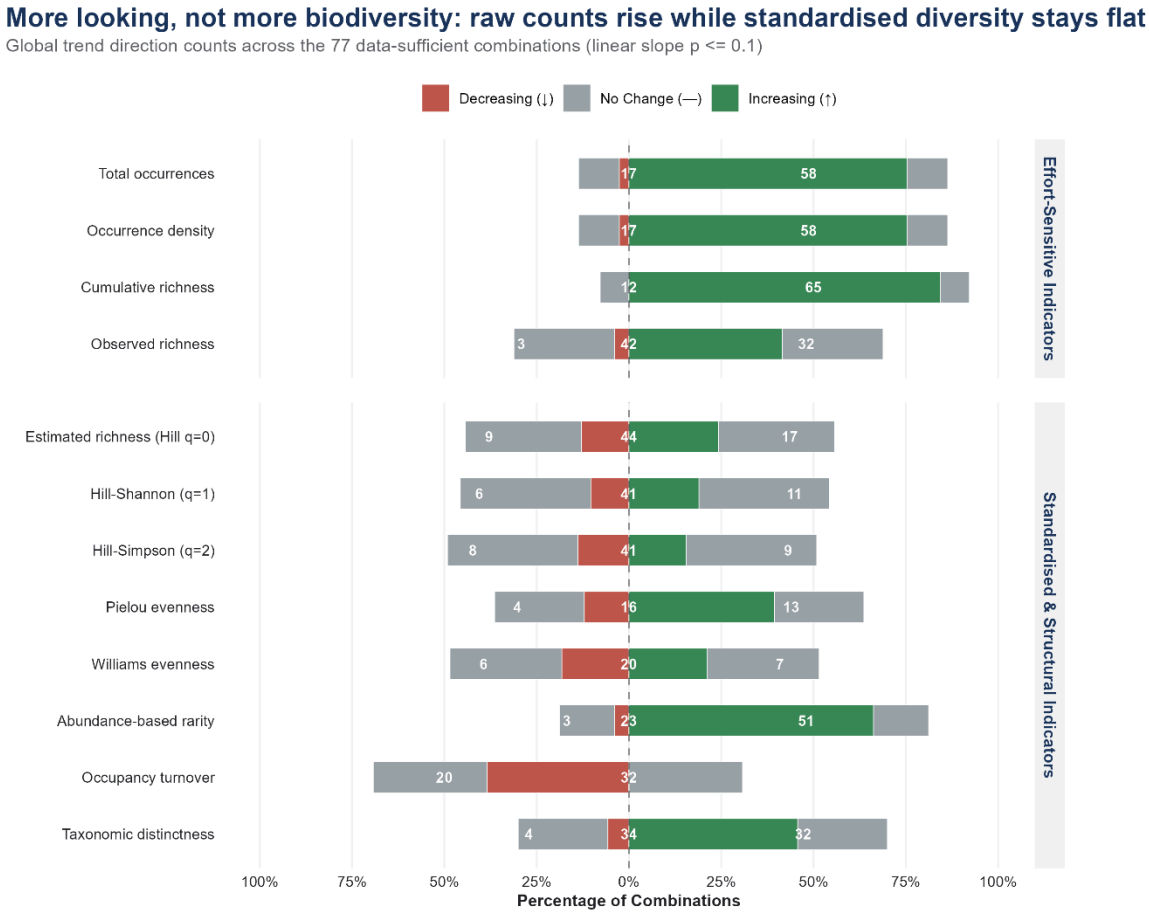

Figure 6. The success illusion. Effort-sensitive indicators (top) rise at most sites, while coverage-standardised diversity and structural indicators (bottom) are flat, mixed or declining. Counts are of data-sufficient site×taxon combinations increasing / stable / decreasing.

The coverage-standardised indicators tell a very different story. Estimated (Hill) diversity, which corrects for sampling completeness, is flat or mixed rather than rising: Hill-Shannon and Hill-Simpson diversity are almost evenly split between increases and decreases, and most sites show no significant change. Community evenness is likewise mixed, with Williams evenness roughly balanced between gains and losses, while occupancy turnover declines at most sites. Rarity rises at the majority of sites, consistent with the steady accumulation of newly recorded rare or vagrant species that inflates richness without signalling ecological improvement.

Europe, the primary focus, shows the same divergence in sharper relief: every European site×taxon combination shows rising occurrence volume and none shows declining observed richness, yet coverage-standardised Hill diversity is flat or mixed and evenness shows no consistent gain. The one indicator that moves consistently (downward) is occupancy turnover, which may reflect stabilising sampling but is also consistent with gradual biotic homogenisation. Because only three combinations possess a MAGV-stable window of five years or more, trends computed over the stable window alone cannot be generalised; the results above are therefore reported over the full 1990-onwards series and should be read with the effort caveats in mind.

7.4. Invasive-species vignette (Part 3a)

As an illustration of the specialised analysis that becomes possible only where data are rich and sufficient, we examined alien and invasive taxa at La Petite Camargue (France), a Mediterranean wetland that passes the sufficiency criteria for both its full community and its bird assemblage. Of the 334 alien species recorded at the site, 51 are listed by GRIIS as invasive, and 127 of the aliens could be matched to EICAT impact assessments in GIDIAS.

The site carries a substantial and characteristic invasion potential (Fig. 7). The most frequently recorded invasive taxa are well-known European wetland invaders spanning plants, a mammal, fish, a reptile and a crustacean, led by pampas grass (*Cortaderia selloana*), false indigo-bush (*Amorpha fruticosa*) and coypu (*Myocastor coypus*). Their EICAT impact categories vary: the red swamp crayfish (*Procambarus clarkii*), topmouth gudgeon (*Pseudorasbora parva*) and common carp (*Cyprinus carpio*) carry Major (MR) assessments, with several others, including coypu, assessed at Moderate (MO), and some, such as the water primrose (*Ludwigia*

peploides), remain unassessed.

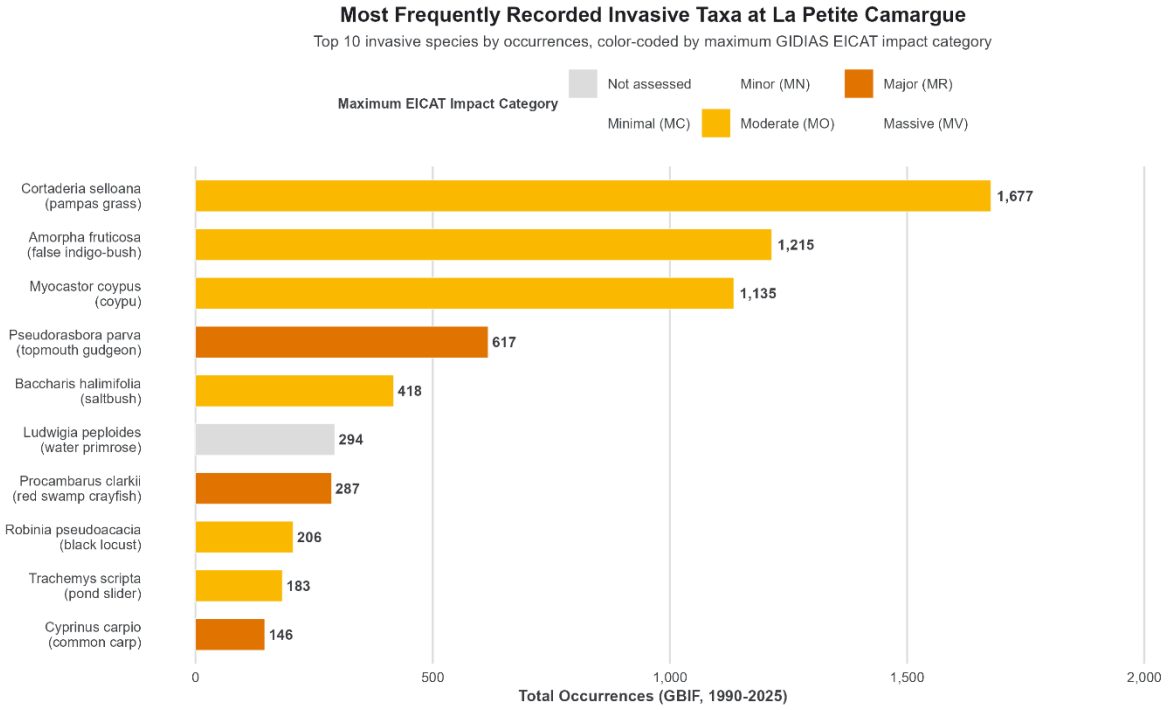

Figure 7. Most frequently recorded invasive taxa at La Petite Camargue (site 786), by total GBIF occurrences (1990–2025), colour-coded by maximum GIDIAS EICAT-equivalent impact category.

The temporal pattern reinforces the report's central caution about effort (Fig. 8). Recorded invasive species richness rose from one or two species per year in the early 1990s to roughly 20–27 by the 2010s, but so did everything else: total occurrences at the site grew from about 500 records in 1990 to nearly 100,000 by 2022 (Fig. 8, Panel A). As a share of recorded richness, invasive species held roughly steady at about 2% (aliens more broadly at 5–7%) across the whole period, so the raw growth in alien records is largely a sampling-effort signal rather than rising invasion pressure.

The impact indicator, computed with the cumulative mean function of `impIndicator` (Fig. 8, Panel B), tells the same cautionary story in a sharper form. Rather than trending cleanly it is volatile: it climbs from near zero in 1990 to a peak of about 0.19 in 2012, fluctuates through a secondary peak near 0.18 in 2022, and collapses to near zero by 2025. It is dominated by episodic bursts; nonetheless, although the coupling is loose, it rises and falls with recording effort overall (Fig. 9).

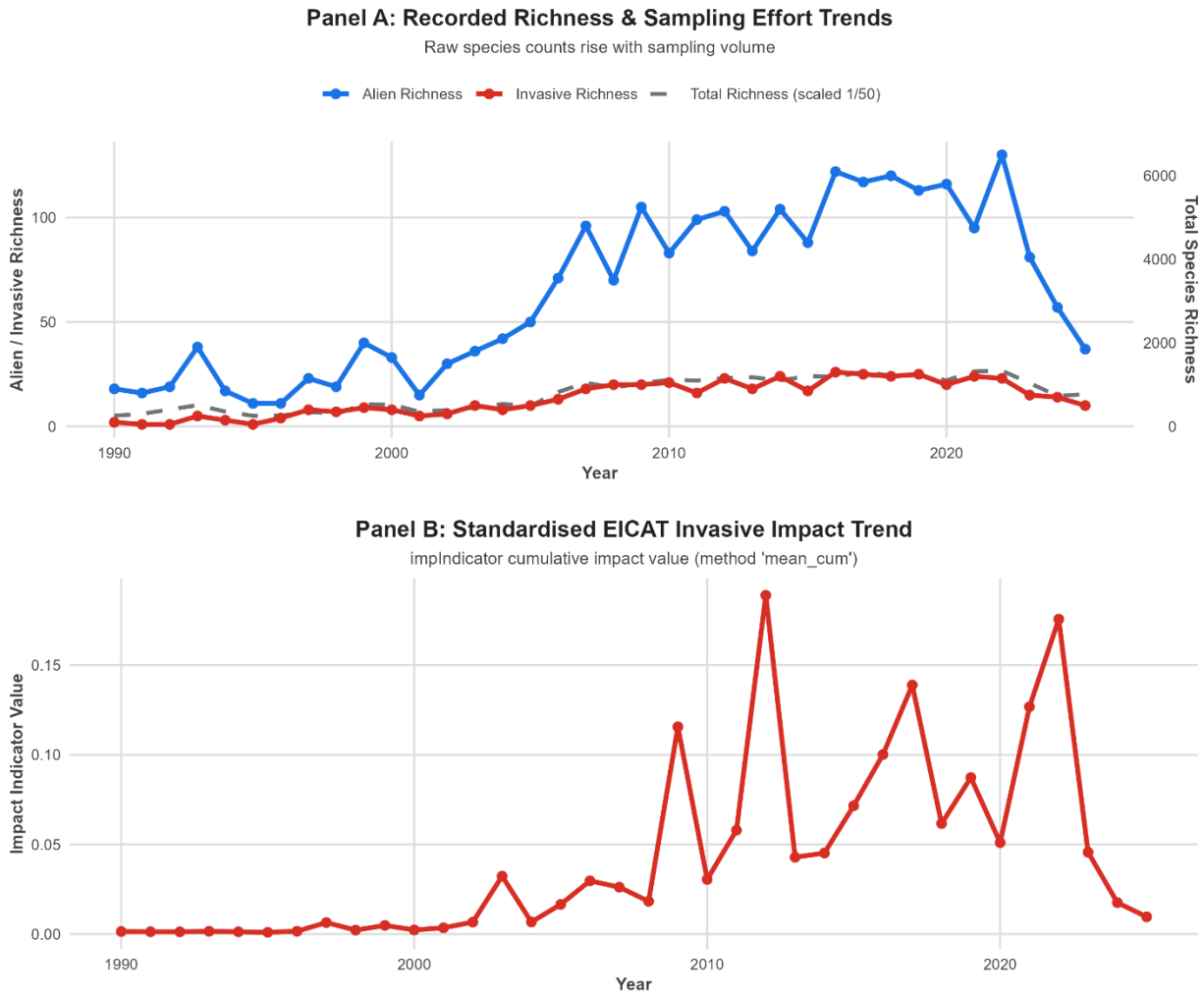

Figure 8. Recorded richness and sampling effort (Panel A) and the invasive-impact indicator (`impIndicator`, using cumulative mean; Panel B) at La Petite Camargue, 1990–2025.

To test whether this effort-scaling is peculiar to La Petite Camargue, we repeated the pilot at two further data-sufficient Wetlands of International Importance of very different character: the Severn Estuary (United Kingdom) and the Okavango Delta System (Botswana). The pattern proves general rather than local. Across all three sites the cumulative EICAT impact indicator is strongly and positively correlated with total recording effort, with a Pearson correlation of r = 0.80 at La Petite Camargue, r = 0.99 at the Severn Estuary and r = 0.94 in the Okavango Delta (Fig. 9); at the two estuarine and deltaic sites the impact curve is almost perfectly collinear with sampling volume. This cross-site replication is strong evidence that, without explicit correction for sampling completeness, even category-weighted invasive-impact indicators built on open occurrence data largely track how much recording has taken place rather than genuine change in invasion pressure.

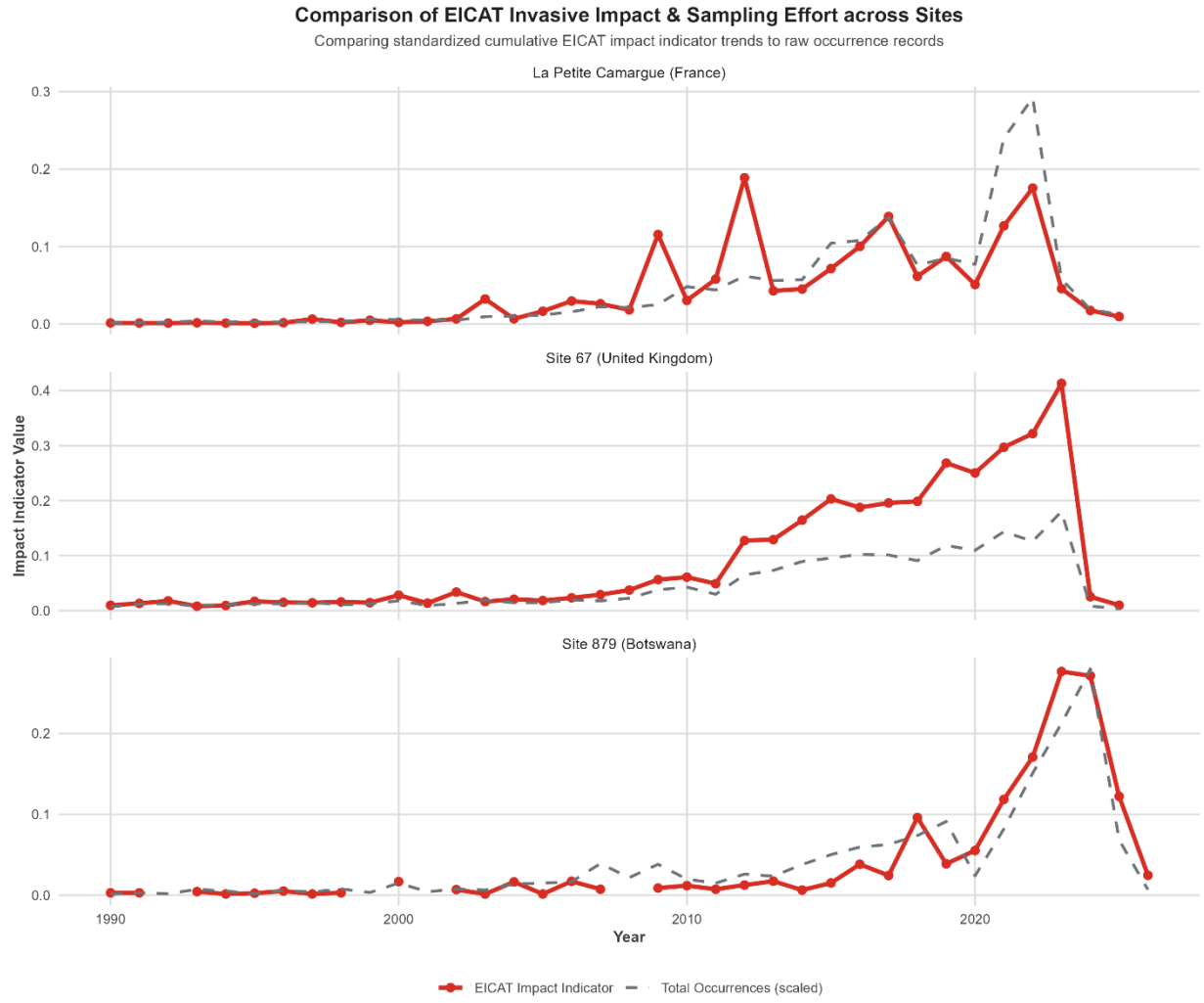

Figure 9. Standardised EICAT invasive-impact indicator (`impIndicator`; solid) versus total recording effort (dashed) across three Wetlands of International Importance, La Petite Camargue (France), the Severn Estuary (United Kingdom) and the Okavango Delta System (Botswana). Impact is closely correlated with sampling volume at every site (r = 0.80, 0.99 and 0.94 respectively).

The question then is whether an interpretable signal survives once effort is controlled. Standardising by sample size removes the coupling but at the cost of leaving almost nothing behind (Fig. 10). The unstandardised indicator varies by a factor of between 51 and 187 across the study period; after rarefaction to a constant number of records the same series varies by a factor of only about 1.5, and the strong positive correlation with recording effort is gone at every site: r = 0.80 to -0.31 at La Petite Camargue, 0.99 to -0.62 at the Severn Estuary, and 0.94 to -0.42 in the Okavango Delta. Most of the unstandardised indicator's range was recording volume rather than impact.

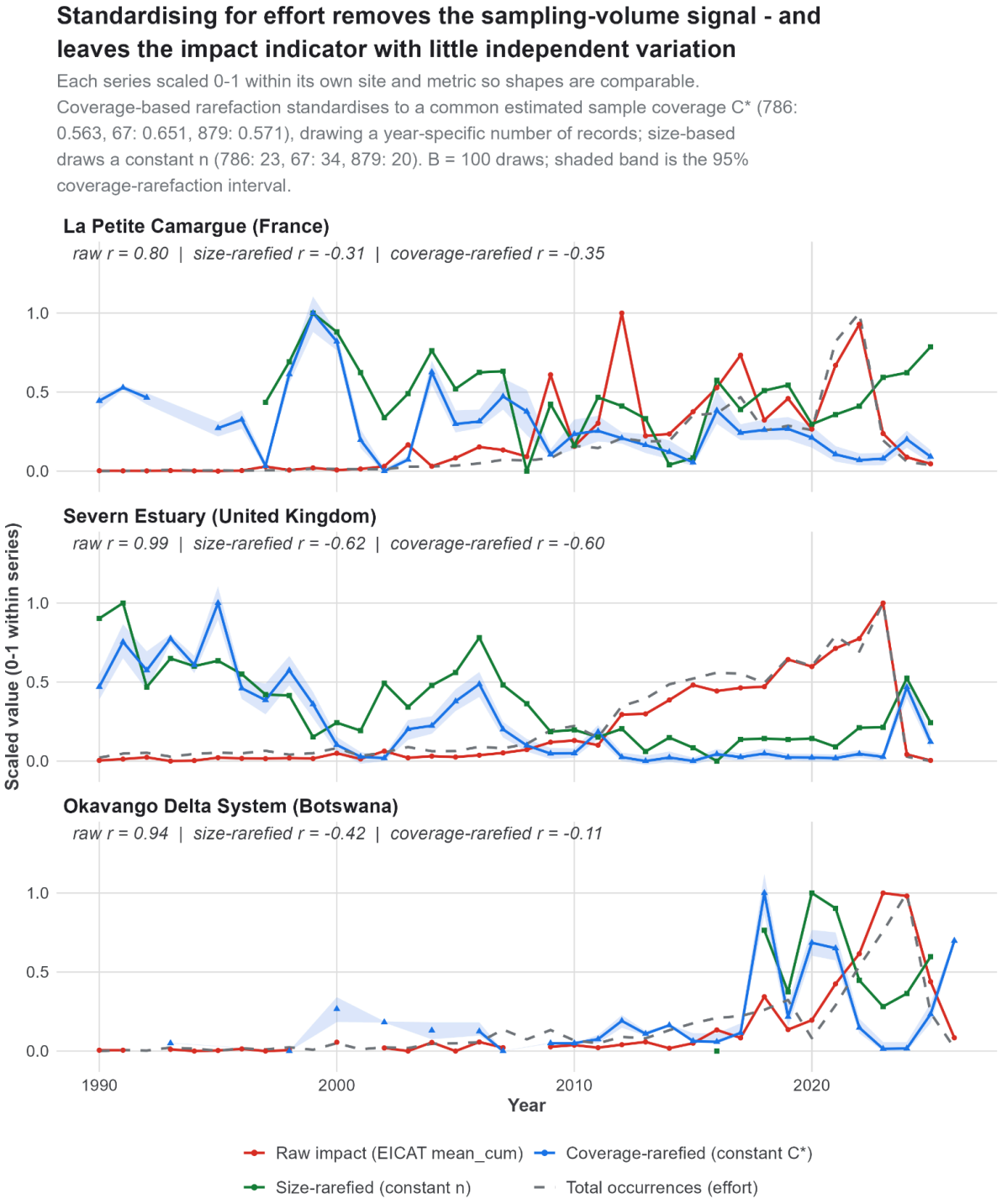

Figure 10. Effort standardisation of the impact indicator at three Ramsar sites, 1990–2025. Each series is scaled to 0–1 within its own site and metric so that shapes are comparable: the raw indicator, the same indicator rarefied to a constant number of records, and rarefied to constant sample coverage (shaded bands are 95% intervals from 100 draws), with total occurrences as a proxy for effort. Gaps indicate years excluded as too sparse to standardise.

Repeating the exercise with coverage-based rarefaction, which standardises sampling completeness rather than sample size, gives similar correlations (-0.35, -0.60 and -0.11 respectively). However, it does reveal why neither approach recovers a usable signal. Since the coverage-based method draws a different number of records each year, the resulting series can be compared against its own draw sizes, revealing a correlation of 0.99 at all three sites. In other words, breaking the correlation between effort and sample size of the input forces the indicator to stop tracking effort but does not prevent it from tracking sample size. This is an inherent weakness of the rarefaction, where all years are standardised against the one with the sparsest sampling.

Expressing impact as a within-year proportion avoids this problem because a ratio cannot inherit a dependence on sample size, and it produces the first effort-independent time series, although only at one of the three sites (Fig. 11). At La Petite Camargue the share of assessed alien records belonging to Major-impact species is not correlated with recording effort ($r = -0.14$ across all 36 years, $p = 0.42$; $r = -0.04$ across the 29 well-sampled years, $p = 0.85$) while still varying between 0.3% and 36.8% of alien records with a median of 7.4%. This is finally an interpretable measure of invasive-impact composition computed entirely from open data.

However, the other two sites show why the approach does not provide a general solution. At the Severn Estuary, the ratio remains correlated with effort ($r = 0.56$, $p < 0.001$). This pattern is dominated by a single species: 93.6% of all Major-impact alien records belong to the feral pigeon (*Columba livia*), with the top three species accounting for 96.8%. The metric therefore largely tracks changes in the proportion of records attributable to feral pigeons. Importantly, increases in record-based effort may reflect both greater observer activity and genuine increases in the abundance or ubiquity of the invasive species, so these processes cannot be cleanly separated. In the Okavango Delta, the estimate is unstable, with the full series giving $r = -0.15$ ($p = 0.42$) and the nine well-sampled years $r = -0.64$ ($p = 0.07$), while many yearly proportions are based on only one to three records. These data are therefore too sparse to support a robust conclusion. This apparent scarcity should not be interpreted as evidence that invasive-species impacts are absent from the Okavango Delta. Local studies and management assessments document several invasive plants, most notably *Salvinia molesta*, which has required sustained control and has affected aquatic habitats and ecosystem services (Kurugundla, 2016). The contrast highlights a broader limitation of relying on globally aggregated occurrence records: locally recognised and actively managed invasions may remain poorly represented in GBIF.

Taken together, the detailed Camargue analysis and the three-site replication show that even a standardised, category-weighted impact indicator remains highly sensitive to uneven open-data sampling. The raw EICAT impact indicator cannot be read as a measure of invasion pressure in open occurrence data. At all three sites we tested, which by our analysis are among the most open-data sufficient of all Wetlands of International Importance, the trend was dominated by recording effort, and controlling for effort proved largely unsuccessful, with common effort-standardisation methods merely replacing effort bias with a less obvious bias that tracks resample size instead. A composition-based metric performed better, and yielded a defensible, effort-independent signal at one of the three sites.

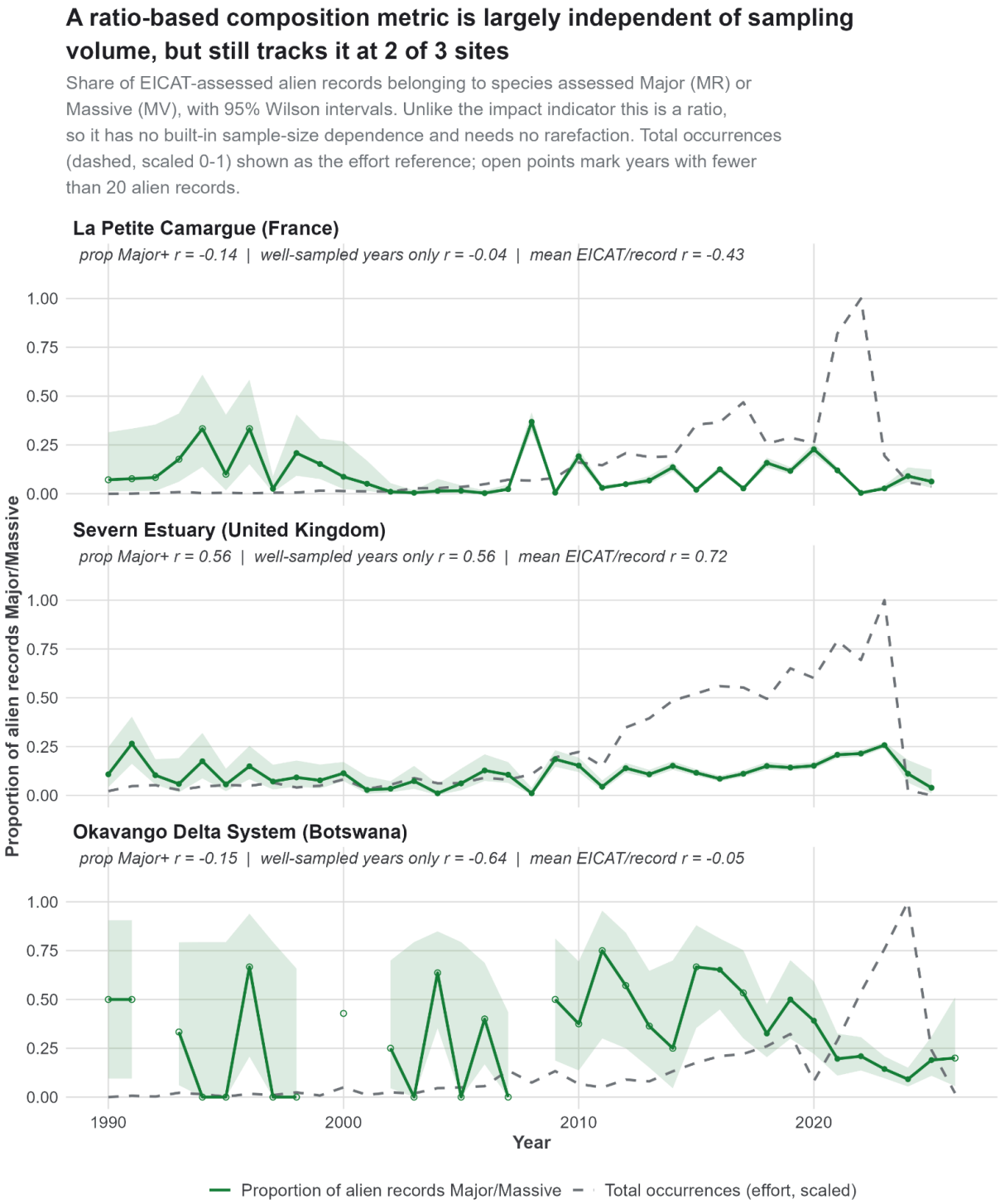

Figure 11. Invasive-impact composition expressed as a within-year ratio: the share of EICAT-assessed alien records belonging to Major-impact species, with 95% Wilson intervals, against recording effort (dashed) at three Ramsar sites, 1990–2025. Wide intervals in sparsely recorded years reflect small record counts; no years are excluded.

7.5. Rate of alien species establishment (Part 3b)

The `b3alien` package allows an initial assessment of the observation effort (both spatially and temporally) of the data cube that is provided. This can be either based on the number of distinct observers per grid cell (if this information is available) or by aggregating counts at a higher taxonomic level. It is this second metric that was used to calculate the observation effort (Fig. 12). This is mainly a way to qualitatively indicate the effort that was done to observe species, and is not intended to be a complete measure.

Distinct geographic clustering is clearly visible on the observation effort maps for all three sites.

Both La Petite Camargue (Fig. 12) and the Severn Estuary (Fig. 13) show relatively constant rates of introduction, since the start of the series (1990) and since 2005, respectively, despite strongly increasing survey effort. The initial falling rate at the Severn Estuary (Fig. 13) is likely an artefact of already established species being counted for the first time, since the Solow-Costello model was fitted along the whole series; that the same did not occur for the other sites is likely due to lower initial survey effort, as they both had comparatively very few occurrences per year at the start of the series. By contrast, the Okavango Delta (Fig. 14) showed an increasing rate of establishment, which appears largely due to strong influence by a massive spike in the observed annual rate of establishment, in 2018. This was not accompanied by a correlated effort spike. In fact, an effort spike occurred in the years 2021-2023 and did not show any effect on the annual rate of establishment. The rate of establishment was thus not coupled to survey effort in any of the three sites we investigated. However, the GRIIS checklist for Botswana is more than an order of magnitude smaller than that for France and nearly two orders of magnitude smaller than that for the United Kingdom, suggesting that it provides a highly incomplete representation of introduced species.

Table 6. Summary metrics on the GRIIS checklist of the 3 sites.

Site	Country	Period	Grid cells	Checklist species	Species detected	Detection rate (%)	Rate years	Change in establishment rate (species/yr)	Matched records
Severn Estuary	United Kingdom	1991-2025	20,232	8,528	472	5.5	35	-0.347 [-0.623, -0.034]	24,566
La Petite Camargue	France	1991-2025	40,269	4,432	309	7.0	35	-0.001 [-0.033, 0.207]	22,068
Okavango Delta	Botswana	1991-2023	95,710	129	52	40.3	30	0.108 [-0.385, 0.156]	598

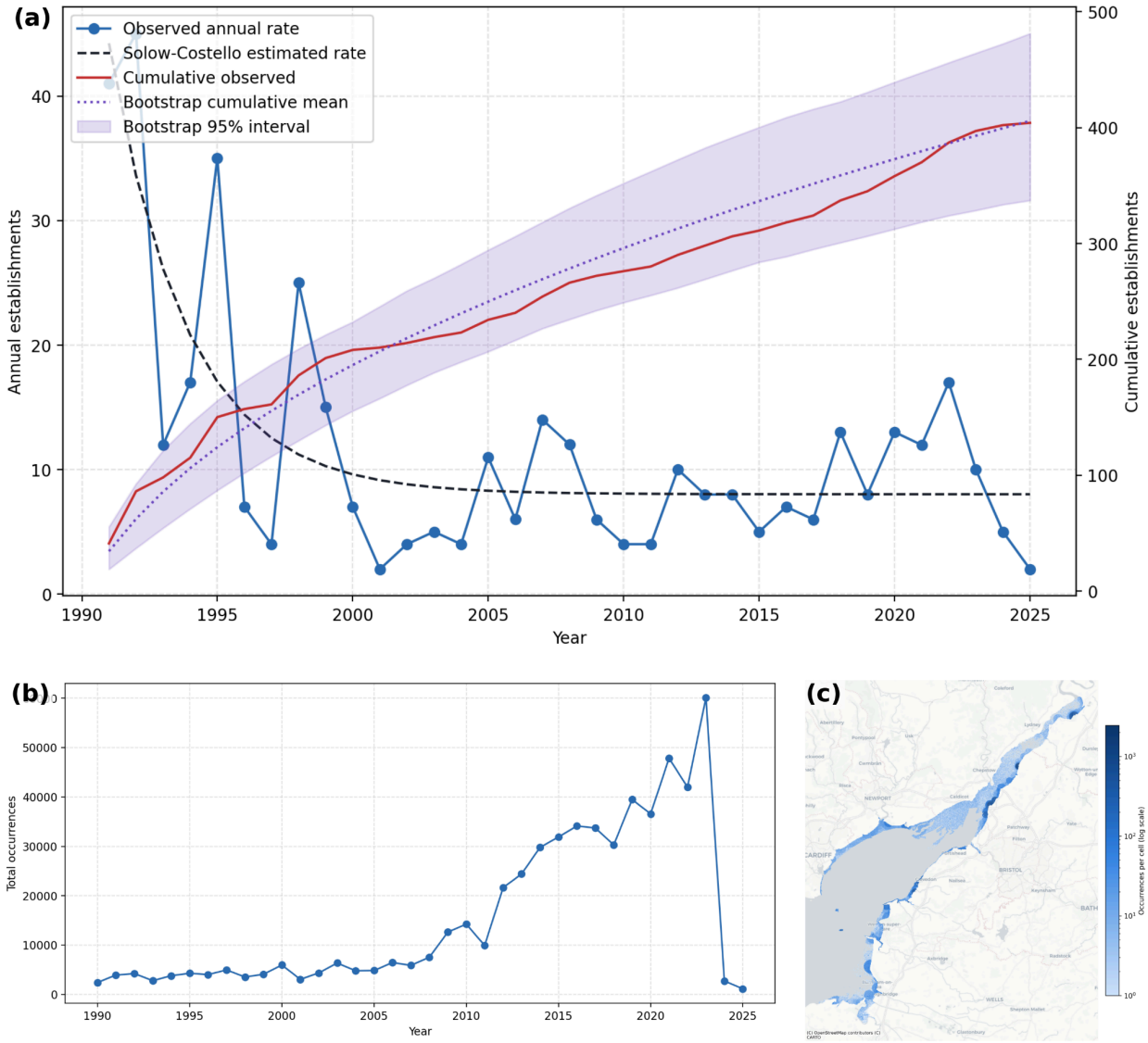

Figure 12. Alien species establishment patterns at the Severn Estuary (United Kingdom). (a) Annual rate of establishment (points) and the fitted Solow-Costello estimate (dashed line) with a 500-iteration bootstrap 95% interval (shaded), against the cumulative number of established alien species (right axis), 1991-2023. (b) Total occurrence records per year, a proxy for observation effort. (c) Spatial distribution of observation effort across the site's 100 m MGRS grid (20,232 cells), coloured by total occurrences per cell (log scale). Of 8,528 GRIIS-listed alien species matched to the GBIF backbone, 472 were detected in the occurrence cube.

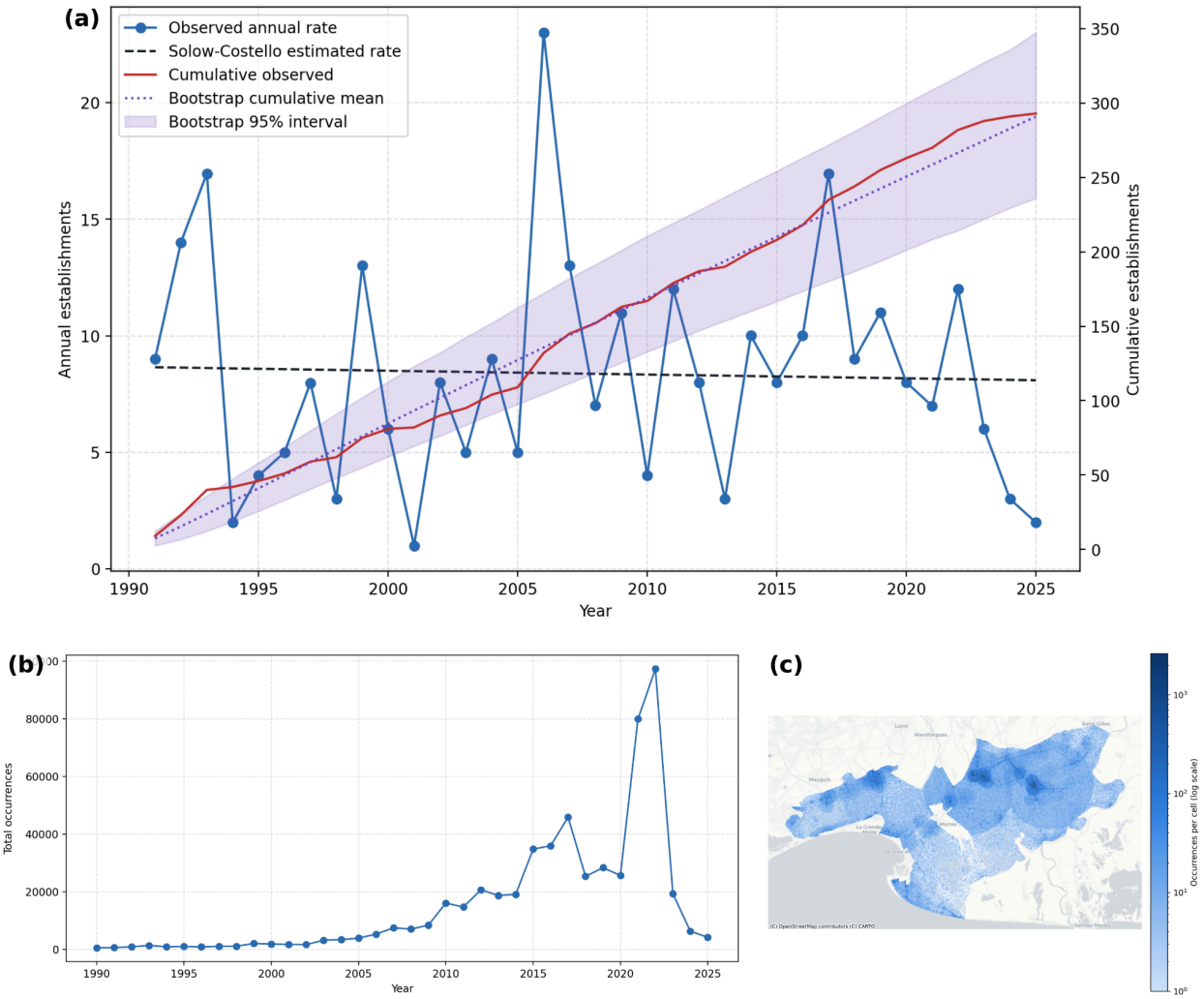

Figure 13. Alien species establishment patterns at La Petite Camargue (France). (a) Annual rate of establishment (points) and the fitted Solow-Costello estimate (dashed line) with a 500-iteration bootstrap 95% interval (shaded), against the cumulative number of established alien species (right axis), 1991-2025. (b) Total occurrence records per year, a proxy for observation effort. (c) Spatial distribution of observation effort across the site's 100 m MGRS grid (40,269 cells), coloured by total occurrences per cell (log scale). Of 4,432 GRIIS-listed alien species matched to the GBIF backbone, 309 were detected in the occurrence cube.

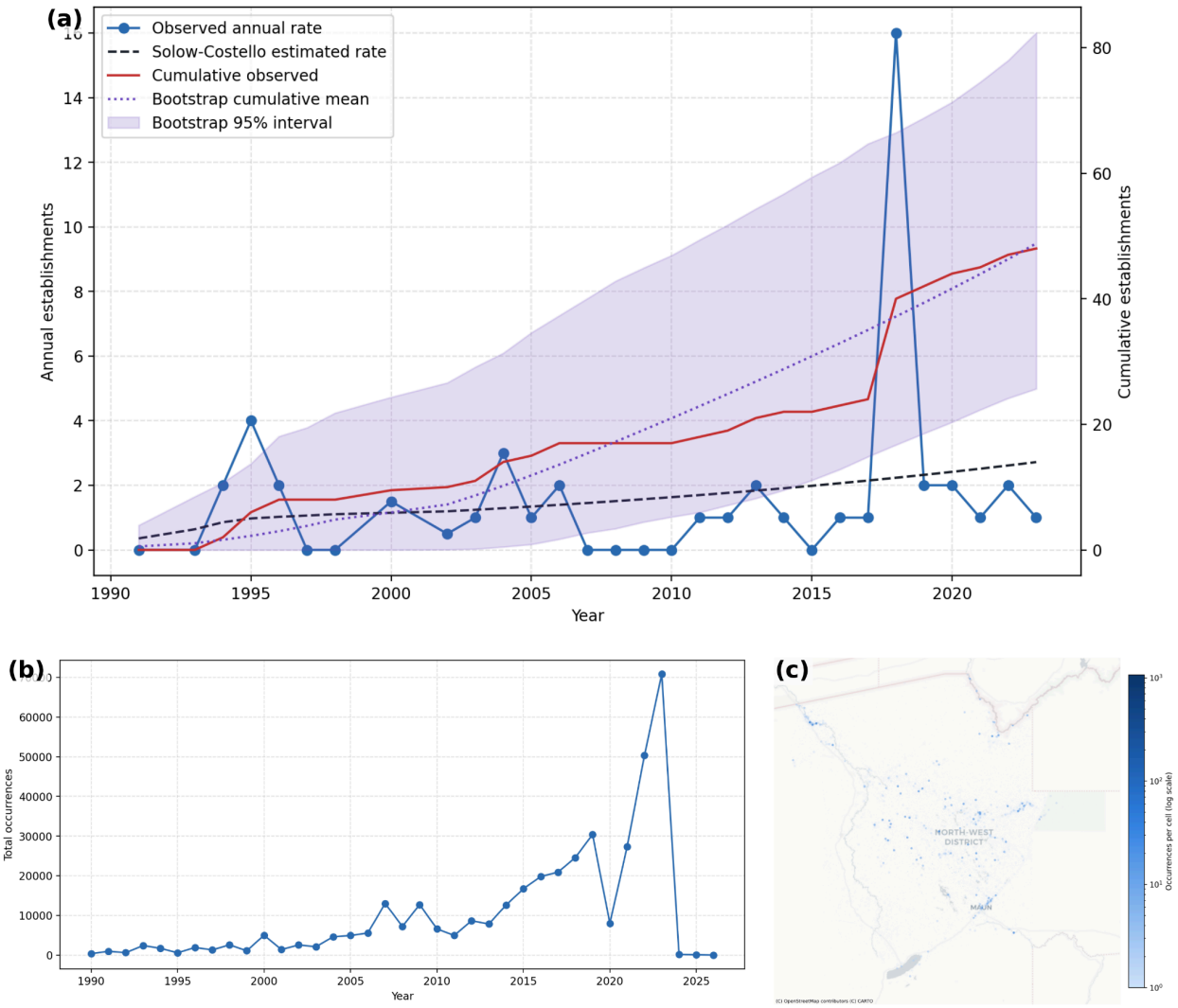

Figure 14. Alien species establishment patterns at Okavango Delta (Botswana). (a) Annual rate of establishment (points) and the fitted Solow-Costello estimate (dashed line) with a 500-iteration bootstrap 95% interval (shaded), against the cumulative number of established alien species (right axis), 1991-2023. (b) Total occurrence records per year, a proxy for observation effort. (c) Spatial distribution of observation effort across the site's 100 m MGRS grid (95,710 cells), coloured by total occurrences per cell (log scale). Of 129 GRIIS-listed alien species matched to the GBIF backbone, 52 were detected in the occurrence cube.

8. Discussion

8.1. The scale of wetland open-data invisibility

The headline result is that, for the overwhelming majority of Wetlands of International Importance, open-access biodiversity data hosted in GBIF cannot presently support trend monitoring. This says nothing about the ecological value or condition of those wetlands, but about our capacity to verify their status from freely available data. That distinction is the policy message: a network of designated sites that expands faster than it can be monitored accumulates designations that creates an expanding gap between site designation and the capacity for independent, open-data verification of ecological change. Identifying where and why

sites fail converts a general data-gap problem into a targeted monitoring agenda. Closing these gaps will also require greater awareness of the constraints facing lower-income regions, alongside improved accessibility, trust and uptake of GBIF infrastructure among local custodians.

8.2. Depth, not coverage, is the binding constraint

The bottleneck cascade shows that the problem is not that Wetlands of International Importance lack records but that the records are too shallow and not always FAIR. Nearly all sites clear the density threshold, yet most fail on completeness and saturation. This points to a specific problem: open biodiversity data mostly represented by moderate-frequency, opportunistic recording, often tourism- or hobby-driven, never accumulates into a taxonomically complete inventory, so the long tail of rare and cryptic species is systematically missed. The policy implication is that simply increasing the volume of casual records will not, on its own, unlock trend monitoring; what is needed is sustained, structured survey effort that drives inventories towards saturation (Chandler et al., 2017; Troia & McManamay, 2016). Structured surveys may be absent from open-data repositories like GBIF (lack of data availability) or may not exist at all (lack of data) which cannot be evaluated if survey data is not at least Findable (F in FAIR).

8.3. A narrow taxonomic and geographic window

Where open data is sufficient for deeper monitoring of the site, it is dominated by birds and by a few high-capacity, largely northern-European countries. This mirrors the well-documented taxonomic and spatial biases of open biodiversity data (Troudet et al., 2017; Hughes et al., 2021) and has two consequences. First, wetland-health assessments built on open data risk being made through a narrow taxonomic lens, potentially missing invertebrate or plant declines that birds do not reveal. Second, the near-total open-data blackout across much of Asia, Africa and Latin America means that regions holding some of the most biodiverse and most threatened wetlands are precisely those where assessing biodiversity trends with open-data is weakest, an equity as well as a scientific concern. These patterns likely reflect broader Global North-South inequalities in infrastructure, capacity, incentives and data governance, as well as differences in the accessibility and mobilisation of existing biodiversity data.

8.4. Interpreting trends where data suffice

A first, sobering observation applies even before indicator trends are examined: the MAGV analysis shows that only three of the sixty data-sufficient sites offer a stable multi-year window, and none sustains high reliability across its full record. Much of the apparent trend-monitoring capacity is therefore fragile; a trend computed over the full series risks conflating ecological change with bursts of recording effort, the very artefact the sufficiency and reliability screens are designed to expose. This reinforces, rather than softens, the central message: reliable open-data monitoring is possible at only a handful of sites, and even there only over short, recent windows.

These trends crystallise into what can be called a ‘success illusion’. At the data-sufficient sites, the indicators most visible to a casual observer, the number of records and the raw or cumulative count of species, almost all point upward, and would, if reported uncritically, suggest that these wetlands are becoming richer and healthier. But those same indicators are the ones most tightly bound to sampling effort, which is itself rising everywhere. Once diversity is standardised for sampling completeness, the apparent gains largely evaporate: estimated Hill

diversity is flat or mixed, evenness shows no consistent improvement, and the rise in rarity is explained by the accumulation of newly detected rare species rather than by genuine ecological change. More looking produces more seeing, not necessarily more biodiversity.

The policy implication is important and slightly counter-intuitive. Even for the tiny minority of sites where open data are sufficient, biodiversity trends must be read through effort-standardised indicators and with explicit understanding that even effort standardisation may be inadequate to fully decouple trends from survey effort. Combined with the MAGV finding that almost no site offers a stable multi-year window, this means that confident, defensible statements about biodiversity change can be made for only a handful of wetlands, and even then only with careful, uncertainty-aware interpretation. Furthermore, even the most data rich sites did not have sufficient open data available on GBIF to support the monitoring of invasive impact trends, even when effort standardisation methods were applied.

The failure reasons differ between sites, and point to different remedies. At La Petite Camargue the constraint is a sparse early record. Rarefaction standardises every year against the sparsest, and the data were very sparse in the 1990s. Restricting the Camargue series to 2010 onwards would raise the standardisation baseline from 23 records per year to 112 and drastically reduce the range of sampling effort. A sustained period of high sampling effort, with trends assessed beginning at a point where data density is already high, could make effort standardisation effective.

At the Severn Estuary the constraint is different. Recording there is dense throughout, but 93.6% of Major-impact alien records belong to a single species, the feral pigeon. This is unlikely to reflect the site's actual invasion pressure, as there are well-established high-impact estuarine invaders including the Pacific oyster, slipper limpet and wireweed present, but with only one to five occurrences each versus more than three thousand for feral pigeon. The estuarine and marine taxa that would characterise invasion at such a site are almost unrecorded in open data, so the metric describes only the terrestrial and avian record pool rather than the entire invaded system. Mobilising marine and estuarine occurrence data, rather than simply increasing the volume of recording, might bring the site closer to being monitorable.

The Okavango Delta illustrates a third constraint. The site is not short of occurrence data, with approximately half a million records available on GBIF, but only 0.15% of those records belong to alien species with an EICAT assessment, compared to roughly 4% at the other two sites. This may be in part due to the site being a landlocked, arid and relatively remote system, which would naturally experience lower invasion pressure than heavily-trafficked European estuaries. However, the GRIIS checklist for Botswana lists only 132 alien species compared to 3,181 for France and 2,848 for the United Kingdom, and species that are not on the checklist cannot be identified as alien regardless of the number of records. So in this case a more complete GRIIS checklist is necessary but not necessarily sufficient. Mobilisation of local occurrence and impact data is also needed.

On the plus side, at least one site was able to support composition-based invasive trend monitoring, and with a continued focus on broad and balanced open data recording more sites may soon be able to reach this milestone.

Our investigation of establishment rate fared better, with the Solow-Costello estimate fully decoupled from the survey effort proxy (total occurrences per year), suggesting that at least for

the best-surveyed Wetlands of International Importance, there is potential for reliable estimation of establishment rates of invasive alien species.

8.5. Limitations and caveats

Several caveats bound the interpretation. The thresholds used (density 0.25 occ/km², Chao2 0.70, SAC slope 0.10) are principled but ultimately conventional choices adapted from prior work; the sensitivity of the passing set to these values should be examined. Because records in GBIF are primarily occurrences rather than systematic counts of individuals (although counts are occasionally recorded), abundance-based interpretations must be made cautiously, and the incidence-based Chao2 adopted here is the more defensible completeness estimator for such data. The Spatial Precision Ratio depends on the quality of reported coordinate uncertainty, which is itself variable. Finally, this assessment concerns only open data available on GBIF. It is possible that national or institutional datasets not published to GBIF may render some 'invisible' sites monitorable, and quantifying that gap is exactly the point: it shows the effort required to complement open data.

A few limitations are specific to the invasive-species analysis. First, these results are based on applying one indicator formulation, the cumulative mean, to individual sites as annual time series, which is a demanding use of opportunistic data; indicators of this kind are more commonly applied at regional or national scales, where recording effort is less volatile. Second, ratio-based composition metrics remove the mechanical dependence on sample size but are not automatically independent of effort. Wherever growth in recording changes which taxa are recorded, the ratio will move with it, as the feral-pigeon dominance at the Severn Estuary demonstrates. Third, all three metrics are sensitive to single-species dominance of the high-impact record pool, with 39% of the major-impact records at La Petite Camargue being topmouth gudgeon, and feral pigeon accounting for 94% at the Severn Estuary and 66% in the Okavango Delta. Finally, the impact records of individual species as provided by GIDIAS are usually not reported from the site under investigation. Although the species is known to pose the reported impact, it remains unknown whether the actual impact has been reported for the specific site. This may result in an over-estimation of the impact score.

8.6. Implications for Convention on Wetlands reporting

For the Convention on Wetlands and its Contracting Parties, the results suggest three practical uses of the B3 workflow. It provides a transparent, reproducible baseline of open-data monitoring capacity against which future improvement can be measured; it identifies, site by site and taxon by taxon, where additional structured survey effort is needed; and, at the minority of data-rich sites, it enables standardised trend and invasive-species reporting that can feed directly into national reports. Used this way, the data-gap reveal is not only negative; it can be used as a tool to reveal where increased monitoring investment will have the greatest impact.

The analysis points to concrete, low-cost actions that would widen the GBIF-monitorable network. Because the earliest and largest losses occur upstream, namely missing boundaries, outdated RISs and a lack of open records for listed species, the highest-leverage interventions are improvements to the Contracting Parties' reporting rather than new field campaigns alone:

- **Standardise reporting workflows**. Provide simple, FAIR and interoperable pipelines for routine biodiversity reporting and data sharing, reducing technical barriers to publishing site-level records.

- **Update site information.** Update Ramsar Information Sheets through RSIS, reporting species with a standardised taxonomy (e.g. Catalogue of Life) so that listed species can be matched to open records reliably.
- **Provide digital boundaries.** Submit georeferenced site boundaries in digital form, so that open records can be linked to a site at scale.
- **Strengthen GBIF–Ramsar interoperability.** Establish a two-way data flow between the Convention and GBIF, so that Parties' own records become open and FAIR and, in return, Parties can draw on all other GBIF datasets to assess their sites more comprehensively.
- **Target the gaps.** Prioritise data-mobilisation effort where open-data coverage is weakest, particularly across the Global South, to counter the strong geographic imbalance.

These measures are complementary to, not a substitute for, sustained field survey: closing the upstream gaps makes existing and future records usable, while structured survey effort is what ultimately drives inventories to the completeness that trend detection requires.

9. Conclusion

This case study set out to test how far open-access biodiversity data can support global monitoring of biodiversity trends in Wetlands of International Importance. The provisional answer is that, for around 96% of mapped sites, they cannot. This is not because records are absent but because they are too shallow, too patchy and too taxonomically skewed to support reliable trend estimation, and because for many sites the internationally important species themselves have no open records at all. More broadly, these gaps expose a persistent challenge in mobilising biodiversity data through FAIR platforms such as GBIF. Addressing the marked geographic imbalance will require greater awareness of the constraints affecting data mobilisation in lower-income regions, alongside investment in capacity, trust, equitable partnerships and accessible data-sharing pathways. A small, mostly northern-European subset of well-recorded sites can be monitored, and for these the `b3gbi` workflow delivers standardised indicators and can support targeted analyses such as invasive-species impact. By making the limits of open data explicit and auditable, and by identifying the upstream fixes that would unlock more of the network, the B3 toolchain turns a data-gap problem into a roadmap for strengthening wetland monitoring.

The lessons here are transferable. The typical way to report biodiversity change over time is a trend, sometimes accompanied by confidence intervals. But the intervals describe sampling variation *within* the data and do not account for the quality or completeness of the data itself, and do not describe the uncertainty between the data or trend and the system they represent. Our own results showed clearly that trends were merely tracking effort even in many of the sites that passed our sufficiency tests.

Some indicators are effort standardised, an important step, but our results also showed that even effort standardised trends do not decouple from effort when sampling is insufficient. While coverage-standardised Hill diversity metrics were effective on the sites passing our tests, neither coverage-standardisation nor sample-size-standardisation were effective at providing an unbiased ecological signal when we computed the invasive-impact trends. That shows that data sufficiency is not a property of a dataset alone but of a dataset and the indicator or model applied to it. Thus it is extremely important to assess data sufficiency before reporting trends,

not only for wetland sites using openly accessible GBIF data, but for any research that involves modelling or indicators.

Nothing in the framework used here is specific to wetlands. It requires only a set of spatial units, an occurrence dataset, and transparent criteria. While the criteria used here may not be appropriate for all data types and analyses, the general principles of data sufficiency hold true. It is necessary that the dataset being used is complete enough taxonomically, spatially, and temporally that the indicator or model is decoupled from effort; otherwise effort standardisation must be applied or, if the data are insufficient even for that, hard decisions must be made about how to interpret the results, and whether to base any decisions on them. As our results have shown, if a robust assessment of data sufficiency is not performed, reported trends may be unreliable at best and actively misleading at worst.

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12. Annex

12.1. Sufficiency criteria and parameters

Table A1: Data-sufficiency criteria applied per site×taxon combination.

Criterion	Metric	Threshold
Spatial Precision Ratio	mean coordinate-uncertainty area / site area	≤ 0.10
Observation density	occurrences per km² (site area)	≥ 0.25
Chao2 completeness	S_{obs} / Chao2 (incidence, species × 100 m cell, bias-corrected)	≥ 0.70
SAC slope	1 − mean annual iNEXT sample coverage	≤ 0.10
Temporal decoupling	Jaccard distance (total occ. vs richness), dynamic elbow	above elbow

12.2. Indicators and metrics

Table A2: Biodiversity metrics with their formulas and references.

Metric	Formula	Reference
Total occurrences	Total occurrences is the sum of all occurrences in the sample at year *t*.	
Pielou's evenness	$E = \frac{-\sum_{i=1}^{S} p_i \ln(p_i)}{\ln(S)}$ where *S* is the number of species and p_i is the proportion of occurrences represented by species *i*.	Pielou, 1966
Williams evenness	$1 - \sqrt{\frac{S\sum_{i=1}^{S} p_i^2 - 1}{S-1}}$ where *S* is the number of species and p_i is the proportion of occurrences represented by species *i*.	Kvålseth, 2015
Observed richness	Observed richness is the count of unique species in the sample at year *t*.	
Cumulative richness	Cumulative richness is the cumulative sum of unique species in the sample from year t_1 to *t*.	
Abundance-based rarity	$\sum_{i=1}^{S} \frac{1}{p_i}$ where *S* is the number of species and p_i is the proportion of occurrences represented by species *i*.	Rabinowitz, 1981

Area-based rarity	$\sum_{i=1}^{S} \frac{N}{n_i}$ where S is the number of species, N is the total number of occupied grid cells, and n_i is the number of grid cells occupied by species i.	Rabinowitz, 1981
Estimated richness	Species richness is estimated using coverage-based standardisation (Chao & Jost, 2012), where each sampled year is standardised to the same coverage value (in this case 0.95). Coverage is the proportion of individuals in the community belonging to species in the sample. Coverage is estimated based on the frequencies of species already in the sample. A coverage value of 0 means the next species detected has a 100% chance of belonging to a species not already in the sample, while 1 means no new species would be uncovered through further sampling. The estimation is computed using the `iNEXT` R package (Hsieh et al., 2022).	Hsieh et al., 2022
Hill-Shannon diversity (estimated)	Hill-Shannon diversity is estimated by the `iNEXT` R package using the same coverage-based method as for estimated richness (Hsieh et al., 2022). $e^{-\sum_{i=1}^{S} p_i \ln(p_i)}$ where S is the number of species, p_i is the proportion of individuals belonging to species i.	Roswell et al., 2019 Hsieh et al., 2022
Hill-Simpson diversity (estimated)	Hill-Simpson diversity is estimated by the `iNEXT` R package using the same coverage-based method as for estimated richness (Hsieh et al., 2022). $\frac{1}{\sum_{i=1}^{S} p_i^2}$ where S is the number of species, p_i is the proportion of individuals belonging to species i.	Roswell et al., 2019 Hsieh et al., 2022
Occupancy turnover	This can be calculated in different ways, but here we use the Jaccard index: $(b + c) / (a + b + c)$ where a is the number of species present in both time periods, b is the number of species present only in the first time period, and c is the number of species present only in the second time period. The index	Jaccard, 1901

	ranges from 0 to 1, where 0 is no turnover and 1 is complete turnover	
Taxonomic distinctness	A distance matrix based on pairwise taxonomic relationships is calculated for each cell using the `taxize` R package (Chamberlain et al., 2020), then taxonomic distinctness is calculated as the Taxonomic Distinctness Index (TDI; Clarke & Warwick, 1999): $$\frac{\sum\sum_{i<j}\frac{\lvert R_i - R_j\rvert}{L}}{\frac{S(S-1)}{2}}$$ where S is the number of species, R_i and R_j are the taxonomic ranks of species i and j (from the GBIF Taxonomic Backbone), and L is the maximum number of taxonomic ranks. The index ranges from 0 to 1, higher values mean greater taxonomic distinctness.	Clarke & Warwick, 1999 Chamberlain et al., 2020
EICAT cumulative impact indicator	$$I_{\text{mean\_cum}}(t) = \frac{1}{C_{\text{total}}}\sum_{c \in \mathscr{C}_t}\sum_{i \in \mathscr{S}_{t,c}}\mu_i$$ where $I_{\text{mean\_cum}}(t)$ is the standardized cumulative impact indicator value for year t, C_{total} is the total number of unique grid cells recorded at the site across the entire time series (a constant spatial baseline), c is a grid cell belonging to the set of active cells in year t ($\mathscr{C}_t$), i is an alien species belonging to the set of unique alien species detected in grid cell c in year t ($\mathscr{S}_{t,c}$), and μ_i is the mean EICAT score for alien species i across all its assessment records in the database, with MC (minimal concern) = 0, MN (minor) = 1, MO (moderate) = 2, MR (major) = 3, and MV (massive) = 4.	

12.3. Notes on data sources & code availability

Occurrence data. All species-occurrence data were obtained from the Global Biodiversity Information Facility (GBIF; https://www.gbif.org). Data were requested as occurrence cubes through the GBIF SQL Download API, aggregated to a 100 m Military Grid Reference System (MGRS) grid by species and year, and subsequently clipped to Ramsar site boundaries. Each download is permanently archived and citable by DOI: https://doi.org/10.15468/dl.qyamab; https://doi.org/10.15468/dl.d5a7c4; https://doi.org/10.15468/dl.eqkqd7; and https://doi.org/10.15468/dl.ywrhss, downloaded 23 June 2025; https://doi.org/10.15468/dl.6xtqh2, downloaded 26 June 2025; https://doi.org/10.15468/dl.je5pet and https://doi.org/10.15468/dl.msj7xs, downloaded 3 July 2025;

https://doi.org/10.15468/dl.47sycn, downloaded 23 June 2026. The specification for occurrence cubes is given in Desmet et al. (2023).

Ramsar site boundaries. Site boundary polygons were obtained from the Ramsar Sites Information Service (RSIS; https://rsis.ramsar.org), maintained by the Secretariat of the Convention on Wetlands. Boundaries were downloaded as the published-polygon layer via the RSIS GeoServer WFS endpoint https://rsis.ramsar.org/geoserver/wfs?request=GetFeature&service=wfs&version=1.0.0&typename=ramsar_sdi:features_published&outputformat=SHAPE-ZIP on 16 June 2026. Note that only a subset of designated sites has a published boundary polygon; this is itself one of the constraints quantified in this report.

Internationally important species listed in Ramsar Information Sheets. Species listed under the designation criteria of each site were taken from the Ramsar Information Sheets held in RSIS, accessed May 2026.

Alien species checklists. Alien status was determined using national checklists from the Global Register of Introduced and Invasive Species (GRIIS; https://griis.org), published through GBIF as Darwin Core Archives (Pagad et al., 2022). Checklists for France, the United Kingdom and Botswana were used, downloaded on 12 May 2026. DOI: UK - https://doi.org/10.15468/8rzqvw (used version 1.8; current version is 1.11); France - https://doi.org/10.15468/up1tr5 (used version 1.7); Botswana - https://doi.org/10.15468/on2dud (used version 1.4).

Impact assessments. Environmental-impact magnitudes were drawn from the Global Impacts Dataset of Invasive Alien Species (GIDIAS; Bacher et al., 2025), available at https://doi.org/10.6084/m9.figshare.27908838, published 21 May 2025. GIDIAS follows the IUCN Environmental Impact Classification for Alien Taxa (Hawkins et al., 2015; IUCN, 2020) in condensed four-level form.

Software. Analyses were performed in `R` (4.3.1). Biodiversity indicators were computed with `b3gbi` (Dove, 2025; https://github.com/b-cubed-eu/b3gbi), coverage-based rarefaction and sample coverage with `iNEXT` (Hsieh et al., 2016; https://cran.r-project.org/package=iNEXT), the Chao2 estimator with `vegan` (https://cran.r-project.org/package=vegan), spatial operations with `sf` (https://cran.r-project.org/package=sf), and invasive-impact indicators with `impIndicator` (https://github.com/b-cubed-eu/impIndicator). Rates of alien establishment were computed with `b3alien` (Trekels, 2026; https://pypi.org/project/b3alien/).

Code. All code written for this study is available at https://github.com/b-cubed-eu/muddymetrics.

12.4. Notes on AI usage

Artificial intelligence tools were used in the preparation of this report, specifically the Google Antigravity platform with Google Gemini Flash 3.1 and 3.5 agents was used to help write code, run R analysis, and create figures. Claude Co-Work with Claude Opus 4.8 and 5.0 was used to help with drafting the text of the report and writing prompts for figures and analysis produced in

Antigravity. The final text of the report was entirely edited and approved by humans, and the authors are responsible for any errors or inaccuracies that may be present in the final product.