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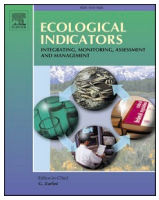

Combining citizen-science data with data from a structured monitoring programme for a Swiss butterfly index

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ABSTRACT

Reliable biodiversity indicators are essential for informed conservation decisions, yet obtaining comprehensive data remains a significant challenge. While structured monitoring programs are considered the gold standard to estimate unbiased species trends, they are resource-intensive and often miss rare species. Conversely, unstructured citizen-science data provide vast spatial and temporal coverage but may be subject to systematic reporting biases. Using adapted site-occupancy models, we were able to estimate reliable temporal trends from the unstructured records of a national faunistic database, which strongly correlated ($r = 0.85$ across species) with the trends estimated from the structured data of the Swiss Biodiversity Monitoring (BDM). The multi-species index (MSI) based on the trends of 179 species exhibited a slight decline contrasting with the increasing species richness that was reported using the BDM data. This discrepancy likely occurred because the MSI effectively captured substantial losses in specialized groups—such as cold-adapted and oligotrophic habitat species—whereas species richness was influenced by the rise of few common species. These findings highlight that both datasets complement each other, the structured monitoring data are central to calibrate the Index whereas the unstructured data extend species coverage by reaching out rarer species. The integration of both datasets into one national index facilitates a more representative national index that covers a broader taxonomic range than traditional indicators alone. Such integrated indicators are vital for evaluating biodiversity policies and capturing the complex responses of species communities to environmental change.

1. Introduction

Data on biodiversity trends are essential for informing conservation decisions (Chandler et al., 2017). This need is heightened as environmental conditions change rapidly (Jetz et al., 2019). Additionally, biodiversity is inherently multidimensional, spanning genetic, species, and ecosystem levels (Mace et al., 2012), and as such requires comprehensive data (Musvuugwa et al., 2021). The challenge remains substantial even when focusing –as in the present work–solely on the species level. To accurately capture changes in species diversity, ideally data would cover as many species as possible and span a broad temporal and spatial range (Jetz et al., 2019). Unfortunately, such comprehensive data are rarely available.

To collect meaningful data on species diversity, structured biodiversity monitoring programmes have been established (Porcher et al., 2024). These programmes are considered as the gold standard to estimate temporal trends in biodiversity if they use standardised field methods and cover space and time evenly (Buckland and Johnston, 2017; Van Strien et al., 2013). The collection of such structured data requires resources and scientific expertise in several domains and are particularly costly if conducted by professionals. Nevertheless, the implementation of such programmes remains a prerequisite if one wants to evaluate the effectiveness of investments in biodiversity conservation policies or to quantify the major drivers impacting the current state of species diversity (Buckland et al., 2012; Buckland and Johnston, 2017; Meier et al., 2022).

Besides structured biodiversity monitoring programmes, species observations have long been recorded by professionals and passionate volunteers. Natural history museums and private collections curate specimens that document past occurrences of species (Schmitt et al.,

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2019). Thanks to modern tools (e.g., data collection with smartphones, automatic identification of pictures and sounds with artificial intelligence), species observations are being captured in ever-larger quantities (Mason et al., 2025). In this study, we use the term "unstructured data" for such citizen science data, as opposed to the structured data from biodiversity monitoring programmes. Note however, that many datasets lie somewhere between these two types. For example, citizen science data may be recorded using defined sampling methods (Mondain-Monval et al., 2024). When species observations are systematically compiled in central databases, vast amounts of data are available, covering most, if not all, species over a wide spatial and temporal range. However, the coverage regarding space, time, and species is highly variable, often with very few observations in remote areas and past centuries, making analysis challenging yet not impossible (Troudet et al., 2017; Van Strien et al., 2013).

To illustrate the temporal changes in species diversity using structured data, simple indicators are often used, such as the mean number of species per study area (species richness), the total number of individuals (also used as a proxy for biomass, Vereecken et al., 2021) or the difference in species lists between study areas (beta diversity). Such biodiversity indicators are used to synthesise the complex and multidimensional nature of biodiversity into a single figure that measures selected aspects of biodiversity and can easily be communicated (Pilotto et al., 2020). However, some of these indicators are criticised because they primarily respond to changes in common species, and sometimes they fail to indicate change even though the composition of species is significantly altered (Buckland et al., 2012; Hillebrand et al., 2018).

As an alternative, multi-species indices (MSI) have proven effective (Buckland et al., 2005). MSI are statistical tools used to summarize the trends across multiple species within a particular ecosystem or region (Buckland et al., 2005; Korner-Nievergelt et al., 2022). However, due to the systematic sampling design of structured biodiversity monitoring programs, many rare species are captured too infrequently to infer temporal trends. Consequently, a MSI based on monitoring programmes might only be calculated based on a subset of species, typically the more common ones. This is problematic, as selecting species based on their commonness likely results in a non-representative sample of species (Buckland and Johnston, 2017; Gregory and Strien, 2010; Korner-Nievergelt et al., 2022). Furthermore, many monitoring programmes were only initiated after the turn of the millennium, often long after the greatest losses in biodiversity had occurred (Bonebrake et al., 2010; Didham et al., 2020; Häberlin and Dengler, 2025).

A combination of structured and unstructured data sources could address these problems (Kühl et al., 2020). Structured data can serve as a reference for calibrating statistical models that account for the highly variable coverage of species, spatial extent and temporal scale in unstructured data (Dennis et al., 2017; Van Strien et al., 2013). A study by Agnoux et al. (2026), based on butterfly schemes in France and the United Kingdom, suggests that the comparability between unstructured and expert-collected data is driven primarily by species traits (identifiability, migratory behaviour). With the calibrated models suggested in this study, it could be possible to account for such differences between species. Furthermore, it may be possible to calculate reliable temporal trends also for rarer species and to extend these trends further into the past, thereby providing a strong basis for biodiversity indicators. Despite this potential, biodiversity indicators based on the integration of structured and unstructured data remain largely absent.

Beyond having a long tradition of monitoring in many countries (Warren et al., 2021), butterflies are relatively easy to identify and therefore a popular group for citizen science projects (Thomas, 2016). In Switzerland, the organisation named info fauna is responsible for systematically collecting and curating faunistic species observations including butterflies (Chittaro and Gonseth, 2025). Additionally, the Swiss Biodiversity Monitoring programme (BDM) has been investigating various species groups on regularly distributed sample plots across the whole country with standardised recording methods since 2001 (Roth et al., 2014; Weber et al., 2004). In this study, using the example of butterflies, we (i) adapted existing site-occupancy models to estimate trends from unstructured info fauna data, (ii) compared the resulting species trends with those obtained from the structured BDM data alone, and (iii) derived a national multi-species index for 179 butterfly species since 1990 that integrates both data sources. We used these temporal trends to demonstrate differences between species groups. Finally, we compared the resulting multi-species index of all 179 butterfly species (i.e., the Swiss butterfly index) with indicators such as species diversity, total number of individuals, and beta diversity that are traditionally calculated from structured BDM data.

2. Materials and methods

2.1. Study region

The study included data from the entirety of Switzerland, which covers 41′285 km^2. Situated between latitudes 45° and 48° N, and longitudes 5° and 11° E, Switzerland comprises three main topographical regions: the Swiss Alps to the south, the Central Plateau, and the Jura Mountains to the north-west. The Alps span across the central and southern parts of the country, making up about 63% of its area, with the highest peak reaching 4′634 m. The Central Plateau, comprising approximately 27% of Switzerland's area, consists of hilly landscapes with a mosaic of forested areas, open agricultural landscapes and settlements. The largest cities and most of the human population are located on the Central Plateau (Wikipedia contributors, 2025). The Jura mountains (about 10% of Switzerland) are a limestone mid-mountain range characterized by elongated ridges and valleys, with extensive forests and pastureland.

2.2. Butterfly data

2.2.1. Unstructured species detection data

We extracted records of butterflies (i.e. all Papilionoidea but also Zygaenidae moths) from the database curated by info fauna, i.e. the Swiss Faunistic Records Centre (Chittaro and Gonseth, 2025). This database unites faunistic records made in Switzerland from various sources including both records by private persons and from projects such as research initiatives, Red-List inventories or monitoring programs. In the info fauna database, nearly all observations were provided and stored as species detection data (presence only), regardless of whether the data originate from a structured, semi-structured, or unstructured source.

For the present analyses, only the species records where the place of recording was known to the precision of 1 km or more precise, were used. All records were aligned within the 1x1km squares of the Swiss national coordinate system. For all records we obtained the information on the species, the location (square within the observation was conducted), the date of observation, the observer and the project (if any). We aggregated all records of the same species made by a person on a day in a 1x1km square to a single observation and analysed all observations from 1990 up to 2023.

2.2.2. Structured monitoring data

We used data from the Swiss Biodiversity Monitoring scheme (BDM) that was launched in 2001 to monitor Switzerland's biodiversity and to meet the Convention on Biological Diversity of Rio de Janeiro (Weber et al., 2004). For the BDM scheme, the 375 1x1km sample squares were selected which were regularly distributed and aligned with the 1x1km units of the Swiss national coordinate system.

The field protocol to record butterflies was based on the British butterfly monitoring scheme (Pollard et al., 1995). Butterfly counts started in 2003 and were performed by qualified entomologists who received special training to reduce among-observer variation. At a sample square during a given year, 2.5 km long transects were inspected

seven times between 21 April and 21 September in the lowlands, and four times between July and August above approximately 2000 m. The difference in numbers of inspections corresponded to the shorter flying season at higher altitudes; sites at high and low altitudes received approximately equal sampling effort per week of flight season (Pearman and Weber, 2007). Surveys were conducted within separate time windows of 14 or 21 days, depending on a seasonal schedule, following a standardised protocol. Inspections of transects were conducted during favourable weather conditions, i.e. sunshine during more than 80% of the duration of the inspection, temperature of more than 13 °C, and wind of less than 19 km/h (Beaufort level 1–2). During each inspection of transects, surveyors walked the transects in both directions and recorded all butterflies within 5 m to each side of the transects on the way forth and back, respectively. Detectability varied by species and averaged 88% per inspection (Kéry et al., 2009).

Each year since 2003, one fifth of the 375 sample squares were surveyed, chosen to constitute a regularly spaced subsample of all squares, and each square was surveyed every five years. Altitudes within the sample squares ranged from 250 m to 2870 m, with a mean ± SD altitude of sample squares of 1199 ± 686 m. We analysed the 1560 surveys from 2003 to 2023. As with the unstructured data, we aggregated all records made by a person on a day in a sample square to a single observation.

2.2.3. Selection of species and species traits

The BDM uses a predefined list of all butterfly species (i.e. all Papilionoidea but also Zygaenidae moths) that can be recorded. This predefined list of taxa includes both species and aggregates of multiple difficult-to-identify species. In the field, the surveyors may record the aggregates (e.g., *Boloria napaea*-complex) or the species that belong to the aggregates (e.g., *Boloria napaea* or *Boloria pales*). We here analysed only aggregates and the species that were not part of an aggregate. These are the 204 taxa listed in Appendix A. All records of species that belong to an aggregate were assigned to this aggregate. Observations of individuals that cannot be assigned to any of the defined species or aggregates (e.g., *Boloria* sp.) were excluded from the analyses. For simplicity, we shall henceforth refer to these species and aggregates as "species".

For all species, we included information on whether they belong to cold- or warm-adapted species, based on the thermal type ("Wärmetyp") according to Klaiber et al. (2017). We classified "thermophob" and "thermophob to mesotherm" species as cold-adapted, and "thermophil" and "mesotherm to thermophil" species as warm-adapted. Additionally, we used the site fidelity data ("Standortstreue") from Klaiber et al. (2017) and considered all wandering species ("vagabundierend") as mobile species. Note that this definition excludes migratory species such as *Vanessa cardui*. Similarly to WallisDeVries and van Swaay (2017), we conducted an expert assessment to determine the nutrient indicator value of the habitat in which the species predominantly live. We did this in 2023 at the initiative of Chris van Swaay independent from the present study. Here, we used these values and classified all species inhabiting areas with "very poor" and "poor" nutrient values as "species of oligotrophic habitats". Whether or not a species was classified as a species of oligotrophic habitat is provided in Appendix A. Finally, we also included the information whether a species is one of the 17 species of the European grassland butterfly index (van Swaay et al., 2025).

2.3. Species' temporal trends

To calculate temporal trends of each species from the unstructured species detection data, we employed the following methods, applied to each species separately (see Appendix A for the list of species including sample sizes):

(a) Raw number of occupied squares.

We calculated the number of squares with observations of the species for each year. This estimate directly depends on reporting activity. Reporting activity increases when more people consistently report their observations or data from more projects are included into the data base. Due to increased reporting activity, the number of occupied squares is likely to increase regardless of whether the species has increased.

(b) Proportion of occupied squares.

To obtain a trend estimate that is not directly dependent on reporting activity, we calculated the proportion of squares with observations of the species relative to the total number of squares with butterfly observations.

(c) Proportion of occupied squares based on reporting types.

We assume that the probability of a species being recognised and reported differs between species. These differences likely depend on how easily species are detected and identified in the field. We defined eleven groups of species for which we assumed similar reporting probabilities, i.e. the reporting types. "Conspicuous species" that are relatively easy to identify or "*Erebia*" that include most of the species of the genus *Erebia* (i.e. predominantly alpine species that are difficult to identify) are two examples of such reporting types. The full list of reporting types for all species is given in Appendix A. Note that although some of these reporting types have systematic names, they are not strict taxonomic classes. Similar as in (b), we calculated the proportion of squares with observations of the species relative to the total number of squares with butterfly observations of the same reporting type.

(d) Random year GLMM of occupied squares.

We selected all square and year combinations for which at least one species of the same reporting type as the focus species was observed. For these square x year combinations we inferred whether the focus species was observed (y = 1) or not observed (y = 0). We modelled y as the dependent variable in a binomial generalised linear mixed model (GLMM) with the intercept as the only fixed factor and year as a the only random effect. We backtransformed the yearly estimates to obtain the proportion of squares occupied by the species for each year.

(e) Site-occupancy model.

We used site-occupancy models to estimate annual mean occupancy of squares (Kéry and Plattner, 2007), following the approach by Neff et al. (2022). Site-occupancy models are hierarchical models in which two interconnected processes are modelled jointly, one of which describes occurrence probability (i.e. ecological process; used to infer mean occupancy), whereas the other describes the probability that the species is detected and reported to info fauna (i.e. observation process).

As is characteristic of a site-occupancy model, we can calculate the actual occurrence of a species by accounting for the reporting probability, provided there are at least some multiple yearly observations per square (e.g. observations from different observers or observations from the same observer at different dates) and a closed population between the observations can be assumed. The two processes are modelled through logistic regression models. The occupancy model estimates occurrence probability for each year, whereas the observation model estimates the probability that a species has been detected by an observer during a visit and reported it to info fauna. More formally, each square s during year t has the latent occupancy status $z_{s,t}$ which may be either 1 (species is present) or 0 (species is absent). This occupancy status is not directly observed and depends on the occurrence probability ψ_t as follows:

$$z_{s,t} \sim \text{Bern}(\psi_t)$$

The occupancy is linked to the number of times $y_{s,t}$ a species was observed during the $V_{s,t}$ visits at square *s* in year *t* as:

$$y_{s,t} \sim \text{Binomial}(z_{s,t}^{*} p_r, V_{s,t})$$

where p_r is the reporting probability for program type *r*. We distinguish only two types of programmes: (i) all records reported through the mobile app "NaturaList," which is part of the online platform "ornitho.ch". This platform was originally developed for reporting bird observations but since 2015 includes various species groups, including butterflies, and (ii) all other records from the info fauna database. During the development of the models and in comparison to the BDM trends, we noticed that a separate treatment of the ornitho.ch data was necessary, as easily identifiable species were reported disproportionately often via this platform. Finer-grained categorisations of data source led to convergence problems and unstable estimates across species. The yearly occurrence probability ψ_t was modelled as a random effect implemented as random walks accounting for dependencies among consecutive years. Conceptually, in random walks, the effect of one year is dependent on the previous year's effect, resulting in trajectories with less sudden changes between consecutive years (Neff et al., 2022).

2.3.1. Reference model

As a reference, we calculated the temporal trends of the species exclusively based on the structured monitoring data using the random year GLMM. We calculated the trends only for species with sufficient data. As a threshold, we included only those species that were recorded in at least 20 of the 375 surveyed squares (>5%) across the entire study period ($n = 135$ species). To estimate yearly occupancies, we used the same model as in (d): For all surveyed squares, we inferred whether the species was observed ($y = 1$) or not observed ($y = 0$). We then modelled y as the dependent variable in a binomial generalised linear mixed model (GLMM) with the intercept as the only fixed effect and year as the only random effect. We backtransformed the yearly estimates to obtain the proportion of squares occupied by the species for each year.

2.4. Statistical analyses

All statistical analyses were performed through R version 4.4.3. Besides the explicitly mentioned packages, the R packages dplyr, ggplot2, raster, sf were key for data handling, data analysis, and plotting. To estimate the yearly occupancies based on the random year GLMM we used the function glmer of the package lme4 (Bates et al., 2015). To estimate the yearly occupancies based on the site-occupancy model we used a Bayesian approach using Stan through the R interface rstan (Stan Development Team, 2025). We ran two Markov chain Monte Carlo chains with 2′000 iterations each, including 1′000 warm-up iterations. Posterior distributions were summarised through means and 95%-credible intervals (CIs). The stan model including the priors is given in Appendix B.

To compare the temporal trends between the different methods and between species, we standardised the annual estimates of a method and species by dividing them by the mean from the years 2003 to 2007, then multiplying the result by 100. The mean of the years 2003 to 2007 was used as the reference period because it corresponded to the initial survey of all squares of the BDM. For each method and species, we then calculated the slope of the linear trend of the standardised yearly estimates from 2003 to 2023. The unit of these temporal trends is the change per decade relative to the baseline value of 100 for the reference period from 2003 to 2007.

We then calculated the correlation of the species' temporal trends based on the unstructured info fauna data with the temporal trend based on reference model. To estimate the bias of the temporal trend estimates, we calculated the species-specific difference between the temporal trend of unstructured data and the temporal trend of structured monitoring data. A bias greater than 0 indicates that the temporal trends of the unstructured data were overestimated compared to the trends of the reference model; conversely, a bias less than 0 indicates they were underestimated.

We calculated the multi-species index (MSI) for all species (i.e. the Swiss butterfly index) and the five specific groups, that is cold-adapted species, warm-adapted species, species of oligotrophic habitats, mobile species, and grassland butterfly index. See section 2.2.3 on how we attributed the species to these five groups. We used the Markov chains of the annual occupancy estimates from the occupancy models. For each year and iteration of the Markov chains, the median of the estimated annual occupancies of the species was calculated. The mean and the 2.5% and 97.5% quantiles of the medians of all iterations provided the estimate and the 95% credible interval of the MSI.

To compare the trends of the MSI with traditional biodiversity indicators, we also calculated from the BDM data the species richness, the total number of individuals per plot, and the Simpson dissimilarity index as a measure of beta diversity (Koleff et al., 2003). For species richness and the total number of individuals, we averaged the surveyed squares per year and inferred the temporal trend using a linear model with log species richness or the number of individuals per square as the dependent variable and year as the predictor. We calculated the dissimilarity in species lists between surveyed squares using the Simpson dissimilarity index for presence-absence data (Bühler and Roth, 2011; Koleff et al., 2003). We calculated the Simpson index between all pairwise combinations of studied squares and averaged them. As it takes five years to cover all survey areas in the BDM, we calculated the averaged Simpson index of all pairwise combinations for each five-year period, that is, 2003–07, 2004–08, …, 2019–23. We inferred the temporal trend using a linear model with the logit-transformed Simpson index as the dependent variable and year as the predictor.

All R scripts used to calculate the temporal trends and to produce the figures are available at https://github.com/TobiasRoth/Publication_Tagfalterindex and archived at https://doi.org/10.5281/zenodo.21804896.

3. Results

3.1. Differences between the structured and unstructured data

Between 1990 and 2023, a total of 783′991 butterfly observations were collected in the info fauna database. The number of observations per year is not evenly distributed over this period but has increased significantly from low values in the 1990s (Fig. 1a). The butterfly surveys for the BDM began in 2003, and since then, a total of 55′509 butterfly observations have been collected. By design, the total number of observations per year in the BDM remained largely stable over the study period (Fig. 1b).

In the info fauna dataset, there were observations from 26′892 squares, representing approximately 65% of the 41′295 km^2 squares in Switzerland. Except for the high alpine regions, the info fauna dataset covered the entirety of Switzerland well. However, the number of observations varies significantly by region, with the squares having the highest numbers of observations typically located close to areas with high human population density (Fig. 1c). The BDM dataset contains observations from the 375 surveyed squares, which is less than 1% of Switzerland. By design, the sample squares of the BDM are regularly distributed across Switzerland (Fig. 1d). The only exception concerns high alpine areas, which are too steep and consequently too dangerous to survey.

Of the 194 species examined (Appendix A), all 194 were recorded in the info fauna dataset, and 191 species were identified in the BDM dataset. On average (±SD) per square and year, 6.6 (± 8.3) butterfly species were recorded in the info fauna dataset and 35.6 (± 16.2) in the BDM dataset, respectively.

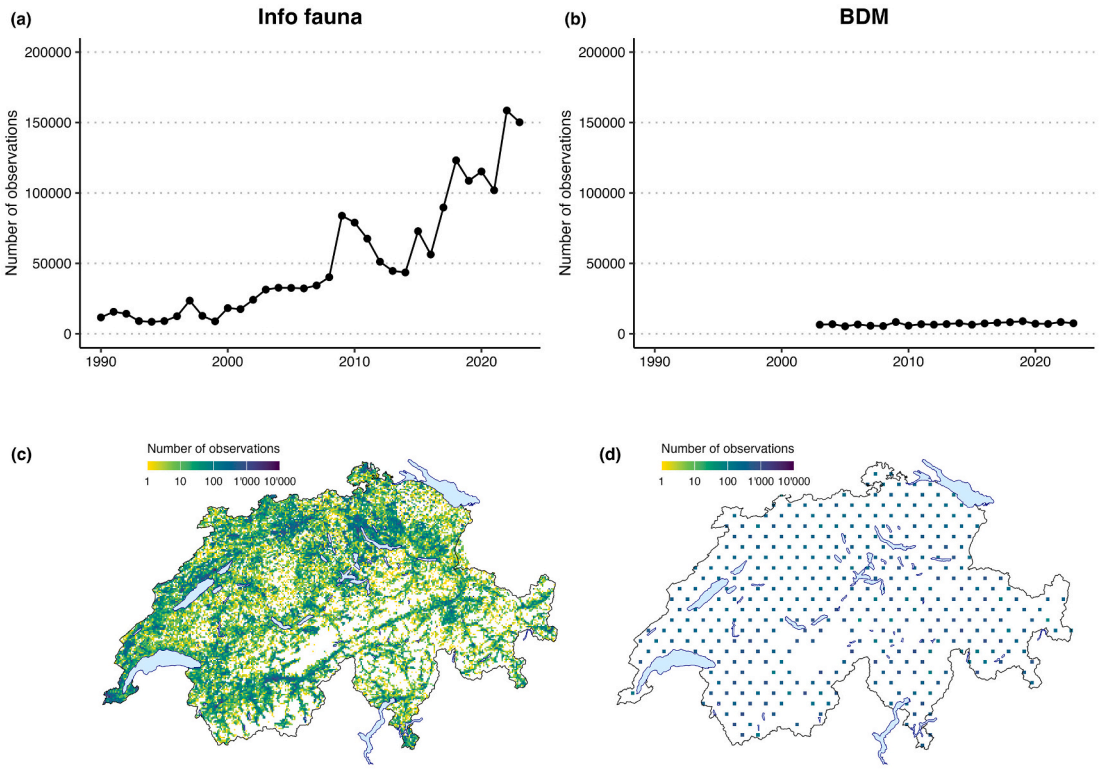

Fig. 1. Temporal change in the number of observations per year (top row) and the number of observations per 1 km grid cell (bottom row) in the info fauna dataset (unstructured data, left column) and the data from the biodiversity monitoring (BDM, structured data, right column). Note that the squares representing the study sites of the BDM in the bottom right map are not to scale (enlarged). An observation represents the record of a species within a 1 km square by an observer per day.

3.2. Accuracy of trend estimates

Between 2003 and 2023, a total of 135 species were recorded in at least 20 BDM squares. For these species, we calculated the temporal trends using only BDM data and compared them with the temporal trends derived from the unstructured info fauna data.

The temporal trend of the raw number of occupied squares shows a weak positive correlation with the BDM trends (r = 0.35) and were clearly overestimated compared to the BDM trends (bias = 10.03; Fig. 2a). When the proportion of occupied squares, rather than the raw number of occupied squares, was used, the correlation with the BDM trends increased (r = 0.59). With this method, the temporal trends were no longer overestimated but slightly underestimated (bias = −3.36; Fig. 2b). The correlation became even stronger when only the proportion of squares with observations of species with the same reporting type was used (Fig. 2c) or when a statistical model with year as a random

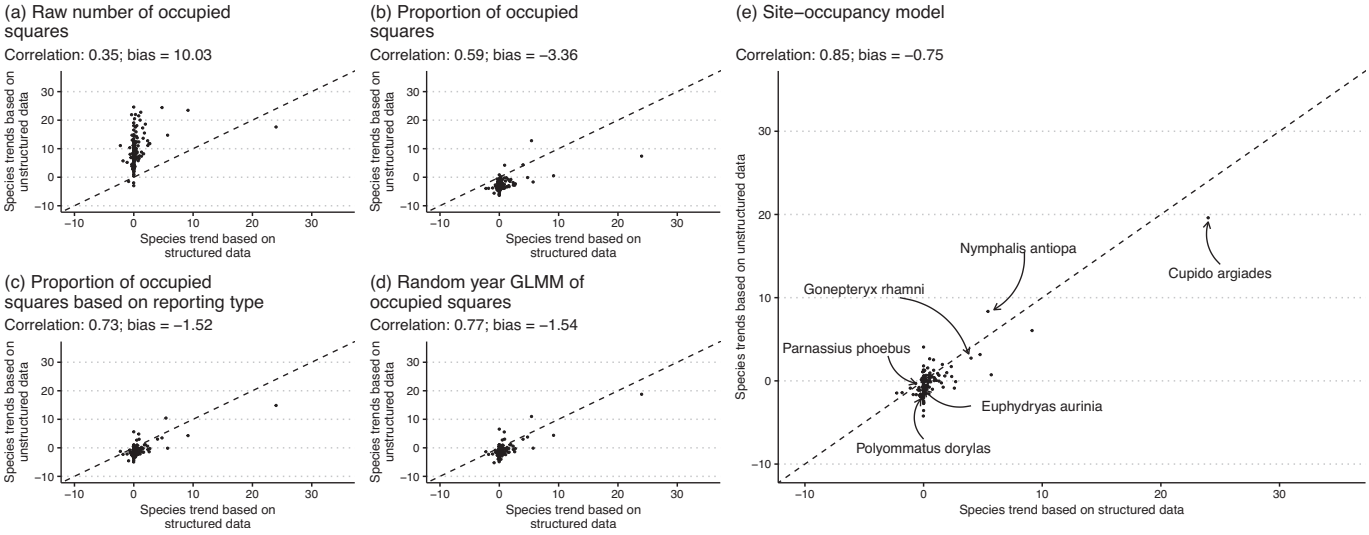

Fig. 2. Comparison of temporal species trends derived solely from the structured data of the biodiversity monitoring (BDM, x-axes in all panels) with trends obtained from unstructured info fauna data using the following methods: (a) raw number of occupied squares, (b) proportion of occupied 1 km^2 squares, (c) proportion of occupied squares with observations of species of the same reporting type, (d) proportion of occupied squares based on a generalised linear mixed model (GLMM) with random year effect, and (e) proportion of occupied squares based on the site-occupancy model accounting for different reporting types from two data sources. In all panels the points represent the 135 species recorded in at least 20 BDM squares. Detailed results for the six species highlighted in (e) are provided in Fig. 3.

effect was applied to estimate yearly trends from the same data (Fig. 2d). In both cases, the bias also decreased further. The strongest correlation and the least bias were observed, however, when the unstructured data were analysed using the site-occupancy model. The trends from the unstructured data correlated with the BDM trends at $r = 0.85$, and the bias was reduced to −0.75 (Fig. 2e). However, this across-species average masks substantial among-species variability: the six species in Fig. 3 illustrate this heterogeneity. *Cupido argiades* was among the species with the most significant increase in occupancy in Switzerland since 2003 (Fig. 2e). Of the six species, it is the only one where the trend in the raw number of occupied sites was not significantly stronger compared to the trends of the other methods. For the other five species, the considerably more positive trend of the number of occupied squares compared to the trends of the other methods can be explained by the increased reporting activity directly affecting the number of squares with observations. For the other methods, the index values were like those estimated from the BDM data.

3.3. The Swiss butterfly index

For $n = 194$ species (i.e., all species in the info fauna database with sufficient records to fit the site-occupancy model), temporal trends were calculated using the site-occupancy model based on the info fauna data. For each species, we created a graph illustrating the trend estimated by the site-occupancy model (results not presented). Two of us (YC and MP) reviewed all species' graphs to assess the plausibility of the trends. For some of the rare species, the yearly occupancy estimates exhibited large annual fluctuations whose magnitude was clearly driven by years with insufficient data for a reliable yearly estimate. To exclude such species, we adopted a minimum number of records as inclusion criterion. We selected 400 observations as the threshold, corresponding to an average of about 15 records per year across the study period (1990–2023). This threshold represents a pragmatic, study-specific decision tailored to our dataset rather than a generally applicable criterion. With this criterion, 179 species entered the main analysis (Fig. 4). This represents a 33% increase over the 135 species for which a trend could be estimated from the structured BDM data alone, illustrating the gain in taxonomic coverage achieved by integrating the two data sources. To verify that the choice of threshold did not affect our conclusions, we repeated the analysis with two alternative selection rules: (i) all 194 species without any threshold (Fig. C1 in Appendix C) and (ii) the subset retained by the expert review of YC and MP (Fig. C2). Neither rule materially changed the Swiss butterfly index (MSI of all species) or the trends of the species groups. For the cold-adapted species, the years 1990 and 1991 showed exceptionally high index values (Fig. 4b). We additionally recalculated Fig. 4 with these two years excluded; the results remained qualitatively the same (Fig. C3).

Of the 179 species, 47 (26%) showed a significant increase, while 77 (43%) showed a significant decrease between 1990 and 2023 (Fig. 4a). Accordingly, the multi-species index across all 179 species showed a slight decline (Fig. 4d). The characteristics of species appeared to determine how their distribution has changed since 1990. There were clearly species with retracting ranges, especially among cold-dwelling species and species of oligotrophic habitats (Fig. 4b and e). However, there were also winners, particularly among warm-adapted and mobile species (Fig. 4c and f).

3.4. Comparison with other biodiversity indicators

Based solely on the BDM data, species richness per square increased by approximately 18% from 2003 to 2023 ($p = 0.014$, Fig. 5a). The species that contributed most to this increase were *Gonepteryx rhamni, Cupido argiades, Lycaena phlaeas, Lasiommata megera, Aricia agestis*-complex, *Cupido alcetas* and *Brintesia circe* (in decreasing order). If these species were removed from the calculation of species richness, the increase was 0.13% and no longer statistically significant ($p = 0.053$). For these seven species, the number of BDM squares with records exceeded the median for all species, indicating that they were widespread. Furthermore, four of the seven species (57%) were both warm-adapted and mobile whereas from all 204 species studied, only 9% were both warm-adapted and mobile. Like species richness, the total number of individuals per square increased from 2003 to 2023 ($p = 0.001$, Fig. 5b). The annual estimates of species richness and total number of individuals were highly correlated ($r = 0.91$, $p < 0.001$). In contrast, however, beta diversity measured by the Simpson index based on occupancy data, decreased from 2003 to 2023 ($p < 0.001$, Fig. 5c).

The multi-species index based on the 17 species of the grassland butterfly index declined regardless of whether it was based on the

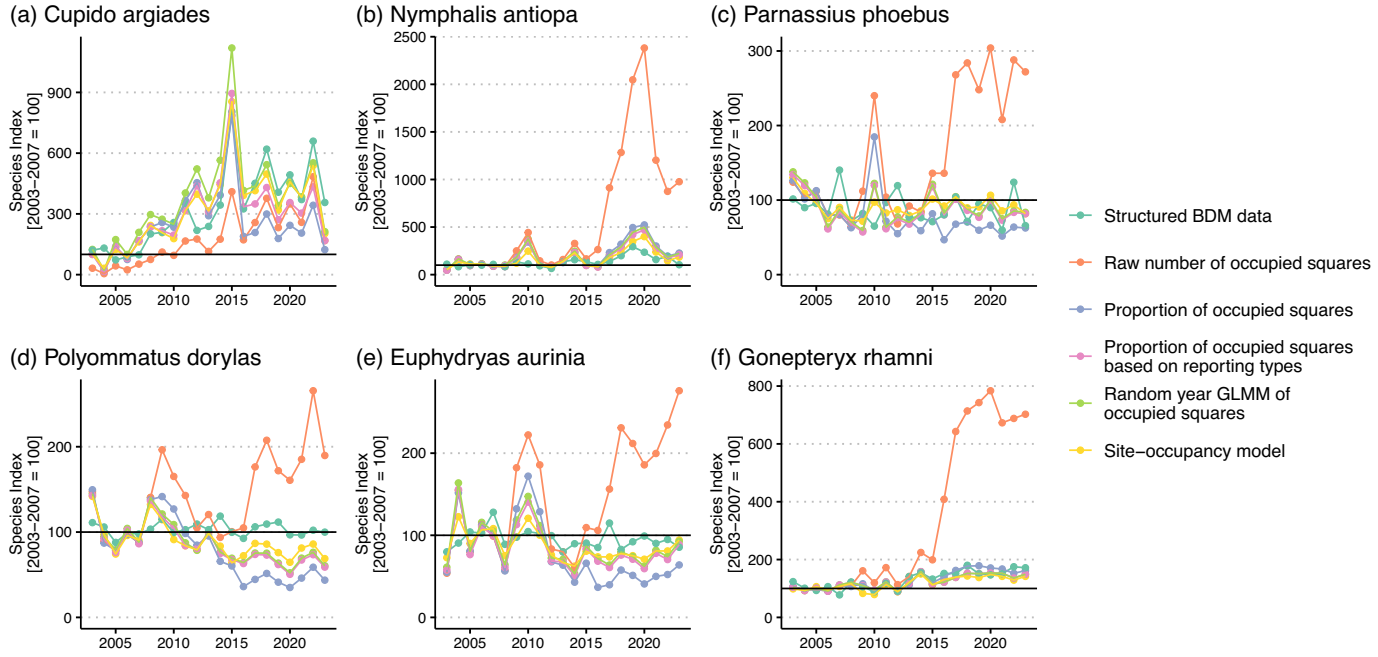

Fig. 3. Comparison of the temporal trend obtained using six different models for (a) *Cupido argiades*, (b) *Nymphalis antiopa*, (c) *Parnassius phoebus*, (d) *Polyommatus dorylas*, (e) *Euphydryas aurinia* and (f) *Gonepteryx rhamni*.

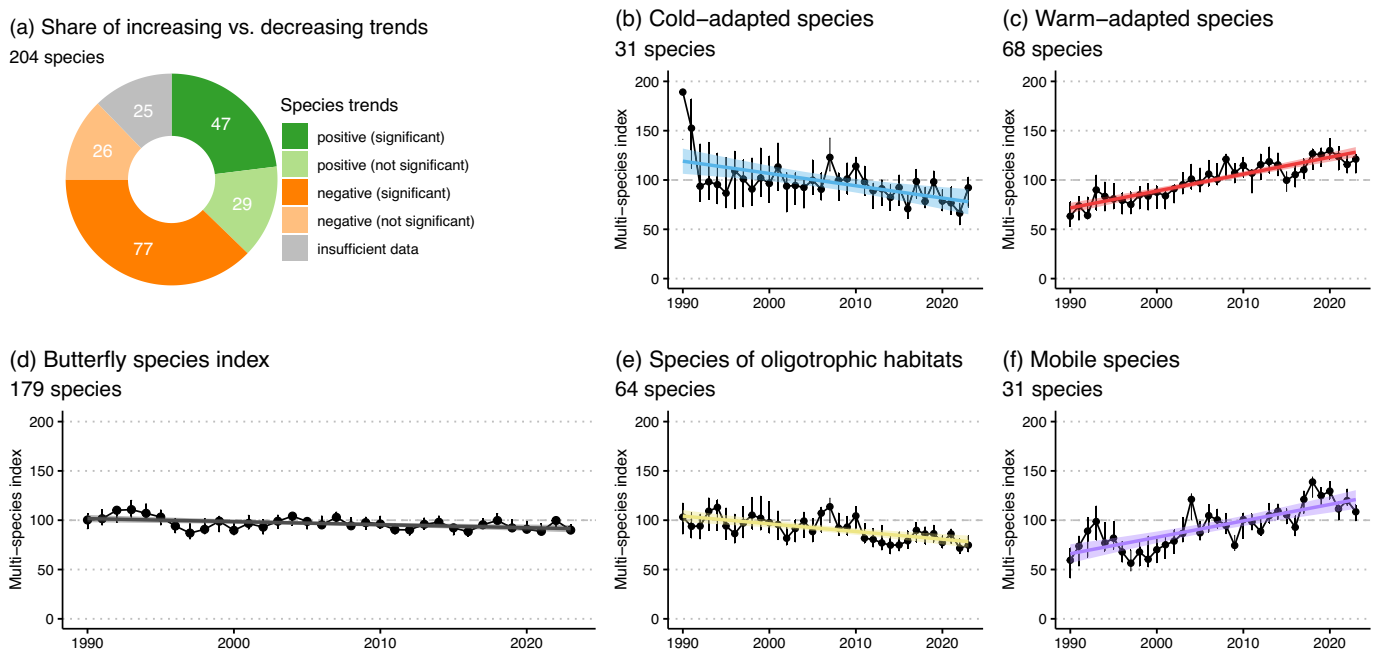

Fig. 4. Results of the Swiss butterfly index. (a) Number of species with increases, decreases, or insufficient data to determine a trend. (b) Multi-species index of the cold-adapted species. (c) Multi-species index of the warm-adapted species. (d) Multi-species index for all species. (e) Multi-species index of the species of oligotrophic habitats. (f) Multi-species index of the mobile species.

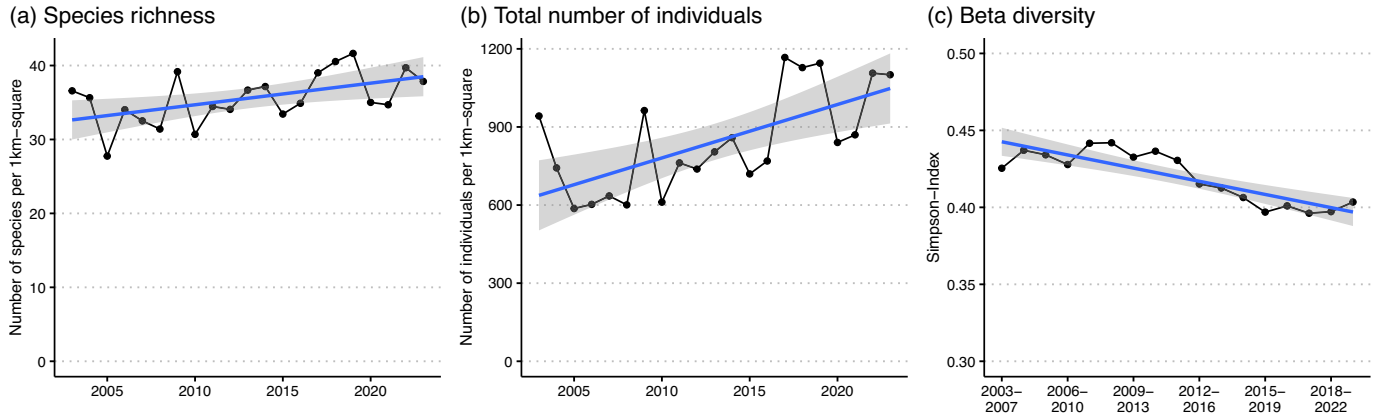

Fig. 5. Results of the traditional indicators used in the biodiversity monitoring Switzerland (BDM), that are (a) species richness, (b) total individual number, and (c) beta diversity (i.e. the dissimilarity in species lists between surveyed squares).

species trends of the EU27 countries (trends from van Swaay et al., 2025) or on the species trends in Switzerland (this study). However, the decrease was stronger in the EU27 countries (Fig. 6), with the yearly estimates correlating between the European and Swiss grassland indicator at $r = 0.35$ ($p = 0.043$). Note that the results of the EU27 trends in the beginning of the study period relied on fewer species and data from fewer countries compared to the end of the study period. For example, the estimate from 1990 is based on only six species, and only from 2010 onwards on all 17 species.

4. Discussion

4.1. The use of unstructured and structured data to estimate species' trends

Various studies emphasise that reliable quantification of trends is only possible with well-designed surveys (Buckland et al., 2005). Our results, however, indicate that reliable trends can also be determined from unstructured data. The trend estimates based on the site-occupancy model showed the highest correlation with the trends of the structured BDM data, and these trends also exhibited the least bias. The correlation of species' trends based on structured and unstructured data with $r = 0.85$ was very high and comparable to previous studies (Dennis et al., 2017; Van Strien et al., 2013). Noteworthy, however, our results show that reliable trend estimates may also be achieved with simpler analyses, without complex statistical models such as site-occupancy models. For example, the proportion of occupied squares with butterfly observations of the same reporting type can be easily calculated from unstructured data and the temporal trend of this proportion was positively correlated with the trends obtained from structured BDM data ($r = 0.73$; Fig. 2c).

We emphasise, however, that reliable quantification of trends from unstructured data is conditional on the calibration of the site-occupancy model against the structured reference. Unbiased inference from unstructured data is only possible if appropriate statistical models that account for changing reporting intensities were used. However, determining whether a model is appropriate seems only possible through comparison with trend estimates obtained from structured data. In our case, structured data was indeed invaluable for model development and

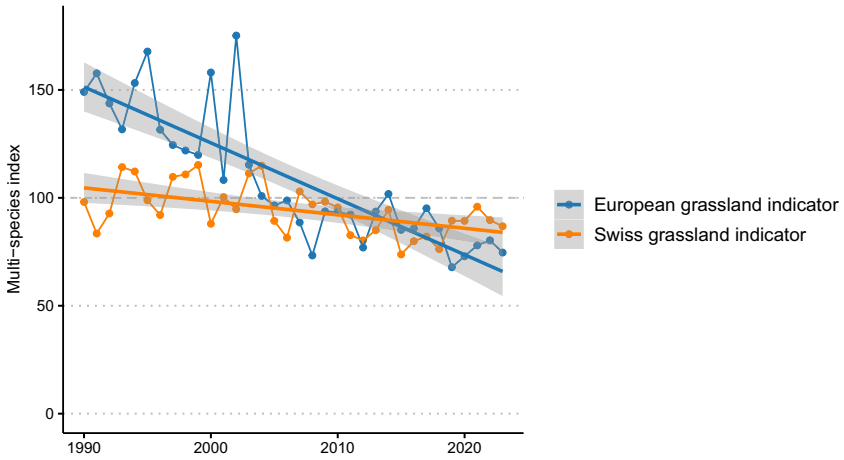

Fig. 6. Temporal trends of the grassland butterfly index based on species trends from the EU27 countries ("European grassland indicator") and from Switzerland ("Swiss grassland indicator") from 1990 to 2023.

plausibility checks. Initially, we used a statistical model that did not differentiate between the reporting probability of ornitho.ch data and other data from the info fauna database. Since ornitho.ch frequently includes reports of common or easily identifiable species, trends of these species were overestimated using the initial model. *Nymphalis antiopa* (Fig. 3b) and *Gonepteryx rhamni* (Fig. 3f) are two examples of such species. For these species, the number of occupied squares strongly increased since it became possible to record butterflies via ornitho.ch from 2015 onwards. Such change in data gathering that affects the reliability of the used model may also occur in the future, and if not addressed, it could obscure the true picture of species trends (Boakes et al., 2010). Therefore, even as the proposed site-occupancy model currently delivers good results, it is essential to continuously verify trend estimations with the structured BDM data. More generally, the transferability of the proposed framework to other regions or taxa relies on the availability of a structured monitoring programme suitable for calibrating and validating the model; where no such structured reference exists, trends derived from unstructured data alone should be interpreted with caution.

4.2. Differences in trends between species groups

The aggregate Swiss butterfly index for all 179 species indicated a stable to slightly declining trend, but this overall pattern masked strong differences among species. Since 1990, 43% of species have declined significantly, while 26% have increased, highlighting the necessity of examining groups separately to better understand the underlying drivers of change. We selected groups based on thermal preference (cold- vs. warm-adapted), habitat specialization (oligotrophic habitat types), and mobility because these traits reflect the primary drivers–climate change, land-use intensification and habitat fragmentation–shaping butterfly communities across Europe (Guariento et al., 2023; Habel et al., 2026; Warren et al., 2021). Cold-adapted species such as *Parnassius phoebus* (Fig. 3c) and specialists of oligotrophic habitats such as *Polyommatus dorylas* (Fig. 3d) and *Euphydryas aurinia* (Fig. 3e) showed clear declines. In contrast, warm-adapted or mobile species such as *Gonepteryx rhamni* (Fig. 3f) have increased. Species that are both warm-adapted and mobile such as *Cupido argiades* (Fig. 3a) are thus the main "winners" in Switzerland since 1990.

Earlier studies using BDM data fit well with these results. For example, nitrogen deposition and nutrient enrichment likely reduce habitat quality through microclimatic cooling or the loss of host plants via competitive exclusion, particularly for threatened species (Roth et al., 2021). Climate warming further contributes to these changes by shifting communities toward species with warmer thermal profiles, consistent with an average uphill shift of communities (Roth et al., 2014). This upward shift in distribution reduces the potential range of cold-adapted species.

In a landscape marked by high fragmentation and rapid environmental changes, typical of the Central Plateau in Switzerland, high mobility is a crucial trait (Guariento et al., 2023). It facilitates the colonisation of new habitats and allows species to track their shifting climatic niches. At the same time, habitat specialists are likely to decline due to increased fragmentation of their habitats. These patterns were particularly evident for grassland species. In Switzerland, the species of the grassland butterfly index, which includes both highly specialized and generalist species that also occupy habitats other than grasslands, showed a declining trend consistent with broader European patterns. In neighbouring Germany, estimates vary by method (stable to moderately declining), but multiple analyses indicate a significant decline over the last decade, largely driven by habitat specialists (Harpke et al., 2025). At the EU scale, grassland specialists have declined by roughly 50% since 1991 (van Swaay et al., 2025), highlighting widespread degradation of grassland habitats due to intensification and abandonment. In Switzerland, the decline was about 20%. One reason for the smaller decline might be the biodiversity promotion measures that have been implemented in the agricultural landscape. Over the last decade, the ecological quality of protected and extensively managed grassland habitats has improved slightly (Bergamini et al., 2025; Boch et al., 2026; Meier et al., 2025). Additionally, much of Switzerland's grasslands are in the Alps, where they are used as summer pastures. Many species under pressure in Switzerland's lower regions may have found refuge at higher altitudes.

4.3. Comparison of multispecies index and traditional biodiversity indicators

Our results demonstrate that the Multi-Species Index (MSI) provides a different view on biodiversity compared to traditional indicators, such as species richness or total individual counts. Structured monitoring data from the BDM indicated a significant increase in both species richness and the total number of butterflies per square between 2003 and 2023. Such increases in the last two decades seem to apply not only to butterflies but to arthropods in general (Fürst et al., 2023). For butterflies, these trends were heavily influenced by the performance of a few widespread species, particularly warm-adapted mobile species. In contrast to species richness, the MSI treats all species equally, revealing that the aggregate status of Swiss butterflies was slightly declining. Furthermore, we found a very high correlation between annual species richness and total individual counts ($r = 0.91$), which likely occurred

because the most abundant species were also the most widespread, causing their population gains to increase both metrics simultaneously.

Despite the recorded increase in species richness, the simultaneous decline in beta diversity (i.e. the dissimilarity in species lists between surveyed squares) revealed a clear trend toward more uniform butterfly communities. When considered together, the combination of species richness and beta diversity metrics thus provides a strong summary of community changes, specifically the homogenization of species assemblages due to the increase of some common species such as *Gonepteryx rhamni* (Fig. 3f; Ekroos et al., 2010; Habel et al., 2026). This process is likely driven by the dual pressures of climate change and land-use intensity (Neff et al., 2022). While traditional richness indicators are useful for tracking common species that usually provide essential ecosystem services, they frequently overlook the rarer specialists that are the primary focus of conservation policy, because by definition they face the greatest extinction threats (Gaston, 2010). Because the MSI includes these rare and specialized species with equal weighting, it offers a more comprehensive and policy-relevant indicator of the overall state of the butterfly fauna than traditional metrics alone. Notably, integrating the unstructured info fauna data with the structured BDM data increased the number of species covered by the index by 33% (from 135 to 179 species), substantially broadening the taxonomic scope of the indicator.

4.4. Limitations

The current version of the Swiss butterfly index relies on a simplified site-occupancy model that does not account for many biological and methodological factors. For instance, the model assumes a closed population during all observations of a year and simplifies the observation process into only two reporting categories, thereby ignoring potentially significant factors such as intra-annual phenological variation (flight periods), weather conditions during surveys, or specific observer expertise. Although more complex hierarchical models were tested (results not shown), they frequently produced inconsistent or implausible results across the highly diverse set of butterfly species. By comparing our results with the structured data from the Swiss Biodiversity Monitoring (BDM) program, we found that the simpler models provided more robust and reliable trend estimates across all species.

A further limitation is the exclusion of the rarest species, as we only included taxa with at least 400 observations to ensure reliable annual occupancy estimates of the estimated trends. Because rare and specialized species are often the most sensitive to environmental degradation (Clavel et al., 2011), their omission may lead to a non-representative multi-species index that provides an overly positive outlook on the state of Swiss butterflies. To address this gap, integrated monitoring must eventually incorporate targeted, species-specific programs designed to collect data on these rare species.

Additionally, our method relies on presence-absence data, as complete abundance information is often not provided to info fauna by the recorders. Since distribution changes may be less sensitive than changes in individual numbers, there is a risk that significant population declines are only be detected with a considerable time lag.

4.5. Outlook

Future iterations of the Swiss butterfly index should expand to include specialized species groups that are highly relevant to conservation policy, such as Red List taxa and target species identified in agricultural environmental objectives. While our current approach demonstrates that combining structured and unstructured data allows for the inclusion of many species, achieving a truly representative national index would require a concerted effort to include the rarest species (Buckland and Johnston, 2017). To reach this goal in Switzerland, it is necessary to close remaining data gaps for rare alpine species found in remote, high-altitude terrain, as well as for taxonomically difficult groups that require significant expert verification for reliable identification. Two complementary avenues may help to close these gaps. First, the existing citizen-science community could be engaged more dynamically by sharing the annual indices with contributors and issuing targeted appeals inviting recorders to fill specific spatial and taxonomic gaps. Second, this engagement must be complemented by targeted, species-specific monitoring programmes and by continued investment in the training of expert naturalists, since the rarest and taxonomically most difficult species are unlikely to be fully covered by general citizen-science efforts alone. Although such efforts are unlikely to change the overall signal of the Swiss butterfly index, they are essential for ensuring that the most specialized and elusive members of the butterfly community are adequately represented in future biodiversity assessments.

5. Conclusions

Site-occupancy models calibrated against a structured monitoring reference make it possible to recover species trends from unstructured citizen-science data that closely track those obtained from the structured monitoring data. Combining the two data sources allowed us to compute a multi-species index for 179 butterfly species. This combination increased the number of species covered by the index by 33%. The resulting index shows a slight overall decline driven by losses in cold-adapted species and species of oligotrophic habitats, a signal that traditional species-richness indicators would have obscured. We conclude that integrated indicators are both feasible and policy-relevant, but their reliability depends on the availability of a structured reference for calibration and on continued investment in the citizen-science recording infrastructure. Citizen-science data are therefore most valuable when they complement, rather than replace, systematic monitoring programmes.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work the authors used NotebookLM in order to scan a selection of scientific papers for specific questions. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

CRediT authorship contribution statement

Tobias Roth: Writing – review & editing, Writing – original draft, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Yannick Chittaro:** Writing – review & editing, Validation, Supervision, Data curation, Conceptualization. **Jérôme Frei:** Writing – review & editing, Validation, Supervision, Funding acquisition. **Glenn Litsios:** Writing – review & editing, Validation, Supervision, Data curation, Conceptualization. **Matthias Plattner:** Writing – review & editing, Validation, Supervision, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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provision.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2026.115230.

Data availability

The R code used for the analyses is available at https://github.com/TobiasRoth/Publication_Tagfalterindex and archived at https://doi.org/10.5281/zenodo.21804896. The raw species records are protected by a code of conduct common to the BDM and info fauna and may be obtained upon request. Species records of info fauna at a coarser spatial resolution are available from GBIF (https://doi.org/10.15468/atyl1j).

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