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ON USING INATURALIST DATA TO ESTIMATE TRENDS IN TIME

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Abstract. A discussion is presented of the use of citizen science data to study trends in population abundance and on numbers of species. The discussion is framed around two widely accepted models of indices of biological signal per unit of effort. When the trend is number of species per unit of effort, the model is the Michaelis-Menten equation, that has an asymptote. When the trend is in abundance per unit effort, the model is the simple linear "catch/effort" model of fisheries. It is found that number of species per unit of effort has an artifactual tendency to negative trends, while abundance per unit effort is more likely to be less influenced by artifacts of the metrics. A calculation shows that, under certain assumptions, the number of records in iNaturalist is a good approximation to number of different individuals sighted. These results are checked by simulation and exemplified using data for three families of butterflies of Mexico.

Key words.—Citizen Science, iNaturalist, Mexico, butterflies

Introduction

It is widely accepted that the populations of many species of insects have a declining trend (Forister et al. 2019; Wagner 2020; Boyle et al. 2025; Edwards et al. 2025). This has been documented mostly in countries in the northern hemisphere that have formal sampling monitoring schemes (Sánchez Herrera et al. 2024). In the tropical countries, data is less abundant, and mostly available for a few species in selected localities (Basset and Lamarre 2019). Since formal insect monitoring schemes are rare in tropical countries, perhaps it would be possible to estimate trends using so-called citizen science (Kullenberg and Kasperowski 2016). Citizen science (CS) means the participation of the general public in scientific research and production of knowledge (Fraisl et al. 2022; Johnston et al. 2023). Biodiversity CS data exist in many countries (Chandler et al. 2017), sometimes with millions of records and thousands of users. CS data has been used to estimate phenology and distributions (Batalden et al. 2014; Soroye et al. 2018; Henckel et al. 2020) and there are examples of it use to assess trends (Horns et al. 2018; Neate-Clegg et al. 2020), although these two examples use eBird in the United States: probably the largest, most-extensive and well-studied CS initiative in the world.

eBird publishes observations in the millions of observations per month (Sullivan et al. 2014), which in some sense is very impressive. However, the size of a database does not guarantee its quality (Meng 2018), and therefore the right statistical tools are needed to use CS (Welti et al. 2021). Scientists using eBird have developed extremely sophisticated statistical methods to report and extrapolate from their database (Tang et al. 2021). eBird data has been used to estimate trends in bird populations (Walker and Taylor 2017; Horns et al. 2018), which is possible mainly because of the sheer numbers, regularity and density of observers in the eBird database, and the fact that eBird is a semi structured platform (Kelling et al. 2009).

There is no equivalent to eBird for insects of the world. Of course, there are CS schemes to monitor butterflies, although these are mostly used in industrialized countries (https://www.e-butterfly.org/ ; https://www.biologia.unipd.it/ricerca/progetti-di-ricerca/progetto-neptis). However, the platform known as iNaturalist contains millions of records for countries in the Southern hemisphere and it would be very interesting to assess the suitability of iNaturalist to estimate trends in some variable of interest, in such countries. To use a source of data like iNaturalist to estimate trends, one needs to decide what variables of interest, suitable to create time-series, can be obtained from the database. Second, since in many countries iNaturalist is growing, in the sense of having more users, or more observations, one needs to standardize by some measure

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of effort. The goal of this work is to understand the theoretical behavior of of metrics of abundance, and number of species derived from iNaturalist, when sampling effort increases over time.

Conceptual Framework

Response variables

Data from iNaturalist may be downloaded directly from its Web Site, via the API, using, for instance, the R package 'rinat,' (Barve et al. 2022), or via the GBIF interface. This includes taxonomic information, observer identity and locality description and time and date of the observation, a link to images, and other assorted fields. From these data two response variables can be readily derived for a given site and a year (i) the number of observations of a given species, and (ii) the number of different species observed. Both variables are commonly used to biodiversity change over time (Lindenmayer and Likens 2011). Although iNaturalist data can also be used to study phenology or species distributions (Soroye et al. 2018; Garretson et al. 2023; Mason et al. 2025), here we focus on metrics directly related to abundance and species richness.

Monitoring population sizes has a long history, perhaps beginning with fisheries (Gulland 1969). In the fisheries literature, the response variable, or "catch" is roughly taken to be proportional to abundance of a focal species, or group of species. Since the individuals taken are physical specimens, one report equals one individual. However, in a CS database like iNaturalist it is in general impossible to assess whether the number of observations of a species, on a date, in a region, represent multiple sightings of a single individual, or single sightings of multiple individuals. Strictly speaking, then, records in iNaturalist may, or may not be a good proxy for the size of a population, and they should be referred to as "sightings", or "encounters." However, in recent literature (Forister et al. 2021) it is reported that iNaturalist records (per unit of effort, see below), correlate well with indices obtained by structured sampling which are supposed to estimate abundance. Moreover, under reasonable assumptions (see section Multiple Sightings) the expected value of the number of different individuals sighted in a population, by a pool of observers, is well approximated by the reported quantity in iNaturalist. This result is an argument in favor of using records in iNaturalist —per unit of effort—to be used as an index to assess trends in abundance.

The response variable may also be the number of species in a community (Moreno and Halffter 2001). From CS databases like iNaturalist lists of species, for a period of time and a group of localities, can be obtained (Forti and Szabo 2023). Moreover, the "research degree" tag in iNaturalist means a species identified by at least three "experts," making the identification reliable to an extent. However, as discussed in the section of estimating slopes, finding trends in number of species per unit of effort has some strong complications.

Finally, one can study trends in the "occupation" of space, meaning the number of sites where a species is reported. In other words, one can model the dynamics of the distributional range of a single species using "occupancy models." This is a hierarchical approach that combines a model of the reality (presence of the species) with a model of the sampling process (Altwegg and Nichols 2019; Outhwaite 2019). This sophisticated approach implies dense sampling and reporting of true absences. For instance, the method has been used in the Netherlands, partitioning it in ~ 1,662 cells of 25 km^2 (van Strien et al. 2019). From 1992 onwards at least 1,000 sites were surveyed, regularly and in a standardized way. However, for many countries this is unrealistic. For instance, in Mexico at this resolution one would need a grid of ~ 8,000 cells, most of which will be empty of data, and true absences would be lacking. Besides, in large countries environmental heterogeneity tend to be high, and for most species suitable environments are poorly modelled by uninformative (i.e., flat) priors, as suggested in the literature of the method (Outhwaite 2019). It is possible to use environmental covariates for this type of model (Pannekoek 1998) but, again, the amount of data required is far above what is available for CS databases in most countries. Occupancy models, therefore, appear to be inappropriate for the type of data available in many tropical countries.

In view of the above, it appears that one can use either the number of records, or the number of species, as response variable. But, at least in some countries, effort is increasing rather fast, and thus a correction for increasing effort is needed (Forister et al. 2021). What is effort?

Measure of effort

For many years it has been known that when more effort (time, personnel sampling, better nets…) is allocated to a survey, the size of the response, or "catch," in fisheries parlance, grows (Gulland, 1969). If effort is not constant, then, it is natural to use indices of response per unit of effort; this means one needs to define how the particulars of the available data allow calculation of a response, and to define effort. Effort may be defined in terms of amount of time, methods, number of observers, number of observations and other quantities (Sutherland 2006). Since for some countries the number of observers and thus the effort is growing (Mesaglio and Callaghan 2021), measures of effort should be used to standardize the values of the

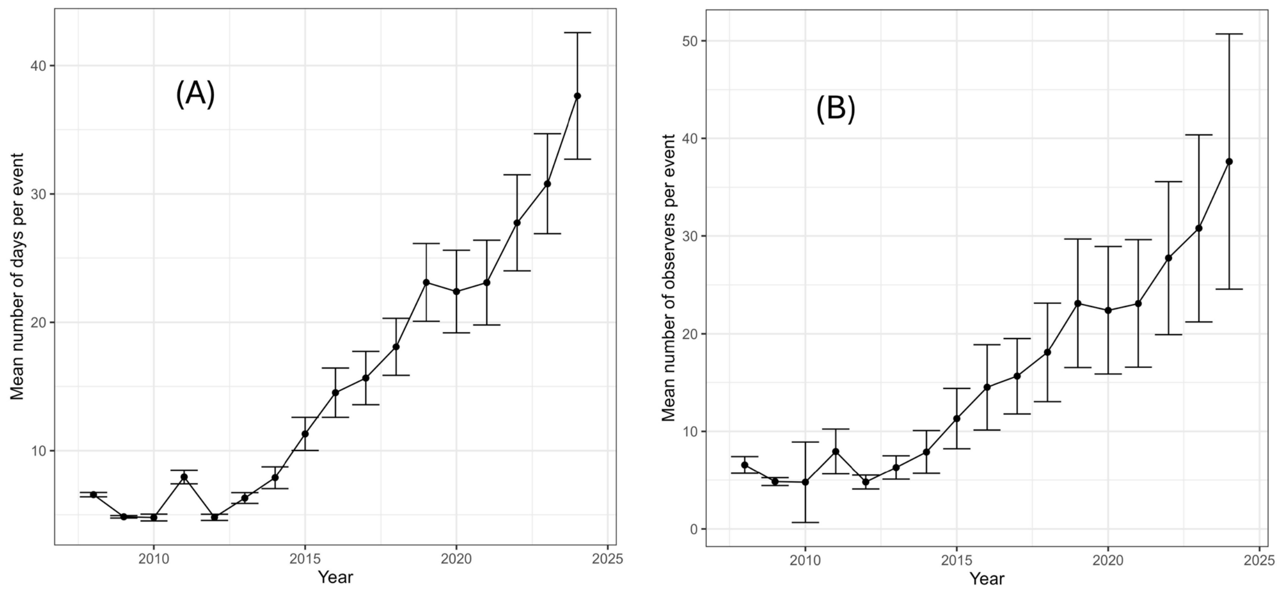

Figure 1. Two measures of effort as a function of time. Data for the butterflies of Mexico, from iNaturalist. Panel (A) is the average number of days of observations in in a year, over two-degrees of resolution hexagons with data. Panel (B) is the average number of distinct observers (with two or more observations) reporting, in a year, over two-degrees of resolution hexagons with data. Bars are one standard error.

"catch" (Isaac et al. 2014). The conventional practice then is to report catch/effort (Gulland 1969). Regrettably, a portal like iNaturalist does not provide a standardized measure of effort, and this is a crucial problem when using it to estimate trends: effort is not standardized, it may change in time and in quality, thus it is a challenge to separate trends in effort from trends in response variable.

In many CS databases, proxies for effort can be defined in just a few ways. The number of different observers is a possibility. This number can be weighted by average number of reports of observers, which in the case of iNaturalist is known to have a very non-normal distribution, since most observers report a single observation over periods of several years (August et al. 2020; Di Cecco et al. 2021)

The number of units of time (hours, days) in a region, in a larger period (years, for instance) is another possibility. iNaturalist reports the date and hour of every observation, but since it is extremely uncommon to have several observations performed at separate times of the same day, then hour is basically useless to calculate effort. In iNaturalist, however, it is possible to calculate how many unique combinations of month and day occur in a year, and to get the average number of different month-days of observations in a year. This would be a measure of effort (Soberon 2025).

Yet another theoretical possibility is using the number of individuals recorded as a measure of effort. This has indeed been recommended (Willott 2001). However, using this unit of effort when the response variable is records of iNaturalist would mean dividing a quantity (recorded observations) by the same quantity, which is useless.

Equally, for certain statistical techniques it is sensible to use as a measure of effort the number of registered species (Szabo et al. 2010). This has the reverse problem of the situation just discussed: if number of species is the response variable, then one would be dividing equals by equals.

Related to the above is the fact that iNaturalist is a non-probability (Boyd et al. 2023) source of data (the sampling scheme is not established *a priori* and sampling may be biased). Very little bias may have substantial effects in the measured variable (Meng 2018; Boyd et al. 2023).

The problem of bias and lack of standardization complicates seriously the modelling and interpretation of data (Kelling et al. 2009; Welti et al. 2021). Professionally designed monitoring schemes standardize the methods, the time used, and the areas sampled (Sutherland 2006). This means that the reported metrics are comparable in time or space. For instance, in a study about Arctiid moths in a site in Barro Colorado, Panama (Lamarre et al. 2022), the same months, type and number of light traps, days of effort, and number of observers were used. The study reports both species with negative and positive trends in the number of moths. Since methods do not change, the trends are highly likely to be due to factors intrinsic to changes in population numbers. Contrast this with a typical iNaturalist set of observations (Di Cecco et al. 2021). Here the number of observers changes in time and space (see figure 1). Methods are not reported (images are often uploaded, however, and experts may confirm the identification of the observation, as far as can be done using field photographs), but total time spent in the field, actively looking for specimens is not reported. The experience and skill of the observer is not reported either.

While unstructured citizen science data may be adequate for documenting species presences and distributions (Di Cecco et al. 2021), their use for detecting temporal trends is far more challenging. Rather than addressing the statistical correction of such biases, this study focuses on understanding the theoretical behavior of abundance- and richness-based metrics derived from iNaturalist under increasing sampling effort, illustrated using butterfly data from Mexico

The objective of this work is not to discuss the statistical problems of using CS, which has an extensive literature (Bird et al. 2014; Desquilbet et al. 2021; Welti et al. 2021; Johnston et al. 2023). The aim is to understand how metrics of (i) abundance (that we argue can be obtained from iNaturalist), or (ii) number of species, per unit effort, behave, based on a theoretical understanding of these metrics, and to illustrate the results with data from Mexico.

Multiple sightings

In iNaturalist one gets data about sightings, not true number of different individuals, as is the case in fisheries data, where an individual reported is a physical specimen. A crucial question then is whether iNaturalist allows to distinguish sightings for individuals. In some situations, this may be the case. Let N be the actual population size of a given species, which is unknown. Let k be the number observers, which can be obtained from iNaturalist data. Let m be the number of sightings in iNaturalist. This is an observed quantity. Finally, let H be the number of different individuals actually sighted. Clearly $m \geq H$. The problem is to assess how good the quantity m, (reported in iNaturalist), is as an estimate of H.

We have observers reporting sightings of individuals of a given species (or taxon). Assuming that sightings are independent and equiprobable this means that, although if k is large, then m is also likely to be large, it is irrelevant whether the m sightings were made by one, two or k observers. The question is how many individuals, out of N, have been seen?

Our problem is to find an estimate of H. If m is large, a low H means a lot of repeated sightings. An H close to m means few repeated reports of the same individual. Let us assume that each individual of the $i = 1,2,\ldots N$ has been seen exactly x_i times. This means that we propose a sequence $x_1, \ldots x_N$ from which we would like to calculate the expectation of the random variable H, $E[H]$. We shall use an indicator variable $I(x_i)$ with a value of 1 if $I(x_i \geq 1)$ and *0* otherwise. Therefore, the number of individuals sighted at least once is: $H = \sum_{i=1}^{N} \mathrm{I}(x_i \geq 1)$, and clearly it is also true that:

$$H = N - \sum_{i=1}^{N} \mathrm{I}(x_i = 0) \tag{1}$$

In words, the number of individuals sighted (even repeatedly) is the total number of individuals in the population minus those that were never sighted. We need the expected value of H.

$$E[H] = E[N - \sum_{i=1}^{N} \mathrm{I}(x_i = 0)]$$
$$= N - \sum_{i=1}^{N} E[\mathrm{I}(x_i = 0)]] = N - \sum_{i=1}^{N} p(x_i = 0) \tag{2}$$

Since we assume that the probability of not being seen is the same for all individuals (equiprobability assumption above), 1.9 reduces to

$$E[H] = N - \sum_{i=1}^{N} p(x_i = 0) = N - Np(x_h = 0)$$
$$= N - Np(x_h = 0) = N[1 - p(x_h = 0)] \tag{3}$$

where $p(x_h=0)$ is the probability of not being seen, equal for everyone. And further assuming an individual is sighted with probability $1/N$ then the probability of NOT being sighted, out of m trials has a binomial distribution and then $p(x_h = 0) = (1 - 1/N)^m$. This means that

$$E[H] = N[1 - (1 - 1/N)^m] = N - \frac{(N-1)^m}{N^{m-1}}.$$

For large N, expanding the numerator using a binomial, to first order, we get $E[H] \approx m$, and to second order:

$$E[H] \approx N - \frac{N^m - mN^{m-1} + m(m-1)N^{m-2}/2}{N^{m-1}}$$
$$= m(1 - \frac{m-1}{2N}) \tag{4}$$

If the number of individuals in the population (N) is much larger than the number of records reported in iNaturalist (m) then the expected value of the number of individuals actually sighted (H) is roughly equal to the reported value in iNaturalist. This is a very important result since it justifies using iNaturalist reported records as an estimate of *distinct* individuals actually sighted, rather than repeated sightings of few individuals.

Notice, that from (3) and the first order approximation, the quantity m, the observed records in iNaturalist, is proportional to N, the proportionality constant being the probability of sight. The proportionality constant probably changes with N (since it is 1-the probability of not being observed, which probably changes with population size).

Expected slope of the trend

If the response variable is the number of records of a given species in every unique combination of year and hexagon (the range of time and space composed this way is called an "event"), then we expect the response to be a proportion of the total abundance (Gulland 1969). As shown above, if the number of sightings recorded in iNaturalist (denoted by "m") is known (or assumed) to be much smaller than the population size, and the probabilities of not being sighted are similar, then the number of records in iNaturalist is approximately equal to the number of distinct individuals sighted. Therefore, it is possible to write, as in classic literature (Gulland 1969):

$$m(t) = q * f(t) * N(t)\,, \tag{5}$$

where $m(t)$ is the response (the number of records in the database) q is a constant of "catchability," with units of catch/effort, $f(t)$ is the effort, and $N(t)$ is the population size.

If, instead, the response variable is the reported number of species per event, it is more appropriate to use a non-linear model, like the Michaelis-Menten equation, that has been used to fit curves of number of species as a function of effort (Clench 1979):

$$s(t) = \frac{a * f(t)}{1 + b * f(t)} \tag{6}$$

In equation (6) s(t) is the response defined as number of species, that, for a given event, can be obtained from iNaturalist data; $f(t)$ is a measure of effort, a is a parameter with units species/effort that measures the rate at which units of catch are recorded when the inventory starts, and b is a parameter related to the asymptote. If the asymptote is denoted by A, then $A=a/b$ and therefore $b=a/A$. It is this asymptote what we assume may present a biological trend, thus it is dentoed as $A(t)$. Substituting:

$$s(t) = \frac{a * f(t)}{1 + a * f(t) / A(t)} \tag{7}$$

The effort is symbolized as dependent of time because in most CS databases this is the case. In the case of iNaturalist in Mexico, all measures of effort we use increase with time (figure 1), and the metric of effort used is the number of different days reported in a given event as in panel (A) of Figure 1. In view of the above, it is interesting to ask what the theoretical trend of an index of response/effort would be, considering that both the effort and the biological signal may change in time.

In both the abundance, and the number of species cases, one would be interested in the derivative with respect to time, which for equation (5) is (assuming detectability is constant):

$$\frac{dm(t) / f(t)}{dt} = q * \frac{dN(t)}{dt}\,, \tag{8}$$

and for equation (7) is:

$$\frac{ds(t) / f(t)}{dt} = \frac{a^2 f(t) \dfrac{dA(t)}{dt} - A(t) \dfrac{df(t)}{dt}}{[A(t) + af(t)]} \tag{9}$$

The case of abundance (equation 8) is the simplest, since the sign of the trend of the index equals the sign of the trend in the biological signal. The situation when using iNaturalist data to estimate number of species is very different (equation 9). Since the slope of effort with time is positive (figure 1), for equation (9) there are four possibilities:

1. There is a negative trend in the total number of species, with time. Or in symbols $\frac{dA(t)}{dt} < 0$. This will create a negative trend in the response/effort curve, due to a combination of decrease in number of species and increase in effort (the denominator of the index).
2. There is no trend in the total number of species with time. In symbols $\frac{dA(t)}{dt} = 0$. In this case, there is still a negative trend in the response/effort curve, now due to the growth in the denominator of the index.
3. Assume that the asymptote is growing with time (more species in events, with time). Then $\frac{dA(t)}{dt} > 0$ and the sign of the derivative of the index depends on the details of the effort and asymptote curves.

The number of total species in the three families of butterflies, in the hexagons we use, is never more than a few dozen and effort is growing. Therefore, the argument above probably applies, and trends in number of species per unit effort would be a mixture of a biological and sampling trends. To illustrate the theoretical results above we now perform simulations and exemplify with data on some butterflies of Mexico.

Methods

Data sources and filtering

Data on three families of butterflies of Mexico was downloaded from the Global Biodiversity Information Facility (GBIF): Pieridae (GBIF.org 2025a), Papilionidae (GBIF.org 2025b) and Nymphalidae (GBIF.org 2025c). Museum specimens were ignored and only data from the source iNaturalist were kept.

The data were further reduced to keep only the family, the scientific name, the identity of the observer, the date (year, month, day) and the latitude and longitude of the observations. No attempt was made to verify the accuracy of the identifications to species, but the latitude and longitude were checked to remove those outside a 1:250,000 polygon of Mexico[1]. The total numbers of records left were: Nymphalidae (20,793 records retained), Pieridae (33,306 records), and Papilionidae (7504 records).

Spatial and temporal aggregation

Using the R package 'terra' (Hijmans et al. 2022), the identity of two degrees of resolution hexagons from a grid covering the map of Mexico (Soberon 2025) was obtained for each observation. Thus, the database was augmented with a column of the hexagon ID of each observation. In this way, for every observation tagged as "iNaturalist research" for those three butterfly families, it was possible to obtain (i) how many records of sightings of a species, in a year, in a hexagon, were reported. Based on the theoretical arguments developed above, this quantity was treated as a proxy for the number of distinct individuals sighted.

Measure of effort

As effort, it was counted how many observers (with at least two observations per year) were reported, per hexagon. It has been proposed to use as a proxy of effort the size of the list of species in an event (Szabo et al. 2010). In this work that is not used because the total number of species per two-degrees hexagon, for the families of butterflies used, is in the order of a few dozen at the most, and thus a strong non-linear effect was expected (see equation 1.2). The indices species, or records/effort was then analyzed using the non-parametric correlation of index with time in the R package 'Kendall' (McLeod 2005).

Simulations

The simulations use the R package 'mobsim' (May et al. 2018). Artificial communities with constant number of species (50, and 500), and (1) constant number of individuals (20,000), and (2) decreasing number of individuals (20,000-500*t, t =1, 2, …19) were created, and an increasing number of samples (5,10,15, … 95) was used to model an increasing number of observers. The data for Mexico show the number of observers with more than two observations growing from about 10 to a mean number of about 150. Our simulation runs the number of "observers" from 5 to 95, well inside the range of one empirical dataset.

A script in the R platform was used to extract records and days in an event. For each one of the simulations, and the butterfly families mentioned above, Kendall's non-parametric correlation tau was obtained, using (number of records)/effort as variable. Calculations were performed using the package 'Kendall' in the R environment (McLeod 2005). Kendall's package assume that the variable of interest is ordered consecutively in time, and thus tau becomes an index of non-parametric correlation with time. This method has been used to assess trends in time series (Mann 1945). We do not report 'significance' because of the problems with the concept (McShane et al. 2019).

Results

One result of this work is that, as explained in the conceptual framework section, under the assumption of population density and constant and equiprobable detection, the value of records reported in iNaturalist is a good approximation to the number of individuals sighted. That records in iNaturalist may approximate the number of individuals sighted is a result we do not think is widely appreciated.

A second result is that attempting to use iNaturalist data to obtain trends on number of species per unit of effort is bound to yield artifactual negative trends. This comes from both a mathematical argument and a simulation. Finally, using iNaturalist data in Mexico, for three butterfly families, aggregated by year and by 2 degrees hexagons, yield most species with an abundance/effort with positive or no trend. Figure 2 indicates that between 5% and 18% of species have a negative trend of reports in iNaturalist (corrected for effort). Significance is not reported (McShane et al. 2019). The trend in number of species per unit of effort was negative for the three butterfly families we assessed (Figure 3).

The simulations yielded results consistent with the above: The species/effort Kendall non-parametric correlation was negative, with very low probability (under a null hypothesis of no trend), even when the number of species was constant. However, the tau correlation index of records/effort was indistinguishable from zero when the number of individuals was constant, and negative, with very low probability, for diminishing number of individuals. See Tables 1 and 2. The simulation thus confirms the

[1] http://www.conabio.gob.mx/informacion/gis/?vns=gis_root/dipol/limite/contdv250kgw.

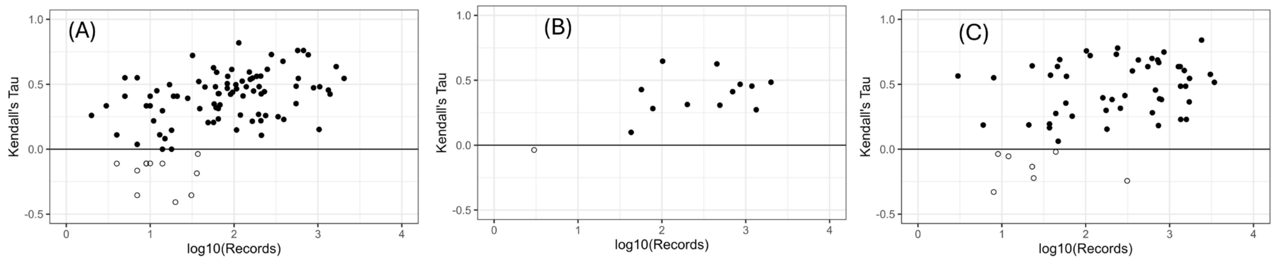

Figure 2. Kendall's value of records/effort with time correlation value (Tau), plotted against the decimal logarithm of number of records. Open circles are positive tau values, closed circles are negative values. Panels are: (A) Nymphalidae (27 out of 187 species with a negative Tau). (B) Papilionidae (1 out of 17 species with a negative Tau). (C) Pieridae (14 out of 77 species with a negative Tau). The dotted line in black indicates zero correlation. Some species have values that make estimating Tau nonsensical (for instance, same records/effort value every year): these were omitted.

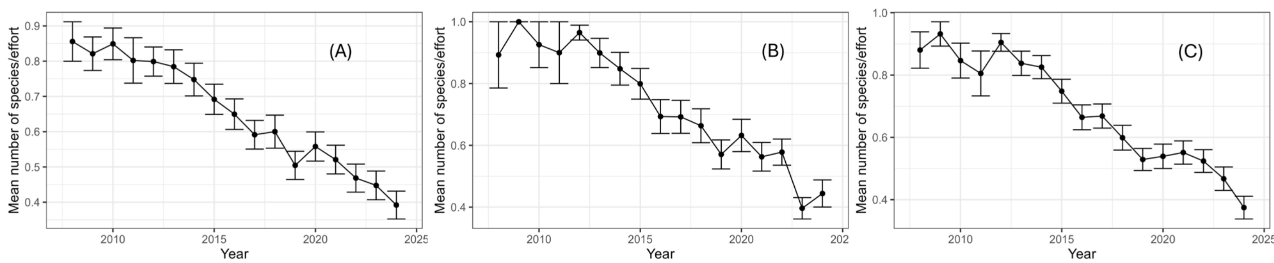

Figure 3. For every year, mean number of species per unit effort (mean taken over 2 degrees hexagons with data) for (A) Nymphalidae (186 species in total); (B) Papilionidae (16 species in total); and (C) Pieridae (77 species in total).

mathematical result that an index of number of species per unit effort is bound to have a negative slope with time, even in the absence of a trend in the biological reality. This is exemplified in tables 1 and 2.

Discussion

There are two main results of this work. The first is that records in iNaturalist approximate the number of different individuals sampled. The second is that, although the data allows counting number of different species in an event, a trend of number of species/effort, is expected to be negative whenever the amount of effort is increasing as it is the case in Mexico, for butterflies. This second result is confirmed by numerical simulation of a virtual community of constant number of species, and constant and decreasing number of individuals.

Finally, the results are illustrated with data for butterflies of Mexico, that show that a trend in the metric of number of sightings per unit effort is rarely negative. However, for the same families, the trend of number of species/effort is always negative.

We showed that as long as two assumptions are met, sightings in iNaturalist may be a good proxy for number of individuals. The first assumption is that the population size is large with respect to records in the database. This assumption is clearly false for some species, like for instance large mammals in small areas. It is probably true for species of small insects, that tend to have large populations (Eggleton 2020). In the results presented in this paper the assumption is simply taken as true, for populations of butterflies in the events in Mexico.

The second assumption is that the probability of not being observed is the same for every individual. There is a very large literature on "probability of detection" in the mark-recapture field (Ramsey and Harrison 2004). For the studied species features like sex, size and individual behavior affect the probability of being sighted (Watkins et al. 2010). Specifically in those few species of butterflies that have been studied (Pellet 2008) probability of detection is variable among species. In birds, detection among individuals of the same species may vary (Alldredge et al. 2006), this variability affects estimates of population size, and correcting the problem is expensive. In the absence of other data, in this work it is assumed that detectability is constant, for each year and group of sites. Although we take the assumptions as valid, checking them empirically should be a priority.

Given that heterogeneous probability of detection is a major problem in monitoring population abundance (Royle and Nichols 2003) some people report presence and absence instead of abundance (Royle and Nichols 2003; Walker and Taylor 2017; Outhwaite 2019). However, such

Table 1. Kendall's non-parametric correlation tau, and probability under a null hypothesis of no trend, for two simulated communities of constant number of individuals and two constant number of species. In both cases the obtained tau value has a large probability under a null hypothesis of no trend.

Species = 50, Individuals= 20,000			Species = 500, Individuals = 20,000		
	tau	p		tau	p
Records	-0.275	0.11	Records	-0.17	0.33
Species	-1	2.7×10^{-9}	Species	-0.94	2.2×10^{-8}

Table 2. Kendall's non-parametric correlation tau, and probability under a null hypothesis of no trend, for two simulated communities of decreasing number of individuals, and two constant number of species. In both cases the obtained tau value for the number of records is negative, with a very low probability under a null a hypothesis of no trend.

Species = 50, Individuals = 20,000-500*t			Species = 500, Individuals = 20,000-500*t		
	tau	p		tau	p
Records	-0.798	2.3×10^{-6}	Records	-0.86	3.3×10^{-7}
Species	-1	2.7×10^{-9}	Species	-0.96	9.6×10^{-9}

approach is, paradoxically, still data-demanding since it requires information of true-absences (non-detection due to absence). In eBird data the assumption that non-report is equivalent to an absence is sometimes made (Walker and Taylor 2017; Horns et al. 2018). This assumption is probably false for iNaturalist in a country like Mexico, which is large and heterogeneous (Sarukhán et al. 1996), and where the density of iNaturalist observations is low ($0.02/km^2$, for the three families of butterflies in this report). However, accepting as valid the two assumptions of large population size and similar probabilities of no detection justifies the argument that the trend in the index of records/effort has the same sign as the trend in population abundance. Although this is a major advantage, we would like to stress that the assumptions must be tested with real data, something we did not do

The trends for number of species per unit of effort are all negative, but our argument using the well-established fact that species observed is a non-linear function of effort, makes the interpretation of a negative trend difficult, since a negative slope is expected due to the asymptotic value of number of species, and the growing amount of effort. For the three families of butterflies we report, number of species per unit of effort has a negative trend. Whether this is an artifact of iNaturalist or a true trend remains to be determined.

Conclusions

CS data can be used appropriately to document phenology and distributions (Batalden et al. 2014; Tye et al. 2017) . Whether it can also be used to document trends is more doubtful (Kamp et al. 2016). In this work, a mathematical argument, confirmed by simulations and illustrated using the iNaturalist database for Mexico, indicate problems that suggest great care must be used when using iNaturalist to assess trends.

The major problem we see is that documenting trends in abundance of individuals in a single species (or group of species), and number of different species, using iNaturalist, are not equivalent problems. If the objective of a study is to document trends in number of species, the analysis presented here would suggest that indices will be a combination of a trend in the amount of effort and its quality, and the biological signal (Johnston et al. 2023). Disentangling these presents a statistical challenge that we have not seen discussed in the literature.

Interest, by the general public, in initiatives like iNaturalist is growing rapidly. In view of this, there is a strong incentive in using iNaturalist for assessment of trends. We find that documenting trends may have problems, most notably in trends in the number of species. However, one thing is the value of CS to monitor biodiversity, and another its value to raise public awareness. CS initiatives have a huge value to engage the public in conservation and scientific activities. Providing training for iNaturalist users, and encouraging the use of standard protocols, as done in Canada, the United States, and many European countries (Streiter et al., 2024) would maintain engagement and raise the value of CS data for monitoring. This approach might be useful only for conspicuous, easily identifiable species, yet the main point would be to influence public environmental awareness (Dickinson et al. 2012). There are alternatives to obtain data on biodiversity. Technological approaches could be used. Monitoring using advanced technologies include computer vision, bioacoustics, and metagenomics (Zamora-Gutierrez et al. 2020; Van Klink et al. 2022) is possible. Adoption of high technology methods, however, would require funding, training, and substantial analytical capacity.

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