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RESEARCH ARTICLE

Citizen science platforms can effectively support early detection of invasive alien species according to species traits

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Abstract

1. Early detection and rapid response are essential to deal effectively with new introductions of invasive alien species (IAS). Citizen science platforms for opportunistic recording of species are increasingly popular, and there is potential to harvest their data for early detection of IAS, but this has not been tested.
2. We evaluated the potential of data from existing citizen science platforms for early detection of IAS by obtaining 687 first records of species from 30 European countries where there was both an official first record (i.e. published in scientific literature or by a government agency) and a record in a citizen science platform. We tested how the difference between the two (time lag) was related to species traits, popularity in citizen science platforms, public and research attention and regulatory status.
3. We found that for 50% of the time lag records, citizen science platforms reported IAS earlier than or in the same year as the official databases. Although we cannot determine causality (the first official record could have been from a citizen science platform, or contemporaneous with it), this demonstrates that citizen science platforms are effective for IAS early detection.
4. Time lags were largely affected by species traits. Compared with official records, vertebrates were more likely to have earlier records on citizen science platforms,

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For affiliations refer to page 289.

than plants or invertebrates. Greater popularity of the IAS in citizen science platforms and its observation in neighbouring countries resulted in earlier citizen science reporting. In contrast, inclusion in the EU priority list resulted in earlier official recording, reflecting the efficacy of targeted surveillance programmes. However, time lags were not affected by the overall activity of citizen platforms per country.

5. *Synthesis and applications*. Multi-species citizen science platforms for reporting nature sightings are a valuable source of information on early detection of IAS even though they are not specifically designed for this purpose. We recommend that IAS surveillance programmes should be better connected with citizen science platforms, including greater acknowledgement of the role of citizen scientists and better data flow from smaller citizen science initiatives into global databases, to support efficient early detection.

KEYWORDS
biosecurity, citizen science, early detection, early warning, non-native species traits, participation, surveillance

1 | INTRODUCTION

Biological invasions are among the leading causes of global environmental change, affecting human well-being (Shackleton et al., 2019), causing biodiversity declines and disruption of ecosystem services (Bellard et al., 2022; Vilà et al., 2010), and economic losses (Diagne et al., 2021). Globally, we are witnessing an exponential increase in invasive alien species (IAS) records (Mormul et al., 2022), with no saturation in species establishment (Seebens et al., 2018). When dealing with IAS, it is necessary to be proactive and ensure an early detection and rapid response (de Groot et al., 2022, 2023; Groom et al., 2019). This implies detecting new IAS introductions rapidly and deploying adequate control measures to mitigate their further spread (Reaser et al., 2020). However, founder populations typically occur at low density and are difficult to detect (Fitzpatrick et al., 2009), and the areas at risk are often vast and difficult to monitor efficiently (Groom et al., 2019).

Documenting the official first introductions of IAS in a country or region is extremely relevant to early detection and rapid response. First, keeping such a registry provides insight into propagule pressure and, if data are pooled across species, colonisation pressure in an area (Roy et al., 2014). Second, first records can reveal pathways of introduction relevant from a biosecurity perspective. Third, the first occurrence of an introduced species outside captivity or cultivation can be used to track temporal patterns of biological invasions (Seebens et al., 2018) and to feed policy indicators on the state of invasions by following introduction rates (Vicente et al., 2022). Lastly, documenting these first records is a legal requirement for some regulated species (e.g. List of Invasive Alien species of Union concern of EU Regulation 1143/2014 reported through EASIN-Notsys) and the notification requirements ensure neighbouring countries or regions are informed on interceptions and new occurrences. Doing this via officially established notification mechanisms allows decision-makers to target resources for further surveillance or management. Traditionally, these official first records (i.e. in written reports or publications by government or researchers) have come from professionals (researchers, conservationists/practitioners and government officials) who made the observations or validated the records. However, citizen science (Heigl et al., 2019) has recently emerged as a potentially effective early warning system for the detection of new IAS introductions (Adriaens et al., 2015; Hulbert et al., 2023; Pocock et al., 2024; Roy et al., 2018) and for tracking of their subsequent spread and impact (de Groot et al., 2022; Johnson et al., 2020; Marchante et al., 2017).

Overall, citizen science, as the 'engagement of non-professionals in scientific investigations' (Miller-Rushing et al., 2012), is on the rise in environmental sciences and biodiversity research (Dickinson et al., 2010; Pocock et al., 2017), becoming especially pronounced over the last 15 years for biological invasions (Price-Jones et al., 2022). This has been facilitated by the onset of novel technologies in biodiversity research (August et al., 2015; Johnson et al., 2020; Starr et al., 2014), including the use of mobile apps and social media (Adriaens et al., 2015; Howard et al., 2022; Schade et al., 2019). Citizen science might promote faster and more efficient flow of data on IAS introductions and spread, as volunteer observers can act as millions of eyes on the ground (Pocock et al., 2024). This public involvement allows detection of new IAS while their populations are still localised and small (Pawson et al., 2020), or when present within large, sparsely populated areas (e.g. forest ecosystems; de Groot et al., 2023; Hulbert et al., 2023). Citizen scientists can record in private or remote areas that are otherwise rarely visited by professionals (Delaney et al., 2008; Dubaić et al., 2022; Palmer et al., 2017). Besides, current surveillance schemes (e.g. for insect pests using pheromone traps) mostly target specific species at high-risk locations such as at ports or airports, whereas citizen science enables surveillance at larger spatial extents and in the wider environment—for example in disease vector mapping for mosquitos (Palmer et al., 2017) or tree health monitoring (de Groot et al., 2023; Hulbert et al., 2023). Consequently, citizen science has the potential to generate a wealth of data on the introduction of IAS across large spatial and temporal scales, which would otherwise be unfeasible and cost-prohibitive for administrations, professionals and scientists (Crall et al., 2010; Pocock et al., 2024; Starr et al., 2014; Sullivan et al., 2009). Furthermore, citizen science approaches in IAS surveillance also provide the potential for awareness raising and learning (Brandt et al., 2022; Roy et al., 2015).

Individual citizen science projects have been usually set up to focus on one or a few IAS (e.g. Price-Jones et al., 2022), which are useful for collating data and targeting management action for certain territories and species. Nevertheless, these projects are limited in time and highly dependent on specific funding. In contrast, there are highly popular citizen science platforms used for opportunistically recording observations of species (e.g. eBird, iNaturalist, iRecord, Observation.org) supported by a range of apps and mobile tools, including automated image and sound identification (August et al., 2015; Wood et al., 2022). Typically, these platforms do not focus on IAS, but—because of their wide audience and public participation—many records of IAS are likely to be made through these platforms, including the first IAS records new to a territory. These citizen science platforms provide a potentially untapped resource for IAS records, but their effectiveness as a tool for early detection has not been assessed. Therefore, the aim of this study was to test the effectiveness of citizen science platforms in supporting early detection of (invasive) alien species. Specifically, we analysed the 'observer lag'—the time lag between the publication of official first records and the first observations of IAS reported on citizen science platforms. We then tested whether differences in time lags are related to species traits, countries or citizen recording activity. We expected that citizen science reporting would be earlier for certain taxonomic groups and types of habitats, due to either their size and charismatic nature of species (e.g. birds; Davis et al., 2019) or greater accessibility of areas to observers (Tiago et al., 2017). We also hypothesised that IAS that were more attractive to the citizen science community or those previously reported in neighbouring countries would be reported earlier by citizens. In contrast, we predicted that official reporting would be earlier (either due to investment in professional monitoring or faster official confirmation of citizen science records) for those IAS for which countries are obliged to conduct official surveillance (i.e. species included in regulated and other priority lists), as such species are usually targeted by tailor-made monitoring programmes (Morisette et al., 2020). Finally, we expected that countries with a stronger citizen science community, i.e. a longer history of citizen science reporting such as the United Kingdom (Pocock et al., 2015), would show a stronger tendency towards earlier citizen science reporting of new alien species introductions than those without such a legacy. Understanding the value of citizen science platforms for early detection of IAS and its context dependency will help to guide their use in informing decision-making on the IAS surveillance systems, the trade-off between professionally framed, active surveillance programmes and passive, risk-oriented surveillance using citizen science or the integration of both.

2 | MATERIALS AND METHODS

2.1 | Data collection

2.1.1 | Official first records

We collated a database on official first records of alien species per country, i.e. published in national peer-reviewed and grey literature for each target country, and official databases (e.g. Global Register of Introduced and Invasive Species; GRIIS, Pagad et al., 2022). First, we extracted first records from the most recent version of the Alien Species First Record Database (https://doi.org/10.5281/zenodo.3690748; Seebens et al., 2018; retrieved on July 2021) for all European countries (excluding Russia) recorded from 2010 up to 2021 inclusive (Figure 1). We used 2010 as the cut-off because multi-species citizen science platforms became popular at that time (Price-Jones et al., 2022). This resulted in 1020 records (species-country combination) for 40 European countries. In some instances, the dates of official record referred to the date of publication rather than the date of the record (e.g. same year of publication and record). In these cases, we obtained the date of the actual first record or removed the record. A group of 28 researchers from 13 countries affiliated with the European Union COST Action 'Alien CSI' network reviewed the dataset for their country and taxonomic group of interest (Table S1) and added further data on the first records that were missing from the initial database. The largest update corresponded to Belgium, where we used the first record per species in GRIIS Belgium (Desmet et al., 2021). We did not include records from citizen science platforms in this phase (although in some cases the official first record may have originally come from those sources). Our final official first records database contained a total of 1981 records of IAS-country combination for 40 countries in Europe and 1607 species (Figure 1).

2.1.2 | Observations from citizen science platforms

We used the Global Biodiversity Information Facility (GBIF) to select citizen science platforms for use in further analysis. Only datasets stating in their methodology that a major part of their observations were collected by volunteer naturalists and largely without a formal sampling design were selected. We selected 22 citizen science datasets of geolocated occurrences (see Data Sources). Selected citizen science platforms were diverse in terms of targeted taxa (e.g. eBird and Pl@ntNet for birds and plants vs. iNaturalist, naturgucker and waarnemingen.be for all taxa) or geographic area (e.g. ArtPortalen and Biodiversidad Virtual for country-level vs.

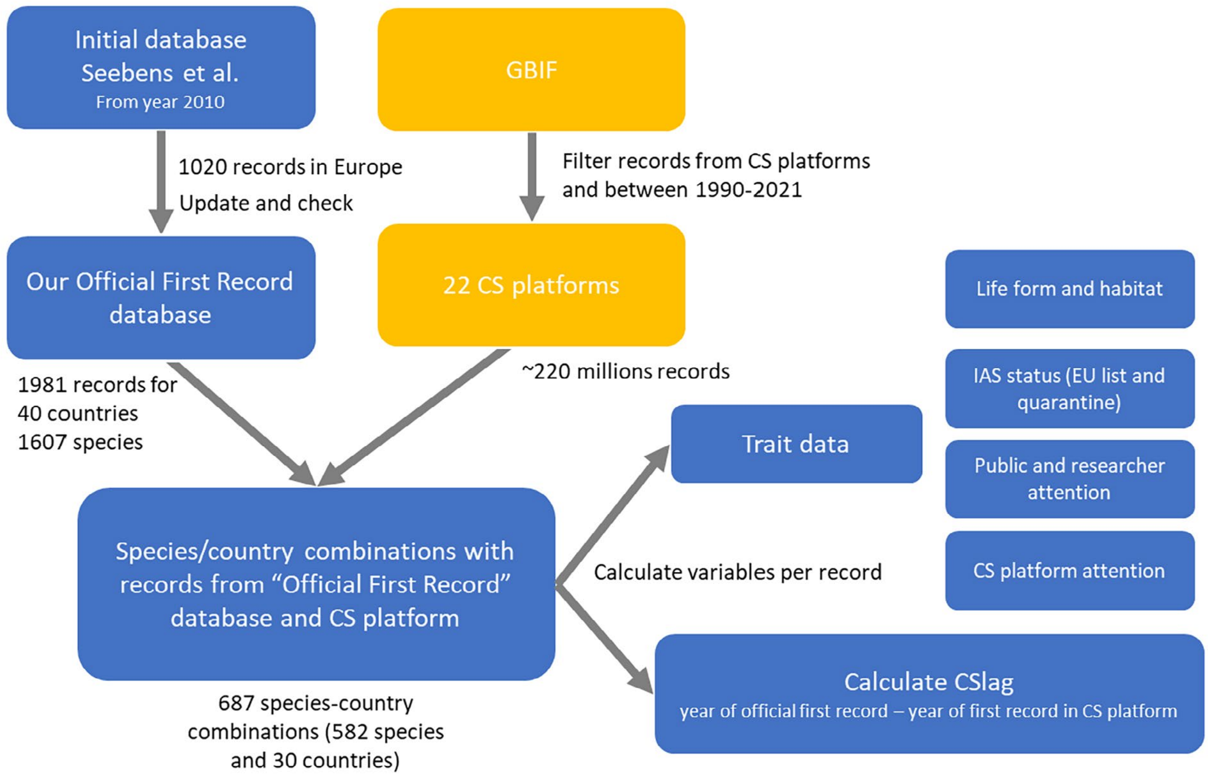

FIGURE 1 Workflow of the methodology summarising the process to obtain time lags between first official reporting and citizen science (CS) platforms reporting per species and country in Europe (excluding Russia).

Waarnemingen.be for region-level platforms). We automatically accessed these databases through standardised queries to GBIF records for (Table S3): (a) species in our official first record dataset, (b) records made between 1990 and August 2021 (to allow for substantial negative time lags: depending on the year of first official record, the maximum negative time lag varied from 20 to 31 years) and (c) restricted to Europe and a buffer of 100 km of marine areas around them. We obtained about 220 million occurrences from all the citizen science datasets. Whenever possible, we kept only verified records from the platform (Table S2; Adriaens et al., 2021). Then, for each official first record in our study area, we extracted the year of the earliest citizen science record among the occurrences of the species in the country. We found records in citizen science platforms for 687 of the species × country combinations of the 2001 official first records (Figure 1) corresponding to 582 species and 30 European countries (Albania, Austria, Belgium, Bosnia and Herzegovina, Bulgaria, Croatia, Czech Republic, Denmark, Estonia, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Netherlands, Norway, Poland, Portugal, Romania, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland, Ukraine and United Kingdom).

2.1.3 | Species traits

We characterised 21 relevant taxonomical, ecological and distribution traits for all the species in the 687 records of the species × country combination (Table 1). Taxonomic traits included species, phylum and class (https://www.itis.gov/). Ecological traits included the assignment of species to broad life forms ['Algae', 'Vascular plants', 'Bacteria and protozoans', 'Bryozoa', 'Fungi', 'Molluscs', 'Invertebrates (excl. Arthropods and Molluscs)', 'Crustaceans', 'Arthropods p.p. (Myriapods, Diplopods etc.)', 'Insects', 'Fishes', 'Amphibians', 'Reptiles', 'Birds', 'Mammals'] as well as to habitat types ('terrestrial', 'freshwater', 'marine' or 'saline') according to EASIN (2022). We aggregated life forms to balance the number of records within categories: 'plants and algae', 'vertebrates', 'invertebrates' and 'fungi & bacteria' ('lifeformB' in Table 1). Specifically, the latter class included one species of bacteria (*Xylella fastidiosa*) and seven fungi species.

In addition, we characterised three traits about alien status based on EASIN (2022). First, we categorised species as alien to Europe (683 records) or cryptogenic (four records; i.e. of unknown origin sensu Carlton, 1996). Records with status 'questionable' in EASIN were checked in the literature and classified accordingly. Second, we also examined whether species were partly native to Europe (i.e. native to one European country but alien to other; 186 records), and third, whether the species in a particular country has also been recorded in neighbouring countries ('obsInNeigborCountryBefore' in Table 1, 337 records). In terms of legislation, we recorded whether species have been included, accepted or are under consideration in the List of Invasive Alien species of Union concern ('eu_status'; 21 records), in the EU list of quarantine species ('quarantine'; 13 records), and within the World's or EU's worst invasive alien species (DAISIE, 2008; Luque et al., 2014) ('worst'; 13 records) (Table 1).

TABLE 1 Traits of species used in the study.

Traits	Level	Abbreviation	Categories	Source(s)
Ecological trait				
Life form A	Species	LifeFormA	Text: Algae, Vascular plants, Bacteria and protozoans, Bryozoa, Fungi, Molluscs, Invertebrates (excl. Arthropods and Molluscs), Crustaceans, Arthropods p.p. (Myriapods, Diplopods, etc.), Insects, Fishes, Amphibians, Reptiles, Birds, Mammals	EASIN (2022) with expert review
Life form B	Species	**LifeFormB**	Text: 'plants and algae', 'vertebrates', 'invertebrates' and 'fungi and bacteria'	EASIN (2022) with expert review
Region	Species × country	**Region**	Text: Country name	N/A
Phylum	Species	Phylum	Text: Corresponding taxonomic level	ITIS (2022), GBIF (2022)
Class	Species	Class	Text: Corresponding taxonomic level	ITIS (2022), GBIF (2022)
Habitat	Species	**Habitat**	Text: Terrestrial, Freshwater, Marine and Oligohaline	EASIN (2022); Miscellaneous; Froese and Pauly (2022); Experts' opinion
Status	Species	Status	Text: Alien or Cryptogenic in Europe	EASIN (2022); Experts' opinion
Partly native	Species × country	partly_native	Text: Yes or No	EASIN (2022); Experts' opinion
Observed by citizen science in neighbouring country earlier than the official record	Species × country	**obsInNeigborCountryBefore**	Text: True or False	Miscellaneous; Country borders from: https://www.geodatasource.com/
Legislation and priority list status				
EU status	Species	**eu_status**	Text: Species included, accepted or under consideration for the IAS of Union Concern List	https://ec.europa.eu/environment/nature/invasivealien/list/index_en.htm
Within EU quarantine species legislation	Species × Europe	**Quarantine**	Text: Yes or No per 2000/29/EC	https://eur-lex.europa.eu/legal-content/EN/TXT/?qid=1571813928611&uri=CELEX:32000L0029; https://pierpestregister.mpi.govt.nz/PestsRegister/ImportCommodity/
Within the worst 100 IAS by ISSG or DAISIE	Species	**Worst**	Text: Yes or No	DAISIE (2009) and GISD (2022): http://www.iucngisd.org/gisd/100_worst.php
Species attention				
Mean of the Google trend per species in comparison to baseline species (*Gingko biloba*) for 2010–2020	Species × country	google_mean	Numerical: Google hits	N/A
Sum of the Google trend per species in comparison to baseline species (*Gingko biloba*) for 2010–2020	Species × country	google_sum	Numerical: Google hits	N/A

TABLE 1 (Continued)

Traits	Level	Abbreviation	Categories	Source(s)
Relative importance of Google trend from 2010 to 2020 in each country per species (0 to 100).	Species × country	google_country_porc	Numerical: 0–100	N/A
Simple multiplication of google_mean times google_country_porc	Species × country	**google_country**	Numerical	N/A
Number of records in Scopus database for the scientific name of the species	Species	**ResearchAtt**	Numerical	N/A
Number of citizen science occurrences in the country for all species of the LifeForm of the species	LifeForm × country	**NumRecCS_CountryLifeform**	Numerical	N/A
Number of all alien species official first records for the country in Seebens database	Country	**NumAliensOff_Country**	Numerical	Seebens et al. (2018)
Number of citizen science records for the species since 1990	Species	**NumRecCS_Species**	Numerical	N/A
Number of citizen science records for the species in the country since 1990	Species × country	**NumRecCS_SpCountry**	Numerical	N/A

Note: In bold final variables used in the final model to explain time lags between official first record and citizen science platform reporting for invasive alien species in Europe.

Finally, we also characterised nine traits describing the attention given to IAS species by the general public, researchers and users of citizen science platforms (Table 1). We extracted information on the general public attention using Google Trends statistics. This is a generic statistic widely used in online marketing that provides the relative importance of specific term searches in Google compared with other terms. For this study, we compared the Google trend of each species' scientific name (genus and epithet) with a widely known species name as a baseline search term, *Gingko biloba*. We chose this species because it had a relatively high number of hits across all countries and because of its ease of identification. Specifically, we catalogued the mean and sum of the Google trend per species globally and by country in comparison to the baseline term for 2010–2020 (respectively 'google_mean', 'google_sum', 'google_country'; Table 1). We estimated all these metrics using gtrendsR (Massicotte & Eddelbuettel, 2022). We quantified research attention ('ResearchAtt') using the number of records in the Scopus database for the scientific name of each species using 'rscopus' (Muschelli, 2019). We estimated species attention in citizen science platforms using three variables: number of records per species and country ('NumRecCS_SpCountry'), number of records per lifeform and country ('NumRecCS_CountryLifeform') and number of records per species in all citizen science databases since 1990 ('NumRecCS_Species') (Table 1). Finally, as a proxy of the concern paid to alien species by official surveillance, we calculated the number of alien species official first records for each country in Seebens et al. (2018) ('NumAliensOff_Country'; Table 1).

2.2 | Data analysis

For each record, we calculated the time lag per species and country as the year of the first occurrence in citizen science platforms minus the year of the first occurrence in official records for that country (hereafter 'citizen science lag'). Thus, negative time lag values indicate that first reports in citizen science platforms are earlier than the official first record, while positive values indicate that first reports in citizen science platforms are later than the official first report. We then analysed the relation between the time lag and species traits in linear mixed models using country as a random factor in a multimodel inference approach (Burnham & Anderson, 2002). Prior to modelling, multicollinearity among continuous predictors using Pearson correlations while tested categorical predictors association using Cramer's V. From all continuous variables, only the Google trend at global and country level were highly correlated ($r > 0.7$), so we kept only the variable at country level. Based on their low pairwise correlation values ($r < 0.5$; Figure S1), we retained all other variables for further analyses (Dormann et al., 2013). We centred (deviation from the mean) and scaled (divided by standard deviation) continuous predictors to facilitate the interpretation of model coefficients and model convergence (Schielzeth, 2010).

We performed multimodel inference, based on the all-subsets selection of predictors, using the corrected Akaike's information criterion (AICc) and keeping the same random effects in all model combinations (country name). We calculated Akaike weights (w_i) for each combination of predictors. Considering the best models given the selected predictors (ΔAICc <4), the relative importance $w_{+(j)}$ of each predictor j was estimated as the sum of the AICc weights across all models in which the selected predictor appeared. Predictors with higher $w_{+(j)}$ (i.e. closer to 1) have a higher weight of evidence to explain the response variable. Finally, we calculated the weighted average regression coefficient within the subset of best models (ΔAICc <4), based on Akaike weight per model (w_i), for the models in which each variable appeared (i.e. conditional averaged). We tested for significant differences in the mean time lag among levels for the categorical variables in the best candidate model (i.e. with the smallest AICc) using a Tukey post hoc test with Bonferroni correction. To test the robustness of the model results and the independence of the data biases, we implemented the same model approach with different subsets of the data considering potential spatial bias: (i) the whole dataset, (ii) excluding Belgium data because it had such a high number of records, (iii) temporal bias in first official records (including year of official reporting as covariate in the model), (iv) a truncated regression model considering that time lags higher than 10 year are not possible due to choosing the year 2010 as cut-off of official records and (v) excluding records of partly native European species to focus only on aliens to Europe. These analyses were carried out with the packages MuMin (Bartoń, 2023), multcomp (Hothorn et al., 2023), lme4 (Bates et al., 2023) and truncreg (Croissant & Zeileis, 2018) in R version 4.1.3.

3 | RESULTS

We collated the 1981 official first records of species × country combinations for 40 countries in Europe corresponding to 1607 species from 2010 to 2021 (Figure 1). Considering all these 1607 species and 40 European countries, we found 9450 records in citizen science platforms. However, from the specific 1981 species × country combinations, we only found 35% had records in citizen science platforms, and we used these for further analysis (687 records). This process resulted in a change of lifeform proportions (Figures S6 and S7) with a higher prevalence of plants, insects and birds. In this dataset, we found that citizen science lags showed a mean close to zero (1.13 years), with 50% of the records showing positive values (the first record in a citizen science platform was after the first official record), 18% with negative values (the first record in a citizen science platform was before the first official record) and the remaining 31% having a lag value of zero (the first record in a citizen science platform is in the same year as the first official record; Figure 2). However, this was a skewed distribution, with a wider tail towards earlier citizen science reporting (Figure 2). The median number of species per country in our analysis was 8, with Belgium particularly contributing to the dataset with 338 records and just one record for Poland, Bosnia and Herzegovina and Latvia (Figure S2). The distribution of citizen science lags was affected by

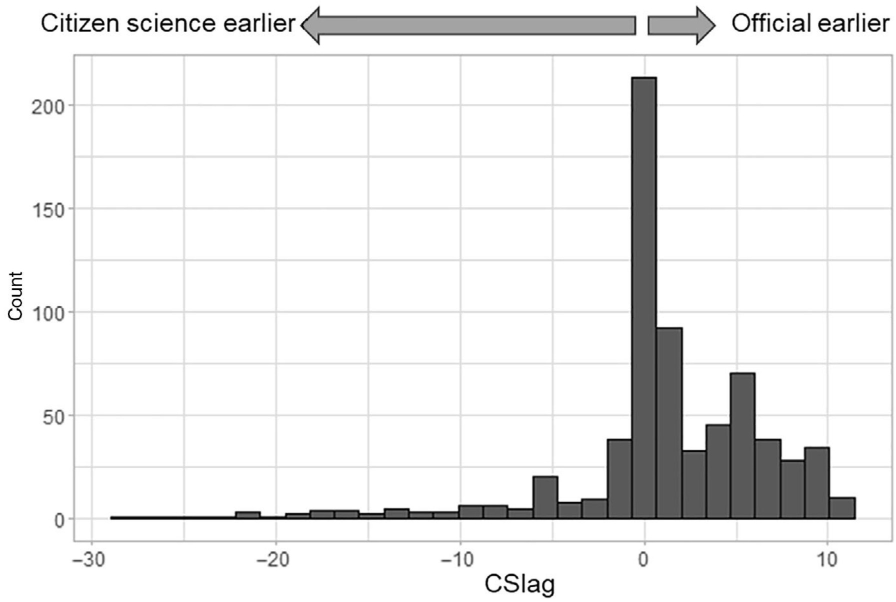

FIGURE 2 Citizen science time lag (CSlag: year of citizen science reporting minus year of official reporting). Positive values indicate that the year of the official first record predates the first record in a citizen science platform; negative values indicate that the first record in a citizen science platform predates the official first record; zero indicates the first record in a citizen science platform occurred the same year as the official first record.

TABLE 2 Averaged coefficients and importance of the species traits used to explain time lags (year of citizen science reporting minus year of official reporting) for the entire dataset ($n = 687$) in a linear mixed model.

	Estimate	Std. error	Adjusted SE	*z*-value	Pr(>|z|)	Weight
(Intercept)	2.56	1.42	1.42	1.80	0.072	
eu_status	4.85	1.26	1.26	3.85	<0.001	1
LifeForm	See Figure 3					1
NumRecCS_SpCountry	−0.77	0.19	0.19	3.98	<0.001	1
NumRecCS_Species	−1.26	0.23	0.23	5.47	<0.001	1
obsInNeigborCountryBefore	−3.10	0.38	0.38	8.05	<0.001	1
Habitat	See Figure 3					0.93
NumAliensOff_Country	−2.27	1.23	1.23	1.85	0.065	0.88
Worst	1.28	1.38	1.38	0.92	0.356	0.65
Quarantine	0.43	1.43	1.43	0.30	0.762	0.57
Scopus	−0.10	0.19	0.19	0.54	0.592	0.16
NumRecCS_CountryLifeform	−0.18	0.23	0.23	0.79	0.431	0.21
google_country	0.04	0.19	0.19	0.24	0.813	0.14

Note: See variable descriptions in Table 1. Comparison across lifeform and habitat types were included in the model but presented in Figure 3. Significant relations are given in bold ($p < 0.05$).

the year of cut-off of the first official record (Figures S4 and S5). Considering more recent data (i.e. official records after 2010), citizen science platform reporting was even earlier (Figure S5).

We explored several species and country factors that could contribute towards increasing time lags in citizen science reporting. Faster citizen science platform reporting was related to higher numbers of records in citizen science platforms per species, both globally and per country, and to being observed in neighbouring countries (Table 2). However, there was no effect with research or public attention per species (i.e. Scopus and Google hits) or the overall citizen science activity per country and lifeform (Table 2). There was a significant positive relationship with citizen science lags when species are included or considered for the List of IAS of Union concern (promoting faster official reporting), but not if they were listed as quarantine species (Table 2) or on the global list of worst IAS.

There were significant differences in citizen science lags between life forms, with vertebrates showing earlier citizen science platform reporting, than invertebrates, plants and algae (Figure 3 and Table S5). In contrast, we did not find significant differences across habitat types (Figure 3). There were also clear differences in

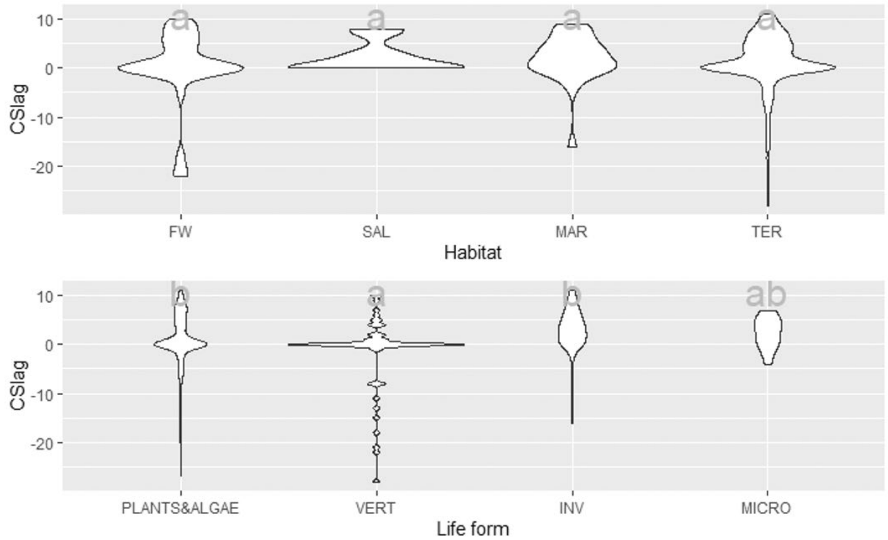

FIGURE 3 Differences in citizen science time lags (CSlag: year of citizen science reporting minus year of official reporting) across habitat (FW-freshwater, SAL-saline, MAR-marine and TER-terrestrial) and life form (Plants & algae, VERT-vertebrates, INV-invertebrates, Fungi and bacteria) groups. Letters above indicate groups significantly different in a post hoc test for a full linear mixed model (see Table S5 for test results).

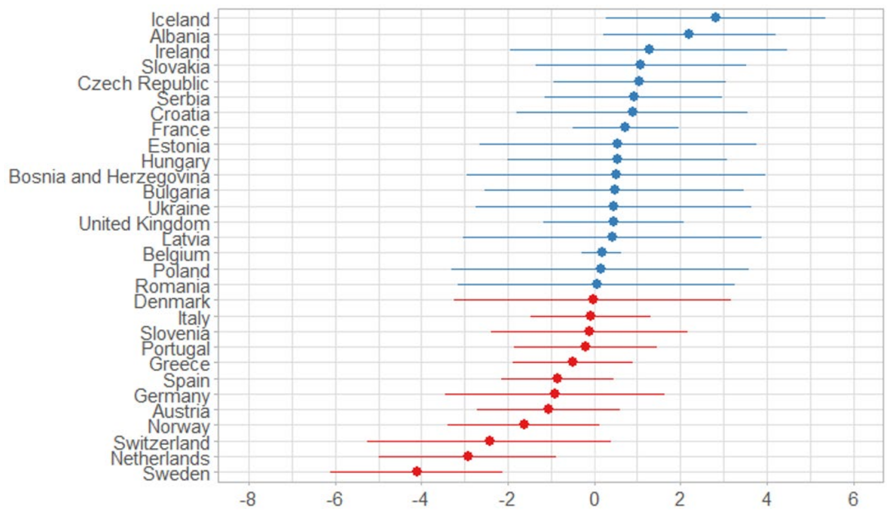

FIGURE 4 Differences in citizen science time lags (year of citizen science reporting minus year of official reporting) across countries implemented as a random effect in a full linear mixed model accounting for other traits and country-based variables (see Table 2). The error bars indicate 95% confidence intervals. Blue indicates positive lags (official first record on average precede records in citizen science platforms), and red indicates negative lags (records in citizen science platforms precede official first records).

citizen science lags across countries (Figure 4): Iceland, Albania and France showed a significant trend towards earlier official reporting while Sweden and Netherlands showed a trend towards earlier citizen platforms reporting. All these patterns were consistent when including year of first official reporting as a covariate (Tables S6 and S7), when excluding records from Belgium (Tables S8 and S9) or from any species partly native to Europe (Tables S10 and S11) from the model, and when considering a truncated regression model (Tables S12 and S13). The only slight difference was noted with the data excluding Belgian records where only the variables lifeform and 'observed in neighbouring country' showed significant relations.

4 | DISCUSSION

It is widely stated within studies on biological invasions that citizen science is a highly effective tool in the detection of new introductions (de Groot et al., 2022, 2023; Pocock et al., 2024; Roy et al., 2018; Thomas et al., 2017). However, its effectiveness compared with official reporting has not been quantified. This study is the first to evaluate the time lag between the first official records of IAS and the first records on publicly available citizen science platforms. Overall, we found that the time lag between official and citizen science platform was in most cases close to zero (see possible reasons for this effect below), confirming the potential for citizen science platforms to be a valuable tool for early warning of introductions of IAS. However, the distribution of time lags revealed a wide range of values that varied across countries and was modulated by different species traits such as life form, citizen science attention and the inclusion on regulated lists.

4.1 | The distribution of time lags

Our results show that where we have data on both alien species official first records and records in citizen science platforms, for a large proportion of cases (31%), there is no lag between the time of the first official and citizen science platform reporting (Figure 2). There are several reasons why citizen science platforms could have the same first year as the official first record. Firstly, a record on a citizen science platform could have been validated and became the first official record itself (Kousteni et al., 2022). This, for instance, could be the result of scientists screening citizen science platforms for occurrences of new species, or scientists/officials being equally active on citizen science platforms, as observers or as validating experts, and using them as their preferred or additional reporting tool. Secondly, a validated record which became the official first record, from any source, could have raised the profile of the IAS and prompted observers to look for it and hence report it on citizen science platforms in that year. Thirdly, it could have been that the species was simultaneously and independently reported through citizen science platforms and other means, for example the widespread arrival of a conspicuous species. Unfortunately, due to the lack of detail in accounts of many official first records and the complexity of citizen science data flows (i.e. a species may have been reported via a citizen science platform, but then re-reported via a bespoke IAS project), it is not possible to distinguish these possibilities. Nonetheless, this shows the potential of CS platforms as a tool for efficient early detection.

For the cases where there was a time lag between citizen science and official reporting, the official record of IAS introduction was usually earlier than its occurrence in citizen science databases (73% of the cases where the time lag was different to zero). This is to be expected because new and rare species might not be known by volunteers participating in citizen science platforms, while researchers and managers might be already familiar with potential IAS not yet introduced due to international regulations and collaboration. Finally, a skewness in the distribution of time lags can also be observed towards citizen science platforms recording earlier than officially. The reason behind this pattern might be explained by a methodological limitation. Using the year 2010 as the beginning of the period used for official records could result in a longer tail towards the negative time lags, as we set the lower threshold for citizen science database records in 1990. Before this time, citizen science platforms were not as well-known, and there was not enough data flow between these databases and the professional scientists (Price-Jones et al., 2022). Additionally, while nowadays the recording takes place in real time, via mobile apps, any data collected prior to the rise of the citizen science platforms had to be transferred from notebooks, leading to the loss of a significant portion of data, as it was either missed during this process or never transferred in the first place. We hypothesise that this skewness pattern might remain in the future (i.e. more negative lags as seen in Figures S4 and S5), as there might be differences in the publication speed of IAS records between official and citizen science platforms in aggregated databases such as GBIF. In fact, several of the most popular citizen science platforms (iNaturalist, observation.org, waarnemingen.be, eBird) are well connected to open repositories such as GBIF. Therefore, there is the possibility that citizen science records of IAS are revealed more rapidly than official records, which are more prone to be reported in closed database systems only accessible to a more limited number of professionals. This trend might be exacerbated in the near future because citizen science projects can still improve the speed and quality of data openness (Groom et al., 2019; Price-Jones et al., 2022). On the contrary, with increasing data flow between citizen science platforms and officials (due to technical ease of access of data, and officials' increased familiarity with and trust in these data), we could also hypothesise that even more time lags would be zero. In this case, any remaining negative time lags would therefore be the cases where the record in a citizen science platform is a sighting of an 'accidental' or 'vagrant' which does not meet the criteria for an 'official first record'.

4.2 | Factors affecting time lags

Across different lifeforms, vertebrates showed more negative time lags than invertebrates, plants and algae, indicating that citizen science platforms were generally faster than official reporting for these taxa (Figure 3). This finding corresponds well with the taxonomic bias in citizen science platforms towards charismatic and large species (Boakes et al., 2016; Davis et al., 2019), particularly for birds, which correspond to a large proportion of the vertebrates in our dataset (66%). We expected a bias towards earlier citizen reporting on terrestrial species as their habitats are more easily accessible and appealing for volunteers than marine or freshwater environments (Tiago et al., 2017). However, we did not find any significant differences across habitat types. Indeed, we found a large variation of citizen science lags within each habitat type, which might refer to variability within habitat types (e.g. different accessibility between beach and open water in marine environment) and possibly the confounding effect of other habitat characteristics not considered in this study, such as disturbance and closeness to human infrastructures (Geldmann et al., 2016).

Several factors related to citizen science attention were associated with earlier citizen science reporting than official (Table 2). Species receiving more attention on citizen science platforms per species (i.e. increased number of records), both nationally and globally, were reported significantly earlier in citizen science platforms than officially. In contrast, we did not find any relation with the total number of citizen science records per country and lifeform. Thus, it seems that earlier citizen science reporting was related to species traits rather than to the overall use of citizen science platforms per country. Similarly, looking at differences across countries we did not find a consistent pattern of countries with higher history on citizen science platforms (e.g. UK and Belgium) being biased towards faster citizen science reporting. We also found a significant trend towards earlier citizen science reporting when the species was also observed in a neighbouring country. We suggest that this is likely to be due to the knowledge spread (e.g. social media or communication among naturalists). Furthermore, citizen science platforms are a global source of information on IAS distribution so naturalists could be well aware of species naturally occurring in neighbouring regions.

The only factor that promoted faster official reporting relative to reporting on citizen science platforms was the inclusion of the species in the List of IAS of Union concern. This legislative regime brings obligations to EU Member States to set up official surveillance programmes which would then favour the rapid translation of reports (from whatever source) to official first records (EU Regulation 1143/2014 reporting through the Notsys system). Furthermore, some of the listed species have a restricted distribution range (e.g. occur only in a few Member States or do not occur at all in the European Union), so targeted official surveillance can be more effective than citizens. Also, the List of IAS of Union concern includes at least a few taxonomic groups that are not very accessible to the average citizen scientist, such as crayfish (difficult for most people to detect) and ants (difficult for most people to identify or photograph). In these cases, official surveillance could prove rather effective, using targeted surveillance (e.g. trapping, environmental DNA for amphibians, crayfish and invasive macrophytes; Ogata et al., 2022) and being most active at either specific points of entry of IAS or their potential recipient ecosystems (Morisette et al., 2020). By adopting this approach, officials might intercept these alien species before they become widespread and thus more likely observable by volunteers. Despite this, the publication of the List of IAS of Union concern coincided with a boom in citizen science projects focused on the listed species (Price-Jones et al., 2022), but probably mostly related to species already established and spreading in each country rather than as programmes for early detection.

Other priority lists such as those provided by plant protection or conservation organisations did not show any significant association. For most of these species, expertise or equipment (e.g. microscopes; Pataki et al., 2021) may be required for identification, especially for organisms relevant for plant health surveillance (pests and diseases, fungi and microorganisms, insects). These species are not easily detected by citizen scientists, as they can be very inconspicuous, often requiring advanced methods (e.g. eDNA, pheromone trapping) for detection, or the access to specialised literature for their identification. Therefore, they are less likely to be recorded on citizen science platforms and so less likely to be included in our dataset. Nevertheless, despite these limitations, there are good examples of citizen science used in monitoring pests affecting tree health (de Groot et al., 2023). We also expected earlier official reporting with well-studied species, as researchers and official bodies might be more familiar with those. However, research attention, quantified as the number of records in the Scopus database per species, did not show any significant association with faster official reporting. One plausible explanation is that researchers are probably more interested in new and rare first species citations as they might be more prone to be published in specialist journals than first citations of well-studied invasives.

4.3 | Biases and limitations

This is the first analysis of its kind, and although we have carefully checked all of the data and revised the relevant information it brings, there are bound to be some limitations. First, there was the limitation that the role of citizen science, including citizen science platforms, is often 'hidden' in official first reports, so we were unable to evaluate the actual impact of citizen science on official first reports. The hidden value of citizen science has been reported in other contexts (Cooper et al., 2014), and so we recommend that official first reports provide greater clarity about the source of the record.

Positive time lags (when an official record is earlier than the citizen science one) could have been caused by limitations in our methodology, where the appropriate citizen science platform was not included in our dataset. This could be the case with some specialist or regional citizen science projects, which we have not considered here, if their data is not being uploaded to the databases we have used. Also, some countries have dedicated social media pages (e.g. Facebook and Twitter) for the exchange of information and new data on invasive alien species (e.g. Cyprus; Periklis K., pers. comm.), thus not making this data available for an analysis without scraping these records from social media, and some communities of potential recorders use social media rather than CS platforms for their reporting (Lennox et al., 2022). Moreover, although as much as 50% of the species occurrences stored in GBIF have been collected by citizen scientists (Waller, 2019), many citizen science projects have not yet opened up their data through this global initiative (Johnson et al., 2020; Price-Jones et al., 2022).

There are also many possible reasons why there would be a negative time lag (when a record from a citizen science platform predates the official first record). On the one hand, it is possible that the citizen science platform was not checked and referred to when publishing the first official record, as some professionals might not be aware of citizen science platforms previously, resulting in a poor data flow to professionals. It could also be the case that the citizen science platform was ignored as a source of official first record, due to concerns over its reliability of identification, or data quality (Aceves-Bueno et al., 2017). It is also possible that the record from a citizen science platform was assessed by professionals but found to be unacceptable to be published in official records, as it cites an observation of an organism in confinement (e.g. cultivated or captive). Furthermore, the spatial bias in citizen science recording, which is often performed in biodiverse natural areas of interest, or areas that are more accessible or closer to naturalist observers' residence

(Geldmann et al., 2016), could cause typical points of entry of IAS to be overlooked (e.g. roads and peri-urban parks), potentially making citizen science a more valuable tool to detect entry into the wild than first introduction into a territory. Finally, here we only considered the value of citizen science platforms for official first records within a country, but we also recognise the huge value that citizen science has in contributing knowledge across the invasion process, and especially for detecting local spread within a country (Price-Jones et al., 2022).

4.4 | Conclusions and recommendations

Our results further demonstrate the value of citizen science for early detection of invasive species because; in most cases, the time lag between first reporting in official sources and citizen science platforms was short. This finding indicates the value of citizen science platforms for early detection, and the possible synergies between citizen science platforms and official first reporting, in terms of flow of data from citizen science platforms, and the value of official first reports in profile raising. Nevertheless, we also found cases with significant time lags both towards earlier records on CS platforms and earlier official first reporting. In the first case, it seems that the species identity and traits are responsible for earlier citizen science reporting, rather than the overall use of citizen science platforms per country. In contrast, earlier official reporting was associated with regulatory aspects such as the inclusion of the species in the EU priority lists. These findings suggest that we still could strengthen the connection between these two sources of information, and we propose three recommendations:

First, we recommend the improvement of connections between citizen science platforms and legal authorities or researchers working on IAS management (de Groot et al., 2023; Larson et al., 2020). This could be achieved by installing mechanisms to assess the validity of the data in invasive species research and management decisions (Delaney et al., 2008), for instance using data quality metrics and trust metrics to efficiently provide a measure of the reliability of citizen science data (Hunter et al., 2013). Furthermore, this linkage could be enhanced by funding dedicated personnel at the administration level to stimulate IAS recording or by developing specific data agreements between citizen science platforms (including those that do not currently share data with GBIF), authorities and research organisations.

Second, we advocate for greater acknowledgement of citizen science sources in official first records. For instance, to avoid the issue of "hidden" citizen science, when publishing the official first records, we encourage that, where appropriate, acknowledgement is given to citizen scientists. Also, we encourage smaller citizen science initiatives to ensure that their data flow into global databases (e.g. GBIF) to enhance the usefulness and reach of their records (Johnson et al., 2020). Moreover, there should be strong adherence to the FAIR principles of open science (findability, accessibility, interoperability and reusability), ensuring that data collected through citizen science initiatives are published at the source, well described with standardised metadata, open and available to all (Anđelković et al., 2022; Price-Jones et al., 2022).

Third, we encourage the reporting of IAS on citizen science platforms, by for instance providing targeted information (identification, potential points of entry and impacts) to citizen science platform users on priority species for early detection (cf. waarnemingen.be/exoten portal provides 'alert lists' for biodiversity) or using information technology (e.g. push notifications) to stimulate IAS recording in relevant places and move beyond purely opportunistic sampling (Callaghan et al., 2019; Pocock et al., 2024). Importantly, citizen science projects should provide feedback to people submitting records about the impact of their reports of IAS, because this can sustain engagement and to further raise awareness.

AUTHOR CONTRIBUTIONS

Maarten de Groot, Michael Pocock, Pablo González-Moreno, Ana A. Anđelković, Tim Adriaens, Christophe Botella and Jakovos Demetriou conceived the ideas and designed the methodology; Ana A. Anđelković coordinated the data collection process; Pablo González-Moreno and Christophe Botella led the analysis of data with input from Maarten de Groot, Michael Pocock, Ana A. Anđelković, Tim Adriaens and Jakovos Demetriou; Pablo González-Moreno and Ana A. Anđelković led the writing; All authors contributed with data, contributed to the drafts of the manuscript and gave final approval for publication.

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CONFLICT OF INTEREST STATEMENT

Helen Roy and Joana Vicente are Associate Editors for *People and Nature*, but were not involved in the peer review and decision-making process. No other conflicts of interest have been identified by any of the authors.

DATA AVAILABILITY STATEMENT

Code and data are available from the GitHub Digital Repository https://github.com/ChrisBotella/CS_alien_detection_time_lag.

DATA SOURCES

List of all DOIs of CS occurrence extractions from GBIF: https://doi.org/10.15468/dl.8j2sdd observation.org 2000-2021 Part 1; https://doi.org/10.15468/dl.nwtb6a observation.org 2000-2021 Part 2; https://doi.org/10.15468/dl.ehkqzn observation.org 2000-2021 Part 3; https://doi.org/10.15468/dl.m5xxj3 observation.org 2000-2021 Part 4; https://doi.org/10.15468/dl.ypyet7 observation.org 2000-2021 Part 5; https://doi.org/10.15468/dl.7wb3qb observation.org 1990-2009; https://doi.org/10.15468/dl.85mdhc Pl@ntNet Automatic; https://doi.org/10.15468/dl.258f2r eBird; https://doi.org/10.15468/dl.292haj SeaSearch; https://doi.org/10.15468/dl.afd658 Other datasets; https://doi.org/10.15468/dl.ehx7z4 (iNat, UKBMS); https://doi.org/10.15468/dl.u8tb27 naturgucker; https://doi.org/10.15468/dl.vdt739 DOF; https://doi.org/10.15468/dl.ztp43h Norwegian Species Observation Service; https://doi.org/10.15468/dl.fyy2xr ArtPortalen 1; https://doi.org/10.15468/dl.kdu6dh ArtPortalen 2; https://doi.org/10.15468/dl.zja32m ArtPortalen 3; https://doi.org/10.15468/dl.gxv24s (New Zealand); https://doi.org/10.15468/dl.ssuu3t (Austrian Mycological Soc).

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

Table S1. List of experts that contributed to the review of the official record database.

Table S2. List of selected citizen science platforms with published dataset in GBIF.

Table S3. Top 20 records with more negative time lag, that is, where the record on a CS platform precedes the official first record.

Table S4. Top 20 records with more positive time lags, i.e. where the official first record precedes the first record on a CS platform.

Table S5. Post-hoc test comparison across habitat (FW-freshwater, SAL-saline, MAR-marine and TER-terrestrial) and life form (Plants&algae, VERT-vertebrates, INV-invertebrates, Fungi & Bacteria) of the linear mixed model explaining time lags (year of citizen science reporting minus year of official reporting) for all the dataset ($n=687$) by different species traits.

Table S6. Averaged coefficients and importance of the species traits used to explain time lags (year of citizen science reporting minus year of official reporting) for all the dataset ($n=687$) in a linear mixed model including year of official reporting as covariate.

Table S7. Post-hoc test comparison across habitat (FW-freshwater, SAL-saline, MAR-marine and TER-terrestrial) and life form (Plants&algae, VERT-vertebrates, INV-invertebrates, Fungi & Bacteria) of the model explaining time lags (year of citizen science reporting minus year of official reporting) for all the dataset ($n=687$) by different species traits and including year of official reporting as covariate.

Table S8. Averaged coefficients and importance of the species traits used to explain time lags (year of citizen science reporting minus year of official reporting) for the dataset excluding records for Belgium ($n=349$) in a linear mixed model.

Table S9. Post-hoc test comparison across habitat (FW-freshwater, SAL-saline, MAR-marine and TER-terrestrial) and life form (Plants&algae, VERT-vertebrates, INV-invertebrates, Fungi & Bacteria) of the model explaining time lags (year of citizen science reporting minus year of official reporting) for the dataset excluding records for Belgium ($n=349$) by different species traits.

Table S10. Averaged coefficients and importance of the species traits used to explain time lags (year of citizen science reporting minus year of official reporting) for the dataset excluding records partly native to Europe ($n=500$) in a linear mixed model.

Table S11. Post-hoc test comparison across habitat (FW-freshwater, SAL-saline, MAR-marine and TER-terrestrial) and life form (Plants&algae, VERT-vertebrates, INV-invertebrates, Fungi & Bacteria) of the linear mixed regression model explaining time lags (year of citizen science reporting minus year of official reporting) for the dataset excluding records partly native to Europe ($n=500$) by different species traits.

Table S12. Averaged coefficients and importance of the species traits used to explain time lags (year of citizen science reporting minus year of official reporting) for all the dataset ($n=687$) in a truncated regression model.

Table S13. Post-hoc test comparison across habitat (FW-freshwater, SAL-saline, MAR-marine and TER-terrestrial) and life form (Plants&algae, VERT-vertebrates, INV-invertebrates, Fungi & Bacteria) of the truncated regression model explaining time lags (year of citizen science reporting minus year of official reporting) for all the dataset ($n=687$) by different species traits.

Figure S1. Correlation matrix of continuous species traits used in the time lags analysis.

Figure S2. Number of first records per country considered in the study.

Figure S3. Number of first records per habitat (FW-freshwater, SAL-saline, MAR-marine and TER-terrestrial) and life form (Plants&algae, VERT-vertebrates, INV-invertebrates, Fungi & Bacteria).

Figure S4. Histogram of time lags organised by year of official first record, with the mean time lag shown by the vertical line (positive in red and negative in green) and the number inside the plot.

Figure S5. Histogram of time lags filtering the data by year of official first record. The mean time lag is shown by the vertical line (positive in red and negative in green) and the number inside the plot.

Figure S6. Records per life form type only with year of official reporting (top; 1294 records) and only with year of CS reporting (bottom, 9540).

Figure S7. Records per life form type with year of official reporting (top; 1981 records) and records with both official and CS reporting date (bottom, 687).

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