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RESEARCH ARTICLE

When do citizen scientists record biodiversity? Non-random temporal patterns of recording effort and associated factors

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Abstract

1. Citizen science data are increasingly used for ecological research, biodiversity conservation and monitoring. However, these data often present significant analytical challenges due to uneven recording efforts by citizen scientists. Biases caused by intra-annual differences in levels of recording activity can be particularly severe, hindering the use of citizen science data in research areas such as population dynamics and phenology. Therefore, understanding the temporal patterns and drivers of recording activity by citizen scientists is essential.
2. In this study, we provide a detailed assessment of how weather and calendar-related factors relate to levels of biodiversity recording activity by citizen scientists at a daily resolution. To perform this, we analyse the recording patterns for six tree species in the Iberian Peninsula, which maintain a consistent appearance throughout the year. Observation data were collected from iNaturalist, a leading platform for citizen science data. We used boosted regression trees (BRT) to compare observed recording activity patterns with those expected by chance. Our analysis included a comprehensive set of explanatory variables, such as the day of the week, the month, holidays, temperature, accumulated precipitation, wind intensity and snow depth.
3. The BRT models demonstrated good predictive performance, with the correlation between predicted and observed patterns of recording activity (left out of model training) ranging from 0.55 to 0.91, depending on the species. The day of the week, month of the year, and daily temperature consistently emerged as the most important predictors. Recording activity was higher on weekends, to some extent on Fridays and during the spring months. Extreme low and high temperatures were generally associated with lower recording activity, although there were exceptions. Precipitation and wind speed had relatively lower importance but remained relevant, with increased precipitation and wind intensity typically associated with reduced recording activity. In contrast, public holidays and accumulated snow demonstrated minimal to negligible importance.
4. Our findings show that citizen scientists record more frequently on weekends, during mild weather and in spring. By addressing these non-random patterns

in recording activity, we can maximise the utility of citizen-collected data for research and applied purposes.

KEYWORDS
biodiversity monitoring, citizen science, iNaturalist, recording activity, temporal bias

1 | INTRODUCTION

Currently, citizen science is an invaluable source of biodiversity data (Callaghan et al., 2021). These data, recorded mostly by non-experts and often empowered by specialised smartphone apps, are now among the most abundant available for several taxonomic groups (Groom et al., 2017; Kelling et al., 2019). Thus, citizen science data are crucial for supporting assessments of the current state of biodiversity (Chandler et al., 2017), monitoring the spread of invasive species (Gallo & Waitt, 2011; Johnson et al., 2020), and tracking the distribution and population trends of species (Dennis et al., 2017; Horns et al., 2018). Additionally, citizen science initiatives play a significant role in ecological research, conservation planning, and policymaking by providing large-scale, geographically diverse datasets that are otherwise difficult and expensive to obtain (Callaghan et al., 2019; Hochachka et al., 2012). Furthermore, the engagement of the public in scientific research fosters a greater awareness and understanding of environmental issues, promoting conservation efforts at a community level (Bonney et al., 2016; Chozas et al., 2023).

Citizen science has greatly advanced biodiversity data collection and environmental research, but it also presents significant limitations and analytical challenges. Key issues include spatial differences in recording effort, which influence the geographic distribution of observations, taxonomic gaps and biases, leading to uneven representation of species or groups, and non-random temporal patterns of recording, which affect the timing and seasonality of data collection (Bird et al., 2014; Tiago et al., 2017; Troudet et al., 2017).

Temporal recording patterns, in particular, can be shaped by factors, such as weather conditions, seasonal events and participants' personal motivations (Hobbs & White, 2012; Peter et al., 2021), all of which influence the quality, consistency and completeness of the data. While various analytical strategies have been proposed to address temporal variations in citizen science recording effort (Bird et al., 2014; Dennis et al., 2013; Gonsamo & D'Odorico, 2014; Kosmala et al., 2016; Weiser et al., 2020), significant challenges persist. These challenges are particularly severe when studying seasonal phenomena requiring high temporal resolution, such as population dynamics and phenological shifts (Callaghan et al., 2019; Primack et al., 2023). Therefore, thoroughly understanding the temporal patterns of citizen science recording and understanding their underlying factors is crucial for improving the comprehensive and accurate use of citizen science data. By accounting for the effects of these factors in data collection, the reliability and validity of conclusions drawn for temporally detailed assessments of ecological phenomena can be significantly enhanced (Mora et al., 2024; Tiago, Leal, et al., 2024).

Variations in the levels of biodiversity recording activity by citizen scientists throughout the year reflect the interplay of two components. The first component pertains to the seasonal dynamics of the actual ecological phenomena being recorded. Variations in the timing and magnitude of these phenomena, such as plant blooming, butterfly emergence in the imago stage, or bird and insect migration events, inherently determine the opportunities for citizens to record them (e.g., Monarch Larva Monitoring Project, 2024; Brenskelle et al., 2021). The second component involves factors external to the ecological phenomena determining citizen scientists' availability and willingness to participate, such as the day of the week, public holidays or the time of year (Courter et al., 2013; Di Cecco et al., 2021), as well as weather conditions. A common aim of researchers using citizen science data to study ecological dynamics is to 'remove' the influence of the later component on the temporal patterns of recording activity (e.g. Capinha et al., 2024). By doing so, the resulting ('unbiased') patterns more accurately represent the true dynamics of ecological phenomena. However, this is often challenging because the effects of both components are intertwined, hindering the interpretation of observed trends in the data.

Previous studies have assessed the role of external factors in driving the levels of activity of biodiversity recording by citizen scientists. The factors assessed are predominantly calendar-related, such as the identified weekend bias and the week-of-the-year bias (Courter et al., 2013; Di Cecco et al., 2021; Díaz-Calafat et al., 2024). Additionally, the impact of citizen-science-specific events, such as 'BioBlitzes' or the 'City Nature Challenge', has also been investigated (Di Cecco et al., 2021; Tiago, Evaristo, & Pinto, 2024). However, most of these assessments were based on the raw number of records contributed by citizen scientists (e.g., Di Cecco et al., 2021; Díaz-Calafat et al., 2024), overlooking how variations in the timing and magnitude of the ecological phenomena themselves influence recording patterns. Moreover, to date, there has been no comprehensive assessment of the role of weather-related factors, despite the well-known influence of weather on the willingness to engage in outdoor activities (Tucker & Gilliland, 2007). Weather-related factors are plausibly relevant drivers of biodiversity recording, potentially more so than calendar-based ones, and their effects may be complex. For instance, some meteorological variables might be expected to have a monotonic effect, such as a consistent decrease in outdoor activity with increasing precipitation. On the other hand, peaks of recording activity plausibly occur at moderate rather than extreme low or high temperatures. Ultimately, it is essential to understand the joint effects of calendar and weather-related factors on the levels of activity of citizen scientists. This understanding must be developed using approaches that are robust to the seasonal variations of ecological phenomena.

Here, we provide a detailed assessment of how calendar-related and weather factors are related to levels of biodiversity recording activity by citizen scientists. We focus on the recording patterns of a set of evergreen tree species that fulfil several key criteria: conspicuousness, ease of identification, and most importantly, consistent appearance throughout the year. Our core assumption is that due to minimal changes in their appearance, the temporal patterns of recording for these 'benchmark' taxa primarily reflect variations caused by external factors. Using observation records from the Iberian Peninsula, we employ a well-established machine learning approach to assess the predictive power and the nature of the correlative relationships for a comprehensive set of calendar- and weather-based predictors. These predictors include the day of the week, month, public holidays, temperature, accumulated precipitation, wind intensity, and snow depth. By assessing the relative importance of each predictor and the type of association with recording activity, we provide a robust evaluation of the external factors shaping biodiversity recording efforts by citizen scientists.

2 | METHODS

2.1 | Species occurrence data

The analysed species observation data were collected from the iNaturalist platform (www.inaturalist.org). iNaturalist is a nonprofit social network designed for naturalists, citizen scientists, and biologists, centred around the concept of mapping and sharing biodiversity observations globally. iNaturalist is accessible via its website and mobile applications. It features an automated species identification tool and fosters a collaborative approach where users collaborate in identifying organisms from photographs or sounds (www.inaturalist.org/pages/about).

From iNaturalist, we collected biodiversity observations from seven evergreen tree species. These were five pines: *Pinus halepensis* (Aleppo pine), *P. nigra* (Austrian pine), *P. pinaster* (maritime pine), *P. pinea* (stone pine) and *P. sylvestris* (Scots pine), and two oaks: *Quercus rotundifolia* and *Q. suber* (holm and cork oak, respectively). We selected these species because they are the pine species and evergreen oaks that are more widely distributed in the Iberian Peninsula and exhibit minimal variation in their appearance throughout the year. Our core assumption is that due to reduced seasonal changes in their appearance throughout the year, the temporal patterns in the recording of these taxa should largely reflect variations in recording activity itself (cf. Capinha et al., 2024). This should be particularly the case with pines, which maintain a similar appearance throughout the year. They grow new leaves as they shed old ones, and their (female) pine cones take longer than a year to mature (e.g. one and a half years for *P. nigra*, 2 years for *P. halepensis and P. pinaster*, and 3 years for *P. pinea*), resulting in cones of various ages and sizes throughout the year (Earle, 2018). For the two oak species, while they are also evergreen and maintain a constant appearance of their foliage and branches, during Autumn they produce acorns (Bonal & Muñoz, 2007; Pons & Pausas, 2012). The acorns may imply, to some extent, a slight increase in attractiveness for recording during this period. Interpretation of results for these taxa (below) takes this possibility into account.

The observation data collected from iNaturalist file included: geographical coordinates of the location of observation, date of observation, username of observer, species' scientific name, and quality grade. We filtered these data and kept only the records supplying geographical coordinates, full date (year, month, and day) and a research quality grade (i.e., species identification confirmed by at least two identifiers). To avoid years in which observation recording may have been affected by anomalous factors, the 2 years of lockdown due to the Covid-19 pandemic were excluded. In addition, the number of records made prior to 2017 was very reduced. Therefore, the observation data collected represented the periods from 2017 to 2019 and 2022 to 2023.

2.2 | Assembly of dependent and predictor data

To compile the data for each species for analysis, we began by retaining only a single record per combination of date and 0.1° × 0.1° (approx. 10 × 10 km) grid cell, corresponding to the spatial resolution of the predictor data (see below). This step aimed to avoid including multiple records from the same recording event, such as a single recorder submitting multiple records of the same specimen (i.e. 'duplicates'). A total of 3532 observation records were kept for *Q. suber*, 4744 for *Q. rotundifolia*, 938 for *Pinus sylvestris*, 1272 for *P. halepensis*, 2118 for *P. pinea*, and 1246 for *P. pinaster*. *P. nigra* was excluded from the analysis because there were few observations (128).

Next, for each species, we generated records with the same geographical coordinates and year of observation but with randomly generated day and month values. These records, referred to as 'temporal pseudo-absences' (Capinha et al., 2024), represent the temporal distribution expected if recording events were randomly distributed throughout the year. To ensure comprehensive representation of annual conditions, we generated 10 sets of pseudo-absences for each observation record. Observation records (coded as '1') were then combined with temporal pseudo-absences (coded as '0') into a single dataset. This resulted in a dataset for each species containing both the actual observation data and data representing random temporal distributions.

Each record in these data sets was then characterised by a comprehensive set of calendar and weather-related variables, chosen for their potential influence on individuals' willingness to go outside and observe and record biodiversity. The calendar variables included the day of the week, the month and whether the day was a public holiday. The first two variables were calculated directly in R (R Core Team, 2024) using base functions, while holidays were identified manually from the website Timeanddate (www.timeanddate.com). These calendar variables were selected based on earlier literature assessing the influence of the day of the week and the time of year on species recording (Courter et al., 2013; Di Cecco et al., 2021). Public holidays were considered, as they could provide additional free time, making it more likely for individuals to participate in biodiversity recording.

The weather variables included the mean temperature of the day (°C), total accumulated precipitation of the day (mm), mean wind speed on the day (m/s) and snow cover depth on the day (cm). These values were sourced from ERA5Ag at 0.1°×0.1° resolution (Boogaard et al., 2020). We selected these weather variables based on previous studies assessing factors that influence outdoor activities, with temperature and precipitation being the most commonly considered (Verbos et al., 2018). Wind and snow may also be relevant factors, impacting, for example, people's outings to natural parks, particularly in higher-altitude areas (Verbos & Brownlee, 2017).

2.3 | Data analysis

To identify predictors of temporal variation in recording effort, we used BRT (Elith et al., 2008; Hijmans et al., 2017). BRTs are ensembles of decision trees, where each tree is fitted iteratively to reduce the prediction errors of the ensemble. This algorithm effectively combines multiple weak learners (decision trees) to create a robust predictive model (Elith et al., 2008).

For each species, we built 10 BRT models, using the species' observation records (coded as 1) paired with a distinct, equal-sized subset of pseudo-absences (coded as 0) as the dependent variable, along with the predictor variables. The models were implemented in R using the 'gbm.step' function from the 'dismo' package (Hijmans et al., 2017). This function supports automated tuning of the optimal number of trees to include in the ensemble through internal cross-validation. Additional important hyperparameters to consider for tuning are tree complexity (tc) and learning rate (lr). Tree complexity indicates the maximum number of interactions in each tree, while the learning rate determines the contribution of each tree to the overall model. Hence, for each of the 10 replicate models of each species, we tested combinations of common values of learning rates (0.0001, 0.0005 and 0.001) and tree complexities (3 and 6).

To evaluate model performances, we randomly set aside 30% of the data for comparison with predictions. The level of agreement between left-out data and predictions was measured using the Boyce index (Hirzel et al., 2006). In the context of our work, this index quantifies the correlation between the probabilities of species recording predicted by the model and the frequency of species observation records across a range of probability intervals. A strong positive correlation indicates that the model assigns higher probabilities to conditions associated with a greater number of actual species records, demonstrating good predictive performance. Conversely, values near zero suggest that predictions are no better than those obtained randomly.

For our data, the Boyce index is preferable to discrimination-based metrics such as the area under the receiver operating characteristic curve (AUC). This is because discrimination-based metrics evaluate the model's ability to correctly predict both classes in the dependent variable. However, in our case, pseudo-absences are randomly generated over time, including periods favourable for biodiversity recording. Therefore, considering the model's ability to predict these records would incorrectly deflate its performance.

We calculated the Boyce Index using the 'ecospat.boyce' function from the *ecospat* package (Di Cola et al., 2017). The Pearson correlation coefficient was used as the Boyce Index measure, ranging from −1 to 1, with higher positive values indicating better model performance.

Using the set of parameters providing the highest mean performance across replicate models for each species, we obtained the relative importance of each variable. These importances are based on the number of times a variable is selected for splitting, weighted by the improvement to the model resulting from each split (Friedman & Meulman, 2003). This is a widely used method in ecology to assess the influence of predictor variables (e.g., Elith et al., 2008). Additionally, we assessed how variation in the values of each predictor relates to the propensity for biodiversity recording. This was performed by extracting partial dependence plots, which show the effect of a variable on the response after accounting for the average effects of all other variables in the model. For each species and variable combination, we extracted partial dependence plots from replicate models and calculated the mean response along with one standard deviation using custom-built R scripts.

3 | RESULTS

3.1 | Model performance

The predictive power of the models varied with the combination of different values of learning rate and tree complexity (Table 1). However, the best-performing models achieved strong to very strong Pearson correlation values between the predictions of species recording effort and the periods when the species were effectively recorded (min average $r=0.55$ and max average $r=0.91$).

3.2 | Predictors of recording effort

Across species, three variables emerged as the most important predictors of timing of recording: 'weekday' (median average relative importance = 28.5%), 'month' (25.9%) and 'temperature of the day' (18.3%) (Figure 1). Notably, depending on the species, there is also some interchange in the ranking of these variables. Following these three main predictors are 'precipitation' and 'wind speed', with lower but still relevant contributions (median average importance = 13% and 8.7%, respectively). On the other hand, the 'holiday' predictor achieved negligible to low importance across species (median

TABLE 1 Results of Boyce index for boosted regression models using distinct combinations of learning rate (Lrate) and tree complexity (TC).

Lrate	0.001	0.001	0.0005	0.0005	0.0001	0.0001
TC	3	6	3	6	3	6
Pinus halepensis	0.81 (±0.13)	**0.84 (±0.08)**	0.67 (±0.27)	0.80 (±0.14)	0.63 (±0.33)	0.49 (±0.33)
Pinus pinaster	0.32 (±0.32)	0.41 (±0.36)	0.05 (±0.22)	0.48 (±0.37)	**0.55 (±0.33)**	0.37 (±0.36)
Pinus pinea	0.63 (±0.16)	0.55 (±0.34)	**0.71 (±0.12)**	0.53 (±0.28)	0.62 (±0.21)	0.40 (±0.30)
Pinus sylvestris	**0.71 (±0.21)**	0.53 (±0.30)	0.59 (±0.21)	0.57 (±0.16)	0.40 (±0.31)	0.60 (±0.16)
Quercus rotundifolia	**0.91 (±0.06)**	0.86 (±0.14)	0.90 (±0.04)	0.87 (±0.22)	0.57 (±0.31)	0.77 (±0.15)
Quercus suber	0.81 (±0.13)	**0.84 (±0.08)**	0.67 (±0.27)	0.80 (±0.14)	0.63 (±0.33)	0.49 (±0.33)

Note: Values represent the mean (± standard deviation) across 10 replicate models, each trained on a distinct subset of pseudo-absence records. Boyce index values correspond to Pearson correlation coefficient between predicted probabilities of species recording and the frequency of species records effectively made. Values range from −1 to 1, with higher positive values indicating better model performance. Best performing models for each combination are shown in bold.

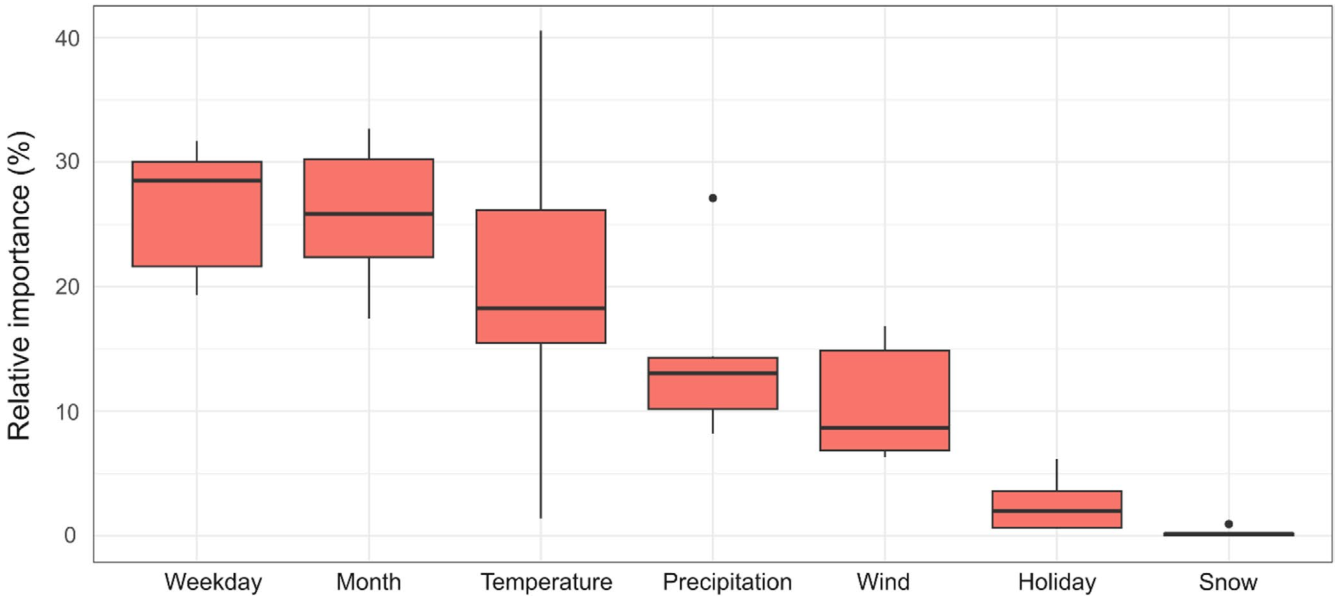

FIGURE 1 Relative importance of variables used for predicting the timing of recording of benchmark taxa. Boxplots represent the distribution of mean relative importance values across species, derived from 10 replicate models. Each replicate model was generated using a unique subset of pseudo-absences. Higher relative importance values indicate a greater contribution of the variable to distinguishing the observed timing of benchmark taxon records from random expectations over time.

average value = 2%; maximum = 6.2%), while 'snow depth' showed consistently negligible importance (maximum <1%).

Partial dependence plots describe the form of the relationship between the predicted probability of species recording and predictor values (Figure 2). For 'weekdays', there is a consistent pattern of higher predicted probabilities of species recording on Saturdays and Sundays compared with weekdays. Additionally, there is also a noticeably higher predicted probability of species recording on Fridays compared with the remaining non-weekend days.

For the 'months' variable, the responses are more varied, with only 2 months, April and May, consistently showing a higher predicted probability of species recording. For the two *Quercus* species, there was no evidence of higher recording activity in the autumn months, when acorns are produced (Figure S1). Concerning 'temperature', distinct general trends can be observed (Figure 2). For most species, moderate to sharp increases in recording activity are associated with rising temperatures at the lower end of the temperature gradient but decrease steeply at higher temperatures. Exceptions to this pattern are observed for *P. pinea* and *P. sylvestris*. In the case of *P. pinea*, there is no consistent increase in recording activity at moderate compared with low temperatures, but predictions of recording activity decline sharply at higher temperatures. Conversely, *P. sylvestris* displays a consistent positive relationship between temperature and recording activity across the entire temperature gradient.

For 'precipitation', there is a largely consistent negative relationship, with increasing accumulated precipitation values associated

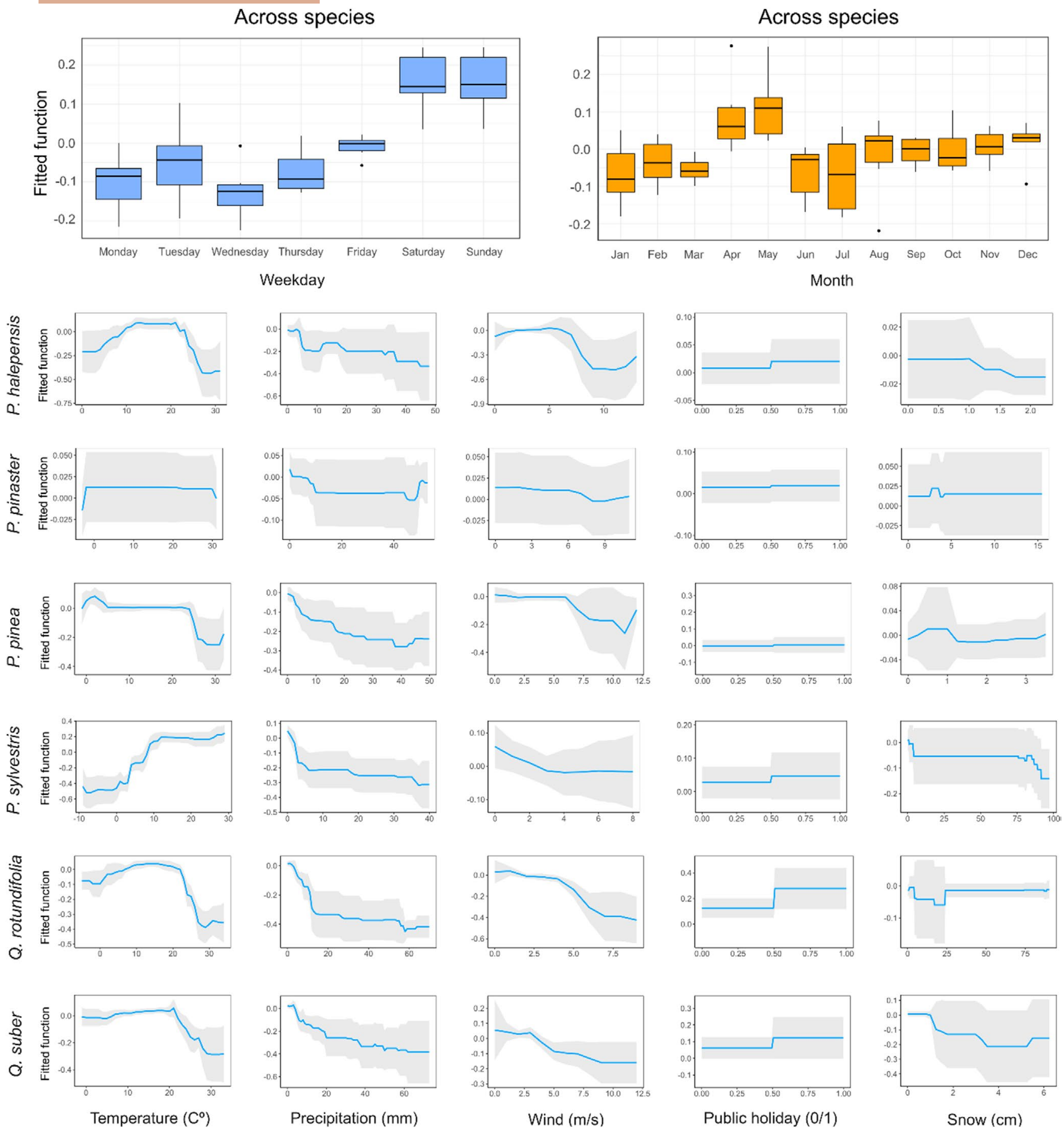

FIGURE 2 Partial dependence plots of variables used to predict the recording of benchmark taxa by citizen scientists. These plots illustrate the relationship between species recording and each predictor variable, with all other variables held at their mean values. Higher values on the *y*-axis indicate a greater predicted probability of species recording. The top two panels show the predictors 'Weekday' and 'Month', with shared *x*-axes, showing variations in average fitted values across the six benchmark species. These averages are based on 10 replicate models, each using a distinct subset of pseudo-absences. The lower panels show the relationships for the remaining predictors. Blue lines represent the average fitted relationships, while shaded areas indicate one standard deviation around the mean for each species.

with lower recording probability. The same general negative relationship is consistently found for wind speed. The variables 'public holidays' and 'accumulated snow' showed low to negligible relative importance across species, and their response plots should be interpreted with caution. Nevertheless, a generally positive relationship with public holidays and a negative relationship with snow accumulation are still evident, with the former consistent across all species and the latter observed for most species.

4 | DISCUSSION

In this study, we analysed the temporal patterns of citizen science recordings for a set of species with minimal phenological changes throughout the year. Using nearly 14,000 citizen science observations of these benchmark taxa across the Iberian Peninsula, we identified the day of the week, month of the year and mean daily temperature as the most important predictors of recording activity levels in our models. Accumulated precipitation and mean wind intensity also emerged as relevant, albeit with slightly lower relative importance. These findings offer novel and deeper insights into the temporal factors driving citizen science recording activity.

Weekday was identified as the most relevant predictor across species, with Saturdays and Sundays (and to a lesser extent, Fridays) having higher levels of recording activity. This 'weekend effect' has been previously identified, particularly in studies focused on birds (Fraser, 1997; Sparks et al., 2008; Surmacki, 2005). Our findings can be easily explained by the greater availability of people to engage in citizen science activities, as most do not work on weekends (Perry-Jenkins & Gerstel, 2020). Weekends serve a crucial social function by providing shared leisure time for families or groups of adults (Bryce, 2021). Activities such as BioBlitzes exemplify how weekends facilitate collective engagement in outdoor and educational activities while promoting a higher number of records on these days (Di Cecco et al., 2021). These events are typically organised to record as many species as possible within a specific period and are usually held on weekends to ensure greater community participation (e.g. Meeus et al., 2023; Tiago, Evaristo, & Pinto, 2024).

The time of year also had a relevant association with levels of recording activity, with a notable increase during April and May. This pattern aligns with findings by Di Cecco et al. (2021), who observed similar trends in global iNaturalist record submission data. These months correspond to spring in the study area, marking the end of the colder season, likely encouraging people to engage in outdoor activities (Tucker & Gilliland, 2007). Spring is also particularly attractive for observing certain taxonomic groups or particular phenological events, such as the arrival of migratory birds (Greenwood, 2007), plants in bloom, or the emergence of insects (Daru et al., 2018). Although the species in our data are not subject to these seasonal fluctuations, it is likely that observers going out to observe more attractive species during these months will also record other species. This behaviour, particularly among pan-listers or generalist recorders who aim to document a wide variety of taxa, could contribute to the observed temporal patterns in recording activity. However, insights into individual motivations and recording behaviours would be needed to assess the contribution of this factor. In addition to this, organised special events, often held in the spring, such as Fascination of Plants Day (https://plantday18may.org/), the Spanish Flora Biomarathon (López-Guillén et al., 2024), the Portuguese Flora Bioblitz (Chozas et al., 2023), Invasive Species Week, and BioBlitzes, may also influence recording activity (Márquez-Corro et al., 2021; Tiago, Evaristo, & Pinto, 2024).

Temperature was also identified as a main predictor of recording activity levels, with its relative importance across species only slightly lower than that of the variables 'weekday' and 'time of year'. We found that days with extremely low or high temperatures had a lower probability of recording for most of our benchmark species. These results are consistent with previous studies indicating that extreme temperatures affect human outdoor activity patterns (Chen & Ng, 2012). During very hot or very cold periods, citizens are less likely to engage in outdoor activities, such as wildlife observation and recording. One notable exception was found for *P. sylvestris*, where a monotonic positive relationship was found between daily temperatures and recording levels. This likely results from this species being mainly found in mountainous areas of the Iberian Peninsula (Earle, 2018), places where warmer temperatures should favour visitation.

Accumulated precipitation and wind intensity were also relevant predictors of recording activity, though their relative influence was lower than that of temperature. Increases in the values of both variables were associated with a reduction in species records. These results align with expectations based on studies of people's predisposition for outdoor activities. Precipitation is widely regarded as the most adverse condition for outdoor activities (Steiger et al., 2016; Wagner et al., 2019), and although wind is less frequently mentioned, it can still impact people's perception of temperature and increase discomfort, particularly at lower temperatures (Andrade et al., 2011). There are cases where extreme weather conditions can be attractive to naturalists, such as experienced birdwatchers seeking rare species brought by storms (Tryjanowski et al., 2023). However, this behaviour does not apply to most cases, especially for the benchmark taxa we assessed, which are specifically used to evaluate citizen scientists' responses to factors external to the recorded phenomena.

The other meteorological variable considered, snow depth, had a negligible influence in predicting the recording patterns of species. This is likely because snow cover in the Iberian Peninsula is relatively limited in both spatial extent and temporal duration, thus reducing its potential impact on recording activities. In other locations, such as Northern Europe, where snow covers large regions for extended periods of the year, this factor could have a relevant and more pronounced effect. However, snow depth has been previously identified as having no significant influence on outdoor activities except for very specific cases that require snow, such as skiing or ice skating (Spinney & Millward, 2011).

It is somewhat surprising that public holidays showed little to no relevance in predicting the recording activity of most species studied, considering that the reasons justifying higher recordings on weekends could also apply to holidays. Similarly, Knape et al. (2022) observed a weekend effect but found that holidays influenced only bird recordings, with no such effect for insects, fungi or plants. These authors examined five taxonomic groups using data from the Swedish Species Observation System (Artportalen; https://www.artportalen.se/) to understand the effects of temporal patterns, such as seasons, weekdays and holidays. They found that only bird records increased during holidays, attributing this difference to a larger sample size for bird data or different observer communities. For instance, if most bird observers are retirees, the weekday effect diminishes, whereas if they are professionals recording as part of their work during the week, the effect is more pronounced. In our case, it is unlikely that the observers belong to different communities since all species are plants, specifically from the genera *Quercus* and *Pinus*. Another possibility is that holidays are often spent with family or friends and involve specific rituals, such as Christmas, Easter, Saints' festivals or Carnival (Santos et al., 2023; Vihalemm & Harro-Loit, 2019), leaving little time for activities like biodiversity recording. Díaz-Calafat et al. (2024) found a negative relationship between the number of observations and holidays, particularly during the winter. These authors suggested the possibility of a confounding effect between holidays and insect activity. This does not apply to our study, as we worked with species that maintain a constant level of attractiveness throughout the year.

Our findings have important implications for initiatives where the temporal dynamics of citizen science recording are relevant. While uneven recording patterns over time are well documented (e.g., Johnston et al., 2023), our results extend this understanding by identifying a comprehensive set of factors, such as weekdays, months and meteorological conditions associated with variations in levels of observation effort. These insights can help improve the reliability and utility of citizen science data. For example, in analyses of seasonal phenomena, these patterns can be included as covariates in models or addressed using methods like inverse probability weighting (Mansournia & Altman, 2016) to reduce bias. This approach is applicable to studies of diverse phenomena, including phenology (Capinha et al., 2024; Mora et al., 2024), road mortality (e.g. Valerio et al., 2021), or habitat use (e.g. Deshwal et al., 2021). Monitoring programmes relying on opportunistic contributions, such as those tracking conservation-relevant (e.g. García et al., 2021) or harmful species (e.g. Howard et al., 2022; Pernat et al., 2021) can also benefit. By identifying periods of predictably lower recording activity, these programmes can implement targeted strategies, such as organizing campaigns, supplementing data with formal surveys, or incentivizing participation during underrepresented periods. These efforts can improve temporal data coverage and strengthen the value of citizen science for ecological research and monitoring. Based on data from the Iberian Peninsula, our findings likely reflect the recording patterns observed in other temperate regions of the world. However, future research should extend to regions with distinct climatic conditions to deepen and broaden our understanding of the timing of citizen science activity. Furthermore, analysing temporal patterns of recording across varying spatial contexts could shed light on how factors like urbanization and the presence of protected areas influence the dynamics of citizen science efforts. For example, in urban areas, recording activities might be less dependent on weekdays. Cities, which maintain a high level of activity during the workweek, may experience increased incidental recording due to higher human presence, potentially mitigating the typical 'weekend effect' associated with leisure time. While our findings provide a robust foundation, additional studies across diverse spatial and environmental contexts would significantly enhance our understanding of the dynamics of biodiversity recording by citizen scientists.

5 | CONCLUSION

Citizen scientists have become an invaluable source of data for ecology and conservation efforts. However, to harness the full potential of these data, it is crucial to acknowledge their inherent challenges, including non-random temporal patterns in recording activity. In our study, we found that the levels of recording activity by citizen scientists are higher on weekends, on days with milder temperatures, with little or no precipitation and wind, and predominantly in the spring. Addressing these patterns (e.g. through robust statistical methods or targeted recording campaigns during underrepresented periods) can improve data coverage and representativeness, thereby enhancing the value of citizen science for both applied and research purposes. As citizen science continues to grow, understanding and mitigating temporal biases will be essential for maximizing its contribution to ecological research and conservation.

AUTHOR CONTRIBUTIONS

César Capinha conceived the idea with input from all other authors, performed the analyses, and contributed to the writing of the manuscript. Patrícia Tiago collected the data and contributed to the writing of the manuscript. Inês T. Rosário and Sergio Chozas contributed to the writing of the manuscript.

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CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflict of interest.

DATA AVAILABILITY STATEMENT

Data and R code are available in Zenodo: https://zenodo.org/records/14845809.

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SUPPORTING INFORMATION

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

Figure S1: Partial dependence plots of 'Month' variable used to predict the recording of *Quercus suber* (a) and *Quercus rotundifolia* (b) by citizen scientists. These plots illustrate the relationship between species recording the month predictor variable, with all other variables held at their mean values. Higher values on the *y*-axis indicate a greater predicted probability of species recording.

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