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A global tour of iNaturalist mammal data: status, trends, and outlook for macroecology and conservation

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Abstract

iNaturalist data are growing rapidly, and researchers are increasingly interested in their utility for ecology and conservation. Yet because iNaturalist data are collected opportunistically, they have taxonomic and geographic unevenness that researchers should be aware of. Here, we describe the taxonomic, geographic, and temporal patterns in the global iNaturalist mammal data; evaluate whether residents or visitors contribute more observations; and illustrate the potential utility and pitfalls for IUCN Endangered or Data-Deficient mammals. As of early 2025, there were 5.29 million observations of mammals on iNaturalist, with >10 K observations from most orders. Larger species were more likely to be observed across the globe, but effects from other species traits on observations varied across countries. Observations of smaller species also tended to be identified by the community less frequently, highlighting a need for additional engagement by taxonomic experts. Geographically, over 20% of the data are from within North America, but observation rates are growing in all countries. Some of this growth is likely driven by tourism, as we estimated that visitors contribute the majority of observations for 63% of countries. iNaturalist data now vastly outnumber museum records for Data-Deficient species and could improve knowledge about species distributions. We pass along several lessons we learned from working with this dataset, including best practices for quality control related to the taxonomic and positional uncertainty of observations. We also highlight 3 key ways in which the utility of iNaturalist can continue to grow for mammals: (i) more observations, particularly for small species and in places with few observations; (ii) more identifications of existing observations by local and non-local experts; and (iii) development of robust methods to estimate (relative) abundance, which could be used for trend analyses. Ultimately, we hope to inspire additional engagement with iNaturalist, both on the platform and within the research community.

Keywords biodiversity, citizen science, community science, conservation, crowdsourced data, data deficient, IUCN

Un recorrido global por los datos de mamíferos de iNaturalist: estado, tendencias y perspectivas para la macroecología y la conservación

Resumen

Los datos de iNaturalist están creciendo rápidamente y los investigadores están cada vez más interesados en su utilidad para la ecología y la conservación. Sin embargo, debido a que los datos de iNaturalist se recopilan de manera oportunista, presentan desigualdades taxonómicas y geográficas de las que los investigadores deben ser conscientes. Aquí describimos los patrones taxonómicos, geográficos y temporales de los datos globales de mamíferos en iNaturalist; evaluamos si los residentes o los visitantes aportan más observaciones; e ilustramos el potencial y las limitaciones para los mamíferos clasificados por la IUCN como En Peligro o con Datos Insuficientes. A principios de 2025 había 5.29 millones de observaciones de mamíferos en iNaturalist, con más de 10000 observaciones en la mayoría de los órdenes. Las especies de mayor tamaño tenían más probabilidades de ser observadas en todo el mundo, pero los efectos de otros rasgos de las especies sobre las observaciones variaron entre países. Las observaciones de especies más pequeñas también tendieron a ser identificadas con menor frecuencia por la comunidad, lo que pone de manifiesto la necesidad de una mayor participación de

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expertos taxonómicos. En cuanto a la distribución geográfica, más del 20 % de los datos provienen de América del Norte, pero las tasas de observación están aumentando en todos los países. Parte de este crecimiento probablemente se debe al turismo, ya que estimamos que los visitantes aportan la mayoría de las observaciones en el 63 % de los países. Los datos de iNaturalist ahora superan ampliamente a los registros de museos para las especies con Datos Insuficientes y podrían mejorar el conocimiento sobre la distribución de las especies. Compartimos varias lecciones aprendidas al trabajar con este conjunto de datos, incluidas las mejores prácticas para el control de calidad relacionado con la incertidumbre taxonómica y posicional de las observaciones. También destacamos tres formas clave en que la utilidad de iNaturalist puede seguir creciendo para los mamíferos: 1) más observaciones, especialmente para especies pequeñas y en lugares con pocas observaciones; 2) más identificaciones de observaciones existentes por parte de expertos locales y no locales; y 3) el desarrollo de métodos sólidos para estimar la abundancia (relativa), que podrían utilizarse en análisis de tendencias. En última instancia, esperamos inspirar una mayor participación en iNaturalist, tanto en la plataforma como dentro de la comunidad investigadora.

Palabras clave biodiversidad, ciencia comunitaria, ciencia ciudadana, conservación, datos generados colectivamente, datos insuficientes, IUCN

Community science and crowdsourced biodiversity data are booming—there are now >2 billion bird observations of ~11 K species on eBird and >250 million observations of ~500 K species spanning the kingdoms of life on iNaturalist. Indeed, the number of observations in iNaturalist (hereafter: iNat) will likely soon surpass the number of specimens within the Smithsonian (Loarie 2024), despite iNat only becoming popular toward the end of the 2010s. Not only does iNat engage people with nature (Unger et al. 2021), the data are increasingly used by scientists to track changes in biodiversity (Callaghan et al. 2025; Mason et al. 2025). For example, iNat data have been used to map global species distributions (Heberling et al. 2021); document undescribed species (Mesaglio et al. 2021); track the spread of invasive species (Howard et al. 2022); and (combined with other data) document widespread declines in abundance (Forister et al. 2021).

Yet iNat data also have limitations. For one, the data are opportunistically collected, making it challenging to estimate effort as can be done in structured surveys. Thus, species that are more detectable tend to be reported at higher rates in iNat (Deitsch et al. 2024). Yet even once detected, observers must elect to report a species (i.e., it must pass through the observer's "engagement" filter; Stoudt et al. 2022), which is dependent on their interest in different species. Similarly, other iNat users must be able to identify the observation to species level in order for the observation to be classified as research grade (Campbell et al. 2023); although there is some concern that achieving research grade is too easy (a minimum of 1 other user agrees with the observer's species identification). Data on iNat also inherently reflect where and when humans engage with the platform, making some regions (e.g., the United States) and habitats (e.g., developed land cover) overrepresented in the data (Di Cecco et al. 2021; Herrera et al. 2025). Although iNat is now used globally, it is unclear how often residents are engaging with the platform compared with visitors (e.g., tourists or visiting researchers; Dimson and Gillespie 2023). Furthermore, the true location of some observations is obscured, either by observers (e.g., for location privacy) or automatically by iNat for species of conservation concern (Contreras-Díaz et al. 2023). Understanding how these processes shape the data available on iNat is a critical step for researchers interested in using these data (Goldstein et al. 2024).

Data on wild mammals on iNat could be particularly valuable for several reasons. First, mammals lack a more specialized community science platform similar to eBird (https://ebird.org/home), Herpmapper (https://www.herpmapper.org/), or Pl@ntnet (https://plantnet.org/en/; Gallagher et al. 2025). Second, although some small mammal species are difficult to detect and distinguish from similar-looking species, many larger species are readily photographed and identifiable (Kays et al. 2022), making them more likely to be classified as research grade. Third, although iNat mammal data are starting to be used globally, such as in Argentina (Aranguren et al. 2023), Ukraine (Melnychuk et al. 2024), and México (Cervantes and Rivas-Villegas 2024), we suspect that there are many more opportunities for these data to support research and conservation.

Here, we provide a global tour of the wild mammal data on iNat. We show which species are observed and identified, as well as how species traits predict the number of observations in each country. We describe spatial patterns in the data and analyze how social and biogeographic factors predict the number of observations. We then highlight temporal patterns in the data, including seasonality and variation in country-level rates of increase in iNat activity. Next, we quantify who makes the observations—either residents or visitors—to better understand to what extent locals are contributing to the data worldwide. Lastly, to consider how iNat data might support global mammal conservation, we highlight the availability of data on Endangered species and illustrate the potential utility of iNat for species classified as "Data Deficient" by the IUCN. Collectively, we aim to describe what data are available, build intuition about their utility, and inspire others to continue improving and using the data on iNat.

Methods

Data download and curation

In the first week of February 2025, we downloaded mammal observations from 1 January 1900 through 31 January 2025 using the export tool on iNaturalist.org. We batch-exported these data since each export was limited to 200,000 observations.

In preparing our iNat dataset for analyses, we undertook several data cleaning steps that may be useful for others. First, care is needed in the handling of species names. In iNat data, the *scientific_name* field reflects the community consensus identification at the time of data export, which can include designations both above and below species level designations (e.g., family or subspecies). In contrast, the *taxon_species_name* field reflects the latin binomial (*Genus species*, if identified to the species level or below) at the time of data export, which is what we used for our analyses. In order to ensure our dataset reflected wild mammals, we excluded records of domestic species (*n* species = 25; Supplementary Data SD1). These species can appear under different naming conventions; some were easily identified by the presence of the word "domestic" in the *common_name* field (e.g., Domestic Brown Rat), but others required closer inspection of the *taxon_species_name* field, where domestication status was not always explicit (e.g., *Rattus norvegicus f. domestica* and *Rattus norvegicus*). We also specifically removed records of domestic dogs (*Canis lupus* *familiaris*) but retained records of dingoes (*Canis lupus dingo*) given they are wild. Similarly, we identified 51 extinct taxa that needed to be excluded to avoid skewing our analyses focused on contemporary biodiversity (Supplementary Data SD2). We also removed observations recorded as *captive_cultivated*, as records from zoos or other artificial environments can bias occurrence data if not properly filtered. Finally, we manually adjusted the *taxon_species_name* field for 17 species to align the taxonomy with those used in trait databases, ensuring that species names and classifications were consistent across all observations (Supplementary Data SD3).

We assigned geographic information (i.e., country name) to each observation using the Natural Earth database (Natural Earth Data 2025) based on the reported *decimalLatitude* and *decimalLongitude* fields. Observations not initially matched to a country (e.g., just off the coastline) were reassigned based on the nearest country boundary within a 5 km buffer. For points still unmatched, we identified corresponding ocean regions where applicable. All unmatched points were labeled with either a country, an ocean name, or marked as "Unknown" if no match was possible. We also separated observations from French Guiana and France for analyses, even though the former is a territory of the latter.

For comparison to iNat data, we also downloaded all mammal records from museums within the Global Biodiversity Facility on 15 February 2025 (GBIF 2025). These data represent the collective digitized records of mammal voucher specimens (e.g., bones and skins) from the world's museums. We were interested in comparing these data to iNat because they are another important source of information on mammal occurrence records worldwide.

Which mammals are observed and identified on iNat?

We first performed descriptive analyses to summarize the taxonomic representation of observations and which species was observed the most in each country. We also summarized the *quality_grade* of observations, where observations can either be "research grade," "needs id," or "casual." Research-grade observations need to: (i) have a date; (ii) be georeferenced; (iii) have photos or sounds; (iv) be not captive or cultivated; and (v) have a species identification that more than two-thirds of identifiers agree upon. Needs id observations meet the criteria needed to be research grade, except consensus on a species-level id, while casual observations do not meet at least 1 of the first 4 criteria listed above. We summarized the proportion of each of these quality grades within each taxonomic order and calculated which orders and species were most and least identified.

In order to better understand how species traits influence representation in the dataset, we modeled observation counts at the country level. We excluded marine species but included terrestrial species not present in the dataset by generating a list of all possible species per country using the Mammal Diversity Database v2.0 (Mammal Diversity Database 2025). We used the COMBINE database for species traits (Soria et al. 2021), focusing on traits we thought would influence detection: body mass, temporal activity, foraging stratum, and trophic level. Although COMBINE imputes some of the non-geographic species trait data, the percentage of species with imputed data was relatively low for these traits (average = 10%, range = 6% to 16%). We excluded countries with <100 research-grade mammal observations and then fit 1 model per country because each country had a unique species pool. For each country, we fit a Poisson generalized linear model with species-level iNat counts as the response variable and (log) body mass, activity cycle, foraging stratum, and trophic-level category as predictor variables. We did not scale and center body mass because it was the only continuous variable, and we wanted to maintain biological interpretability. Each model was estimated via "glm" (., family = poisson(link = "log")) in base R. We checked model fit by examining dispersion statistics, which were generally close to 1, indicating that the Poisson distribution adequately fit these count data.

Where are the mammals of iNat?

To summarize the data spatially, we counted the number of observations in each country and calculated the percentage of mammalian diversity reported via iNat within each country relative to the number of species the country is known to contain. For the latter, we used the same MDD dataset mentioned above to know which mammal species are present in each country.

We performed a spatial analysis to better understand the factors that influence the number of observations across the world. We first overlaid a 100×100 km grid over all landmasses and summed the number of observations within each grid cell. We also calculated the proportion of protected area using the proportion of public land (Protected Planet 2025) and log-transformed human population density (CIESIN 2017) within each cell. Finally, we retained the name of the country that the cell overlapped. In cases where the cell overlapped multiple countries (i.e., international borders), we retained the name of the country that comprised the majority of the cell's overlapping area. We then performed a Poisson regression of the number of mammal observations per grid cell using the scaled population density, scaled proportion of protected land, an interaction between population density and protected land, and country as a factor. This analysis was performed in base R.

When are mammals observed on iNat?

We described seasonal and long-term trends in the number of observations over time. For seasonal trends, we split the data into northern, southern, and equatorial regions, with equatorial falling between 23.5 and –23.5 degrees. To estimate the growth rate of observations over time, we counted the number of observations within each country each year from 2008 (the launch year of iNat) to 2024, including all observations regardless of quality grade but excluding countries with <100 total observations. We then fit a univariate Poisson regression model to each country's time series, with the number of observations per year as the response variable and the number of years since 2008 as the covariate, and estimated the log-scale growth rate. We graphically validated that a log-scale growth rate—corresponding to a constant percent increase in observations each year—was appropriate for describing the rate of increase in most countries. We calculated the percent increase in each country (where 0 corresponds to no growth and 1 corresponds to a 100% annual increase, i.e., doubling each year) as (eβ^ –1) where $\hat{\beta}$ was the point estimate of the effect of year from the Poisson regression.

Who observes mammals on iNat?

Here, we were interested in whether residents or visitors contributed more observations on iNat. To do this, we estimated which country each observer resided in based on the assumption that citizen scientists tend to be more active closer to home (McGoff et al. 2017; Farias et al. 2022). Following Dimson and Gillespie (2023), we calculated for each country–observer combination the metric $h_c = 0.4(o_c) + 0.6(d_c)$, where o_c is the proportion of the observer's observations in country c and d_c is the proportion of an observer's unique days with observations in country c. This procedure resulted in a metric that ranged from 0 to 1, where scores closer to 1 indicated more concentrated activity in a country. We classified observers as residents of whichever country had the highest h_c. We then classified each observation as from a resident if the country matched the observer's country of residence and as a visitor otherwise. We calculated the percentage of observations from residents for each country, excluding countries with <100 observations and water bodies.

Endangered and data-deficient species

To better understand how useful iNat data are for species of conservation concern, we classified each observation according to its IUCN Red List rank (version 3.1; IUCN 2025), focusing on Endangered, Critically Endangered, Extinct in the Wild, and Data-Deficient species. We described these data, including how these classifications influence the positional accuracy of the observation's location.

We then took a closer look at the Data-Deficient species, which included a comparison of the available data within iNat and museums. For the museum data, we downloaded records of all preserved mammal specimens within the Global Biodiversity Information Facility on 15 February 2025 (GBIF 2025; https://www.gbif.org/occurrence/download/0001203-250214102907787). In addition to a sample size comparison, we performed a spatial analysis to quantify how often iNat observations extended the known range of a species. For each species, we generated a minimum convex polygon using just the museum records, then another using both the iNat and museum observations, and recorded whether the MCP with iNat data was larger. Lastly, we chose 11 species to investigate further, which included learning diagnostic features and evaluating how easy the species is to tell apart from other sympatric species. Each of these 11 species had more iNat observations than GBIF records, and we selected species that represented a variety of orders (Supplementary Data SD4).

Results

Which mammals are observed and identified on iNat?

We downloaded 5,293,425 observations of 3,410 species of wild mammals from iNat. Rodentia was the most common mammal order with 1.1 M observations, followed by Artiodactyla (953 K) and Carnivora (843 K) observations (Fig. 1A). We have made these data publicly available on Figshare here: https://figshare.com/s/3f42252a8f7473a3358a?file=57443704. Within each order, a single family was often the majority of observations, such as Sciuridae for rodents and Cervidae for Artiodactyla. We also recorded which species was observed the most in each country (Fig. 1B; Supplementary Data SD5), which was quite taxonomically diverse. For example, elephants were the most observed species in many countries in southern Africa, primates (e.g., Panamanian White-faced Capuchin; *Cebus imitator*) in many equatorial countries, and marine carnivores (e.g., South American Sea Lion; *Otaria flavescens*) in several countries with extensive coastlines.

We found that species traits partially explained the number of observations, but this varied across countries (we report all model estimates in Supplementary Data SD6). Across most countries, models explained on average ~55% of the deviance (range ≈ 30% to 76%), indicating moderate to strong explanatory power of species-level traits. However, only body size had a consistent relationship across countries, with larger species nearly always being more frequently reported (Fig. 2A). Other traits such as diet (Fig. 2B; Supplementary Data SD7), activity period (Supplementary Data SD7), and substrate use (Supplementary Data SD8) were much more variable across countries, suggesting local cultural differences in reporting or strong effects of local abundance, which we were not able to include in the model. Dispersion tests showed that most models were well within the expected range for Poisson variance, with only moderate overdispersion in some countries.

In terms of data quality, we found that 79% of observations were research grade, 15% were needs id, and 6% were casual. These ratios were relatively consistent across orders (Fig. 3A), although more than 90% of observations were research grade for some orders, e.g., colugos (*Dermoptera*) = 98%, while less than 50% of observations were research grade for others, e.g., bats (*Chiroptera*) = 46%. The average number of identifications per observation was 1.8, though elephants (*Proboscidea*) were an exception at 4.7 identifications/observation (Fig. 3B). The least identified orders included the most diverse orders—*Rodentia*, *Chiroptera*, and *Eulipotyphla*—which averaged 1.3 to 1.5 identifications/observation. The most identified species tended to be charismatic but exceedingly rare species (Fig. 3C), including the Colombian Weasel (*Neogale felipei*), Sumatran Rhino (*Dicerorhinus sumatrensis*), and Bay Cat (*Catopuma badia*), each of which had only 1 observation in the data. In contrast, the species with the least identifications (<0.14 per observation) were a mix of *Chiroptera*, *Rodentia*, and *Eulipotyphla* (Fig. 3D).

Where are the mammals of iNat?

Nearly half (2.4 M) of the observations were in North America, followed by Europe with 434 K, while Sub-Saharan Africa and Central America contributed 360 K and 226 K, respectively. Asia and South America had moderately high representation, with 166 K and 174 K observations. Oceania and Southeast Asia each had 200 K and 96 K observations, respectively. In contrast, the Caribbean (2.5 K), North Africa (8.1 K), and the Middle East (16 K) were among the least represented regions (Fig. 4A). There were also 225 K observations from small islands or water bodies. When comparing species represented in our dataset to the potential species richness within each country, we found that 43% of species were reported (on average; Fig. 4B), though country-specific percentages ranged from 92% (Switzerland) to 3% (Saint Vincent and the Grenadines).

What explains where mammals are observed?

Our gridded analysis of iNat observations suggested that human population density (β = 1.52, 95% CI = 1.52 to 1.52, SE = 0.0005) had a stronger effect than proportion of protected area (β = 0.44, 95% CI = 0.44 to 0.45, SE = 0.0006). While we found a statistically significant interaction between population density and protected area (β = 0.18, 95% CI = 0.18 to 0.18, SE = 0.0005), the mediated effect of the 2 variables was not as strong as either variable on its own. Country-level effects on mammal observations varied widely (Supplementary Data SD8). Although some countries were estimated to have negative effects on iNat observations (e.g., Nauru, Tokelau, Marshall Islands, etc.), all negative estimates were statistically insignificant. Cuba had the smallest statistically significant country-level effect (β = 1.99, 95% CI = 0.03 to 3.96), while the British territory of South Georgia/the South Sandwich Islands had the largest country-level effect (β = 8.38, 95% CI = 6.42 to 10.34). The mean country-level effect was 3.01, and was represented by countries such as Kazakhstan (β = 2.96, 95% CI = 1.00 to 4.92),

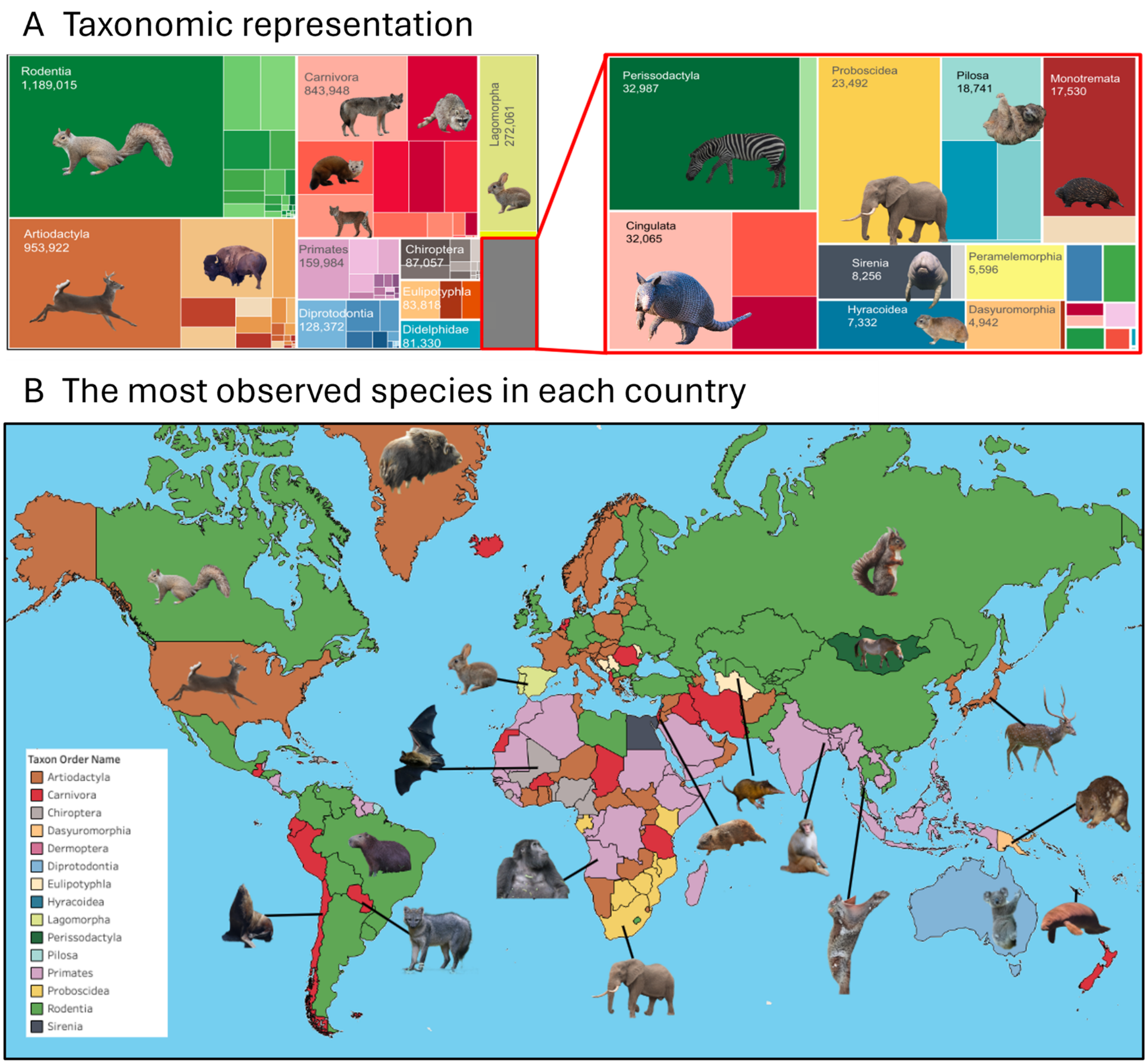

Fig. 1 Visuals showing the representation and diversity of mammal observations on iNat. A) Treemap of research-grade observations per order (colors, with counts) and family (shades, some with pictures). B) Map of the species most observed in each country, where each color represents a different order. Each order is represented by at least 1 species, although some orders are only represented by small countries, making them hard to see on the map (e.g., Dasyuromorphia, Hyracoidea). We list species names, counts, and photo credits in Supplementary Data SD14.

Barbados (β = 3.02, 95% CI = 1.05 to 4.98), and Anguilla (β = 3.04, 95% CI = 1.07 to 5.01). All country-level effects are available in Supplementary Data SD9.

When are mammals observed on iNat?

We found notable seasonal patterns in mammal observations. First, there were more observations in warmer months in both the northern and southern hemispheres (Fig. 5A). Second, there was a noticeable spike in late April in all regions, coinciding with the "City Nature Challenge," a friendly competition sponsored by the iNat platform. We also report fairly consistent growth rates across countries, with 90% of countries growing by 13% to 47% per year (Fig. 5B; Supplementary Data SD10). We highlight several of these countries in Fig. 5C, where a dip concurrent with the COVID-19 pandemic can be seen, despite variation in trends across countries.

Who observes mammals on iNat?

Across 749,177 unique observers and 182 countries, we estimated that 80% of the total observations were from residents and 20% were from visitors. Nearly all (97%) observers had the majority of their observations in a single country. Sixty-eight countries (37%) had more observations by residents, with the greatest percentages from Benin (97%), the United States (93%), and Russia (93%; Fig. 6). The median percentage of observations by residents was 35%, and the majority of countries where residents contributed <50% of observations were in Africa and Asia (Fig. 6).

Endangered and Data-Deficient species

There were 16,652 observations of 136 (out of 235) Critically Endangered species and 150,910 observations of 330 (out of 550) Endangered species. Likely due to the sheer volume of data, the most observations of

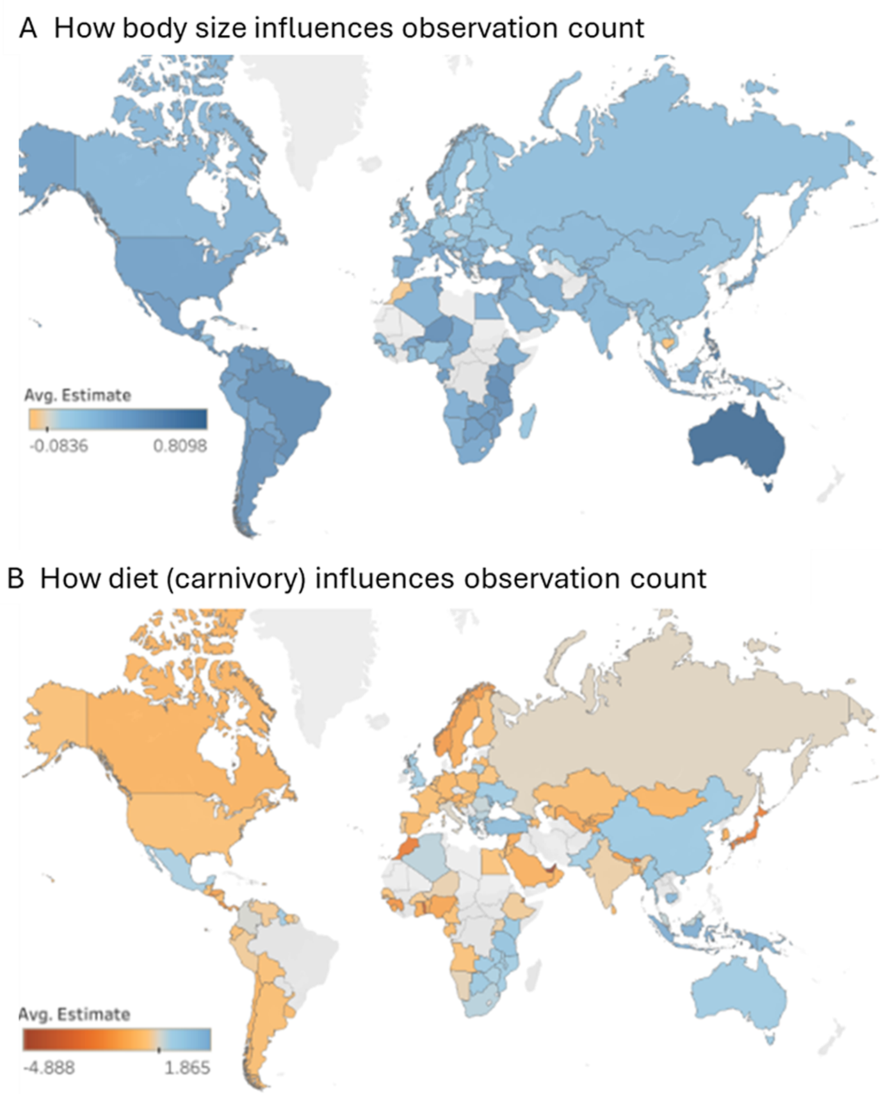

Fig. 2 Maps of the effect sizes of 2 traits on the number of mammal observations of a given species in each country. Gray countries had nonsignificant relationships with the trait. A) Larger species are usually more likely to be reported. B) The effect of a carnivorous diet on reporting varies greatly from country to country. Other diet, substrate, and activity period traits were also highly variable across countries (Supplementary Data SD7 and SD8).

Critically Endangered and Endangered species were in the United States (54 K), though there were also hotspots in western Europe and Southeast Asia (Supplementary Data SD11). There were also 73 observations of an Extinct in the Wild species: the Chinese Milu (Père David's Deer; *Elaphurus davidianus*), which was reintroduced in China beginning in the mid-1980s (Cheng et al. 2021). Notably, the location of most (81%) observations within these 3 endangered categories has been obscured by iNat to protect the true location of the observations. These species make up a particularly high proportion of the observations in Central Africa and Southeast Asia, skewing the mean positional accuracy of observations in these places close to 30 km (Supplementary Data SD12).

There were 15,026 observations of 252 (out of 797) Data-Deficient mammal species on iNat, compared to 19,585 records of 222 Data-Deficient mammals in GBIF. Despite having a comparable number of total observations, they have very different temporal distributions (Supplementary Data SD13); iNat observations have substantially outnumbered museum records since the mid-2010s. Of the 19,585 GBIF records, 9,688 (49%) had valid coordinates. We found that iNat observations extended the area apparently occupied in 83.2% of cases (example in Fig. 7A). However, when we investigated 15 of these species in detail, we found variation in the utility of the data for learning more about the species. iNat data were particularly useful in some cases, including the Karoo Rock Sengi (*Elephantulus pilicaudus*) and the Black Flying Squirrel (*Aeromys tephromelas*; Fig. 7A). Both of these species are identifiable from photographs; they had more iNat observations than museum records, and the iNat observations substantially expanded their range. We also discovered that there were several species that were often too difficult to tell apart from sympatric species using typical observation photos. For example, Bang's Mountain Squirrel (Fig. 7B) is a Data-Deficient species in Central America that looks very similar to the more common Central American Dwarf Squirrel (IUCN status: Least Concern; Fig. 7B).

Discussion

As of early 2025, there were over 5 million observations of mammals on iNat, with around 1,800 new observations added every day.

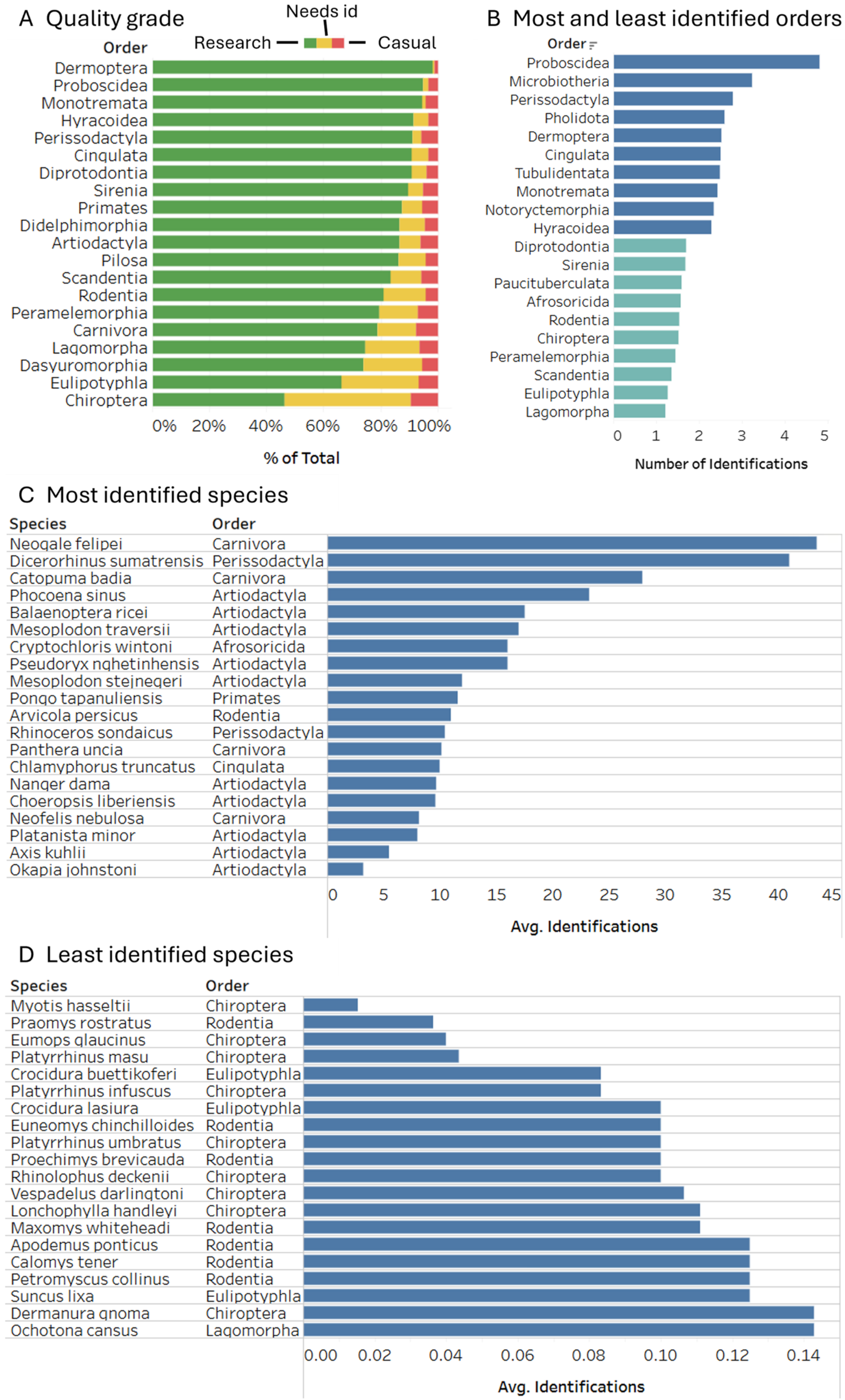

Fig. 3 Summaries and counts related to quality grade and the number of identifications of mammals on iNat. A) Proportion of observations by quality grade for the 20 orders with the most observations. B) The 10 most and 10 least identified orders within the data. C) The average number of identifications for the top 20 most-identified species. D) The average number of identifications for the top 20 least-identified species, excluding species with 0 identifications.

Although some orders are better represented than others, 69% of all mammal species are present within the dataset. These data are fairly well distributed across the world, and the number of observations within most countries was growing by 20% to 40% every year. We show that this global growth is primarily driven by residents for countries containing the bulk of observations and by visitors for most countries with relatively few observations. We also show that there are data on hundreds of Endangered or Data-Deficient mammal species, but researchers should be cautious when using these data because many locations are obscured, and some species

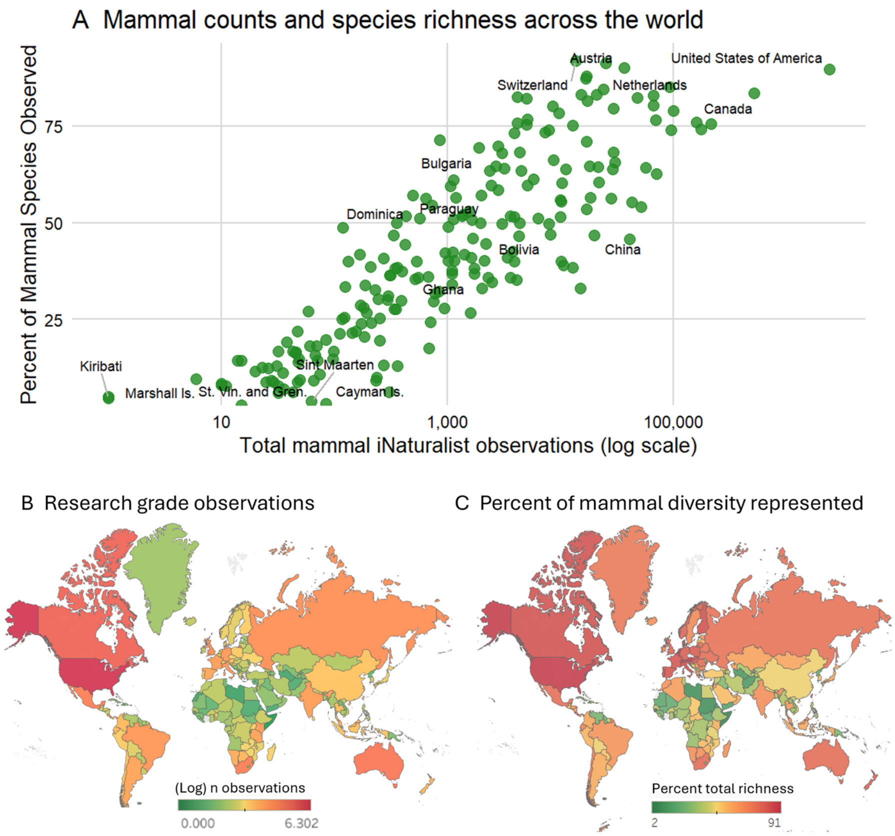

Fig. 4 How iNat mammal observations are distributed across the world. A) A scatterplot showing the log number of research-grade observations and mammal species richness in each country, based on the mammal diversity database. B) and C) show maps of each of these data.

identifications might be wrong. We encourage more people around the globe to observe and help identify mammals on iNat so that this amazing platform can continue supporting research and conservation.

Which mammals are observed and identified on iNat?

Taxonomic biases are inevitable within opportunistically collected datasets, and it is important that users are aware of these. We found a positive relationship between body size and mammal observations in nearly every country, suggesting that this is a nearly universal species trait that shapes which species are observed on iNat (Forti and Szabo 2025). Indeed, more data on larger animals are a well-known bias in research, including birds within iNat (Callaghan et al. 2021), biodiversity databases (Troudet et al. 2017), and camera trap data (Burton et al. 2015). Yet, other traits (diet, activity period, and substrate use) had much more variable relationships with observation rates across countries. For example, carnivores were observed more often in southeastern Africa and southeast Asia, while herbivores were observed more often in western Europe and Central America. Likewise, while diurnality had a positive relationship with the number of observations in most countries, it had a negative association in most of Europe and some of South America. The spatial variability that we found for some traits could have at least 2 explanations. First, it could simply reflect variation in other unmodeled traits that affect detectability and likelihood to report. For example, carnivores in southeastern Africa are generally more conspicuous, more charismatic, and often targeted by tourists on safari compared to carnivores in western Europe. Similarly, mismatches between expected activity time and actual activity times (Forti and Szabo 2025) could result in regional variation in the species-level traits. Second, this variability could also reflect local underlying patterns of abundance. The trend for nocturnal species to be more reported in southern South America (Supplementary Data SD7) might not be related to human behavior but be the result of high regional abundance of coypu, a large nocturnal rodent that is among the top 5 most reported mammal species for Argentina, Chile, and Paraguay.

Given the variation in reporting rates among species, iNat users may falsely omit or overrepresent select taxa, impacting the inference that can be drawn from those data regarding regional species richness (Goldstein and Stoudt 2025). On average, we found that iNat observations reflected only 43% of the mammal species that are known to persist in a country. Prior research has shown that iNat observations tend to better represent the local species pool in areas with high survey effort and relatively low species richness (Jacobs and Zipf 2017; Herrera et al. 2025). Indeed, our analysis found that iNat records best reflected the known species pool in the United States and Canada, which both have a substantial number of iNat observations and have relatively low species richness compared to other countries (Fig. 1B; Ceballos and Ehrlich 2006). Although iNat data may not accurately capture the entire species pool, other studies have found that species richness derived from iNat data can be comparable to richness data derived from alternative sampling methods (Périquet et al. 2018; Herrera et al. 2025). Thus, provided there are sufficient data, iNat data can offer a proxy for species richness and can inform conservation efforts that seek to protect regions of high biodiversity.

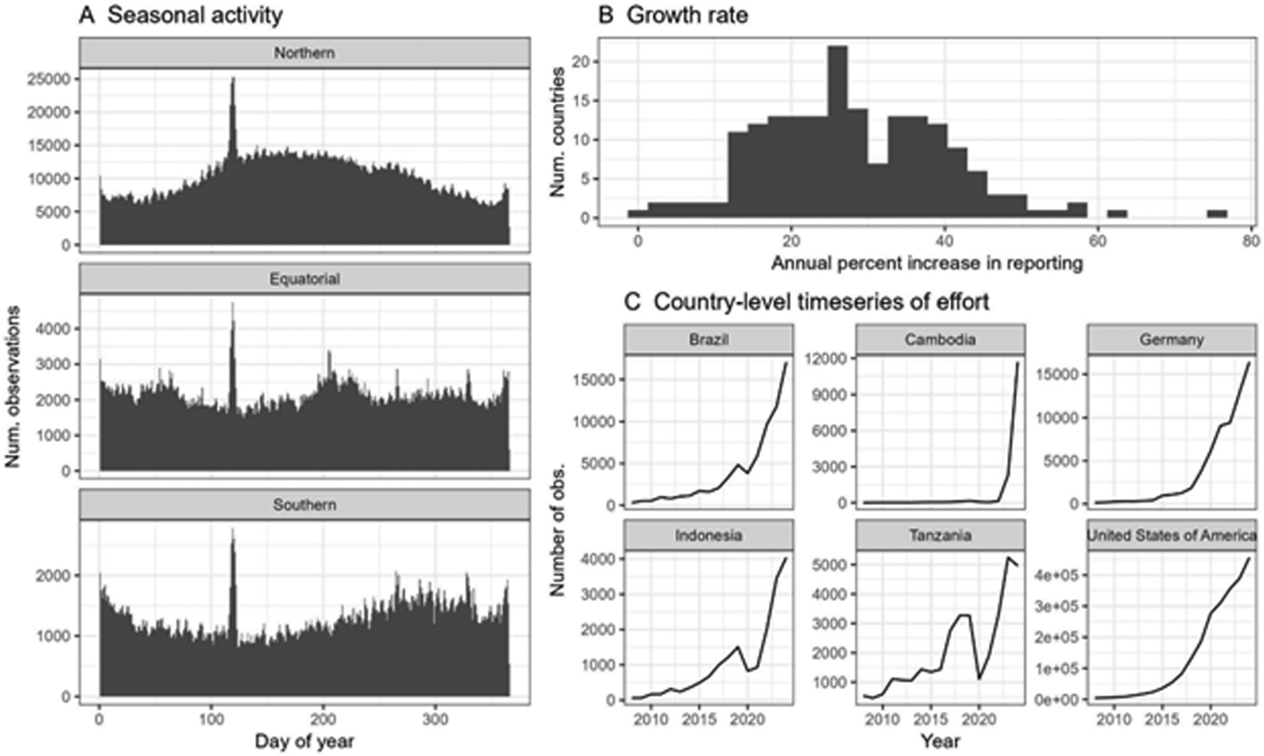

Fig. 5 Temporal patterns in mammal observations on iNat. A) Annual patterns grouped into latitudinal bands (with equatorial ranging from –23.5 to 23.5 decimal latitude). The background trend of observations in the northern band peaks in May to June, while observations in the southern latitudes peak in October to November. In all regions, activity spikes dramatically in mid-April during iNat's City Nature Challenge. The overall volume of observations is much higher in the northern latitude band than the equatorial or southern bands. B) The pace of annual growth varies by country, with most increasing their annual rate of mammal observations by 15% to 40% each year. C) Time series showing the growth trajectories of mammal observations in 6 select countries, where a dip concurrent with the COVID-19 pandemic is evident for several of the countries.

When and where are mammal observations on iNat?

Our spatial and temporal analyses highlight the growing global volume of this dataset for mammals. Forty-seven countries outside of North America had >10 K observations, including countries in South America, southern Africa, Asia, and Europe (*sensu* Di Cecco et al. 2021). Not surprisingly, human population, protected area, and geographic area were positively associated with the number of observations, although we also found wide variability in how strong these effects were. This variation suggests that other factors also explain the number of observations within countries, including internet access, GDP, or tourism (Sullivan et al. 2014). While fully exploring these factors was beyond the scope of this paper, our temporal trend analysis suggests that tourism may be strongly contributing to the relatively consistent rate of growth across countries, especially in places with relatively few observations (e.g., Central Africa, the Middle East). The rates of growth also underscore how new iNat is—only 8% of observations are from prior to 2015. This pattern means that other types of data are better suited for asking questions related to long-term trends (e.g., museum specimens; Suarez and Tsutsui 2004).

Our findings underscore an urgent need for more iNat engagement in areas with little data. Indeed, iNat data suffer from the same sampling bias toward the global north as biodiversity data more broadly (Guerrero-Casado and Monge-Nájera 2021; Hughes et al. 2021), despite the tropics generally containing greater biodiversity (Alves et al. 2018; Pillay et al. 2022). Moreover, there is increasing recognition that biodiversity data are shaped by socioeconomic factors, including income, war, and colonialism—with important implications for where conservation dollars get spent (Chapman et al. 2024). iNat (and other community science platforms) are well-positioned to close these gaps because they require little to no monetary or logistical investment from governments and institutions.

Best practices for working with iNat data

We learned several lessons while working with these data, which we think are valuable to pass on to other potential users. First, the scientific name assigned to a given observation can change over time. Names can change if identifiers disagree with the current identification (particularly for more recent observations) or there has been an update to current taxonomic understanding (Loarie 2019). Regardless, this dynamism means that the metadata associated with the same observations can change if downloaded at different times, and care is needed when integrating these data with other databases (Feng et al. 2022). Second, users interested in fine-scale analyses should know that the positional uncertainty for some observations can be quite high. If the observation is "obscured," then the coordinates provided (the *public_positional_accuracy*) represent a random location within a ~30 km × ~30 km cell containing the true location. This concern means that obscured observations should not be used for fine-scale analyses, which could be particularly limiting for species of conservation concern because their observations are usually automatically obscured by iNat. Although automatic obscuration is well-intentioned, this practice may actually hinder the conservation of some species if

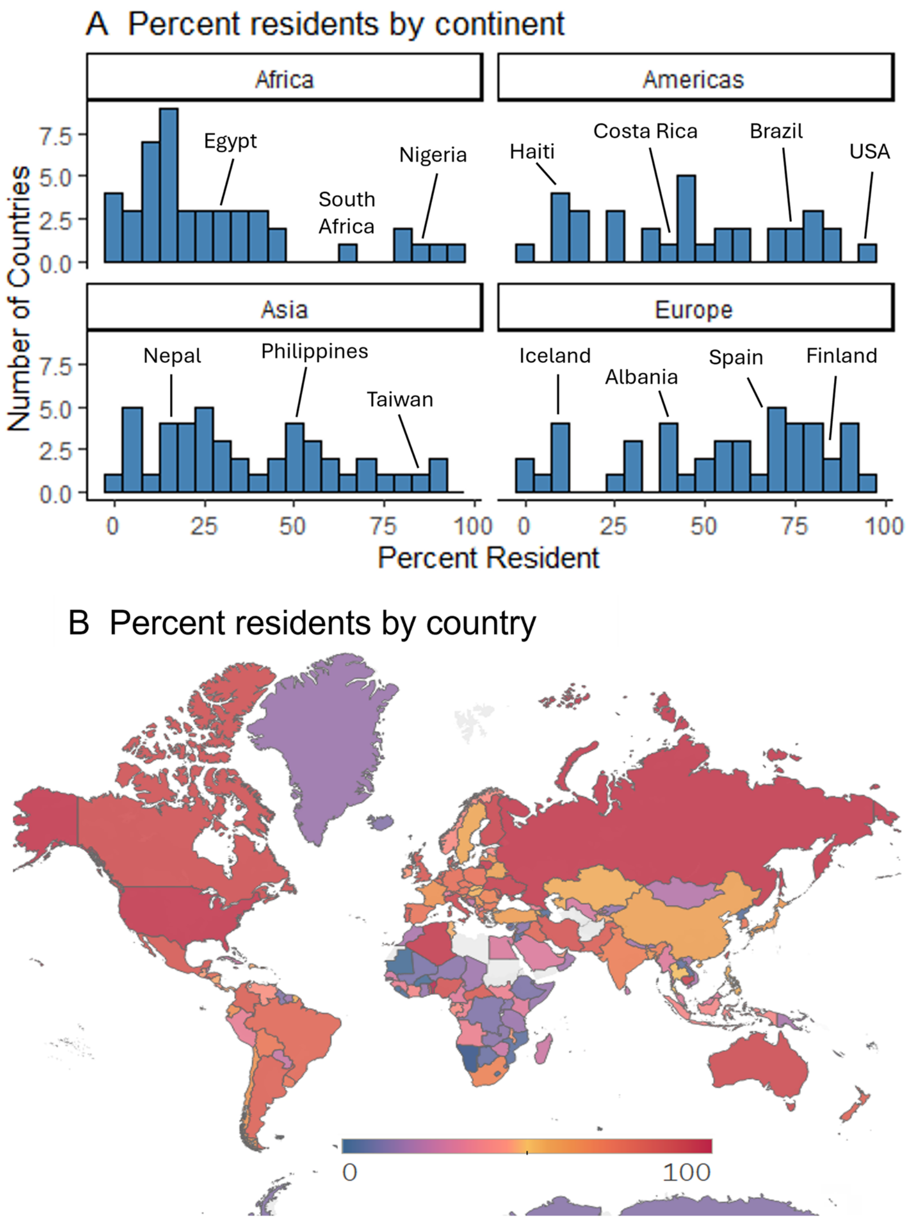

Fig. 6 The percentage of mammal observations on iNat that we estimate to be from residents of each country. A) Histograms showing the fraction of observations by residents in countries across each major continent. We excluded Oceania and Antarctica because they each had small sample sizes. B) A map of the percent of observations estimated to be from residents of each country. We excluded countries with <100 observations in both A and B (colored gray).

credible researchers cannot access the true locations (Baranzelli et al. 2023; Contreras-Díaz et al. 2023).

Third, users should be cautious about species misidentifications, particularly with sympatric species that look very similar. Indeed, we found widespread potential misidentifications for several Data-Deficient species, where observations were identified as our focal species, but they should likely have been identified at a higher taxonomic level based on the features that were distinguishable in the image. Recognizing which species can and cannot be distinguished in photographs, and how the distribution of similar species overlaps with a given observation, can help improve identification accuracy. We found the "compare" feature on the iNat platform to be very helpful in showing distributions of taxonomically similar species. We also recommend more systematic assessments of which species can be identified from typical photographs, similar to what has been done for North American mammals (Kays et al. 2022).

There are also additional quality control steps that researchers can use depending on the scope of their questions. Although using research-grade observations is standard, researchers concerned by the ease with which observations can attain this status can use the *num_identification_agreements* and *num_identification_disagreements* columns to select observations that they trust more. If feasible, researchers may consider manually inspecting observations to remove species misidentifications or location errors (Jensen et al. 2025). For example, sometimes obscured observations can be placed on an island where the focal species is not known to occur, while the true location is somewhere nearby on the mainland. Researchers may also be interested in filtering based on evidence type, as the species

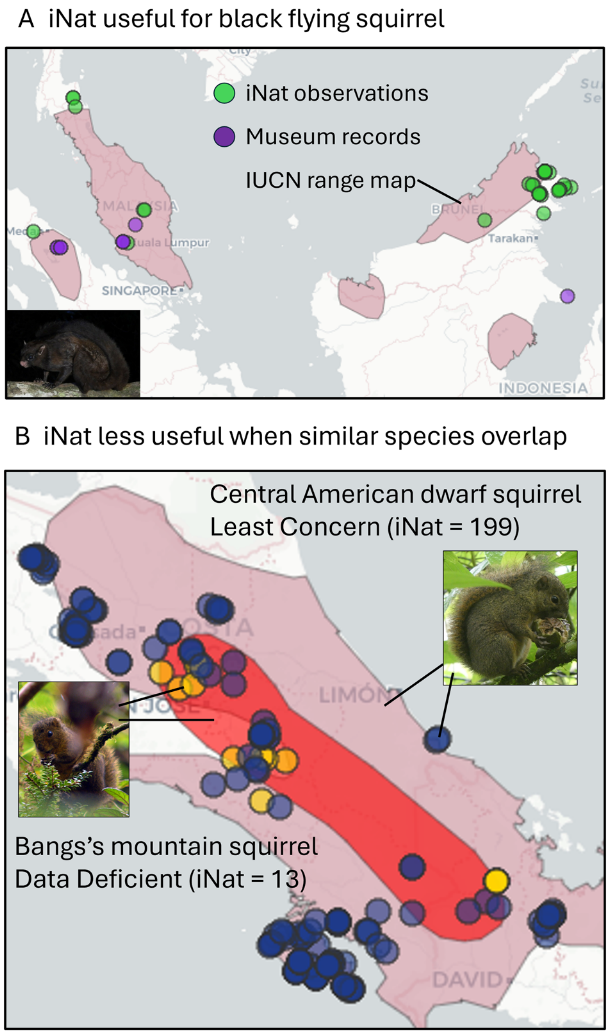

Fig. 7 Two contrasting examples of the utility of iNat data for Data-Deficient mammal species. A) The Black Flying Squirrel is an example of a Data-Deficient species with more iNat observations compared to museum records, including observations outside the IUCN range (in Northwest Malaysia). B) An example of 2 species in Central America, which are very hard to distinguish from photographs, raising questions as to the validity of the records.

identification of some types of observations (e.g., live animals, dead animals) may be more trustworthy than other types (e.g., tracks, scat; Morin et al. 2016; Spitzer et al. 2019). Fortunately, these observation metadata are now partially available via GBIF (Seltzer 2024) and a stand-alone computer vision model that some of the authors of this paper worked on (under review while this manuscript is in press). Lastly, researchers should be cognizant of the potential for individual animals (particularly charismatic species) to be repeatedly observed and consider spatially thinning observations.

A vision for the future of mammal science with iNat

Using iNat data to capture the relative abundance of mammals would make it even more valuable for conservation. The value of large-scale abundance measures derived from community science has been illustrated for hundreds of bird species by the seasonal abundance maps (Fink et al. 2010) and more recent population trend analysis (Fink et al. 2023) produced from eBird observations. Mammal records in iNat are still much less numerous than eBird observations, but early research suggests that they can represent relative abundance, at least for some species at some scales. Pease et al. (2022) used the total number of mammal records at a 50 km^2 scale as a measure of observer effort and found estimates of relative abundance for American Black Bear (*Ursus americanus*) across the United States aligned well with abundance measures from standardized camera trap surveys. This application presumes that, for a given species, the likelihood of iNat reporting compared to other mammals is consistent across the study area. More work is needed to evaluate this assumption at a global scale.

We have 3 recommendations for the global iNat community and researchers using these data. First, although iNat is growing—**we still need more data**! It is important to continue adding observations of mammals over time in areas that are already covered, but especially in the places with little data. Mammalogists should encourage iNat use by local students and citizens and contribute as much as possible when traveling to places with less iNat activity. We also need local and non-local experts to **help identify observations** on iNat (Campbell et al. 2023), particularly for small and less charismatic species. We found that the most diverse groups of mammals—bats and small rodents—which are often difficult to distinguish at the species level, are also the least likely to be identified by the community and thus become research grade. We call on taxonomic experts of these groups to explore the iNat database to help identify these observations (Callaghan et al. 2022). Species-level identifications are ideal because they help the observation rise to research grade, but assigning a genus and explaining why species level identification is not possible is also helpful. This type of discourse is generally appreciated by the iNat community that is keen to learn about obscure species. Lastly, we see potential to **estimate relative abundance** (and potentially population trends; Fink et al. 2023) for thousands of species at a global scale using iNat data, and would greatly increase the conservation utility of iNat and not just for mammals.

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Supplementary data

Supplementary data are available at *Journal of Mammalogy* online.

Supplementary Data SD1. List of domestic, feral, or anthropogenic species we excluded from the dataset, which are not representative of wild biodiversity.

Supplementary Data SD2. List of extinct species we excluded from the dataset.

Supplementary Data SD3. List of renamed species to ensure taxonomic consistency.

Supplementary Data SD4. Names and counts of the most observed species in each country or body of water.

Supplementary Data SD5. Beta coefficients for an analysis of traits with significant relationships that were associated with more observations in a particular country.

Supplementary Data SD6. Model estimates from our country-specific analyses of how traits influence reporting rates for mammals on iNaturalist.

Supplementary Data SD7. Beta coefficients for an analysis of traits with significant relationships that were associated with more observations per country.

Supplementary Data S8. Estimated effect of country on mammalian iNaturalist observations.

Supplementary Data SD9. Rates of growth of iNaturalist mammal data through time. We excluded countries with <100 observations (in gray).

Supplementary Data SD10. Number of Observations of Endangered and Critically Endangered mammal species on iNaturalist.

Supplementary Data SD11. Mean positional accuracy of observations in each country.

Supplementary Data SD12. Photo credits for images used in Fig. 1.

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Conflict of interest

None declared.

Data availability

We have made the cleaned version of our iNaturalist download available here: https://figshare.com/s/3f42252a8f7473a3358a

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